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Multi-Objective Optimization of Steel Off-Gas in Cogeneration Using the ε-Constraint Method: A Combined Coke Oven and Converter Gas Case Study

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Abstract: Increasingly demanding environmental regulations are forcing companies to reduce their impacts caused by their activity while defending the economic viability of their manufacturing processes, especially energy and carbon-intensive ones. Therefore, these challenges must be addressed by posing optimization problems that involve several objectives simultaneously, corresponding to different conditions, and often conflicting between. In this study, the residual gases of an integral steel factory were evaluated and modeled with the goal of developing an optimization problem considering two opposing objectives: CO_2 emissions and profit. The problem was first approached in a mono-objective manner, optimizing profit through Mixed Integer Linear Programming (MILP), and then was extended to a bi-objective problem solved by means of the ε-constraint method, to find the Pareto front relating profit and CO_2 emissions. The results show that multiobjective optimization is a very valuable resource for plant managers' decision-making processes. The model makes it possible to identify inflection points from which the level of emissions would increase disproportionately. It gives priority to the consumption of less polluting fuels. The model also makes it possible to make the most of temporary buffers such as the gas holders, adapting to the hourly price of the electricity market. By applying this method, CO_2 emissions decrease by more than 3%, and profit amounts up to 14.8% compared to a regular case under normal operating conditions. The sensitivity analysis of the CO_2 price and CO_2 constraints is also performed.

Keywords: multiobjective optimization; ε-constraint; off-gas; steel gases; cogeneration process

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1. Introduction

The iron and steel industry is one of the largest energy consumers and is, therefore, also responsible for approximately 25% of the direct greenhouse gas (GHG) emissions of the global industrial sectors [1]. 1.1 Gt and 2.6 Gt of indirect and indirect CO_2 emissions, respectively, are caused by this industry [2], representing almost 9% of the total energy and global CO_2 emissions [3]. The steelmaking industry's world crude steel production in the year 2019 reached 1869 million tons (Mt), the energy intensity 19.84 GJ, and the CO_2 emissions of 1.83 GJ for each ton of crude steel cast [4].

To drastically reduce total CO_2 emissions from steel production, the development of innovative technologies is essential. Currently, a large number of innovative technology projects are being carried out in the most varied parts of the world [5]: ULCOS program in EU [6]; SALCOS in Germany [7], COURSE 50 program in Japan [8], among others. Some projects are in the initial research phase, while others are in the pilot or demonstration phase [9]. Although their goals are similar, the approaches differ and can be classified as follows: Hydrogen as a reducing agent [10,11]; Carbon Capture and Storage [12]; Carbon Capture and Utilization [2]; and biomass as a reducing agent [13].

Without a doubt, the correct valorization of steel gases is a key issue to reduce dependence on fossil resources, minimize emissions, and increase the sustainability and competitiveness of companies. In this context, and in the face of growing market demands, reducing energy costs and CO_2 emissions in the steelmaking process has become increasingly important.

Furthermore, steel factories traditionally generate considerable volumes of off-gas that can be considered by-products [14]. During the integral steelmaking process, three types of gases are constantly and inevitably produced, and are characterized by their interesting energy content: coke oven gas (COG), blast furnace gas (BFG), and Linz-Donawitz converter gas (LDG) [15]. These gases can be captured and used to produce heat and electricity. They can be considered as an alternative to other fuels. For example, Caillat shows examples of the application of by-product gases from different parts of the steel production process (coke oven, blast furnace and Linz-Donawitz converter) in annealing lines with radiant tube burners [16].

Every 1 million cubic meters of LDG can be transformed into about 707 MWh of electricity; for COG, each million cubic meters can be converted into approximately 9912 MWh of thermal energy in the form of steam. This is an excellent use of a by-product industrial pollutant, as these gases would otherwise have to be burned in a torch before emitting them into the atmosphere, with a high environmental impact, bringing an increase in both cost and CO_2 emissions. Therefore, cogeneration may be the solution aimed at the search for efficient energy consumption and the reduction of polluting emissions. Accordingly, most integrated iron and steel corporations have developed a Steel Gases Cogeneration Process (SGCP) to provide up to 50–80% of the power demand [17].

