Universidad de Oviedo

Programa de Doctorado en Energía y Control de Procesos

Transacciones energéticas entre pares en redes de distribución de baja tensión

Doctorando:

Komal Khan

Gijón, Septiembre 2024

Universidad de Oviedo

Departamento de Ingeniería Eléctrica, Electrónica, de Comunicaciones y de Sistemas

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RESUMEN DEL CONTENIDO DE TESIS DOCTORAL

1.- Título de la Tesis	
Español/Otro Idioma: Transacciones energéticas entre pares en redes de distribución de baja tensión	Inglés: Peer-to-Peer Energy Transactions in Low Voltage Distribution Networks

2.- Autor	
Nombre: Komal Khan	
Programa de Doctorado: Energía y Control de Procesos	
Órgano responsable: Centro Internacional de Postgrado	

RESUMEN (en español)

El sector energético está experimentando una importante transformación impulsada por la integración de fuentes de energía renovables, la proliferación de vehículos eléctricos (VE) y la evolución de las demandas de las redes eléctricas modernas. Esta tesis explora estructuras de mercado innovadoras y estrategias de gestión de carga para abordar estos desafíos. Se centra en el desarrollo de mecanismos de comercio de energía local entre pares (P2P) que gestionen eficazmente la generación distribuida y la carga de vehículos eléctricos, empoderando a los prosumidores y consumidores para que participen activamente y proporcionen servicios auxiliares a la red.

La investigación presenta un marco de comercio de energía P2P que optimiza el bienestar social para los propietarios de vehículos eléctricos a través de un mecanismo de negociación de múltiples problemas y la gestión de la carga de vehículos eléctricos en tiempo real. También examina un modelo multiagente para el comercio de energía P2P, diseñado para maximizar los beneficios individuales a través de negociaciones compuestas concurrentes de uno a muchos. Además, el estudio explora el uso de las tecnologías blockchain y de contratos inteligentes para implementar sistemas automatizados de comercio de energía P2P.

Las contribuciones clave incluyen un protocolo de negociación de múltiples problemas para la carga de vehículos eléctricos en redes congestionadas y un marco multiagente para el comercio eficiente de energía P2P. La investigación demuestra reducciones significativas en la sobrecarga de la red y mejora la adaptabilidad de los programas de carga a las condiciones en tiempo real. También destaca el potencial de blockchain para mejorar la eficiencia y la transparencia de las transacciones energéticas.

El trabajo futuro se centrará en el desarrollo de estrategias complejas para servicios públicos y vehículos, la integración de fuentes de energía renovables, la habilitación del intercambio de energía entre pares y el avance de los sistemas de comercio de múltiples agentes. El estudio tiene como objetivo mejorar la eficiencia y la flexibilidad de los sistemas de comercio de energía y promover ecosistemas energéticos sostenibles y orientados a la comunidad.

RESUMEN (en Inglés)

The energy sector is experiencing a significant transformation driven by the integration of renewable energy sources, the proliferation of electric vehicles (EVs), and evolving demands of modern electricity grids. This thesis explores innovative market structures and load management strategies to address these challenges. It focuses on developing peer-to-peer (P2P) local energy trading mechanisms that effectively manage distributed generation and EV charging, empowering prosumers and consumers to actively participate and provide ancillary services to the grid.

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The research introduces a P2P energy trading framework that optimizes social welfare for EV owners through a multi-issue negotiation mechanism and real-time EV charging management. It also examines a multi-agent model for P2P energy trading, designed to maximize individual benefits through one-to-many concurrent composite negotiations. Additionally, the study explores the use of blockchain and smart contract technologies to implement automated P2P energy trading systems.

Key contributions include a multi-issue negotiation protocol for EV charging in congested networks and a multi-agent framework for efficient P2P energy trading. The research demonstrates significant reductions in network overload and enhances the adaptability of charging schedules to real-time conditions. It also highlights the potential of blockchain to improve the efficiency and transparency of energy transactions.

Future work will focus on developing complex strategies for utilities and vehicles, integrating renewable energy sources, enabling peer-to-peer energy exchange, and advancing multi-agent trading systems. The study aims to enhance the efficiency and flexibility of energy trading systems and promote sustainable, community-oriented energy ecosystems.

SR. PRESIDENTE DE LA COMISIÓN ACADÉMICA DEL PROGRAMA DE DOCTORADO EN ENERGÍA Y CONTROL DE PROCESOS

To my parents, for giving me strength and courage to show the best of my abilities, for earning an honest living for me and making me what I am today....

Acknowledgements

First and foremost I am highly grateful to Almighty Allah for never letting my efforts go unrewarded and for the successful completion of this doctoral program. I am deeply obliged to my advisor Dr. Pablo Arboleya, for his unwavering support to me throughout my thesis with his patience and knowledge whilst allowing me to explore on my own, and at the same time the guidance to recover when my steps faltered. You have been a tremendous mentor and a role model for me, one simply could not wish for a better or friendlier advisor. I would also like to take this opportunity to greatly thank for the most important personality, without whom this project could never have been successful, my co-supervisor Dr. Islam ElSayed for his guidance and support throughout the project, especially his critical analysis on my work and his confidence in me. A big credit goes to him since he directed me in the development of this project and encouraged me to attend various valuable courses which helped me in improving my programming skills and understanding of the subject technicalities.

I would also like to extend my gratitude to all my colleagues and research collaborators who helped me during the process with their valuable suggestions and guidance to be where I am today especially Prof. Bassam Mohammed and Prof. Umit Cali. Also worth mentioning here my peers from the LEMUR research group, with whom I've shared an amazing experience and made so many memories over the course of these five years.

My sincere thanks to my friends and all those that in any way contributed or helped me to be where I am today. Last but not the least, I am grateful to my family and in particularly my parents for always being the beacons of light that guided me on my journey to this point and for providing me with every kind of support I needed throughout my life.

Abstract

The energy sector is experiencing a significant transformation driven by the integration of renewable energy sources, the proliferation of electric vehicles (EVs), and evolving demands of modern electricity grids. This thesis explores innovative market structures and load management strategies to address these challenges. It focuses on developing peer-to-peer (P2P) local energy trading mechanisms that effectively manage distributed generation and EV charging, empowering prosumers and consumers to actively participate and provide ancillary services to the grid.

The research introduces a P2P energy trading framework that optimizes social welfare for EV owners through a multi-issue negotiation mechanism and real-time EV charging management. It also examines a multi-agent model for P2P energy trading, designed to maximize individual benefits through one-to-many concurrent composite negotiations. Additionally, the study explores the use of blockchain and smart contract technologies to implement automated P2P energy trading systems.

Key contributions include a multi-issue negotiation protocol for EV charging in congested networks and a multi-agent framework for efficient P2P energy trading. The research demonstrates significant reductions in network overload and enhances the adaptability of charging schedules to real-time conditions. It also highlights the potential of blockchain to improve the efficiency and transparency of energy transactions.

Future work will focus on developing complex strategies for utilities and vehicles, integrating renewable energy sources, enabling peer-to-peer energy exchange, and advancing multi-agent trading systems. The study aims to enhance the efficiency and flexibility of energy trading systems and promote sustainable, community-oriented energy ecosystems.

Contents

Chapter 1

Introduction

1.1 Background

Electrification is accelerating across all end-use sectors. Distributed energy resources (DERs) like rooftop solar, battery storage, electric vehicles, and digital technologies are proliferating and transforming the landscape. According to the International Energy Agency (IEA), global adoption of renewables and electric vehicles has accelerated enormously over the past decade. In 2022, renewables accounted for 30% of power generation, up from below 20% in 2010 [1]. Electric vehicle sales exceeded 10 million in 2022, bringing their total to over 25 million vehicles globally. Meanwhile, annual investment in battery storage tripled from 2021 to over $5 billion in 2022.

The energy sector is pivotal in reducing greenhouse gas emissions and averting catastrophic climate change. Achieving net-zero carbon dioxide emissions globally by 2050, as targeted by the 2015 Paris Agreement, requires the rapid decarbonization and transformation of the energy system [1]. Two major trends are enabling this clean energy transition: (1) the proliferation of distributed and renewable energy resources; and (2) the digitalization and smartening of energy infrastructure through advanced sensors, controls, and data analytics.

Higher electrification and more distributed, variable generation create grid management challenges related to peak loads, potential congestion on distribution grids, and coordinating numerous devices. Consequently, traditional ways of operating distribution systems struggle to accommodate evolving system requirements.

Modern, smart, and expanded grids are essential for successful energy transitions. Planning for transmission and distribution grids needs to be further aligned and integrated with broad long-term planning processes by governments. New grid infrastructure often takes five to 15 years to plan, permit, and complete, compared with one to five years for new renewables projects and less than two years for new EV charging infrastructure. Grid plans need to integrate inputs from long-term energy transition plans across sectors, anticipating and enabling the growth of distributed resources, connecting resource-rich regions including offshore wind, and reflecting links with other sectors including transport, buildings and industry, and fuels such as hydrogen.

Modernized distribution infrastructure and integrated planning aligned to economy-wide deep decarbonization roadmaps are essential but lacking currently, even as clean energy deployments accelerate. Financing and investment overhauls are key to accelerating and optimizing grid capacity expansion Grid development is currently falling short of the pace needed to ensure secure, reliable, and cost-effective energy transitions. Substantial policy and regulatory reforms are urgently needed to incentivize timely grid upgrades enabling renewable integration while maintaining reliability [2, 3].

To address the near-term challenges of integrating high penetrations of distributed energy resources (DERs) while avoiding grid upgrades, innovative decentralized coordination strategies are emerging as a promising solution. Specifically, localized transactive energy systems can help harness the inherent flexibility of DERs to provide grid services and ease constraints, without needing traditional infrastructure investments [4].

Transactive energy (TE) transitions the power grid from a traditional centralized, hierarchical structure to a decentralized network enabling communication between distributed energy resources. Rather than one-way, top-down dispatch, TE allows bidirectional coordination between assets of all sizes - from utility-scale generation to customer-owned solar panels or batteries. This shift encourages the proliferation of distributed energy nodes and empowers consumers as active market participants [5].

In summary, the imperative for reinvented distribution architectures to handle two-way power flows and orchestrate numerous assets is critical to realize deep decarbonization. This background motivates examining transactive solutions tailored to localized coordination challenges. The thesis examines next-generation peer-to-peer energy trading platforms and technical implementation details leveraging emerging digital innovations. The goal is to provide a comprehensive roadmap to realize transactive energy markets as a key enabler of deep decarbonization.

1.2 Motivation

The energy trilemma refers to the challenge of simultaneously achieving three core energy policy goals: energy security, energy equity, and environmental sustainability. As countries transition to clean, low-carbon energy systems, new complexities arise in balancing these three pillars. Potential solutions fall into two main categories: further developing large, interconnected energy systems to enable greater coordination of resources across regions, or alternatively, creating more localized, distributed energy systems that can operate autonomously [6].

Experts believe a hybrid approach incorporating both interconnected and localized solutions will likely be needed to fully address the energy trilemma. While large grids allow optimal dispatch of energy resources, localized systems reduce infrastructure requirements and mitigate grid issues like congestion and voltage violations. As such, self-managed local energy systems can serve as robust building blocks in the broader power distribution framework.

The integration of distributed energy resources (DERs) enables new opportunities for coordination and control at the distribution level. Additionally, employing local market mechanisms to manage DERs and harness customer flexibility adds further complexity in the design of distribution management systems. Consequently, innovative local energy market structures are required to effectively coordinate distributed generation and demand-side participation [7].

Local energy markets and transactive energy systems show particular promise for enabling decarbonization, digitalization, customer empowerment, and supporting grid stability. By applying strategies to utilize available DERs and customer flexibility, the potential of distributed clean energy can be fully harnessed. This thesis examines recent literature on transactive energy systems and local market solutions, focusing specifically on peer-to-peer energy trading frameworks. The goal is to explore existing mechanisms for local energy markets and peer-to-peer trading, identify opportunities for further innovation, and propose new developments to advance this critical area of localized energy system coordination.

1.3 Scope

The scope of this thesis is to research transactive energy solutions, specifically peer-to-peer energy trading frameworks, for coordinating distributed energy resources (DERs) and harnessing customer flexibility in distribution grids. The research aims to explore market design mechanisms, coordination techniques, and develop innovative models to enable local energy trading. Additionally, this thesis examines the application of blockchain technology and multi-agent systems to advance peer-to-peer trading platforms.

While prior work on implementing these technologies in transactive energy systems exists, detailed technical explanations for developing such frameworks are lacking. Providing explicit implementation details and architectures for enabling peer-to-peer energy trading comprises a key contribution and focus of this thesis.

In summary, the scope encompasses designing and technically specifying next-generation peer-to-peer trading platforms leveraging emerging technologies to unlock the potential of DER coordination and customer participation through localized energy markets. Forecasting methodologies are considered outside the scope, as prediction techniques are largely decoupled from market clearing and trading optimization in localized coordination frameworks.

1.4 Approach

The approach taken in this thesis is to develop innovative market models and negotiation techniques tailored for local energy markets and peer-to-peer transactive systems. Specifically, multi-issue bargaining (See Papers 1, 2, and 4) and one-to-many concurrent composite negotiations (See Paper 5) are implemented in a transactive energy context for the first time. These methods allow more complex trades between distributed energy resources compared to traditional techniques.

Additionally, this thesis leverages emerging technologies including the blockchain (See work in Papers 6,7,8, and 9) and multi-agent systems (See work in Papers 4 and 5) to enable decentralized peer-to-peer trading platforms. Detailed technical architectures, frameworks, and roadmaps are provided to equip energy sector researchers and developers to build upon these solutions for real-world deployment.

In summary, the core innovations lie in designing specialized negotiation protocols and integrating cutting-edge decentralized technologies to unlock new localized coordination models. By open-sourcing these platforms and documentation, the goal is to catalyze further research and accelerate the adoption of transactive coordination schemes to fully harness distributed clean energy resources.

1.5 Contributions

- Proposed a negotiation algorithm that coordinates Electric Vehicles (EVs), providing system flexibility and reducing congestion, thereby mitigating the need for heavy investments in distribution infrastructure for EV chargers.
  Paper 1 Appendix B

- Established a load coordination mechanism between active consumers and a management platform in a highly congested network, which has been successfully applied to coordinate the charging of EVs in a distribution network where building loads represent critical loads.
  Paper 2 Appendix A

- Developed a software tool that generates artificial scenarios to study the impact of EV charging on the distribution grid, adaptable to any defined characteristics and capable of generating the schedule of EV charging, achieving the EV load profile.
  Paper 3 Appendix B

- Collaborated in developing a multi-agent system based real-time negotiation framework for EV charging coordination systems. The application allows each agent (representing the aggregator/seller and EV owners/buyers) to set their preferences and negotiate charging terms like price, energy, and time flexibility.

The algorithm helps reduce overloads and improve the satisfaction of both aggregators and EV owners. The proposed framework is adaptive to real-time EV charging stations and onboard EV systems with enhancements.
Paper 4 Appendix B

- Developed a three-stage multi-agent model that optimizes individual benefits, ensures efficient grid support, and facilitates rapid computations and communications, achieving the primary objectives of maximizing social welfare, supporting grid balancing and congestion management at the distribution power system, and minimizing potential delays in the trading process.
  Paper 5 Appendix A

- Provided comprehensive insights about the use of blockchain technology in smart power systems, discussed the diverse background of blockchain applications, addressed the driving factors for the adoption of blockchain in the power sector, summarized the main aspects of blockchain technologies, explored prominent blockchain use cases and applications in the field of smart power systems, and discuss future challenges pertaining to the adoption of blockchain technologies in the mainstream.
  Paper 6 Appendix C

- Provided a roadmap for researchers and developers in the energy sector, addressing the growing trend in research on smart contract applications and the lack of scientific articles providing detailed information on the smart contracts' development process, particularly in the energy domain.
  Paper 7 Appendix B

- Addressed the growing energy demand due to population growth, higher penetration of electric vehicles, smart appliances, and superior living standards, facilitating the emerging requirements of prosumers (producers and consumers) to participate in the electricity market and monetize their efforts towards distributed energy deployment, and proposing blockchain-based ledger technology as a feasible solution for a unique distributed local energy market model for beneficial energy exchanges among participants.
  Paper 8 Appendix B

- Contributed to the work that highlights the potential of smart contracts to enable the digital green transition of the energy industry towards more sustainable and decentralized energy systems (Transactive Energy Systems). It also analyzes policy, legal, and legislative considerations regarding the adoption of smart contracts, highlighting issues like governance, enforceability, and adapting to external events beyond the contract terms.
  Paper 9 Appendix B

1.6 Thesis Structure

The remainder of this thesis is divided into four chapters. These chapters are:

- **Chapter 2** provides a brief introduction to give broader perspective to the Transactive Energy concepts and its relation to the Peer-to-Peer energy market.

- **Chapter 3** presents a comprehensive literature review on peer to peer energy trading covering all aspects of the domain.

- **Chapter 4** introduces the proposed frameworks for peer to peer energy trading for LV distribution networks that involves the developed algorithms, simulation results, discussion and conclusion.

- **Chapter 5** introduces blockchain and smart contracts technology. The basic components of this technology are discussed and its useful implementations in transactive energy systems along with the simplified technical guidelines in the published work, are indicated.

- **Chapter 6** concludes this thesis by summarizing the relevant findings drawn from the case studies undertaken throughout the research, providing comprehensive conclusions, and outlining directions for future work in this field.

1.7 Publications Originating from Thesis

Fig. 1.1 illustrates the classification of the peer-reviewed publications resulting from this thesis work. The following papers are attached to this thesis:

1.7.1 Journal Papers

1. **K. Khan**, I. El-Sayed and P. Arboleya, "A Multi-Agent Framework for Coordinating One-to-Many Concurrent Composite Negotiations in a Multi-Stage Postpaid P2P Energy Trading Model," Electric Power Systems Research, 1:16, 2024 (Submitted for Publication).
2. **K. Khan**, I. El-Sayed and P. Arboleya, "Multi-Issue Negotiation EVs Charging Mechanism in Highly Congested Distribution Networks," in IEEE Transactions on Vehicular Technology, vol. 71, no. 6, pp. 5743-5754, June 2022, doi: 10.1109/TVT.2022.3175266.

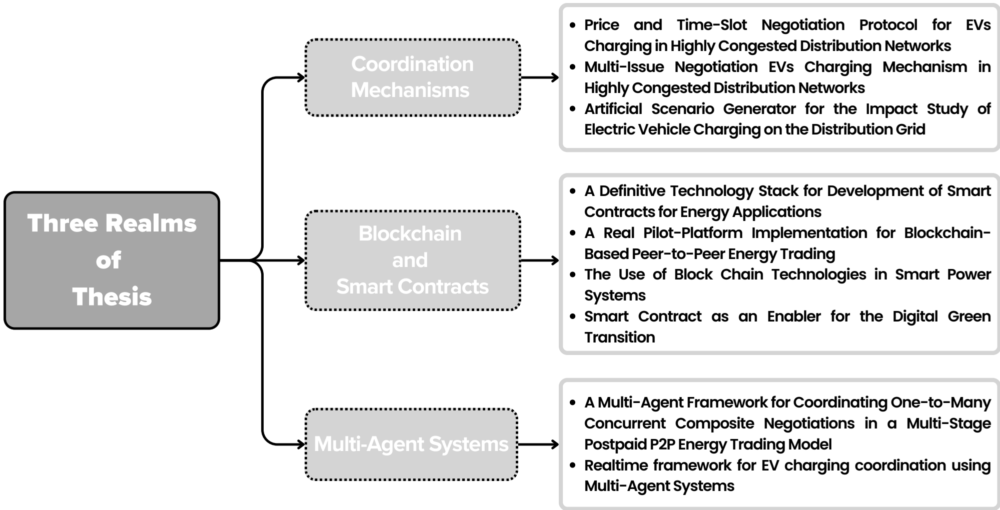

Figure 1.1: Classification of Publications Aligned with the Three Realms of this Thesis

1.7.2 Conference Papers

1. **K. Khan**, U. Cali, P. Arboleya et al., "A Definitive Technology Stack for Development of Smart Contracts for Energy Applications," 2023 IEEE PES General Meeting (PESGM), pp. 1-5.

2. **K. Khan**, I. El-Sayed and P. Arboleya, "Artificial Scenario Generator for the Impact Study of Electric Vehicle Charging on the Distribution Grid," 2021 IEEE Vehicle Power and Propulsion Conference (VPPC), Gijon, Spain, 2021, pp. 1-5, doi: 10.1109/VPPC53923.2021.9699197.

3. **K. Khan**, I. El-Sayed and P. Arboleya, "Price and Time-Slot Negotiation Protocol for EVs Charging in Highly Congested Distribution Networks," 2020 IEEE Vehicle Power and Propulsion Conference (VPPC), Gijon, Spain, 2020, pp. 1-6, doi: 10.1109/VPPC49601.2020.9330999.

4. I. El-Sayed, **K. Khan**, X. Dominguez and P. Arboleya, "A Real Pilot-Platform Implementation for Blockchain-Based Peer-to-Peer Energy Trading," 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, QC, Canada, 2020, pp. 1-5, doi: 10.1109/PESGM41954.2020.9281855.

5. I. El-Sayed, **K. Khan** and P. Arboleya, "Realtime framework for EV charging coordination using Multi-Agent Systems," 2021 IEEE Vehicle Power and Propulsion Conference (VPPC), Gijon, Spain, 2021, pp. 1-5, `doi:10.1109/VPPC53923.2021.9699306`.

1.7.3 Book Chapter

1. **K. Khan**, I. El-Sayed, and P. Arboleya, “The Use of Block Chain Technologies in Smart Power Systems,” The Encyclopedia of Power Engineering, Elsevier, 2023, Pages 478-485, ISBN 9780128232118, https://doi.org/10.1016/B978-0-12-821204-2.00071-4.

1.8 Other Contributions from Author

Since 2020, the author has been a member of the IEEE 2418.5 Smart Contract Task Force, operating under the IEEE Standards Association. This task force has produced several publications through collaborative efforts, as follows:

1. Umit Cali, K. Khan et al., “Smart Contract as an Enabler for the Digital Green Transition”, 2022 IEEE Transactive Energy Systems Conference (TESC), 2022, pp. 1-5. doi: 10.1109/TESC53336.2022.9917261

2. Umit Cali, et al., ”Standardization of Smart Contracts for Energy Markets and Operation,” 2022 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), New Orleans, LA, USA, 2022, pp. 1-5, doi: 10.1109/ISGT50606.2022.9817542.

3. D. J. Sebastian-Cardenas et al., ”Cybersecurity and Privacy Aspects of Smart Contracts in the Energy Domain,” 2022 IEEE 1st Global Emerging Technology Blockchain Forum: Blockchain & Beyond (iGETblockchain), Irvine, CA, USA, 2022, pp. 1-6, doi: 10.1109/iGETblockchain56591.2022.10087129.

Chapter 2

Transactive Energy and Peer-to-Peer Energy Trading

2.1 Transactive Energy Concept and Definition

Transactive energy is not a thoroughly novel concept, it builds upon existing wholesale energy markets that already utilize price signals to balance supply and demand. However, the key innovation of transactive energy is extending this concept to distribution networks [8]. Transactive Energy (TE) encourages a network environment for decentralized energy nodes in comparison to the traditional hierarchical grid structure. TE systems expand the current concepts of wholesale transactive power systems into retail markets with end-users equipped with intelligent Energy Management Systems (EMSs) to enable small electricity customers to have active participation in the electricity market. TE-based power systems allow faster and two-way power flow and communication and utilize the demand-side resources to manage the network and perform energy transactions in the retail markets by employing decentralized intelligent devices and systems.

This decentralized, transactive approach confers multiple advantages compared to conventional energy systems:

- Better utilization of grid infrastructure assets as distributed energy resources can provide targeted grid services where needed.
- Increased consumer empowerment and satisfaction by enabling their direct participation in energy markets.
- Reduced energy costs and improved affordability through more transparent price signals and the ability to shift usage to lower price periods.

- Enhanced reliability from the coordination of many flexible distributed assets to balance supply and demand.

Among various definitions of TE have been proposed by different individuals and organizations, the extensive definition found to be is: “A software-defined grid managed via market-based incentives to ensure grid reliability and resiliency. This is done with software applications that use economic signals and operational information to coordinate and manage devices’ production and/or consumption of electricity in the grid. TE describes the convergence of technologies, policies, and financial drivers in an active prosumer market where prosumers are buildings, electric vehicles, microgrids, VPPs or other assets” [9].

While one of the most accepted definitions is proposed by the Gridwise Architecture Council, as follows:

"A system of economic and control mechanisms that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter” [10].

TE system comprises several layers of market, system, control mechanism, etc., which maintain a dynamic equilibrium between load and generation using economic or market-based designs to increase electric power system reliability. It uses operational data to coordinate and manage device production and grid utilization.

2.2 Key Drivers of Transactive Energy

The motivations for employing TE systems span technological maturation, regulatory reform, environmental sustainability, and evolving consumer preferences - all steering toward more decentralized, interactive, and transactive electricity systems [9].

Technological Drivers

Grid modernization through advanced sensors, automation, controls and data analytics is enabling better visibility and control of distribution systems. This allows coordinated management of decentralized energy resources. Integration of diverse communication networks, artificial intelligence/machine learning based control systems, and data analytics facilitates system-wide, real-time optimization and balancing. Interoperability standards also allow coordination between hardware and software systems across the energy value chain.

Regulatory Drivers

Ongoing industry restructuring to separate generation, transmission, distribution and retail entities provides an avenue for decentralized energy services and peer-to-peer transactions. Deregulation enables new customer-centric business models beyond the traditional utility structure.

Environmental Drivers

The growth of renewable energy is driving improved integration and coordination capabilities to balance supply variability. Transactive platforms provide better asset utilization and system efficiency to enable sustainability.

Social Drivers

Customers are seeking more participation in energy management, trading, and sharing. User-friendly interfaces and controls allow optimization of efficiency and savings. Localized coordination solutions between electric vehicles, buildings and distribution grids is another area of interest.

2.3 Transactive Energy System Architecture

TE applies at all levels of the grid. It consists of a layer-type structure (i.e., independent system operators (ISOs), distribution system operators (DSOs)) or even a single customer can act as one layer), and there is an exchange of only boundary information as communication with others, i.e., each layer has its optimization objectives. TES has various functionalities and operations in the energy transactions mechanism. These functionalities have been divided into seven main layers [11] as elaborately demonstrated in Fig. 2.1.

2.4 Transactive Energy Markets and P2P Transactions

In the TE framework, the energy market is considered as the platform or place that enables different entities (buyers, sellers) to trade energy through various bilateral contracts to maintain the balance between demand and supply. Transactive energy (TE) markets do not necessarily have to involve only peer-to-peer (P2P) transactions, although some proponents tend to equate TE with P2P exchange. A broader and more evolutionary approach is to consider the staged implementation of markets at the distribution level. A distribution-level market for DERs to voluntarily provide bid-based services to the distribution system is a transactive market. Such a market may be a place to start with distribution-level markets because it is the simplest and may offer the greatest source of revenues for DERs in the near term P2P transactive exchanges are in an exploratory or infancy stage. One should note that there are TE

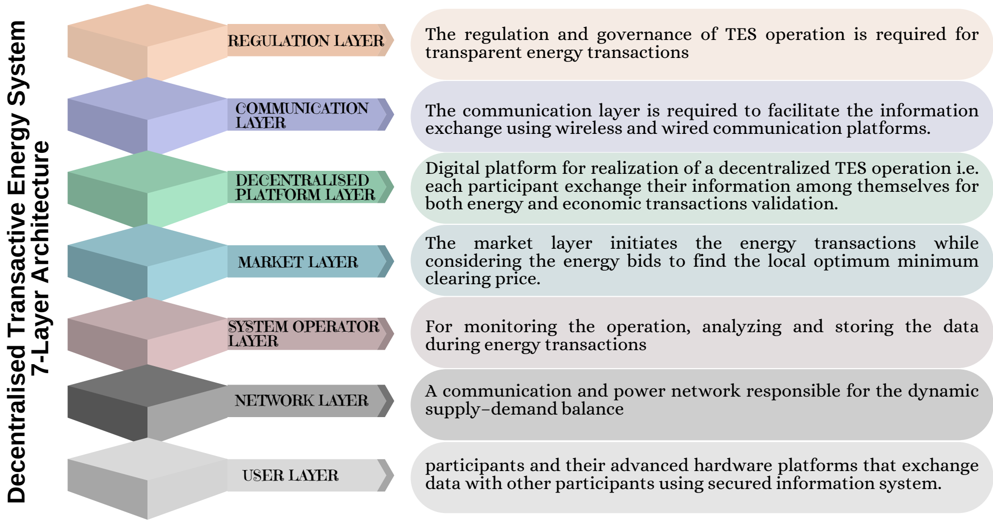

Figure 2.1: 7-Layer Architecture of Transactive Energy System

systems designs where the message flow does not follow a hierarchy. The flow, for example, might be P2P. The relation between the two is further clarified later in this section.

Transactive energy (TE) markets comprise several key components that work together to enable decentralized coordination and optimization [12]:

1. Distributed assets like solar panels, batteries, electric vehicles, and flexible loads that can respond to external signals or remote commands to modify generation/charging or consumption behaviors. Sensors and control devices enable this automated responsiveness.

2. Monitoring and telemetry devices like smart meters, sensors, and outage detectors that provide visibility into localized grid conditions and communicate this data to optimization platforms.

3. Communication networks and protocols that allow the exchange of data and signals between distributed resources, devices, and software platforms. This includes public/private networks and internet connectivity.

4. Software-based platforms that utilize wholesale market pricing signals and grid condition data to run algorithms and simulations to determine optimal dispatch of distributed assets.

5. Optimization engines and applications that process the inputs and outputs from assets, markets, and grids to coordinate devices and deliver automated, decentralized grid balancing through economic signals.

The core innovation of transactive energy is thus leveraging advanced devices, communications, software, and price signals to incentivize distributed resources to dynamically balance localized supply and demand in a market-based manner. The collective interactions of these technologies enable optimized, automated coordination of the grid edge.

In this context, transactive energy (TE) has become a fundamental component of the envisioned future grid. TE utilizes economic and control mechanisms to maintain a dynamic equilibrium of supply and demand throughout the electrical system, with value serving as a crucial operational metric. Successfully adopting this innovative concept necessitates leveraging the inherent flexibility of the demand side to support future energy balance and provide ancillary services at the distribution level. Consequently, one of the critical prerequisites for TE is the effective integration of distributed energy resources (DER) into power systems, considering both technical and economic aspects. This requirement drives the exploration of various methods and strategies designed to enhance the integration of DER efficiently. Expanding on the above description of the TE system, a concise overview of notable strategies for DER integration is found in the literature [13]. This review begins by identifying major distinctions in how DER integration strategies are developed, their ability to meet the needs of the system or consumers, and their awareness of network conditions. Generally, DER integration strategies are categorized into three types: (i) uncoordinated, (ii) coordinated, and (iii) peer-to-peer [14, 15].

2.4.1 Uncoordinated Strategies

The initial steps toward leveraging the potential of distributed energy resources (DER) involve uncoordinated approaches that focus on individual users with DERs, operating solely for the owner's benefit without any collective coordination. Two prevalent uncoordinated approaches include:

Home Energy Management System (HEMS)

This system equips users with tools to minimize their electricity costs by optimizing local generation, storage, and consumption. It incorporates various tariff schemes like feed-in tariffs and time-of-use tariffs to provide economic benefits [16]. However, this approach does not consider the broader network constraints, potentially leading to issues like overvoltage and overloading in networks with high DER penetration.

Home Energy Management System with Operating Envelopes (HEMS-OE)

Similar to HEMS, this approach aims to reduce electricity costs but includes operating envelopes that restrict DER operations to prevent negative impacts on the network. These envelopes are defined and published by the Distribution System Operator (DSO), who may also require visibility into the network state to effectively manage these constraints [17].

2.4.2 Coordinated Strategies

Transitioning to more collaborative models, coordinated approaches facilitate the orchestration of DER operations for mutual benefits between users and intermediaries like aggregators or DSOs. This is achieved through dynamic interactions involving control and price signals that adjust consumption and generation patterns. Such participation often offers financial incentives to end-users. Key coordinated approaches include:

Virtual Power Plants (VPP)

VPPs aggregate numerous DERs across different locations, coordinating them to utilize their flexibility. Unlike microgrids, VPPs are not geographically confined, cannot operate in isolation, and face fewer regulatory challenges, making them more adaptable to existing frameworks [18].

Optimal Power Flow (OPF)

This approach integrates traditional OPF methods with a broader range of market participants to optimize DER dispatch while adhering to technical and network constraints [19].

2.4.3 Peer-to-Peer Strategies

Peer-to-peer (P2P) energy sharing concept has gained attention as a prominent alternative solution in the TE frameworks [20]. Unlike the traditional systems, the P2P scheme enables energy sharing and trading among all consumers equipped with DERs, which converts them into active customers (prosumers) in the market by selling/buying energy from each interconnected nodes of the network. The P2P distributed market platforms are currently possible due to continuing advances in information and communication technology, multi-agent systems, and distributed ledger technologies such as blockchain, which support transparent and decentralized transactions. This approach has been further dissected and studied in depth in the following chapter as it serves the basis of this thesis.

Chapter 3

Peer-to-Peer Energy Trading

3.1 Overview of Key Concepts

In recent years, the increase in distributed energy resources has changed energy distribution systems. How energy is produced and consumed is changing dramatically, with traditional consumers becoming "prosumers" who can both produce and consume electricity. The generation of electricity by prosumers is intermittent and difficult to predict, as it is highly influenced by weather conditions which constantly change. When prosumers have an electrical surplus, they have options: store it for later use, export it to the electricity grid, or sell it directly to other consumers through peer-to-peer (P2P) energy trading. P2P energy trading has emerged in recent years as an alternative model where prosumers equipped with distributed energy resources can trade and share surplus energy directly with consumers in need, for mutual financial benefit [21]. Like the sharing models of Uber and Airbnb, P2P energy trading creates a "sharing economy" where underutilized energy assets are shared for cheaper than bulk grid prices. This win-win model matches producers and consumers directly. The potential of P2P energy trading stems from the differing generation and demand profiles among customers. Some customers need energy at times when others have a surplus to share, creating opportunities for mutual exchange. Additionally, in most countries the feed-in tariff for selling excess energy back to the grid is lower than the retail price for buying that same energy. This price differential incentivizes customers to trade peer-to-peer before interacting separately with the grid. Moreover, declining feed-in tariffs in the United States, United Kingdom, Australia, New Zealand, Portugal and Spain further motivate the formation of local P2P markets as an alternative. By matching supply and demand directly, P2P trading allows customers to capture more value from their distributed energy resources [6].

In light of the idea outlined by some researchers [22], a P2P energy network can be defined as follows:

A P2P energy network can be defined as a network, in which the members of the network can share a part of their resources (for example, renewable energy and storage space) and information to attain certain energy-related objectives. Example of such objectives includes renewable energy usage maximization, electricity cost reduction, peak load shaving, and network operation and investment cost minimization. Each member can be a provider, a receiver or both of the network resources and can directly communicate with the rest of the peers of the network without any intervention from a third party controller. Further, a new peer can be added to or an old peer can be removed from the network without altering the operational structure of the system.

3.2 Benefits of P2P Energy Trading

Peer-to-peer (P2P) energy markets offer several key advantages over traditional centralized flexibility solutions [23]:

1. The only incentive for prosumers to provide flexibility in centralized markets is lowering energy costs. In contrast, P2P markets allow prosumers to achieve extra profits by directly trading their excess energy with other users.

2. Centralized markets require expensive capacity reserves to account for uncertainty from variable renewable generation. In P2P markets, peers with diverse technologies and locations can collectively cover uncertainty and variability at lower cost.

3. Consumers bear the costs of capacity contracts equally in centralized markets. P2P markets attribute costs directly to the peers involved in each trade.

4. Centralized markets handle risks from load and generation variability by charging consumers extra fees. Information sharing in P2P markets allows prosumers to collaboratively contract their supplier and manage risks more efficiently.

5. Centralized markets treat energy as a homogeneous product focused narrowly on system operation and balancing at low cost. P2P markets recognize energy source as a factor in consumer preferences and usage decisions.

6. Grid operation in centralized markets follows a hierarchical structure that pushes problems upstream to be solved by the main grid. Well-designed P2P markets can solve local grid issues cooperatively at lower cost, while also providing valuable grid services.

P2P trading better aligns market incentives, costs, risks, and preferences while strengthening local and system-wide resilience.

3.3 Components

A P2P energy network generally consists of two layers [20]: (1) a virtual energy trading layer and (2) a physical energy transfer layer.

3.3.1 Virtual Layer

- Provides a secure virtual platform for participants to decide on energy trading parameters
- Ensures equal access for all participants to the virtual platform
- Facilitates transfer of information, creation of buy/sell orders, matching orders through a market mechanism, and financial transactions upon successful order matching
- Essentially handles all the trading activities and financial settlements between buyers and sellers

The main elements are explained below:

Information system

The core of any peer-to-peer (P2P) energy trading network is a sophisticated and secure information system. This system is crucial for facilitating communication among all participants in the energy market, integrating them into a suitable trading platform, ensuring equal market access for all, overseeing market operations, and imposing necessary restrictions on trading activities to maintain network security and reliability. Technologies such as blockchain-based smart contracts, consortium blockchain, and platforms like Elecbay [24] are examples of such information systems. These systems are designed to help end-users identify the most suitable energy market for their needs and enhance communication efficiency. A well-secured information and communication technology (ICT) environment is essential for ensuring that all trading peers have equal access to information, protecting the privacy of traders, and ensuring the smooth operation of the market.

Energy Management System

An Energy Management System (EMS) plays a pivotal role in peer-to-peer (P2P) energy trading by enabling prosumers to effectively manage their energy supply and demand. The EMS operates by accessing real-time data on a prosumer's energy production and consumption through a transactive meter. This information is used to create a detailed profile of the prosumer's energy generation and usage patterns. Based on this profile, the EMS devises a strategic plan for bidding in the energy market, ensuring that the prosumer secures energy at optimal prices and times.

For instance, a well-calibrated EMS for a rational prosumer would automatically purchase energy from the microgrid market whenever the market price drops below a pre-set maximum price threshold. This approach allows the prosumer to capitalize on lower prices while maintaining a steady energy supply. The EMS can also control flexible loads, adjusting energy consumption in response to fluctuating market conditions and prices. Users have the ability to customize their EMS policies according to their specific energy needs, market trends, and available energy sources, thereby optimizing their participation in P2P energy trading [25].

Market Operation

The information system within a peer-to-peer (P2P) network underpins the functioning of market operations, which include the distribution of market resources, the establishment of payment protocols, and a well-defined bidding structure. The primary aim of these market operations is to facilitate an effective and efficient energy trading experience for participants by aligning sellers' and buyers' orders with a high degree of temporal precision. In this system, the energy output from each producer sets the parameters for the maximum and minimum energy distribution. Market operations may encompass various timeframes, each designed to ensure sufficient energy distribution throughout the operational stages. Pricing mechanisms are integral to market operations, crafted to maintain equilibrium between energy supply and demand. The pricing strategies employed in P2P energy trading differ fundamentally from those in conventional electricity markets, where prices often include substantial surcharges and taxes. Given that renewable energy sources typically incur minimal marginal costs, participants in P2P networks—known as prosumers—have the opportunity to increase their profits by strategically setting energy prices. Nevertheless, these pricing mechanisms must accurately reflect the network's energy status, meaning that an abundance of energy should lead to lower prices, while scarcity should drive prices up.

3.3.2 Physical Layer

- Represents the physical electricity network that enables the actual transfer of electricity from sellers to buyers
- Could be the traditional distributed grid network maintained by the system operator
- Or it could be a separate microgrid distribution network used in conjunction with the traditional grid
- Facilitates the physical delivery of electricity once the financial settlements are completed on the virtual layer

In essence, the virtual layer handles all the trading activities and financial aspects, while the physical layer is the underlying electricity network that enables the physical transfer of energy from sellers to buyers after the trading is finalized on the virtual platform. Following are the main elements of physical layer:

Distribution Network

The distribution network plays a crucial role in transferring physical energy between peers and managing the power flow within the system. This infrastructure is typically provided and maintained by Distribution Network Operators (DNOs), which are companies responsible for the ownership and operation of the cables and towers that distribute electricity. Peer-to-peer (P2P) energy trading introduces a dynamic component to both grid-connected and islanded microgrid systems. In grid-connected setups, identifying the main grid's connection points is vital for balancing energy demand and generation. The integration of smart meters at these points enables the evaluation of the P2P network's performance, including potential energy and cost savings. For islanded microgrids, it is imperative that participants possess sufficient generation capacity [25]. This ensures a reliable and secure energy supply to consumers, maintaining the system's integrity and functionality. Through these mechanisms, P2P trading enhances the efficiency and resilience of both grid-connected and islanded microgrid systems, offering a sustainable and flexible approach to energy distribution.

Metering

To fully engage in P2P trading, it is imperative for prosumers to be outfitted with the proper metering infrastructure. This includes not only traditional energy meters but also transactive meters, which are sophisticated devices that enable prosumers to make informed decisions about entering the P2P market. These decisions are based on a thorough analysis of demand and generation data, along with an understanding of current market conditions such as energy prices, overall demand, available generation, and network status. Transactive meters also possess the capability to communicate with other prosumers within the network through various communication protocols, ensuring a cohesive and efficient trading environment [25].

Communication Infrastructure

In the context of peer-to-peer (P2P) energy trading, a critical aspect of the communication infrastructure is the ability to identify prosumers and facilitate the exchange of information across the network. The literature presents a variety of P2P communication architectures, such as structured, unstructured, and hybrid models. Selecting an appropriate communication architecture is essential to meet the performance criteria set forth by IEEE 1547.3-2007 for the integration of Distributed Energy Resources (DER) [26]. These criteria encompass latency, throughput, reliability, and security, ensuring that the communication infrastructure supports efficient and secure energy trading activities.

3.4 Market Designs

Market design refers to the way in which various mechanisms for price formation are interconnected to establish a comprehensive market structure. For a more granular examination of these individual mechanisms, one can refer to [27]. Fig. 3.1 presents the workflow of each of the archetypal market designs covering pre-, peri-, and post-settlement period. Each archetypal market designs cater to specific trading and settlement needs within energy markets. For instance, futures markets involve

Market Designs	Before Settlement Period	During Settlement Period	After Settlement Period
Futures Market	Market participants contract with other participants to buy or sell energy based on predictions	Market participants demand or supply energy they have bought or sold	Billing and settlement accounting for energy imbalances
Real Time Market		Market participants contract with other participants to buy or sell energy they are in the process of producing or consuming	Billing. No energy imbalances due to real time market
Mixed decentralised/centralised market	Market participants engage in bilateral negotiation without participation of market operator and clear as much demand/supply as possible. Market operator clears remainder of supply/demand through single or double auction	Market participants demand or supply energy they have bought or sold	Billing and settlement accounting for energy imbalances.
Mixed futures/real time market	Market participants contract with other participants to buy or sell energy based on predictions in a futures market	Market participants can adjust their position based on actual supply and demand of energy in a real time market	Billing and settlement
Multi-layer market	Market participants at lowest market level clear as much supply and demand for energy as possible. Aggregate supply or demand for energy not cleared in lower level market passed up to next market level usually through an aggregator. Process continues for each market layer	Market participants demand or supply energy they have bought or sold	Billing and settlement accounting for energy imbalances
Settled after the fact		Actual energy supplied or demanded by market participants is netted off against each other	Billing and settlement

Figure 3.1: Six Archetypal Market Designs

advance trading with settlement adjustments based on actual performance, commonly mirroring traditional electricity market operations. Real-time markets adjust trades within the settlement period itself, aiming for immediate balance based on live supply and demand. Mixed decentralized/centralized markets combine initial bilateral negotiations with subsequent centralized auctions to clear any remaining imbalances. Mixed futures/real-time markets allow for both predictive trading and real-time adjustments, providing flexibility to correct forecasting errors. Multi-layer markets operate with mul-

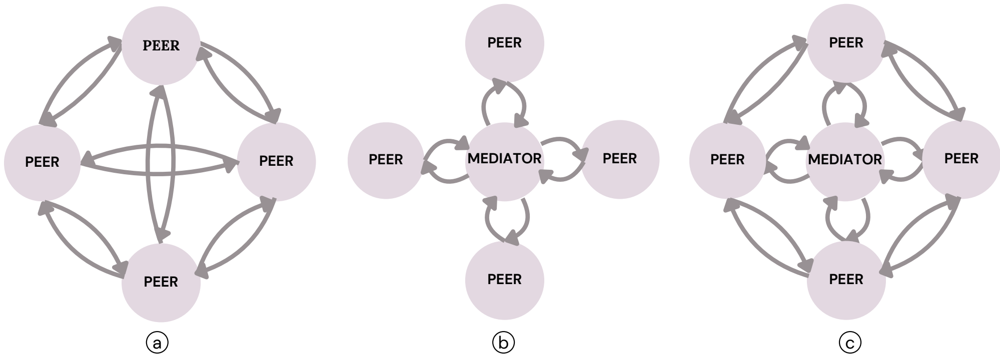

Figure 3.2: Types of Peer to Peer Energy Market Structures

tiple settlement layers, where internal market imbalances are managed by higher-level aggregators. Lastly, markets settled after the fact are characterized by post-settlement adjustments where trades are not made in advance but are instead settled based on a predetermined price, simplifying the trading process but potentially increasing risk. Each design offers different mechanisms and strategies to optimize energy trading and management, reflecting the diverse needs and dynamics of modern energy systems.

3.5 Market Structures

Based on the level of decentralization and the method of engaging DERs in the network, a transactive energy market can be classified into three different structures (as presented in Fig. 3.2): (a) Full P2P market. (b) Community-manager based P2P market and (c) Hybrid P2P market. The key difference between the three types of market structure is that in full P2P market peers trade energy directly without a mediator. In contrast, mediators or aggregators are needed in community-based markets to organize the trading process. In the hybrid market, the peer can choose whether to trade with other peers directly or through a mediator [14].

3.5.1 Full P2P Market

A fully peer-to-peer (P2P) transactive energy market architecture involves distributed energy resources owners and consumers directly negotiating and establishing bilateral transactions with each other to trade or share energy, without needing a centralized intermediary platform or authority [28]. Participants can autonomously agree on trades based on their preferences, motivations, and negotiated terms. This allows incorporating product differentiation criteria beyond just cost, such as valuing local renewable generation or specific green energy attributes. A prosumer-centric P2P architecture for a residential community to cooperatively exchange and plan energy usage.

3.5.2 Community Manager Based P2P Market

A centralized P2P model includes a community manager (CM) entity to oversee and coordinate energy trading activities between peers in a defined region or community [29]. The CM acts as an intermediary interface between local prosumers and consumers and the wider system. Trades occur between producers and consumers internal to the community, with the CM interfacing with external markets. The CM enables more centralized optimization, coordination of multi-objective priorities, and collaborative participation compared to fully decentralized exchanges.

3.5.3 Hybrid P2P Market

Fully P2P systems can have unpredictable behaviors and convergence issues that hybrid models help mitigate through some central coordination [30]. Prosumers defining their own economic and environmental preferences in an unregulated P2P market. However, unchecked self-interest could lead to unintended consequences like gaming and price volatility without mechanisms to align market signals with system reliability needs. Hybrid architectures maintaining some central roles may aid adoption [31]. Hybrid architectures allow the blending of the benefits of peer autonomy and platform-based transactions under centralized supervision. The oversight and coordination help manage pricing dynamics, grid integration challenges, and risk exposures.

3.6 Key Stakeholders

Peer-to-peer (P2P) energy trading requires a robust network of participants, with a portion capable of energy production. The specific aims of P2P trading significantly shape pricing strategies and market structures, necessitating clear definition. The type of energy exchanged, whether electrical or thermal, is a crucial factor. In this model, prosumers and consumers interact directly, while also engaging with platform facilitators, grid managers, and energy retailers, creating a dynamic ecosystem of energy exchange.

In P2P markets, around 94% feature prosumers, while 55% include pure consumers, 46% involve central market operators, and 29% incorporate grid operators as per literature survey [27]. Additionally, these markets also host aggregators and retailers, though pure generators appear less frequently. This participant distribution underscores the emphasis of P2P markets on empowering individual energy end-users with a platform for energy trading. Moreover, the presence of diverse participants like retailers, grid operators, and aggregators illustrates the varied ways in which P2P markets integrate into the broader energy market landscape, highlighting their diversity and adaptability.

Entities Generating Energy

Any player capable of generating or storing energy can participate as a seller in the local energy trading market. Typically, Distributed Energy Resources (DER) such as Distributed Generations (DGs), Energy Storage Systems (EESs), Plug-in Hybrid Electric Vehicles (PHEVs), utility companies, and generators, or a combination of these entities as prosumers, energy cells, smart homes, and microgrids, can act as producers in the market.

Traditionally, generation companies have participated in the wholesale market. However, with the advent of Peer-to-Peer (P2P) energy trading schemes, it has become more profitable for some generation companies with distributed generations to trade directly with local consumers.

The generation company model can be represented using a quadratic cost function as eq.(3.1), a linear marginal cost function as eq.(3.2) , and power limit constraints as eq.(3.3) . This model assumes the company owns a single generation unit.

Quadratic Cost Function:

$$C_G^t = c_G + l_G \cdot p^t + q_G \cdot (p^t)^2 \tag{3.1}$$

Where:

- p^t is the generation power at time t
- c_G, l_G, and q_G are constant, linear, and quadratic cost coefficients, respectively

Linear Marginal Cost Function:

$$M_G^t = l_G + 2 \cdot p_G \cdot p^t \tag{3.2}$$

Power Limit Constraint:

$$0 \leq p^t \leq p^{max}, \forall t \tag{3.3}$$

Key Points:

- For renewable generation assets, the cost function can be simplified to a linear model $q_G = 0$.
- Renewable generation typically involves an initial installation cost $c_G$and a linear operation and maintenance cost l_G.
- To avoid non-linearity, the quadratic cost function can be approximated by a piece-wise cost function with several generation blocks that are expressed as equations (3.4),(3.5) and (3.6).

Piece-wise Approximation (for each time block b):

- Cost function:

$$C_G^b = l_G^b \cdot p^b \tag{3.4}$$

- Marginal cost:

$$M_G^b = l_G^b \tag{3.5}$$

- Power limit:

$$0 \leq p^b \leq p^{max}, \forall b \tag{3.6}$$

This piece-wise approximation results in a step-wise linear marginal curve, simplifying the model while maintaining its essential characteristics [32].

Entities Consuming Energy

Participants in the local energy market who solely require energy are known as buyers. These buyers can be either consumers who only consume energy or prosumers who, at times when their energy production exceeds their needs, act as sellers. However, when prosumers find themselves in need of additional energy, they switch roles and become buyers within the market. Additionally, entities equipped with flexible load capabilities, which allow for the reduction and modification of energy consumption, also participate as buyers in the market.

Entities Generating and Consuming Energy

An increasing number of distributed generators and energy storage systems, equipped with smart energy management systems, enable residential consumers to generate electricity and feed it back into the distribution system. This transformation elevates residential consumers from mere consumers to prosumers. Consequently, prosumers are active participants in the Peer-to-Peer (P2P) energy market, capable of producing, consuming, and providing demand response services.

The prosumer aims to minimize their energy costs formulated as in eq.(3.7) while balancing generation, consumption, storage, and trading activities that are defined as in eq.(3.8) [32]. A generalised model for this purpose is stipulated below:

Objective Function:

$$C_{PS}^{t} = \alpha_{ToU}^{t} \cdot p_{P2P}^{+,t} - \beta_{FiT}^{t} \cdot p_{P2P}^{-,t} \tag{3.7}$$

Where:

- C_{PS}^{t} is the prosumer's energy cost at time t
- $p_{P2P}^{+,t}$ is the energy bought from the retailer
- $p_{P2P}^{-,t}$ is the energy sold to the retailer
- α_{ToU}^{t} is the time-of-use tariff for buying energy
- β_{FiT}^{t} is the feed-in tariff for selling energy

Energy Balance Constraint:

$$h^{t} + p_{P2P}^{+,t} + p_{P2P}^{-,t} - u^{t} - v^{t} = 0, \quad \forall t \tag{3.8}$$

Where:

- h^{t} is the prosumer's generation at time t
- u^{t} is the prosumer's consumption at time t
- v^{t} is the storage system's charging ($v^{t} > 0$) or discharging ($v^{t} < 0$) amount

Key Components:

1. Generation (h^{t}): Prosumer's power production, typically from renewable sources.
2. Consumption (u^{t}): Prosumer's energy demand.
3. Energy Storage (v^{t}): Allows for temporal shifting of energy use or sale.
4. Energy Trading ($p_{P2P}^{+,t}$, $p_{P2P}^{-,t}$): Enables buying from or selling to the retailer.

Additional Considerations:

- Storage Constraints: Limits on charging/discharging rates and capacity.
- Network Constraints: Potential limits on energy export/import.
- Voltage Regulation: May be necessary to maintain grid stability.
- Peer-to-Peer Trading: Could be incorporated for trading with other prosumers.

Aggregator

The definition of an aggregator as an "independent agent who combines two or more consumers into a single purchasing unit to negotiate the purchase of electricity from retailers" aligns with common definitions found in the literature [33]. Aggregators can also take on various roles, such as smart energy service provider scheduling flexible energy resources, acting as local energy market operators which perform like balance scheme management, recording of closed contracts and operational forecast, as community manager entity to oversee and coordinate energy trading activities between peers in a defined community or serving as energy brokers to match sellers and buyers.

Aggregators can be classified into different types based on their functions, such as production aggregators, demand aggregators, and commercial aggregators. Each type has specific roles and responsibilities in the energy market.

Entity Connecting to Larger Markets

In the context of Peer-to-Peer (P2P) energy markets, prosumers often face limitations in achieving complete self-sufficiency through direct trades. Moreover, these individual participants typically lack the necessary resources or scale to engage directly with the wholesale energy market. Consequently, energy retailers continue to play a crucial role in the P2P ecosystem. These retailers serve as intermediaries, representing a collective of energy consumers in wholesale market transactions, thereby bridging the gap between small-scale prosumers and large-scale energy markets.

They serve several key functions:

- Market Intermediary: Retailers purchase energy from the wholesale market and sell it to contracted users, accommodating prosumers who aren't self-sufficient or lack direct wholesale market access.
- Profit Maximization: Retailers aim to maximize profits by setting retail buying (time-of-use) and selling (feed-in tariff) prices, while managing wholesale market trading quantities.
- Energy Balance: They balance customer generation and demand with wholesale market trading quantities.

- Consumer Protection: Local regulators impose price caps on retail prices, based on wholesale prices, to ensure fair market practices and protect consumer interests [34].

Central Market Operator

A central market operator is a single entity responsible for running the market or platform. This role can be fulfilled by a dedicated market operator, an aggregator, a Distribution System Operator (DSO), or a transaction server. It does not involve multiple entities sharing this task in a decentralized manner.

While terms such as "Transmission System Operator" (TSO) or "system operator" (including subvariants like Independent System Operator, ISO) and "Distribution System Operator" (DSO) are well-defined and consistent, the term "market operator" is less clear and varies by country. Typically, a market operator performs certain "system" roles in the electricity market, which may include tasks usually handled by the TSO, such as balance scheme management, recording closed contracts, operational forecasting, market balancing, and imbalance settlement.

The tasks of a market operator can be summarized as follows [35]:

- **Administration of the Bilateral Electricity Market**: Managing the market where electricity is traded bilaterally between participants.
- **Imbalance Calculation**: Calculating the imbalances of the balancing responsible parties based on the final daily schedule and measurements from the electricity transmission system operator and electrical distribution system operators.
- **Information Submission**: Timely submission of all necessary information to the electricity transmission system operator for the preparation of final daily schedules for electricity purchase and sale.
- **Contract Management**: Keeping records of all contracts for market participation concluded with market participants.
- **Balance Group Management**: Keeping records of all agreements for the establishment of balance groups between market participants and the market operator.
- **Daily Market Plan Preparation**: Preparing a daily market plan.
- **Market Participant Register**: Maintaining a register of market participants.
- **Balance Group Register**: Maintaining a register of balance groups in the market.
- **Contract Conclusion and Balance Responsibility**: Concluding purchase and sale contracts and taking balanced responsibility for the electricity generated by privileged producers using a feed-in tariff.

3.7 Technical Approaches

3.7.1 Game Theory Methods

Game theory is a specialized field within applied mathematics that provides a systematic approach to analyzing and forecasting the behavior of rational agents who are motivated by self-interest in competitive scenarios. This includes a variety of contexts such as board games like chess, card games like poker, social dilemmas exemplified by the prisoner's dilemma, political processes involving coalition building, and the dynamics of auction markets. By applying game theory, one can deduce the most advantageous strategies for the participants and predict the likely results of these strategies when put into action [36].

In the context of electrical power systems, game theory has proven to be an effective tool for understanding the actions of players in liberalized energy markets and for distributing costs among these participants. Research into game-theoretic methods for local energy exchange has highlighted a range of game types that are relevant for managing smart energy systems efficiently. Game theory is particularly adept at modeling the interactions between independent distributed energy resources (DERs), each seeking to optimize their individual gains [37].

Games can be sorted into different types based on several attributes, such as the number of players involved, the extent of information available to them, the logic behind their rationality and behavior, the variety of strategies they can employ, and the nature of their potential rewards. The core division within game theory, however, revolves around the behavioral logic of the players or peers, which falls into two main categories: cooperative games, where players work together towards a common goal, and non-cooperative games, where each player acts independently.

Non-cooperative games

In non-cooperative games, the emphasis is on examining how multiple independent players, who may have partially or entirely opposing interests, make strategic decisions. The results of these games are determined by the individual actions of each player. Importantly, these decisions are made without any communication or collaboration between the players [20].

The resolution of a non-cooperative game is achieved through a Nash equilibrium, which is a condition in the game where no player can enhance their payoff by altering their actions, provided the other players' actions remain unchanged.

Strategic Form Game Model

A strategic form game can be represented as follows [36]:

- Players: $N = 1, 2, ..., n$
- Strategy Sets: For each player i, S_i is their set of possible strategies
- Strategy Profile: $s = (s_1, s_2, ..., s_n)$ where $s_i \in S_i$
- Payoff Functions: $U_i(s)$ for each player i
- The game is formally defined as: $G = N, (S_i)i \in N, (U_i)i \in N$

Nash Equilibrium

A strategy profile $s^* = (s_1^*, s_2^*, \ldots, s_N^*)$ is a Nash equilibrium if criteria in eq.(3.9) is fulfilled i.e.:

$$U_i(s_i^*, s_{-i}^*) \geq U_i(s_i, s_{-i}^*) \quad \forall i \in N, \forall s_i \in S_i \tag{3.9}$$

Where s_{-i}^* represents the strategies of all players except i. Key Points:

- Each player aims to maximize their own payoff
- In a Nash equilibrium, no player can unilaterally improve their payoff
- Multiple Nash equilibria may exist, requiring further analysis for game resolution.

In the literature on non-cooperative games applied to peer-to-peer (P2P) energy trading, several key references stand out [38]. The Stackelberg game, a strategic model where players are divided into leaders and followers[39], is prominently used to design trading strategies within P2P markets. This game type facilitates a hierarchical decision-making process, where the leader commits to a strategy first, followed by the followers who adjust their strategies accordingly, aiming to reach a Stackelberg equilibrium where no participant has an incentive to deviate from their chosen strategy [40]. Additionally, the Nash equilibrium concept is widely applied across various studies to determine optimal bidding strategies in P2P energy trading, demonstrating its utility in modeling market behaviors and enhancing transaction security within smart grids and microgrids. Furthermore, the adaptation of game-theoretic models to optimization problems using the Nikaido–Isoda function highlights the versatility of non-cooperative games in addressing complex issues like energy cost minimization and demand balancing [41]. These references collectively underscore the significant role of non-cooperative game theory in advancing the operational efficiency and strategic development of P2P energy trading systems.

Cooperative games

Conversely, cooperative games emphasize the collaborative actions and combined outcomes of players who have the ability to communicate and work together. The goal is to encourage players to establish coalitions and collaborate towards a solution that serves the common good. This category of game theory includes Nash bargaining and coalition games. Nash bargaining is concerned with the conditions under which players decide to cooperate, whereas coalition games focus on the formation of these groups [42]. In these games, a value function v is used to measure the worth of a coalition $C \subset N_c$, where N_c represents the group of players interested in forming cooperative alliances. Therefore, the objective is to create coalitions C that maximize the value $v(C)$ derived from their formation.

In cooperative game theory, we can model coalition formation using the following framework: Let N_c be the set of all players interested in forming cooperative alliances. For any subset $C \subseteq N_c$, we define a characteristic function $v : 2^{N_c} \to \mathbb{R}$ that assigns a real value $v(C)$ to each possible coalition C. The value $v(C)$ represents the worth or utility that the coalition C can achieve by working together. The goal in these games is to find coalitions C^* that maximize the value function as expressed in eq.(3.10):

$$C^* = \arg\max_{C \subseteq N_c} v(C) \tag{3.10}$$

This formulation captures the key elements:

- The set of potential cooperating players (N_c)
- The coalition value function (v)
- The objective of maximizing coalition value

It allows for analyzing different coalition structures and determining which groupings of players can generate the most value through cooperation. The specific properties of v will determine the incentives for coalition formation and the resulting equilibrium outcomes [36].

In the realm of cooperative games, three primary categories stand out, each with distinct objectives and methodologies:

Canonical Coalition Game

Canonical coalition games focus on the formation of a grand coalition involving all players, ensuring that no player is worse off by joining. The primary goal in these games is to assess the stability of the grand coalition and to devise methods for equitable distribution of the coalition's gains among the players [42]. The core concept is typically employed to solve these games, alongside other distribution methods such as the Shapley value, Kernel, nucleolus, and strong epsilon-core. These games are pivotal in scenarios like peer-to-peer (P2P) energy trading, where they help form stable, optimal cooperative groups among prosumers, maximizing their monetary benefits through efficient energy storage management.

Coalition Formation Game

This category explores the formation and dynamics of coalitions within a network. Coalition formation games can be static, examining the network's coalitional structure at a single point, or dynamic, adapting to environmental changes such as fluctuations in player numbers or network topology. The main focus is on how coalitions are formed and evolve over time, their structural properties, and their adaptability to changes. These insights are crucial for forming grand coalitions among prosumers in P2P energy trading, encouraging their participation and optimizing the trading process.

Coalitional Graph Game

Coalitional graph games utilize graphs to facilitate and optimize communication among players. These games are essential for developing distributed algorithms that are low in complexity but effective in building and analyzing network graphs[42]. Such games are particularly relevant in the context of smart grids and microgrid systems, where they aid in maximizing social welfare and achieving fair profit allocation among all stakeholders, including distribution network operators, buyers, and sellers in the cooperative P2P energy market.

Each of these game types plays a crucial role in enhancing cooperation and optimizing outcomes in various networked systems, particularly in energy sectors and other utilities.

A generalized mathematical representation for cooperative games, particularly in the context of a cooperative Stackelberg game can be presented as below:

Mathematical Framework

In the cooperative Stackelberg game, the grid G and a set of prosumers N interact within a dynamic power system. The game is defined by the following elements:

Players : The grid G acts as the leader, and the prosumers N are the followers.

Strategies :

- $\pi_{g,s}(t)$: The pricing strategy chosen by the grid to influence prosumer behavior.
- $\epsilon_{n,p2p}(t)$ and $\pi_{p2p}(t)$: The amount and price of energy that each prosumer n decides to trade in the P2P market.

Utilities :

- $U_n(t)$: represents the utility of prosumer n for trading energy as either a seller or buyer.
- $C_g(t)$: represents the net cost to the grid for engaging in energy trades with prosumers.

Game Representation The cooperative Stackelberg game Γ can be represented as eq.(3.11):

$$\Gamma := \{(N \cup G), U_n(t), C_g(t), \pi_{g,s}(t), \epsilon_{n,p2p}(t), \pi_{p2p}(t)\} \tag{3.11}$$

Objective The objective of the game is to find a cooperative Stackelberg equilibrium where the strategies $(\pi^*_{g,s}(t), \epsilon^*_{n,p2p}(t), \pi_{p2p}(t))$ satisfy the equilibrium conditions and form a stable coalition structure. This involves:

- Ensuring that the grid's strategy $\pi^*_{g,s}(t)$ optimally influences the prosumers' decisions.
- Prosumers' responses $(\epsilon^*_{n,p2p}(t), \pi_{p2p}(t))$ are such that they maximize their utilities while contributing to a stable coalition.

Equilibrium Condition The equilibrium condition can be formally stated as:

$C_g(\pi^*_{g,s})(t) = 0$

This condition implies that the optimal strategy for the grid results in zero net cost, indicating an efficient and balanced energy trade.

This representation captures the essence of cooperative interactions within a Stackelberg framework, highlighting the dependencies and strategic considerations between the grid and prosumers [40]. It provides a structured way to analyze and solve for optimal strategies that benefit all parties involved in the dynamic energy trading market.

3.7.2 Agent-Based Methods

Agent-Based Simulation (ABS) represents another decentralized approach, widely recognized for its effectiveness in simulating the behavior of electricity markets. This technique is particularly suited for extensive systems involving diverse interacting entities, each with unique roles and capabilities. Within ABS, every entity is modeled as an agent, ranging from a basic variable in a software application to a sophisticated entity capable of a potentially limitless array of behaviors and choices.

Agent

As per definition proposed by Pipattanasomporn et al. (2009), A group of computational entities that can operate without human intervention (Autonomous), interact with each other (sociality), perceive and react to its environment (re-activity), and exhibit goal-oriented behavior by taking initiatives (pro-activity) are called agents.

This agent can be software, a hardware component, or a combination of both. For example, software agents living on the Internet. Indeed, the Internet can be viewed as the ultimate platform for interaction among self-interested, distributed computational entities. Such agents can be trading agents of the sort discussed above, "interface agents" that facilitate the interaction between the user and various computational resources (including other interface agents), game-playing agents that assist (or replace) human players in a multiplayer game, or autonomous robots in a multi-robot setting [43].

Environment

This refers to the place where the agent is located. An agent uses the information sensed from the environment for decision-making. There are a few key types of environments that agents can operate in within multi-agent systems [44]:

1. Single-agent vs multi-agent environments
2. Competitive vs collaborative environments
3. Discrete vs continuous environments
4. Deterministic vs stochastic environments
5. Static vs dynamic environments
6. Accessible vs inaccessible environments

Action

Each agent can perform an action that results in some changes in the environment. To achieve this aim, the agent first senses parameters from the environment. Empowered with this data, the agent can build up knowledge about the environment. An agent might also use the knowledge of its neighbors. This knowledge along with the history of the previous actions taken and the goal is fed to an inference engine which decides on the appropriate action to be taken by the agent [45].

Consider a simulation of multiple stock trading agents competing in a stock market environment. Each trading agent senses real-time data like stock prices, volumes, news events etc. from the environment. The trading agent's machine learning-based inference engine takes the current stock data, environment knowledge, historical trading outcomes, shared competitor information, risk tolerance, and profit goals as inputs. It decides the optimal trading actions to take - whether to buy, sell, or hold stocks to maximize profits while minimizing risks.

Design Stages of MAS

The development of multi-agent systems involves adapting traditional software engineering and knowledge engineering approaches to create design methodologies tailored for specifying and designing these complex systems. Typically, the design process consists of three main phases: conceptualization, analysis, and design [43]. In the conceptualization phase, the problem at hand is clearly defined. The analysis phase involves a thorough examination of the specified problem, and the insights gained from this analysis are then used in the design phase to create the agents and determine their communication strategies.

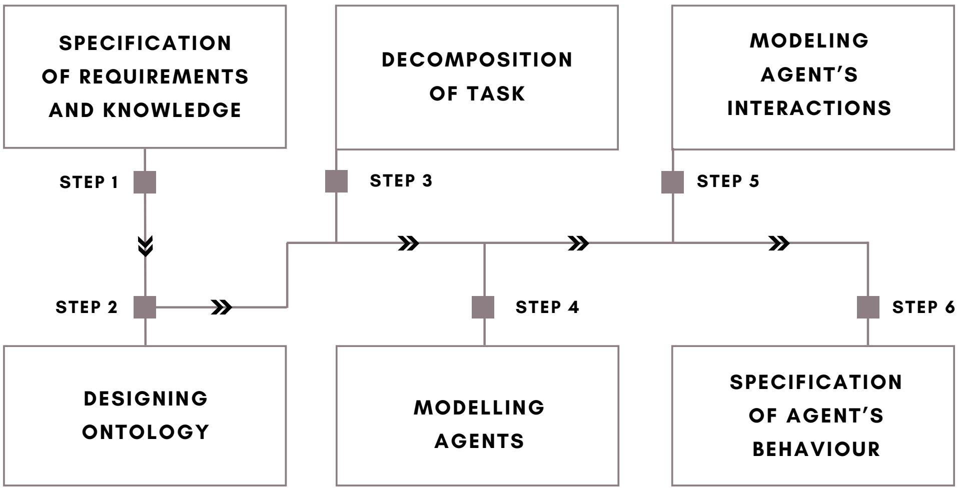

Figure 3.3: Multi Agents Designing Process

The methodology depicted in Fig. 3.3, starts by specifying the system requirements and gathering the necessary knowledge to meet those requirements. During the task decomposition stage, the specified requirements and acquired knowledge are organized into a hierarchy of tasks and subtasks. The next stage focuses on designing the vocabulary for agent communication, known as the ontology. The task hierarchy and ontology are then utilized in the agent modeling stage to identify a group of autonomous agents capable of performing the required tasks. This stage results in a set of agents, each with specific tasks assigned to them. Following the agent modeling, the interactions between the agents must be clearly defined to ensure effective collaboration and coordination within the multi-agent system.

Agents in Smart Grids

In smart grids, agents are utilized to tackle various challenges such as balancing energy supply and demand, negotiating energy prices between consumers and producers, managing energy storage in homes, and restoring energy supply. A common and useful tool i.e. Agent-Based Simulation (ABS) which is a distributed method is utilised for modeling dynamics of the electricity market [46]. An agent-based service introduced for smart grids supports distributed energy storage, employing switching and energy storage agents[47]. The switching agent manages energy load and isolates faults, while the energy storage agent supplies energy to the grid, enhancing system efficiency and enabling dynamic islanding for disconnected grid parts.

Another method for energy storage management is found in [48] where each energy producer, represented by an agent with a storage device, aims to maximize profit by analyzing price signals from other agents. This involves recording storage usage in a unique profile and using game theory to predict future usage, thereby deciding whether to sell or store energy.

Multi Agent System Architectures

MAS is suitable for simulating the behaviours of the multiple prosumers that behave autonomously to maximise their individual benefits in P2P energy sharing mechanisms.The architectures and models of the agents are described in a general and abstract way to highlight the major structure, functionalities and input/output relationship.

The energy sharing system can be conceptualized as a multi-agent architecture with three key components:

1. Agent Types
    - Energy Sharing Coordinator Agent (CA)
    - Prosumer Agents (PAs)
    - Retailer Agent (RA)
2. Functional Models
    - Pricing Model (CA)
        - **Function:** Calculate and issue internal prices
        - **Input:** Bids from Prosumer Agents
        - **Output:** Market clearing price
    - Decision-Making Model (PAs)
        - **Function:** Schedule energy consumption/generation
        - **Output:** Bids for energy trading

  - **Considers:** Local constraints and preferences
- Implementation Model
  - **Function:** Govern interactions between CA and PAs
  - **Defines:** Rules and protocols for energy exchange
  - **Ensures:** Fair and efficient market operation

3. Interaction Flow

   (a) PAs submit bids based on their decision-making model
   (b) CA processes bids using the pricing model
   (c) CA issues internal price signals
   (d) Energy exchanges occur according to implementation model rules
   (e) RA interfaces with external grid/market as needed

This structure also represented in Fig. 3.4, enables decentralized decision-making by prosumers while maintaining coordinated energy sharing through the central agent. The modular design allows for flexibility in implementing different pricing mechanisms, decision strategies, and market rules within the same overall framework [49].

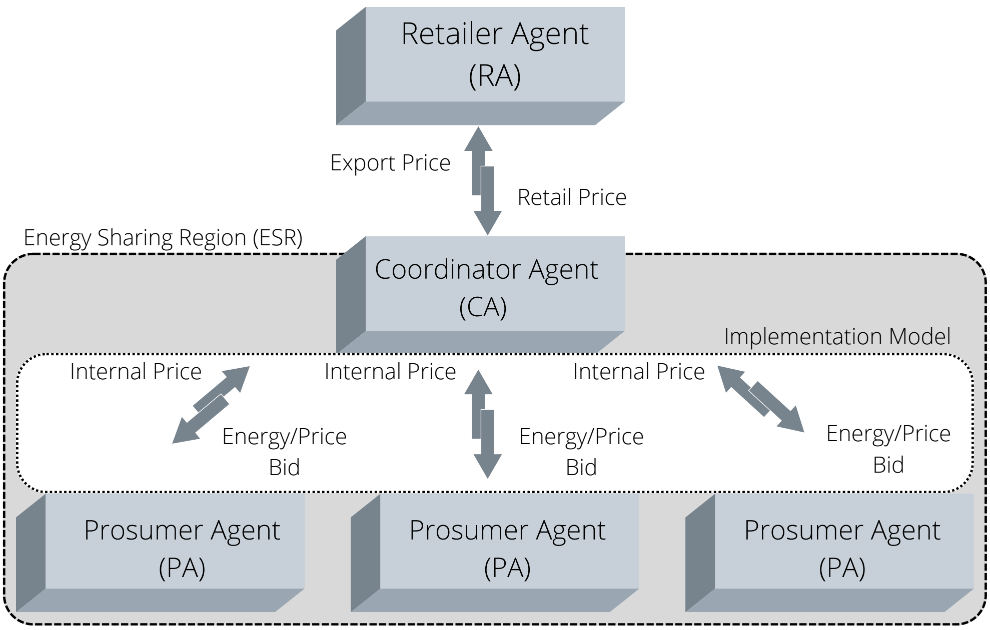

Figure 3.4: A General Architecture of Multi Agent Systems for Peer-to-Peer Energy Trading

Note that consumers can be seen as a special type of prosumers who do not own any local generation. Therefore, for convenience, both prosumers and consumers are collectively referred as prosumers.

Prosumer Agent Model in P2P Energy Sharing

Agent Representation The P2P energy sharing system is composed of multiple autonomous prosumer agents, represented as[44, 49]:

$$PA = \{PA_1, PA_2, ..., PA_N\} \tag{3.12}$$

where N is the total number of participating prosumers.

Environment Variables Each prosumer agent PA_i operates within an environment ε_{PA_i} defined by four key components:

1. **Internal Pricing** ($\mathbf{p}^{internal}$): Set of prices used within the P2P sharing mechanism
2. **Device Parameters** ($\mathbf{A}$): Characteristics of electrical devices, including:
    - Appliances
    - Energy storage systems
    - Distributed generators
3. **Demand Profile** ($\mathbf{D}$): Time-varying energy consumption patterns (e.g., daily hot water usage)
4. **Renewable Generation** ($\mathbf{P}^{renewable}$): Power output from uncontrollable renewable sources owned by the prosumer

Thus, the environment for each prosumer agent is formally defined as:

$$\varepsilon_{PA_i} = \{\mathbf{p}^{internal}, \mathbf{A}, \mathbf{D}, \mathbf{P}^{renewable}\} \tag{3.13}$$

This environment encapsulates the input data set for the prosumer agent's decision-making process. The data is sourced from both external entities (e.g., the system coordinator) and internal systems (e.g., the prosumer's energy management system).

Prosumer Agent Decision-Making Model

The prosumer agent's decision-making process in P2P energy sharing can be formulated as an optimization problem:

Objective Function Minimize the total electricity cost over the scheduling horizon:

$$\min_{\mathbf{x}} \sum_{t \in T} \mathrm{Cost}_t(\mathbf{p}^{\mathrm{internal}}, \mathbf{P}^{\mathrm{renewable}}, \mathbf{x}) \tag{3.14}$$

Constraints Subject to:

$$\mathbf{f}(\mathbf{x}, \mathbf{A}, \mathbf{D}) = 0 \quad \text{(Equality constraints)} \tag{3.15}$$

$$\mathbf{h}(\mathbf{x}, \mathbf{A}, \mathbf{D}) \leq 0 \quad \text{(Inequality constraints)} \tag{3.16}$$

Where:

- T: Set of time steps in the scheduling horizon
- $\mathbf{x}$: Decision variables (operational status of controllable devices)
- $\mathbf{p}^{\text{internal}}$: Internal electricity prices
- $\mathbf{P}^{\text{renewable}}$: Renewable generation output
- $\mathbf{A}$: Device parameters
- $\mathbf{D}$: Demand profile

Action Set The prosumer agent's action set is defined as:

$$AC_{PA} = \{\mathbf{x}, \mathbf{e}^{\text{bid}}, [\mathbf{p}^{\text{bid}}]\} \tag{3.17}$$

Where:

- $\mathbf{x}$: Control signals for controllable devices
- $\mathbf{e}^{\text{bid}}$: Energy bid (resulting load profile)
- $\mathbf{p}^{\text{bid}}$: Price bid (optional, depending on the mechanism)

This formulation captures the prosumer's goal of minimizing electricity costs while adhering to device constraints and user preferences. The resulting actions include device control signals and bids for the P2P energy sharing market.

Coordinator Agent Framework

The coordinator agent plays a pivotal role in managing local energy trading and external grid interactions. Its functions can be broken down as follows:

Environment Variables The coordinator agent operates within an environment defined by:

$$\varepsilon_{CA} = \{\mathbf{p}^{external}, \mathbf{e}^{bid}, \mathbf{p}^{bid}\} \tag{3.18}$$

Where:

- $\mathbf{p}^{external}$: External electricity prices for buying/selling with the retailer
- $\mathbf{e}^{bid}$: Energy bids from prosumers
- $\mathbf{p}^{bid}$: Price bids from prosumers

Pricing Model The coordinator uses a pricing function to determine internal trading prices:

$$\mathbf{p}^{internal} = \text{Pricing}_T(\mathbf{p}^{external}, \mathbf{e}^{bid}, \mathbf{p}^{bid}) \tag{3.19}$$

This function is central to the efficiency and fairness of the P2P market.

Action Set The coordinator's actions are represented as:

$$AC_{CA} = \{\mathbf{p}^{internal}, \mathbf{e}^{exchange}\} \tag{3.20}$$

Where:

- $\mathbf{p}^{internal}$: Internal prices issued to prosumers
- $\mathbf{e}^{exchange}$: Energy traded with the external retailer

Key Responsibilities

1. **Local Market Management**:
   - Receive bids from prosumers
   - Issue internal prices
   - Facilitate energy trading within the community
2. **External Grid Balancing**:
   - Trade with retailer to balance local energy deficits/surpluses
   - Act as an intermediary between the P2P community and the wider grid

This framework enables the coordinator to efficiently manage the local energy market while ensuring grid stability through external interactions.

Implementation model

The implementation model defines the trading process between the coordinator agent and prosumer agents, specifically the bidding and pricing procedures during peer-to-peer energy sharing. Based on the number of iterations required to determine the internal price, there are two main types of implementation: one-shot and iterative. The implementation model may also establish additional rules for the bidding process to enhance convergence performance or mitigate the risk of market power abuse [50].

Retailer agent

The retailer agent represents the retailer and acts as a passive agent, buying and selling electricity to and from the energy sharing coordinator agent at pre-announced retail and export prices. The retailer is assumed not to adopt dynamic prices associated with wholesale market price fluctuations, consistent with current practices in many countries.

Designing P2P energy sharing mechanisms with an active retailer adopting dynamic prices or demand response measures remains an open question, as existing mechanisms assume a passive retailer providing electricity at pre-announced prices. An active retailer would have strong market power compared to prosumers, necessitating additional rules to limit their power and protect prosumers' interests. In the presented paradigm, the coordinator negotiates with the retailer on behalf of all prosumers to balance energy within the sharing region, which is applicable to grid-connected microgrids with a single point of common coupling [51].

Agent-based simulation (ABS) techniques are adaptable, scalable, and can model dynamic interactions among market players as agents. These methods have been applied to various power system applications, such as electricity markets. In the literature, agents are used to represent homes [52], neighborhoods [53], and market players in the distribution network [54], often utilizing the Java Agent DEvelopment (JADE) framework. These agent-based models aim to minimize costs, manage energy, and facilitate energy trading within communities and among smart microgrids.

3.7.3 Auction-Based Methods

An auction is a mechanism for distributing economic resources by employing a competitive bidding process to equilibrate demand and supply [55]. An auction is described as a clearly established negotiation process in which the negotiation is conducted through an intermediary, which may not be an actual agent but rather a set of automated guidelines. Within an auction market, numerous buyers and sellers can place various bids and offers to the auctioneer, who then determines a clearing price for the commodities. Specifically, an energy auction aims to secure the most favorable transaction that equates demand with electricity supply at the lowest possible cost. This auction-based method draws inspiration from the stock market, treating

P2P electricity trading as an auction where the auctioneer sets the market clearing price, with the flexibility of distribution depending on the bidding strategies of the participants.

The primary categories within auction theory include the reverse auction, forward auction, and double auction models. In a reverse auction, multiple sellers compete to offer goods or services requested by a single buyer, whereas in a forward auction, many buyers vie for goods or services on sale. The double auction model allows multiple buyers to submit bids for goods or services from multiple sellers. However, the reverse and forward auction models are generally not considered suitable for electricity trading, which typically involves multiple sellers and buyers simultaneously [56].

Double auction mechanism

In recent times, double-auction models have become a popular method for simulating the clearing of the peer-to-peer (P2P) electricity market [57, 58]. These models serve as the mechanism for clearing the market in P2P energy trading platforms, facilitating the pairing of buyers and sellers interested in engaging in P2P transactions.

The peer-to-peer (P2P) energy market operates on a bid-ask system for future energy timeslots. The process can be broken down as follows:

1. Bid and Ask Submissions

During the open market period, participants submit two types of orders:

Bids (from energy consumers):

$$o_{b,t}(\zeta_t, \pi_{b,t}, \varepsilon_{b,t}, \tau_t) \tag{3.21}$$

Where:

- ζ_t: Consumer identifier
- $\pi_{b,t}$: Bid price (Rs/kWh)
- $\varepsilon_{b,t}$: Energy quantity (kWh)
- τ_t: Timestamp

Asks (from prosumers):

$$o_{a,t}(\rho_t, \pi_{a,t}, \varepsilon_{a,t}, \tau_t) \tag{3.22}$$

Where:

- ρ_t: Prosumer identifier
- $\pi_{a,t}$: Ask price (Rs/kWh)
- $\varepsilon_{a,t}$: Energy quantity (kWh)
- τ_t: Timestamp

2. Order Book Formation After the market closes, orders are sorted to create the supply and demand curves:

- Bids: Sorted in descending order of $\pi_{b,t}$
- Asks: Sorted in ascending order of $\pi_{a,t}$

3. Market Clearing The intersection of the bid and ask curves determines:

- Market clearing price: $\pi_{p2p,t}$
- Market clearing volume: $\varepsilon_{p2p,t}$

This mechanism ensures an efficient allocation of energy resources based on participants' willingness to buy and sell, creating a balanced and competitive P2P energy market.

Recent studies have applied auction methods to small-scale energy trading. For instance, an auction-based strategy for allocating storage among residential communities is suggested [57], while another work maximizes the social welfare of plug-in hybrid electric vehicles through a localized P2P trading using an iterative double auction [59].

3.7.4 Constrained Optimization Methods

Optimization, also referred to as mathematical programming, is a systematic approach for addressing quantitative problems encountered in various domains and real-world situations. The core objective is to identify the optimal values $(x_1^*, x_2^*, \ldots, x_n^*)$ for a set of decision variables $(x_1, x_2, \ldots, x_n)$ that affect an objective function $f(x_1, x_2, \ldots, x_n)$, which needs to be either minimized or maximized.

Optimization problems can be classified into several categories:

1. Continuous or discrete
2. Constrained or unconstrained
3. Stochastic or deterministic
4. Single-objective or multi-objective

5. Linear or nonlinear

Furthermore, based on the method used to solve them, optimization problems can be categorized as:

1. Centralized
2. Decentralized
3. Distributed

This classification framework helps in understanding and approaching different types of optimization challenges across various fields.

Recent studies [36], particularly in the context of peer-to-peer (P2P) energy trading within smart grids, highlight the application of both centralized and distributed optimization strategies. These include methods such as linear programming, mixed-integer linear programming, nonlinear programming, and the alternating direction method of multipliers.

Linear Programming

Linear Programming is an optimization technique used to find the best possible solution within a set of constraints. It can be conceptualized as follows:

1. **Goal**: Maximize or minimize a specific outcome
2. **Decision Variables**: Quantities to be determined (x)
3. **Objective Function**: Linear equation to be optimized ($c^T x$)
4. **Constraints**: Linear inequalities or equations that limit possible solutions ($Ax \leq b$)
5. **Non-negativity**: Decision variables must be non-negative ($x \geq 0$)

The standard form of an LP problem is:

$$\begin{aligned} \text{Maximize: } & c^T x \\ \text{Subject to: } & Ax \leq b \\ & x \geq 0 \end{aligned}$$

Where:

- x is the vector of decision variables
- c is the vector of coefficients in the objective function
- A is the matrix of coefficients for the constraints
- b is the vector of right-hand side values for the constraints

LP has diverse applications, including:

- Resource allocation
- Production planning
- Transportation and logistics
- Financial portfolio optimization

In a specific application [60], researchers have utilized LP to develop an innovative multi-energy management strategy for prosumers. This approach aims to optimize energy scheduling by leveraging the complementary nature of multi-energy demand, potentially leading to more efficient and cost-effective energy systems.

MILP

Mixed Integer Linear Programming (MILP) is an optimization technique that incorporates both continuous and discrete variables within a linear framework. It can be formulated as:

$$\begin{aligned} \text{Maximize: } & b^T x \\ \text{Subject to: } & Ax + s = c \\ & x \geq 0, s \geq 0 \\ & x \in \mathbb{Z}^n \text{ (for some entries)} \end{aligned}$$

Where:

- x represents decision variables (some integer, some continuous)
- b, A, and c are coefficient vectors/matrices
- s is a slack variable vector

Application in P2P Energy Trading

MILP has several applications in Peer-to-Peer (P2P) energy trading systems:

Home Energy Management

- Optimizes scheduling of local energy generation and storage
- Determines energy surplus/deficit for trading

Market Optimization

- Maximizes revenue from solar PV power
- Allocates forecasted and uncertain PV generation to flexible loads

Problem Formulation

- Linearizes non-linear and bilinear terms
- Balances time-flexible and power-flexible consumer demands [61]

This MILP approach enables efficient optimization of P2P energy trading systems, considering both discrete decisions and continuous variables within the constraints of linear programming.

ADMM

ADMM is an optimization algorithm for solving large-scale convex problems by breaking them into smaller, more manageable sub-problems. It combines the benefits of dual decomposition and augmented Lagrangian methods.

Key Features

- Decomposes complex problems into simpler sub-problems
- Enables parallel processing
- Employs augmented Lagrangian method with partial dual variable updates

Mathematical Formulation

For a problem with two objectives and variable sets:

$$\begin{aligned} \text{Maximize}_{x,z} \quad & f(x) + g(z) \\ \text{subject to} \quad & Ax + Bz = c \\ & x \in X, \quad z \in Y \end{aligned}$$

Where:

- x and z are variable vectors
- $f(x)$ and $g(z)$ are objective functions
- A and B are parameter matrices
- c is a constraint vector

Advantages

1. Efficient for large-scale problems
2. Handles problems with separate but coupled objectives
3. Suitable for distributed optimization

ADMM iteratively solves sub-problems related to x and z, updating dual variables to converge on a solution that satisfies the coupling constraint $Ax + Bz = c$.

Within the context of P2P energy trading, authors in [62] have used ADMM to find the generalized Nash equilibrium of a noncooperative game used to derive the energy sharing profiles of energy buildings. Adaptive penalty parameter selection is used to improve the convergence of the standard ADMM algorithm.

Nonlinear Programming

Nonlinear Programming (NLP) is an optimization technique that addresses problems where:

- The objective function is nonlinear, and/or
- The constraints are nonlinear

NLP aims to find the optimal solution within a feasible region defined by nonlinear equations and inequalities. It's particularly useful for problems where linear approximations are inadequate.

General Form

A nonlinear programming problem can be expressed in the following general form:

$$\begin{aligned} \text{Optimize} \quad & f(x) \\ \text{subject to} \quad & g_i(x) \leq 0, \quad i = 1, \ldots, m \\ & h_j(x) = 0, \quad j = 1, \ldots, p \\ & x \in X \end{aligned}$$

Where:

- $f(x)$ is the nonlinear objective function
- $g_i(x)$ are inequality constraints
- $h_j(x)$ are equality constraints
- X is the feasible region

Application in P2P Energy Sharing

Researchers applied constrained NLP to develop an optimization algorithm with a rolling time horizon [63]. This approach:

- Minimized energy costs in P2P energy sharing communities
- Achieved a 30% cost reduction compared to traditional P2G (Peer-to-Grid) energy trading

This example demonstrates NLP's potential in optimizing complex energy systems with nonlinear characteristics.

3.8 Price Formation Mechanisms

Price formation mechanism refers to the process of determining market prices. This occurs within the framework of a market institution, which outlines the rules for communications (such as bids from buyers and asks from sellers), identifies the participants allowed to exchange these messages, and dictates the manner in which transactions are conducted. Therefore, market institutions establish the price formation mechanisms. A survey in [27] shows classification of price formation methods as follows:

Single Auction

In single auctions, only one group, either buyers or sellers, submits bids or offers. This format is often used when there's just one buyer, like in procurement auctions where a buyer requests bids from multiple suppliers with a market operator facilitating the process[64]. This operator could be an aggregator, a local energy operator, or a distribution system operator.

Double Auction

Double auction allows both buyers and sellers to submit bids and offers, reflecting their utility and costs, respectively. Double auctions promote efficiency and learning among participants due to their iterative nature. The two main types are the double clock auction [65], which clears at set times, and the continuous double auction [66], which clears constantly, similar to stock markets.

System-determined Mechanisms

Price formation through system-determined mechanisms where prices are not based on market bids but are set by a platform operator using specific formulas or agreements. The "system operator" role varies, potentially being a community energy aggregator, local retailer, or DSO. Common pricing mechanisms include uniform prices, fixed feed-in tariffs, time-of-use pricing, fixed ratios for local renewable energy prices, demand-based pricing formulas, and redistribution of benefits using cooperative game theory methods like the Shapley value [67].

Negotiation-based Mechanisms

Auction-based market platforms centralize buyer and seller interactions, while a decentralized approach uses negotiation-based mechanisms for peer-to-peer (P2P) transactions. These negotiations are often facilitated by AI software, enabling automated bargaining between parties. This method is less structured than auctions and relies on individual or small group offers to determine prices, supporting truly decentralized P2P energy trades.

Equilibrium-based Mechanisms

Equilibrium-based pricing mechanisms determine prices through the interaction of bids and offers from market participants, such as prosumers or suppliers, reaching a balance derived from game-theoretic principles [68]. Research shows that repeated bidding can lead to a stable price equilibrium, often using the Nash equilibrium concept, though Cournot and Stackelberg equilibria are also applied.

These price formation mechanisms are strung together by the market design to form a complete market.

Chapter 4

Bilateral Negotiation Mechanisms for Peer-to-Peer Energy Trading

4.1 Research Context

As discussed in previous chapters, there is demand for innovative transactive energy spaces and market structures capable of effectively managing distributed generation and EV charging. Local transactive energy markets and peer-to-peer (P2P) energy trading have emerged as potential solutions, providing market mechanisms that enable prosumers and consumers to actively participate, gain monetary benefits, and provide ancillary services to the grid.

Researchers are focused on improving these solutions and introducing novel approaches using various technical methods. By developing effective strategies, the flexibility of both DERs and EVs can be harnessed to support grid stability and efficiency while accommodating the ongoing electrification trend.

Significant efforts are dedicated for developing mechanisms for regulating vehicle charging at various levels, including coordination for vehicle-to-grid (V2G) applications [69]. Recent studies project that by 2030, V2G applications could cover one-third of peak hour demand [70]. Methodologies for coordination of electric vehicles include transactive energy mechanisms, such as multi-agent systems [71], game theory approaches [72, 73], and market-based mechanisms [61, 74].Regardless of whether the coordination of vehicles is done explicitly or implicitly, and the methodology employed for obtaining the control signals, the aggregator is somehow able to perform this management and use the flexibility for different purposes depending on its business model. Aggregators can use EV flexibility for various purposes, including optimizing energy costs for vehicle owners [75], providing services to energy communities [76], participating in day-ahead markets [77, 78], frequency regulation [79], balancing markets [80], other ancillary services [81], and reducing congestion in distribution networks [82]. Decentralized user-oriented EV charging control is also a significant application [83].

In the local energy market (LEM) context, research has focused on enhancing bidding strategies and market mechanisms. Distribution system operators can achieve globally optimal DER dispatch in a decentralized manner, helping prosumers obtain optimal bidding curves [84, 85]. Market-clearing schemes have been developed to preserve participant privacy by focusing on bidding parameters rather than detailed preferences and profiles [59, 86].

P2P energy trading has been enhanced through iterative peer-matching and negotiation using a "greediness factor" [87] and asynchronous online consensus negotiation mechanisms [88]. Retail energy brokers have been introduced to control player bidding strategies using advanced decision-making methods [89]. Multi-step optimal bidding strategies for autonomous agents have been developed, considering risk preferences and expected profit [90]. Home energy management systems have been optimized from an aggregator's perspective [91, 92, 61, 93].

Game theory, contract theory, and auction theory have been employed to capture the dynamics of competition and cooperation in P2P energy trading markets [94, 95, 96]. Game theoretical analyses of prosumer behavior in combinatorial auctions with resource constraints have been conducted [97, 98], and iterative double auction mechanisms have been used to maximize social welfare [99].

Multi-agent system (MAS) theory has been applied to energy markets, with agent-based architectures aiming to maximize social welfare [100]. Multi-agent decision support systems have been designed to assist market players in various negotiation types [101]. Multi-agent deep reinforcement learning has been proposed for power dispatch optimization in systems with multiple uncertainties [102], and technical constraints such as line loadings and losses have been considered in multi-agent distribution systems [103]. A multi-actor-attention-critic algorithm has been developed to reduce community costs and peak demand while addressing scalability, non-stationarity, and privacy limitations [104].

These approaches demonstrate the diverse range of bilateral negotiation mechanisms being explored for P2P energy trading in local energy markets, including game-theoretic models, multi-agent systems, and automated negotiation techniques.

Building upon these existing approaches, this chapter focuses on two pivotal aspects: the development of peer-to-peer (P2P) local energy trading markets and strategic infrastructure management for accommodating increasing electricity demands. Addressing the overarching research question, 'How can innovative market structures and load management strategies mitigate the challenges posed by the evolving energy landscape?' we introduce two innovative P2P energy trading frameworks designed to integrate EVs seamlessly and manage infrastructure investments efficiently.

The first part of the chapter delves into a framework aimed at coordinating EV charging within the distribution grid, presenting technical advancements for efficient energy distribution. The second part introduces a multi-agent-based P2P energy trading framework that not only ensures efficient grid support but also facilitates rapid computation and communication. Through these frameworks, we explore market mechanisms and management techniques that empower participants, offering both monetary benefits and ancillary services to the grid.

This chapter is organized as follows:

- Section 4.1 presents a concise review of current literature on P2P energy trading and EV integration challenges.
- Section 4.2 provides a detailed exploration of a novel P2P energy trading framework for EV charging coordination.
- Section 4.3 introduces and technically analyzes a multi-agent-based P2P energy trading framework.
- Section 4.4 offers a comparative analysis and discussion on the implications and benefits of the proposed solutions for the energy sector's transformation.
- Section 4.5 examines the current limitations of the proposed frameworks and identifies potential areas for improvement and future research.
- Section 4.6 summarizes the main contributions of the research works and concludes the chapter.

By focusing on these innovative strategies, this chapter contributes to the body of knowledge on managing energy distribution systems in the face of modern power system challenges.

4.2 Study 1: Multi-Issue Negotiation for EV Charging in Congested Networks

4.2.1 Problem Statement

A typical European urban distribution network is selected to demonstrate the extended model and a single line diagram of which has been represented in Fig. 4.1. This network, operated by EDP in Spain, consists of 30 power transformer stations serving 8,500 consumers. The focus is on one such station and its components.

Fig. 4.1 represents one of these power transformer stations along with its elements. All of the power transformers are with delta-wye (grounded) configuration. There are 4-wire 3 phase feeders (F.1, F.2,..) which connects power transformer secondary with circuit breaker (BR_1), and are protected by a set of fuses (F$_{F1}$, F$_{F2}$,...). Each

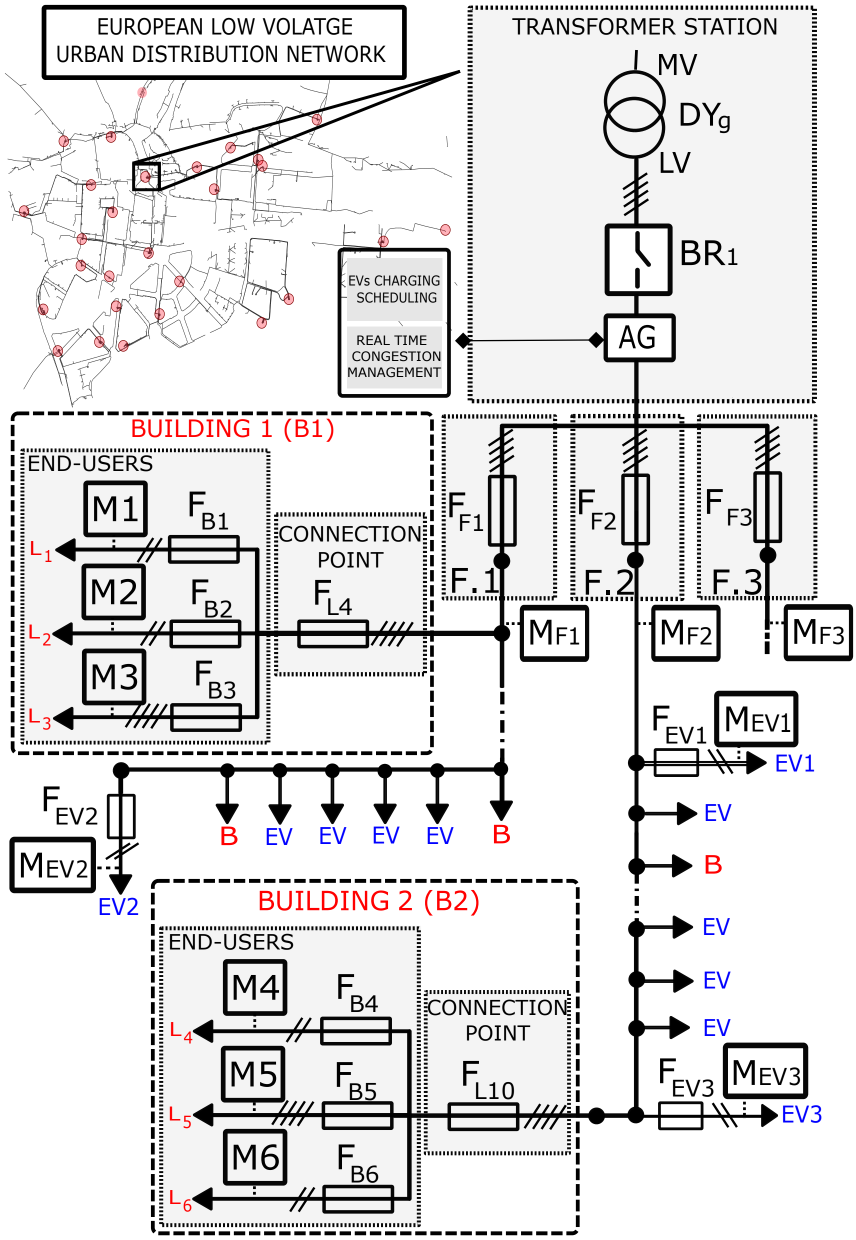

Figure 4.1: European low voltage urban distribution network representing the case defined in the problem statement.

feeder can be monitored by means of an advanced supervisor monitoring equipment (labeled in Fig. 4.1 as M_{F1}, M_{F2},...). There are around 25 buildings per power station distributed in around 4 feeders, where the average distance is less than 300 meters from power transformer to the connection points. Mostly, buildings have 3 phase connections while the end-users inside buildings (L_1,...,L_6) are single phase constituting unbalanced total load. Generally, there is a set of 3 phase fuses (for instance F_{L4}) installed for the protection of each building. Moreover, each end-user is also protected by it own fuse (such as F_{B1}) and supported with advance metering infrastructure (for instance M_1).

The network faces significant congestion during peak hours, limiting the addition of new loads like EV chargers without substantial infrastructure investments. This constraint hinders the large-scale introduction of EV chargers by Distribution System Operators (DSOs). However, the average daily load across feeders is less than 10%, suggesting potential for flexible load management to alleviate congestion and accommodate new loads.

In this case study, certain buildings represent critical loads that must be continuously supplied. Electric vehicles serve as flexible loads, negotiating charging parameters (price, duration, energy) with an aggregation platform. The aggregator's role is to manage non-supplied energy while adhering to DSO-defined physical constraints.

The challenge is to develop a multi-issue negotiation model and real-time congestion management algorithm that can:

1. Coordinate EV charging activities
2. Balance EV charging demand satisfaction with network congestion reduction
3. Avoid critical load shedding
4. Respect all physical constraints imposed by the DSO

The goal is to achieve this coordination using only low-latency measurements at the power transformer's secondary, demonstrating the negotiation protocol's capacity to manage congestion effectively. This approach aims to optimize the network's capacity to adopt new loads without requiring extensive infrastructure upgrades.

As detailed in the Appendix of the thesis, to simulate realistic conditions, a load profile of EVs at public EV chargers in the network is generated using the EV load simulation model. This model provides a foundation for testing the proposed negotiation and congestion management strategies under various scenarios of EV charging demand [105].

4.2.2 Methodology

Overview of Multi-issue negotiation protocol

The proposed methodology introduces a novel multi-issue negotiation protocol for coordinating electric vehicle (EV) charging in congested networks. This protocol is inspired by the Rubinstein Alternating Offer Protocol, a well-established bargaining model that provides a perfect equilibrium solution to negotiation problems between transacting agents. While this protocol has been widely applied in automated negotiations across various fields, this marks its first adaptation for peer-to-platform energy trading applications.

Key Components

a. Negotiating Agents:

The negotiation process involves two key agents: EV owners and the aggregator. EV owners represent flexible loads in the network, seeking to charge their vehicles efficiently and cost-effectively. The aggregator, on the other hand, plays a crucial role in managing non-supplied energy and adhering to system constraints imposed by the Distribution System Operator (DSO). The aggregator's primary objective is to coordinate EV charging activities in a way that minimizes non-supplied energy while ensuring that all physical constraints of the network are respected. This dual-agent system allows for a balanced negotiation that considers both the individual needs of EV owners and the overall stability and efficiency of the distribution network.

b. Negotiation Parameters:

In this framework, the negotiation revolves around three crucial elements: Price (Pr), Time (T), and Energy (E), making it a novel 3D protocol. Specifically, agents (EV owners and the aggregator) negotiate on the price per unit energy (Pr), time slots and duration required for the charging activity (T), and energy packets (E) needed to achieve a certain State of Charge (SoC) level.

Negotiation Process

To initiate a charging activity, the EV charger identifies the owner and negotiates with the aggregator on the three key parameters: price, time duration, and energy required for charging. These negotiations are based on the parameters defined in the EV owner's tariff. The aggregator's role is crucial in this process. While the aggregator's utility function may benefit from higher prices, its primary objective is to minimize non-supplied energy by coordinating with EV owners. This coordination must be achieved while adhering to all physical constraints imposed by the distribution system operator (DSO).

Given the specific characteristics of this case study - namely, the limited number of EVs that can connect to a feeder and the high speed of the negotiation algorithm - the aggregator adopts a FIFO (First In, First Out) strategy. This approach means the aggregator negotiates sequentially with EV owners as they connect to the charging station.

Utility Function

Throughout the negotiation process, the algorithm determines the corresponding benefits or satisfaction levels of the agents for each potential deal. This is quantified as a number between 0 and 1, termed as utility. Each element of the negotiation is evaluated by its utility for the agent, which is calculated using a utility function.

Information Flow

To initiate a negotiation, both the aggregator and the EV owner specify their preferences for (Pr, T, E), along with other negotiation parameters such as negotiation rounds and deadlines, and strategies like time-dependent concessions. For simplicity, it's assumed that when an EV connects to a charging station, the advanced metering infrastructure provides the aggregator with information about the EV's current SoC. Based on this SoC level and the forecast of building power consumption, the aggregator determines its (Pr, T, E) preferences and adapts its negotiation strategies accordingly.

Protocol Flexibility

It's worth noting that forecasting techniques are beyond the scope of this research, as the prediction methodology is decoupled from the trading methodology. The proposed approach is formulated independently of the prediction methodology, assuming that the aggregator may use aggregated building consumption forecasts. The paper does, however, consider deviations between real and forecasted consumption, as these significantly affect the network's capacity to allocate EVs. Furthermore, while this study uses a FIFO strategy, the methodology's generality allows for adaptation to other scenarios, such as parallel negotiations. This comprehensive approach aims to balance the needs of EV owners with the constraints of the distribution network, providing a flexible and efficient method for managing EV charging in congested urban environments.

Utility Functions Description

The negotiation protocol employs four primary utility functions to quantify the preferences and satisfaction levels of both EV owners and the aggregator. These functions - Price, Time, Energy, and Total utility - form the backbone of the bilateral negotiation strategies. Let's explore each in detail.

Price Utility Function:

The negotiation process begins with both parties establishing a price window. This window is bounded by their most favorable price (initial price Pr_I) and least favorable price (reserved price Pr_R). These boundaries are set to align with each party's economic interests.

The aggregator's price window is dynamic, responding to price signals in the market. During peak hours, the aggregator sets prices to discourage EV charging, while during periods of surplus power, prices are adjusted to encourage more EV charging, optimizing resource utilization.

Both parties also set a minimum acceptable price utility ($u_{Pr_{min}}$). Any offer falling below this threshold is automatically rejected. In subsequent negotiation rounds, counteroffers are made while ensuring the price utility remains above this minimum.

The price utility functions for EV owners and aggregators are defined in equations (4.1) and (4.2) respectively. These functions calculate the utility derived from a given price point within the negotiation range.

$$U_{Pr}^{EV}(Pr) = \begin{cases} u_{Pr_{min}}^{EV} + (1 - u_{Pr_{min}}^{EV}) \left| \frac{Pr_R^{EV} - Pr}{Pr_R^{EV} - Pr_I^{EV}} \right|, & Pr_I^{EV} \leq Pr \leq Pr_R^{EV}, \\ 0, & \text{otherwise} \end{cases} \tag{4.1}$$

$$U_{Pr}^{AG}(Pr) = \begin{cases} u_{Pr_{min}}^{AG} + (1 - u_{Pr_{min}}^{AG}) \left| \frac{Pr_R^{AG} - Pr}{Pr_I^{AG} - Pr_R^{AG}} \right|, & Pr_R^{AG} \leq Pr \leq Pr_I^{AG}, \\ 0, & \text{otherwise} \end{cases} \tag{4.2}$$

Notably, the EV owner's utility ($U_{Pr}^{EV}(Pr)$) is inversely related to price, while the aggregator's utility increases with price. The price is defined per energy packet, a concept elaborated on later.

Time Utility Function:

EVs are treated as flexible loads to manage network constraints. The protocol allows for discontinuous charging to prioritize critical loads (such as buildings). This flexibility necessitates a time utility function.

Both parties define their time preferences within a range bounded by their most preferred (initial) and least preferred (reserved) time durations $[T_I, T_R]$. The time utility functions, defined in equations (4.3) and (4.4), calculate the utility derived from a proposed charging time slot and duration.

$$U_T^{EV}(T) = \begin{cases} u_{T_{min}}^{EV} + (1 - u_{T_{min}}^{EV}) \left| \frac{T_R^{EV} - T}{T_R^{EV} - T_I^{EV}} \right|, & T_I^{EV} \leq T \leq T_R^{EV}, \\ 0, & \text{otherwise} \end{cases} \tag{4.3}$$

$$U_T^{AG}(T) = \begin{cases} u_{T_{min}}^{AG} + (1 - u_{T_{min}}^{AG}) \left| \frac{T_I^{AG} - T}{T_I^{AG} - T_R^{AG}} \right|, & T_R^{AG} \leq T \leq T_I^{AG}, \\ 0, & \text{otherwise} \end{cases} \tag{4.4}$$

EV owners typically prefer shorter charging times, setting a small T_I^{EV} for maximum utility. Conversely, aggregators prefer longer T_I^{AG} to maintain flexibility in case of sudden demand from critical loads.

Energy Utility Function:

The aggregator forecasts demand from critical loads and quantifies available power in each time slot as the number of EVs that can be accommodated. Energy is discretized into packets of fixed duration Δt and amplitude based on charger capacity.

Both parties define their energy preferences as a range of acceptable energy packets $[E_I, E_R]$. The energy utility functions, given in equations (4.5) and (4.6), calculate the utility derived from the proposed number of energy packets.

$$U_E^{EV}(E) = \begin{cases} u_{E_{min}}^{EV} + (1 - u_{E_{min}}^{EV}) \left| \frac{E_R^{EV} - E}{E_R^{EV} - E_I^{EV}} \right|, & E_R^{EV} \leq E \leq E_I^{EV}, \\ 0, & \text{otherwise} \end{cases} \tag{4.5}$$

$$U_E^{AG}(E) = \begin{cases} u_{E_{min}}^{AG} + (1 - u_{E_{min}}^{AG}) \left| \frac{E_R^{AG} - E}{E_R^{AG} - E_I^{AG}} \right|, & E_R^{AG} \leq E \leq E_I^{AG}, \\ 0, & \text{otherwise} \end{cases} \tag{4.6}$$

Total Utility Function:

The individual utilities (Price, Time, and Energy) are weighted and combined to form a total utility for each agent. These weights (w_{Pr}, w_T, w_E) allow agents to adjust their preferences and make trade-offs during negotiation. The total utility, defined in equation (4.7), is used to evaluate offers and guide decision-making throughout the negotiation process.

$$U_{total}(Pr, T, E) = \begin{cases} 0, & \text{if any of } U_{Pr}, U_T, U_E = 0, \\ w_{Pr} \cdot U_{Pr} + w_T \cdot U_T + w_E \cdot U_E, & \text{otherwise} \end{cases} \tag{4.7}$$

This comprehensive utility function framework enables a nuanced and flexible negotiation process, allowing both EV owners and aggregators to balance their preferences and constraints while working towards a mutually beneficial agreement. The utility functions are designed to reflect the different priorities of EV owners (who prefer lower prices and shorter charging times) and aggregators (who aim to manage network constraints and optimize resource utilization).

Negotiation Process and Strategies

The multi-issue negotiation protocol incorporates sophisticated strategies to enhance efficiency and accelerate the negotiation process. These strategies are designed to facilitate rapid agreement while balancing the interests of both EV owners and aggregators. The two primary strategies employed are the Burst Offer Mode and Time Dependent Concession.

Burst Offer Mode

The Burst Offer Mode is an innovative approach that allows each agent to propose multiple concurrent offers in a single negotiation round. This strategy significantly expedites the negotiation process by providing a range of options that all yield the same total utility for the proposing agent while potentially meeting the preferences of the receiving agent.

In this mode, an agent can generate a burst proposal consisting of various combinations of price, time, and energy elements. Each combination in the burst satisfies the proposing agent's utility requirements but offers different trade-offs among the negotiation elements. This approach increases the likelihood of finding a mutually acceptable offer more quickly.

Mathematically, a burst proposal from agent $A1$ to agent $A2$ at negotiation round r can be expressed as eq.(4.8):

$$BP_r^{A1 \to A2} = [(Pr_1, T_1, E_1), (Pr_2, T_2, E_2), ...(Pr_n, T_n, E_n)]_r \tag{4.8}$$

Where each tuple (Pr_i, T_i, E_i) represents a distinct offer within the burst, all yielding the same total utility for agent $A1$.

Time Dependent Concession

The Time Dependent Concession strategy introduces a dynamic element to the negotiation process, encouraging agents to reach an agreement more swiftly. This strategy operates on the principle that the expected utility (U_{exp}) of each agent should decrease over time, creating an incentive to conclude negotiations before losing too much potential value.

The concession in utility is calculated based on three key factors:

1. The current negotiation round (r)
2. The predetermined negotiation deadline (τ)
3. The negotiation strategy parameter (λ)

Eq.(4.9) exhibits the formula for calculating the expected utility for the next round is:

$$U_{exp}^{r+1} = U_{exp}^{r} - U_{exp}^{r} \cdot \left(\frac{r}{\tau}\right)^{\lambda} \tag{4.9}$$

This formula ensures that the expected utility decreases with each passing round, with the rate of decrease determined by the strategy parameter λ.

The value of λ defines the nature of the concession strategy:

1. Linear concession: $\lambda = 1$
2. Conciliatory strategy: $0 < \lambda < 1$
3. Aggressive strategy: $\lambda > 1$

In the context of EV charging negotiations, a linear concession strategy ($\lambda = 1$) has been adopted. This choice provides a balanced approach, allowing for steady and predictable concessions throughout the negotiation process.

The combination of burst offer mode and time dependent concession creates a dynamic and efficient negotiation environment. The burst offer mode increases the probability of finding a mutually acceptable solution in each round, while the time dependent concession strategy ensures that both parties are motivated to reach an agreement before their potential utility diminishes significantly.

By employing these strategies, the protocol aims to achieve rapid, fair, and mutually beneficial agreements that satisfy the requirements of both parties while ensuring efficient utilization of the electrical grid.

Objective Function and Constraints

The multi-issue negotiation protocol is designed to facilitate a dynamic exchange between EV owners and aggregators, with the primary goal of maximizing total utility for both parties. This process is governed by a well-defined objective function and a set of critical constraints that ensure the negotiation remains within practical and operational limits.

Objective Function

The core of the negotiation algorithm is centered around maximizing the total utility for each agent. This objective is mathematically expressed as equation (4.10):

$$maximize(U_{total}(Pr, T, E)) \tag{4.10}$$

Where U_{total} represents the total utility, which is a function of Price (Pr), Time (T), and Energy (E). This objective function encapsulates the desire of both EV owners and aggregators to achieve the most favorable outcome across all three negotiation elements.

Constraints

The negotiation process is subject to several important constraints that reflect the physical and operational realities of the electrical grid and charging infrastructure:

1. Grid Capacity Constraint:

$$P_{EV} < P_{tf}^{max} - P_b \tag{4.11}$$

   This constraint as expressed in eq.(4.11) ensures that the power allocated for EV charging (P_{EV}) does not exceed the available capacity of the transformer. The available capacity is calculated as the difference between the maximum transformer capacity (P_{tf}^{max}) and the forecasted power consumption of buildings (P_b). This constraint is crucial for preventing grid congestion and ensuring that critical loads (buildings) are always prioritized.

2. Charging Point Availability Constraint:

$$n_{EV}^{inst} <= n_{CP} \tag{4.12}$$

   This constraint limits the number of EVs that can charge simultaneously (n_{EV}^{inst}) to the total number of available charging points (n_{CP}). It reflects the physical limitations of the charging infrastructure and prevents overbooking of charging stations.

3. Minimum Utility Constraint:

$$(U_{total}, U_{Pr}, U_T, U_E) \geq u_{min} \tag{4.13}$$

   This constraint ensures that the negotiation remains within acceptable bounds for both parties. It stipulates that the total utility and the individual utilities for price, time, and energy must all remain above a specified minimum threshold (u_{min}). This prevents either party from accepting a deal that is significantly unfavorable in any aspect of the negotiation.

4.2.3 Implementation Details

Multi-Issue Pr-T-E Negotiation Algorithm

This section provides a detailed explanation of the algorithm's implementation, highlighting its key features and operational steps.

Algorithm 1 Multi-Issue Negotiation Mechanism

Require: $(P_I, P_R, T_I, T_R, E_I, E_R, u_{min}, \lambda, \tau)$ for EV owner and AG.
Ensure: (Pr, T, E) final price, time and energy.
1: AG prepares burst offer based on SoC_{init} of EV.
2: $r \Leftarrow 0$ Set $A1 = EVowner$ & $A2 = AG$.
3: $(Pr, T, E) := f_{A2}^{init}(SoC_{init})$ $A2$ burst offer preparation.
4: **if** $(Pr, T, E)_{A2}$ is empty **then**
5: Process terminated, **no agreement**.
6: **else**
7: $r \Leftarrow r + 1$ Update negotiation round.
8: Execute eq.(4.9) for both agents.
9: Update $Agent1$ utility $U_{exp,r}^{A1}$
10: $(Pr, T, E) := f_{A1}^{-1}(U_{exp,r}^{A1})$ $A1$ burst offer generation.
11: $U_{x,r}^{A2} := f_{A2}(Pr, T, E)$ $A2$ burst offer evaluation.
12: **if** $(r = \tau$ & $U_{x,r}^{A2} < U_{min}^{A2})$ **then**
13: Process terminated, **no agreement**.
14: **else if** $(r = \tau$ & $U_{x,r}^{A2} \geq U_{min}^{A2}) \mid U_{x,r}^{A2} \geq U_{exp,r+1}^{A2}$ **then**
15: Process terminated, **agreement reached**.
16: **else**
17: Switch EV onwer and Aggregator in $A1$ and $A2$ roles.
18: Goto line 7 to create **counter-offer**.
19: **end if**
20: **end if**

Initialization Phase:

- Preference Declaration: Both the EV owner and aggregator begin by declaring their initial preferences. These preferences are crucial for setting the boundaries of the negotiation and include:
  - Price window (Pr_I, Pr_R): Defining the most and least preferred prices
  - Time duration window (T_I, T_R): Specifying the acceptable time ranges for charging
  - Energy packets window (E_I, E_R): Indicating the desired range of energy to be transferred
- Parameter Setting: Additional parameters are set to govern the negotiation process:
  - Minimum utility (u_{min}): The lowest acceptable utility for reaching an agreement
  - Negotiation strategy (λ): Determines the concession rate over time

  - Negotiation deadline (τ): The maximum number of allowed negotiation rounds

- Agent Designation: Initially, $A1$ is designated as the EV owner and $A2$ as the aggregator. These roles alternate in subsequent rounds to ensure fairness.

- Aggregator's Initial Strategy: The aggregator prepares a burst offer based on the initial State of Charge (SoC_{init}) of the EV. This offer includes packages ranging from 10% to 100% SoC, each with corresponding price and time values. This pre-prepared burst offer strategy is designed to accelerate the negotiation process.

Negotiation Process:

1. First Round ($r = 1$):
   - The EV owner initiates the negotiation by sending a request to the aggregator.
   - This request contains the EV owner's most preferred (Pr, T, E) combination.
   - The EV owner's expected utility ($U^{A1}_{exp,r}$) is set to its maximum value.
2. Offer Evaluation:
   - The aggregator evaluates the EV owner's request using its utility function: $U := f(Pr, T, E)$
   - The aggregator compares the calculated utility against its expected utility (U_{exp}), which is initially set to 1 (maximum).
3. Counter-Offer Generation:
   - If the aggregator's utility criteria are not met, it generates a counter-offer.
   - The counter-offer is created using inverse utility functions: $(Pr, T, E) := f^-1(U)$
   - Note: These inverse functions often involve complex optimization methods and may return approximated results.
4. Burst Offer Strategy:
   - The aggregator sends multiple concurrent proposals (burst offer) to the EV owner.
   - This strategy increases the likelihood of finding a mutually acceptable solution quickly.
5. Offer Evaluation by EV Owner:
   - The EV owner evaluates each proposal in the burst offer.