However, neither the production nor consumption of these gases is stable, causing instability situations due to the imbalance between both parameters. Therefore, gasometers are essential to neutralize these oscillations. Obviously, the main objective is to find the best possible use of the steel gases and avoid their combustion in a torch without any type of energy recovery. Therefore, maintaining the stability of the gasometer is very important and has been the aim of many previous studies [18,19]. Decision-makers around the operation of SGCP systems must consider this and other factors, such as the variation in the price of electricity, fluctuations in gas production, steam demands, and the operating conditions of the plant. This turns the decision-making system into a very complex process, which, in the absence of a suitable tool, means that the decisions made may not be optimal.

The objective of the present work was to obtain the optimal gas distribution that simultaneously verifies the requirements from an environmental and economic point of view. To solve the problem, we applied the ε-constraint method, which is one of the most widely used a posteriori methods (it is also considered a generation method) for solving multiobjective optimization (MOO) problems [20]. The method optimizes one of the objectives functions using the other objective functions as constraints, incorporating them into the constraint part of the model. Through parametrical variation of the constrained objective functions, efficient solutions to the problem are achieved.

To validating the proposed approach, the possibilities of an efficient and reliable decision-making tool in the management of singular steel cogeneration plants are explored and evaluated. This work is a continuation of the research developed by Garcia et al. [21]. In that paper, a MILP model for the optimization of the management and use of steel waste gases in a SGCP and MILP was analyzed with the aim of maximizing profits. Here, the goal was to progress one step further by expanding to a multiobjective approach with two functions: minimizing CO_2 emissions and maximizing profits.

This paper is organized as follows: In Section 2, the state of art is detailed. The method is explained in Section 3. Section 4 shows a case study. In Section 5, the system is modeled, and the optimization algorithm is described, and in Section 6 the results are presented and discussed. Finally, in Section 7, conclusions are exposed.

2. State of the Art

In steel factories, the reduction of polluting emissions and energy consumption is essential, and, therefore, the management of Mono-Objective Optimization techniques can be beneficial to establish objectives within the parameters of the viability of the process, as described by Akimoto et al. [22]. Thus, there are many publications on the optimization and management of steel gases using Mono-Objective Optimization applications, especially from an economic point of view. For example, Wei et al. [23] presented an optimization model for the programming of an energy system in a steel plant. The objective function was developed through various operating parameters, such as energy price, gasometer penalty, and the expense caused by CO_2 emissions. Kim et al. [24] proposed an approach that simultaneously optimizes the byproduct gasometer levels and gas distribution among conflicting objectives. De Oliveira et al. [25] addressed the analysis of a mixed-integer linear programming model (MILP) to optimize the distribution of off-gases in order to maximize energy production. In most of the previous studies, only one performance criterion was considered, and the optimal solution calculated would be limited and incomplete for ensuring the global optimization of the analyzed processes.

Nevertheless, regarding MOO, few studies have been applied to the steel industry. Zhang et al. [26] developed a MOO based on the constraints of the production process and equipment conditions. Dettori et al. [27] applied neural networks with the aim of optimizing the reuse of waste gases, minimizing costs, and maximizing income. Liang et al. [28] focused on integrated scheduling of waste gases, steam, and electricity in multi-periods. Maddaloni et al. [29], with the aim of minimizing CO_2 emissions and optimizing the consumption of raw materials and energy at the same time, detailed Process Integration Methods that can be applied with good results in steel processes. Porzio et al. [30] described the use of a tool for the optimization of the gas network of a steel factory. Subsequently, the different operating scenarios were modeled within a MOO in order to minimize costs and CO_2 emissions simultaneously. Additionally, in the work of Porzio et al. [31], the MOO problem was first developed by linear programming and was solved using the ε-constraint method. As an alternative, an innovative evolutionary algorithm was exposed. For comparison and analysis, an evolutionary algorithm was exposed, and later the two approaches were discussed. Zhang et al. [32] analyzed the process of manufacturing iron in a blast furnace and, through the MOO application, a mathematical model was developed with energy consumption, costs, and CO_2 emissions taken as objectives. There are more MOO applications, such as that outlined by Zhao et al. [33], where the MOO was used to identify the penalty factors used in the model to obtain a reasonable optimization of by-product gases. Finally, Kong et al. [18] developed a model for optimization of by-product gas distribution to achieve total cost reduction.

Considering the current state of the art, this work contributes, with respect to previous studies, in the following aspects: a cogeneration plant with a unique configuration consisting of an engine and boiler is studied, as an alternative to the classic set-up of a boiler and turbine, as detailed by Zhao et al. [34]. The boiler feedwater is preheated with the water jacket from the engine, thus any restriction on LDG consumption has a significant impact on the plant's performance. Very short-term planning of only 2 or 3 h is carried out; this reflects the storage capacity of the gasometer, compared with most studies that have much longer time windows. This study could be extrapolated to other energy resources with the possibility of storage. For example, for the storage of water in the case of hydroelectric energy or in batteries for photovoltaic energy, the method could be the same. All of them seek to maximize the use of the energy stored in the form of water, chemicals or gases during the hours of the highest price in the electricity market and simultaneously trying to minimize the environmental impacts associated with their own activity.

3. Materials and Methods

MOO is an essential component of decision-making problems. These problems contain multiple evaluation criteria that are generally in conflict. It searches for options considering the optimization of several objectives simultaneously and usually opposed. According to Marler et al. [35], a MOO is a process of optimizing, systematically, and simultaneously, a set of objective functions. In these cases, there is no single solution, thus it is mandatory to define a collection of points that correspond to the best solutions. The method of the present study was based on MOO. MOO techniques are mandatory when a conflict between competing targets and observing complex constraints must be solved [29]. These tools help plant managers choose the best compromise solution based on the requirements imposed by the process.

For MOO problems, the use of a series of determined methods is inevitable to obtain optimized results. Pareto optimality is the most commonly applied method for dealing with MOO problems [36]. A generic MOO can be defined as follows in Equation (1), where x, f (x), and h (x) refer to the problem solution, objective vector, and constraint vector, respectively.

$$\begin{gathered} \min f(x) = f1(x),\ f2\ (x),\ \ldots,\ fK\ (x) \\ \text{subject to } h(x) = h1(x),\ h2(x),\ \ldots,\ hm(x) \leq 0 \\ \text{where } x = (x1,\ x2,\ \ldots,\ xn)\ \epsilon\ X \end{gathered} \quad (1)$$

For non-trivial multiobjective problems, there is no single optimal solution, thus the optimization process must determine the set of so-called Pareto optimal solutions (or the Pareto set), which also constitute and represent the Pareto front. Another important aspect is that all the solutions within the Pareto set are not dominated, and it can be described ed as follows [29]:

$$a > b\ \leftrightarrow\ fi\ (a) \leq\ fi\ (b)\ \forall\ i\ \Lambda\ \exists\ j:\ fi\ (a) < fi\ (b) \quad (2)$$

There are 2 approaches for solving multiobjective models: The first is optimization of mathematical programming models, and the second group is approximation algorithms or heuristics to the Pareto set [36]. In the first, there are two approaches to generate multiobjective solution sets: scalarization methods and non-scalarization methods. Scalarization methods involve the formulation of a mono-objective model related to a multiobjective model by means of a scalar function [35] and include the Goal Programming method, Weighted Sum method, and ε-Constraint. Non-scalarization methods imply a brief treatment based on optimality or efficiency concepts.

Within the context of this study, the ε-constraint method was identified as a useful method. This method allows the adaptation of an existing mono-objective optimization in a simple way to a MOO, especially for the case of bi-objective studies. Proposed by Haimes in 1971 [37], it is within the group of scalarization methods that imply the formulation of a model to solve a multiobjective problem through a scalar function [38]. These methods incorporate parameters, which are the constraint limits that can be adjusted to reflect the preferences of the decision-maker. The ε-constraint method modifies one of the targets into a constraint limited by the coefficient ε. It consists of carrying out multiple iterations for different values of the limitation ε and thus originating a discrete set of solutions belonging to the Pareto front.