- It selects the (Pr, T, E) combination that maximizes its utility (U_x).

6. Decision Making:
   - The EV owner first checks if the negotiation deadline (τ) has been exceeded. If so, the offer is rejected, and negotiations terminate.
   - If the utility from the offer is below the minimum acceptable utility (u_{min}), the offer is automatically rejected.
   - In the final round $(r = \tau)$, the offer is accepted if the utility is equal to or greater than u_{min}.
   - In other rounds, the utility is compared with the expected utility for the next round $(U_x, r \geq U_{exp}, r + 1)$.
7. Concession Strategy:
   - Both agents adjust their expected utility in subsequent rounds based on their concession strategy (λ).
   - This gradual reduction in expected utility encourages convergence towards an agreement.
8. Iteration:
   - The process repeats with agents alternating roles until an agreement is reached or the deadline is met.

Utility Function Usage:

- f functions are used to evaluate incoming offers.
- $f^{-}1$ functions are employed to create outgoing offers.

By incorporating burst offers, time-dependent concessions, and flexible utility evaluations, the protocol aims to achieve rapid, fair, and mutually beneficial agreements in the complex domain of EV charging coordination.

Real Time EV Charging Management

The real-time EV charging management algorithm is designed to dynamically adjust the charging schedule of electric vehicles (EVs) in response to real-time load deviations at the feeder level. These deviations can impact the pre-negotiated charging schedules, as they depend on forecasted energy consumption by buildings. To address this, the algorithm leverages the flexibility provided by EV owners during negotiations, ensuring that the system remains balanced and efficient.

Algorithm 2 Real Time EV Charging Manager

Require: $d\ \{P_I, P_R, T_I, T_R, E_I, E_R, u_{min}, \lambda, \tau\}$
Ensure: Real Time EV Charging Management.
1: **for** $\forall t \in T$ **do**
2:   **if** $t = t_i^a$ **and** CP is available **then**
3:     $\{EV_i$ owner assigned to set $d_i\}$
4:     Send d_i as input to Algorithm 1 to negotiate
5:     **if** Negotiation is successful **then**
6:       $EV_{\text{plugged}} = EV_{\text{plugged}} + \text{output(Algorithm1)}$
7:     **else**
8:       continue;
9:     **end if**
10:   **end if**
11:   **if** $P_{RT} < P_F$ **then**
12:     execute eqs. (4.15), (4.16), and (4.17);
13:     Disconnect $EV_{\text{plugged}}^{\text{dis}}(t+1)$ and update Schedule;
14:   **else if** $P_{RT} > P_F$ **then**
15:     execute eq. (4.15);
16:     Charge more connected EVs than planned;
17:     Update Schedule;
18:   **else if** $P_{RT} = P_F$ **then**
19:     continue;
20:   **end if**
21:   Evaluate EV_{plugged};
22:   **if** $E_i = E_{\text{neg}}$ **and** $T_i = T_{\text{neg}}$ **then**
23:     $EV_{\text{charged}} = EV_{\text{charged}} + EV_i$;
24:     $t_i^d = t$ and update Schedule;
25:   **end if**
26:   **if** $E_i = E_{\text{neg}}$ **and** $T_i < T_{\text{neg}}$ **then**
27:     Disconnect electrically;
28:   **end if**
29:   **if** $E_i < E_{\text{neg}}$ **and** $T_i = T_{\text{neg}}$ **then**
30:     Penalize Aggregator and repeat line 25;
31:   **end if**
32:   $t = t + 1$;
33: **end for**

Algorithm Overview:

1. Monitoring and Initialization:

    - At each time instant t, the algorithm checks for the arrival of EVs at any available charging stations (CP).

- For each arriving vehicle i at time t_i^a, the EV owner specifies initial parameter settings, which are recorded in a dataset labeled d_i.
- This dataset d_i is then passed to the negotiation algorithm to begin the negotiation process.

2. Negotiation and Update:

- Upon successful negotiation, the list of plugged-in EVs ($EV_{plugged}$) is updated with the negotiated parameters (Pr, T, E) for the i^{th} EV.
- The algorithm accounts for potential deviations from closed negotiations due to real-time changes.

3. Objective Function:

- The primary goal formulated as eq.(4.14) is to minimize the deviation $\Delta P_{total}(t)$ between real-time power capacity (P_{RT}) and forecasted power capacity (P_F) at time t.

$$minimize(\Delta P_{total}(t)) \tag{4.14}$$

- This deviation is caused by unexpected changes in critical loads (e.g., buildings) and is managed by adjusting flexible loads (EVs).

4. Control Equations:

- Disconnecting EVs: If a negative deviation is observed, the number of EVs to be disconnected ($n_{EV}^{dis}(t)$) is calculated using eq.(4.15):

$$n_{EV}^{dis}(t) = n_{EV}^{F}(t) - n_{EV}^{RT}(t) \tag{4.15}$$

Here, $n_{EV}^{F}(t)$ is the forecasted number of EVs, and $n_{EV}^{RT}(t)$ is the real-time capacity.

- Sorting EVs: EVs are sorted based on their remaining time ($T_{i_{(left)}}$) and energy ($E_{i_{(left)}}$) required for charging:

$$EV_{plugged}^{sort}(t) = sort(E_{i_{(left)}}/T_{i_{(left)}}) \tag{4.16}$$

- Disconnecting Strategy: The top $n_{EV}^{dis}(t)$ EVs from the sorted list are disconnected:

$$EV_{plugged}^{dis}(t+1) = EV_{plugged}^{sort}(t)[1 : n_{EV}^{dis}(t)] \tag{4.17}$$

5. Handling Positive Deviations:

- If a positive deviation is observed, more EVs are connected using the reverse order of the sorted list, prioritizing those with less remaining time relative to energy.

6. Ongoing Evaluation:

- The algorithm continuously evaluates the charging process of currently connected EVs, updating the schedule as needed. Three scenarios are considered:
  (a) Completion Within Time: EV completes charging within the negotiated time and departs, updating the schedule.
  (b) Early Completion: EV completes charging early and is disconnected, with a penalty if it stays beyond the negotiated time.
  (c) Incomplete Charging: If the EV is not fully charged by the negotiated time, it is disconnected, and the aggregator is penalized for the shortfall.

This real-time management algorithm ensures that the charging schedule remains adaptable and responsive to real-time conditions, optimizing the use of available resources while maintaining system stability. By dynamically adjusting to deviations and leveraging the flexibility of EVs, the algorithm effectively balances the needs of both EV owners and the grid infrastructure.

Simulation Set-up

To evaluate the efficacy of our proposed model, we conducted a comprehensive case study based on the network configuration detailed in Section 2. Our aim was to assess the algorithm's performance using real-world datasets, providing a robust and realistic testing environment.

- **Network Configuration and Load Profiles:** We simulated a network comprising 7 buildings, each housing 30 households. The load curves for these consumers were generated using authentic data from the ADRES-CONCEPT dataset [ADRES2010]. This approach ensured that our baseline load profiles accurately reflected real-world energy consumption patterns.

- **Introduction of EV Chargers:** To simulate the challenges of EV integration, we introduced EV charger loads into the network. This addition allowed us to observe and quantify the congestion issues arising from uncoordinated EV charging, providing a clear baseline for comparison with our coordinated approach.

- **Implementation of Negotiation Protocol:** We then applied our proposed multi-issue negotiation protocol to coordinate EV charging within the network. This was complemented by a real-time management algorithm designed to handle any deviations from predicted loads, ensuring the system's responsiveness to dynamic conditions.

- **Simulation Environment:** The entire simulation was developed and executed using MATLAB R2019b. We utilized MATLAB's object-oriented programming capabilities, implementing Classes to emulate the interactions between EVs and the Aggregator. This approach allowed for a more realistic representation of the negotiation process and system dynamics.

- **EV Load Profile Generation:** To create a diverse and realistic set of EV charging scenarios, we employed the EV load simulation model presented in [105]. This model generated a set of 100 EV charging profiles, each with unique characteristics:

  1. Battery Capacity: Randomly assigned within the range [22, 32, 40, 60] kWh, reflecting the variety of EV models in the market.
  2. Charging Power: A constant 7 kW charging power was assumed across all 10 public chargers (CP) in the network, simplifying the model while maintaining realism.
  3. Waiting Time: To simulate varying user behaviors and preferences, we assigned random waiting times to each EV, ranging from 5 to 30 minutes. This feature captures the realistic scenario where EV owners have different levels of patience and flexibility when faced with system congestion.
  4. Arrival and Departure Times: These were generated to reflect typical usage patterns of public charging stations.
  5. Initial State of Charge: Varied for each EV to simulate different charging needs.

This comprehensive simulation setup allows us to test our negotiation protocol and management algorithm under conditions that closely mimic real-world scenarios. By incorporating authentic load profiles, diverse EV characteristics, and dynamic waiting times, we can assess the model's effectiveness in managing network congestion and coordinating EV charging in a practical, scalable manner.

4.2.4 Key Findings and Analysis

Simulation Results

The simulation results demonstrate the effectiveness of our proposed multi-issue negotiation algorithm and real-time management model in addressing congestion issues caused by uncoordinated EV charging. We present a detailed analysis of the network's performance before and after implementing our model.

- **Uncoordinated EV Charging Scenario:** Fig. 4.2a illustrates the initial scenario where uncoordinated EV charging leads to network congestion:
  - The red dotted line represents the transformer's maximum capacity.

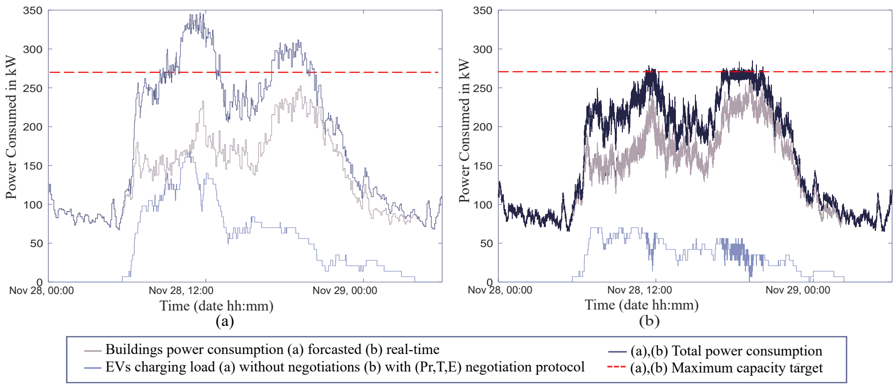

Figure 4.2: Performance of the system before and after applying the multi-issue negotiation algorithm

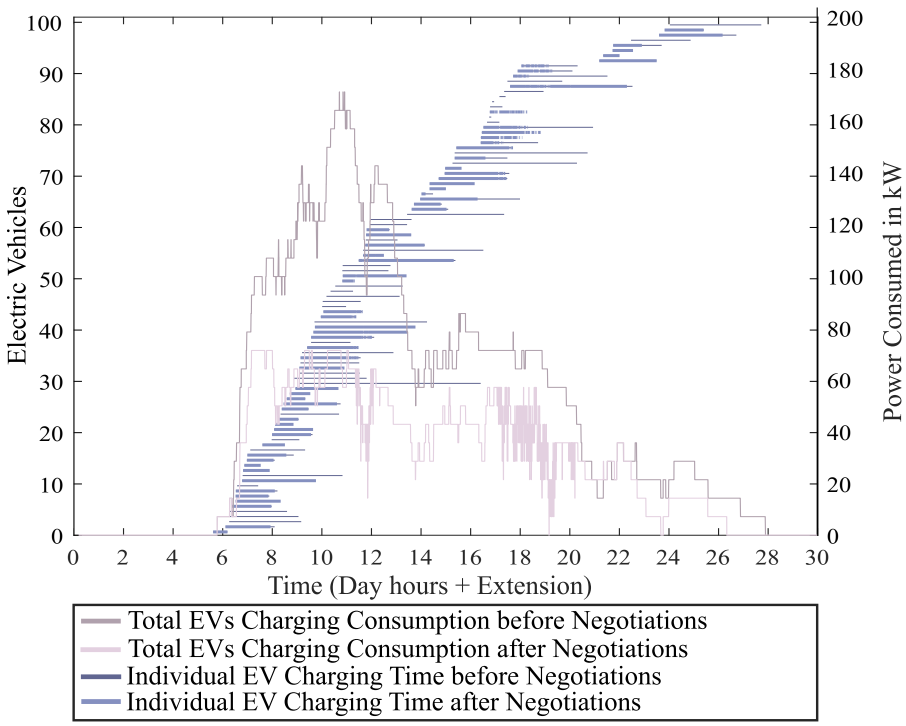

Figure 4.3: EV Charging before and after negotiations

- The grey curve shows the total EV charging consumption over time.
- The blue curve indicates the critical load (power consumption by buildings).
- The black curve represents the combined load of critical loads and EV charg-

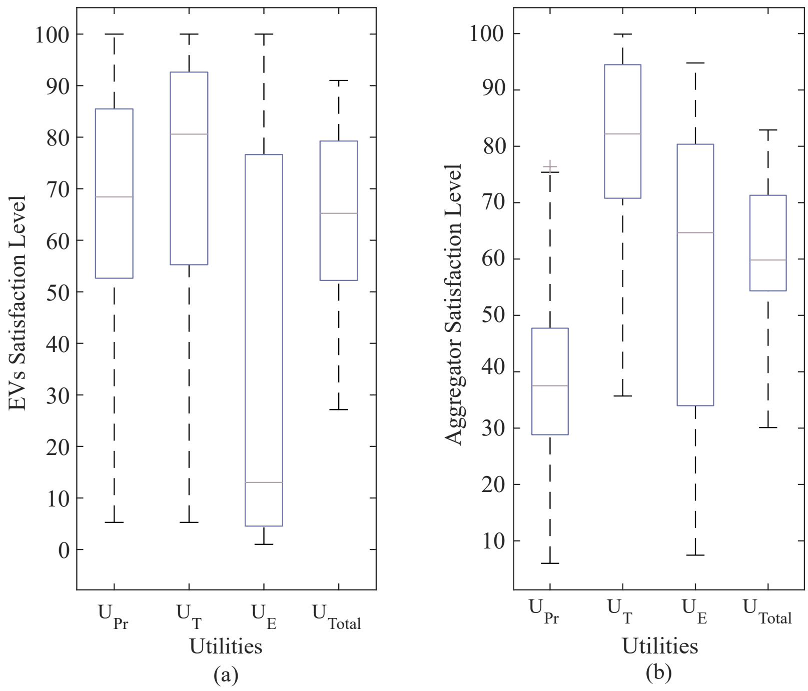

Figure 4.4: Achieved Satisfaction levels

ing.

Notably, the combined load exceeds the transformer's maximum capacity, particularly during morning and evening peak hours, indicating severe congestion.

- **Implementation of Proposed Model:** To resolve this congestion, we applied our multi-issue negotiation algorithm with the following initial parameters:
  - Aggregator price range: [10, 200] price units
  - EV owners' initial price range: [5, 75] units
  - EV owners' final price range: [125, 200] units
  - Maximum negotiation rounds (τ): 50
  - Strategy parameter (λ): 1

  Time duration $[T_I, T_R]$ and energy packet $[E_I, E_R]$ windows were defined based on EV state of charge requirements and the aggregator's assessment of critical load forecast and transformer capacity.

- **Results After Implementation:** Fig. 4.2b shows the results after implementing our model:

  - Congestion is effectively removed from the feeder.
  - The combined load remains within the transformer's capacity limits.

- **Detailed EV Charging Analysis:** Fig. 4.3 provides a comparative view of EV charging patterns before and after model implementation:

  - 52% of EVs successfully negotiated and charged (represented by blue lines).
  - 48% of EVs couldn't charge due to various reasons:
  - 2% failed negotiations
  - 46% left due to unavailability of chargers
  - 3% were insufficiently charged due to real-time load deviations (resulting in penalties for the aggregator)

  The graph extends beyond 24 hours to account for charging periods starting at midnight and continuing into the next day.

- **Satisfaction Levels and Utility Analysis:** Fig. 4.4 illustrates the satisfaction levels of EV owners and Aggregator in terms of price, time, energy, and total utility:

  - Boxes represent the range of utilities achieved.
  - Marks indicate the average utility received.

- **Key observations:**

  1. EV owners showed significant flexibility in energy utility, contributing to network load management.
  2. This flexibility was compensated with higher time and price utilities.
  3. Overall, EV owners achieved a high satisfaction level of 70%.
  4. The aggregator provided great flexibility in price utility while achieving higher time and energy utilities.

- **System Stress Test:** It's important to note that this scenario represents a highly congested network, where even critical loads alone occasionally exceed the transformer's rated power. This extreme case was deliberately chosen to stress-test the system and evaluate its performance under challenging conditions.

The results demonstrate that our proposed model effectively utilizes EV flexibility to alleviate network congestion while maintaining a high level of satisfaction for both EV owners and the aggregator. This balanced approach ensures efficient grid management without compromising user experience, showcasing the potential of our multi-issue negotiation protocol in real-world applications.

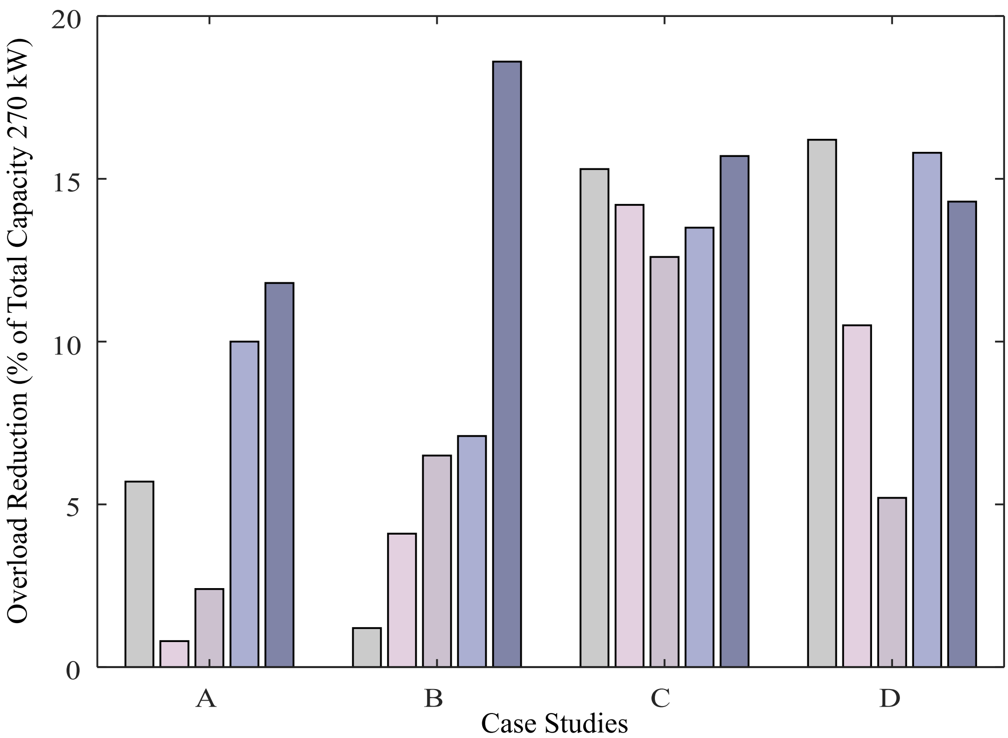

Figure 4.5: Overload Reduction Achieved in Case studies A,B,C,D

Case Studies

To thoroughly evaluate the performance of our proposed multi-issue negotiation algorithm and real-time management model, we conducted an extensive set of simulations across various scenarios. These simulations were categorized into four main case studies (A, B, C, D), each with five sub-cases, allowing us to assess the model's effectiveness under different conditions.

Base Scenario: Our base scenario consisted of 7 buildings with 30 households each, 10 EV chargers, and 100 EVs arriving throughout the day. This setup represented a highly congested network where even critical loads occasionally exceeded the transformer's rated power.

Case Studies Overview:

1. Case A: Varied building load profiles
2. Case B: Varied number of EVs (40, 50, 60, 80, 100)

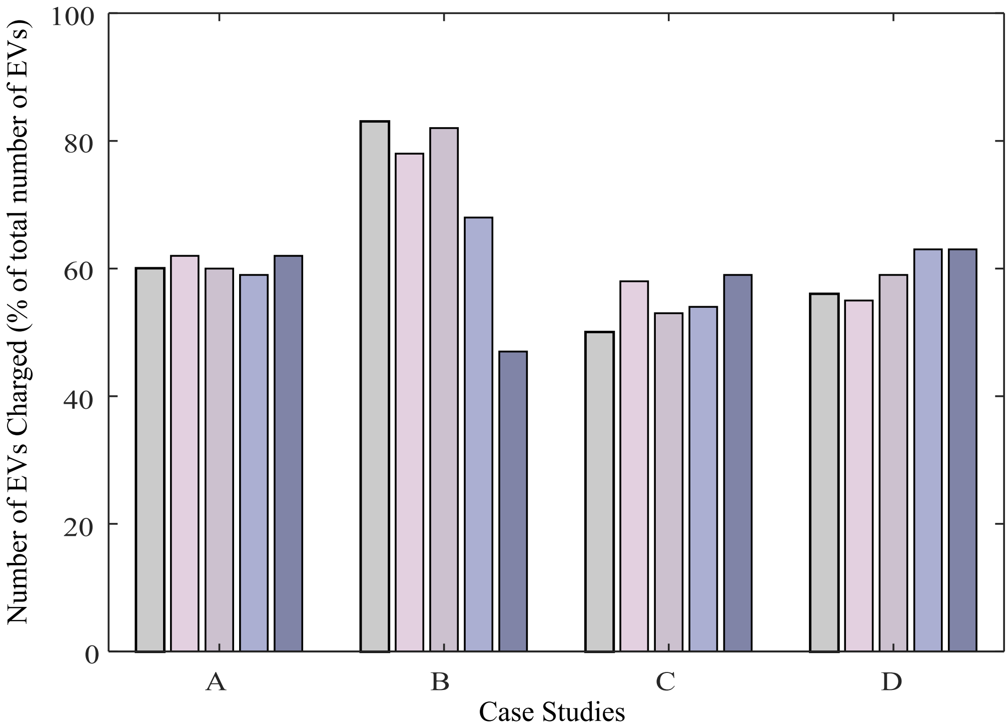

Figure 4.6: Number of EVs Charged Achieved in Case studies A,B,C,D

3. Case C: Varied number of charging points (5, 7, 10, 12, 15)
4. Case D: Varied EV preferences (energy, price, time)

Key Performance Metrics:

1. Overload Reduction: Percentage reduction in network overload relative to total capacity.
2. EV Charging Success Rate: Percentage of EVs successfully charged out of total arrivals.

Results Analysis:

1. Case A - Impact of Building Load Profiles:
   - Peak powers at mid-day ranged from 201 to 250 kW
   - Peak powers at noon ranged from 197 to 267 kW

- EV charging success rate remained consistent at around 60%
- Overload reduction varied significantly from 2% to 12%

Insight: The algorithm demonstrated robustness in maintaining a consistent EV charging rate despite variations in building loads, though overload reduction effectiveness varied.

2. Case B - Impact of EV Numbers:

   - EV charging success rate decreased from 80% to 50% as EV numbers increased
   - Maximum overload reduction (20%) achieved with the highest number of EVs

   Insight: Interestingly, more EVs led to better overall charging success due to increased likelihood of arrivals during off-peak times. This showcases the algorithm's ability to efficiently utilize available capacity.

3. Case C - Impact of Charging Points:

   - Increasing charging points from 5 to 15 did not substantially increase charging success or overload reduction

   Insight: In highly congested networks, simply adding charging points is not an effective solution. This underscores the importance of intelligent scheduling and negotiation.

4. Case D - Impact of EV Preferences:

   - EV charging success rate remained relatively stable
   - Overload reduction varied significantly from 5% to 17%

   Insight: EV preferences, especially price sensitivity, significantly impacted the negotiation success and consequently the system's ability to manage overload.

Across all scenarios, our model demonstrated:

1. Consistent ability to maintain EV charging services even under varying loads and constraints.

2. Significant reductions in network overload, ranging from 2% to 20% depending on conditions.

3. Adaptability to different EV numbers and preferences, showcasing the robustness of the negotiation protocol.

These comprehensive case studies validate the effectiveness of our multi-issue negotiation algorithm in managing EV charging in congested networks. The model shows particular strength in:

1. Maintaining consistent charging services across varied scenarios.
2. Significantly reducing network overload, especially in high-congestion situations.
3. Adapting to different EV preferences and network conditions.

The results highlight the importance of intelligent negotiation and scheduling in EV charging management, demonstrating that our approach can effectively balance grid constraints with user needs across a wide range of realistic scenarios.

This work was extended under the collaboration, to a multi-agent system based real-time negotiation framework for EV charging coordination systems [106]. The application allows each agent (representing the aggregator/seller and EV owners/buyers) to set their preferences and negotiate charging terms like price, energy, and time flexibility. The algorithm helps reduce overloads and improve the satisfaction of both aggregators and EV owners. The proposed framework is adaptive to real-time EV charging stations and onboard EV systems with enhancements.

4.3 Study 2: A Multi-Agent Framework for Coordinating One-to-Many Concurrent Composite Negotiations in a Multi-Stage Postpaid P2P Energy Trading Model

4.3.1 Problem Statement

In the context of evolving urban distribution networks, we focus on a microcosm of a typical local community to address the challenges and opportunities presented by peer-to-peer (P2P) energy trading. This section outlines the physical infrastructure, key stakeholders, and the overarching problem we aim to solve through our proposed energy market model.

Network Infrastructure

Our study centers on a small unit of an urban distribution network, representative of a local community. The core components of this network include:

1. Power Transformer: The central node of our local grid.

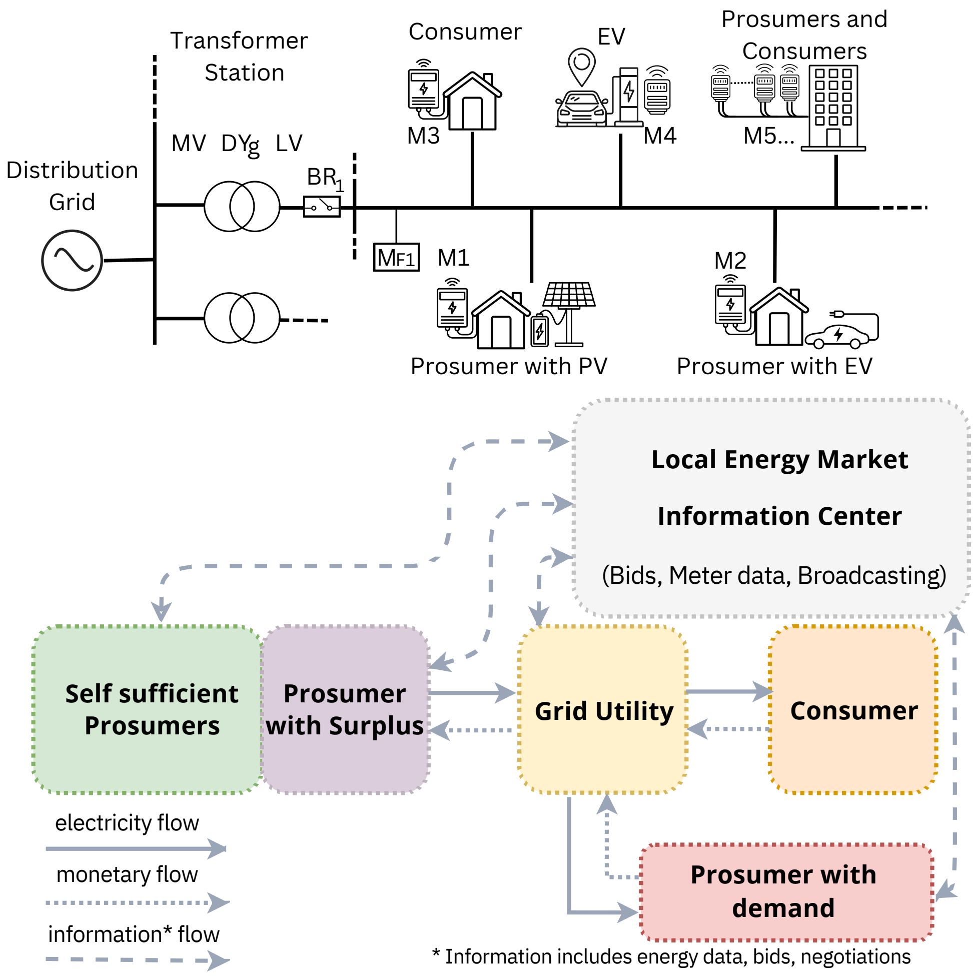

Figure 4.7: Power Distribution Network and P2P energy Trading

2. 4-wire 3-phase Feeders: Connected to the transformer's secondary, protected by a circuit breaker (BR_1) as represented in Fig. 4.7.

3. Advanced Monitoring Equipment: Each feeder is equipped with supervisor monitoring devices (labeled in Fig. 4.7 as M_{F1}), enabling real-time data collection and analysis.

4. Smart Meters: Every end-user is outfitted with advanced metering infrastructure (M_1, M_2, M_3, etc.), facilitating precise energy consumption and production measurements.

Stakeholders

1. End-users: Comprising both traditional consumers and prosumers. Prosumers are equipped with Distributed Energy Resources (DERs) such as solar panels, electric vehicles (EVs), and batteries, capable of both consuming and producing energy.
2. Utility: An overseeing entity responsible for managing energy imbalances and serving as a backup system. The utility employs dynamic pricing schemes to incentivize optimal energy consumption and injection patterns.

Problem Definition

The primary challenge we address is the efficient integration of prosumers and their DERs into the existing distribution network through a P2P energy trading framework. Specifically, we aim to:

1. Develop a robust energy market model that facilitates direct energy transactions between prosumers while maintaining grid stability.
2. Implement a dynamic pricing mechanism that reflects real-time grid conditions and encourages beneficial energy behaviors.
3. Utilize advanced metering and monitoring infrastructure to enable precise, real-time energy trading and grid management.
4. Design a scalable system that can be applied across various aggregation levels, from individual feeders to multiple power transformer groups.

Proposed Solution Approach

To tackle these challenges, we propose a multi-agent system (MAS) platform that will:

1. Enable direct P2P energy transactions within the local community.
2. Incorporate the utility's role in balancing energy supply and demand.
3. Implement adaptive pricing strategies to optimize grid operations.
4. Leverage advanced monitoring and metering data for real-time decision-making.

The subsequent sections will delve into the specifics of our proposed energy market model, detailing the roles of each entity, the intricacies of the trading mechanism, and the architecture of our MAS platform.

By addressing these challenges, we aim to create a more resilient, efficient, and sustainable urban distribution network that empowers end-users while maintaining grid stability and reliability.

4.3.2 Methodology

Trading Mechanism Overview

The proposed trading mechanism for the local energy community involves a structured approach with distinct roles for the Utility and community members. This section will delve into the key aspects of this mechanism.

Utility's Role

The Utility plays a central role in the trading process:

1. Price Setting: The Utility is responsible for establishing and regularly broadcasting energy prices.
2. Grid Optimization: Leveraging historical market data, the Utility strategically reorganizes to balance the grid and maximize economic benefits.
3. Final Trading Phase: The Utility engages in energy transactions at its predetermined price, without peer negotiations.

Community Members' Participation

Consumers and prosumers are active participants in the market:

1. Designated Trading Periods: Community members engage in energy trading during specific timeframes.
2. Negotiation Phases: Participants have the opportunity to negotiate deals within set periods.
3. Fallback Option: If agreements are not reached during the allocated time, community members must trade directly with the Utility without further negotiations.

This section will explore these key elements of the trading mechanism in greater detail, examining their implications and potential impacts on the local energy community.

Multi-Agent System in Local Energy Markets

The proposed trading scheme for the Local Energy Market (LEM) incorporates three primary types of participants, each modeled as agents within a Multi-Agent System (MAS) platform. These agents are designed with specific behaviors and roles to facilitate efficient energy trading within the community.

Agent Types and Their Characteristics

1. Utility Agent (α_u) This agent oversees the power flow both entering and exiting the power distribution transformer. Its primary responsibilities include:
   - Selling grid energy to distributed energy end users
   - Purchasing surplus distributed energy from local producers when there's a deficit
   - Controlling price signals to maintain a balance between grid demand and supply
2. Prosumer Agent (α_p) This agent represents a local distributed energy producer with the following capabilities:
   - Generates energy to support its own needs
   - Sells excess energy to other agents within the distributed network
   - Purchases energy to cover any deficits from other LEM participants or the utility
   - Actively participates in the LEM by negotiating with multiple agents or peers for energy trading
   - Self-sufficient prosumers, as depicted in Fig. 4.7, remain inactive in the market
3. Consumer Agent (α_c) This agent is characterized by the following behaviors:
   - Purchases energy from the utility or other LEM participants to meet its energy demands
   - Engages in negotiations and transactions with multiple agents or peers to secure energy at economical prices
   - Prosumers with energy demands, as shown in Fig. 4.7, may adopt consumer agent behavior to participate in the market as consumers

Pricing Mechanism in Local Energy Markets

The pricing mechanism serves as a critical regulatory factor in Local Energy Markets (LEM). The utility plays a central role in this mechanism by monitoring power flows, including both injection and consumption, and analyzing any imbalances in grid demand and supply, as well as congestion at power distribution transformers.

It's important to note that while other control signals, such as voltages at various points in the feeders, could be used to determine the price scheme, this model uses transformer power as the control signal for simplicity while maintaining generality.

Utility's Objective Function The primary objective of the utility is to minimize the difference between the real energy demand (E_d^r) and the optimal energy demand (E_{opt}) as committed day-ahead, for each time period t. This can be formulated as eq.(4.18):

$$minimise \quad | \, E_d^r - E_{opt} \, | \quad \forall t \in T \tag{4.18}$$

The difference between E_{opt} and E_d^r represents deviations in the form of positive or negative energy imbalances that need to be addressed through price control.

Price Control Function To balance demand and supply or prevent congestion at the power distribution transformer, the utility controls the buying (pr_u^b) and selling (pr_u^s) prices of energy units. The control function is defined as eq.(4.19):

$$pr_u^x = \begin{cases} pr_u^N, & E_d^r = E_{opt} \\ a_1 * pr_u^N, & E_d^r \leq E_{opt} \\ a_2 * pr_u^N, & E_d^r \geq E_{opt} \end{cases} \quad \forall t \in T \tag{4.19}$$

Where:

- pr_u^N represents the nominal selling or buying price set by the utility, valid for the time period t when the distribution network is balanced and congestion-free
- x can be either s or b , corresponding to selling or buying prices respectively
- $a_1 < 1$ and is a positive real number
- $a_2 > 1$ and is a positive real number

Price Adjustment Strategy The utility employs the following strategy to adjust prices based on network conditions:

1. When transformer consumption falls below the nominal level:
   - Both purchase and selling prices are decreased by a factor of a_1
   - This reduction in selling price encourages greater consumption among agents
   - The decrease in purchase price discourages excessive generation
2. In situations of high demand or network congestion:
   - Both buying and selling prices are increased by a factor of a_2
   - This increase stimulates prosumers to promote generation

- It also deters agents from consuming excessively

The overarching goal of the utility is to encourage peer-to-peer (P2P) energy trading during periods of high demand by increasing the unit price. This strategy allows other peers to impose slightly lower prices for selling their excess energy, making P2P transactions more attractive. Conversely, when demand is low, the utility reduces energy unit prices to encourage peers to purchase energy directly from the utility, thereby maintaining grid stability and economic efficiency.

Response to Price Signal

Prosumer Behavior Prosumers are assumed to be economically rational entities who aim to maximize their individual economic surplus through participation in peer-to-peer (P2P) trading, either as sellers or buyers. At the beginning of each trading session, prosumers receive a price signal from the utility. Based on this signal, they set their preferential selling price for their surplus energy.

The prosumer controls the selling price of their exported surplus energy (e_s) using a trade preferential coefficient, as defined in equations (4.20) and (4.21). This approach ensures that their price is slightly lower than the utility's price, making their offer more attractive to potential buyers while still maintaining financial returns.

Prosumers set their orders with preferred selling prices (pr_p^s) by selecting a desired value for τ, which they can later negotiate:

$$pr_p^s = \tau * pr_u^s \quad \forall t \in T \tag{4.20}$$

$$\text{s.t. } 0 < \tau \leq 1, \; \tau \in \mathbb{R}^+ \tag{4.21}$$

It is important to note that the mechanism governing agent prices is automated rather than manual. To further optimize agent prices, a tariff system can be implemented. This system offers various pricing schemes, including premium tariffs, allowing customers to choose between strategies that prioritize surplus sales through significant price reductions or those that focus on profit improvement, even if it means risking unsold energy due to prices closely aligned with utility rates.

Customers also have the option to inject their own intelligence and business rules into the pricing engine. This customer-specific pricing engine can be integrated at the platform level, with accessibility and configurability determined by the chosen scheme.

The term "utility" could be replaced with a more encompassing entity, such as an aggregator, marketer, or even a Distributed System Operator (DSO). Another innovative approach involves transforming the utility into an energy community where other agents actively participate. This system offers remarkable flexibility. The paper's primary focus is on exploring trading mechanisms applicable to various configurations and case studies.

The prosumer's main objective, as expressed in equations (4.22) and (4.23), is to optimize profits by selling their energy at the most advantageous price point:

$$\max\ u(\alpha_p) = (pr_p^s - pr_u^b)e^s \tag{4.22}$$

$$\text{s.t. } pr_u^b \leq pr_p^s \leq pr_u^s \tag{4.23}$$

This strategy considers that if the prosumer sets a selling price higher than the utility's rate, potential buyers are more likely to purchase from the utility. Conversely, by reducing the selling price, the prosumer increases the likelihood of selling energy to peers. However, it's crucial that the selling price never falls below the utility's purchase price, as this would result in losses for the prosumer.

Finding the ideal balance involves selecting a price that ensures sales while maximizing overall profit. Future implementations could involve artificial intelligence tools to aid in this process, leveraging historical data to determine optimal price coefficients for consumers. However, this topic is beyond the scope of the current paper.

Consumer Behavior Consumers receive a list of offers (prices and amount of energy) from the utility and different prosumers, as represented in equations (4.24), (4.25), and (4.26):

$$O = \{(o_1, ..., o_n)\} \tag{4.24}$$

$$o_i = (pr_i, e_i) \text{ where } i \in \{1, ..., n\},\ i \in \mathbb{N} \tag{4.25}$$

$$pr_1 \leq ..... \leq pr_n \tag{4.26}$$

Consumers choose the most economical options based on prices (pr_i) and the amount of available energy (e_i) that may fulfill their demand (e_{di}). They then negotiate these offers with respective prosumers to reach mutually beneficial, economical deals. This negotiation strategy is similar to that used in service composition and mashups, where a buyer wants to purchase several atomic services to compose a composite service.

To strike multiple deals, a consumer (α_c) engages in multiple negotiations with prosumers ($\alpha_{p1}, ..., \alpha_{pn}$) and combines their outcomes. The consumer's goal, as expressed in equations (4.27) and (4.28), is to maximize the utility $u(\alpha_c)$ of the aggregate outcome of all negotiations:

Algorithm 3 Utility Agent Behaviour

Require: (usr, pwd, id) for α_u registration in the system.
Ensure: (pr_u^b, pr_u^s) per unit energy for each $t \in T$, satisfying eq.(4.18)

for $\forall t \in T$ **do**
  $(pr_u^b, pr_u^s) := f(E_d^r, E_{opt}, t)$ using eq. (4.19) satisfying eq.(4.18), a_1, a_2
  Broadcast pr_u^b, pr_u^s to all market agents.
  if $\rho \Leftarrow 3$ $(\rho \in t)$ **then**
    Receive buying/selling requests from all α_p ,α_c .
    Accept all requests and trade @ pr_u^b, pr_u^s.
    Process terminated
  end if
end for

$$\max \ u(\alpha_c) = -\sum_{i,c} pr_i e_i(c) \tag{4.27}$$

$$\sum_j e_j(c) \leq e_{di} \text{ where } j, c \in \mathbb{N} \tag{4.28}$$

Here, c represents each composite unit of energy offered (e_j) as discrete values, and j denotes the number of deals or agreements.

The consumer views this as a coordination problem, aiming to aggregate and coordinate multiple, potentially overlapping agreements such that the composite outcome satisfies the buyer's overall demand at the minimum price.

4.3.3 Implementation Details

Negotiation Mechanism

The proposed model implements a sophisticated One-to-Many Concurrent Composite Negotiations strategy, which represents a significant advancement in energy trading systems. This approach allows for complex, multi-faceted negotiations where the final outcome can be composed of multiple partial outcomes, each resulting from a separate deal with different sellers. This strategy is particularly well-suited to the dynamic nature of energy markets, where supply and demand can fluctuate rapidly.

Algorithm 4 Prosumer Agent Behaviour

Require: (usr, pwd, id) for α_p registration in the system.
Ensure: maximum $u(\alpha_p)$ for each $t \in T$.
1: **for** $\forall \rho \in t$ **do**
2:    identify e_s
3:    $pr_p^s := f(pr_p^s, t)$ using eq. (4.20)
4:    Broadcast (pr_p^s, e_s) to all market agents
5:    **if** requests received **then**
6:       Accept requests based on *first come first serve*
7:       trade and update e_s
8:       rejects others
9:    **end if**
10:    **if** $e_s > 0$ AND $\rho \Leftarrow 2$ **then**
11:       Repeat the process from lines 5 to 14
12:    **end if**
13:    **if** $e_s > 0$ AND $\rho \Leftarrow 3$ **then**
14:       make request/s to utility and trade at pr_u^b
15:       Terminate Process
16:    **end if**
17:    **if** $e_s = 0$ **then**
18:       Terminate Process
19:    **end if**
20: **end for**

Key Features of the Negotiation Mechanism

1. Composite Negotiations: The buyer (typically a consumer or prosumer needing energy) has the capability to engage in multiple simultaneous bilateral interactions. This concurrent approach allows for greater efficiency in the negotiation process, as the buyer doesn't have to wait for one negotiation to conclude before starting another.

2. Aggregation of Partial Deals: The primary objective of the buyer is to satisfy their total energy demand at the lowest possible price. This is achieved by combining multiple partial deals from different sellers. The aggregation of these deals forms the complete solution to the buyer's energy needs.

3. Complex Decision-Making Process: Given that multiple sellers may offer the same product (energy) in different quantities and at varying prices, the buyer faces a complex decision-making challenge. They must determine:

    - Which sellers to negotiate with
    - What specific quantities to negotiate for with each seller
    - How to optimally combine these partial deals to meet their overall demand

Algorithm 5 Consumer Agent Behaviour

Require: (usr, pwd, id) for α_c registration in the system.
Ensure: maximum $u(\alpha_c)$ for each $t \in T$.

1: **for** $\forall \rho \in t$ **do**
2: receive pr_u^b, pr_u^s and save
3: Identify e_d
4: **if** $\rho \Leftarrow 1$ **then**
5: Receive O and evaluate $u(\alpha_c)$ using eq. (4.27),(4.28)
6: Send requests to the best offers.
7: **if** acceptance received **then**
8: trade and update e_d
9: **end if**
10: **if** rejection recieved **then**
11: update e_d
12: **end if**
13: **end if**
14: **if** $e_d > 0$ AND $\rho \Leftarrow 2$ **then**
15: Repeat the process from lines 5 to 14
16: **end if**
17: **if** $e_d > 0$ AND $\rho \Leftarrow 3$ **then**
18: make request/s to utility and trade at pr_u^s
19: Terminate Process
20: **end if**
21: **if** $e_d = 0$ **then**
22: Terminate Process
23: **end if**
24: **end for**

4. Combinatorial Optimization: The buyer must navigate the complexities related to the combinatorial explosion of possible sets of partial deals. This is done using equation (4.27) while satisfying the constraints in equation (4.28). This process involves sophisticated algorithms to find the optimal combination of deals that meets the buyer's demand at the lowest total cost.

Illustrative Example To better understand this mechanism, consider the following scenario:

- Prosumer α_{p1} offers 2 kWh energy units at \$3 each: $o_1 = (3, 2)$
- Prosumer α_{p2} offers 5 kWh energy units at \$4 each: $o_2 = (4, 5)$
- Consumer α_c has an energy demand (e_d) of 3 kWh

In this case, a deal might be reached as follows:

- $e_1 = \{2kWh \times \$3\}$ from α_{p1}
- $e_2 = \{1kWh \times \$4\}$ from α_{p2}

The final aggregated deal would be: $e_1 \oplus e_2 = \{2kWh \times \$3 + 1kWh \times \$4\} = 3kWh for \$10$

This example demonstrates how the buyer can optimally combine offers from different sellers to meet their exact energy needs while minimizing costs.

Negotiation Strategy and Phases The model employs an aggressive negotiation strategy, characterized by strict time constraints. This approach is designed to:

1. Encourage rapid decision-making by agents
2. Facilitate quick deal closures
3. Maximize benefits for all parties involved

The negotiation process is structured into three distinct phases:

1. Initial P2P Trading Phase: User agents (consumers and prosumers) engage in peer-to-peer trading, attempting to close deals directly with each other.
2. Secondary P2P Trading Phase: A continuation of the first phase, allowing for further negotiations and deal closures between peers.
3. Utility Trading Phase: Any agents unable to close deals in the first two phases must trade with the utility at the utility's set price. This serves as a fallback option, ensuring that all energy needs are met, even if not at the most optimal price for the agent.

This phased approach ensures that the market operates efficiently, with most trades occurring between peers, and the utility serving as a reliable backstop for any unmet demand or excess supply. It also incentivizes agents to actively participate in the P2P phases to potentially secure more favorable deals than what the utility might offer.

Structured Energy Trading Period

A realistic timeframe is established for conducting energy trades, divided into three distinct stages. A graphical overview is provided in Fig. 4.8.

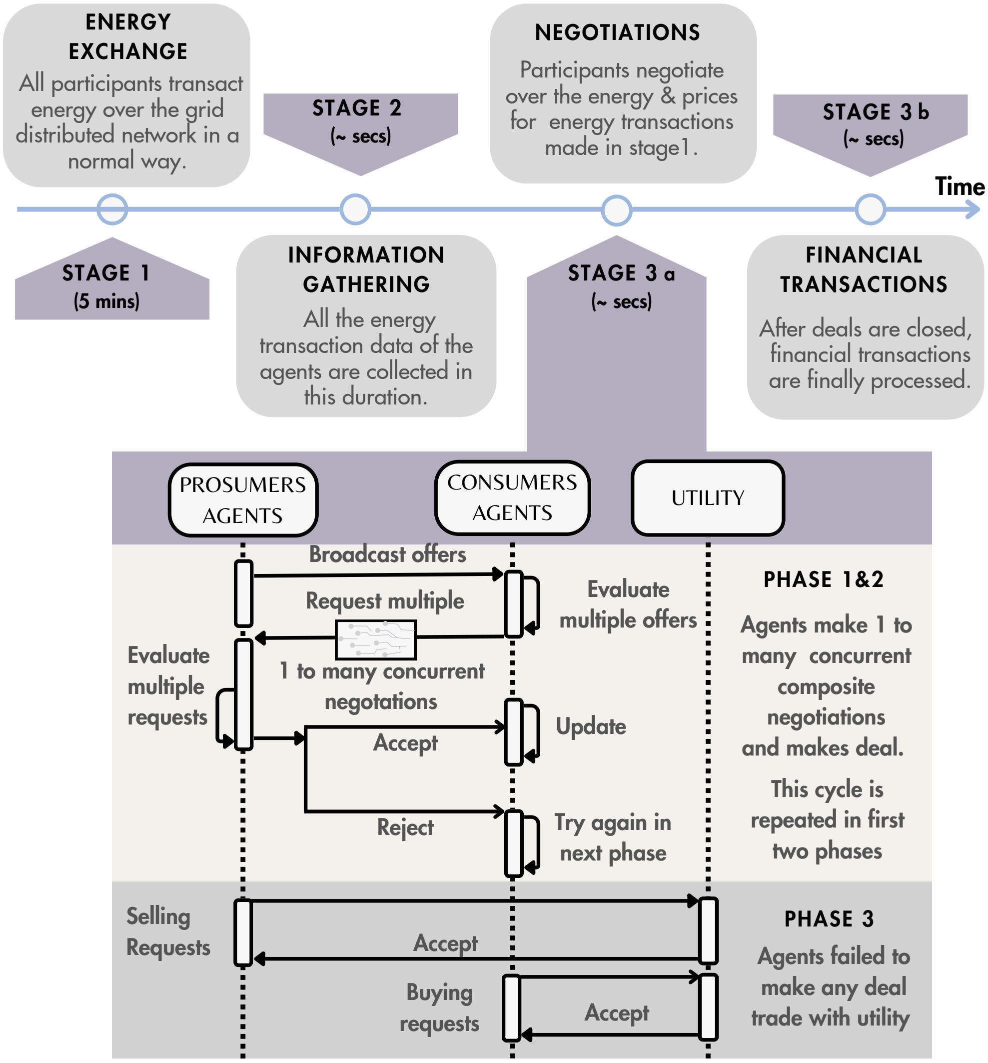

Figure 4.8: Timeline of Trading Mechanism

Stage 1: Energy Exchange

During this initial stage, all participants, including prosumers and consumers, engage in the routine exchange of energy over the grid distribution network. Prosumers inject their surplus energy into the grid, while consumers draw energy from it. It is important to note that the strategies for energy consumption and injection should ideally be influenced by historical price data. However, developing specific strategies for each agent is beyond the scope of this work, which focuses on proposing a framework for trading.

Stage 2: Data Collection

In this stage, the distribution network, equipped with advanced metering infrastructure, collects all data related to energy exchanges by prosumers and consumers. This data is crucial for processing market operations. The utility uses this information to set the market price, as previously described, and broadcasts it to all agents. Following this, prosumers determine their selling prices and prepare offers or bids for the surplus energy they wish to sell to peers through negotiations.

Stage 3: Negotiation and Financial Transaction Settlements

This stage involves the negotiation and settlement of financial transactions and is divided into two sub-stages:

Sub-stage 3a: Negotiation Process The negotiation algorithms for all three agent types—utility, prosumer, and consumer—are detailed in Algorithms 3, 4, and 5. Prosumers broadcast their offers to all market participants, including buyers and consumers, as outlined in lines 2-4 of Algorithm 4. Buyers receive a list of available offers from various sellers and select the most suitable ones to cover their energy usage from Stage 1, as indicated in lines 4-13 of Algorithm 5. They then enter into negotiations with these sellers to fulfill their energy needs within the specified negotiation timeframe, aiming to close deals efficiently. If agreements are not reached, participants have the opportunity to iterate the process, re-evaluating offers and continuing negotiations.

Sub-stage 3b: Final Negotiation Phase This aggressive negotiation strategy is designed to encourage rapid deal closure within the first two phases, promoting efficient and environmentally friendly networking and communication. However, a third negotiation phase is available for participants who were unable to secure deals in the initial stages. In this phase, they can trade directly with the utility at its predetermined buying and selling prices, as directed in lines 4-7 of Algorithm 3.

Financial Settlements Once deals are finalized, all financial transactions are executed. These settlements are verified by the utility against the clients' energy usage data, ensuring accuracy and transparency in the trading process. This structured approach not only facilitates efficient energy trading but also supports the broader goals of sustainability and optimized resource management within the energy market.

Simulation Environment

To evaluate the proposed framework, we designed a simulation scenario representing a local energy market with a group of agents. The simulation employs multi-agent

Table 4.1: DATA INPUT

Agents/Peers	Count	Energy Units	Pricing per unit energy
Utility	1	grid supply	(pr_u^s: 5, pr_u^b: 3)
Consumers	3 3	3 7	-
Prosumers	2 2	10 7	$[0.6, 1]pr_u^s$

systems technology to create autonomous software entities that act as prosumers, consumers, and the utility. These intelligent agents are programmed to interact and communicate naturally with each other.

Technical Framework

We chose SPADE (Smart Python Agent Development Environment) as our multi-agent system platform. SPADE is based on instant messaging (XMPP) and offers several advantages:

1. Incorporates modern technologies
2. Addresses open issues such as communication protocol standardization
3. Provides elasticity in communication
4. Supports human-agent integration
5. Facilitates open systems
6. Enables device-independent agent connection

SPADE 3, the version used in this implementation, is built on the XMPP (eXtensible Messaging and Presence Protocol). This communication protocol provides an open, decentralized, and federated architecture for multi-agent systems, which was a key factor in our selection of SPADE.

Simulation Scenario

To implement the proposed strategies and assess the model's overall performance, we conducted a simulation with the following parameters:

- Total agents: 11 (including the utility)

- Composition: 1 utility and 10 other agents (mix of consumers and prosumers)

Table 4.1 outlines the input settings for the simulation, including:

- Number of consumers and prosumers
- Energy demands/surplus for each agent type
- Trading preferential settings for prosumers (used to propose selling prices or make offers)
- Strategic coordination function parameters for consumers (used to strike and combine multiple offers)

This setup allows us to test the effectiveness of the proposed framework in a realistic local energy market scenario, evaluating how agents interact, negotiate, and trade energy within the defined parameters.

4.3.4 Key Findings and Analysis

Simulation Results

Peer-to-Peer Energy Trading Dynamics

Fig. 4.9 provides a visual representation of the peer-to-peer (P2P) energy trades within the simulated group, illustrating the outcomes of the one-to-many concurrent composite negotiations strategy. In this diagram, arrows with tails represent sellers, while arrows with heads denote buyers. The results show that prosumer agents [0, 1, 2] successfully completed transactions, selling all their available energy units to consumer agents [4, 5, 9, 6]. However, prosumer agent 3 was unable to sell its entire energy surplus and consequently engaged in transactions with the grid utility to offload the remaining units.

Energy Transaction Analysis

Figure 5 presents a comparative analysis of energy transactions between peers and the utility, showcasing two scenarios (Case A and Case B) before and after the implementation of our P2P energy trading model. The input data for both cases is detailed in Table 1.

In Case A:

- Prosumer agents collectively generated [3, 3, 10, 10] kWh of energy, totaling 26 kWh.

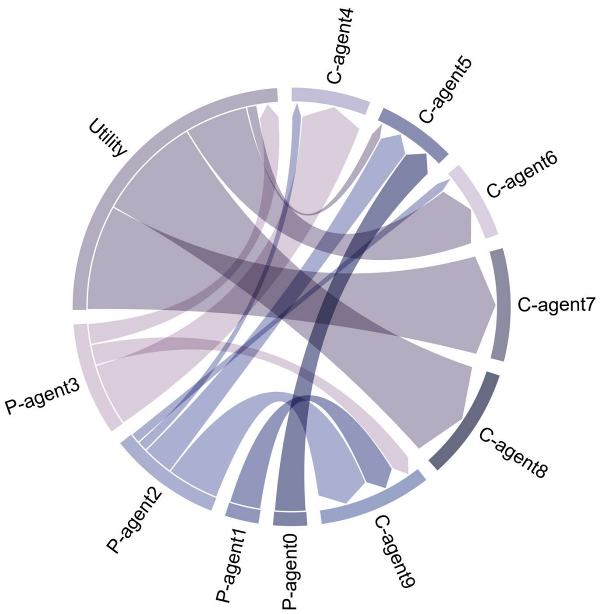

Figure 4.9: Graph illustrating 1 to many concurrent composite energy trading between peers.

- After applying the proposed local energy trading algorithm, they sold [7, 6, 1, 10] kWh.
- This resulted in 24 kWh of energy being conserved for consumer use within the local network.
- Only 2 kWh was sold back to the utility grid.

In Case B:

- Prosumer agents generated [3, 3, 2, 2] kWh of energy.
- All generated energy was successfully sold to consumer agents [4, 6, 7].
- The consumers closed deals for [4, 1, 5] kWh respectively.

These results demonstrate the efficiency of the P2P trading model in maximizing local energy consumption and minimizing grid dependence.

Individual Trading Performance

Fig. 4.5 offers insights into the trading activities of individual peers, detailing:

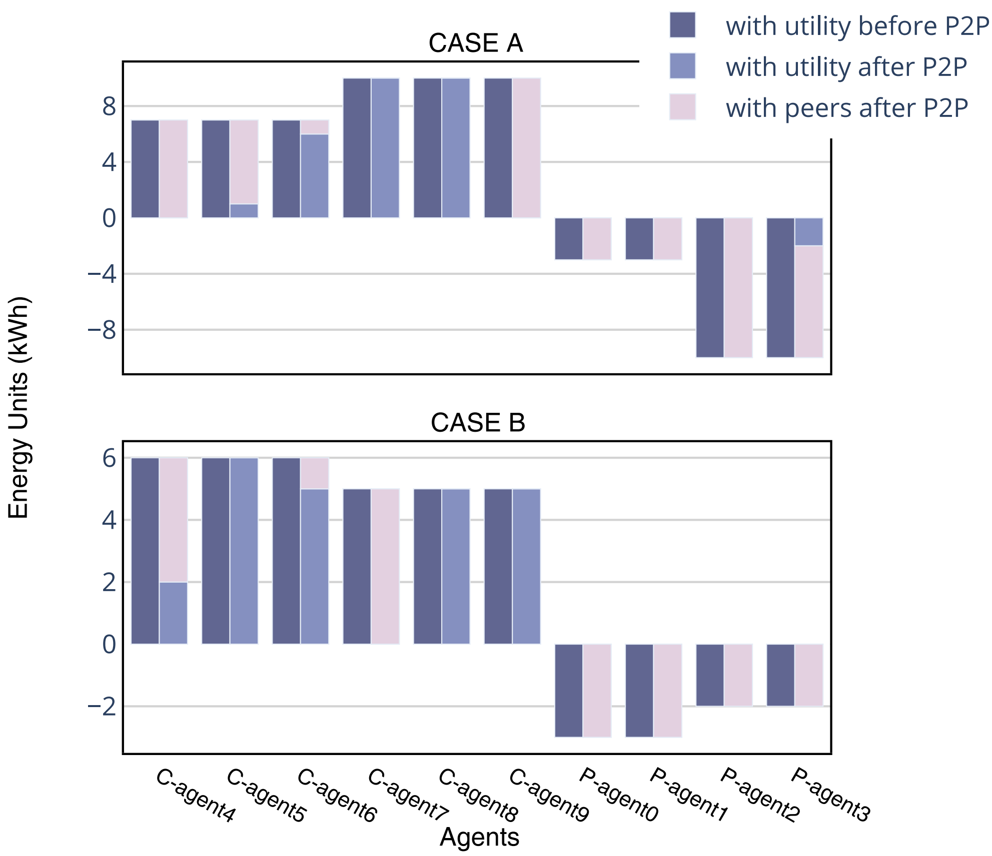

Figure 4.10: Energy transaction before and after model implementation.

1. The number of trades executed by each prosumer and consumer.
2. Individual savings achieved through P2P trades compared to utility trading.

Key observations

- The graph only includes agents who successfully completed peer transactions.
- Prosumer agent 2 emerged as the most active trader, executing 5 deals with multiple consumers.
- Prosumer agent 2 accumulated 250 price units, the highest among all participants.
- This emphasis on multiple small trades (atomic services) with various consumers is expected to encourage greater participation in local energy trading among peers in future scenarios.