For bi-objective problem, Carvalho, Lozano, and Serra [39] described the mathematical criterion, as illustrated in Equation (3), where $f1$ (x), $f2$ (x), A, b, and lim *inf*, lim *sup* are the objective functions, the constraint vectors and the limits of the parameterized interval, respectively.

$$\begin{gathered} \min f1\ (x) \\ s.t.\ f2\ (x) \leq\ \varepsilon_J\ \mathbf{A} \times X\ \leq b \\ \varepsilon_J = \varepsilon_1\ ,\ \ \varepsilon_2\ \ldots\ \varepsilon_m \\ \lim_{inf} < \varepsilon_J < \lim_{sup} \end{gathered} \quad (3)$$

Daily data are needed to model and validate the process. Operational data were registered from the studied plant, as described in the next section. The dataset contained the applicable information on the main inputs and outputs of the SGCP. These data were used for validating and verify the optimization results detailed in Section 7.

In this study, the pursuit objectives were to increase economic profitability and decrease CO_2 emissions. The system was first modeled with linear equations, where some simplifying assumptions were made. At the beginning, gases were characterized according to their calorific value (GJ), and CO_2 emissions were obtained through the multiplication of the flows of each gas by its factor emissions (t CO_2/Nm^3). Natural gas was used when the steel gases were insufficient to satisfy the demand for thermal energy. Finally, the variation in temperature over the volume of gases was not considered.

In summary, the work was developed in 6 steps, as described in Figure 1. The first 2 steps were developed mainly in previous research [21,40], and, therefore, a short summary was given later to facilitate understanding of the present work. A greater level of detail was required for the description of the last 4 steps. The steps were as follows:

- First, the system was defined and structured. The different processes that make up the system were established and formulated mathematically.
- Second, taking into account the appropriate restrictions, the model was built, and the corresponding optimization tool was used.
- Third, a mono-objective model for maximizing profit was developed. In this study, the software CPLEX was used to solve the MILP problem.
- Fourth, the mono-objective problem was extended to a bi-objective problem (profit and CO_2) through the application of the ε-constraint method.
- Fifth, the model was tested and verified by means of the case study, and the results were evaluated and discussed.
- Sixth, a sensitivity analysis was presented, varying CO_2 price and comparing it with CO_2 constraint parameters and its impact on the profitability of the process.

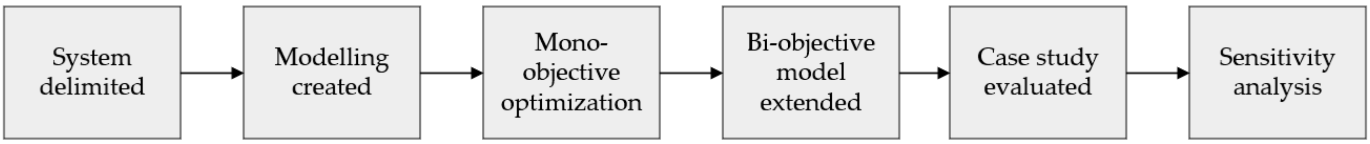

Figure 1. Description of the steps of the method.

The model was developed in CPLEX [41] and it has been included as Supplementary Materials. CPLEX is software for solving optimization problems developed by IBM. It is a prescriptive analytics solution that accelerates the development and deployment of decision optimization models using mathematical and constraint programming. It uses the algebraic modeling language called Optimization Programming Language (OPL). The case study was implemented on an Intel (R) Core (TM) i5-8365U CPU 1.90 GHZ with 16.00 GB RAM. The MILP problem contained 336 variables and 361 constraints.

4. Case Study

The studied plant was a cogeneration process that produced electricity and steam from the energetic valorization of steel gases. At present, it is the only steel factory with the complete process, which goes from the reception and treatment of raw materials to the obtaining of molten steel. The facility produces more than 5 million tons of steel annually. The steel factory consists of 8 coke battery with 30 ovens in each one, and an LD steelmaking process with 2 converters and an LDG gasometer.

In the studied site, the off-gases were valued and used in 12 engines to produce electricity, and in 3 steam generators to produce thermal energy. The engines have a nominal power of 1.7 MW and boilers of 27 MW. With regard to performance, the engines and boilers present efficiency of 35.5% and 92%, respectively. The engines consume LDG, while the boilers consume COG, LDG, and natural gas primarily when there is an unavailability of steel gases. The main characteristics of these gases are shown in Table 1.

Table 1. Heating values and factor emissions for steel gas cogeneration.

Gas	Heating Values (MJ/m^3)	Factor Emission (kg CO_2/GJ)
COG	16.9	42.32
LDG	8.8	185.47
NG	36.1	55.83

A diagram of the process and gas networks is shown in Figure 2.

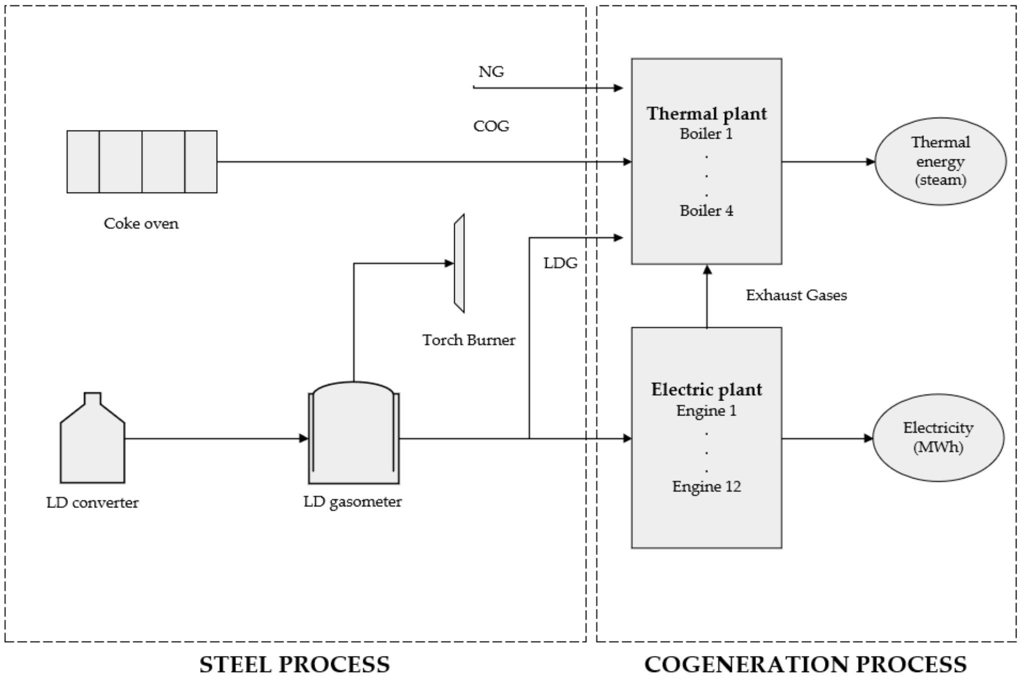

Figure 2. Diagram of the steel and cogeneration processes and gas networks.

5. Problem Formulation

5.1. Objective Functions

There were two objectives to optimize simultaneously: maximize profits and minimize CO_2 emissions. Although CO_2 emissions are a cost that also impacts profits, they are analyzed as a different objective and, therefore, the treatment was independent for each of them. The time window analyzed [t] was 24 h. This choice has been established based on the billing periods of SGCP, starting from hour 0 to hour 23.

5.1.1. Emissions

The process emissions were calculated by multiplying the flow rates consumed by the emission factors corresponding to each of the gases and described in Table 1, according to Equation (4):

$$CO_2 = \sum_{t=0.23} (Q_{LDG}[t] * \mu_{LDG} + Q_{COG}[t] * \mu_{COG} + Q_{NG}[t] * \mu_{NG}) \quad (4)$$

where μ represents the emission factor of each type of gas described in Table 1, multiplied by their corresponding flow rates.