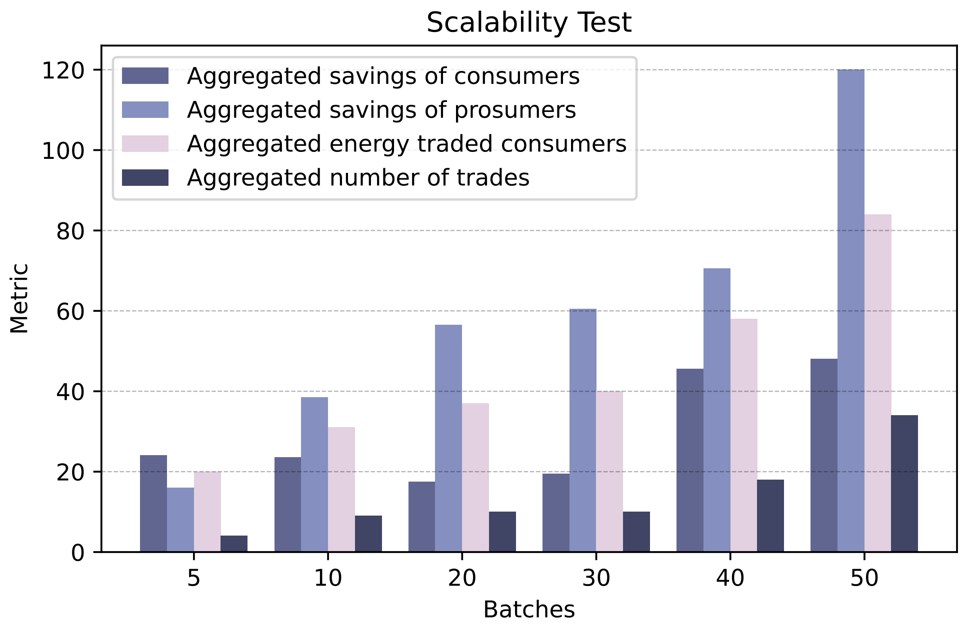

Figure 4.11: Aggregated simulation results of model conducted on batches of 5 - 50 agents.

Table 4.2: PARAMETERS SETTING FOR BATCHES

Parameter	e_d,e_s	τ	pr_u^s,pr_u^b
Value	rand(10,30)	rand(0.6,1)	5,3

Scalability Tests

To demonstrate the model's scalability beyond the initial 10 user agents and 1 utility agent, additional simulations were conducted. These tests maintained the same time horizon as the earlier case studies to ensure efficient computation and communication using the SPADE3 multi-agent system.

Methodology

- 6 experiments were conducted, progressively increasing the number of prosumer and consumer agents.
- Various system parameter combinations were tested.
- Agent batches ranged from 5 to 50, as detailed in Table 2.

Evaluation Metrics

1. Aggregated profits
2. Traded energy
3. Total trade count among peers

Results Analysis Fig. 4.11 visualizes the scalability test results across the batch simulations.

Key Findings

1. Local energy trading volume grows substantially with the increase in prosumer numbers, leading to higher overall profits.
2. The proposed approach demonstrates excellent scalability in terms of computational and communication demands, even with a consistent time horizon across all experiments.
3. Prosumer agents consistently earn higher rewards compared to consumer agents. This disparity is attributed to:
   - Incentives for surplus energy generation
   - Active participation in local energy markets
4. While consumers engage in economic transactions within local energy markets, their participation also indirectly benefits the utility by:
   - Alleviating grid imbalances
   - Reducing distribution network congestion

The results indicate that the proposed model not only scales effectively but also creates a fair mechanism that benefits all participants while contributing to overall grid stability and efficiency.

4.4 Comparative Analysis and Discussion

Both studies present market-based solutions for managing congestion in distribution networks, but they differ in their specific approaches. Study 1 focuses on EV charging, utilizing a multi-issue negotiation protocol implemented in MATLAB, while Study 2 addresses broader P2P energy trading using a one-to-many concurrent composite negotiation mechanism built on the SPADE platform. A key distinction lies in their level of centralization: Study 1 relies on a utility-dependent management platform, whereas Study 2 aims for a more decentralized approach.

The strengths and unique contributions of each study are noteworthy. Study 1's multi-issue negotiation protocol for EV charging simultaneously addresses timeslots, energy packets, and prices, demonstrating robustness in handling real-world constraints. It also lays the groundwork for flexible tariffs and EV charging strategies. In contrast, Study 2's three-stage multi-agent framework for P2P energy trading offers a scalable solution for local markets, providing flexibility to optimize individual benefits or support grid balancing. Its simplicity in design facilitates real-world deployment.

Synthesizing insights from both studies suggests that market-based mechanisms can effectively manage congestion in distribution networks. Multi-issue and multi-agent negotiation protocols offer promising solutions for complex energy trading scenarios. The research highlights the importance of balancing individual benefits with system-level objectives for successful implementation, while emphasizing scalability and simplicity as key factors for real-world applicability.

These studies have significant implications for advancing negotiation algorithms in energy trading. Future development should focus on integrating multiple flexible loads and distributed energy resources in negotiation protocols. More sophisticated agent behavior models are needed to better reflect real-world decision-making processes. Exploring hybrid approaches that combine centralized and decentralized negotiation mechanisms could yield more comprehensive solutions. Additionally, investigating incentive structures to promote cooperation and flexibility in energy communities, and considering network constraints and grid stability in negotiation algorithms, will be crucial.

By addressing these aspects, future research can build upon the foundations laid by these studies to create more comprehensive and effective negotiation algorithms for energy trading and congestion management in smart grids. This work paves the way for more efficient, flexible, and sustainable energy systems that can adapt to the evolving needs of modern power networks.

4.5 Limitations and Future Research Directions

Both studies have identified areas for improvement and expansion. This section outlines the current limitations and proposes future research directions for each study.

4.5.1 Study 1: Multi-Issue Negotiation Protocol for EV Charging

Current Limitations

The study primarily focused on a parametric negotiation methodology that allows strategy variation by both vehicles and utilities. However, the definition of complex strategies associated with different types of flexible tariffs was beyond the scope of this paper.

Future Research Directions

1. Complex Strategy Definition: Future work will explore the development of complex strategies for both utilities and vehicles, associating them with various types of flexible tariffs.
2. Integrated Load Management: The authors are working on a methodology to simultaneously manage flexible vehicle loads along with other flexible household loads.
3. Renewable Integration: Incorporation of solar production at the household level is planned for future research.
4. Peer-to-peer Energy Exchange: Enabling users to exchange energy with each other and with vehicles on public roads is a key area for future development.
5. Multi-agent Trading System: The future trading system will be multi-agent based, moving away from the utility-dependent intermediate management platform used in the current study.

4.5.2 Study 2: Three-Stage Multi-Agent Framework for Peer-to-Peer Energy Trading

Current Limitations

While the study demonstrated successful P2P energy trading, there is room for improvement in agent behavior modeling and community-level energy management.

Future Research Directions

1. Advanced Agent Behavior Modeling: Future research will focus on adding advanced features to the agent's behavior modeling.

2. Energy Communities: Exploration of establishing energy communities at common coupling points in the network, allowing prosumers and nearby consumers to form bilateral contracts.

3. Coordinated Response to Price Signals: Research into how energy communities can coordinate their responses to price signals to aid grid stability.

4. Network Loss Minimization: Study of how close-knit energy communities can minimize network losses.

5. Collaborative Energy Management: Investigation of community collaboration during high demand periods, including surplus energy sharing by prosumers and adaptive charging of electric vehicles.

6. Incentive Mechanisms: Development of incentive structures to promote cooperation and flexibility within energy communities.

4.6 Conclusion

Research studies demonstrate how effective approaches for managing congestion in distribution networks through market-based mechanisms. Key findings of both studies can be summarised as follows:

1. Multi-Issue Negotiation Protocol for EV Charging

   The study introduced an innovative multi-issue negotiation protocol for electric vehicle (EV) charging. This approach represents a significant advancement in managing EV charging in congested distribution networks. Key features and findings of the study include:

   - Comprehensive Negotiation Mechanism: The protocol considers multiple factors simultaneously, allowing for more nuanced and effective negotiations between EVs and the charging management platform.
   - Realistic Testing and Validation: The algorithm's effectiveness was validated through testing in a realistic environment, demonstrating its stability and performance in line with expectations.
   - Robustness in Handling Constraints: Importantly, when agreements could not be reached, it was due to inherent system constraints rather than flaws in the algorithm design. This indicates the protocol's ability to handle real-world scenarios where EV charging requirements may conflict with power system limitations.
   - Practical Utility in Congestion Management: The research showcased the algorithm's practical utility in resolving congestion issues within a realistic power system using market mechanisms.

- Foundation for Flexible Tariffs: The work laid the groundwork for developing flexible tariffs that can define negotiation strategies for EVs, enabling efficient management of their flexibility to address network congestion.
- Implementation Methodology: The proposed algorithms were implemented using MATLAB classes, emulating a multi-agent system where each vehicle acts as an agent interacting with the management platform.
- Potential for Broader Applications: While the study focused on EV charging, the protocol's design is generic and could potentially be applied to other scenarios requiring multi-issue negotiations in energy systems.

2. Three-Stage Multi-Agent Framework For Peer-To-Peer Energy Trading

   The proposed peer-to-peer (P2P) energy trading framework represents a significant advancement in the field of decentralized energy markets. This innovative system leverages intelligent software agents developed on the SPADE (Smart Python Agent Development Environment) platform, incorporating a sophisticated one-to-many concurrent composite negotiation mechanism to facilitate local energy transactions. Key aspects of this framework include:

   - Intelligent Agent Architecture: The use of SPADE-based intelligent agents allows for autonomous decision-making and adaptive behavior in the energy trading process. These agents can represent various market participants such as prosumers, consumers, and grid operators.
   - Flexible Optimization: The framework's design allows for customization to either maximize individual benefits for market participants or to support broader grid balancing objectives. This flexibility makes it applicable in various regulatory and market contexts.
   - Successful Negotiation Demonstration: Through rigorous testing, the model has proven its capability to facilitate successful negotiations and transactions between agents. This demonstrates the framework's potential to create efficient and effective P2P energy trading ecosystems in local markets.
   - Simplicity and Ease of Deployment: Despite its sophisticated functionality, the mechanism boasts remarkable simplicity. This characteristic significantly reduces barriers to implementation, making it highly suitable for real-world deployment across diverse energy market environments.
   - Scalability: One of the most promising aspects of this framework is its scalability. Extensive examinations conducted with larger groups of agents yielded exceptionally positive results, closely aligning with projected performance expectations. This scalability is crucial for the framework's viability in larger, more complex energy markets.
   - Potential for Market Transformation: By enabling effective P2P energy trading at the local level, this framework has the potential to revolutionize traditional energy market structures. It could facilitate greater integration

of distributed energy resources, enhance grid flexibility, and empower consumers to become active participants in the energy market.

- Grid Balancing Support: The framework's ability to be adjusted for grid balancing purposes suggests its potential role in maintaining grid stability and reliability, especially in scenarios with high penetration of renewable energy sources.

Both research studies highlight the potential of market-based solutions for managing congestion in distribution networks, offering promising avenues for integrating renewable energy sources and flexible loads while maintaining grid stability.

Chapter 5

Blockchain and Smart Contracts in Power Systems

5.1 Blockchain Beyond Cryptocurrencies

Although mostly known for its digital financial asset applications (like Bitcoin), blockchain technology has the potential to transform the functioning of a wide range of industries. Its features can increase the transparency and traceability of goods, data, and financial assets, facilitate market access, and improve the efficiency of transactions. Fulfilling blockchain's potential, however, depends on a policy environment that allows innovation and experimentation, while balancing the risks of misuse. Governments will play a significant role in shaping policy and regulatory frameworks that help address challenges presented by the technology, and foster transparent, fair and stable markets as blockchain develops.

Fundamentally, blockchain is a combination of already existing technologies that together can create networks that secure trust between people or parties who otherwise have no reason to trust one another. Specifically, it utilizes distributed ledger technology (DLT) to store information verified by cryptography among a group of users, which is agreed upon through a pre-defined network protocol, often without the control of a central authority. The amalgam of these technologies gives blockchain networks key characteristics that can remove the need for trust, and therefore enable a secure transfer of value and data directly between parties. Due to this unique ability, blockchain technology can diminish the role of intermediaries, who can command market power, collect significant fees, slow economic activity, and are not necessarily trustworthy or altruistic keepers of personal information.

Definition

A blockchain is a shared ledger of transactions between parties in a network, not controlled by a single central authority. You can think of a ledger like a record book: it records and stores all transactions between users in chronological order. Instead of one authority controlling this ledger (like a bank), an identical copy of the ledger is held by all users on the network, called nodes[107].

5.2 Structure of Blockchain

Blockchain technology is a revolutionary digital ledger system that operates in a decentralized and distributed manner. Its name derives from its unique data structure, where encrypted information is stored in "blocks" that are cryptographically linked in a "chain," ensuring data integrity and preventing tampering or forgery.

The blockchain grows as new data or transactions are verified through a consensus mechanism and added to the ledger. Each block is assigned a unique cryptographic hash, analogous to a human fingerprint, for identification. With the exception of the initial "genesis block," every block contains the cryptographic hash of its predecessor, creating an unbroken chain as depicted in Fig. 5.1.

A typical block consists of two main components:

1. **Header:** Contains metadata such as timestamp, current and previous block hashes, and mining details (nonce).
2. **Payload:** Comprises the actual set of data or transactions.

The cryptographic linking of blocks provides tamper-resistance. Any alteration to a block's content would change its hash, causing a mismatch with the stored "previous hash" in the subsequent block and invalidating the entire chain.

Blockchain's decentralized nature is maintained by replicating the entire chain across all nodes in the network. This distributed ledger is kept in sync through continuous updates and consensus mechanisms, ensuring data consistency and security across the system.

5.3 Properties of Blockchain

Some key features make blockchain a game-changing technology across industries. These characteristics solve issues of trust and transparency in transactions. Prominent one's include [108]:

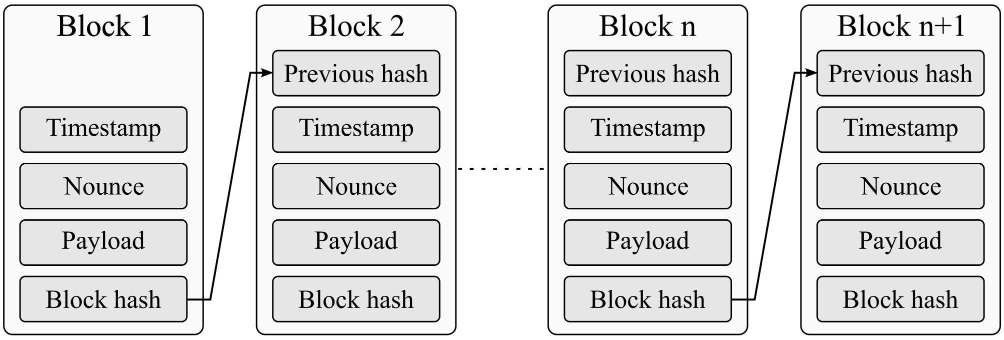

Figure 5.1: Block Structure

1. One of the core aspects of a blockchain is that it is a distributed ledger, meaning that the database is maintained and held by all nodes in the network. No central authority holds or updates the ledger, rather each node independently constructs its own record by processing every block (group of transactions), deciding if it is valid, then voting via the consensus mechanism on their conclusions. Once a change in the record is agreed, each node updates its own ledger. In contrast, traditional databases are stored and maintained centrally, which can make them high-value targets for hackers and criminals.

2. In general, once a transaction is added to a blockchain ledger, it cannot be undone. This immutability is one of the principal aspects that contribute to the trustworthiness of blockchain transactions. A blockchain's immutability is secured through its use of cryptography (see below for an explanation of hashing). In a traditional, centralised database, an authorised user can connect to the server to add or modify the data without the approval or detection of other users. Because all the data is held in one place, if the security of the server or the authority that runs the server is compromised, data can be modified or permanently deleted. This may sometimes be irreversible and occur without anyone else realising it.

3. Agreed by consensus No block can be added to the ledger without approval from specified nodes in the network. Rules regarding how this consent is collected are called consensus mechanisms. Consensus protocols are crucial in ensuring that every block is valid and that all participants agree and maintain the same version of the ledger. They heavily affect the incentives for nodes to act honestly and are therefore the most important variables when designing a blockchain.

5.3.1 Hashing: A Cryptographic Fingerprint

A hash is like a digital fingerprint; it is unique to each piece of data on the blockchain. Users put information regarding their transaction (name of receiver and sender along with the amount transferred) into a cryptographic hashing algorithm –

a complex mathematical formula – and receive a set of letters and numbers that is distinct to that transaction. The specific input, if unchanged, will always produce the same exact hash. If, however, any part of the data input is changed (for example a malicious actor changes the amount transferred), the hash would change to an entirely different set of characters and make it incompatible with the rest of the chain. Therefore, even without seeing the details of the transaction, nodes can quickly tell that the data within the block has been tampered with and reject that version of the ledger. It is this cryptographic security that makes blockchain ledgers more trustworthy and "almost" immutable.

5.3.2 Mining

For some blockchains, in order to add blocks to the ledger, transfers must go through a mining process. Mining is a way of adding transaction records, via blocks, onto a public ledger. Miners are nodes in the network that ensure the transactions in the block are valid. Specifically, they ensure that senders have not already used the funds they want to send to receivers. Once miners finish the verification, they have to ask the network for consent to add the new block to the ledger. In order to do so, they have to follow the consensus mechanisms chosen for the platform.

5.3.3 Consensus Mechanism

One of blockchain's key characteristics is the consensus mechanisms it uses to gather consent. Agreement among nodes regarding the "state" of the ledger is essential for the function of the blockchain. The bitcoin blockchain utilizes a consensus model called Proof of Work (PoW), which requires miners to compete against each other to create and broadcast blocks for approval. If successful, they are rewarded in Bitcoin.

There are other consensus mechanisms like Proof of Stake (PoS), Proof of Authority (PoA), Proof of Elapsed Time (PoET), and Proof of Burn – all variations on the means for the network to agree on changes to the ledger [109]. These protocols aim to improve the efficiency of Byzantine Fault Tolerance (BFT) and PoW.

While there are even more proposed consensus protocols e.g. few mentioned in Fig. 5.2, there is still a demand for more work to practically design and implement these protocols.

Blockchain allows for the secure management of a shared ledger, where transactions are verified and stored on a network without a governing central authority. Blockchains can come in different configurations, ranging from public, open-source networks to private blockchains that require explicit permission to read or write. Computer science and advanced mathematics (in the form of cryptographic hash functions) enable transactions and protect a blockchain's integrity and anonymity [110, 107].

CONSENSUS PROTOCOLS	
Proof of Work	The original consensus mechanism used by Bitcoin. Miners compete to solve complex mathematical puzzles, consuming significant computational power and energy
Proof of Stake	Validators are chosen to create new blocks based on the amount of cryptocurrency they hold and are willing to "stake" as collateral
Practical Byzantine Fault Tolerance (PBFT)	A consensus algorithm designed to work efficiently in asynchronous systems and tolerate byzantine faults
Delegated Proof Of Stake (DPoS)	A variation of PoS where token holders vote for "delegates" who are responsible for validating transactions and maintaining the blockchain.
Proof of Authority (PoAu)	Reputation-based consensus algorithm where blocks are validated by approved accounts known as validators
Proof of Capacity/Storage	Miners use available hard drive space to solve challenges. The more space a miner has, the higher their chances of mining the next block
Proof of Elasped Time	Developed by Intel, this protocol uses a trusted execution environment to enforce random waiting times for block construction
Proof of Burn	Miners show proof that they burned coins (sent them to an unspendable address) to gain mining rights
Proof of Activity	A hybrid approach that combines elements of PoW and PoS
Federated Byzantine Agreement (FBA)	It allows nodes to select their trusted peers, ensuring that consensus can be reached even in the presence of malicious or faulty nodes.

Figure 5.2: Types of Consensus Mechanisms

5.4 Types of Blockchain

	Permissionless			Permissioned
	PUBLIC	HYBRID	PRIVATE	CONSORTIUM
CONTROL	No central authority	Controlled by 1 authority with some permissionless process	Controlled by 1 authority	Controlled by a group
PERMISSIONS	Anyone can run a full node to transact, validate, and read transactions	Not just anyone can run a full node to transact, validate, and read transactions. Everyone can execute write transactions, while few can validate and read transactions	Only individual or selected members can run a full node to transact, validate, and read transactions. A few can execute write transactions and validate transactions, while everyone can read	Only members of the consortium can run a full node to transact, validate, and read transactions. In addition, only permissioned users can read
CONSENSUS MECHANISM	PoW	PoS, PoA	PBFT	PBFT and FBA
EXAMPLES	Bitcoin, Ethereum, and Litecoin	Ethereum	Hyperledger Fabric	Hyperledger Fabric, R3, and Corda

Figure 5.3: Types of Blockchain Technology from an Organizational Perspective

Fig. 5.3 presents different types of blockchain based on accessibility, permissions and modification capabilities.

5.5 Technical Evolution of Blockchain

Blockchain technology has undergone significant evolution since its inception and continues to develop. Four generations of blockchain have been identified based on their target audience [111]. As depicted in Fig. 5.4, Blockchain 1.0, the initial stage, introduced bitcoin blockchain and focused on digital cryptocurrency transactions. Blockchain 2.0 brought smart contract technology through Ethereum, enabling decentralized blockchain applications beyond just cryptocurrencies. Blockchain 3.0 expanded to include decentralized applications (Dapps) in various fields such as governance, law, healthcare, and society.

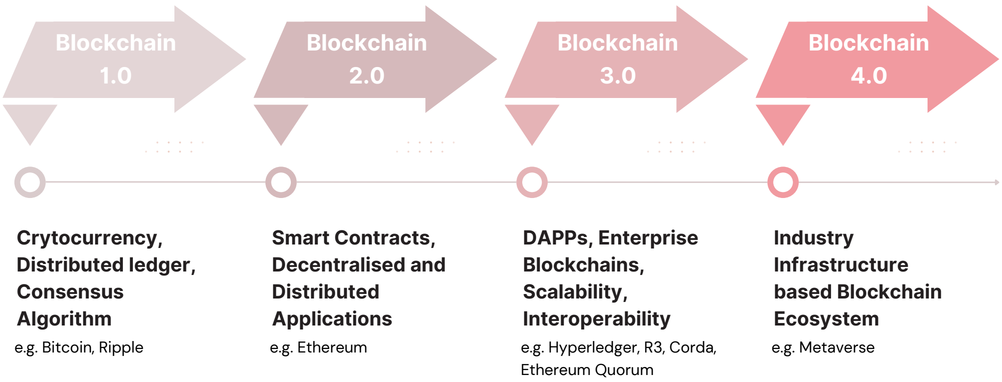

Figure 5.4: Generational Evolution of Blockchain Technology

Blockchain 4.0 aims to provide blockchain technology as a business-ready platform for creating and running applications, potentially integrating with other advanced technologies like Artificial Intelligence, Virtual/Augmented Reality, Internet of Things and Cloud Computing. It seeks to enable seamless integration of different platforms under a single system to meet business and industry demands [112]. The latter two generations of blockchain are still in early stages of development and undergoing modifications to reach their full potential for serving humanity [113, 110].

5.6 Smart Contracts

Smart contracts are automated agreements that self-execute and enforce terms between parties. While primarily digital, they can incorporate human input. The lifecycle of a smart contract involves four key steps: agreement, establishment, criteria verification, and value transfer execution [114]. In energy systems, particularly local electricity markets, smart contracts offer a novel advantage by enabling automated peer-to-peer energy trading. Smart meter data can verify energy transactions and initiate billing processes, leading to faster and fairer settlements that benefit both consumers and producers. The primary objectives of smart contracts are to enhance transaction security and reduce processing time and costs compared to traditional methods. Despite their suitability for cryptocurrency transactions, smart contracts in the energy sector are still evolving. Challenges persist in areas such as security, privacy, scalability, and billing, indicating that further development is needed in this field.

5.6.1 Technology Stack for Energy Applications

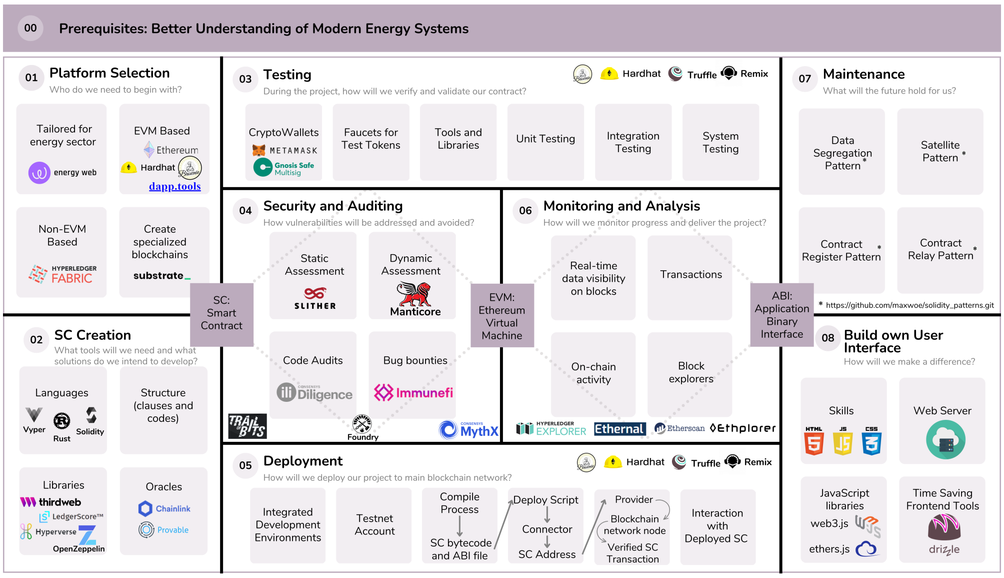

Figure 5.5: Technology Guide Stack for Smart Contracts Development for Decentralised Energy Applications

Blockchain technology and smart contracts have emerged as powerful tools in the energy sector, offering new possibilities for decentralized and automated energy management systems. This section explores the fundamental concepts of blockchain and smart contracts, with a particular focus on their applications in the energy domain. Furthermore, it presents a comprehensive technology stack for developing smart contract energy applications, providing researchers and practitioners with a structured guide for contribution opportunities in this field [115].

Fig. 5.5 illustrates the developmental stages of smart contract applications, detailing essential elements at each level and highlighting prominent examples. This stack serves as a valuable resource for developers, offering direct and relevant information about each stage to align with specific project requirements. The following subsections introduce and discuss key elements of this technology stack, emphasizing their significance in the creation of smart contract energy applications.

5.6.2 Development Essentials

Integrated Development Environments (IDEs)

Smart Contract Integrated Development Environments (IDEs) offer specialized tools for writing, compiling, and deploying smart contract applications to blockchain networks. These IDEs streamline the development process and simplify deployment procedures. Popular options include Remix IDE, Brownie, Truffle, Embark, Buidler, and Hardhat. Developers choose among these based on personal preferences and project requirements. For energy-specific applications, the Energy Web (EW) chain, built on Ethereum, provides a tailored blockchain solution. The EW ecosystem features a decentralized operating system with an energy web stack, offering a comprehensive framework for developing smart contract energy applications. This ecosystem is particularly valuable for newcomers to energy-focused blockchain development [1].

Languages

Smart contract development primarily relies on three programming languages: Solidity, Rust, and Vyper. Solidity and Vyper are the predominant choices for creating smart contracts compatible with the Ethereum Virtual Machine (EVM). In contrast, Rust is utilized for developing non-EVM smart contracts.

These languages draw inspiration from widely-used programming languages such as Java and Python. This familiarity in syntax and structure makes it easier for developers with experience in these popular languages to transition into smart contract programming. As a result, newcomers to blockchain development can leverage their existing programming knowledge to quickly adapt to these specialized languages, facilitating a smoother entry into the field of smart contract creation.

Wallets and Faucets

Interacting with a blockchain network requires a cryptocurrency wallet, which serves as a digital identity for transactions, validation, and authorization. These wallets store the cryptocurrency necessary for developing, testing, and deploying smart contract applications on the network. For enhanced security, multi-signature wallets, similar to

[1] https://www.energyweb.org/tech/

joint bank accounts, are available. To facilitate development and testing, various platforms offer free cryptocurrency through channels known as faucets. These resources provide developers with the means to experiment and refine their smart contract applications without incurring real-world costs, thus lowering the barrier to entry for blockchain development.

Libraries

Open-source smart contract libraries provide developers with pre-built, secure components reusable functions and implementations of various standards for blockchain development. OpenZeppelin, a prominent example, is widely used for Solidity development. It offers a comprehensive set of tools and contracts that enable developers to enhance their smart contracts with additional functionalities. By leveraging these libraries, developers can streamline the creation of decentralized applications, reduce potential vulnerabilities, and build upon a foundation of tested, industry-standard code.

Oracles

Oracles play a pivotal role in smart contract ecosystems by bridging the gap between blockchain networks and external systems. These entities facilitate the integration of off-chain data, enable external computations, and allow smart contracts to interact with various external platforms and data sources. In the realm of blockchain oracles, ChainLink has emerged as a prominent solution, widely adopted for developing hybrid smart contracts. These hybrid contracts leverage ChainLink's capabilities to connect with existing energy infrastructure, incorporating diverse data sources such as consumption profiles, IoT sensor outputs, and weather information. This integration opens up possibilities for applications like renewable energy credits and ownership certifications.

Testing

Smart contracts, once deployed, are inherently immutable on the blockchain. This characteristic necessitates thorough quality assessment prior to deployment to identify and rectify any errors or vulnerabilities that could lead to computational complexities or increased costs. To ensure robustness and reliability, smart contracts undergo a comprehensive evaluation process that includes various levels of functional testing [2]. This testing process is typically divided into three main categories:

1. Unit testing: Focuses on individual components or functions of the smart contract
2. Integration testing: Examines how different parts of the contract work together

[2] https://ethereum.org/en/developers/docs/smart-contracts/

3. System testing: Evaluates the entire smart contract system as a whole

By conducting these rigorous testing procedures, developers can significantly reduce the risk of deploying flawed smart contracts, thereby enhancing the overall security and efficiency of blockchain-based applications.

Security and Auditing

Before deploying smart contracts on the blockchain, it's crucial to conduct thorough security analyses and audits. These processes involve both automated and manual testing methods to ensure the contract's integrity and protect user funds. Automated security analysis employs two main tools [116]:

- Static analysis: Examines the code without execution
- Dynamic analysis: Tests the code during runtime

These automated tools help identify potential vulnerabilities and defects in the smart contract code, enhancing its quality and efficiency. Manual testing approaches include:

- Code audits: Involve detailed examination of the code, either through automated tools or human expertise, to detect security flaws and potential failure points
- Bug bounty programs: Engage the wider developer community to find and report bugs in exchange for rewards

Figure 5.5 provides examples of these testing methods. Upon completion of the audit, a comprehensive report is generated. This report details the findings, resolutions, and any outstanding issues, along with a plan for addressing them. This thorough process allows projects to deploy their smart contracts with confidence, ensuring application integrity and user fund protection.

Deployment

Once a smart contract has undergone compilation, testing, security analysis, and auditing, it is ready for deployment on the blockchain network. The deployment process varies depending on the development platform used.

For most Ethereum Virtual Machine (EVM) compatible smart contracts, deployment involves several steps:

1. Preparation of a deployment script using the bytecode and Application Binary Interface (ABI) files generated during compilation
2. Translation of this script by Web3 into JavaScript terms

3. Communication of these terms to an Ethereum node

Developers have multiple options for connecting to an Ethereum node:

1. Running a local node
2. Connecting to a public node
3. Using a node service like Infura [3] or Alchemy [4] via an API key

These methods allow the deployment script to interact with the Ethereum network, facilitating the smart contract's placement on the blockchain.

Analysis and Monitoring (Block Explorer)

Following smart contract deployment on the blockchain network, developers can leverage block explorers to monitor and analyze their contracts' performance. These explorers, provided by various development platforms, offer a range of functionalities:

1. Transaction visualization and confirmation
2. Access to real-time and historical blockchain data
3. Detailed information on blocks, transactions, and addresses

Block explorers serve as powerful tools for developers to track and evaluate their smart contracts' operations. They provide insights into contract interactions, transaction histories, and overall network activity.

Several prominent block explorers exist for the Ethereum blockchain:

1. Etherscan [5]: Widely recognized as one of the most comprehensive and free Ethereum block explorers
2. Ethplorer [6]: Offers competitive features and services

These platforms enable developers to gain valuable insights into their smart contracts' behavior and performance on the blockchain.

[3] https://www.infura.io/
[4] https://www.alchemy.com/
[5] https://etherscan.io/
[6] https://ethplorer.io/

Maintenance Tools

The smart contract ecosystem has evolved to address the unique maintenance challenges posed by blockchain's immutability [117]. Developers have devised various strategies and patterns to manage deployed smart contracts effectively. However, potential maintenance issues can still arise, potentially resulting in significant costs or complications down the line.

To mitigate these risks, it's crucial for developers to conduct thorough evaluations of their smart contracts, particularly for more complex implementations. This process involves identifying and implementing appropriate maintenance patterns and mechanisms. Given the rapidly evolving nature of blockchain technology and smart contract development, staying informed about the latest advancements, best practices, and emerging patterns is essential for developers working in this field.

Front-end Utilities

Front-end development for smart contract applications requires a blend of traditional web technologies and blockchain-specific tools. Developers need proficiency in core web languages like CSS, HTML, and JavaScript to create intuitive user interfaces. Popular frameworks such as Angular[7] and React[8] provide robust architectures for building complex, interactive front-ends.

To bridge the gap between the blockchain and the user interface, developers often utilize specialized JavaScript libraries. Web3.js[9] and Ethers.js[10] have gained prominence for their ability to facilitate seamless interaction with smart contracts from the front-end. These libraries enable developers to integrate blockchain functionalities into web applications effectively.

Environments like Hardhat[11] offer streamlined architectures that simplify the process of constructing application user interfaces tailored for blockchain interactions. By leveraging these technologies, developers can create sophisticated, user-friendly interfaces that interact seamlessly with smart contracts, enhancing the overall user experience of decentralized applications.

[7] https://angular.dev/
[8] https://react.dev/
[9] https://web3js.readthedocs.io/en/v1.10.0/
[10] https://docs.ethers.org/v5/
[11] https://hardhat.org/

5.7 Pilot-Platform for Blockchain-Based Peer-to-Peer Energy Trading

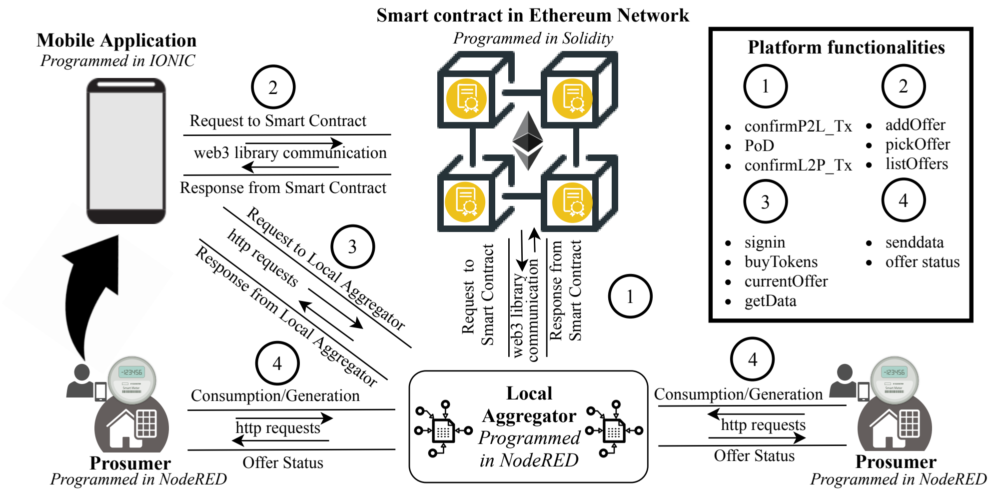

Figure 5.6: Design Model of Blockchain-Based P2P Energy Trading using IoT Devices

This section intends to impart technical implementation details of a simple yet practical demonstration on how the energy trade occurs between the peers [118]. Moreover, all the source codes are accessible online in IEEEDataPort repository[119].This may support academics and entrepreneurs at the initial development stage of these kind of initiatives.

5.7.1 Key Players in P2P Energy Trading

It is important to define main players in the P2P energy market.

Peers

They come in two types:

1. Consumers: These are regular electricity users who only consume energy.
2. Prosumers: These are both producers and consumers of energy, typically owning renewable energy systems like solar panels.

Local Aggregator

Think of the local aggregator as a neighborhood energy broker. Their role includes:

- Managing smaller community-based energy networks
- Facilitating energy trades between peers in their community
- Handling the token economy by:
  - Purchasing tokens from public exchanges
  - Selling tokens to local participants as needed

The local aggregator essentially acts as a middleman, making it easier for peers to trade electricity within their community. This structure helps organize larger P2P energy networks into more manageable local groups.

5.7.2 Case Scenario

To demonstrate the functionality of our peer-to-peer energy trading platform, a user-friendly mobile application is developed. This app serves as the interface for participants to engage in energy transactions within a regulated market framework. A typical trading scenario involving two registered users, Peer A and Peer B is stated below:

1. **Listing Surplus Energy:** Peer A, who has excess energy to sell, uses the mobile app to create and publish an offer on the trading platform.

2. **Purchase Decision:** Peer B, in need of energy, browses available offers through the app and decides to purchase from Peer A.

3. **Energy Transfer Initiation:** Upon confirmation of the transaction, the local aggregator signals Peer A to begin exporting energy and notifies Peer B to start consumption.

4. **Verification Process:** The local aggregator utilizes smart meter data from both peers to confirm the Proof of Delivery (PoD) for the energy transfer.

5. **Financial Settlement:** Once the PoD is verified, the local aggregator completes the transaction by transferring payment to Peer A, deducting the corresponding amount from Peer B's token balance.

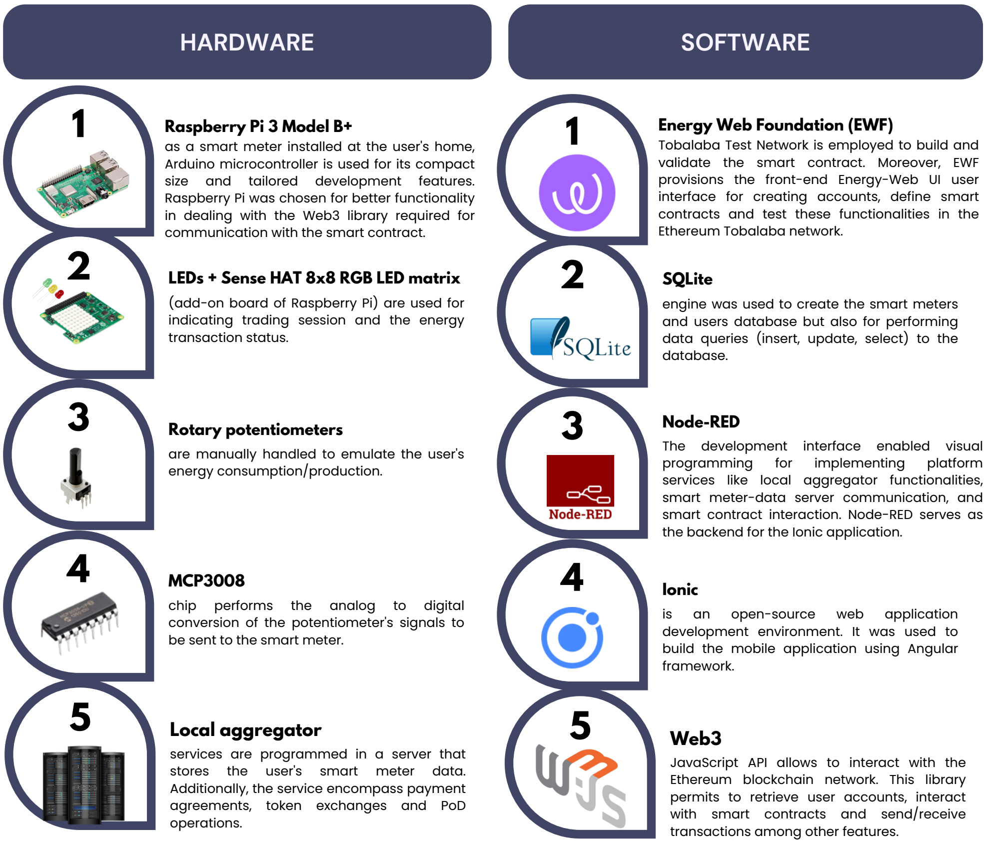

Figure 5.7: Components used for Peer-to-Peer Energy Trading Platform

5.7.3 Tools

In the process of conducting our comprehensive literature review, we evaluated a wide range of technological solutions. After careful consideration, we selected the tools and approaches illustrated in Fig. 5.7. This figure showcases the hardware and software components that were deemed most suitable for our research objectives.

It is crucial to emphasize that while the most current software tools available during this implementation were utilised, the rapidly evolving nature of blockchain technology necessitates ongoing vigilance and adaptability. As the field progresses, certain tools may become deprecated or undergo significant updates. Therefore, researchers and practitioners must:

- Stay informed about the latest developments in blockchain technology
- Regularly assess the relevance and efficiency of their toolsets

Table 5.1: Energy Trade Offer.

Structure of an Offer		
Size	Arguments	Details
4 bytes	ID	offer ID
20 bytes	seller	seller address
4 bytes	energy	amount of electricity for sale (Wh)
4 bytes	price	price of electricity for sale (tokens)
4 bytes	timeOffered	time when offer is added

- Be prepared to adapt their methodologies and implementations as needed

5.7.4 Proposed Methodology

Leveraging the Energy Web Foundation Ecosystem

To establish our blockchain-based energy trading platform, we chose to deploy our Ethereum-based smart contracts using the Energy Web Foundation (EWF) ecosystem. This decision was driven by EWF's prominence in the energy sector:

- EWF is recognized as the world's largest energy-focused blockchain framework.
- It caters specifically to regulatory energy sectors and addresses unique business and market requirements.

Deployment Process

Our implementation began with the following steps:

1. **Client Installation**: We downloaded and installed the Energy Web Client UI from the EWF platform.

2. **Environment Setup**: This user interface provided a desktop environment crucial for:

- Connecting peers within the blockchain network
- Creating user accounts
- Facilitating transactions
- Enabling interactions with smart contracts

By utilizing the EWF ecosystem and its associated tools, we were able to create a robust foundation for our Ethereum-based smart contract structure.

Account Creation Process

To facilitate our peer-to-peer energy trading platform, we established Parity Ethereum wallet accounts for all registered users and the local aggregator. This process was streamlined through the Energy Web UI, providing a user-friendly interface for account setup.

Accessing Test Tokens

For development and testing purposes, we leveraged the Energy Web Tobalaba network. This testnet environment allows developers to:

1. Obtain simulated tokens at no cost
2. Deploy and interact with smart contracts in a risk-free setting
3. Validate the functionality of the trading platform before live implementation

Developing the Smart Contract

To implement our peer-to-peer energy trading scenario, we utilized the Energy Web UI's smart contract development capabilities. Using Solidity, we created a comprehensive smart contract with the following key functions:

- addOffer
  - Purpose: Enables prosumers to list their surplus energy for sale
  - Details: Prosumers specify energy amount and price
  - Note: Offer structure details are available in Table X
- pickOffer
  - Purpose: Allows consumers to choose and reserve available offers
  - Action: Locks the selected offer in the system
- confirmP2L_Tx
  - Purpose: Confirms the consumer's payment to the local aggregator
  - Action: Updates the transaction status in the system
- PoD
  - Purpose: Enables the local aggregator to verify energy transfer
  - Trigger: Initiates the final stage of the transaction

- confirmL2P_Tx
  - Purpose: Records the local aggregator's payment to the prosumer
  - Action: Finalizes the P2P energy trade

This smart contract design reflects the core components of our P2P energy trading model, facilitating interactions between prosumers, consumers, and the local aggregator.

Design Model

A model is designed to demonstrate how a local energy trading community might function within a regulated market environment. This model consists of four key elements:

1. A blockchain-based smart contract
2. A local aggregator
3. Smart meters
4. A mobile application service

These components work together to create the foundation of the energy trading system. The relationship between these elements is visually represented in a Fig. 5.6.

Advanced Metering

As earlier mentioned, smart meters are modelled with Raspberry Pi's (programmed employing Node-Red visual programming) and the user's energy generation/consumption are emulated with potentiometers. Moreover, the user's smart meters are registered in the platform with a unique ID. They send their measured energy information to the local aggregator server once per second.

Smart Meter Simulation and Data Transmission

A system was developed to simulate smart meters for our local energy trading community model. The set up is described as follows:

Hardware and Software Setup

We chose to model our smart meters using Raspberry Pi devices. To program these compact computers, we employed Node-Red, a visual programming tool that allowed us to create data flows with ease.

Energy Data Simulation

To replicate real-world energy generation and consumption patterns, potentiometers were utilised. These adjustable resistors enabled us to manually vary the "energy" readings, effectively simulating the fluctuations one would observe in actual household energy use or solar panel output.

Meter Identification and Data Reporting

The simulated smart meters were assigned a unique identifier, mirroring the individual serial numbers found on real smart meters. This ID system allowed our platform to distinguish between different "households" or energy sources within our model.

Communication with Central System

The simulated meters were configured to communicate with a central server, which we referred to as the local aggregator. We set up each meter to send its current energy reading to this server every second. This frequent reporting schedule was designed to emulate how real smart meters might continuously update a utility company about energy usage.

Through this setup, a small-scale model was created that closely approximated the functioning of a network of smart meters in a local energy trading community.

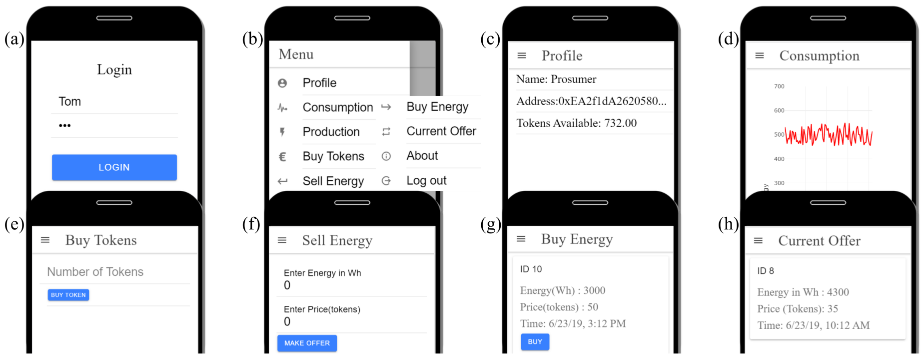

Figure 5.8: Energy Trade Mobile Application Panels

PANEL	DESCRIPTION
a	It contains the login access. As part of the back-end, the mobile application makes a signin http request to the local aggregator server. Once the credentials are validated, the user us redirected correspondingly to the menu.
b	It displays the general menu of all services provided.
c	It exhibits the profile page, where the personal user data (name, address, available tokens) is displayed so that a balance of the account can be inferred.
d	It provides the user with real time monitoring regarding the energy consumption/production. The mobile application makes getdata http request to the local aggregator server to have in turn the corresponding smart meter data.
e	It permits the user to buy tokens from the local aggregator.
f	In this panel, the user is able to make an energy offer invoking a specific function (**Add Offer**) of the smart contract so that details such as transaction ID, energy, price, time and user data are passed as arguments.
g	The system displays available energy offers to the user. The back-end uses a smart contract to list offers and allow selection. Once an offer is chosen, user details are provided as arguments. The selected offer is removed, and the energy price is transferred from the user to the aggregator account.
h	It displays the selected energy offer being now in the transaction process.

Figure 5.9: Details of Energy Trade Mobile Application Panels

Mobile Application

To enhance user interaction with this energy trading platform, a mobile application was developed that serves as the primary front-end interface. This app was designed to be intuitive and user-friendly.

Multi-panel Design

Our mobile application features a multi-panel layout, with each panel dedicated to a specific service or function within the energy trading ecosystem.

Visual Representation

For a clearer understanding of the application's structure, two visual aids have been provided:

- Fig. 5.8: This figure presents a visual representation of the app's interface, showcasing the layout and design of the various panels.

- Fig. 5.9: This table offers a detailed breakdown of the different panels available in the app, along with a brief description of each panel's purpose and functionality.

Local Aggregator Server

The local aggregator server serves as the core component of the energy trading platform, functioning as the central management system for the entire operation. The following details outline its implementation:

Development Environment

Node-Red was selected as the primary programming tool for developing the local aggregator services. This visual programming tool facilitates the creation of complex data flows and logic, making it suitable for the requirements of this system..

Server Configuration

The local aggregator services were implemented on a dedicated server to ensure robust performance and reliable data management for the energy trading community.

Functionality

The local aggregator server is responsible for a wide range of tasks, including:

- Processing data from smart meters
- Managing energy trading transactions
- Coordinating communication between various system components

The presentation of a generic model offers readers a foundational understanding of blockchain implementation principles that can be adapted to various contexts and technological advancements. This approach ensures that the core concepts remain applicable even as specific tools and technologies evolve.

5.8 Applications in P2P Energy Trading

When blockchain technology converges with smart power systems, it opens up a wide array of innovative applications across various domains of the energy sector [108, 120]. These applications can be broadly categorized into three main areas: data storage, energy trading, and energy financing[121].

In the realm of data storage, blockchain offers solutions for:

5.8.1 User and Asset Management

Blockchain technology offers secure, tamper-proof, and decentralized storage of ownership records and related transactions in the energy sector. This technology can regulate the ownership and management of various energy assets, including:

- Smart meters
- Renewable energy generation units
- Batteries
- Electric vehicle charging stations
- Thermostats

Benefits of Blockchain in Energy Asset Management can be summarised as:

1. **Operational Flexibility:** Energy assets can be automatically registered with a blockchain ledger of identities, enabling operational flexibility for grid services, particularly in frequency regulations and reactive power support.

2. **Transparency and Traceability:** Blockchain supports audit trails from asset registration and ownership records to sales, transfers, and credit claims.

3. **Automated Energy Credit Recording:** In pilot projects, existing rooftop solar customers can automatically record their generated energy credit data to systems like the Energy Web Chain.

4. **Standardized Asset Registration:** Projects like recorDER (formerly DER Asset Register) provide blockchain-based shared registers for transmission and distribution system energy resources, standardized for system operators.

Smart contracts in the energy sector primarily facilitate energy trades, with key functions focusing on user and asset management [122, 30]:

User Management:

- Registration of different users (prosumers, consumers, producers)
- Profile definition and linking to monitoring devices
- Authentication using smart meter addresses
- Money deposits for participation validation
- Access granting to data streams
- User list updates and statistics recording

Asset Management:

- Sorting and categorizing assets
- Managing energy storage systems (charging/discharging)
- Recording producer types for buyer preferences[123]

These functions enable efficient management of both users and assets in blockchain-based energy systems, facilitating transparent, secure, and automated energy transactions.

5.8.2 Billing and Operations

The integration of blockchain with smart metering infrastructure offers new possibilities in the energy sector, including automated billing and increased consumer control over meter data and electricity contracts. This combination enhances transparency and traceability in metering and billing processes [124, 30].

Blockchain's decentralized nature could reduce intermediary reliance, potentially lowering service charges and addressing data security issues[125]. It enables peer-to-peer transactions and secure sharing of smart meter data with stakeholders like DSOs and TSOs, potentially improving power system management.

In electric vehicle (EV) charging, blockchain is being explored for automatic billing. Companies like LO3 are developing transactive grid smart meters that interact directly with blockchain systems.

Smart contracts are being developed to enable various services without third-party involvement, including smart charging for EVs, managing charging station distribution, and facilitating Vehicle-to-Grid energy trading.

In distributed energy generation, prosumers trade energy using blockchain technology, which records energy flow, clears pricing, and stores data in a distributed ledger. Utility companies are also exploring micro-payments for pre-paid or pay-as-you-go billing solutions [126].

5.8.3 Energy Certifications

Blockchain technology is being explored as a potential solution to address challenges faced by small-scale prosumers in claiming renewable energy certificates or carbon credits [127, 128]. These challenges arise from the complex, fragmented market structure and costly procedures currently in place.

The technology offers a new approach to issuing energy certificates that demonstrate the origin of renewable energy and could help create supportive markets. Blockchain's key features in this context include:

1. Providing an immutable and transparent record of certificate generation and transactions
2. Enabling faster, more detailed, and potentially more accurate tracking of energy production compared to traditional methods
3. Allowing for advanced incentive schemes to be encoded in smart contracts that execute automatically on the blockchain

One notable development in this area is the Energy Web Origin toolkit [129], being developed by the Energy Web Foundation. This open-source toolkit aims to:

1. Facilitate the recording of renewable energy generation provenance
2. Automatically track ownership of renewable energy
3. Support various green energy attribution systems globally

The goal of these blockchain-based solutions is to make the process of claiming and trading renewable energy certificates more accessible, efficient, and transparent, particularly for smaller-scale energy producers. However, it's important to note that these applications are still in development, and their effectiveness in real-world scenarios is yet to be fully proven.

The energy trading category encompasses:

5.8.4 Peer-to-peer Energy Transactions

Peer-to-peer energy trading has emerged as a prominent blockchain application in the energy sector, representing one-third of all blockchain initiatives in power systems. This innovative approach enables consumers and prosumers to trade energy directly, providing greater control over consumption and generation. Blockchain technology offers a decentralized energy trading market infrastructure that can be integrated into existing distribution grids, managed by utilities, retailers, or grid operators.

The advantages of blockchain-based P2P energy trading are numerous. It provides enhanced privacy and transaction security compared to traditional centralized approaches. Additionally, it offers lower transaction costs, reduced intermediary involvement, and increased transparency for all participants. These benefits, coupled with maintained data privacy and integrity, are expected to encourage wider participation and faster adoption of Distributed Energy Resources (DERs) [130].

Several companies and startups are making significant strides in this field. Power Ledger, an Australian blockchain startup, has introduced two energy trading models: a retail model for existing regulated market structures and a direct peer-to-peer model for deregulated markets.Real-world examples of blockchain-based P2P energy trading are already in operation. The Brooklyn Microgrid [12] in New York City allows rooftop solar panel owners to sell excess electricity directly to their neighbors using an Ethereum-based blockchain for smart contracts. Similar pilot projects have been launched globally, including SOLshare[13] in Bangladesh, powerpeers[14] in the Netherlands, and Grid Singularity[15] in Germany. The application of blockchain technology extends to the e-mobility sector as well. In Germany, bloXmove [16] has built the framework for a worldwide decentralized mobility infrastructure to create a multi-modal, efficient, and frictionless mobility world.

The shift towards P2P energy trading is driven by growing environmental concerns and awareness of resource depletion [131]. Consumers are becoming increasingly proactive in purchasing electricity from sources with minimal carbon footprints. This trend necessitates a move towards decentralized grid infrastructure, where nodes can function as either consumers or prosumers at any given time.

5.8.5 Wholesale Energy Market Participation and Operation Flexibility

Blockchain technology has the potential to transform wholesale energy markets (WEM), including both regulated and deregulated bilateral markets, by addressing key challenges and introducing new efficiencies. It promises to reduce counterparty risk in bilateral markets while enhancing transparency and maintaining privacy. The technology offers solutions to trade confirmation and reconciliation issues in wholesale energy trading, replacing current email and fax-based systems used by trading offices.

By introducing decentralized ledgers, blockchain creates shared logs of trades among trading offices, eliminating the need for individual data storage by traders. This allows counterparties to reconcile and verify transactions in real-time, increasing workflow efficiency and significantly reducing human error. Furthermore, blockchain enables the convergence of market mechanisms and system operations, leading to better resource management, improved operational flexibility, and incentives for renewable energy generation, storage, and demand response.

In response to these opportunities, multi-energy trading firms are collaborating to develop EnerChain, a blockchain-based P2P trading platform designed to complement and potentially replace the wholesale energy market.

Wholesale Energy Market operations typically involve three main processes [132]. The first encompasses pre-market clearing inputs such as contracts, trade executions, regulations, and logistics. The second process consists of market operation, including optimization, economic dispatch, and contingency management, which may vary by

[12] https://www.brooklyn.energy/
[13] https://solshare.com/
[14] https://powerpeers.nl/
[15] https://gridsingularity.com/
[16] https://bloxmove.com/bloxlab

jurisdiction. The third process covers post-market activities like settlement, billing, and reporting.

Blockchain technology can be applied across these processes. It can store WEM rules, regulations, and analysis using smart contracts. Financial trading to clear the WEM via market clearing price (MCP) can be performed on blockchain platforms using digital assets. Additionally, executed trading information and subsequent billing settlements can be recorded permanently on the blockchain ledger.

This technological shift represents a significant advancement from traditional methods, offering a more efficient, transparent, and flexible approach to wholesale energy trading and market operations.

Energy financing applications include:

5.8.6 Fundraising for Renewable Energy Projects and Energy Tokens

Blockchain initiatives in the energy sector extend beyond peer-to-peer trading, with the second largest category focusing on using cryptocurrency to fund energy projects. This approach leverages blockchain technology to create energy tokens, enabling secure investments and shared ownership in green energy ventures.

Several startups have pioneered this method:

1. WePower[17] and Sun Exchange[18] have conducted token sales to crowdfund renewable energy projects.

2. These sales are recorded on blockchain platforms, allowing token owners to access discounted services or sell tokens at a profit once the project is operational.

3. Smart contracts automatically distribute generated revenues to investors, while the blockchain tracks ownership.

SolarCoin[19] represents another innovative use of blockchain, aiming to incentivize renewable energy production by monetizing global solar energy output. These energy-focused cryptocurrencies can often be exchanged for fiat currencies or other digital assets.

Recent research has explored tokenizing Renewable Energy Certificates (RECs), providing a decentralized, trustworthy mechanism for REC issuance, trading, verification, and retirement [128]. This approach aims to optimize energy management procedures and offer industry stakeholders a secure environment for transactions.

[17] https://we-power.com.my/
[18] https://sunexchange.com/
[19] https://solarcoin.org/

These examples represent only a fraction of the ongoing research and development in this field. Collaborations between companies, foundations, industries, and academics are driving extensive innovation. The International Renewable Energy Agency (IRENA) report from 2019 provides comprehensive statistics on blockchain project development in the power sector [133]. Additionally, a survey has cataloged details of approximately 140 blockchain-based energy projects, including their focus areas, platforms used, consensus mechanisms, and deployment locations [130].

5.9 Challenges of Applying Blockchain to Smart Power Systems

The growing interest in blockchain technology for power systems is evident from the numerous energy projects, research initiatives, and investor attention in this field. This surge of activity underscores the potential value that blockchain could bring to the energy sector. However, the technology's implementation in power systems is still in its early stages. Many projects remain at the proof-of-concept level, while others are in various phases of development or small-scale trials. The industry has yet to witness substantial, concrete benefits from blockchain integration in power systems. As a result, the path to mainstream adoption of blockchain technology in the power sector is fraught with challenges, stemming from this lack of proven, large-scale success stories. Some of these challenges across various domains are listed below [134, 108].

5.9.1 Infrastructure and Performance Challenges

The application of blockchain technology to smart power systems faces significant infrastructure and performance hurdles. These include high costs for upgrading existing systems, substantial expenses for mining and transaction validation, and increased bandwidth requirements. Such challenges lead to communication overhead, reduced efficiency, and potential limitations during emergencies. Scalability is a major concern, with current blockchain platforms processing only a limited number of transactions per second, which is insufficient for the vast number of devices in smart grids.

5.9.2 Consensus Algorithm Limitations

Consensus algorithms present another set of challenges for blockchain implementation in power systems. There is a pressing need for an efficient algorithm that balances energy savings, security, privacy, and scalability. Existing algorithms like Proof-of-Work, Proof-of-Stake, and others have limitations ranging from high energy consumption to potential monopoly formation and privacy concerns. These issues have significant implications for power systems, including excessive energy consumption and potential market inefficiencies.

5.9.3 Regulatory and Legal Obstacles

Regulatory and legal issues pose substantial obstacles to blockchain adoption in the energy sector. The digitization of assets and actions creates difficulties in taxing digital currencies and legal ambiguities surrounding smart contracts. User anonymity raises concerns about unregulated transactions and the lack of a central intermediary for regulatory enforcement. The industry is grappling with the choice between permissionless and permissioned blockchains, with a growing preference for the latter in the energy sector due to better control and privacy features.

5.9.4 Security Vulnerabilities

Security concerns remain a critical challenge for blockchain implementation in power systems. The technology is vulnerable to various attacks, including 51% attacks, Sybil attacks, and Denial of Service attacks. Long-term concerns about quantum computing threats to cryptography also loom large. These security issues could potentially lead to market monopolies, major power supply interruptions, and data breaches, underscoring the need for advanced cybersecurity measures.

5.9.5 Adoption and Integration Hurdles

Adoption and integration of blockchain in power systems face additional hurdles. The technology lacks long-term usage experience, which affects its acceptance. The complexity of scheduling mechanisms for distributed energy markets and challenges in interoperability with other technologies further complicate adoption. The immutable nature of blockchain ledgers makes it difficult to implement changes, and the substantial power consumption from mining and advanced metering infrastructure raises concerns among users and producers [135].

Chapter 6

Conclusions and Future Work

6.1 Conclusions

The energy sector is undergoing a significant transformation, driven by the integration of renewable energy sources, the proliferation of electric vehicles (EVs), and the evolving demands of modern electricity grids. This thesis addresses the overarching research question: 'How can innovative market structures and load management strategies mitigate the challenges posed by the evolving energy landscape?' The focus is on developing peer-to-peer (P2P) local energy trading market mechanisms capable of effectively managing distributed generation and EV charging, while empowering prosumers and consumers to actively participate, reap monetary benefits, and provide ancillary services to the grid.

This research investigates a P2P energy trading framework that optimizes the social welfare of EV owners through a multi-issue negotiation mechanism and real-time EV charging management, while also providing grid services such as congestion mitigation through EV flexibility. The thesis then examines a three-stage multi-agent model for P2P energy trading, strategically designed to maximize individual benefits by orchestrating one-to-many concurrent composite negotiations. Additionally, the research explores in depth how blockchain and smart contract technologies can be leveraged to implement automated P2P energy trading systems.

Specifically, we studied how to empower P2P energy trading using efficient market mechanisms from the following two aspects:

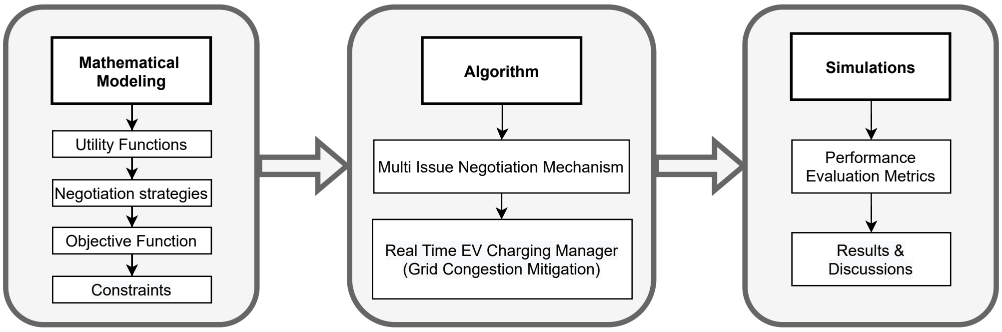

Figure 6.1: Graphical Abstract of Multi-Issue Negotiation EVs Charging Mechanism

6.1.1 Multi-Issue Negotiation for EV Charging in Congested Networks

This research addresses the challenge of coordinating electric vehicle (EV) charging in highly congested distribution networks. The problem statement highlights the need for effective load coordination in networks where building loads represent critical loads that cannot be shed, and uncoordinated EV charging could lead to network congestion and overloading.

The paper proposes a multi-issue negotiation protocol between active consumers (EVs) and a management platform. This protocol simultaneously considers three key aspects: the consumption interval, the price, and the size of energy packages. The approach uses MATLAB classes to emulate a multi-agent system, where each vehicle is an agent interacting with the platform (another agent). The algorithm is designed to coordinate EV charging while considering network constraints. A graphical abstract of the research is presented in Fig.6.3.

The case study applied the proposed multi-issue negotiation protocol to a distribution network consisted of 10 EV chargers with 100 EVs and 7 buildings with 30 households. Varying building load profiles, number of charging points and EV preferences(energy, price and time), reduction in network overload related to total capacity and overall EV charging rate success was examined. Model demonstrated consistent ability to maintain EV charging services even under varying loads and constraints. Significant reductions in network overload, ranging from 2% to 20% depending on conditions.Adaptability to different EV numbers and preferences, showcasing the robustness of the negotiation protocol.This real-time management algorithm ensures that the charging schedule remains adaptable and responsive to real-time conditions, optimizing the use of available resources while maintaining system stability. By dynamically adjusting to deviations and leveraging the flexibility of EVs, the algorithm effectively balances the needs of both EV owners and the grid infrastructure.

This comprehensive simulation setup allows us to test our negotiation protocol and management algorithm under conditions that closely mimic real-world scenarios. By

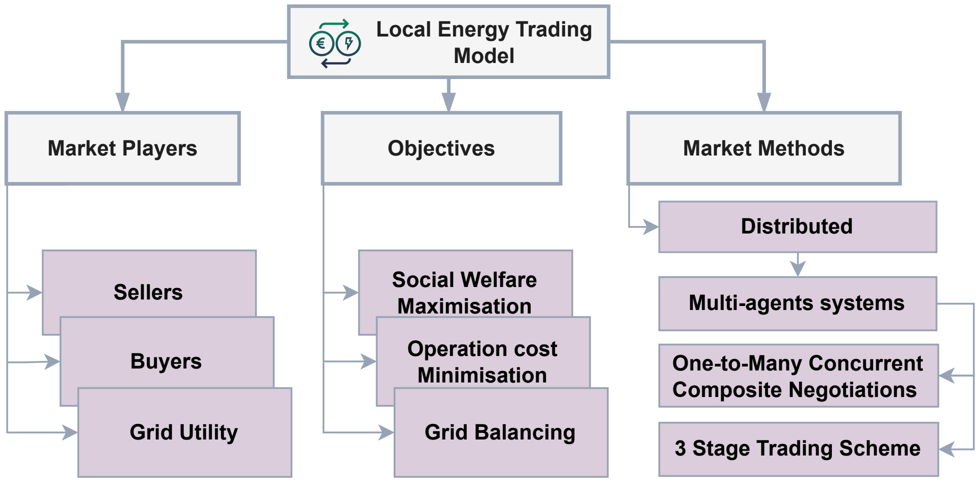

Figure 6.2: Graphical Abstract of Multi-Agent Framework for P2P Energy Trading

incorporating authentic load profiles, diverse EV characteristics, and dynamic waiting times, we can assess the model's effectiveness in managing network congestion and coordinating EV charging in a practical, scalable manner.

The research also investigates the broader applicability of the proposed algorithm. Although designed for EV charging coordination, the paper notes that the algorithm is presented in a generic form and could potentially be applied to other scenarios requiring load coordination in congested networks.

6.1.2 Three-Stage Multi-Agent Framework for Peer-to-Peer Energy Trading

This study underscores the need for an efficient and scalable peer-to-peer (P2P) energy trading framework that can simultaneously optimize individual market player profits, support grid balancing, and minimize trading process delays. Existing solutions often rely on complex computations and precise predictions, leading to scalability issues and implementation difficulties. Uncoordinated trading and energy management could result in grid instability, congestion, and inefficient resource allocation.

To address these challenges, the paper proposes an innovative multi-stage postpaid P2P energy trading model based on a multi-agent systems framework. The approach achieves three key objectives: maximizing social welfare, supporting grid balancing and congestion management, and minimizing trading process delays. The core of the methodology is the implementation of a "One-to-Many Concurrent Composite Negotiations" strategy within a three-stage scheme, featuring a distinctive postpaid method that ensures seamless service delivery and payment. A graphical abstract of the research is presented in Fig.6.4.

The proposed approach's simplicity and computational efficiency, which does not rely on ultra-precise predictions, enables easy deployment on edge platforms and facilitates large-scale scalability. This contributes significantly to the evolving landscape of P2P energy trading by offering a practical and efficient solution to modern energy market challenges.

The effectiveness of the proposed framework was tested in a realistic local energy market scenario, evaluating how agents interact, negotiate, and trade energy within the defined parameters. The case study implemented two specific scenarios to evaluate the proposed peer-to-peer (P2P) energy trading model.The case studies collectively demonstrated the model's efficiency in facilitating P2P energy trading, optimizing energy distribution, and supporting increased participation among market agents.

The methodology of this research work also involved a series of six experiments designed to evaluate the scalability and effectiveness of the proposed peer-to-peer energy trading model. These experiments progressively increased the number of prosumer and consumer agents, with agent batches ranging from 5 to 50. Various system parameter combinations were tested to assess the model's performance under different conditions. The experiments were conducted with a consistent time horizon across all scenarios, enabling direct comparisons and insights into the model's scalability in terms of computational and communication demands.

This methodological approach provided a robust foundation for analyzing the model's performance, its impact on local energy trading volumes, overall profits, and the distribution of benefits among different types of agents.

The results showed that the model could effectively handle energy transactions, promote economic benefits for prosumers by allowing them to sell surplus energy directly to consumers, and reduce grid dependency, thereby enhancing the sustainability and efficiency of local energy markets.

6.1.3 Blockchain in the Realm of P2P Energy Trade

This thesis additionally explores the integration of blockchain technology within smart power systems, particularly focusing on its application in peer-to-peer (P2P) energy trading. The chapter provides a comprehensive overview of how blockchain can enhance the efficiency and transparency of energy transactions. It discusses the decentralized nature of blockchain, which eliminates the need for intermediaries, thereby reducing transaction costs and improving data security and privacy. The chapter highlights the potential of blockchain to facilitate direct energy trading between producers and consumers, leveraging smart contracts to automate and secure transactions. It addresses both the benefits and challenges of implementing blockchain in energy systems.

The thesis also examines the transformative potential of DLT-based smart contracts in energy systems, presenting an illustrative technology stack as a guide for developing energy applications. By providing this framework, the thesis aims to accelerate innovation in decentralized energy solutions, motivate energy experts to engage with smart contract technology, and foster a community of developers in this field. The research not only highlights the capabilities of smart contracts to simplify and decentralize energy operations but also offers practical guidelines for implementation. While establishing this foundation, the thesis anticipates future expansions to include more detailed aspects of the technology stack, further supporting the advancement of decentralized energy applications.

Furthermore, the study explores the practical implementation of blockchain technology in facilitating peer-to-peer (P2P) energy trading. The study focuses on developing a pilot platform that leverages blockchain's decentralized and transparent nature to enable direct energy transactions between producers and consumers without the need for intermediaries.

6.2 Future Work

The current studies have laid a foundation for innovative approaches in EV charging coordination and peer-to-peer energy trading. However, there are several areas for improvement and expansion. Future research will focus on the following key directions:

1. Complex Strategy Development: Exploration of complex strategies for both utilities and vehicles, associated with various types of flexible tariffs. This will enhance the parametric negotiation methodology to allow for more sophisticated strategy variation.

2. Integrated Load Management: Development of a methodology to simultaneously manage flexible vehicle loads along with other flexible household loads, creating a more comprehensive energy management system.

3. Renewable Integration: Incorporation of solar production at the household level, furthering the integration of renewable energy sources into the local energy ecosystem.

4. Peer-to-peer Energy Exchange: Enabling users to exchange energy with each other and with vehicles on public roads, fostering a more dynamic and flexible energy trading environment.

5. Multi-agent Trading System: Evolution towards a multi-agent based trading system, moving away from the utility-dependent intermediate management platform used in the current studies.

6. Advanced Agent Behavior Modeling: Enhancement of agent behavior models with more advanced features to better reflect real-world decision-making processes.

7. Energy Communities: Exploration of establishing energy communities at common coupling points in the network, allowing prosumers and nearby consumers to form bilateral contracts and collaborate on energy management.

8. Coordinated Response to Price Signals: Investigation into how energy communities can coordinate their responses to price signals to aid grid stability and optimize energy use.

9. Network Loss Minimization: Study of how close-knit energy communities can minimize network losses through localized energy trading and management.

10. Collaborative Energy Management: Research into community collaboration during high demand periods, including surplus energy sharing by prosumers and adaptive charging of electric vehicles.

11. Incentive Mechanisms: Development of incentive structures to promote cooperation and flexibility within energy communities, encouraging participation in peer-to-peer trading and grid support activities.

12. Decentralized Energy Applications: This thesis also explored the potential of blockchain technology in power systems, particularly in the context of peer-to-peer (P2P) energy trading. This research initiative aims to promote the development of energy-focused smart contract applications and to build a strong community of developers working on decentralized energy solutions. Future work is planned to include a more detailed and granular examination of various aspects of this technology stack. The development of decentralized applications (DApps) based on Blockchain 4.0, with extensive features for P2P energy trading platforms that meet business and industry demands, is a priority in our future research agenda.

Future research directions aim to address current limitations, enhance the efficiency and flexibility of energy trading systems, and promote the development of sustainable, community-oriented energy ecosystems. By pursuing these avenues, we can further advance the field of peer-to-peer energy trading and EV charging coordination, contributing to the ongoing transformation of the energy sector.

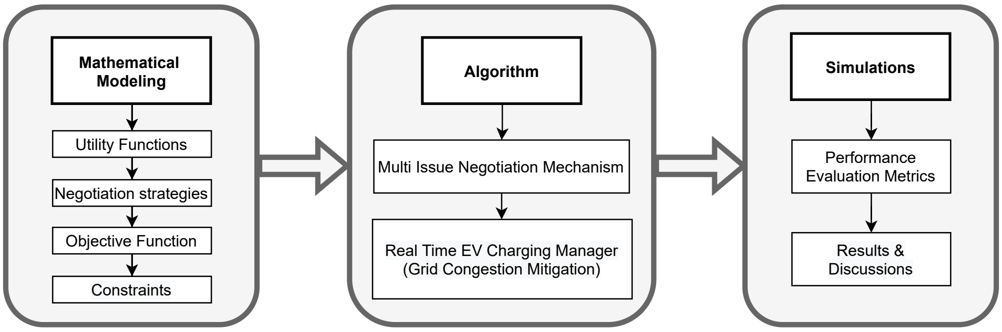

Figure 6.3: Graphical Abstract of Multi-Issue Negotiation EVs Charging Mechanism

6.3 Conclusiones

El sector energético está experimentando una importante transformación, impulsada por la integración de fuentes de energía renovables, la proliferación de vehículos eléctricos (VE) y la evolución de las exigencias de las redes eléctricas modernas. Esta tesis aborda la pregunta de investigación general: '¿Cómo pueden las estructuras de mercado innovadoras y las estrategias de gestión de la carga mitigar los retos que plantea el cambiante panorama energético?'. La tesis se centra en el desarrollo de mecanismos de mercado local de comercio de energía entre pares (P2P) capaces de gestionar eficazmente la generación distribuida y la carga de vehículos eléctricos, al tiempo que permiten a prosumidores y consumidores participar activamente, obtener beneficios económicos y prestar servicios auxiliares a la red.

Esta investigación estudia un marco de comercio de energía P2P que optimiza el bienestar social de los propietarios de vehículos eléctricos a través de un mecanismo de negociación de múltiples temas y la gestión de la carga de vehículos eléctricos en tiempo real, al tiempo que proporciona servicios de red como la mitigación de la congestión a través de la flexibilidad de los vehículos eléctricos. A continuación, la tesis examina un modelo multiagente de tres etapas para el comercio de energía P2P, diseñado estratégicamente para maximizar los beneficios individuales orquestando negociaciones compuestas concurrentes de uno a muchos. Además, la investigación explora en profundidad cómo las tecnologías blockchain y de contratos inteligentes pueden aprovecharse para implementar sistemas automatizados de comercio de energía P2P.

En concreto, estudiamos cómo potenciar el comercio de energía P2P utilizando mecanismos de mercado eficientes desde los dos aspectos siguientes:

6.3.1 Negociación multiproblema para la recarga de vehículos eléctricos en redes congestionadas

Esta investigación aborda el reto de coordinar la carga de vehículos eléctricos (VE) en redes de distribución muy congestionadas. El planteamiento del problema pone de relieve la necesidad de una coordinación eficaz de la carga en redes en las que las cargas de los edificios representan cargas críticas que no pueden desprenderse, y la carga no coordinada de VE podría provocar la congestión y sobrecarga de la red.

Este artículo propone un protocolo de negociación multitemática entre consumidores activos (VE) y una plataforma de gestión. Este protocolo considera simultáneamente tres aspectos clave: el intervalo de consumo, el precio y el tamaño de los paquetes de energía. El planteamiento utiliza clases de MATLAB para emular un sistema multiagente, en el que cada vehículo es un agente que interactúa con la plataforma (otro agente). El algoritmo está diseñado para coordinar la recarga de vehículos eléctricos teniendo en cuenta las restricciones de la red. En la Fig.6.3 se presenta un resumen gráfico de la investigación.

El estudio de caso aplicó el protocolo de negociación multitemática propuesto a una red de distribución formada por 10 cargadores de VE con 100 VE y 7 edificios con 30 hogares. Variando los perfiles de carga de los edificios, el número de puntos de recarga y las preferencias de los VE (energía, precio y tiempo), se examinó la reducción de la sobrecarga de la red en relación con la capacidad total y el éxito general de la tasa de recarga de VE. El modelo demostró una capacidad consistente para mantener los servicios de carga de VE incluso bajo cargas y restricciones variables. Este algoritmo de gestión en tiempo real garantiza que el programa de recarga se adapte y responda a las condiciones en tiempo real, optimizando el uso de los recursos disponibles y manteniendo la estabilidad del sistema. Al ajustarse dinámicamente a las desviaciones y aprovechar la flexibilidad de los VE, el algoritmo equilibra eficazmente las necesidades tanto de los propietarios de VE como de la infraestructura de la red.

Este completo sistema de simulación nos permite probar nuestro protocolo de negociación y algoritmo de gestión en condiciones muy similares a las reales. Mediante de carga auténticos, diversas características de los vehículos eléctricos y tiempos de espera dinámicos, podemos evaluar la eficacia del modelo para gestionar la congestión de la red y coordinar la carga de los vehículos eléctricos de forma práctica y escalable.

La investigación también estudia la aplicabilidad más amplia del algoritmo propuesto. Aunque está diseñado para la coordinación de la recarga de vehículos eléctricos, el documento señala que el algoritmo se presenta de forma genérica y podría aplicarse a otros escenarios que requieran la coordinación de la carga en redes congestionadas.

6.3.2 Marco multiagente de tres etapas para el comercio de energía entre pares

Este estudio subraya la necesidad de un marco eficiente y escalable de comercio de energía entre pares (P2P) que pueda optimizar simultáneamente los beneficios individuales de los agentes del mercado, apoyar el equilibrio de la red y minimizar los retrasos en el proceso de comercio. Las soluciones existentes suelen basarse en cálculos complejos y predicciones precisas, lo que plantea problemas de escalabilidad y dificultades

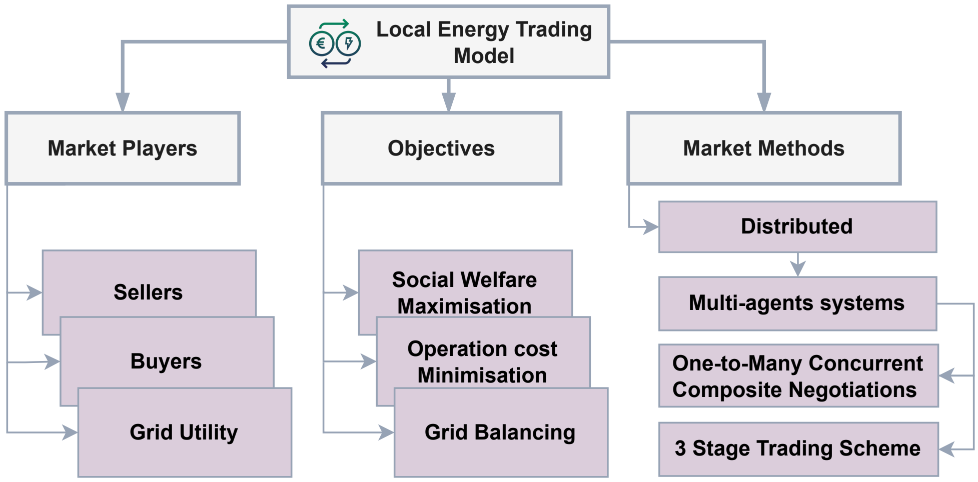

Figure 6.4: Graphical Abstract of Multi-Agent Framework for P2P Energy Trading

de aplicación. La falta de coordinación en el comercio y la gestión de la energía puede provocar inestabilidad en la red, atascos y una asignación ineficiente de los recursos.

Para hacer frente a estos retos, este artículo propone un innovador modelo de comercio de energía P2P postpago basado en un marco de sistemas multiagente. El enfoque persigue tres objetivos clave: maximizar el bienestar social, apoyar el equilibrio de la red y la gestión de la congestión, y minimizar los retrasos en el proceso de negociación. El núcleo de la metodología es la aplicación de una estrategia de negociaciones compuestas concurrentes de uno a muchos dentro de un esquema de tres etapas, con un método de pospago distintivo que garantiza la prestación de servicios y el pago sin fisuras. En la Fig.6.4 se presenta un resumen gráfico de la investigación.

La simplicidad y eficiencia computacional del enfoque propuesto, que no depende de predicciones ultraprecisas, permite un fácil despliegue en plataformas periféricas y facilita la escalabilidad a gran escala. Esto contribuye significativamente a la evolución del comercio de energía P2P, ofreciendo una solución práctica y eficiente a los retos del mercado energético moderno.

La eficacia del marco propuesto se puso a prueba en un escenario realista de mercado energético local, evaluando cómo los agentes interactúan, negocian y comercian con energía dentro de los parámetros definidos. El estudio de casos puso en práctica dos escenarios específicos para evaluar el modelo propuesto de comercio de energía entre pares (P2P). Los estudios de casos demostraron colectivamente la eficiencia del modelo para facilitar el comercio de energía P2P, optimizar la distribución de energía y apoyar una mayor participación entre los agentes del mercado.

La metodología de este trabajo de investigación también incluyó una serie de seis experimentos diseñados para evaluar la escalabilidad y eficacia del modelo de comercio de energía entre iguales propuesto. Estos experimentos aumentaron progresivamente el número de agentes prosumidores y consumidores, con lotes de agentes que oscilaban entre 5 y 50. Se probaron varias combinaciones de parámetros del sistema para evaluar el rendimiento del modelo en distintas condiciones. Se probaron varias combinaciones de parámetros del sistema para evaluar el rendimiento del modelo en diferentes condiciones. Los experimentos se llevaron a cabo con un horizonte temporal coherente en todos los escenarios, lo que permitió realizar comparaciones directas y comprender la escalabilidad del modelo en términos de demandas computacionales y de comunicación.

Este enfoque metodológico proporcionó una base sólida para analizar el rendimiento del modelo, su impacto en los volúmenes locales de comercio de energía, los beneficios globales y la distribución de beneficios entre los distintos tipos de agentes.

Los resultados mostraron que el modelo podía gestionar eficazmente las transacciones energéticas, promover beneficios económicos para los prosumidores al permitirles vender el excedente de energía directamente a los consumidores, y reducir la dependencia de la red, mejorando así la sostenibilidad y eficiencia de los mercados energéticos locales.

6.3.3 Blockchain en el comercio energético P2P

Esta tesis explora además la integración de la tecnología blockchain en los sistemas energéticos inteligentes, centrándose especialmente en su aplicación en el comercio de energía entre pares (P2P). El capítulo ofrece una visión general de cómo blockchain puede mejorar la eficiencia y la transparencia de las transacciones energéticas. Analiza la naturaleza descentralizada de blockchain, que elimina la necesidad de intermediarios, reduciendo así los costes de transacción y mejorando la seguridad y privacidad de los datos. El capítulo destaca el potencial de blockchain para facilitar el comercio directo de energía entre productores y consumidores, aprovechando los contratos inteligentes para automatizar y asegurar las transacciones. Aborda tanto los beneficios como los retos de la implantación de blockchain en los sistemas energéticos.

La tesis también examina el potencial transformador de los contratos inteligentes basados en DLT en los sistemas energéticos, presentando una pila tecnológica ilustrativa como guía para el desarrollo de aplicaciones energéticas. Al proporcionar este marco, la tesis pretende acelerar la innovación en soluciones energéticas descentralizadas, motivar a los expertos en energía a comprometerse con la tecnología de contratos inteligentes y fomentar una comunidad de desarrolladores en este campo. La investigación no sólo destaca las capacidades de los contratos inteligentes para simplificar y descentralizar las operaciones energéticas, sino que también ofrece directrices prácticas para su aplicación. Al tiempo que establece esta base, la tesis anticipa futuras ampliaciones para incluir aspectos más detallados de la pila tecnológica, apoyando aún más el avance de las aplicaciones energéticas descentralizadas.

Además, el estudio explora la aplicación práctica de la tecnología blockchain para facilitar el comercio de energía entre pares (P2P). El estudio se centra en el desarrollo de una plataforma piloto que aprovecha la naturaleza descentralizada y transparente de blockchain para permitir transacciones directas de energía entre productores y consumidores sin necesidad de intermediarios.

Appendix A

Journal Publications

A.1 Multi-Issue Negotiation Protocol for EV Charging

IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, VOL. 71, NO. 6, JUNE 2022 5743

Multi-Issue Negotiation EVs Charging Mechanism in Highly Congested Distribution Networks

Komal Khan, *Student Member, IEEE*, Islam El-Sayed, and Pablo Arboleya, *Senior Member, IEEE*

***Abstract*—The work presented in this paper describes a multi-issue negotiation protocol between active consumers and a management platform in order to establish load coordination in a highly congested network. The multi-issue negotiation protocol considers simultaneously the consumption interval, the price, and the size of the energy packages, which is the main contribution of this work . Regarding the implementation methodology, the proposed algorithms have been implemented using MATLAB classes that allow emulating the behaviour of a multi-agent system in which each vehicle is an agent that interacts with the platform, which is another agent. In the present work, and without loss of generality, the algorithm is applied to coordinate the charging of electric vehicles (EVs) in a distribution network in which building loads represent critical loads. The algorithm is tested in a realistic environment, and its stability and performance are evaluated. Furthermore, the description of the algorithm is provided in a generic form, and it could be applied to any other scenario.**

***Index Terms*—Congestion management, coordinated charge, distribution systems, electric vehicles, flexibility, market mechanism, multi-issue negotiation.**

Nomenclature

Pr	price.
T	time.
E	energy.
Pr_I	initial price.
Pr_R	reserved price.
T_I	initial charging time duration.
T_R	reserved charging time duration.
E_I	most preferred number of energy packets.
E_R	least preferred number of energy packets.
$u_{Pr_{min}}$	minimum required price utility.
$u_{T_{min}}$	minimum required time utility.
$u_{E_{min}}$	minimum required energy utility.
$U_{Pr}(Pr)$	price utility.
$U_T(T)$	time utility.
$U_E(E)$	energy utility.
$U_{total}(Pr,T,E)$	total utility.
n_{CP}	number of charging points.
P_{EV}	available power or energy packets for the EV charging.
P_{tf}^{max}	maximum transformer capacity.
P_b	forecast of buildings power consumption.
r	negotiation rounds.
τ	maximal number of negotiation rounds.
U_{exp}^r	expected utility at r.
λ	negotiation strategy.
w_{Pr}	weight of price utility.
w_T	weight of time utility.
w_E	weight of energy utility.
SoC_{init}	initial state of charge of EV.
CP	available charging points.
P_{RT}	feeder power capacity in real-time.
P_F	feeder power capacity forecasted.
ΔP_{total}	deviation of P_{RT} from P_F
n_{EV}^{dis}	number of EVs disconnected electrically from chargers.
n_{EV}^F	number of EVs forecasted.
n_{EV}^{RT}	number of EVs in real-time.
$EV_{plugged}^{sort}$	sorted list of electrically connected EVs to chargers.
$EV_{plugged}^{dis}$	disconnected EVs from chargers.
E_{neg}	negotiated energy.
T_{neg}	negotiated time.

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I. Introduction

A. Background and Research Motivation

ELECTRIFICATION is an unstoppable trend nowadays since it has become an extremely useful tool for achieving decarbonisation targets defined by most countries. Transportation will be one of the sectors where electrification will have the greatest impact. Electric vehicles are one of the key players in the paradigm change that the transportation sector will undergo [1]. By 2030, a huge rise in EV circulation worldwide is projected by the International Energy Agency from being 5 million in 2018 to around 230 million, largely due to falling battery costs with the expansion of battery manufacturing capacity and increasing fuel density [2].

Despite the benefits offered, the fast-growing EVs development may introduce a profound influence on the existing power grid. It must be considered, for instance, that nowadays, electricity demand from EVs accounts for only about 1% of current electricity total final consumption worldwide. According to [2], by 2030, in the Stated Policies Scenario and Sustainable Development Scenario, electricity demand for EVs will account for at least 2% of global electricity total final consumption. Even when that amount of energy does not represent a major impact on the total energy delivered by the distribution network, the uncoordinated charging of electric vehicles would create peak power that at best requires large infrastructure investments, generating large increases in the electricity tariff for end users. To reduce the aforementioned investments and avoid problems in the distribution grid such as grid congestion, voltage violations, transformer overloading, and impact on power quality, it is necessary to implement load management strategies [3]. With the correct strategies, the flexibility of the EVs could be used to mitigate their impact in the transmission or distribution system [4].

B. Related Works

For the reasons stated above, researchers are devoting an enormous amount of effort to research on mechanisms for regulating vehicle charging at different levels. Recently, coordination for vehicle-to-grid (V2G) applications was considered [5]. Recent studies [2] demonstrated that one third of the demand at peak hours could be covered by 2030 using V2G applications. The ways of coordinating vehicles are based on three criteria: 1) how charging control is performed (centralized or distributed); 2) the methodology used to obtain the signals with which they coordinate the electric vehicles; and 3) the business model of the aggregators and what they use the flexibility of the EVs for. Regarding how the charging control is executed, it can be distinguished between; a) Techniques based on implicit demand response, in which case the load of the vehicles is normally controlled in a distributed way, generally based on price [6], [7]. With respect to the methodology employed by the aggregator, it can be distinguished basically between signals [8], since there is no central agent that explicitly connects or disconnects the vehicles. Different EVs respond in different ways to the price signals, and thus a certain degree of coordination can be executed [9]. b) Techniques based on explicit demand response in which a central manager, usually an aggregator, controls the load of the vehicles in a centralized way according to different criteria [10]. In this case, there are two groups of techniques, those that use optimization algorithms [11]–[15] or those that use transactive energy mechanisms. In this last group, a wide variety of approaches can be found, such as multi-agent systems [16], game theory approaches [17], [18], market based mechanisms [19], [20], among others. Regardless of whether the coordination of vehicles is done explicitly or implicitly, and the methodology employed for obtaining the control signals, the aggregator is somehow able to perform this management and use the flexibility for different purposes depending on its business model. The models in which an aggregator can participate vary and can range from optimizing the cost of energy for vehicle owners [21] or providing some service to the energy community [22], participating in operating markets such as the day-ahead market [23], [24], or participating in operating markets such as frequency regulation [25] or balancing markets [26] or other ancillary services markets [27] or the use of flexibility to reduce congestion problems in the distribution network [28]. Aggregator-based EV charging control in a decentralized, user-oriented fashion is also one of the most important applications [29].

In the case presented in this paper, the vehicles negotiate with an aggregation platform both the charging interval and the charged energy packages, as well as their price. The aggregation platform exercises centralized control over the vehicles, and in the case study, the target of the aggregation platform is to avoid overloading at a given transformer station, considering the load of the buildings as a critical load that cannot be shed.

C. Key Contribution

The main contribution of the article is the negotiation protocol that simultaneously considers the charging interval, price, and energy. None of the works presented to date consider all three aspects simultaneously in the negotiation protocol. For instance, [30] aims to maximize the utilities of EVs and charging stations by proposing a negotiation scheme based on two aspects, that is, time and energy. The algorithm does not leverage the EVs to make negotiation with stations over the prices. There is more flexibility provided to charging stations for constraining EVs. However, [22] proposes an iterative auction framework to compute optimal charging schedules that maximize the social welfare of all users given their time preferences and the state of charge, but it does not consider the impact of charging schedules on grid stability. Most of the papers, in the context of negotiation mechanisms, differ in the way they model the negotiation elements and flexibility for EVs and the grid, so an explicit comparison between metrics could not be justified. This paper captures the social welfare of EV owners with a multi-issue negotiation mechanism and real time EV charging management along with the grid service support, i.e., congestion removal by EV flexibility. The concept of multiple negotiation has been successfully used in systems in the field of cloud services (see, for instance, the work presented in [31]), where different users automatically negotiate according to their tariff to obtain computational intervals and computational power. The algorithm presented in this paper is an extension of the one presented in [32]. In this work, the main core of the algorithm was presented, but the negotiation did not include the energy packets, and only independent negotiation rounds were tested. The present work has the next contributions:

- It presents a multi-issue negotiation algorithm in which the EVs can negotiate simultaneously the charging interval, the price and the amount of energy charged.
- The negotiation parameters can be varied to emulate different tariffs or user preferences.
- The system uses forecast consumption of critical loads during the negotiation process but it is able to adapt the charging patterns in real time when deviations from predicted critical loads occur.

It should be noted that what is presented as a contribution in this article is the multiple negotiation methodology. In this case, the methodology has been applied to a case study whose purpose

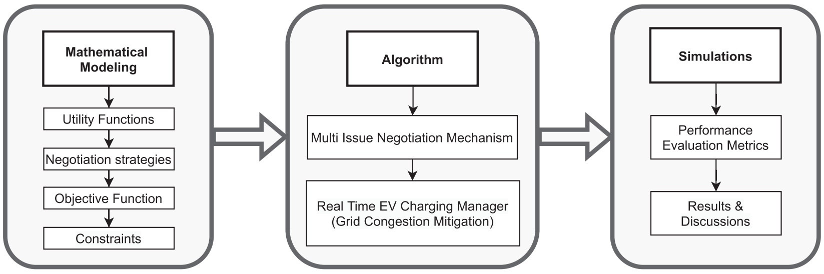

Fig. 1. Schematic overview of paper.

is to solve a congestion management problem in the distribution network. However, the negotiation algorithm is general, and it can be applied in other scenarios in which the aggregator pursues a different target.

D. Organization

The remainder of this paper is organized as follows: Section 2 entails the description of the problem being taken into consideration for the application of the proposed negotiation protocol. Section 3 covers the detailed systematic description of the proposed multi-issue negotiation mechanism. Section 4 includes the case study and simulation results to prove the effectiveness of the proposition. Section 5 concludes the research work presented in this paper. The schematic overview of the proposed work is presented in Fig. 1.

II. Problem Statement

A typical European urban distribution network, the same as considered in [32], is selected to test the extended model and a single line diagram of which has been represented in Fig. 2. It is a part of a real network in Spain that is operated by Energias de Portugal (EDP) and is composed of 30 power transformer stations supplying energy to 8,500 consumers. Fig. 2 represents one of these power transformer stations along with its elements. All of the power transformers are in a delta-wye (grounded) configuration. There are 4-wire 3 phase feeders (F.1, F.2,..) which connect the power transformer secondary with the circuit breaker (BR1), and are protected by a set of fuses (F_{F1}, F_{F2},...). Each feeder can be monitored by means of an advanced supervisor monitoring equipment (labeled in Fig. 2 as M_{F1}, M_{F2},...). There are around 7 buildings per power station distributed in around 4 feeders, where the average distance is less than 300 meters from the power transformer to the connection points. Mostly, buildings have 3 phase connections while the end-users inside buildings (L_1,...,L_6) are single phase, constituting an unbalanced total load. Generally, there is a set of 3 phase fuses (for instance F_{L4}) installed for the protection of each building.

Moreover, each end-user is also protected by it own fuse (such as F_{B1}) and supported with advance metering infrastructure (for instance M_1). During the peak hours of the day, the feeders are highly congested, which makes it impossible to add more loads, such as installing EV chargers, without making huge investments in network extensions or deploying new infrastructure. This scenario restricts distribution system operators (DSOs) from introducing EV chargers into the network on a large scale. However, the statistics reveal that the average load of different feeders during a complete day is less than just 10%. This fact opens the possibility of utilising flexible loads to reduce congestion problems and increase the system's capability to adopt new loads. Under our specific case study, buildings in Fig. 2 (labeled in red) present critical loads that need to be fed under all circumstances. On the other hand, electric

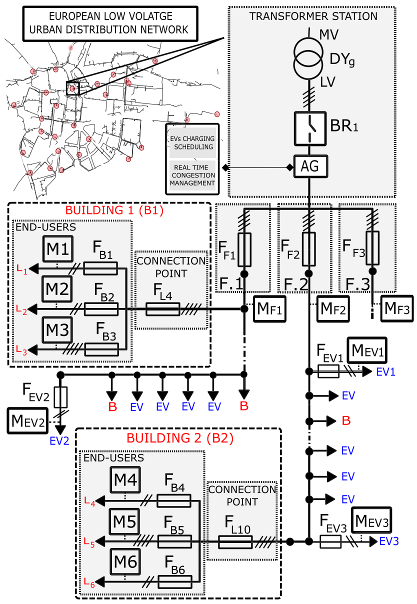

Fig. 2. European low voltage urban distribution network representing the case defined in the problem statement.

vehicles (labeled in blue) will take part as flexible loads and will negotiate price, charging duration, and energy packets required for charging with the aggregation platform (represented as AG). The role of the aggregator will be to manage the non-supplied energy while respecting all physical constraints defined by the DSO. For this purpose, the aggregator will use the price signals, demand forecast, and proposed multi-issue negotiation model (the main contribution of this paper), to coordinate the charging activity with each EV connected to the system. Furthermore, the proposed real time congestion management algorithm will be implemented to balance out any deviation with respect to predicted demand. The ultimate goal of the aggregator is to accomplish a trade-off between EV charging demand satisfaction and congestion reduction in the network without critical load shedding and violating any physical constraint imposed by DSO. Moreover, only low latency measurements at the secondary of the power transformer are considered to demonstrate the capacity of the negotiation protocol for dealing with congestion, and a simple but realistic model is used to avoid overloads in the transformer. In future work, more detailed models of the grid that keep under consideration possible voltage drops in order to update the hosting capacity of the specific nodes will be developed.

III. Methodology

A. Multi-Issue Negotiation Protocol

Electric vehicles in the network will represent flexible loads, and to initiate a charging activity, an EV charger will identify the EV owner and will negotiate with the aggregator the price, time duration, and energy required for charging using the negotiation parameters defined in the EV owner tariff. Even when the aggregator increases its utility function (later defined) with higher prices, its final target will be to minimise the non-supplied energy by coordinating with EV owners while meeting all the physical constraints imposed by the DSO. In this pursuit, the aggregator uses a multi-issue negotiation protocol to negotiate with EVs and obtain a mutually beneficial EV charging schedule without exerting congestion on the system. Furthermore, considering the two important aspects of this specific case of study, i.e., 1). the limited number of EVs that can be connected to a feeder 2). the high speed of the negotiation algorithm (explained later), FIFO (first in first out) strategy is acquired by the aggregator to negotiate with the incoming EVs owners for charging. Aggregator will negotiate with the EV owner which connects first to the charging station, and then to the others in sequence. This will not reduce the generality of the methodology that could be adapted under other premises, for instance, parallel negotiations.

The proposed multi-issue negotiation mechanism (price/time-slot/energy package) is inspired by the Rubinstein Alternating Offer Protocol, which is basically a bargaining model that provides a perfect equilibrium solution to a bargaining problem among the transacting agents. The model basically finds an agreement upon which the payoff of each agent is not lower than the minimum acceptable payoff. This protocol is well known and has been extensively applied to automated negotiations in different fields [20], [31], but this is the first time that it has been adapted to be used in peer-to-platform energy trading applications. Price Pr, Time T and Energy E are the three crucial elements involved in the whole negotiation process, therefore making it a novel 3D protocol. In other words, agents (EV owners and aggregators) will negotiate on the price per unit energy Pr, time slots and duration required for charging activity T and E energy packets required to achieve a certain state of charge (SoC) level. To start a negotiation, both agents i.e aggregator and EV owner will specify their preferences of (Pr, T, E), other negotiation parameters (negotiation rounds, deadline..) and strategies (time dependent concessions..). For the sake of simplicity, it is assumed that when an EV is connected to the charging station, the advanced metering infrastructure provides information to the aggregator about the current SoC of the EV. Hence, based on the actual SoC level and the forecast of the building's power consumption, the aggregator decides Pr, T, E and adapts its negotiation strategies. Forecasting techniques are beyond the scope of this research work since the prediction methodology is completely decoupled from the trading methodology. Therefore, the proposed methodology is formulated independently from the prediction methodology. It is assumed that the aggregator may use the aggregated building consumption forecast. Deviations between real consumption and forecasted deeply affect the network capacity to allocate EVs and are considered in this paper. Based on the agent's preferential settings, the negotiation algorithm determines corresponding benefits or the level of satisfaction of the agents for a deal, which is quantified as a number between 0 and 1, and termed "utility." During a negotiation process, each element of the negotiation is evaluated for its utility for the agent, which is achieved using a utility function.

1) Utility Functions Description: Utility functions are defined for each negotiation element to calculate its corresponding utility under the lens of prescribed preferences by the agent. The proposed negotiation algorithm is based on four main utility functions: price, time, energy, and total utility functions, which are used to calculate the respective utilities of the EV and aggregator to implement the bilateral negotiation strategies acquired in this paper. This section will provide details about the above-referred functions.

a) Price Utility Function: Both agents set a price window (bargain margin of price) for price negotiation, bounded by most preferred price (initial price Pr_I) and least preferred price (reserved price Pr_R), which are decided accordingly to target individual economic benefits. Aggregator controls its price window based on the price signals, the details of which are not the aim of this research. Therefore, in the peak hours of the day, the aggregator's price window setting is to discourage EV charging, and in the case of surplus power available, the target of the price window setting will be to accommodate more EVs for efficient utilisation of the resources. Moreover, both agents will set their threshold or minimum required price utility ($u_{Pr_{min}}$) below which the offer will not be accepted. In the successive negotiation rounds the agents will make counter offers keeping its price utility not less than $u_{Pr_{min}}$, and the same criteria is followed for the other negotiation elements. Based on these settings, price utility functions, as defined below in (1) for EV owners and (2) for aggregators, calculate utility for them against the price under negotiation. Superscripts EV and AG are used to correspond to the EV owner and aggregator, respectively.

$$U_{Pr}^{EV}(Pr) = \begin{cases} u_{Pr_{min}}^{EV} + \left(1 - u_{Pr_{min}}^{EV}\right) \left| \frac{Pr_R^{EV} - Pr}{Pr_R^{EV} - Pr_I^{EV}} \right|, \\ Pr_I^{EV} \leq Pr \leq Pr_R^{EV} \\ 0, \text{otherwise} \end{cases} \tag{1}$$

$$U_{Pr}^{AG}(Pr) = \begin{cases} u_{Pr_{min}}^{AG} + \left(1 - u_{Pr_{min}}^{AG}\right) \left| \frac{Pr_R^{AG} - Pr}{Pr_I^{AG} - Pr_R^{AG}} \right|, \\ Pr_R^{AG} \leq Pr \leq Pr_I^{AG} \\ 0, \text{otherwise} \end{cases} \tag{2}$$

Both functions are similar, however, as it can be observed that EV owner's utility($U_{Pr}^{EV}(Pr)$) is high at low prices while aggregator utility function provides low utility at high prices.Pr, Pr_I and Pr_R are defined as the cost per energy packet (energy packets ep are discussed later). The prices drastically determine the negotiation strategy. However, the definition of complex strategies by both the utility and the vehicles, which will be associated with different types of flexible tariffs, is beyond the scope of this paper and is being studied for proposal in future work.

b) Time Utility Function: EVs are treated as flexible loads to cope with the net load constraint according to the transformer capacity restrictions. EVs are facilitated with a discontinuous charging process because of the fact that critical loads (buildings in this case) are required to be fed primarily. Hence, additional time may be required to meet an EV charging demand, and for this reason, some time flexibility is expected from EV owners for charging activities. To negotiate the time slot and duration T required for a charging activity, both agents define their margin of bargaining, confined by initial (most preferred) and reserved (least preferred) time duration $[T_I, T_R]$ based on their flexibility. The time utility function for EV owners in (3) and for an aggregator in (4), is used to calculate their utility against the given time slot and duration. This time utility is significant for both agents to offer or assess the time element under the negotiation, keeping in view their respective T_I and T_R.

$$U_T^{EV}(T) = \begin{cases} u_{T_{min}}^{EV} + \left(1 - u_{T_{min}}^{EV}\right) \left| \frac{T_R^{EV} - T}{T_R^{EV} - T_I^{EV}} \right|, \\ T_I^{EV} \leq T \leq T_R^{EV} \\ 0, \text{otherwise} \end{cases} \tag{3}$$

$$U_T^{AG}(T) = \begin{cases} u_{T_{min}}^{AG} + \left(1 - u_{T_{min}}^{AG}\right) \left| \frac{T_R^{AG} - T}{T_R^{AG} - T_I^{AG}} \right|, \\ T_R^{AG} \leq T \leq T_I^{AG} \\ 0, \text{otherwise} \end{cases} \tag{4}$$

It can be seen that EV owner prefers to finish charging activity early therefore defining a small time duration as T_I^{EV} to recieve maximum utility whereas aggregator prefers to keep T_I^{AG} large so that it may use this flexibility to coordinate with the schedule in case of a sudden demand from critical loads.

c) Energy Utility Function: Based on the aggregated demand forecast of critical loads (buildings in this case without lost of generality), aggregator quantifies each time-slot of available power as number of EVs that can be accommodated in that time, considering in this case that all chargers provide the same maximum power for the sake of simplicity. Therefore, depending upon the capacity available in each time-slot, charging facilities can be provided to EVs. For this reason, the aggregator requires some flexibility in terms of charging demand from EV owners to facilitate the charging while meeting all the operational constraints (discussed later). Energy is discretised into energy packets of length Δt and amplitude of charger power capacity, which makes it convenient for agents to deal in terms of energy packets. Both agents define their margin/window for negotiating energy packets with each other within these respective windows and agree on the number of energy packets which may facilitate EV charging while meeting all constraints. Both agents specifies their bounds of energy window i.e most and least preferred number of energy packets $[E_I, E_R]$, as per their preferences. Similar to the other elements, energy utility is calculated against the number of energy packets based on the window prescribed by the agent. Energy utility functions in (5) for EVs and in (6) for aggregator are defined to calculate energy utilities respectively.

$$U_E^{EV}(E) = \begin{cases} u_{E_{min}}^{EV} + \left(1 - u_{E_{min}}^{EV}\right) \left| \frac{E_R^{EV} - E}{E_R^{EV} - E_I^{EV}} \right|, \\ E_R^{EV} \leq E \leq E_I^{EV} \\ 0, \text{otherwise} \end{cases} \tag{5}$$

$$U_E^{AG}(E) = \begin{cases} u_{E_{min}}^{AG} + \left(1 - u_{E_{min}}^{AG}\right) \left| \frac{E_R^{AG} - E}{E_R^{AG} - E_I^{AG}} \right|, \\ E_R^{AG} \leq E \leq E_I^{AG} \\ 0, \text{otherwise} \end{cases} \tag{6}$$

d) Total Utility Function: All three utilities, i.e., U_{Pr}, U_T, U_E are adjusted and aggregated to receive the total utility of an agent. The total utility is evaluated to take decisions like accepting or rejecting an offer or making a counter offer during a negotiation process. w_{Pr}, w_T and w_E are the weights set by the negotiating agents to adjust their respective preferences for price, time and energy utilities, such that $w_{Pr} + w_T + w_E = 1$. Using these weights, agents make trade-offs in the offers or counteroffers to show flexibility, e.g., reducing the weight of the price because the agent is in a rush to receive the service, which will reduce the portion of the price in total utility and keeping the other factors the same. Hence, this offer is more likely to be accepted. In general, the total utility $U_{total}(Pr, T, E)$ for a specific agent (EV owner or aggregator) can be stated as (7):

$$U_{total}(Pr, T, E) = \begin{cases} 0, \text{ if any of } U_{Pr}, U_T, U_E = 0 \\ w_{Pr} \cdot U_{Pr} + w_T \cdot U_T + w_E \cdot U_E, \\ \text{otherwise} \end{cases} \tag{7}$$

2) Negotiation Process and Strategies: Agents adopt different negotiation strategies to accelerate the negotiation process, which makes the protocol more efficient. The following are

5748 IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, VOL. 71, NO. 6, JUNE 2022

the detailed descriptions of the applied negotiation process and strategies:

a) Burst Offer Mode: Agents adopt different negotiation strategies to accelerate the negotiation process, which makes the protocol more efficient. The following are the detailed descriptions of the applied negotiation process and strategies:

During the negotiation process, it is devised that each agent can make multiple concurrent proposals, i.e. different combinations of price, time, and energy elements, which yield the same total utility, satisfying the preferences (utility) of the agent. Burst offer mode is useful for speeding up the negotiation process where opponents can provide multiple choices to each other, making it more likely to get one of the offers accepted. A burst proposal from agent $A1$ to agent $A2$ at negotiation round r can be expressed as (8).

$$BP_r^{A1\rightarrow A2} = [(Pr_1, T_1, E_1), (Pr_2, T_2, E_2), \ldots (Pr_n, T_n, E_n)]_r \tag{8}$$

b) Time Dependent Concession: The second adopted strategy to fasten the process of negotiations is to make time dependent concessions. In simple words, the expected utility (U_{exp}) of each agent will be reduced by the amount of concession with each passing round that will encourage the agents to get to the agreement without losing utility w.r.t time. This degradation, or concession in utility, is dependent on the negotiation round r, the maximal number of negotiation rounds τ, and the negotiation strategy λ, and is calculated using the following expression:

$$U_{exp}^{r+1} = U_{exp}^{r} - U_{exp}^{r} \cdot \left(\frac{r}{\tau}\right)^{\lambda} \tag{9}$$

Depending on the value of λ the negotiation strategy can be classified as 1) linear: $\lambda = 1$, 2) conciliatory: $0 < \lambda < 1$, and 3) aggressive: $\lambda > 1$. In our specific case, agents have acquired the linear strategy to make concessions.

3) Objective Function: Both agents will engage in alternating offers while establishing a trade-off in the price, time, and energy elements to maximize their total utility. The operation of the proposed automated negotiation algorithm is centered on the main objective, which is to maximise the total utility of each agent, expressed as an objective function in (10):

$$maximize(U_{total}(Pr, T, E)) \tag{10}$$

The objective of the negotiation mechanism is subjected to following constraints:

$$P_{EV} < P_{tf}^{max} - P_b \tag{11}$$

Aggregator will decide the available power or energy packets for the EV charging (P_{EV}) based on forecast of buildings power consumption(P_b) and maximum transformer capacity(P_{tf}^{max}). The constraint in (11) ensures EV charging load must not cause congestion in the system because critical loads, i.e., buildings in the community, must be fed at all times. EVs will behave like flexible loads.

$$n_{EV}^{inst} <= n_{CP} \tag{12}$$

The second constraint in (12) specifies that at any instant, the number of vehicles that charge simultaneously (n_{EV}^{inst}) must not exceed the total number of charging points (n_{CP}).

$$(U_{total}, U_{Pr}, U_T, U_E) \geq u_{min} \tag{13}$$

Finally, (13) ensures that all the negotiation elements (Pr, T, E) must remain above the minimum specified utilities.

Algorithm 1: Multi-Issue Negotiation Mechanism.

Input: $(P_I, P_R, T_I, T_R, E_I, E_R, u_{min}, \lambda, \tau)$ for EV owner and AG.
Output: (Pr, T, E) final price, time and energy.
1: AG prepares burst offer based on SoC_{init} of EV.
2: $r \Leftarrow 0$ Set $A1 = EV owner$ & $A2 = AG$.
3: $(Pr, T, E) := f_{A2}^{init}(SoC_{init})$ $A2$ burst offer preparation.
4: **if** $(Pr, T, E)_{A2}$ is empty **then**
5: Process terminated, **no agreement**.
6: **else**
7: $r \Leftarrow r + 1$ Update negotiation round.
8: Execute (9) for both agents.
9: Update $Agent1$ utility $U_{exp,r}^{A1}$
10: $(Pr, T, E) := f_{A1}^{-1}(U_{exp,r}^{A1})$ $A1$ burst offer generation.
11: $U_{x,r}^{A2} := f_{A2}(Pr, T, E)$ $A2$ burst offer evaluation.
12: **if** $(r = \tau$ & $U_{x,r}^{A2} < U_{min}^{A2})$ **then**
13: Process terminated, **no agreement**.
14: **else if** $(r = \tau$ & $U_{x,r}^{A2} \geq U_{min}^{A2}) \mid U_{x,r}^{A2} \geq U_{exp,r+1}^{A2}$ **then**
15: Process terminated, **agreement reached**.
16: **else**
17: Switch EV onwer and Aggregator in $A1$ and $A2$ roles.
18: Goto line 7 to create **counter-offer**.
19: **end if**
20: **end if**

4) Multi-Issue Pr-T-E Negotiation Algorithm: The main features and steps of the proposed multi-issue negotiation mechanism are summarised in Algorithm 1. At first, EV and aggregator declare their initial preferences which are mainly consist of price window (Pr_I, Pr_R), time duration window (T_I, T_R) and energy packets window (E_I, E_R). Apart from them, there are other parameters which include the agent's minimum utility, negotiation strategy, and maximal number of negotiation rounds (u_{min}, λ, τ). u_{min} is minimum utility received by the agent for reaching an agreement at its least preferred price or time duration or energy. Initially $A1$ is set to be an EV owner and $A2$ to be an aggregator (AG) which are later switched in the successive rounds. The initial strategy of the aggregator, which is acquired in this protocol, is that the aggregator prepares beforehand the burst offer using function $(Pr, T, E) := f(SoC_{init})$ based on SoC_{init} that is measured when the EV is connected to the charger. This burst offer consists of packages ranging from 10 to 100 percent SoC level with corresponding price and time. This strategy speeds up the negotiation process. At first round $(r = 1)$ of the negotiation, EV owner initiates a request to aggregator which consist of a set of its most preferred (Pr, T, E), keeping his utility $U_{exp,r}^{A1}$ to the maximum. The expected utility in the first round is always kept at the maximum. However, based on the concession strategy, the agents diminish this utility through the successive negotiation rounds. The aggregator evaluates this request by first calculating (U) utility obtained from the requested (Pr, T, E) by means of its utility function $U := f(Pr, T, E)$. This proposal should maximise aggregator utility i.e. equal or greater than its expected utility (U_{exp}) which is the maximum '1' in the first round. If the utility obtained from the requested proposal doesn't meet the expected utility criteria, then AG makes a counter offer with its earlier created multiple concurrent proposals, so called a burst offer. An agent creates the burst offer using the inverse functions $(Pr, T, E) := f^{-1}(U)$. It must be noted here that there are no analytical expressions for these inverse functions. On many occasions, the calculations involve complex optimization methods that return approximated results. In short, it can be stated that f^{-1} functions are used for creating offers while f functions are used of evaluate offers. EV receives a burst counter offer from the aggregator, evaluates the proposals and selects the set of (Pr, T, E) that maximises its utility, referred to as (U_x). The evaluation includes the first check that the negotiation deadline has not been violated; if yes, the offer is rejected and the negotiation process is automatically terminated. There is another factor that causes the automatic rejection, i.e., the utility obtained from the offer is lower than the minimum utility accepted by the agent. In the last round of negotiation $(r = \tau)$, agent evaluates the utility obtained from the proposed offer by comparing it with its minimum acceptable utility, i.e., if it is equal or greater, the offer is accepted, otherwise rejected. In other rounds, this utility is compared with the agent's expected utility for the next round $(U_{x,r} \geq U_{exp,r+1})$. This means the agent is expecting a utility that should be higher than the utility that it can achieve by making a counter offer in the next round. In this manner, the negotiation protocol is followed until an offer meets the criteria of both agents.

B. Real Time EV Charging Management

In real time, load deviations at feeder are anticipated, which may possibly cause a direct impact on the negotiated schedule. It must be considered that the trade depends on the forecasted energy of the buildings, so there must be a mechanism to deal with the deviations in the forecast with respect to the real consumption. Therefore, a real time management algorithm is designed to handle these differences by taking advantage of the flexibility provided by EV owners in the negotiations. The main functionalities of the proposition are summarised in Algorithm 2. For each time instant t, Algorithm 2 checks if there is an arrival of EV at any of the available charging points CP, then for each vehicle i arriving at time t_i^a, it asks the EV_i owner to specify its initial parameters settings which are recorded in a set (labeled as d_i). d_i is then passed to Algorithm 1 to start negotiation process. After a successful negotiation process, $EV_{plugged}$ which is the list of plugged-in EVs is updated with the output of Algorithm 1 i.e. negotiated parameters (Pr, T, E) of i^{th} EV. As it will be observed, on some occasions, the real time management requires making deviations with respect to closed negotiations.

Algorithm 2: Real Time EV Charging Manager.

Input: $d \rightarrow \{ P_I, P_R, T_I, T_R, E_I, E_R, u_{min}, \lambda, \tau\}$
Output: Real Time EV Charging Management.
1: **for** $\forall t \in T$ **do**
2: **if** $t = t_i^a$ & $CP\ available$ **then**
3: $\{ EV_i$ owner assigned to set $d_i\}$;
4: Send d_i as an input to Algorithm 1 to negotiate
5: **if** Negotiation is successful **then**
6: $EV_{plugged} = EV_{plugged} + output(Algorithm 1)$;
7: **else**
8: continue;
9: **end if**
10: **end if**
11: **if** $P_{RT} < P_F$ **then**
12: execute (15),(16) & (17);
13: Disconnect $EV^{dis}_{plugged}(t+1)$ & Update Schedule;
14: **else if** $P_{RT} > P_F$ **then**
15: execute (15);
16: Charge more connected EVs than planned;
17: Update Schedule;
18: **else if** $P_{RT} == P_F$ **then**
19: continue;
20: **end if**
21: Evaluate $EV_{plugged}$;
22: **if** $E_i == E_{neg}$ & $T_i == T_{neg}$ **then**
23: $EV_{charged} = EV_{charged} + EV_i$;
24: $t_i^d = t$ & Update Schedule;
25: **end if**
26: **if** $E_i == E_{neg}$ & $T_i < T_{neg}$ **then**
27: Disconnect electrically;
28: **end if**
29: **if** $E_i < E_{neg}$ & $T_i == T_{neg}$ **then**
30: Penalise Aggregator & repeat lines 24,27;
31: **end if**
32: $t = t + 1$;
33: **end for**

The next step, which is the main objective of Algorithm 2, is to minimise the $\Delta P_{total}(t)$ as stated in (14), which is the value of deviation of P_{RT} from the reference P_F at time t. Where P_{RT} is the real time power capacity of the feeder available to accomodate EVs and P_F is the forecast power capacity of the feeder to facilitate EVs charging based on which negotiations are carried out. These deviations are caused by the unexpected changes in critical loads (buildings) that are compensated for in real time by the flexible loads (EVs), which is the aim of Algorithm 2. As will be seen below, real-time management in some cases involves making changes to the negotiated terms.

1) Objective Function:

$$minimize(\Delta P_{total}(t)) \tag{14}$$

2) Control Equations:

$$n^{dis}_{EV}(t) = n^F_{EV}(t) - n^{RT}_{EV}(t) \tag{15}$$

5750 IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, VOL. 71, NO. 6, JUNE 2022

$$EV^{sort}_{plugged}(t) = sort(E_{i(left)}/T_{i(left)}) \quad (16)$$

$$EV^{dis}_{plugged}(t+1) = EV^{sort}_{plugged}(t)[1 : n^{dis}_{EV}(t)] \quad (17)$$

If there is any negative deviation observed, using (15), the number of EVs $n^{dis}_{EV}(t)$ that need to be disconnected electrically to keep the total load of the community less than the maximum capacity of the transformer can be calculated. In (15), $n^{F}_{EV}(t)$ represents the number of EVs forcasted and $n^{RT}_{EV}(t)$ stands for the number of total EVs that can only be accommodated in the real time. In order to choose among the electrically connected EVs, which ones need to be disconnected, the strategy is acquired that is to sort them all based on their remaining time $T_{i(left)}$ and energy $E_{i(left)}$ required for charging. Equation (16) is used to create a sorted list of EVs $EV^{sort}_{plugged}(t)$ that are electrically connected to the chargers, so that the EVs that have the most remaining time relative to the remaining energy to complete their charging are placed first in the list. This disconnection strategy has been chosen, but any other strategy could be implemented with no loss of generality. Depending on this sorted list, EVs on the top are disconnected electrically $EV^{sort}_{plugged}(t)[1 : n^{dis}_{EV}(t)]$. It must be remarked that the meter readings are not of the current instant but of the past one, so the control action is actually taking place in $(t+1)$ after the deviation is observed. Equation (17) represents the disconnected EVs $EV^{dis}_{plugged}(t+1)$.

In the case of positive deviation observed in (14), more EVs are entertained acquiring the same strategy. The only difference is that instead of disconnecting, more EVs are connected electrically if there are any, in the reverse order of sorted list $EV^{sort}_{plugged}(t)$ so that the EVs which have less remaining time relative to remaining energy are connected first. The other part of the algorithm 2 is based on the evaluation of the currently charging EVs that keeps a check on their charging process and keeps the schedule updated. Three cases were undertaken in this evaluation, and their respective actions are scripted below:

1) The EV completes its charging within the negotiated time and leaves. The departure time of the EV t^d_i is recorded. The list of $EV_{charged}$ has been updated. The schedule has been updated for the incoming EVs.
2) The EV completes charging earlier than the time negotiated. It is electrically disconnected and charges a penalty if the EV stays beyond the negotiated time. The schedule is updated accordingly.
3) The EV is not charged up to E_{neg} however, negotiated time has passed. The EV is electrically disconnected. In that case, the aggregator is penalized for the unattended charge.

IV. Simulation Results Analysis

A. Simulation Set-Up

A simple case study has been carried out in order to test the performance of the presented model. Considering the network, the details of which are explained in Section 2, The performance of the proposed algorithm is evaluated using real-world datasets. The load curve of consumers of 7 buildings with 30 households per building is generated based on the real dataset provided by ADRES-CONCEPT [33] that provide secondly sampled load profiles. The load of EV chargers is introduced into the network to observe the congestion caused by uncoordinated EV charging in the system. Later, our proposed multi issue negotiation protocol is applied to coordinate EV charging in the network with the real time management algorithm to handle any deviations in the predicted load. Simulation results are presented to show the effectiveness and validity of the proposed model in solving the congestion management problem in the network. The algorithm was designed and implemented in MATLAB R2019b using the script language. The participation and co-ordination of EVs and aggregator are emulated and implemented using MATLAB Classes.

A load profile of EVs at public EV chargers in the network, is generated using the EV load simulation model presented in [34]. Some parameters are discussed next, which were considered for generating these load profiles in this case study. The battery capacity of an EV is randomly generated within the range defined as $[22, 32, 40, 60]kWh$. For the sake of simplification, a constant/fixed charging power level of 7 kW is assumed at all 10 public charging points (CP) in the studied network. It is assumed that EV owners will not wait more than their maximum waiting time for their turn to charge their EVs. Realistically, each EV owner has different preferences, flexibility, and patience levels that decide their waiting time in case of congestion in the system. To achieve a realistic situation, a random waiting time for each EV is assigned using a realistic range of $5 - 30$ $minutes$ waiting time. A set of 100 EV charging profiles, including arrival time, departure time, state of charge, and battery capacity, are generated using the earlier mentioned scenario generator.

B. Simulation Results

The EVs charging load profiles, as generated, are introduced into the network to observe the congestion on the feeder caused by the uncoordinated EVs charging. In Fig. 3(a), red dotted line represents the transformer's maximum capacity to supply load, the pink curve indicates the total EVs charging consumption over the time period, while the blue curve shows the critical load, i.e., power consumption by the buildings in the community. The overall load exerted by the critical loads plus EVs charging is represented by the black curve. It can be observed that this exceeds the maximum capacity defined for the transformer, thus causing congestion in the system due to higher EVs charging demands during the morning and evening hours. This congestion problem is resolved by applying the proposed multi-issue negotiation algorithm and real-time management model, which efficiently coordinates flexible loads, i.e., EV charging consumption. There are some initial settings of parameters made by the aggregator and EVs to execute negotiations. In this simulation, the aggregator fixes its initial and reserve prices $[Pr_I, Pr_R]$ to be 200 and 10 price units, respectively. It should be noted that prices are measured in price units since no specific currency is selected. Besides, EV owners may have different settings, which is why the initial and reserve prices of the EV owners may be different. In this simulation, the initial price oscillates between

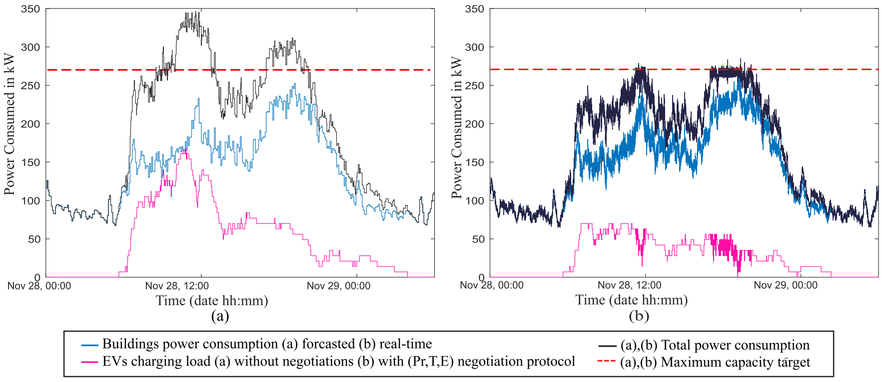

Fig. 3. Performance of the system before and after applying the multi-issue negotiation algorithm.

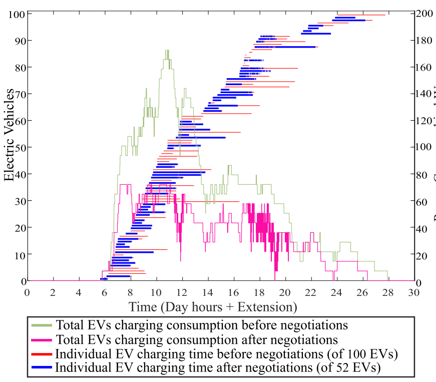

Fig. 4. EV charging before and after negotiations.

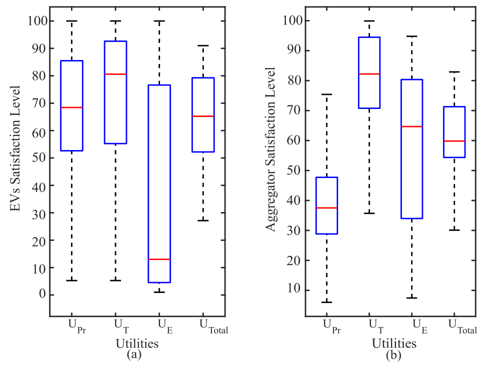

Fig. 5. Achieved satisfaction levels.

5 and 75 units, and the final price oscillates between 125 and 200 depending on the EV owner. Moreover, τ is fixed to be 50 and the strategy λ to be 1.

Furthermore, EV owners define time duration windows $[T_I, T_R]$ and energy packets windows $[E_I, E_R]$ based on their state of charge requirements, while aggregator determines these windows taking the critical load forecast and available transformer capacity into account. After the implementation of the proposed model with these settings, the congestion is removed from the feeder, which can be observed in Fig. 3(b).

A clear representation of EVs charging consumption before and after the implementation of the proposed model is depicted in Fig. 4. Blue lines in this figure represent the charging time of the 52% of EVs that had successful negotiations, while the rest of them couldn't charge mainly because of congestion, of which 2% had failed negotiations and 46% EVs left because of unavailability of chargers. Whereas, 3% of the EVs were not charged sufficiently because of real time load deviation for which the aggregator is penalised. The extension in the 24 hours of the day is to account for the charging period of the EVs, which started charging at midnight and continued charging till the next day. It should be noted that the chosen scenario represents a highly congested network in which the rated power of the transformer is only exceeded at some points when the critical loads are present. This scenario was selected in order to stress the system and test its performance. The proposed model utilises the flexibility of EVs to remove congestion from the network while achieving a certain level of EV owner satisfaction, which is exhibited in Fig. 5(a) in terms of its price, time, energy, and total utility. In this study, the satisfaction level of an agent can be defined by the utility or benefit achieved from closing a negotiation deal for a charging service. It is scaled by percentage. The blue boxes represent the range of utilities achieved by the agents, while the red marks represent the average utility that agents received. The main objective of the proposed mechanism is to satisfy both the EV owners and the aggregator. It can be observed that EVs show a lot of flexibility in energy utilization to participate in network load management, thus receiving a lower

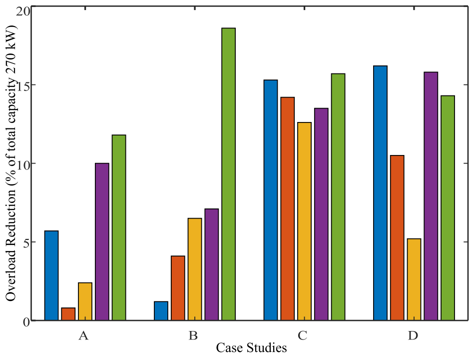

Fig. 6. Overload reduction achieved in case studies A,B,C,D.

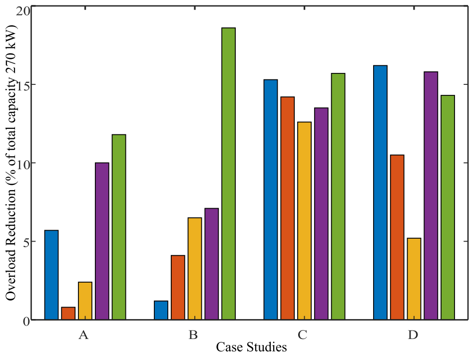

Fig. 7. Number of EVs charged achieved in case studies A,B,C,D.

energy utility as in Fig. 5(a). However, EVs are rewarded in the form of higher time and price utilities, therefore achieving an overall higher satisfaction level, i.e., 80% and 70% respectively. On the other hand, the aggregator offers great price flexibility to EVs, which results in lower price utility for the aggregator in Fig. 5(b). But, the aggregator achieves higher satisfaction levels for time and energy utilities.

C. Case Studies

In order to test the model's performance under various scenarios, a set of simulations varying different parameters is carried out that can be categorised into four different case studies. The aim is to observe the overload in the network under different situations that is reduced with the implementation of the algorithm and the charging service provided to the EVs has been analysed and a comparison has been made. A total of four cases or scenarios (A,B,C,D) are presented, and for each case, five sub-cases were tested. The four cases are represented by the different blocks represented in Figs. 6 and 7 labeled with A, B, C and D. For each of the four scenarios A, B, C or D, the five subcases are represented with bars of different colors. In Fig. 6 the overload reduction obtained by the charging procedure in percentage related to the total capacity is depicted. Fig. 7 represents the number of EVs charged successfully in percentage with respect to the total number of vehicles arriving on the street searching for a parking spot for charging. It must be noted that the number of EV chargers in the base case (10 in total) is very reduced compared to the number of cars arriving on the street during the day (100 in total in the base cases).

1) Case A: In this case, the same simulation set-up as in the base case is used, with seven buildings and 30 households per building. The 5 sub-cases are random variations using different load profiles in the 30 houses, so the total load of the seven buildings will be different in each of the 5 sub-cases of the scenario A. In the base case, the peaks at mid-day and noon reached 250 and 267 kW, respectively. The peak power reached by the buildings in kW for midday and noon in the five sub-cases was respectively [209,201,205,238,250] and [197,233,228,220,267]. In all cases, around 60% of the vehicles were successfully charged (see Fig. 6), and the overload reduction varied from around 2% to 12% depending on the sub-case.

2) Case B: In this case, the used building load profiles are similar to the ones used in the base case scenario as described in the previous section, but the number of EVs arriving during the day varied, considering 40, 50, 60, 80, and 100 EVs arriving on the street, respectively in the 5 sub-cases. The percentage of EVs charged in the sub-cases goes from 80% to around 50%. It must be remarked that in the case of a lower number of vehicles (40 vehicles), vehicles are more likely to arrive at times of peak congestion, so having fewer vehicles does not mean that the number of charged vehicles increases. In fact, the number of charged vehicles increases as the number of vehicles arrives, because this means that, statistically, many of them will arrive at times when there will be overcapacity. The maximum overload reduction reaches 20% with the maximum number of vehicles. However, it must be noted that in this case, the percentage of charged vehicles also dropped to 50%.

3) Case C: In this case, the same building profiles as in base case are used, but the number of charging points is varied. There were 5 simulations performed for different numbers of charging points in the network, i.e., [5,7,10,12,15]. As it can be observed, the number of vehicles charged and the overload reduction does not increase substantially when the number of EV chargers is increased. That is because the system is highly congested already in the base case, so increasing the number of EV chargers does not allow us to increase the number of vehicles managed during the congested hours. In this case, the bottleneck is created by the network capacity, so increasing the number of chargers does not have a positive impact on the overload reduction or the number of charged EVs.

4) Case D: Finally, case D used the same building load profile as the base case, but in this case, for each of the 5 sub-cases, different EV charging profiles were generated by randomly changing their preferences as to the desired energy, price, and time. As it can be observed in Fig. 7, the changes did not have a high impact on the total EVs successfully charged. However, these parameters do have quite an impact on the overload reduction, which varies from around 17% to 5% (see

Fig. 6). The case with the lower overload reduction corresponds to a case in which fewer cars arrive during the peak hours, so the overload reduction is lower. It must also be considered that the preferences of the vehicles, mostly in terms of price, have a lot of impact on the probability of achieving a successful negotiation with the platform.

V. Conclusion

This paper demonstrates how congestion problems in low voltage distribution networks can be managed by means of market mechanisms. The main findings of the presented work can be summarized as follows:

- A multi-issue negotiation protocol has been proposed to handle the simultaneous timeslot, energy packets and prices.
- The algorithm has been tested in a realistic environment to check the convergence and performance, and the work demonstrated that it is stable and behaves according to the plan.
- In cases where agreement is not reached, it is not due to incorrect design of the algorithm but to boundary conditions that make the vehicle requirements incompatible with the existing situation in the power system.
- This research work has shown that the algorithm is useful for solving congestion problems in a realistic system using market mechanisms.
- The development carried out in this work is applicable to the creation of flexible tariffs that define the negotiation strategies of the vehicles and that allow the flexibility provided by the vehicles to be managed efficiently for the resolution of network congestion.

A parametric negotiation methodology has been presented that allows the strategy to be varied by both the vehicles and the utility. However, the definition of complex strategies by both the utility and the vehicles, which will associate them with different types of flexible tariffs, is beyond the scope of this paper and is being studied for proposal in future work. In addition, work on a methodology is currently under process that will simultaneously manage flexible vehicle loads along with other flexible household loads, add solar production at the household level, and allow users to exchange energy with each other and with vehicles on the public road. The main core of the algorithm will be similar to the one presented in this paper with multi-issue trading, but much more complexity will be added to the trading system, which in the future will be multi-agent and will not rely entirely on a utility-dependent intermediate management platform as is the case in this paper. This information will be added in future work.

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A.2 Three-stage multi-agent framework for peer-to-peer energy trading

ransactive energy ; Electric vehicles; Prosumers; Distributed energy resources ; Congestion management; Loc
nergy markets; Decentralized bilateral negotiations; Multi-agent systems; Peer-to-peer energy trading ; Energy storag
naring

/Iulti-agent framework for coordinating one-to-many concurrent :omposite negotiations in a multi-stage postpaid peer-to-peer :nergy trading model[⋆]

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ABSTRACT

Fast-growing distributed energy resources, prosumers, and electric vehicles are going to overlo: the grid and may require heavy investments in redesigning and extending the infrastructure power distribution systems that may not be sustainable. In this respect, local energy markets see to be a promising solution that enables the participation of prosumers and consumers in the loc energy market for peer-to-peer energy transactions. To address this paradigm shift, we prese an advanced three-stage multi-agent model for peer-to-peer energy trading within the conte of local energy markets. This model is strategically designed to optimize individual benefi by orchestrating a one-to-many concurrent composite negotiations strategy. This approach n only ensures efficient grid support but also facilitates rapid computation and communicatio Empowered by the smart python multi-agent development environment, which harnesses tl instant extensible messaging and presence protocol, our model ensures seamless executi(of peer-to-peer energy transactions while maintaining performance excellence. Furthermo1 the methodology presented is of extreme simplicity when compared, for example, with oth procedures presented in the literature. This simplicity is one of the main characteristics since allows the implementation in edge devices with low computational power and the scalability the proposed system.

/ord count: 4770 words

Nomenclature

Number sets

$\mathbb{N}$	Natural numbers
$\mathbb{R}^+$	Positive real numbers

Parameters

pr, e	price per unit energy (p.u), energy units (kWh)
pr_u^{Nb}	Utility nominal buying energy unit price (p.u)
pr_u^{Ns}	Utility nominal selling energy unit price (p.u)
pr_u^b	Utility buying energy unit price (p.u)
pr_u^s	Utility selling energy unit price (p.u)
E_d^r	Energy demanded actually (kWh)
E_{opt}	Optimum energy demand (kWh)
a_1, a_2	utility price setting coefficients
τ	trading preferential coefficient
usr	username of agent account
pwd	password of agent account
id	identification number of agent

Sets and Indexes:

α_u	Utility agent

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α_c	Consumer agent
α_p	Prosumer agent
o, O	O is a set of offers o including pr, e by Consumer
T	Time
t	market session time period
ρ	negotiation phases
Variables:	
pr^s_p	Preferred selling energy unit price by prosumer (p.u)
pr^b_c	Preferred buying energy unit price by consumer (p.u)
e_d	Consumer energy demand (kWh)
e_s	Surplus energy injected by prosumer (kWh)

. Introduction

.1. Background and Research Motivation

he proliferation of distributed energy resources (DERs) in power systems has been observed over the past decade, wi :edit attributed to advancements in information and communication technology and their cost reduction [1]. This tren :ings both benefits and challenges to the power grid. Among the benefits, it reduces the load burden on the grid ar :pendence on fossil fuels/carbon, while also creating opportunities for prosumers to participate in the market. This als :esents challenges, such as introducing complexities to manage, including network congestion and the requirement ɩordinate a significant number of devices. This underscores the necessity for revising the infrastructure of pow /stem networks, as traditional ways of operating distribution systems struggle to accommodate evolving syster :quirements. Consequently, there exists a demand for innovative transactive energy spaces and market structur ɩpable of effectively managing distributed generation. These structures can facilitate prosumers in participating ar :veraging their involvement optimally to support the grid.

ı this pursuit, many solutions have come to the surface and have gathered the attention of researchers. Among ther :e local transactive energy markets and peer-to-peer(P2P) energy trading. These solutions provide market mechanisn ıd market-based management techniques that help the prosumer and consumer to actively participate, gain monetar :nefits, and provide ancillary services to the grid [2, 3]. Researchers are focused on improving these solutions ar ıtroducing novelty using various technical approaches.

.2. Related Works

umerous research endeavors have been directed toward enhancing the bidding strategies employed by participants i ıe local energy market (LEM). For instance, in [4, 5] distribution system operators (DSO) are able to achieve a global ptimal DER dispatch in a decentralized manner that helps each prosumer obtain its own optimal bidding curv orrespondingly, market-clearing schemes discussed in [6, 7] focus on players' offering or bidding parameters rath ıan their preferences and profiles (detailed utilization parameters of each appliance), helping preserve the privacy articipants. Researchers enhance P2P energy trading with iterative peer-matching and negotiation using a "greedine: ıctor" [8]. Another method reduces computation using an asynchronous online consensus negotiation mechanism [9 ı the context of [10], scholars introduce retail energy brokers controlling player bidding strategies via Markov decisi :ocess, reinforcement learning, and data-driven methods for day-ahead bidding, similar to wholesale electrici ıarkets. Minuto et al. [11] assess energy-sharing mechanisms within renewable energy communities, proposing thre gorithms for distributing net profit among members based on their contribution to financing and self-consumpti :rvices.

esearchers in [12] present a multi-step optimal bidding strategy for autonomous agents, considering agents' ris :eferences and expected profit, and analyzing their impact on local electricity markets. Concurrently, specif ıvestigations delve into optimizing home energy management systems from an aggregator's perspective managin :sidential flexibilities [13], employing strategic bidding to reduce day-ahead operational costs [14, 15], and addressin ıcertainties while adhering to market obligations [16, 17]. Hahnel et al. [18] investigate the pricing decisions in pee -peer and prosumer-centered electricity markets through a cross-national experiment in Germany and the Unite ingdom, revealing that trading decisions are influenced by political orientation, place attachment, and climate chang eliefs.

substantial body of research is dedicated to employing game theory, contract theory, and auction theory to captu ie dynamics of competition and cooperation among diverse participants in the P2P energy trading market. The ɔjective is to achieve optimal and mutually beneficial trade for all involved parties [19–21]. A framework considerin ɔth cooperative game theory and non-cooperative game theory is proposed in [22], where a pivotal player acts as ɔntroller to distribute revenue among the peers fairly. In some specific studies [23, 24], researchers conduct a gam ieoretical analysis of the strategic behavior exhibited by intelligent agents representing prosumers in combinatori ıctions with resource constraints. In this context, a community manager assumes the role of making energy allocatic ecisions for a community of prosumers. The iterative double auction mechanism is used to elicit hidden informatic om all participants to achieve maximum social welfare [25, 26]. In a recent work [27], researchers employed esterov-based algorithm for generalized Nash equilibrium using distributed communication in an energy-sharin ame of prosumers. Some scholars emphasized Bayesian learning methods for optimal decision-making amon eneration companies in a power pool [28].

number of recent studies have addressed the application of multi-agent system (MAS) theory to energy market n agent-based architecture where seller and buyer entities modeled as agents, aim to maximize social welfare whi ɔnsidering real-time imbalance penalties [29]. A multi-agent decision support system is designed that uses real mark ata derived from past and current simulations, and external sources to support the decision-making process of ıanager agent supporting market players for each different market negotiation type and participation in auction-base ıarkets [30]. Adaptive agent-tracking strategies have been developed for generation company agents, which resulte ı greater payoffs in bilateral negotiations compared to utility-based strategies [31]. A multi-agent deep reinforceme earning-based control framework is proposed for multi-dimensional power dispatch optimization in systems featurin ıultiple uncertainties [32, 33] and to analyze risk-averse strategic interactions in complex market environments [34 ome researchers concentrate on considering line loadings and losses, as technical constraints in the management ıulti-agent distribution systems [35]. The authors in [36], propose a multi-actor-attention-critic algorithm reducing th ɔmmunity's cost and peak demand and overcoming scalability, non-stationary, and privacy limitations of multi-age eep reinforcement learning approaches. A systematic review of barriers and policies affecting the adoption of energ fficient technologies by households is provided, emphasizing the role of agent-based modeling in understanding ar ıfluencing consumer behavior [37, 38].

.3. Key Contribution

ur paper proposes a multi-stage postpaid P2P energy trading model based on a multi-agent systems framework. Oı rimary focus lies in achieving simultaneously three goals:

1. Maximize social welfare i.e. each individual market player's profit.
2. Support grid balancing and congestion management at the distribution power system.
3. Minimize any potential delays in the trading process by prioritizing fast and less complex computations ar communications.

o fulfill these objectives, we propose the implementation of the "One-to-Many Concurrent Composite Negotiation rategy. Our model operates through a three-stage scheme: energy exchange, data exchange, and negotiations, a ılminating in efficient financial transactions. A key characteristic is the postpaid method, where energy exchang ccurs before negotiations. This creates a seamless flow, ensuring that services are availed first, and payments aı ıen made. The simplicity of the method is also one of its main contributions, since unlike the proposals describe ɔove, this methodology does not depend on ultra-precise disaggregated consumption and generation predictions ar extremely light computationally speaking, which makes it very easy to deploy on edge platforms, thus also favorin rge-scale scalability.

SPADE (Smart Python multi-Agent Development Environment) a multi-agent system platform is used to develc ır three-stage P2P trading model with participants as agents. Specifically, SPADE incorporates XMPP (eXtensib lessaging and Presence Protocol), which is an open communication protocol for instant messaging and presenc ɔtification [39]. This distinctive feature significantly reduces computation and communication overheads. Simulatic esults demonstrate the effectiveness of the proposed scheme for energy trading in the local electricity market.

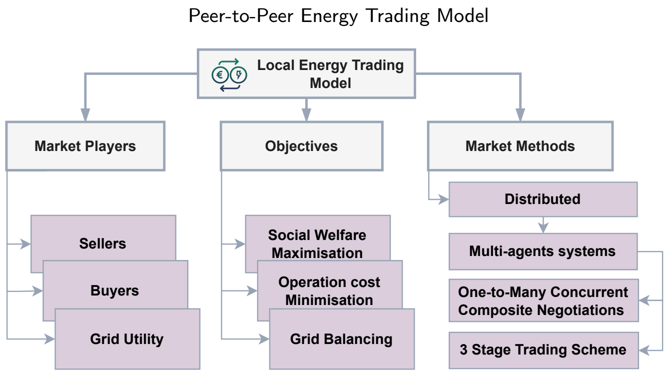

Figure 1: Schematic overview of proposed model

.4. Organization

he remainder of this paper is organized as follows. Section 2 entails the description of the distribution networ :osystem taken into consideration for the application of the proposed multi-agent-system (MAS) based P2P loc nergy trading model. This section also includes a detailed systematic description of the proposed trading mechanisı ıd it's implementation. Section 3 includes the case study and simulation results to prove the effectiveness of th :oposition. Section 4 and 5 concludes the research work presented in this paper and the expected future work. Th :hematic overview of the proposed work is presented in Fig. 1.

. Methodology

/e are considering a small unit of a typical urban distribution network as a local community, that consists of a pow ansformer with 4-wire 3-phase feeders connected to its secondary with circuit breaker (BR_1) as represented in Fi . Each feeder can be monitored by means of advanced supervisor monitoring equipment (labeled in Fig. 2 as M_{F1} ach end-user connected to the feeders is also supported with advanced metering infrastructure (M_1, M_2, M_3...). En ısers may include consumers and prosumers (i.e. consumers with DERs such as solar panels, electric vehicles (EVs ıd batteries, having the ability to produce energy). This local community is supervised by an entity called utilit he utility will cover the energy imbalances and will act as a backup system absorbing any net surplus or deman ır energy. The utility will vary the price scheme as a signal to incentivize end-users to consume or inject more i :der to operate the system within the limits. The proposed energy market model is designed taking into account th ɔnfiguration of the local community. The role of each entity, trading mechanism, and MAS platform details are goin ı be discussed in the following subsections.

 is significant to clarify at this stage that the proposed methodology without losing its generality can be applied acro ırious aggregation levels, such as a feeder, a phase of a feeder, or even a group of multiple power transformers as th ıost common aggregation unit in Europe is the MV/LV power station.

.1. Trading Mechanism

/ithin the local energy community setting under consideration, a proposed approach involves the Utility taking charg f setting and periodically broadcasting its prices. Drawing insights from past market behavior, the Utility adeptl :organizes itself to achieve grid balancing and economic advantages. In the final phase of financial trading, the Utilit ıgages in buying or selling energy at its established price, bypassing any negotiations with peers.

Ieanwhile, consumers and prosumers actively participate in the market during the designated periods and negotiatic ıases. In the event that deals cannot be reached within these time frames, they are required to conduct trades with th tility directly, without the need for further negotiations. The main aspects of the suggested trading mechanism aı ɔing to be the topic of discussion in this section.

.1.1. Multi Agents

here are basically three main types of players in the LEM suggested in this trading scheme. These players are modele ; agents in the MAS platform and their behaviors are designed.

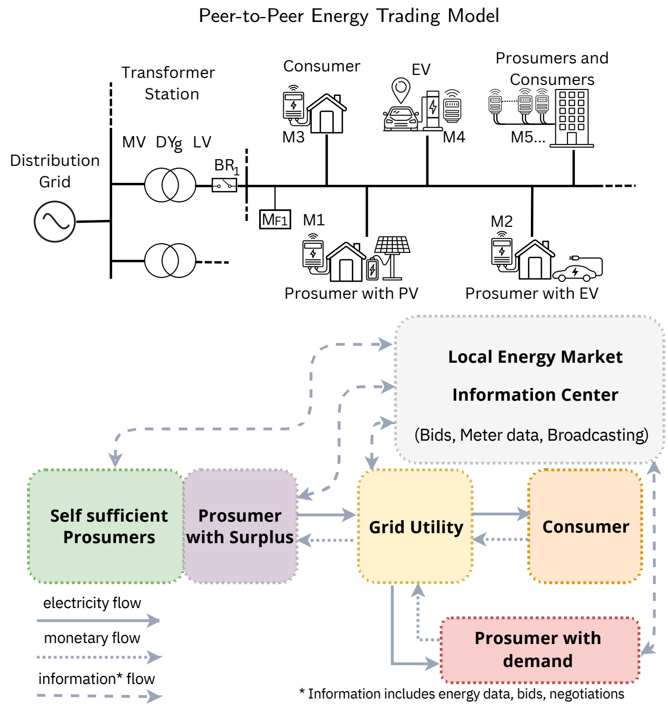

Figure 2: Power Distribution Network and P2P energy Trading

- **Utility(α_u):** This agent which supervises in and out of the power distribution transformer, is responsible fo selling the grid energy to the distributed energy end users and buying from them the surplus distributed energ in case of deficit. It controls the price signal to balance the grid demand/supply.
- **Prosumer(α_p):** This agent is a local distributed energy producer that supports its own energy needs, sells surplu energy to the other agents in the distributed network, or buys the deficit from other LEM players or the utilit It participates in the LEM by negotiating with multiple agents/peers to trade energy. However, self-sufficie prosumers in Fig. 2 will stay stagnant in the market.
- **Consumer(α_c):** This agent buys energy from the utility or from the LEM players to fulfill its energy demand This agent may negotiate and make deals with multiple agents/peers to buy the energy at economical price Moreover, prosumers with demand as presented in Fig. 2 adopt the consumer agent behavior to participate i the market as consumers.

1.2. Pricing Mechanism

he pricing mechanism is one of the significant regulating factors of the local energy markets (LEM). The utili ıonitors the power flows (injection and consumption) and analyzes the unbalancing of grid demand/supply ar ɔngestion at power distribution transformers. It is worth mentioning here that other control signals like for instance tl ɔltages in the different points of the feeders could be used to determine the price scheme, but in this case, for the sak f simplicity while maintaining generality we used the transformer power as control signal. In order to balance out tl emand/supply or to avoid congestion at the power distribution transformer of the grid, utility controls buying pr_u^b ar elling prices pr_u^s of energy unit according to the given real energy demand E_d^r during operation and optimum energ emand E_{opt} as committed day-ahead, for time period t. The difference between E_{opt} and E_d^r represents deviations a ɔsitive/negative energy imbalances that are required to be settled by price control. So the main objective function o ıe utility can be formulated as (1) and the control function as (2):

$$minimise \ \mid E_d^r - E_{opt} \mid \ \forall t \in T \quad (1$$

$$pr_u^x = \begin{cases} pr_u^N, & E_d^r = E_{opt} \\ a_1 * pr_u^N, & E_d^r \leq E_{opt} \ \ \forall t \in T \\ a_2 * pr_u^N, & E_d^r \geq E_{opt} \end{cases} \quad (2$$

$$s.t. \ a_1 < 1, a_1 \in \mathbb{R}^+ \quad (3$$

$$s.t. \ a_2 > 1, a_2 \in \mathbb{R}^+ \quad (4$$

/here pr_u^N in (2) represents the nominal selling/buying price as set by the utility, valid for the time period t whe ıe distribution network is balanced and congestion-free where superscript x can be s or b that corresponds to sellin : buying prices respectively. According to Equation (2), when the transformer consumption falls below the nomin: vel, both the purchase price and the selling price of the utility are decreased by a factor of a_1. This reduction i ıe selling price encourages greater consumption among agents, while the decrease in the purchase price discourage ‹cessive generation. In contrast to previous scenarios, in situations of high demand or network congestion, the buyin ıd selling price of the utility is increased by a factor of a_2 to stimulate prosumers to promote the generation and det gents from consuming excessively.

he target of the utility is to encourage P2P energy trading in case of high demand by increasing the unit price whi :her peers impose a little lower price for selling their excess energy. Similarly, when the demand is low, the utilit :duces the energy unit prices to encourage peers to buy energy from the utility.

.1.3. Response to Price Signal

rosumers are assumed to be economically rational who try to maximize their individual economic surplus throug articipating in P2P trading, either as a seller or a buyer. Prosumers receive a price signal from the utility at the start ‹ /ery trading session and then set their preferential selling price. Prosumer controls the selling price of their exporte ırplus energy e_s using the trade preferential coefficient as stated in eq. (5) and (6) to ensure that it is a little lower tha ıe utility price in order to attract more buyers and gain financial returns. They set orders with their preferred sellin :ices pr_p^s by selecting a desired value for τ which they can negotiate later.

$$pr_p^s = \tau * pr_u^s \ \ \forall t \in T \quad (5$$

$$\text{s.t. } 0 < \tau \leq 1, \tau \in \mathbb{R}^+ \quad (6$$

 is important to highlight that the mechanism governing agent prices is inherently automated rather than manual. T ıhance the optimization of agent prices, a tariff system can be implemented. This system offers a range of pricin :hemes, including premium tariffs, giving customers the freedom to choose between strategies that ensure surplı ıles by significantly reducing selling prices, or tariffs that prioritize profit improvement, even if it involves the risk ‹ ɔt making sales due to closely aligning prices with those of the utility. Alternatively, customers can inject their ow ıtelligence and business rules into the pricing engine. This customer-specific pricing engine can be integrated at tl latform level, with accessibility and configurability determined by the chosen scheme.

.dditionally, we have the option to replace the term "utility" with a more encompassing entity, such as an aggregato ıarketer, or even a Distributed System Operator (DSO). Another innovative approach involves transforming the utilit ıto an energy community, in which other agents actively participate. This system offers remarkable flexibility. In th aper, our primary focus centers on exploring the trading mechanisms applicable to a myriad of diverse configuration ıd case studies.

$$\max \ u(\alpha_p) = (pr_p^s - pr_u^b)e^s \quad (7$$

$$\text{s.t. } pr_u^b \leq pr_p^s \leq pr_u^s \tag{8}$$

he prosumer's primary goal as expressed in eq. (7) and (8), is to optimize profits by aiming to sell their energy at th ıost advantageous price point. This strategy considers the dynamic that if the prosumer sets a selling price surpassin ıe utility's rate, potential energy buyers are more inclined to purchase from the utility. Conversely, by reducing th ›lling price, the prosumer can increase the likelihood of selling energy to peers. However, it's crucial to note that th ›lling price should never drop below the utility's purchase price. Doing so would result in the prosumer incurrin ›sses by selling surplus energy to peers when a more profitable option exists in selling to the utility at a higher rate inding the ideal balance revolves around selecting a price that ensures sales while maximizing overall profit. I ıe future, implementing artificial intelligence tools could aid in this process, leveraging historical data to determir ptimal price coefficients for consumers. It's worth mentioning, though, that this topic falls beyond the scope of th aper.

$$O = \left\{ (o_1, ..., o_n) \right\} \tag{9}$$

$$o_i = (pr_i, e_i) \text{ where } i \in \{1, ..., n\}, \, i \in \mathbb{N} \tag{10}$$

$$pr_1 \leq ..... \leq pr_n \tag{11}$$

onsumers, as represented in eq. (9) and (10), receive a list of offers (prices and amount of energy) including frot ility and different prosumers. Subsequently, they choose the most economical options based on prices pr_i (as p ı. (11)) and the amount of energy e_i available that may fulfill their demand e_{di}. Then, they negotiate over the offe ith respective prosumers to reach economical deals mutually beneficial for both negotiating parties. This negotiatic rategy is used in service composition and mashups e.g. a buyer wants to buy several atomic services to compose ›mposite service. In this case, the goal of the agent negotiating with multiple opponents is to reach an agreement wi ıore than one (maybe all) of its opponents.

o be able to strike multiple deals, a consumer α_c needs to engage in multiple negotiations with prosumers $\alpha_{p1}, ..., \alpha$ ıd combine their outcome. The consumer's goal as expressed in eq. (12) and (13), is to maximize the utility $u(\alpha_c)$ ıe aggregate outcome of the entire negotiations by viewing it as a coordination problem, in which the buyer neec › aggregate and coordinate multiple, overlapping agreements such that the composite outcome satisfies the buyer verall demand with minimum price.

$$\max \; u(\alpha_c) = -\sum_{i,c} pr_i e_i(c) \tag{12}$$

$$\sum_j e_j(c) \leq e_{di} \text{ where } j, c \in \mathbb{N} \tag{13}$$

represents each composite unit of energy offered e_j as discrete values and j denotes the number of deals or agreement

1.4. Negotiation Mechanism

- Our model coordinates a One-to-Many Concurrent Composite Negotiations strategy that allows for composi negotiations, in which the outcome can comprise multiple partial outcomes, each originating from a deal with different seller.

- The buyer is able to obtain multiple deals through each of the concurrent bilateral interactions, with the goal satisfying, in the aggregate, a predefined demand for the lowest possible price.

- Several sellers might offer the same product at different quantities (as illustrated in the example), the buyer neec to decide which sellers to negotiate with, and over what. Moreover, while doing so, the buyer needs to deal wi complexities related to the combinatorial explosion of possible sets of partial deals using eq. (12) satisfyin eq.(13).
  Example: Different prosumers supply units of energy in bundles of varying quantities and unit prices; let

rocedure 1 Utility Agent Behaviour

ıput: (usr, pwd, id) for α_u registration in the system.
ıutput: (pr_u^b, pr_u^s) per unit energy for each $t \in T$, satisfying eq.(1)

1: **for** $\forall t \in T$ **do**
2: $(pr_u^b, pr_u^s) := f(E_d^r, E_{opt}, t)$ using eq. (2) satisfying eq.(1),(3),(4)
3: Broadcast pr_u^b, pr_u^s to all market agents.
4: **if** $\rho \Leftarrow 3$ $(\rho \in t)$ **then**
5: Receive buying/selling requests from all α_p ,α_c .
6: Accept all requests and trade @ pr_u^b, pr_u^s.
7: Process terminated
8: **end if**
9: **end for**

rocedure 2 Prosumer Agent Behaviour

ıput: (usr, pwd, id) for α_p registration in the system.
ıutput: maximum $u(\alpha_p)$ for each $t \in T$.

1: **for** $\forall \rho \in t$ **do**
2: identify e_s
3: $pr_p^s := f(pr_p^s, t)$ using eq. (5)
4: Broadcast (pr_p^s, e_s) to all market agents
5: **if** requests received **then**
6: Accept requests based on *first come first serve*
7: trade and update e_s
8: rejects others
9: **end if**
10: **if** $e_s > 0$ AND $\rho \Leftarrow 2$ **then**
11: Repeat the process from lines 5 to 14
12: **end if**
13: **if** $e_s > 0$ AND $\rho \Leftarrow 3$ **then**
14: make request/s to utility and trade at pr_u^b
15: Terminate Process
16: **end if**
17: **if** $e_s = 0$ **then**
18: Terminate Process
19: **end if**
20: **end for**

assume, α_{p1} may have 2 kWh energy units for \$3 each, and seller α_{p2} may have 5kWh energy units for \$4 eac on offer (which we denote as $o_1 = (3, 2)$, $o_2 = (4, 5)$). And α_c has an energy demand e_d of 3 kWh, and a de is reached with two sellers: $e_1 = \{2kWh \times \$3\}$ and $e_2 = \{1kWh \times \$4\}$. The aggregation of these two dea results in $e_1 \oplus e_2 = \{2kWh \times \$3 + 1kWh \times \$4\}$.

- Aggressive negotiation strategy is applied that is negotiations are restricted with time constraints to ensure agen behave fast and close the deals shortly with greater benefits. Therefore, our negotiation model is comprised o three phases. The first two phases are for the user agents to trade with each other and close the deals while th last phase is for the rest of the agents who could not close the deals will have to trade with utility and accept i price.

rocedure 3 Consumer Agent Behaviour

ıput: (usr, pwd, id) for α_c registration in the system.
'utput: maximum $u(\alpha_c)$ for each $t \in T$.
1: **for** $\forall \rho \in t$ **do**
2: receive pr_u^b, pr_u^s and save
3: Identify e_d
4: **if** $\rho \Leftarrow 1$ **then**
5: Receive O and evaluate $u(\alpha_c)$ using eq. (12),(13)
6: Send requests to the best offers.
7: **if** acceptance received **then**
8: trade and update e_d
9: **end if**
0: **if** rejection recieved **then**
1: update e_d
2: **end if**
3: **end if**
4: **if** $e_d > 0$ AND $\rho \Leftarrow 2$ **then**
5: Repeat the process from lines 5 to 14
6: **end if**
7: **if** $e_d > 0$ AND $\rho \Leftarrow 3$ **then**
8: make request/s to utility and trade at pr_u^s
9: Terminate Process
0: **end if**
1: **if** $e_d = 0$ **then**
2: Terminate Process
3: **end if**
4: **end for**

.2. Time Horizon

. realistic time period for the energy trade is set. The trading time is split into 3 stages and a graphical summary rovided in Fig. 3

- **Stage 1 - Time for energy exchange:** During this time, all participants/multi-agents(prosumers and consumer exchange energy normally over the grid distribution network i.e. Prosumers inject their surplus energy into th grid while consumers consume the grid energy. It is to be noted that the strategy for consuming or injectin energy should be clearly affected by the historic prices but defining such strategy for each agent is beyond th scope of this work that is focused on proposing the framework for trading.
- **Stage 2 - Data Collection:** Since we are considering a distribution network that is equipped with advance metering infrastructure, all exchanged energy data of the prosumers and consumers will be collected. This who data is then used for processing the market operation. In this stage, the utility will set the market price as explaine in the previous sections, and broadcast it to all agents. Subsequently, the prosumers will set their selling price an prepare the offers/bids for the injected surplus energy to the grid which they want to sell to the peers followin negotiations.
- **Stage 3 (a,b) - Negotiation and Financial Transaction Settlements:** The training behavior algorithms of a three types of agents including utility, prosumer, and consumer are outlined in Procedures 1, 2 and 3.In th stage, prosumers broadcast their offers to all participants/buyers/consumers in the market following lines 2-4 c Procedure 2. Buyers receive a list of offers from different sellers available in the market and choose the potenti offers to pay for the energy usage in phase 1 as indicated in lines 4-13 in Procedure 3. They start negotiation with suitable sellers to meet the energy demand within the specific time duration allowed for negotiations an the deals are closed. However, if participants cannot reach a deal and want to continue negotiations, anoth chance is provided by iterating the process of offers, collection, and negotiations. Two phases of negotiation

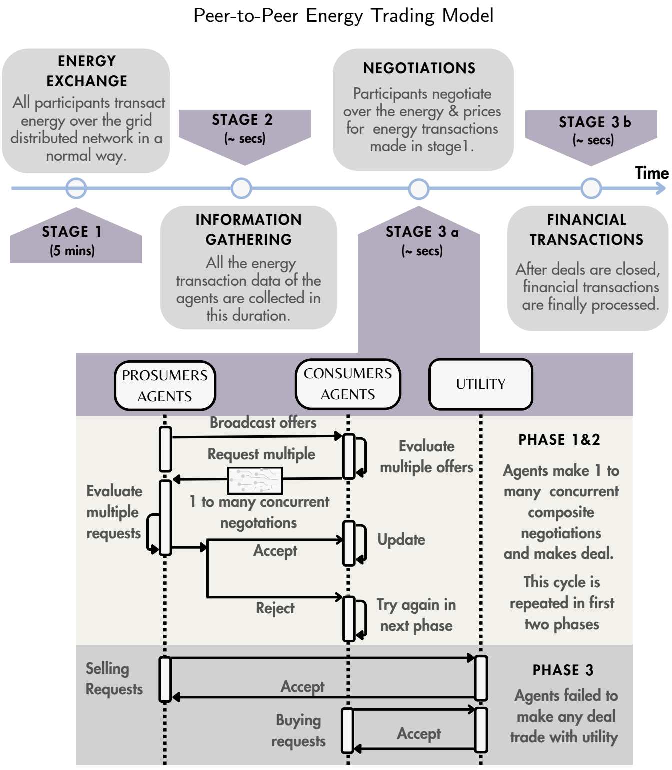

Figure 3: Timeline of Trading Mechanism

are dedicated to allowing players to close deals. Moreover, due to the aggressive negotiation approach, the dea are expected to be concluded in the first two phases, promoting green networking and communications. The is a third phase of negotiation that is for the rest of the peers who were not able to get any deal in the previou two phases to trade with utility at utility's defined buying and selling prices as directed in lines 4-7 in Procedu 1. All financial transactions are executed once the deals are closed. These settlements are verified by the utili against the energy usage data of the clients.

.3. Implementation

he proposed framework is tested with a simple case scenario of a group of agents in a local energy mark etting. Multi-agent systems technology is used to develop autonomous software entities i.e. intelligent agen cting as prosumers, consumers, and utility. These agents are designed to naturally communicate or intera ith each other. SPADE, a multi-agent system platform based on instant messaging (XMPP), is used to develo e proposed framework. It incorporates modern technologies and addresses open issues such as communicatic otocol standardization, elasticity in communication, human-agent integration, support for open systems, and devic dependent agent connection. SPADE 3 is based on XMPP (eXtensible Messaging and Presence Protocol) i.e. ommunication protocol, which provides an open, decentralized, and federated architecture for multi-agent systen nd that is one of the reasons for choosing SPADE.

. Results

o implement the proposed strategies and evaluate the overall performance of the model, a simulation is conducte onsidering a scenario that involves a group consisting of a utility and 10 agents. In Table 1, input settings are define hich include the number of consumers and prosumers, along with their energy demands/surplus. Trading preferenti

able 1
ata input

Agents/Peers	Count	Energy Units	Pricing per unit energy
Utility	1	grid supply	(pr_u^s: 5, pr_u^b: 3)
Consumers	3 3	3 7	-
Prosumers	2 2	10 7	$[0.6, 1]pr_u^s$

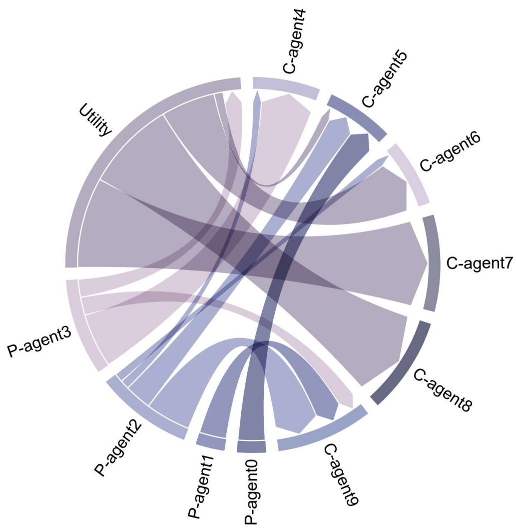

Figure 4: Graph illustrating 1 to many concurrent composite energy trading between peers.

:ttings are established for the prosumers to propose their selling prices or make offers, while consumers will utiliz ıeir strategic coordination function to strike and combine multiple offers.

. simple illustration of the P2P energy trade within the group, resulting from the one-to-many concurrent composi egotiations strategy, is presented in Fig. 4. Arrows with tails represent sellers, while arrows with heads represe ıyers. It can be observed that prosumer agents [0, 1, 2] successfully closed deals and transacted all energy units wi onsumer agents [4, 5, 9, 6]. Prosumer agent 3, however, was unable to sell all energy units and therefore engaged i ansactions with the grid utility.

ig. 5 illustrates the energy transactions taking place between peers and the utility. This illustration showcases tw ıses (A and B) of energy trading before and after the implementation of our P2P energy trading model. Data inpu ır both cases are defined in Table. 1. Notably, in case A, the prosumer agents collectively generated [3, 3, 10, 1(Wh of energy units, resulting in a total injection of 26 kWh of energy into the grid. However, after applying th :oposed local energy trading algorithm, they managed to sell [7, 6, 1, 10] kWh of energy units. This conserved 2 Wh of energy for consumer use, in contrast to the mere 2 kWh sold to utility to feed back into the grid. In case B, th :osumer agents were able to sell all generated [3, 3, 2, 2] kWh of energy units to the consumer agents [4, 6, 7] closin eals of [4, 1, 5] kWh. Further insights into the peers' trading activities are presented in Fig. 6. This visualizatic :ovides a breakdown of the number of trades executed by each prosumer and consumer. Additionally, it sheds ligl

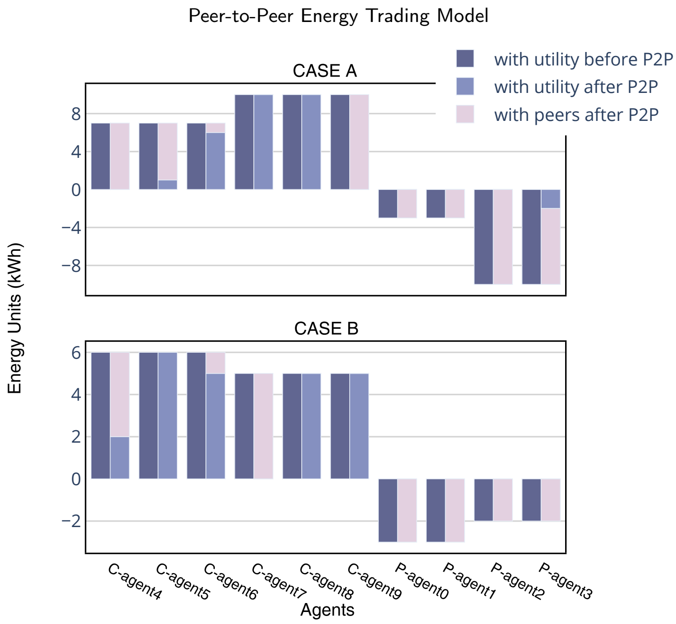

Figure 5: Energy transaction before and after model implementation.

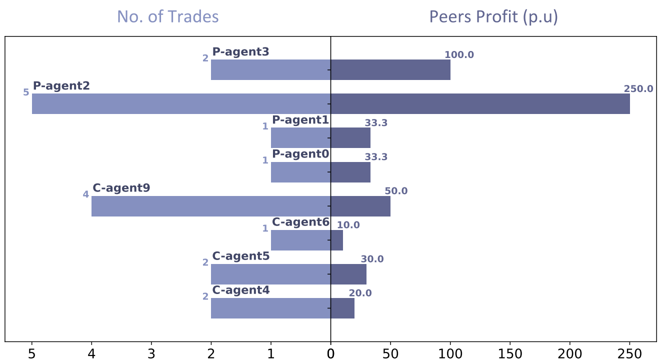

Figure 6: Agent-wise representation of gained benefits in terms of number of trades and profits

ı the individual savings achieved through P2P trades as opposed to trading with the utility. The graph exclusivel ɔrtrays agents who have achieved successful transactions with their peers. Notably, prosumer agent 2 engaged in tł ighest number of trades, striking 5 deals with multiple consumers and amassing a total of 250 price units—the highe nong all participants. This emphasis on atomic services to multiple consumers encourages greater participation i ɔcal energy trading among peers in the future.

.1. Scalability Tests

revious simulations were carried out based on 10 user agents and a utility agent, demonstrating the applicability ‹ ıe algorithm. However, to showcase the model's scalability, further simulations were conducted. The time horizc :mained consistent with the earlier case studies, ensuring efficient computations and communications using tł

able 2
arameters settings for batches

Parameter	e_d,e_s	τ	pr_u^s,pr_u^b
Value	rand(10,30)	rand(0.6,1)	5,3

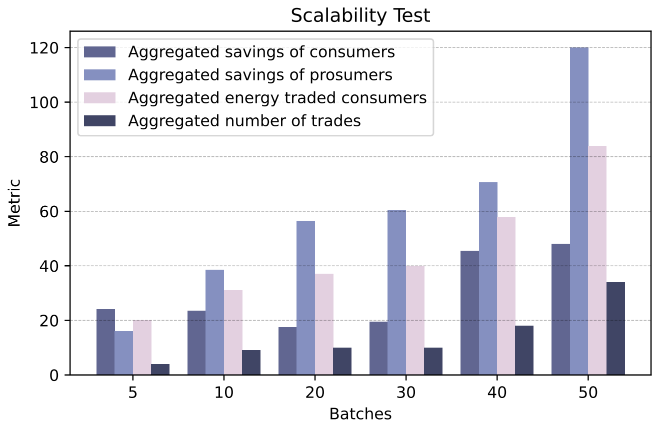

Figure 7: Aggregated simulation results of model conducted on batches of 5 - 50 agents.

PADE3 multi-agent system. A series of 6 experiments was executed by gradually increasing the number of prosum ıd consumer agents in each iteration, along with diverse system parameter combinations. The aggregated profit aded energy, and total trade count of peers were evaluated by deploying agent batches ranging from 5 to 50, ıtlined in Table 2. Fig. 7 visually encapsulates the aforementioned aspects across a sequence of batch simulations. vidently, local energy trading experiences substantial growth alongside the rise in the number of prosumers, epicted in Fig. 7, leading to increased profits. Despite maintaining a uniform time horizon across all experiment ıe proposed approach exhibits exceptional scalability in the face of computational and communication deman dditionally, prosumer agents notably earn higher rewards compared to consumer agents. This discrepancy arises fro rosumers being incentivized for both surplus energy generation and participation in local energy markets. Conversel ›nsumers engage in economic transactions with peers within the local energy markets. Importantly, this not on enefits consumers but also assists utility in alleviating imbalances and distribution network congestion, reflecting ıir mechanism.

. Conclusion

he proposed P2P energy trading framework utilizes intelligent software agents developed using the SPADE platfor ıd coordinating one-to-many concurrent composite negotiation mechanism to support local energy markets. Th amework may be adjusted to optimize individual benefits and/or support grid balancing. The model demonstrat ıccessful negotiations and transactions between agents, indicating the potential for effective P2P energy tradin ı local markets. The expreme simplicity of the mechanism makes it very easy to deploy in real environments an ıe results of the scalability examinations conducted on larger groups of agents were exceedingly positive, in clos ignment with the projected expectations.

. Future Work

ur next approach is to add advanced features to the agent's behavior modeling and research further on the followin nergy communities can be established at common coupling points in the network, allowing prosumers and near

Peer-to-Peer Energy Trading Model

onsumers to form bilateral contracts, coordinating their responses to price signals, and aiding grid stability. Thes ose-knit communities minimize network losses. In times of high demand, members collaborate to meet energy need ith prosumers sharing surplus energy and electric vehicles adjusting their charging. However, incentives are cruci promote such cooperation, as flexibility often requires a reward.

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Appendix B

Conference publications

B.1 EV Load Simulator

Artificial Scenario Generator for the Impact Study of Electric Vehicle Charging on the Distribution Grid

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***Abstract*—Ongoing fast paced research work on electric vehicles (EVs) demands efficient software tools to emulate different aspects of the EVs for more advancement and development of EV charging infrastructure in the power systems to assist massive adoption in coming years. In this regard an efficient EV load simulation model has been developed acquiring probabilistic method for characterizing the stochastic nature of EVs which generates the schedule of EVs charging to ultimately achieve the EV load profile for impact study of EVs on distribution network. Model has been tested under different settings and by generating different scenarios to make it viable, realistic and adaptable to any defined characteristics. Moreover, all the source codes have been socialised and uploaded to the IEEEDataPort repository.**

***Index Terms* – electric vehicles, charging systems, battery SOC, EV chargers, EV charging infrastructure, charging load simulation, transactive energy, power distribution system.**

I. Introduction

One of the recent hot research topic in the field of transactive energy is the coordination of electric vehicles (EVs) and design of smart charging systems to support high penetration of EVs in power systems. Electric vehicles may potentially alter load profile in a distribution network as it represents remarkable differences when compared with other electrical loads due to its unexpected charging locations and iterations. Since EVs are still not adopted at a big scale in worldwide therefore real data-sets of EVs charging load profile are not readily available at all platforms and global regions. These data-sets are of high significance for distribution grid planning, evaluating voltage profiles, transformer loading, grid peak power, power losses and so on. Therefore, to analyse the impact of these mobile loads on the existing power system and to plan EV charging infrastructure accordingly, such modeling and simulation tools are required which can simulate different EV operation schedules and charging load profiles under various scenarios. In this regard, various studies have been performed to develop these models with different approaches and targets.

Several stochastic models have been developed based on behavioral characteristics of EVs to simulate the charging demands of individual and groups of EVs [1], [2].The impacts of slow and fast charging services of different geographical locations and different time periods are considered in stochastic collaborative planning model for distribution systems and EV charging infrastructure [3]. The authors in [4] and [5] presented stochastic methodology to model EVs charging load and analyse its impact on distribution grid under various scenarios. A comparative study has been presented on different battery charging scenarios which are simulated using stochastic methodology Moreover, the spatial-temporal dynamics of EVs are investigated in [6] and [7] to capture the moving EV flows among power system buses. Different approaches have been acquired for EV load modeling. For example, queuing theory has been discussed in [8] and [9] for predicting EVs charging demand while other works in [10] and [11] adopted agent based model approach to predict human charging behavior to model charging demands of EVs. The authors in [12] validated the predicted charging patterns of plug-in EVs with the actual vehicle usage data in the city of Winnipeg, Canada from a large database. Furthermore, to achieve realistic models of large scale EVs mobility scenarios, electric vehicle supply equipment, and bidirectional communication between simulated and real components of a scenario, a cosimulation platform composed of SUMO (a vehicular traffic simulator) and OMNET++ (a network simulator) has been developed in [13].

In this paper, we have developed an artificial stochastic scenario generator for modeling EV load profiles under various scenarios. The model is parametric which can be adaptive to defined characteristics. Unlike other related works, this simulation model has been socialised and the source codes are available online on IEEEDataPort at [14]. Moreover, it is simple, scalable and does not posses complex computations like other models and it can be adapted to create any scenario by it's configurable parameters.This model is generalized for systems with different EV specifications and to anticipate increased EV population in the future which could not be served because of congestion. It can further be used for other variety of applications such as for designing peer to peer energy trading platforms, one such application is referenced in the article submitted for publication [15]. A stochastic approach has been acquired in this simulation model which considers realistic factors namely EV battery capacity, state of charge, plug-in/out time, charging power rate, residential, commercial and industrial load profiles, seasonal variations in load profile. The model provides user friendly, with simple and quick features to manage parameters, constraints and results for the scenario generation.

The rest of the paper is structured as follows. Section II introduces the artificial scenario generator algorithm

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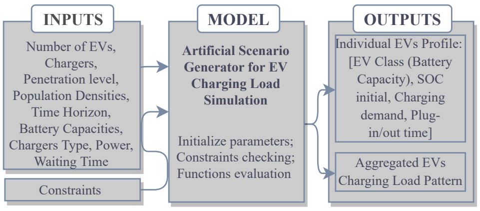

Fig. 1: Basic Structure of the Adopted Scheme

formulation and other details including assumptions and constraints to set up the idea of the work. Section III presents simulation results including EVs charging load profiles obtained under different generated scenarios considering residential, commercial and industrial sectors with different penetration levels of EVs. Finally, the conclusion of the work is drawn in Section IV.

II. Artificial Scenario Generator for EVs charging load simulation

A simulation model for generating EV charging load scenerios is implemented using MATLAB.The basic structure of adopted scheme in this work is represented in Fig. 1. The simulation model intakes the definition of EVs population densities in percentages over the time periods. This statistical information is inferred from the analysis of the EVs charging behaviour or acquired from travel survey data depending on the regions. This simulation model allows user to create own profiles with different statistics. Therefore, a set of factitious EV charging profiles, which can represent charging profiles on day of the week, will be generated instead. However, these profiles are based on the charging behavior of EVs at different sectors of the region which has been analysed to provide a probabilistic method for characterizing the stochastic nature of EVs. This section follows up with the details of the Algorithm 1 which has been developed to generate the schedule of EVs charging and ultimately achieve the load profile in a more realistic manner.

Assuming a community with n_{CP} charging points where n EVs as an average number of cars are charged in a normal weekday. Based on the general EVs charging behaviour, time intervals have been defined over the time horizon of a normal winter weekday by means of $\mathbf{t_I}$ that is a vector containing m specific hours that divide the day in $m-1$ time intervals. For each interval, an expected percentage of EVs arriving to the charging stations is declared using the vector $\mathbf{ev_{t_I}^{exp}}$ that contains $m-1$ elements. Each time interval may have a duration of hours. However, the day is divided in k time slots of fixed duration (usually 15 minutes). t_{slot}^i represent the i^{th} time slot of the day. The duration of all time intervals must be an exact multiple of the duration of the time slots, even when different time intervals may have different duration. The number of electric vehicles (n_{EV}^i) arriving in each specific t_{slot}^i can be calculated according to the next expression.

$$n_{EV}^i = f_d(\mathbf{t_I}, \mathbf{ev_{t_I}^{exp}}, t_{slot}^i);\ \text{where } lb < n_{EV} < ub \quad (1)$$

Where f_d is a probability density function that provides the number of EVs arriving during every 15 minutes of the day.

Algorithm 1 EVs load simulation model

Input: $\mathbf{t_I}, \mathbf{ev_{t_I}^{exp}}, lb, ub, parameters$ in Table 1.
Output: $pd_j(ev_j, t_j^a, soc_j^a, bc_j, soc_j^e, t_j^d, ev_j load)$.

```
for ∀j ∈ n do
    execute eqn1 & obtain n_EV(t);
    apply constraints eq.3, 4, 5, 6 to eq.2;
    execute eqn2 ;
    obtain ev_j, t_j^a, soc_j^a, bc_j, soc_j^e, t_j^d;
    while n_EV(t) > n_CP do
        if w_EV < w_max then
            t_j^a++;
        else
            ev_j exits;
        end if
        load_j= d(soc_j^a, bc_j, soc_j^e)*cc;
    end while
end for
```

n_{EV}^i is bounded to a minimum lb and a maximum ub numbers of EVs. These bounds are defined keeping in view the real scenario e.g. there could be a maximum of 5 EVs arriving in a 15-minute time-slot or at minimum there could be no EV at the charging station. Based on these definitions, a scheduler function is built to generate the arrival time of each EV along with its charging characteristics, following the output of eq.1 and respecting some constraints as in eq.3 to 5.

$$pd_j[ev_j, t_j^a, soc_j^a, bc_j, soc_j^e, t_j^d] = f_s(n_{EV}, t_{slot}) \quad (2)$$

$$n_{EV}^{inst} <= n_{CP} \quad (3)$$

$$\forall j \quad w_{EV} <= w_{max} \quad (4)$$

$$\forall j \quad t^d >= t^a + d \quad (5)$$

Considering $j = 1$ to n. Eq. 2 represents the scheduling function f_s based on n_{EV} and t_{slot}, which generates the profile data pd_j of jth electric vehicle ev_j. This profile data includes t_j^a arrival time, soc_j^a actual state of charge, bc_j battery capacity, soc_j^e state of charge after charging process and t_j^d departure time of j^{th} electric vehicle ev_j. In addition, Eq. 3 to 5 are the constraints which need to be satisfied by Eq. 2, while Eq.3 doesn't allow the count of charging cars at any instant(second) of the day symbolised as n_{EV}^{inst}, to exceed the total number of available charging points n_{CP}. Besides, it is also assumed that an EV waiting time denoted as w_{EV} cannot wait for more than the maximum waiting time represented as w_{max}, if all the EV-chargers are occupied, so this constraint is applied in Eq. 4. Whereas Eq. 5 imposes our assumption that EVs cannot leave before its departure time and d represents the charging duration of the EV. Moreover, for the sake of simplification, a constant/fixed charging power level cc is assumed at all charging stations for charging EVs. Using these charging parameters, charging load $load_j$ is calculated to draw the load profile. A summary of how these functionalities are executed

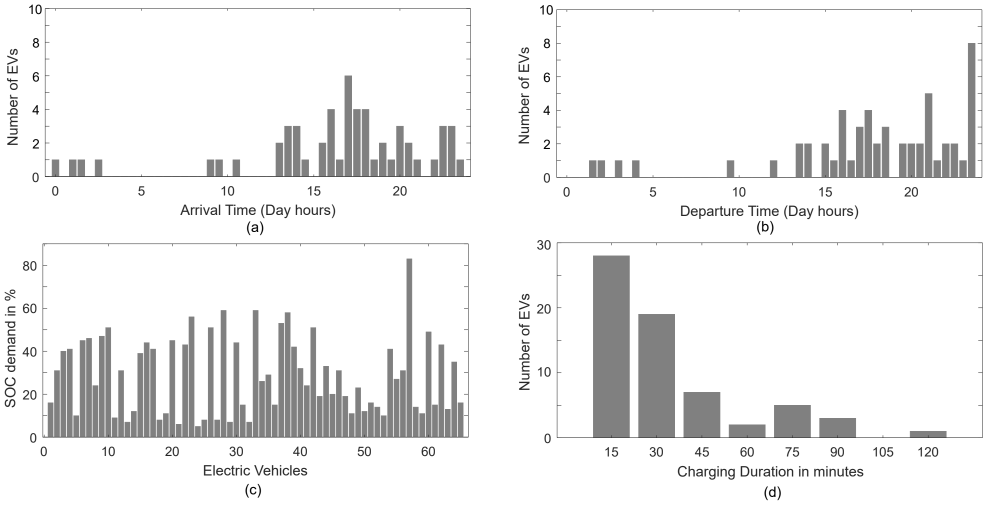

Fig. 2: Different Aspects of Generated EV Charging Profile at Residential Sector with 65% Penetration Level

step wise including the main considerations, is represented in Algorithm 1. Finally, all the parameters acquired in these simulations are defined in Table I.

Using Algorithm 1, a set of n EVs charging profiles pd_j including arrival time, departure time, SoC and other parameters as mentioned in the output of Algorithm 1, can be generated in a random fashion under defined configurations.

III. Results and Discussion

In this section, the simulation results are presented for the different generated scenarios considering the default parameters as stated in Table I, however these parameters are configurable. These parameters are assumption based and applied to all the generated profiles, i.e. for any moment of the simulation, these parameters are the same. These are default values but can be changed according to user preferences. The scenarios of area considered consist of domestic, commercial and industrial zones i.e. (a) residential area, (b) workplaces, (c) academic sector, (d) commercial buildings and shopping mall. The presented work gives probabilistic model of EV charging pattern over a period of 24 hours of a normal winter weekday for three different EV penetration levels of 35%, 50% and 65%.

Fig.2 illustrates different aspects of the generated EV load

TABLE I: Parameters for EV load simulation model

Charging Points, n_{CP}	10
Electric Vehicles,n	100
Fixed charging power,cc	7kW
Battery Capacities,bc	[22,32,40,60] kWh
Maximum Waiting Time,w_{max}	15 minutes

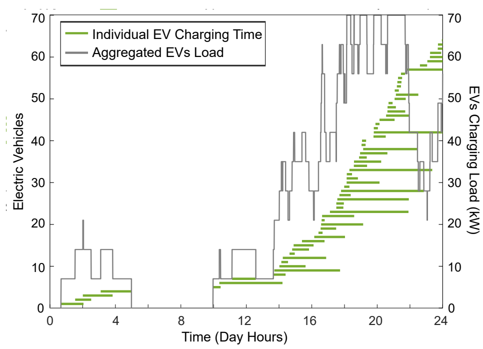

Fig. 3: Aggregated Electric Vehicles Charging Load at Residential Sector with 65% Penetration Level

profile in a residential sector with 65%. As per assumed population densities and parameters, the algorithm generated arrival time of each EV with different battery capacities and calibrated its departure time based on its SOC demand which is a randomly defined entity matching the stochastic nature of EVs. Fig.2 (a) represents majority of the EVs arriving in the evening of a weekday between hours 16:00 to 20:00 which is because usually people return home a bit early during working days and prefer to plug-in their cars for recharging so that their EV battery is fully charged on time. SOC demanded by EVs are generated in random fashion which are expressed in Fig.2 (c) corresponding to each EV. Moreover, the frequency of the

EVs w.r.t to their charging durations can be observed from Fig.2 (d) where trends in charging intervals can be visualised. This generated data is then used to model the aggregated charging load of EVs over the day period in the network.

As depicted in Fig.3, the overall power consumption by the EVs charging (represented in grey) along with each individual EV charging periods (represented in green). Charging peaks could be observed during the late hours of the evening since the probability of coincidence of several EVs to be recharged simultaneously at these hours are high. This data helps in estimating, analysing and predicting the load coming from EVs penetration in the grid, for planning EV charging infrastructure accordingly.

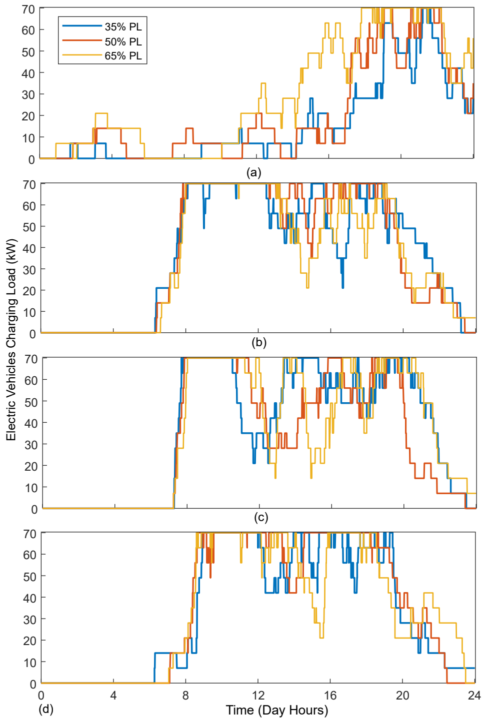

Fig. 4: Generated Electric Vehicles Charging Load Profiles with 3 different Penetration Levels(PL) at (a) Residential Sector (b) Workplace (c) Academic Sector (d) Commercial Sector

Fig. 4 shows the pattern of aggregated EVs charging load for different sectors of a region under different penetration levels. Fig. 4 (a) represents generated charging load in a residential area where a general pattern can be observed for the three penetration levels that in the office hours (8:00 – 16:00) the EV charging load is only around 10-30% while in the evening time (16:00 – 24:00) it gets high around 60% and in the night it dips. In the workplace area, Fig. 4 (b) demonstrate that from (8:00 – 12:00 Noon) the load is around 40–45% and it drops at 14:00 while in evening from (17:00 – 20:00) it goes to 40–45% again. In the academic sector, as expressed in Fig. 4 (c) there is 10–30% load insertion in the morning (7:00 -11:00) which dips to around 20% at mid noon and then rises to 40–60% from (13:00 – 16:00). However, there is no load observed in the night time. For the commercial sector in Fig. 4 (d), general pattern reflects a high load insertion during 7:00 – 20:00 and there is a fall observed at 20:00 P.M. The simulation results demonstrate that realistic patterns can be generated using this model with configurable parameters to analyse EVs integration with the grid system and its impact study.

Furthermore, different scenarios can be developed to analyse EV charging load pattern e.g. presented results were based on a normal winter weekday however, seasonal effects of summers, winters and spring can also be analysed while taking into account different activity behaviour of the individuals.

IV. Conclusions

A generic, scalable and less-complex artificial scenario generator has been presented for modeling EVs charging load profile in any region. Scenarios for areas including residential, industrial and commercial under different penetration levels have been generated. Results demonstrate realistic pattern of community life. Model is configurable and can be extended with various feature depending on the location and network conditions i.e. grid loading conditions, usage diversity and so on. Moreover, the model has been shared on IEEEDataPort which can be used as a basis for further investigation in the respective field. The proposed EV load modeling approach and associated test platform can also be used as a benchmark to simulate different EV penetration levels and market patterns and to assess the impacts of different EV charging infrastructure expansion plans on the power grid operation.

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B.2 Price and Time-Slot Negotiation Protocol for P2P Energy Trade

Price and Time-Slot Negotiation Protocol for EVs Charging in Highly Congested Distribution Networks

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***Abstract*—This paper presents a multi-issue bargaining mechanism in order to negotiate simultaneously the price and time-slot for electric vehicles (EVs) charging in congested power distribution networks. Alleviating the need for investments in distribution infrastructure to install EV chargers, an aggregator coordinating EVs provides flexibility to the system and reduces congestion. The proposed negotiation algorithm is based on well known Rubinstein alternating offers which is implemented and tested using a simple case scenario between EV and aggregator. Results achieved validates application of proposed negotiation mechanism for EV charging systems. Moreover, the general detailed description of the protocol as well as the implemented utility functions in this paper could expand its viability for more complex applications.**

***Index Terms*—electric vehicles, charging systems, energy trading, transactive energy, congestion management.**

I. Introduction

Transactive energy has been one of the most widely debated disciplines in the recent years. There is not a single definition of this term. However, Edison Electric Institute [1] proposal is fairly general and integrates in a holistic way all the tendencies present in this very broad concept that is in itself a highly multidisciplinary field of study. Basically, referring to the term transactive energy means grouping a set of economic management techniques that are combined with traditional control techniques which allow an integral management of power systems.

Among the tools provided by this new power system control framework, there is a vast set which is related to trading techniques. Even when electrical markets and trading techniques are widely implemented at transmission level in nearly all developed power systems, the degree of penetration of these techniques in real terminal distribution systems is still marginal due to several reasons listed hereafter; 1) The lack of regulation, or in many cases the existence of a very restrictive one. 2) The size of the data generated by the terminal distribution systems containing from hundreds to million nodes and users. 3) The latency with which we obtain data, that is far from real time in the majority of cases. 4) The heterogeneity of the different devices present in the distribution network and in many cases the impossibility of their remote operation.

The adverse conditions described above may be a delay, but in no way represent a medium-term brake on this new paradigm of electrical systems operation. This system advances in an unstoppable way supported by emerging technologies such as all those related to the internet of things, big data management systems, fast, robust and efficient communications, artificial intelligence, blockchain technology, the development of distributed generation and energy storage systems, electric vehicles, ...among others.

The efforts of the researchers during the last years proposing and implementing new solutions have been tremendous. A huge part of these efforts was invested in investigation related to the peer-to-peer energy trading as a tool to coordinate different agents participating in the terminal distribution network. A good set of examples are provided in [2]. The case presented in [3] proposes a trading system codified using blockchain technology in order to trade with the reactive power injected by PV generators in a microgrid. An open code example of how to implement a simple blockchain-based trading platform can be observed in [4]. In [5], the researchers use a transactive energy approach to coordinate the charging/discharging of the energy storage systems and the electric vehicles in commercial buildings considering some uncertainties for instance, those coming from PV generation. The framework proposed in [6] allows the coordination of a set of residential buildings trading with the energy stored in the PV storage systems. In most of the cases, the authors focus their proposal in solving a specific problem since the coordination of the entire system is too broad a problem to be attacked in a single work. Even the research works that propose a "general framework", like the

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one presented in [7] for coordinating a distribution system combining optimal power flow with transactive energy trading, assume a large set of simplifications of the real problem.

A common denominator of all research works is the implementation of some kind of market mechanism applied to the flexible loads. The basic differences between the proposals lie in: 1) the agents involved in the market mechanism; 2) the time-horizon in which the market is operated (real-time, day ahead,...); 3) the rules applied to the market; 4) the level of hierarchy of the system (a central agent controls the system or it is controlled in a distributed way).

The work proposed in this paper is mainly focused on the coordination of the EVs in a congested distribution system in which the buildings represent the critical loads and the EVs provide some flexibility. Of course, with such perspective, the work is not new since there are many researchers that propose different techniques to implement this coordination. For instance, the work presented in [8] proposes a framework in which the aggregators run the market where the prosumers participate. The DSO operates the distribution network and an external agent has the role of price coordinator. The idea is to operate the network fulfilling all physical constraints using the price signal among the other parameters. In [9], a market mechanism proposes the interaction between the EV aggregators and TSOs. The solution proposed in [10] allows the consumers to create coalitions in a multi-agent environment. These coalitions of prosumers are able to negotiate with each other. Probably, one of the most sophisticated approaches is the one presented in [11], in which the authors use a price signal as indirect control of the EV owners managed by aggregators. As a conclusion, the authors state that the monopolistic profitability of the aggregator must be somehow limited in order to guaranty an adequate competition in the market. Among the above-described research works, we find cases in which the charging schedule is determined by using different market mechanisms. However, in none of them, the trading mechanism consider simultaneously the price and time-slot negotiation. Therefore, this is the contribution of the presented work. This combined price and time-slot negotiation has been employed in the last years to determine the optimal cloud services reservation (see for instance the work presented in [12] that constitutes the conceptual basis of our proposal). However, this is the first time that this multi-issue bargaining technique is being implemented in a transactive energy environment.

The document is structured as follows. In section II, the specific problem in which we applied the proposed negotiation protocol, is stated. Of course, this problem is a simplification of the real case scenario but it is still valid to test the performance of the price and time-slot negotiation protocol presented in section III. In section IV, the description of the utility functions used during the bargaining process are presented. In section V, the performance of the implemented

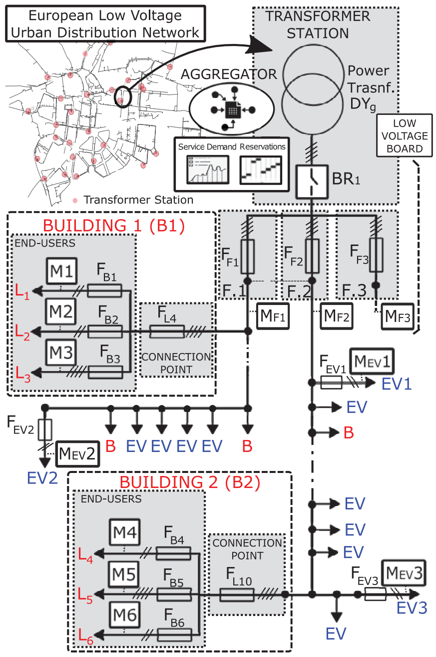

Fig. 1: European low voltage urban distribution network representing the case defined in the problem statement.

negotiation protocol is analysed and the conclusions are discussed in section VI.

II. Problem Statement

The scenario selected to test the system is a typical urban distribution network. In Fig. 1, a real network is represented in the top left corner. This network is a portion of a real network operated by EDP in Spain containing 30 power transformer stations and around 8500 customers. The details about this network can be found in [13]. As it can be observed, European low voltage networks are operated in small islands fed through power transformers. It must be considered that the elements belonging to a specific island may vary depending on the position of the breakers (BR) in the secondary side of the power transformer. Usually, each island contains several four wires three-phase feeders (F.1, F.2,..) protected by a set of fuses (F_{F1}, F_{F2},...). Each feeder can be monitored by means of an advanced supervisor monitoring equipment (here labeled as M_{F1}, M_{F2},...). Buildings have mostly three-phase connections however, most of the loads and also the end-users inside the buildings (L_1,...,L_6) are single phase unbalancing the total load. Usually each building is protected by a set of three-phase fuses (see for instance F_{L4}) and each individual user also has its own fuse protection (See for instance F_{B1}) and its own advance metering infrastructure (see for instance M_1). As a general data, we could state that the average distance from the power transformer to the connection points is less than 300 meters with around 25 buildings per power stations distributed in around 4 feeders. In many cases, the feeders are highly congested during the peak hours and it is not possible to add more loads, like the ones represented by the EV chargers without deploying new infrastructure or making new investments in the existing one. This situation prevents the DSOs from installing public EV chargers in a massive way. However, according to statistics, the average load during the whole day of the different feeders is less than 10%. That is the reason why flexible loads may help to reduce the congestion and make the system more receptive to embed new loads.

In this specific case of study, the existing buildings labeled in red in Fig. 1 represent the critical loads and that should be fed under all circumstances. Electric vehicles (in blue) will represent flexible loads that will negotiate with the aggregator the price and the time-slot in which they are going to receive the requested power. As it is mentioned earlier, this scenario is quite simple yet representing a real problem. The target of the aggregator will be to minimize the non-supplied energy fulfilling all the physical constraints defined by the DSO. To achieve this, the aggregator will use price signals and the proposed multi-issue negotiation technique to determine the price of the energy supplied and the charging period for each of the electric vehicles connected to the system. Even if the ultimate goal of the aggregator is to obtain an economic benefit. This benefit is limited by a pre-set range of variation in price signals and the imperative to minimize as much as possible the energy not supplied to flexible loads. This is a common practice in monopolistic scenarios such as the one we are discussing [11].

III. Alternating Offers Protocol

Each EV owner will have a specific contract in which all the parameters that define its negotiation strategy will be determined. The full set of parameters will be described later in this paper. However in this section, and for the sake of simplicity let us assume that when the vehicle is connected, the aggregator will receive the information from the vehicle that will cross with the one provided by the metering infrastructure and the forecast energy in order to adapt in real time its negotiation strategy. It is far beyond the scope of this paper to define the forecasting techniques or the negotiation strategy of the aggregator and the one defined in the contracts of the EV owners. This work focuses in defining the negotiation protocol but not the negotiation strategy that should be addressed in future works. In addition, in this specific case of study, and due to the limited number of vehicles that can be connected to a feeder and the high speed of the negotiation algorithm (demonstrated later), the negotiation between the EVs and the aggregator will be made in a sequential way using a first in first out strategy (FIFO). The first vehicle connected will be the first starting the negotiation with the aggregator, this will not reduce the generality of the methodology that could be used under other premises for instance parallel negotiations.

The proposed price and time-slot negotiation protocol is based on Rubinstein alternating offers protocol [14], with the whole procedure shown in Algorithm 1. Rubinstein alternating offers is a bargaining model which presents perfect equilibrium solution (see [15]) to a bargaining problem that is to find an agreement upon which the payoff of each agent is no less than the payoff received from the disagreement. This protocol is well recognized and extensively applied to automated negotiations in different fields [7], [12].

In Algorithm 1, the agents are referred as $Agent1$ $(A1)$ and $Agent2$ $(A2)$. $A1$ and $A2$ represent the EVs and AG. $A1$ will be the one that make the offer and $A2$ the one that evaluate the offer. $A1$ is initialised to be the EV and $A2$ to be the AG but these roles will be switched in the successive rounds. In this specific case and w.l.o.g., EV is selected as the agent that starts the negotiation. Both agents will set their initial preferences and time ranges for each negotiation process. These preferences consists mainly in the initial and reserve prices (IP, RP) and the first and last time slot (FT, LT) selected for this negotiation by each agent. Apart from the previous parameters, there are other parameters that define the negotiation strategy. For instance, agents utility ranges (U_{min}, U_{max}) and (λ) that will be defined in the next paragraphs. EV will query the AG for the set of available time slots (T_a) depending on its required power and its charging time horizon. In order to compute the available time slots, the AG will use real measurements from the critical loads and other EVs, information about already reserved time slots by other EVs and forecast values. If the set of available time-slots is not empty, them both agents fix a deadline (τ) for the negotiation (expressing the number of allowed rounds) and the initialise the first round $(t = 1)$ of the negotiation process.

$A1$ $(EV$ in the first round) will update it expected utility $U^{Ag1}_{exp,t}$. The expected utility in the first round is always the maximum. The agents diminish their expected utility through the successive negotiation rounds according to a concession protocol determined by the next expression. The parameter λ determines the negotiation strategy.

$$U^{t+1}_{exp} = U^{t}_{exp} - U^{t}_{exp} \cdot \left(\frac{t}{\tau}\right)^{\lambda} \tag{1}$$

The EV evaluates the sets of available time-slots if any, and generates an offer containing multiple concurrent proposals of time slots and prices in a so called burst offer generation procedure. These proposals should maximize the EV utility being the target utility the expected utility (U_{exp}). In the first round the expected utility is the maximum one. Each agent can calculate the utility (U) obtained from a set of (P, T) by means of its utility function $U := f(P, T)$ (a deep description of the utility functions is provided in the next section). Inversely, an agent can generate an offer containing a

Algorithm 1 Multi-Issue Negotiation Mechanism

Input: $(IP, RP, FT, LT, U_{min}, U_{max}, \lambda, \tau)$ for EV and AG.
Output: (P, T) final price and reserved time-slots.

```
1: EV query AG for the available time slots (T_a).
2: AG obtain (T_a) and send to EV.
3: t ⇐ 0; Set Agent1 = EV & Agent2 = AG.
4: if T_a is empty then
5:     Process terminated, no agreement.
6: else
7:     t ⇐ t + 1 Update negotiation round.
8:     Update Agent1 utility U^{A1}_{exp,t}
9:     (P,T) := f^{-1}_{Ag1}(U^{A1}_{exp,t}) Agent1 burst offer generation.
10:    U^{A2}_{x,t} := f_{A2}(P,T) Agent2 burst offer evaluation.
11:    if (t = τ & U^{A2}_{x,t} < U^{A2}_{min}) then
12:        Process terminated, no agreement.
13:    else if (t = τ & U^{A2}_{x,t} ≥ U^{A2}_{min}) | U^{A2}_{x,t} ≥ U^{A2}_{exp,t+1} then
14:        Process terminated, agreement reached.
15:    else
16:        Switch EV and AG in Agent1 and Agent2 roles.
17:        Goto line 7 to create counter-offer.
18:    end if
19: end if
```

set of (P, T) using the inverse of its utility function $(P, T) := f^{-1}(U)$. It must be remarked that there is no analytical expressions for these inverse functions, in many occasions, the calculations involve complex optimization methods that return approximated results. In short, we could state that f^{-1} functions are used for creating offers while f functions are used of evaluate offers.

Once EV generates the burst offer, it is evaluated by the AG that will select the pair of prize and time-slot (P, T) that maximizes its utility. Let us refer to this utility as (U_x). In order to accept the offer or make a counter offer, the AG check first that the negotiation deadline is not violated, in such case the offer is automatically rejected and the negotiation is terminated. Another condition that will trigger an automatic rejection is that the utility obtained by the AG with the best set of (P, T) is lower than the minimum utility accepted by the AG. In case that the agents are in the last allowed negotiation round $(t = \tau)$, the AG will accept automatically the offer if it provides a utility greater or equal than the minimum. Other condition for accepting the offer provides a utility greater than the utility expected in the next round $(U^{AG}_{x,t} \geq U^{AG}_{exp,t+1})$. Otherwise the AG will make a counter proposal, this means that the AG is expecting a utility in the next round higher than the utility provided by the best proposal in the actual round.

IV. Utility Functions Description

Proposed negotiation algorithm is based on three main functions: Price, Time-slot and Aggregated utility functions which are used to model the preferences of the EV and AG to implement bilateral negotiation strategies acquired in this paper. These utility functions defines the level of satisfaction of the agents in the form of a number between 0 to 1 (low to high) for any negotiation deal. In this section we will describe the above-referred functions.

A. Price Utility Function

Price utility functions for EVs and AG are described below (see 2 and 3). They are similar, however, as it can be observed EV utility is high at low prices while AG utility functions behaves in an opposite way. An agent always get maximum price utility when the price (P) is equal to its initial price (IP) and minimum price utility (u^p_{min}) when P is equal to its reserve (least preferred) price (RP).

$$U^{ev}_p(P) = \begin{cases} u^p_{min} + (1 - u^p_{min}) \left| \frac{RP-P}{RP-IP} \right|, & IP \leq P \leq RP \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$U^{ag}_p(P) = \begin{cases} u^p_{min} + (1 - u^p_{min}) \left| \frac{P-RP}{IP-RP} \right|, & RP \leq P \leq IP \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

B. Time-Slot Utility Function

Time is another factor governing the decisions of the EV and AG. Both agents define their preferences of charging time of EV, prior to start a negotiation based on these settings. Time utility functions are applied model of these order of preferences.

1) EV's Time-Slot Utility Function: The EV owner establishes the preferred charging time intervals according to its utility function. These preferences can be predefined or set manually. For instance, the expression (3) represents how the utility vary in a given interval of time (x) being T^x_h and T^x_t the starting time slot and the final time slot of that specific time interval. In that specific time interval, the utility reaches its maximum (U^x_m) between time slots T^x_{mh} and T^x_{mt} and decreases outside this interval according to the cited expression in which the coefficient (α^x_h) determines the rate of variation of the utility outside the maximum interval. The function represented in (4) is an example, but other functions could be proposed. The total utility function during the whole horizon of negotiation $(U^{ev}_t(T))$ can be obtained as an aggregation of the different partial utility functions $(U^{ev}_t(T)^x)$. In case of overlap of two partial utility functions, the total utility is defined as the highest of them. The time utility would be zero for that time region where no partial function is defined. This is just a general example of how to build this function but other methodologies may be applied.

$$U^{ev}_t(T)^x = \begin{cases} u^t_{min} & T \leq T^x_h \text{ or } T \geq T^x_t \\ U^x_m & T^x_{mh} \leq T \leq T^x_{mt} \\ U^x_m \cdot \left\{ \frac{T-T^x_h}{T^x_{mh}-T^x_h} \right\}^{\alpha^x_h} & T^x_h < T < T^x_{mh} \\ U^x_m \cdot \left\{ \frac{T^x_t-T}{T^x_t-T^x_{mt}} \right\}^{\alpha^x_t} & T^x_{mt} < T < T^x_t \end{cases} \tag{4}$$

2) Aggregator's Time-Slot Utility Function: Prioritising the available time for AG depends on several factors since aggregator has the key responsibility to coordinate with grid services, multiple EVs requests and managing the distributed energy produced by the prosumers within the community.

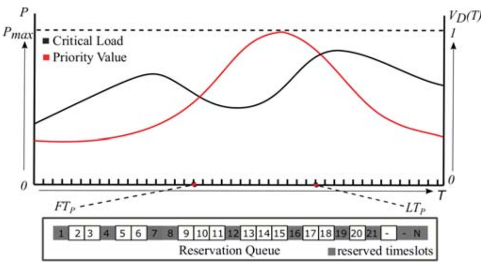

Fig. 2: Prioritised time-slots regarding available power and reservation queue

Therefore, aggregator's time-slot preferences are based on the following.

Energy Demand and Grid Infrastructure Availability: AG selects the time range specifying LT_P and FT_P, and then splits the time into time-slots. Each time-slot indexed T is assigned with the priority value $V_D(T)$ depending on the aggregated energy demand forecast of the community, actual consumption, grid availability and other factors. The study of the influence of such factors in the priority curve is far beyond the scope of this paper but in general we could state that for higher expected demand or peak time-slots, AG will assign low priority and vice versa. Fig. 2 represent an example of the priority curve and the power forecast for the critical loads.

Time and Energy Devaluation: Since the unused energy would be the loss of revenue for the aggregator therefore it will prefer to reserve the earliest available time-slots.

Request Accommodation: Depending on the EV charging requirements i.e. number of time-slots fulfilling the energy requirement, the request is accommodated to best fit set of the available time-slots. Aggregator prepares the reservation queue for the selected time range which provides information about already reserved time slots and available time-slots. This queue is updated after every successful negotiation when an agreement is confirmed.

Assuming L_J be the requested charging demand by the EV. And L_A^i represents the length of i sets of continuous time-slots available to the aggregator in the reservation queue which fulfills the L_J. Relying on the earlier mentioned three main factors, the available time slots are finally prioritised using (5).

$$V^i = w_D \frac{1}{L_J} \sum_{T=i}^{i+L_j-1} V_D(T) + w_F \frac{LT_P - i}{LT_P - FT_P} + w_B \frac{L_J}{L_A^i} \quad (5)$$

w_D ,w_F and w_B are the weights selected by the aggregator to prioritise i sets of available time-slots satisfying the above mentioned preferences i.e. 1) energy demand and grid infrastructure availability, 2) energy devaluation and 3) request accommodation. Thus, keeping $w_D + w_F + w_B = 1$. Based on V^i in equation (5), all indexed i sets of available time slots are prioritised in a way that for highest value of V^i the priority of ith set becomes 1 and for the lowest value of V^i the priority of ith set becomes the last number of the index set. To translate these indices to the time-slots and return the respective priority, a mapping function $f_T^P(T)$ is used. These priorities for the i sets of available time-slots are then transformed to time-slot utility using time utility function in (6).

$$U_t^{ag}(T) = \begin{cases} u_{min}^t + (1 - u_{min}^t)\left[1 - \frac{f_T^P(T)-1}{N_{AT}^P - 1}\right], & FT_P \leq T \leq LT_P \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where u_{min}^t is the minimum utility received by the aggregator for reaching an agreement at its least prioritised time-slot. N_{AT}^P is the total number of available time-slot sets. The utility is zero for all the time-slots which are out of i sets of available time-slots.

C. Total Utility

Both price and time utilities are then adjusted and added up to receive total utility for reaching an agreement after successful negotiation. w_P and w_T are the weights set by the negotiating agents to adjust their respective preferences for price and time utilities, such that $w_P + w_T = 1$. In general, the total utility for a specific agent (EV or AG) can be expressed as:

$$U_{total}^{ag}(P,T) = \begin{cases} 0, \text{ either } U_p(P) = 0 \text{ or } U_t(T) = 0 \\ w_P \cdot U_p(P) + w_T \cdot U_t(T), \text{otherwise} \end{cases} \quad (7)$$

V. Negotiation Protocol Performance Analysis

We will present in this section a simple case of study. We will analyze the different negotiation rounds between an AG and an EV. The main parameters of the negotiation round are specified in Table I.

The different negotiation rounds are represented in Table II. EV starts the negotiation trying to maximize its utility, offers its initial price. In the case of the time slots, EV offers the one that provides the maximum utility i.e. $T = 8$ with a time utility of 0.7. According to the weights the total utility of the first offer made by the EV is 0.79. Even when the burst offer mode is activated, in this case there is only one combination that maximises the utility. The EV pass this offer $(P = 10, T = 8)$ to the AG, but this combination produces the minimum utility to the AG (0.01). Despite with the concession that the AG is willing to do in the counter offer, it is expecting to get an utility of 0.98 so the AG decides to make the counter offer

Preferences	AG	EV
Initial price (IP)	200	10
Reserve price (RP)	10	200
First Time slot (FT)	1	5
Last Time slot (LT)	30	41
Charging Demand (L_J)	3	3
Price weight (w_P)	0.3	0.3
Time-slot weight (w_T)	0.7	0.7
Negotiation Strategy (λ)	1	1
Negotiation Deadline(τ)	50	50
Minimum Utility(u_{min})	0.01	0.01

TABLE I: Preference Settings

EV	Rounds/Proposals	AG
U_p=1 U_t=0.70. U_{total}=0.79	$\xrightarrow[P=10,T=8]{t=1}$	U_p=0.01 U_t=0.01 U_{total}=0.01 U_{exp}=0.98
U_p=0.076 U_t=0.63 U_{total}=0.46 U_{exp}=0.76	$\xleftarrow[P=187,T=7]{t=2}$	U_p=0.93 U_t=1 U_{total}=0.98
U_p=0.8 U_t=0.70 U_{total}=0.76	$\xrightarrow[P=30,T=8]{t=3}$	U_p=0.11 U_t=0.01 U_{total}=0.04 U_{exp}=0.92
U_p=0.27 U_t=0.63 U_{total}=0.52 U_{exp}=0.70	$\xleftarrow[P=149,T=7]{t=4}$	U_p=0.73 U_t=1 U_{total}=0.92
U_p=[0.86,0.69] U_t=[0.63,0.70] U_{total}=0.70	$\xrightarrow[P=[35,69],T=[7,8]]{t=5}$	U_p=[0.14,0.31] U_t=[1,0.01] U_{total}=[0.74,0.10] U_{exp}=0.83
U_p=0.57 U_t=0.63 U_{total}=0.62 U_{exp}=0.62	$\xleftarrow[P=90,T=7]{t=6}$	U_p=0.43 U_t=1 U_{total}=0.83
U_p=[0.58,0.40] U_t=[0.63,0.70] U_{total}=0.62	$\xrightarrow[P=[89,123],T=[7,8]]{t=7}$	U_p=[0.42,0.60] U_t=[1,0.01] U_{total}=[0.82,0.18] U_{exp}=0.71
U_p=0.58 U_t=0.63 U_{total}=0.62	$\xleftrightarrow[P=89.8,T=7]{RESULT}$	U_p=0.4 U_t=1 U_{total}=0.82

TABLE II: Different negotiation rounds in the case of study

($P = 187.2, T = 7$) that produces the expected utility 0.98. The process is repeated. In round ($t = 5$) the EV makes an offer of 0.7 utility. Evidently, in this case the burst mode produces two combinations. Finally the agreement is reached in round 7 with a price of 89.88 and time slot 7 producing a utility of 0.62 for the EV and 0.82 for the AG. Average negotiation time is 30ms per round.

VI. Conclusions

In this paper a multi-issue negotiation protocol is presented, considering simultaneously price and time-slot during the different negotiation rounds. As previously mentioned, this kind of multi-issue bargaining technique is widely accepted in cloud services reservation environments. However, for the first time, it has been used in a transactive energy environment. This research exploited the similarities of the problem of energy management in a congested distribution network and the use of the limited capacities of cloud services, in order to employ highly effective techniques already implemented in the former case to solve real problems in the latter. A clear limitation of the present work is the simplification of the scenario which is used to test the algorithm (that will be extended in the final paper). However, this does not lessen the generality of the multi-agent framework presented in this paper. Multi-issue negotiation, it is intended to be the cornerstone of an integral terminal distribution network transactive energy-based control system to be developed in future work.

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B.3 EV charging coordination using MAS

Realtime framework for EV charging coordination using Multi-Agent Systems

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***Abstract*—In this paper, a multi-agent based negotiation algorithm is proposed for EV charging management. The paper provides the main scheme to develop a realtime framework for EV charging management. The proposed application permits defining the preferences for the aggregator and a list of buyers with their arrival time and preferences. Using the negotiation technique allows each agent to set his own preferences and making a bargaining process with the other agent. The same structure can be applied on managing flexible loads installed in a smart grid.**

***Index Terms* – Multi-Agent Systems, Smart grid, EV charging management, Simulation Framework.**

I. Introduction

Energy management nowadays is one of the most worrying topics as a result of the increasing number of Electric Vehicles (EVs). Sometimes, EV charging results an overload that may cause a fail in the electric transportation system. To resolve this problem, a good management and scheduling of these loads is required to avoid these possible overloads in the grid. One possible solution is to simulate the roles in this system.

A multi-agent based simulation system is presented in [1] to study EVs operation. Different roles are integrated in that work like government, power grid EVs' owners and charging stations' operators. A map agent is introduced to show and manage the visible agents. A similar multi-agent based system is presented in [2] where it is simulating the role of micro grid energy sources like PV panels, wind turbine and storage systems and micro grid loads. In that works it is concluded that using a multi agent system boosts the performance of micro grids in diverse aspects. Another multi agent based simulation system is presented in [3]. In this system, an algorithm is developed to optimize the charging scheduling based on non-cooperative game theory. [4] presents an intelligent energy management controller for EV integration. In this controller EV's trip is forecasted to obtain the optimal charging and discharging schedule. Some other works like [5] used a combination between multi agent system and blockchain to eliminates the security gaps by the integration of decentralized applications technologies. In most of cases, the proposed applications are non-cooperative where the preferences of the EV owners are collected and then a specific algorithm is run to obtain the optimal scheduling. Another technique to use is the negotiation or bargaining process as used in [6], where each agent has his own role in the process. A negotiation based technique is developed in [7] where a multi-issue bargaining mechanism is presented to negotiate price and time-slot simultaneously.

In this paper, a multi-agent based negotiation process is developed where agents can negotiate service's price, energy and time's flexibility. The proposed framework is implemented using a multi agent based system which can be used in real situations. The flexibility is added as a parameter in the negotiation to allow the seller to disconnect the cars if there is any overload due to buildings consumption an EV charging.

In next section, a simple description about multi-agent system is introduced. In section III, Proposed multi-agent system is described. Section IV explains the proposed negotiation process. Section V presents a case study simulation using the proposed system. Section VI explains how the proposed framework can be implemented in real life. Finally, section VII highlights the main conclusion of the work and the possible enhancements that can be added in future works.

Nomenclature

B	Seller's benefit
E	EV charging Energy
F	Buyer's flexibility
U_B	Benefit utility
U_E	Energy utility
U_F	Flexibility utility
w_B	Benefit utility weight
w_E	Energy utility weight
w_F	Flexibility utility weight
U	Total offer utility
$U_{B_{min}}$	Minimum benefit utility
$U_{E_{min}}$	Minimum energy utility
$U_{F_{min}}$	Minimum flexibility utility
B_I	Initial / Desired benefit
E_I	Initial / Desired energy
F_I	Initial / Desired flexibility
B_R	Reserved / Acceptable benefit
E_R	Reserved / Acceptable energy
F_R	Reserved / Acceptable flexibility
P_{max}	Maximum supplied power
N_{ch}	Number of chargers
P_{ch}	Charger power capacity
R_{max}	Maximum negotiation rounds
R	Current negotiation round
λ	Negotiation strategy

II. Multi Agent System

Multi agent system allows the interaction between agents within an environment. Each agent is responsible of a specific

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action resulting to break down a composite process into simple duties represented by agents [1], [8]. Multi agent system can be implemented in a decentralized way where each agent is living in his own platform acting with each other using the infrastructure supported by the multi agent platform.

There many different tools for the implementation of a multi agent system [9]. In this work, JADE platform is used to develop the proposed framework. As Jade framework is totally implemented in java, so it can be used in used in different machines without the need of sharing the operating system [10]. It is also supporting FIPA (The Foundation for Intelligent Physical Agents) specifications to implement the multi-agent systems [11].

The JADE architecture as shown in figure 1 contains some main components like agents, containers, platforms and AMS and DF agents. Agents have their own unique names and perform a specific task exchanging information between them. These agents are living in platforms that are serving them to be able to communicate between each other. Each platform contains at least one container and the first created container in the each platform called a main container. The main container contains two special agents AMS for platform management and DF for yellow pages service.

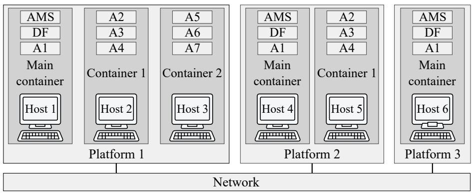


Fig. 1: JADE architecture

III. Proposed system agents

In this work, two types of agents are defined, seller and buyer agents. Based on each type, multiple agents can be created to act as sellers or buyers. Initially a seller agent is created to start monitoring the buildings consumption and to be ready to receive EV charging requests. Then a buyer agent is created for each EV at its arrival time.
Seller agent is the agent that acts the seller role. The seller agent started publishing a service in yellow pages to be found by buyer agents when they are created. Once the service is published, a *CyclicBehaviour* is attached to the seller agent to start listening to incoming buyers requests as shown in the procedure 1. Based on the type of the received message, seller agent make some actions. The type of these messages can be one of these types:

- *CFP*: is a call for proposal message that will be received from new buyer agents to start a negotiation process. In this case, seller answer this request with *ACCEPT* message if there is no other negotiation in process. Otherwise, seller answers with *REFUSE* message.
- *PROPOSE*: is a proposal message from another agent during negotiation process. The content of this message contains the offers proposed from the other agent. In this case, agent who receives this message evaluates all proposed offers and makes a decision depending on the maximum utility of these offers and the round of the negotiations that represents the time pressure. This decision can be one of these three decisions:
  - *ACCEPT_PROPOSAL*: if the seller is satisfied with one of proposed offers.
  - *REJECT_PROPOSAL*: if the seller is not satisfied with any of proposed offers and there is no chance to make a counter offer.
  - *PROPOSE*: if the seller is not satisfied with any of proposed offers but there is a chance to make a counter offer.
- *ACCEPT_PROPOSAL*: is the acceptance message that means that the other agent accepted one of the received offers. The contents of this message contains the details of the accepted offer.
- *REJECT_PROPOSAL*: is the rejection message that means that the other agents rejected all proposed offers.

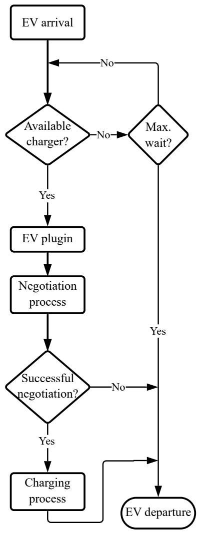


Fig. 2: EV scenario

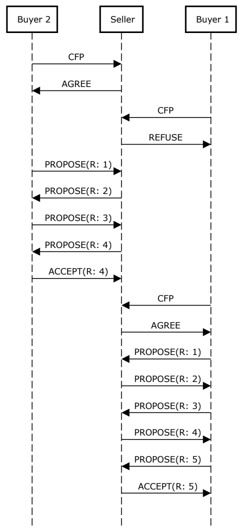


Fig. 3: Negotiation process

Buyer Agent is the agent that acts the buyer role and is created for each EV at its arrival. Buyer agent sets a timeout to be disconnected if there is no negotiation process established within this timeout. Then the buyer agent starts searching for the seller service in yellow pages to make the negotiation process. Once a seller service is localized, the buyer agent sends a *CFP* message to the seller asking to start a negotiation process. Then, a *CyclicBehaviour* is attached to the buyer agent to start listening to incoming messages from the seller as shown in the procedure 2. If *ACCEPT* message is received, the buyer agent starts making proposals

Procedure 1 Seller behaviour

```
Check ACLmessage
if ACLmessage received then
    Find or Add trade with that buyer
    if CFP then
        if BUSY then
            Refuse negotiation process
            Send REFUSE message
        else
            Accept negotiation process
            Set BUSY to true
            Send AGREE message
        end if
    else if PROPOSE then
        Evaluate offers using procedure 3
    else if ACCEPT_PROPOSAL then
        Update reservation curve
        Set BUSY to false
        End negotiation process
    else if REJECT_PROPOSAL then
        Set BUSY to false
        End negotiation process
    end if
end if
```

Procedure 2 Buyer behaviour

```
Check ACLmessage
if ACLmessage received then
    if REFUSE then
        Send CFP message
    else if AGREE then
        Prepare offers with U = 1
        Send PROPOSE message
    else if PROPOSE then
        Evaluate offers using the procedure 3
    else if ACCEPT_PROPOSAL then
        End negotiation process
    else if REJECT_PROPOSAL then
        End negotiation process
    end if
end if
```

to the seller and listening the messages from seller as defined before. If *REFUSE* message is received, the buyer agents keeps trying with *CFP* message till timeout event occurs or *ACCEPT* message is received. The full scenario of EV from its arrival to departure is shown in figure 2.

IV. Negotiation Process

Negotiation process presents an environment where users can negotiate the cost and the service they are requesting. In this work, the service is the energy for EV charging, the cost is the seller's benefit B and charging time flexibility F. Seller's benefit can be defined as the extra percentage of cost respect to the normal cost. Charging time flexibility can be defined as the extra percentage of time respect to required time for EV charging. This charging time flexibility allows the seller to make a discontinuous charging to overcome the possible overload during charging time.

In a negotiation process, each agent specifies his own preferences to start a negotiation process with the other agent. These preferences contains some parameters to be used in negotiation process:

- Initial values X_I: are the desired values for the negotiated parameters like a highest benefit for the seller or a minimum charging time flexibility for the EV owner.
- Reserved values X_R: are the accepted values for the negotiated parameters like a minimum benefit for the seller or a maximum charging time flexibility for the EV owner.
- Minimum utility $U_{X_{min}}$: is the minimum accepted utility by an agent that is corresponding to the reserved value X_R of the parameter X.
- Weights w_X: is the weight assigned to the utility U_X to calculate the total utility. The summation of weights should be unity.
- Negotiation strategy λ: is a parameter to determine the behaviour of an agent during negotiation process as shown in figure 4.

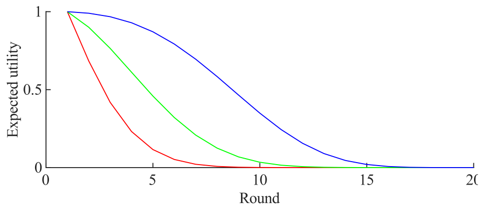


Fig. 4: Expected utility U_{exp} with round R applying different negotiation strategies: —— $\lambda < 1$, —— $\lambda = 1$, —— $\lambda > 1$

Utility functions are those functions with which the profitability of an offered parameter can be calculated. Seller's benefit B, required energy E and buyer's flexibility F can be evaluated using some custom functions as in equations (1) that can be defined as agent's preferences. In this work, these utility functions are supposed to be linear with unity as the maximum utility for the initial value of the parameter X_I. And $U_{X_{min}}$ as a minimum utility for the reserved values of the parameter X_R as shown in equations (2), (3).

$$U_B = f(B), U_E = f(E), U_F = f(F) \tag{1}$$

$$U_X = \begin{cases} U_{X_{min}} + (X - X_R)m_X, & X \in \{X_R, \dots X_I\} \\ 0, & otherwise \end{cases} \tag{2}$$

$$m_X = \frac{1 - U_{X_{min}}}{X_I - X_R} \tag{3}$$

$$U = \begin{cases} \sum w_X \cdot U_X & \forall U_X \geq U_{X_{min}} \\ 0, & otherwise \end{cases} \tag{4}$$

$$U_{exp} = U_{exp} - U_{exp} * (\frac{R}{R_{max}})^{\lambda} \tag{5}$$

Procedure 3 Offers evaluation

Calculate utilities for proposed offers using equation (4)
Obtain the offer with the maximum utility
if $R \geq R_{max}$ **then**
  if $U > U_{min}$ **then**
    Accept offer and update reservation curve
    Send *ACCEPT_PROPOSAL* message
    End negotiation process
  else
    Reject offer
    Send *REJECT_PROPOSAL* message
    End negotiation process
  end if
else
  Calculate U_{exp} using equation (5)
  if $U > U_{exp}$ **then**
    Accept offer and update reservation curve
    Send *ACCEPT_PROPOSAL* message
    End negotiation process
  else
    Prepare offers with $U = U_{exp}$
    Send *PROPOSE* message
  end if
end if

To calculate the total utility U of a proposed offer, equation (4) can be used where $X \in \{B, E, F\}$, $U_X \in \{U_B, U_E, U_F\}$, $w_x \in \{w_B, w_E, w_F\}$ and $U_{X_{min}} \in \{U_{B_{min}}, U_{E_{min}}, U_{F_{min}}\}$

The diagram shown in figure 3 represents an example of two negotiation processes with two buyers. In the beginning, Buyer 2 sends a *CFP* message to the seller. As the seller is free in that moment, he replies with *AGREE* message. In that moment, the seller rise a BUSY flag. So, any other *CFP* messages are answered with a *REFUSE* message as occurred with Buyer 1. When Buyer 2 receives the *AGREE* message, he starts a negotiation process with the seller. Buyer 2 sends his first proposal in the first round of the negotiation. The seller receives the *PROPOSE* message from Buyer 2 and evaluates his offers using the procedure 3. The seller decided to make a counter offer to increase his utility and sent a *PROPOSE* message to Buyer 2. After some rounds of counter offers decreasing the self total utility in each round using the equation (5), Buyer 2 accepts the offer from the seller and sent *ACCEPT* message. When the seller receives the *ACCEPT* message, he confirms the reservation of that service for Buyer 2 and sits the BUSY flag to accept new negotiation requests. As Buyer 1 received a *REFUSE* message from the seller, he tried again to send a *CFP* message to seller. As the seller sits the BUSY flag, he can accept new negotiation requests and sends *AGREE* message to Buyer 1. Buyer 1 starts the negotiation process with the same procedure as Buyer 2.

V. Case study

The case under study contains 20 EVs required to be charged during a period of 3 hours. The seller supplies the buildings consumption with a maximum power capacity of 270kW. The schedule of the 20 EVs arriving each 5 minutes is applied over multiple periods of time each 4 hours to study the effect of the negotiation algorithm and the EV owner's flexibility to avoid the overload. The results in table I show the different periods of time with the result of the simulation for each period of time that has different consumption percentages. The 1^{st} column represents the period in which the EVs schedule is applied. The 2^{nd} column represents the average consumption in that period. The 3^{rd} column represents the overload reduction achieved by applying the negotiation process and the flexibility offered by EV owners. The 4^{th} column represents the number of successful negotiations with EVs owners. The 5^{th} column represents the maximum number of EVs that have to be paused during charging to avoid power overload instants. As a result of negotiation, most of EVs have successful negotiation with a grade of satisfaction of 66% for the seller and 48% for most of EV owners.

Period	Consumption	Overload reduction	Charged EVs	Paused EVs
04 → 07	36.8%	-	20	0
08 → 11	57.7%	92.5%	20	1
12 → 15	63.4%	87.7%	15	5
16 → 19	77.2%	83.0%	15	13
20 → 23	71.9%	88.1%	15	7

TABLE I: Results applying the negotiation process

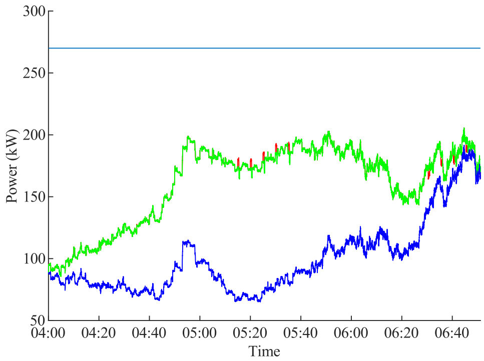
The figure 5 shows the results of different periods. The red curve shows the buildings consumption with EV charging without the discontinuous charging technique having total overload instants as shown in the 2^{nd} column in the table II respect to the experiment time. While the green curve represents the overall consumption applying the discontinuous charging technique reducing the overload instants to values shown in the 3^{rd} column in the table II. The using of discontinuous charging technique attempts to flatten the consumption curve distributing the EV charging taking advantage of the offered flexibility reducing the percentages of overload instants as shown in the 4^{th} column in the table II. The total overload power in experiment time is reduced with a percentage of more than 80% of reduction as shown in the 3^{rd} column in the table I. All these results couldn't be accomplished without the flexibility offered by the EV owners that allows the seller to make a discontinuous charging process to avoid overload instants. They presented about 35% of flexibility and got about 92.84% of the desired charging energy.

Period	Percentage of Overload instants Continuous charging	Discontinuous charging	Reduction
04 → 07	0 %	0 %	-
08 → 11	0.4 %	0.1 %	75%
12 → 15	4.1 %	1.6 %	61%
16 → 19	9.6 %	5.6 %	42%
20 → 23	10 %	3.7 %	63%

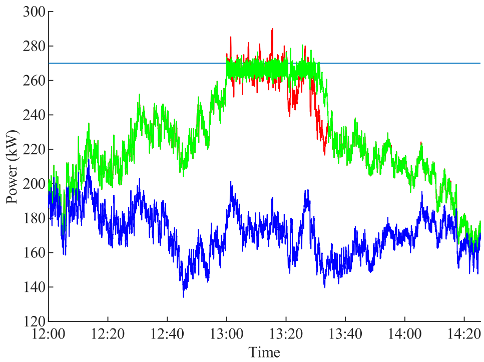
TABLE II: Percentages of overloads instants applying the continuous and discontinuous charging

VI. Framework implementation

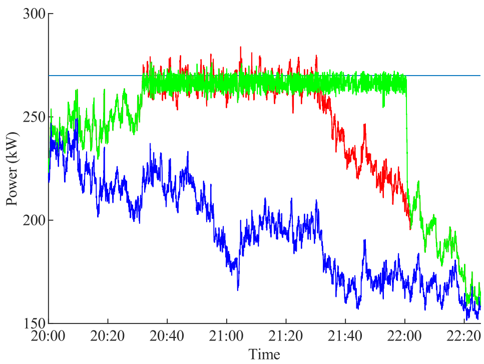
The proposed work is simulated and executed using a Java environment. As the negotiation time is about 20 ms, it is applicable to be used in realtime negotiation. The seller agent should be run on the EV charging stations and the buyer agent should be run on the EV system. In this simulation the negotiation process starts using a table with arrival times of EVs. In real work, the negotiation process should be started once the EV is plugged into the charger using the configured



(a) 04:00 to 07:00



(b) 12:00 to 15:00



(c) 20:00 to 23:00

Fig. 5: Power consumption: —— Buildings consumption, —— Overall consumption without real time control, —— Overall consumption with real time control

parameters by EV owner. The same framework can also be applied with some modifications to make a reservation system for EV charging. In that case the buyer agents will be run on a web server or mobile phones to make the negotiation process with the seller agent.

VII. Conclusion and Future Work

In this work, a multi-agent system for EV charging negotiation and management is designed. It adapts the trade with the EV owner depending on multiple parameters like seller's benefit, supplied energy and buyer's flexibility. The system can be used as a simulation process and also can be applied to a real situation. The results shows better management of the EV charging with a good satisfaction for both seller and buyers. The full program is available on [12] to be tested.

Some enhancements can be added to this framework like a graphical interface to add, edit and delete agents. Analyzing the the negotiation results to be able to give some suggestions to EV owners to tune their parameters due to the expected load of the grid. Supporting multiple negotiation process at the same time can be better for the seller to adapt his requirements. Another enhancement that could be useful is to enable EV discharging to be used in critical situations of overload.

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B.4 Blockchain-Based Peer-to-Peer Energy Trading

A Real Pilot-Platform Implementation for Blockchain-Based Peer-to-Peer Energy Trading

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***Abstract*—The ever growing energy demand due to population growth, higher penetration of electric vehicles and smart appliances, as well as superior living standards, is a demanding incentive to the better utilization of conventional and renewable energy systems. Moreover, to facilitate the emerging requirements of prosumers to participate in the electricity market and monetise their efforts towards distributed energy deployment, traditional centralised energy trading architectures are no longer viable. In this context, blockchain-based ledger technology emerges as the most feasible solution which offers a peer to peer (P2P) energy trading platform providing a unique distributed local energy market model for beneficial energy exchanges among participants. This will represent a significant evolution for future smart grids. In this regard, this work provides a ground understanding as well as all the necessary technical details and procedures required to implement a pilot-platform P2P energy trading system based on blockchain technology. All the source codes have been uploaded and socialized. This may support academics and entrepreneurs at the initial development stage of these kind of initiatives.**

***Index Terms* – blockchain, energy trading, peer-to-peer, transactive energy, ethereum.**

I. Introduction

In the last years, a sustained increasing use of renewable energy sources (RES) has been witnessed worldwide. Moreover, by 2022 around 30 percent of the overall electricity production will come from RES [1]. Nonetheless, the electricity demand is expected to increase by 20 percent in the next decade as a consequence of population growth, higher penetration of electric vehicles (EVs) and smart appliances, as well as superior living standards [2]. In the pursue to face this challenging scenario and properly meet the renewable energy generation with the demand, the microgrid concept was proposed as a convenient alternative. Nevertheless, microgrids present some difficulties on its coordination and control when they are connected to the conventional grid by means of network operators and utility companies which in most cases impose high logistics and costs for the electricity use. To overcome this issue, the latest advancements in digital communication and measurement systems added to the IoT technology have contributed to the development of smart grid infrastructures that permit a safe and reliable energy exchange between energy players (producers, consumers and prosumers) [3]. In this context, the ongoing challenge consists on decentralizing the energy production and consumption. To do so, energy blockchain has been exhibited as the required disrupting technology towards a new paradigm change in the power industry. Indeed, Blockchain 2.0 will permit the democratisation of power systems by means of the peer-to-peer (P2P) energy trading and the smart contract technology [4]. In turn this will promote local electricity trade, the reduction of electricity transmission losses, optimization of power flow, grid stability improvements, demand-side management and cost-effective employment of distributed energy [5]. Furthermore, P2P trade represents a win-win situation for prosumers but also for typical consumers as energy prices could be agreed with lower values compared with the ones defined by conventional electrical markets [3].

In this context, several systematic efforts have been exhibited regarding the use of blockchain, smart contracts and P2P in the power energy sector in the last years. The various applications, advantages and use cases when using blockchain are exhibited in [6] and [7]. References [8], [9] and [10] deal with adding privacy and security in energy market transactions by means of providing smart contract algorithms, decentralized knowledge graph construction and public-key cryptosystems respectively. Other security aspects for secure energy delivery and a credit-based payment schemes are analyzed in [11] and [12]. In [13], the benefits of using blockchain when procuring voltage regulation with reactive power control are mentioned. A further ancillary services discussion is held in [14] where relevant distributed ledger platforms for energy transaction in microgrids are also discussed. A proposal to perform continuous double auction market to match the distributed generation (DG) offer and demand is detailed in [15]. There, blockchain is proposed to cooperate with financial institutions by means of a multi signature system. Workflows and algorithms for developing agent coalition and electricity negotiation mechanisms are presented in [16]. In [17], thousands of smart contracts are analyzed. The ones having greater transactions are discussed. An adaptive blockchain-based electric vehicle participation (AdBEV) scheme is proposed in [18]. A framework based on a blockchain network able to carry on simulation of market clearing operations with a payment process is exhibited in [19]. Blockchain application's frameworks for crowdsourced energy systems and smart grid data security have been reviewed in [20] and [6] correspondingly.

The aforementioned references provide different frameworks and concepts to guide the planning for blockchain-based projects at the power energy sector. However, they lack on providing detailed technical explanations to implement a real

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pilot platform blockchain-based system able to perform P2P energy trading, which is in turn the aim of this work. Specific technical guidelines to deploy P2P energy projects would be of high significance for academics and entrepreneurs to fasten the development process at the initial stage. To achieve this goal while providing a comprehensive understanding, this work is organized as follows. Section II specifies the key foundations to unfold a blockchain-based P2P energy project. Physical and Virtual network requirements with the related hardware and software tools are detailed in Section III. A detailed implementation methodology is exhibited in Section IV. Finally, some conclusions are inferred in Section V.

II. Blockchain as a Key-Enabler for Peer-to-Peer Energy Platforms

A. Transactive Energy Using Blockchain. Core Technologies.

The advent of smartgrids and the participation of more prosumers in the electricity market have increased the requirements for enabling energy transactions among all players [21] and thus promoting a decentralised vision for the power grid by means of Transactive Energy (TE) platforms.

Indeed, this technology could turn conventional power grids into modernised systems which expedite the collaboration of the different participants in the network. This qualitative improvement could be attained in coming years thanks to the rapid and constant evolution of the blockchain technology. Hereof, three blockchain generations have been traced [21]. In the first one, bitcoin was introduced. Then, in the second generation, the automated smart contract technology was presented by Ethereum to process and record any logical operation in a reliable and secured ledger.

In these last years, Blockchain 3.0 has been exposed as a mature technology which has been already employed in some P2P TE pilot projects [22]–[24]. The main technological foundations that support this disrupting energy trading innovation are:

1) ***IoT and Energy Digitalisation****:* Around 20 billion smart devices will be worldwide connected to the internet by 2020 [25]. To face this challenge and deploy advanced power metering infrastructure, an increasing number of smart meters and information-communication technologies (ICTs) are being installed [25]. Smart meters integrated with blockchain can ease to record and track the data on temper-proof ledgers at suitable time intervals. Moreover, some companies are offering smart devices having ultra high resolution sampling and also including controllability via mobile applications [26].

2) ***Cloud and Edge Computing****:* A reliable transactive control in local energy markets is being affordably achieved by virtue of cloud and edge computing as they permit autonomous contract depletion for network edge users and avoid the need for trusted third party platforms [27].

3) ***Big Data and Artificial Intelligence****:* By means of artificial intelligence (AI), optimized automated decision-making can be achieved for energy players according to their needs, energetic patterns, weather forecast and storage conditions. Moreover, due to the increasing volumes of information, advanced computing, data mining and machine learning are required for handling big data [28].

B. Initiatives, Platforms and Challenges

In the last years, several startups and pilot projects have been developed under the P2P energy trading umbrella taking advantage of the blockchain decentralised architecture. Grid+ and Verv. However, there are tens of companies, foundations and consortiums related to blockchain-based energy projects as references [29] and [30] exhibit. On the other hand, some collaborative platforms have been established by some organizations to extend blockchain applications. Among these, the most popular are the Ethereum-based Energy Web Chain software and the Linux-based Hyper Ledger framework. Reference [30] provides further details on blockchain platforms employed in the energy sector.

Despite the fact that blockchain arises as a revolutionary application for P2P energy trading, it also presents some significant challenges. Most of them are related with security and privacy concerns as public blockchains are accessible for all the parties. Hence, novel solutions are needed to preserve anonymity and privacy so that energy usage data can not be traced by other individual users. In this regard, permissioned blockchain is emerging as a potential solution. Another relevant concern is the storage and processing of ever-increasing data that could not be handled with the current infrastructure capabilities. Last but not least, the role of transmission and distribution system operators (TSOs/DSOs) should be highlighted as key enablers of this revolution since they hold the physical infrastructure and operation of the system. They should support P2P trading platforms to permit a decentralised access to the power grid given the physical constraints, but they are not required to centrally manage the energy transactions [30]. Therefore, proper coordination between TSOs/DSOs and the other energy players is crucial to permit a reliable and rapid incorporation of this technology. Once these logistic aspects are overcome, the role of AI will be again highly relevant to suitably forecast the energy supply and demand so that early adjustments in the system can take place even before the trading starts.

Since blockchain-based P2P energy trading is nowadays not mature enough to be adapted by the mainstream as it is still in early development stages, sustained research and contributions are needed to take progressive benefits of its fullest potential at a social, commercial and energetic level. In this respect, next sections detail an entire procedure to implement a blockchain-based P2P energy trading mainly intended for regulated markets but still flexible enough to be adapted in a non-regulated context.

III. Pilot Platform Implementation

A. Physical and Virtual Networks

A P2P transactive energy scheme is comprised of two systems, the physical and the virtual energy networks. The former is responsible for the physical transfer of energy between peers. This could be achieved by a distributed grid network managed by an independent system operator (ISO) or also by a separate microgrid tied to a conventional grid. On the other hand, the virtual network provides the blockchain-based architecture for energy trading platform capable to handle all kinds of data transfer related to electricity generation/consumption and buy/sell offers. The bids have to be matched and accepted for the payments to then take place. Payments are made by consumers to prosumers in order to inject their renewable energy into the grid.

The present work intends to impart technical implementation details of a simple yet practical demonstration on how the energy trade occurs between the peers. Moreover, all the source codes later explained have been uploaded to the IEEEDataPort

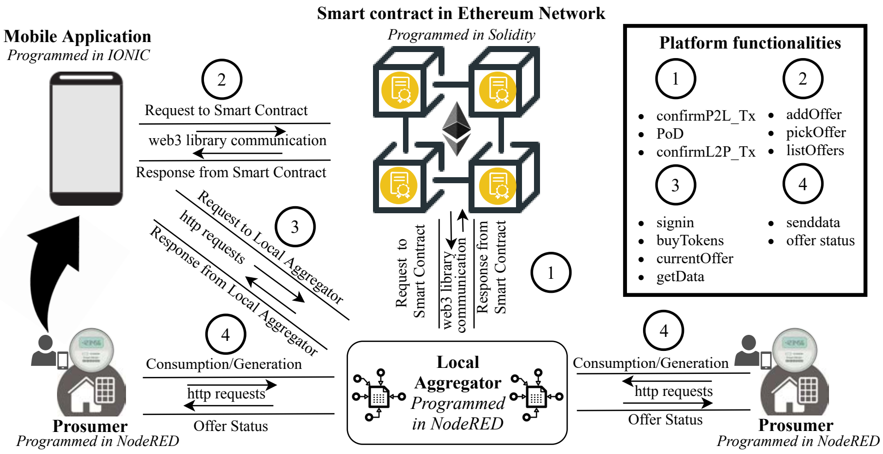

Fig. 1: Design Model of Blockchain-Based P2P Energy Trading using IoT Devices

To begin explaining the implementation, lets define the roles of the participants first:

1) Peers: They can be seen as the energy players who are selling or buying their surplus renewable energy . In turn they can be classified as:

- Consumer: A participant who merely consumes electricity.
- Prosumer: A participant owning a renewable energy system and thus producing and consuming electricity.

2) Local Aggregator: Wide P2P energy trading networks are usually divided into some communities where each of those possess its own local aggregator which acts as a broker and allows the peers within the community to trade electricity. Indeed, local aggregators buy tokens from public exchange and sell tokens locally to the participants on request.

B. Case Scenario

Considering the aforesaid, a simple scenario has been built under a regulated market scheme considering Peer A and Peer B as registered participants in our energy trade platform. To provide the participants an easy accessibility to perform the trading, a mobile application has been developed (the code of this app is also shared in the repository). The procedure is as follows:

- Peer A desires to sell his surplus energy. By means of our energy-trade platform he will make an offer through the mobile application.
- Peer B is interested in the offer and buys the energy via the mobile application.
- The local aggregator requests Peer A to begin exporting the energy while Peer B begins to consume energy.
- The local aggregator checks for the proof of delivery (PoD) making use of smart meter data on both ends.
- After PoD is confirmed, the local aggregator pays Peer A for the exported energy deducting the tokens

TABLE I: HARDWARE AND SOFTWARE TOOLS

HARDWARE
Raspberry Pi 3 Model B+ is used as smart meter installed at the user's dwelling. Initially, Arduino microcontroller was considered due to its compact size and tailored development features compared to Raspberry Pi. However, the latter exhibited better functionalities when dealing with Web3 library which is needed for communicating with the smart contract.
Leds and **Sense HAT 8x8 RGB LED matrix** (add-on board of Raspberry Pi) are used for indicating trading session and the energy transaction status.
Rotary potentiometers are manually handled to emulate the user's energy consumption/production.
MCP3008 chip performs the analog to digital conversion of the potentiometer's signals to be sent to the smart meter.
Local aggregator services are programmed in a server that stores the user's smart meter data. Additionally, the service encompass payment agreements, token exchanges and PoD operations.
SOFTWARE
Energy Web Foundation (EWF) - Tobalaba Test Network is employed to build and validate the smart contract. Moreover, EWF provisions the front-end Energy-Web UI user interface for creating accounts, define smart contracts and test these functionalities in the Ethereum Tobalaba network.
SQLite engine was used to create the smart meters and users database but also for performing data queries (insert, update, select) to the database.
Node-RED development interface permitted a flow-based visual programming for implementing the platform services such as local aggregator functionalities, smart meter - data server communication and smart contract interplay. Furthermore, Node-RED acts as back-end for the Ionic application.
Ionic is an open-source web application development environment. It was used to build the mobile application using Angular framework.
Web3 JavaScript API allows to interact with the Ethereum blockchain network. This library permits to retrieve user accounts, interact with smart contracts and send/receive transactions among other features.

C. Hardware and Software

During the state-of-the-art review, a variety of tools were explored and considered. Ultimately, the alternatives exposed in Table I were adopted.

IV. PROPOSED METHODOLOGY

A. Ethereum-based smart contract deployment

First of all, the Ethereum-based smart contract structure has to be deployed. This was achieved by means of the Energy Web Foundation (EWF) ecosystem. Indeed, EWF is the largest energy blockchain framework worldwide intended

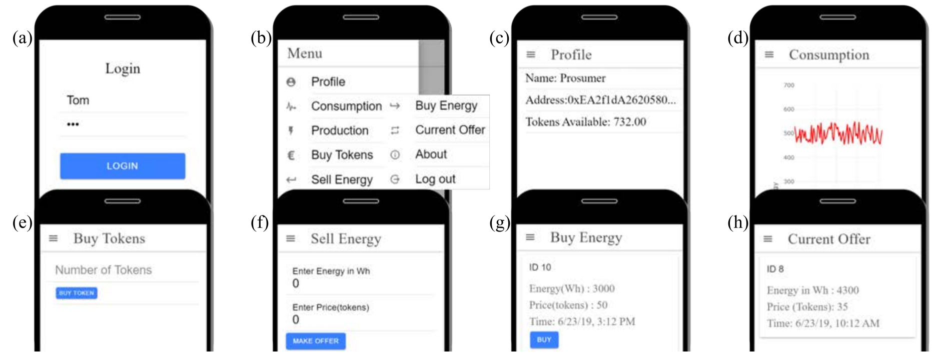

Fig. 2: Energy Trade Mobile Application Panels

TABLE II: ENERGY TRADE OFFER.

Structure of an Offer		
Size	Arguments	Details
4 bytes	ID	offer ID
20 bytes	seller	seller address
4 bytes	energy	amount of electricity for sale (Wh)
4 bytes	price	price of electricity for sale (tokens)
4 bytes	timeOffered	time when offer is added

and market needs [32]. To begin the implementation, from the EWF platform, Energy Web Client UI was downloaded and installed. This referred to a user interface which provides a desktop environment for connecting the peers in the blockchain network, creating accounts, sending transactions and interacting with smart contracts.

B. Accounts Creation

For the registered users and the local aggregator, Parity Ethereum wallet accounts were created using Energy Web UI. This environment redirects to Energy Web Tobalaba to issue fake tokens to developers for testing and deployment purposes regarding smart contracts.

C. Smart Contract Creation

Energy Web UI provides functionalities to develop smart contract. To implement the proposed scenario earlier described, the following functions of the smart contract were programmed using Solidity:

- `addOffer`: This function permits peers (prosumers) to create their offers by defining some details such as the intended amount of energy to be sold and its price. The structure of an offer is exhibited in Table II.
- `pickOffer`: If a peer (consumer) is interested in any offer, this function allows to confirm his choice and holds the offer in the system.
- `confirmP2L_Tx`: Now the status of the transaction (requested by the consumer to the local aggregator) is checked. Once the consumer payment is done, the confirmation is registered.
- `PoD`: The local aggregator calls this function to confirm the energy delivery by the prosumer, provoking the subsequent process.
- `confirmL2P_Tx`: This function confirms the payment made by the local aggregator to the prosumer

TABLE III: MOBILE PANEL VIEWS

Panel	Explanation
ⓐ	It contains the login access. As part of the back-end, the mobile application makes a `signin` http request to the local aggregator server. Once the credentials are validated, the user us redirected correspondingly to the menu.
ⓑ	It displays the general menu of all services provided.
ⓒ	It exhibits the profile page, where the personal user data (name, address, available tokens) is displayed so that a balance of the account can be inferred.
ⓓ	It provides the user with real time monitoring regarding the energy consumption/production. The mobile application makes `getdata` http request to the local aggregator server to have in turn the corresponding smart meter data.
ⓔ	It permits the user to buy tokens from the local aggregator.
ⓕ	In this panel, the user is able to make an energy offer invoking a specific function (`Add Offer`) of the smart contract so that details such as transaction ID, energy, price, time and user data are passed as arguments.
ⓖ	It shows the user a list of the different available offers with their details (as in the previous panel). The back-end demands the smart contract `list offer` function that in contrast return all the accessible energy offers. Once the user selects an offer, the `Pick Offer` function is recalled so that the user details are given as arguments. Then the offer is deleted from the overall list and energy price is transferred from the user account to the local aggregator account
ⓗ	It displays the selected energy offer being now in the transaction process.

D. Design Model

The proposed model was intended to create a practical demc of a local energy trading community under a regulated marke scheme. To do so, four main components can be distinguished: (i) blockchain-based smart contract, (ii) the local aggregator, (iii) smart meters and (iv) the mobile application service. The correlation between these components is sketched in Figure 1.

E. Advanced Metering

As earlier mentioned, smart meters are modelled with Raspberry Pi's (programmed employing Node-Red visual programming) and the user's energy generation/consumption are emulated with potentiometers. Moreover, the user's smart meters are registered in the platform with a unique ID. They send their measured energy information to the local aggregator server once per second.

F. Mobile Application

The platform front-end interface is provided by the mobile application and it consists of different panel views for the

G. Local Aggregator Server

Using Node-Red, the local aggregator services were programmed on a server. For further details, all the different program flows with their corresponding explanations can be found in [33].

V. Conclusions and Future Work

In this paper a simple but yet fully functional blockchain based P2P energy trading platform was presented and explained. All the code for developing the platform has been shared and the functionalities of the platform explained in detail. With this work the authors wanted to demonstrate how the whole trading framework can be implemented in a simple way using open source solutions. This work intends to be a stepping stone for researchers to investigate in this line. In future works we will add real advanced metering infrastructure with actual energy consumption/generation and more complex and automatize trading routines.

Appendix: Platform Code

The whole platform code can be downloaded from: http://dx.doi.org/10.21227/hc2g-9807

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B.5 Smart Contracts for Energy Apps: A Definitive Technology Stack

A Definitive Technology Stack for Development of Smart Contracts for Energy Applications

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***Abstract*—In recent years, there has been a growing trend in research on smart contract applications. Smart contracts potential in the energy landscape is visible in their major applications such as peer-to-peer energy trading, electric vehicle charging, energy market management, and many more. Many studies have been conducted that produced a lot of literature in this area and many startups and companies have surfaced that exhibit large scope of its application in the energy sector. However, in comparison to other domains, there is still more development required. The literature available focuses on the different technical aspects and use cases, but there is no such scientific article providing gathered details of the smart contracts development process that invites the attention of researchers in the energy domain for development or provides basic knowledge of available tools. It is therefore necessary to contribute with academic articles that summarize this information, thus opening up paths of development in this field and strengthening the community. This paper is the first step towards the implementation of this idea and that is intended to be extended in the future.**

***Index Terms*—Smart Contracts, Distributed Ledger Technology, Decentralised Applications, Blockchain, Energy Systems, Smart Grids**

I. Introduction

Digitization technologies are, in some form or another, causing waves of disruption across several industries. While some business sectors are making tremendous progress, others are just in the preliminary phases of the move to digital technology. The energy industry is one of the most dynamic industries out there. Innovative solutions that enable dependable and tamper-proof data and energy exchange are being sought after in order to improve self-consumption in local energy communities and assist in the implementation of increasingly dispersed control systems. This is being done in order to improve local energy communities. The current tendencies toward decentralization and digitization are the primary forces behind this initiative. In a similar vein, the anticipated growth of new forms of decentralized load (such as the widespread use of electric vehicles, for example) may provide the grid with the necessary flexibility, allowing, among other things, load shifting, peak shaving, and demand-side response. The fact that the system's existing operating paradigm is unable to handle and make use of the great majority of these minuscule dispersed assets is the source of the issue. These kinds of issues are the primary motivators for innovation and development in the electricity business. In order to improve the efficacy of their integrated operations and processes, modern power systems are beginning to use cutting-edge digitization technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and distributed ledger technology (DLT). DLT and its associated smart contract technology facilitates the creation of user-defined digital contracts that are capable of running specific functionality in accordance with predetermined terms and circumstances. With these characteristics, DLT has a significant potential to revolutionize the electricity systems and markets of the future. Additionally, smart contracts, which are significant components of the DLT ecosystem, are one of the facilitators of digital energy services and use cases.

There is a lot of ongoing research and development on smart contract decentralized energy applications, [1] and [2] contain a systematic review of more than 100 blockchain research projects and initiatives undertaken by companies and research organizations. Going through the literature review, it is observed that most of the works propose smart contract-based solutions for energy and flexibility trading (peer to peer [3], [14], peer to grid [4]), market design [5], distributed control(electric vehicle management [18], battery management [19]), grid management [20], [21], carbon audits and certifications [6]. Some research papers address standardization of smart contracts within the field of energy [7] and its role in digital green transition of energy industry [8]. However, it is noticed that there is no specific research publication that is dedicated to provide technical guide for development of smart contracts for energy applications. One must go through multiple platforms, blogs, or tutorials to gather information in bits and pieces required for developing smart contract energy applications. As the world is turning to open source platforms, there is also a need to add value to the academic literature to guide the use of these platforms in the creation of various energy applications. There is a need to globalize, attract and promote more smart contract developments in the energy sector and strengthen this development culture and community. This can be done by making an ultimate guideline for the developers/seekers to track the complete pathway for the development of smart contracts on different open-source platforms. This technical guide may provide ease to the developers or even beginners to decide which essential

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tools are required to start with or how they can contribute. The proposed research will include gathering and organizing authentic information to develop content for an ultimate resource leveraging educational and developers community, helping them to identify potential growth opportunities, to gain a specific or broad understanding of the process. In this regard, the authors already published our research work on how to simply develop and deploy a smart contract, however that was specific to the Ethereum platform [9]. This paper is intended to investigate more on the technical aspects of the smart contract's development that would add significant value in the literature related to blockchain smart contracts development in the energy landscape.

The rest of this article is organized as follows. Section II summarizes and discusses the applications of blockchain technology in the energy sector and identifies a number of research opportunities. Section III introduces a development stack for smart contracts energy applications. In section IV, privacy, security, and scalability concerns pertaining to smart contracts are discussed. Finally, the authors conclude this article in the last section along with future outlook.

II. Blockchain Smart Contracts in the Energy Landscape

Smart contracts communicate with the system when certain conditions are fulfilled and can automatically accomplish and manage energy trading events [10] or various other tasks. A hardware setup is utilized to handle data, verify conditions, deal with negotiations, and authenticate contracts. Smart contracts are designed to guarantee that all the energy, storage units, and network streams are automatically regulated and certify that the energy will be released/stored according to the required demand [11]. In addition, smart contracts can facilitate transactive energy by adopting some of its characteristic disputes, such as security and cost.

A. Smart Contract Benefits

In comparison with traditional contracts, smart contracts have several benefits for the energy sector. Smart contracts along with blockchain technology build a more reliable, transparent, and decentralized system, moreover, increase its security, efficiency, and other competencies as well in the subsequent aspects [12]:

- **Transparency and accessibility:** For all the blockchain members, smart contracts are accessible and transparent. Consequently, in the event of permissioned ledger a few users could be restricted, whereas in event of permissionless ledger, everyone can retrieve smart contract data.
- **Security:** Due to the prominent cryptography and blockchain features such as tamper-proof entries, the data cannot be altered by anybody, and their accomplishment is automated.
- **Speed and Reliability:** Smart contracts are small-sized codes, shared among the blockchain nodes that are executed under a specific situation in a well-defined, isolated environment. This characterizes high speed of response and verification. Moreover, high reliability is also ensured as code execution does not depend on a single server because of the decentralized architecture scheme.
- **Accuracy:** Built-in rules are defined and followed by the smart contract, significantly decreasing the possibility for error, and can be validated by third parties.
- **Cost:** Streamlined transactions will eliminate the middleman, thereby reducing the transaction cost. The smart contract owner contains the operation cost (i.e., smart contract deployed node).

B. Impact of Blockchain in Energy Sector

With the energy revolution, the blockchain application can transform the industry catalyzed by inventions comprising electric vehicles, smart metering, energy storage and heat pumps. In this context, the blockchain offers itself as the next evolving technology through its system interoperability and smart contracts to drive the energy sector growth. Moreover, distributed ledger technology enhances the efficiency of utility suppliers by following the chain of charge for grid items [1]. In addition, blockchain provides distinctive solutions for renewable energy distribution as well. Legacy energy sectors such as oil and gas companies are pursuing to devote and execute blockchain to diminish harmful environmental influences, lower costs, and enhance transparency without compromising privacy. Moreover, to cope with privacy and trade concerns, the private blockchain network provides data permissioning, specific parties access, and temporary solutions before the public blockchains employ the requisite privacy access businesses demand [13]. Smart contracts and decentralized software certified by blockchain can be employed to build a smooth, reliable, and well-distributed energy system capable of resolving up to 80 percent of these underlined difficulties.

C. Smart contracts Applications Areas in Energy Sector

Besides reviewing key aspects and benefits of smart contracts, and determining certain significant methods and stages needed in their execution, the authors offer a methodical evaluation of related applications in the energy field.

1) Peer-to-peer (P2P) Trading: P2P trading execution is employed by utilizing smart contracts. The smart contracts need credit from the consumer and get the bids and offers from distinct investors followed by empirical and complex methods to unite the consumer with the seller through a comparison among the amount of energy and received bids and offers [14]. These methods include double auction and power flow validation, which also help to reduce the cost of the Ethereum platform. However, smart contracts enable the transaction among peers and the grid when P2P trades don't deal with all the requirements of consumers or production from the sellers. Furthermore, at run time the matching of accessible energy with consumer energy demand is made beyond the blockchain [15].

2) Demand Side Response: In terms of flexibility, the stability between the accountable partners and investors can contract ancillary assistance to accomplish the energy trade and necessary balance. In the demand response event, a smart contract can determine and save the registered requisite and baseline profiles and utilize them to establish a contract between concerned consumers and investors [16], [17]. Smart contracts can use automated billing and payments to compensate or penalize buyers who meet the targeted load profile or not respectively.

3) Electric Vehicles (EVs) Charging Managament: Smart contracts can be employed for distinct purposes in the EVs area. Different optimizing algorithms are utilized by the smart contracts while accomplishing fair profit allocation between the owners of EV charging stations to steady the distribution of EV users [18]. By limiting the flexibility of EV loads, smart contracts are utilized for peak load shaving and shifting and allow P2P trading among EVs as well.

4) Battery Managament: Through smart contracts, distributed resources can be managed securely. Smart contracts can be used for battery control such as the distributed batteries' data can be collected including state of charge and health to prioritize the charging/discharging of distributed cases automatically by sending them recommendations [19]. Besides, a smart contract enables the management of domestic batteries to contribute in wholesale markets.

5) Grid Managament: At present, the improvement of Internet of Things (IoT) devices results in superior control, knowledge, monitoring of the grid, and the entire power system. In this aspect, when any fault arises in the grid, the data can be securely synchronized from the Phasor Measurement Unit (PMU) by employing smart contracts [20]. Furthermore, automatically managing actuators or getting control evaluations among inconsistent set point demands from various resources of the grid can easily be done through smart contracts. Considering the security features of smart contracts, they can be utilized to allow access to grid data as well [21].

III. Technology Stack of Smart Contracts Development for Energy Applications

As mentioned earlier, this is an initial step towards preparing an ultimate guide to help researchers and practitioners in the energy domain look for contribution opportunities in developing smart contract energy applications. Fig. 1 provides the stack of developmental stages of smart contract applications where each stage is explicitly covering essential elements, each featured with some prominent examples. This facilitates the developer to get relevant and direct information about each stage from relevant resources according to their requirements. This section briefly covers the introduction to some of the essential elements ranked in Fig. 1 that are required for the development of smart contract energy applications.

A. Development Essentials

1) Integrated Development Environments (IDEs): Smart Contract IDEs are designed to provide a source code editor for smart contracts compilation and migration scripts that fosters fast development and simplify the deployment of smart contract applications to the relevant blockchain. Remix IDE, Truffle and Hardhat are among the most popular choices of smart contract developers to create, compile, test, and deploy smart contract applications.

Energy Web (EW) chain is the blockchain built over Ethereum, which is tailored for energy applications. EW ecosystem provides a decentralized operating system with an energy web stack for the development of smart contract energy applications that is significant for new developers in the energy field to start with[1].

2) Languages: The programming languages commonly used for writing smart contracts are Solidity, Rust, and Vyper. Solidity and Vyper are compatible with Ethereum virtual machine (EVM) based smart contracts, while Rust is designed for non-EVM smart contracts. These languages are influenced by popular languages such as Java and Python, which helps new developers to adapt.

3) Wallets and Faucets: To identify oneself, and be able to transact, validate and authorize transactions over the blockchain network, a cryptocurrency wallet account is required. These cryptocurrency wallets stores cryptocurrency that is utilized for developing, testing, and deploying smart contracts applications over the network. Multi-signature wallets analogous to joint bank accounts are also used for more secure operations. Various platforms provide free cryptocurrency facility for the testing and development of smart contracts through their channels called faucets.

4) Libraries: Open-source smart contract libraries are available for developers that offer ready-to-use building blocks or reusable functions and implementations of various standards. For instance, OpenZeppelin is a well known standard library for Solidity and offers packages for multiple functionalities which assist developers in deploying decentralized applications by adding new functions to smart contracts.

5) Oracles: Oracles serve as bridging entities to external systems for the smart contract as they enable external inputs data ingestion, off-chain computation, and sending outputs to external systems and inter-operate across blockchains. ChainLink is one of the widely used blockchain oracle in the development market for hybrid smart contracts. These hybrid smart contracts can enable the connection of existing energy infrastructure and data such as consumption profiles, IoT sensor output, and weather information, allowing renewable credits, ownership certifications, and much more.

6) Testing: Smart contracts are immutable in nature therefore prior to deployment, quality assessment is required to identify any errors or vulnerabilities that may cause computational complexities and costs. Therefore detailed evaluation of smart contracts is carried out with functional testing[2] that is categorized into unit testing, integration testing, and system testing.

7) Security and Auditing: Along with functional testing, security analysis and audits of smart contracts are crucial before deployment over the blockchain. Security analysis is

[1]https://www.energyweb.org/tech/

[2]https://ethereum.org/en/developers/docs/smart-contracts/

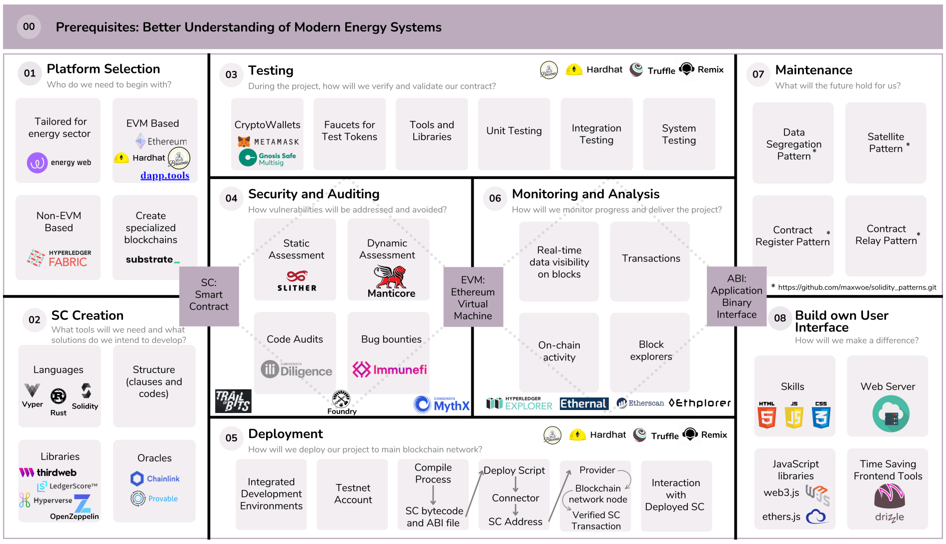

Fig. 1. Technology Guide Stack for Smart Contracts Development for Decentralised Energy Applications

composed of two automated testing tools named static and dynamic analysis. These procedures employ different approaches to identify any present security vulnerabilities or defects in the developed smart contract code and help improve quality and efficiency.

There are two types of manual testing tools[3] that can be used to audit smart contracts. One is a code audit that can be automated or human-aided analysis of the code to detect poor development, security flaws, and failure points. The other type is a bug bounty program that is outsourcing audits to the wider developer community to get rewarded for catching bugs. Examples of each type are presented in Fig. 1.

8) Deployment: After compilation, testing, security analysis, and auditing, the smart contract is deployed on the blockchain network. The steps involved in deployment differs based on the platform used for development. For most EVM smart contracts, a deployment script is prepared using bytecode and ABI files generated from smart contracts compilation which is then translated by Web3 to Javascript terms which are then communicated to an Ethereum node, either by running its own local node, connecting to a public node or via an API key using a node service like Infura or Alchemy.

9) Analysis and Monitoring (Block Explorer): After deploying smart contracts over the network, developers can visualize and confirm transactions on the block explorers provided by the development platforms. Block explorers may have many in-built services and distinctive features such as real-time and historical information, data related to blocks, transactions, addresses, and more. It enables the developer to monitor and analyze their smart contract performance. Etherscan is one of the biggest free block explorers of the Ethereum blockchain. Ethplorer and Etherchain are also in competition.

10) Maintenance Tools: The developer community has figured out many maintenance patterns for the deployed smart contracts. There can be maintenance issues with the smart contract that may charge developers heavily later on. Therefore, developers need to thoroughly evaluate their smart contracts to acquire such patterns and devices more so in case of advanced level. This is an evolving field therefore developers need to be updated.

11) Front-end Utilities: Developers have the opportunity to build their user interface and add advanced front-end functionalities to their smart contract applications. However, basic practice and skills in CSS, HTML, JavaScript, and frameworks such as Angular or React are mandatory. Truffle suite offers Drizzle which is a collection of libraries that simplify building application user interfaces. Moreover, JavaScript libraries such as web3.js and ethers.js have risen in popularity for defining front-end functionalities.

IV. Privacy, Security and Scalability Concerns

The implementation of smart contracts in the energy domain leads to several challenges including privacy, security, and scalability issues. For instance, leakage of private-public keys, analysis of transaction patterns revealing user information (such as real identities, activities, assets, and energy profiles),

[3]https://ethereum.org/en/developers/docs/smart-contracts/

reputation, manipulation, and service based attacks highlight some of the prominent security breaches and privacy violations. Discrepancies in a smart contract may also attract malicious attacks. Quantum attacks are another potential risk to encryption schemes. Some of the solutions that are proposed to provide immunity to these attacks include private or consortium blockchain with temporary session keys, public-key encryption with time stamps, use of lattice-based signatures, and physical layer security [23]. Furthermore, in the last few years, the US and EU have made several laws and legal frameworks to govern how data is shared and kept safe. Such a legislative framework aims to safeguard private persons' data privacy. The most important data processing activities which are subject to protection are data collection, processing, storing, and deletion. With this regard, it is essential to make sure that processed energy-related data that is transacted via DLT is processed in compliance with international norms and regulations.

Moreover, higher adoption of distributed energy resources in the energy industry results in scalability issues, requiring increased storage, high computational power and throughput, low latency and secure communication to execute proportionally increased energy transactions and system operations. The incorporation of AI, 6G, and big data technologies with blockchain schemes are considered to be promising solutions to meet these requirements. Moreover, some typical methods that are identified to overcome scalability issues related to DLTs include the utilization of the payment channels, sharding technique, layer 2+ solutions, sidechains, and directed acyclic graph-based DLTs. These solutions have still not reached the level of maturity in the research as well as in practical implementation, therefore requiring further investigation.

V. Conclusion and Outlook

DLT-based smart contracts could radically simplify energy system operations and its decentralized capabilities would enable an entirely new energy system. This is the time to accelerate developments in this domain and to do so technical guidelines must be prepared that motivate energy experts to take interest in developing smart contract energy applications. This paper presents an illustrative technology stack for smart contract development that is a step-wise guide to help beginners and developers build energy applications. This is an initiative to promote the culture of energy smart contract applications development and to build a strong developers community working on decentralized energy applications. Further advancements are intended to be included in this work in the future that may involve a more detailed view and granular knowledge of various aspects of this technology stack.

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Appendix C

Book Chapter publication

C.1 Block Chain Technologies in Smart Power Systems

The use of block chain technologies in smart power systems

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Abstract

This article aims to explore the benefits of blockchain technologies in regards to smart power systems. The diverse background of blockchain applications will be discussed to understand the potential of this technology. The article will address the driving factors for adoption of blockchain in power sector. The main aspects of blockchain technologies will be briefly summarized. Moreover, the prominent blockchain use cases and applications in the field of smart power systems will be explored along with the future challenges pertaining to the adoption of blockchain technologies in the mainstream.

Overview of blockchain applications

Blockchain received its popularity worldwide for its cryptocurrency like bitcoins. However, in reality Blockchain has a wide range of features and applications far more than bitcoins. There are generations of Blockchain technology, Blockchain 1.0 is the first generation which enabled digital cryptocurrency transactions like bitcoins, Blockchain 2.0 extending beyond cryptocurrency with the introduction of smart contract technology enabling automated society with the concepts of Decentralized Applications (Dapps), Decentralized Autonomous Organizations (DAOs) and Decentralized Autonomous Corporations (DACs) whereas Blockchain 3.0 intends to improve the capabilities of Blockchain 1.0 and 2.0 and the integration of services such as machine learning onto a blockchain for advanced tasks (Lu, 2019).

In general, Blockchain has a vast array of application fields as it holds potential to disrupt the economic systems, commercial and industrial sectors, governmental structures, taking them to a whole new levels of efficiency and effectiveness. This promising technology can bring ease to sustainability, environmental and human development initiatives. Blockchain can introduce transparency to the corrupt systems and improve the commercial processes with its verifiable and immutable digital ledger technology. It can protect critical infrastructures providing them resilience and security. Blockchain can ensure individual autonomy while preserving privacy and promotes cooperation with trust as per requirements. Precisely, blockchain may improve system in which individuals require to store or access data, send or verify it. This data could be any information such as a person's identity, record of a product's shipment, transaction or any digital asset (U. N. D. Programme (UNDP), 2018).

The amalgam of properties such as decentralization, immutability, transparency, enhanced security and distributed ledger, makes it a promising technology across a wide range of use cases ranging from financial technology and supply chain management to digital rights and healthcare. In banking, blockchain can provide secure transaction and immutable record keeping. In supply chain and logistics, it can add transparency. In energy sector, it can enable decarbonization and issue green energy certificates. In healthcare system, blockchain can provide secured electronic health records in a distributed way. With advanced smart contracts offered in Blockchain 2.0, processes between several parties can be codified or programmed to execute automatically under preset conditions defined. This feature enabled development of many advanced applications such as crowdfunding, energy trading, e-Voting and so on. Moreover, there are numerous research institutes that are increasingly collaborating on open source platforms development to encourage innovation. Open source platforms provide opportunity to design, develop, test and deploy blockchain applications, with greater flexibility and freedom. This aspect can scale the potential of blockchain applications to a global context. Government and banking systems are also taking interest to learn and participate in the blockchain environment. Academic, public and private institutions are collaborating to combine political power, commercial experience, technical capabilities and research fundings, to create a strong partnership.

In coming years, a series of open source platforms will enable development of wide range of blockchain applications particularly in the energy sector. The use of blockchain technologies for smart power systems brings autonomy, decentralization, traceability, asset management, distributed peer to peer energy trading, democratization and cyber security. The trusted distributed consensus algorithm of this technology eliminates the dependence over intermediaries or third parties. Blockchain can empower the market participants to make secure and transparent energy transactions directly with each other. Blockchain can complement other advanced technologies such Internet of things that may potentially improve market operations, grid management and operations, billing and metering processes. The cutting-edge cryptographic security benefits of blockchain may assist in transforming conventional centralized power systems toward more decentralized and resilient power systems with improved security, trust and privacy. The power grid of the future will create significant opportunities for blockchain applications with new operational flexibilities to achieve the efficiency, security and resilience of the power system.

Motivation of applying blockchain to smart power system

The paradigm shift of the power systems from large power plants running on conventional energy resources (fossil fuels, coal, natural gas) toward meeting decarbonization goals and policies which includes large scale deployment of the distributed energy resources, energy storage devices, controllable loads, electric vehicles, is pushing forward some challenges to the existing power systems which mainly includes (Wang et al., 2019):

- **Centralized management system**: system operators control power supply to manage the fluctuating energy demands but now there is addition of fluctuating energy supplies i.e., varying RES which makes the management more complex.
- **Complex Electricity transmission**: Traditional power systems have relied upon unidirectional power flow from centralized generators to decentralized consumers. The distributed energy production makes the power system vulnerable to bidirectional variable flow of electricity which challenges the grid capacity.
- **Minimal real-time information**: Grid operators require real time information about the distributed energy production by prosumers (DERs owners), to monitor local imbalances between supply and demand at distribution level and harness demand flexibility. Therefore a bidirectional communication system between operators and prosumers is required.
- **Complex Transactions**: Transactions among grid operators, markets, utility, consumers and prosumers (DERs owners) becomes complicated to be managed in a centralized structure.
- **Grid and Market Architecture**: Prosumers need access to the energy markets to participate in energy transactions and assist in grid stability which requires a new grid and market architecture.
- **Risks and Threats**: The stochastic nature of DER production imposes risks on the system equilibrium if not managed properly. Centralized architecture is vulnerable to physical threats and cyber attacks.

The smart grid concept has been introduced in the last decade as a new vision to the traditional power grids. Smart grids bring together smart metering, communication technology, advanced control techniques and interconnected power system, to support bidirectional power and information flow with efficient operational management and integration of DERs. Currently, most of the smart grid models are built on centralized architecture where grid components are dependent on intermediaries or centralized platforms for operations such as monitoring, billing, bidding, energy trading and more. In order to facilitate the large scale integration of continuously growing number of EVs, distributed and scalable energy resources, the grid itself is adapting and shifting from centralized topology to decentralized and autonomous network thus enabling enhanced interaction among the grid components. With the help of Energy Internet concept, smart grid market is transforming from centralized governed prosumers network to decentralized autonomous prosumers network (Mollah et al., 2021).

In this regard, blockchain technology finds an opportunity to support this transformation toward decentralized systems due to its following beneficial properties which makes its application a suitable fit.

- **Decentralization**: Blockchain is maintained by a network of decentralized nodes through a consensus mechanisms. It has a distributed peer to peer network structure which doesn't need to trust or rely on a central authority/intermediaries for authorization and maintenance, instead trust is distributed among the nodes of the network.
- **Immutability and Data Security**: All the records, transactions, events, and logs inside the blocks are secured using cryptographic techniques and public key signatures ensuring data confidentiality. Moreover, the blockchain is copied and synchronized among the nodes thus making it an immutable ledger where data can not be tampered unless majority of the nodes comes out to be malicious.

- **Transparency**: Blockchain technology keeps the track record of all transactions or logs into immutable and transparent ledgers which provides easy traceability for different purposes such as auditing, compliance.
- **Local Energy Markets**: Blockchain may disrupt the current market operations as it enables local customer-oriented markets to support peer to peer energy trading. This may result into improved economics for local energy producers and consumers who can make flexibly sell or buy practices under this platform depending on their preferences and needs.
- **Scalability and Resiliency**: Distributed architecture of blockchain is capable of scaling up the network, allows multiple and many entities to join the network. Decentralized architecture of blockchain brings resiliency since there's no point of failure and the entire chain is copied to all nodes in their premises. Using one of the best consensus mechanism design, blockchain technology ensures a resilient network where any fault or malicious activities can be determined and recovered.
- **Automaticity**: Blockchain based smart contracts which are automated executable scripts or codified tasks under predefined criteria. These contracts are stored on the blockchain which executes independently without intervention of any human, broker and central authorization.

Main aspects of blockchain technology

Blockchain, firstly introduced in (Satoshi and Nakamoto, 2008), is a decentralized, distributed and digital ledger technology. Named for its data structure, these are the blocks of stored collection of data or information encrypted and are linked together in a chain cryptographically as depicted in (Fig. 1) so that data can not be tempered or forged. The collection of data or transactions are added to the ledger upon verification through a consensus mechanism. Each block is assigned with a unique identity called cryptographical hash just like as finger prints are for human identification. Each block contains cryptographical hash of the previous block except the first block known as genesis block. The chain starts from genesis block, the hash of this block becomes the previous hash of the next block, hence the chain continues. A block contains a header and a payload, the header includes timestamp, previous and current block hash, mining details (nonce) while a payload includes set of data or transactions. The cryptographical linking of blocks makes it tamper proof because any modification in a block changes the cryptographical hash which does not match with previous hash saved in the proceeding block and thus the chain becomes invalid. The blockchain is replicated to all the nodes across the network which is continuously synchronized and updated through consensus mechanism.

Smart contract

It is a computer script which is deployed and stored in a blockchain. Smart contract follows "If this, Then that" functionality which means when a certain input or event occurs, some action is executed automatically according to the script. In contrast to a legal contract, smart contract consist of codified terms and conditions of agreement upon which involved parties interact with each other. Smart contracts once deployed on the blockchain, executes independently and automatically without any centralized control. Among other blockchain platforms with smart contract functionality, Ethereum is the most actively used platform.

Consensus protocol

In a decentralized blockchain network, nodes making transactions and creating blocks must also participate in validating the blocks to be added to the chain following a consensus algorithm. Since there is no trusted centralized system to make such authentication, consensus among nodes is required. In order to reach such an agreement, various consensus mechanisms have been proposed which holds common purpose but are different with respect to the entity adding blocks, blocks generation rate, and strategy adopted to implement consensus. Consensus mechanisms involve a difficult problem or puzzle to solve generally called "mining" for creating blocks, and validation process. Some prominent consensus protocols developed so far are introduced below.

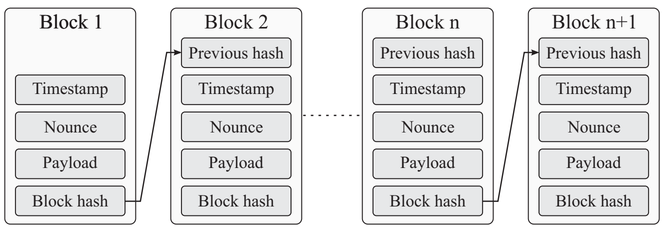

Fig. 1 Structure of blockchain.

- **Proof of Work(PoW)**: This consensus algorithm is used in blockchain 1.0. All nodes (miners) in the network try to solve a very difficult cryptographical puzzle using their computational power. The node (miner) who finds first the solution receives reward (financial incentive) and the chance to create block then broadcast it to the network to be verified by the others node. On validation from all nodes, the block is appended to the chain. Due to significant electricity expenses on computation, majority of the mining is centralized in the areas where electricity is cheap. However, blockchain needs more energy efficient and less centralized consensus protocols. Therefore, some other consensus protocols as better alternatives have been explored and being adopted by several blockchain platforms.
- **Proof of Stake(PoS)**: One of the viable alternative to PoW is PoS in which the nodes rather than investing their computational power, holds the stake i.e., cryptocurrency in the blockchain network. PoS secures the membership of these stakeholders and grants them chance to mine a block. Stake amount and the time of membership, are effective factors for winning the chance to create the block. A new created block then goes through signing process and verification by other member nodes. Based on majority vote the block is then added to the chain. Peercoin, Tezos, Tendermint and Ethereum's Casper, are few of the blockchain platforms which has utilized this consensus mechansim. Some blockchains for example Ethereum and Power Ledger are shifting from PoW to PoS.
- **Proof of Authority(PoA)**: This consensus protocol can be think of a modified form of PoS. In this protocol, one or more authorized members of the network have special permissions to validate or sign the block to be added to the chain. These validators are chosen by voting and their stake is their own identity. Although it seems centralized approach suitable for governing structures, it is becoming popular in energy sector with utility companies. This method can be useful for the applications where security and trust can't be put at stake. Energy Web blockchain has utilized PoA with which they achieved 30 times more network capacity than ethereum and faster execution.

Other than these popular and extensively used consensus mechanisms, there are several other protocols developed so far which includes Practical Byzantine Fault Tolerance (PBFT), Proof of Burn (PoB), Proof of Elapsed Time (PoET), Proof of Capacity (PoC), Delegated Proof of Stake (DPOS), Proof of Space (PoSp), Proof of Activity (PoAc), Proof of Ownership (PoO) which exhibits different strengths for particular configurations.

Types of blockchain

Based on accessibility, permissions and modification capabilities, there are mainly four different types of blockchain.

- **Public Blockchain**: These are fully decentralized and open to the public. Every node of this network is able to access blockchain, make transactions and participates in a consensus mechanism. Due to these properties, public blockchains are widely used. These blockchain commonly implements PoW and PoS as consensus algorithms.
- **Private Blockchain**: This type of blockchain allows only its owners to access, write and verifies the transactions. Owners could be a group of individuals or a company. Other network nodes have limited access to private blockchain. With restricted permissions, a great level of privacy can be achieved. Moreover, this type offers cheaper transactions and faster consensus process. Private blockchains are useful for internal processes of any organization e.g., auditing, database management, intranet. PBFT and Raft are most commonly used consensus algorithms in private blockchains.
- **Permissioned Blockchain**: Only authorized nodes maintain this blockchain however it may restrict access to read and send transactions. Thus, this type of network may allow anyone read access and issue transactions to the blockchain or restrict it to only authorized nodes. This feature is useful for the organizations which requires to work with business partners but doesn't trust them fully. Permissioned blockchain provides transparency and holds accountable misbehaving nodes. Consensus mechanisms used in these blockchains are computationally faster and less expensive.
- **Permission-less Blockchain**: These are decentralized ledger open source platforms accessible to all nodes creating blocks, where they may read and write to the blockchain. There is no permission required from specific authorized nodes. To avoid malicious attacks, consensus mechanisms such as PoW and PoS are utilized. Moreover, nodes publishing blocks are rewarded with cryptocurrency to promote non-malicious behaviors.

Other concepts of blockchain type such as hybrid and federated blockchains have also come into view however there is no proof of concept developed yet.

Use cases and applications of blockchain in smart power systems

When blockchain technology intersects with smart power systems, various potential applications come into existence. Most of the current blockchain projects are focused on different domains of power systems such as peer to peer trading, grid management and operations, financing development of renewable energy sources (RES), RES management and certification of origin, wholesale energy trading for utilities and energy system stakeholders, electric mobility. Blockchain applications in the power system are extremely diverse. Blockchain mainly provides data storage, trading and energy financing services to the power sector under which these applications can be classified. Applications that fall under the category of "Data Storage" includes asset registration, billing and operations and energy certifications. Under the category of "Energy Trading", there exist blockchain applications such as peer to peer energy transactions, operation flexibility, Wholesale energy market. While "Energy Financing" includes applications such as Fundraising, Energy tokens.

Asset registration

Ownership and related transactions can be documented with blockchain distributed ledger technology which offers secure storage of ownership records in a tamper-proof and decentralized way. It can regulate the ownership and management of energy assets such as smart meters, renewable energy generation units, batteries, electric vehicles charging stations, thermostat. Energy assets can automatically be registered with a blockchain ledger of identities, which enables operational flexibility of these assets for grid services in particular frequency regulations, reactive power support. Moreover, owing to the transparency and traceability properties, blockchain supports audit trail from the registration of the energy asset and ownership record to the sale or transfer and credit claim.

In the pilot, existing rooftop solar customers would be able to automatically record their generated energy credit data to the Energy Web Chain. recorDER (formerly DER Asset Register) is a blockchain based shared register developed jointly by UK power networks and Electron, for transmission and distribution system energy resources (assets) standardized for system operators.

Billing and operations

Blockchain technology integration with smart metering infrastructure, provides opportunity of automated billing and gives autonomy to the consumers as well as prosumers over their meter data and electricity supply contracts. This brings a significant disruption in traditional metering and billing processes, adding transparency and traceability. Removing the service charges of intermediaries or central authorities (energy metering and billing companies) and data security concerns, the blockchain enables anonymous P2P transaction on decentralized platforms. Smart meter data can be secured with distributed ledger technology and shared with DSOs, TSOs or other stakeholders for better management and planning of power system network.

Moreover, blockchain technology enables the automatic billing at EV charging stations. EV drivers can park their car which can autonomously connects to EV charging station and recharged automatically, later the charging station automatically bill them for the used electricity. LO3, USA based company, introduced transactive grid smart meters which transmits data directly to users accounts in blockchain.

Energy certificates

Due to the fragmented and complex market structure and highly expensive procedures small scale prosumers are unable to claim renewable energy certificates or carbon credits. In this respect, blockchain technology has been focused on automatic issuance of energy certificates demonstrating the provenance of renewable energy and creating supportive markets. Blockchain offers immutable, transparent and reliable record of generation and transaction of certificates. Moreover, blockchain enables tracking the energy production fast, deep and more accurate than traditional methods could. Advanced incentive schemes could be codified in smart contracts which automatically executes on the blockchain.

Energy Web Foundation is developing Energy Web Origin which is a state of art toolkit for energy markets around the world that facilitates in recording provenance of renewable energy generation and automatic tracking its ownership. This toolkit is open source that supports any green energy attribution systems.

P2P energy transactions

One of the prominent blockchain applications in the energy sector is the peer to peer energy trading covering one-third part of all blockchain initiatives in the power system. Blockchain provides a decentralized energy trading market infrastructure which enables consumers and prosumers to trade energy directly and take control over their consumption and generation. This platform can also be functional for existing distribution grids, where it can be administered by a utility or a retailer, or it can be centrally managed by grid operators DSO or TSO that matches buyers and sellers to provide technical support to the grid. However, decentralized platform provides more identity privacy and secured transactions as compared to the traditional centralized approach. Other advantages include low cost transactions, reduced volumes, intermediary omission, increasing transparency for all participants while maintaining required data privacy and integrity would encourage more participation and faster adoption of DERs.

Power ledger, Australia blockchain startup presented two energy trading models, a retail model for existing regulated market structure as well as direct peer to peer model for the deregulated markets. Large group of companies, startups and organizations are focused in this field, the prominent ones such as Verv, LO3, Grid+, Powerpeers have shown great achievement toward development of peer to peer energy trading platforms.

Wholesale energy market and operation flexibility

Blockchain technology holds the potential to revolutionize wholesale energy markets including regulated or deregulated bilateral markets by reducing counter party associated risk and bringing transparency while preserving the privacy aspect. Blockchain provides solution to trade confirmation and reconciliation issues pertaining to wholesale energy trading. Since, these issues are currently managed by counterparties (trading offices) via emails and fax. Blockchain technology introduces decentralized ledgers which holds the log of trade, shared among trading offices therefore, traders no more required to store data individually. Counterparties can reconcile and verify the transactions in real-time on blockchain. With this system, workflows become efficient and human error significantly reduces. Moreover, it allows convergence of market mechanisms and system operations enabling better resource management to provide operational flexibility and incentivizing renewable energy generation, storage and demand response.

Multi energy trading firms are jointly developing EnerChain, blockchain based P2P trading platform to complement the whole sale energy market which can also be fully replaced with this platform.

Fundraising and energy tokens

The second largest category of blockchain initiatives in the power system is the use of blockchain cryptocurrencies to raise funds for the energy projects. Energy tokens are created using blockchain cryptocurrency facilitating secured investments and assets co-ownership for the ventures in green energy projects. Many startups e.g., WePower, Sun Exchange conducted cryptocurrency token sales to crowdfund for renewable energy projects. These sales are recorded in their respective blockchain platforms and once the project begins operation, the token owners are able to use the services at discounted rates or sell the tokens with profit. Their blockchain platforms keep the track of ownership and generated revenues are automatically transferred to investors through smart contracts. Similarly, SolarCoin a blockchain cryptocurrency introduced to incentivize the renewable energy production, the company aims to monetize the global solar energy production in future. Moreover, these cryptocurrencies can be exchanged for fiat currencies or other cryptocurrencies.

These are just few prominent projects mentioned (as in Fig. 2) infact there is an extensive research and development in progress under the collaborations of various companies, foundations, industries and academics. The latest statistics of all the blockchain projects development in power sector are documented in IRENA report 2019 (Sean Ratka and Anisie, 2019). Moreover, a survey (Andoni et al., 2019) has tabulated the details of around 140 blockchain based energy projects including their field area, platform used, consensus mechanism applied and locations of deployment.

Development tools for blockchain-based energy applications

Different organizations are focusing on building several collaborative open source platforms in order to explore more potential blockchain applications in power sector. One of the largest blockchain platforms, Ethereum provides framework that enables developers to build decentralized blockchain applications (Dapps). One of the prominent organization, Energy Web Foundation (EWF) built Energy Web Chain on top of ethereum core technology that aims to accelerate the blockchain technology adoption across the energy space to achieve a resilient, decentralized, decarbonized and democratized energy system. EW chain is an open source, publicly available blockchain based software infrastructure, on which decentralized blockchain energy applications are built and run. This blockchain platform is specially designed for energy sector's regulatory, operational, and market needs. Based on ethereum, with some adjustments it achieved high scalability, low transaction costs, and energy consumption, using permissioned Proof-of-Authority consensus mechanism. EWF launched "Volta" a public test network of the EW chain. This test network is useful for the developers to develop, test and deploy applications before production. There are some useful tools for the beginners for developing Dapps (Fig. 3).

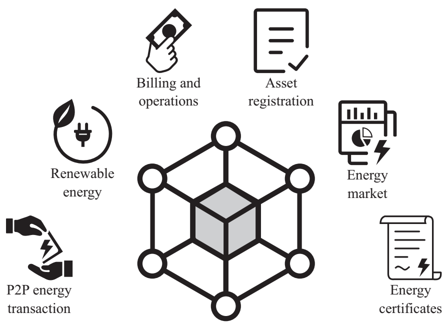

Fig. 2 Use cases of blockchain.

Metamask

Metamask provides user a crypto wallet account and a gateway to blockchain. Using remote RPC(remote procedure call) protocol given by EWF, metamask connects the user to the volta test network without need of setting up a local node.

Volta faucet

Test tokens "Volta Ethers" are facilitated for the users or developers to make transactions on Volta in order test their applications. These are not real cryptocurrency but specifically design for testing purposes on Volta test network.

Remix IDE

Open source tool for writing smart contracts directly from the browser. It provides a solidity compiler as smart contracts are written using solidity which is a Javascript like general purpose programming language, designed by Ethereum core contributors. Remix IDE has modules for debugging, testing and deploying smart contracts.

Web3.js

A JavaScript API(application programming interface) is a library which is a collection of modules that enables interaction with the blockchain i.e., send transactions, get account balance, address, and interact with smart contract.

Volta testnet explorer

To examine smart contract deployment, blockchain transactions and activity. EWF provides Volta testnet block explorer which is derived from an open source block explorer for Ethereum based networks. It provides user-friendly interface to search, view and confirm transactions, accounts, balances, verify smart contracts.

For further understanding (El-Sayed et al., 2020), can be reviewed which provides useful details to implement a simple pilot-platform for energy trading based on blockchain technology.

Challenges of applying blockchain to smart power system

The large number of blockchain based energy projects and research initiatives, as well as investors interest in this area reflects potential value of blockchain technology for power systems. However, most of the projects are still proof-of-concept, some are in the development phase while some of them have trialled the technology on a small scale. Tangible benefits of blockchain in power systems are yet to be seen. These facts gave rise to many challenges in the way of mainstream adoption of blockchain technology in the power systems.

- Lack of acceptance could be a possible concern because blockchain technology doesn't posses its long term value i.e., long term usage and experience. Therefore, it may take time to be adopted at a large extent.
- Legal rules and regulations are still required to be standardized for blockchain in the energy sector e.g., contract laws, energy laws, data protection, to resolve any conflicts and disputes. Regulatory frameworks need to be revisited to allow adoption of blockchain technology at large e.g., in several P2P energy trading projects, generally the current regulatory frameworks restricts trading between consumers. Moreover, blockchain API needs standards for interoperability with other technologies. Data protection regulations are yet to be clarified.
- Distributed energy markets will result in high number of energy transactions that may complicate the scheduling mechanism, impose requirements of storage and transmission capacities inducing high computation and communication costs. Blockchain

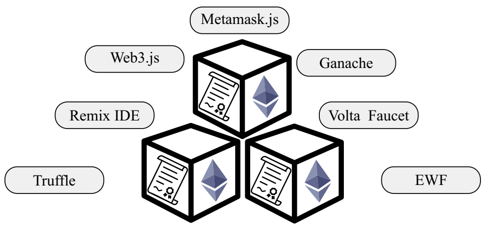

Fig. 3 Development tools of blockchain.

scalability and performance issues may arise with the increased number of nodes in the network that may cause delay in the verification process due to difficulty in reaching consensus and also put additional (hardware and energy) costs of increased data storage. However, transition to improved consensus algorithms such as PoS, PoA in future may reduce these costs.

- Various cryptographic algorithms that are used for encryption, essentially makes the blockchain secured technology. However, if powerful quantum computers cracking these highly developed encryption become reality then blockchain technology will likely adopt quantum-safe encryption. However, old data will be affected.
- Some security concerns still exist e.g., programming errors in smart contracts may expose blockchain to the possibility of cyber attacks. Moreover 51% attacks may happen, if attackers form 51% nodes of the network, they can create malicious blocks. Therefore, blockchain developers are working for smart contract security and efficient consensus mechanisms that are resistant to these attacks.
- Immutable ledger technology makes it difficult to make changes to the code once deployed and require great effort. Therefore a middle way must be allowed to remove any discrepancies where vote of majority of nodes with standard regulations must approve new version.

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Relevant websites

Energy Web Volta Testnet Faucet, voltafaucet.energyweb.org.
Metamask, metamask.io.
Remix IDE, remix.ethereum.org.
Volta Testnet Explorer, volta-explorer.energyweb.org.
Web3.js—Ethereum JavaScript API, web3js.readthedocs.io.

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