5.1.2. Profit

The profit of the plant is calculated from the following expression:

$$Profit = R - C_{FUELS} - C_{CO2} \quad (5)$$

Each of these partial targets was analyzed independently. Later they were all associated in a single global objective Equation (5) to maximize the profit of the process, where (R) is revenue from energy sales, consisting of:

- Reward obtained for electric power (R_{EE}): the electric production is multiplied by the market price of the electricity, $P_{POOL}[t]$. The price is determined by the day-ahead market that aims to carry out electrical energy transactions for the twenty-four hours of the following day.
- Reward obtained for thermal energy (R_{TE}): corresponds to the production of thermal energy multiplied by the price agreed between the cogeneration and the steel factory (P_{TE}).

$$R = \sum_{t=0.23} (R_{EE}[t] + R_{TE}[t]) = \sum_{t=0.23} (PR_{EE}[t] * P_{POOL}[t] + PR_{TE}[t] * P_{TE}). \quad (6)$$

The production of electrical energy (PR_{EE}) corresponds to the LDG destined for the generation of electricity and taking into account its calorific power and the performance of the engines. The production of thermal energy (PR_{TE}) corresponds to the production of steam multiplied by its heating value of the gases consumed and also considering the performance of steam generators.

C_{FUELS} is obtained by multiplying the flow rates of each of the gases by the established price in €/Nm^3 (P_{LDG}, $P_{COG,}$ and P_{NG}):

$$C_{FUELS} = \sum_{t=0.23} (Q_{LDG}[t] * P_{LDG} + Q_{COG}[t] * P_{COG} + Q_{NG}[t] * P_{NG}) \quad (7)$$

Q_{LDG}, Q_{COG}, and Q_{NG} are the flow rates consumed of each of the gases consumed by the plant.

Regarding C_{CO2}, it is obtained by multiplying the tons previously calculated in Equation (4) by the cost per ton of CO_2 emissions during the period considered (2014).

5.2. Constraints

The objectives of this study were to increase the benefits and reduce the cost of CO_2 emissions according to the following restrictions.

5.2.1. Gas Availability

The availability of natural gas and COG was continuous and constant, however, the LDG was produced intermittently and discontinuously depending on the manufacturing process in the steel mill where it is captured and transported to a gasometer, as depicted in Figure 2. Therefore, the first restriction refers to the fact that LDG consumption must not exceed the gasometer's amount available at any time:

$$\sum_{i=0.t} (Q_{LDG\_TE}[i] + Q_{LDG\_EE}[i]) \leq \sum_{j=0.t} F_{LDG}[i] + stock_{LDG} \; \forall \; t \; in \; [0.23] \quad (8)$$

Q_{LDG_ET} and Q_{LDG_EE} are the flow rates of LDG valued for the generation of thermal and electrical energy, F_{LDG} is the flow of LDG generated in the steel plant, and $stock_{LDG}$ represents the volume of excess stored by the gasometer.

5.2.2. Gasometer Constraints

The storage volume of the gasometer was limited by the maximum capacity (V_{LDG_MAX}) and the minimum capacity (V_{LDG_MIN}). Storage management is important to optimize the benefits of the plant. Equations (9) and (10) model these constraints:

$$stock_{LDG} + \sum_{i=0.t} (F_{LDG}[i] - Q_{LDG}[i]) \leq V_{LDG\_MAX} \; \forall \; t \; in \; [0.23] \quad (9)$$

$$stock_{LDG} + \sum_{i=0.t} (F_{LDG}[i] - Q_{LDG}[i]) \geq V_{LDG\_MIN} \; \forall \; t \; in \; [0.23] \quad (10)$$

5.2.3. Steam Demand Satisfaction Constraint

The SGCP has to supply the thermal requirements of the steel factory (D_{TE}) for each period, which are detailed in Equation (11):

$$PR_{TE}[t] \geq D_{TE}[t] \; \forall \; t \; in \; [0.23] \quad (11)$$

5.2.4. Boiler Constraints

Boilers require a minimum flow of technical gas to start combustion. These flows are generally related to the calorific value of each gas and cannot be operated below these limits, as detailed in Equations (12)–(14):

$$Q_{LDG\_TE}[t] \geq LDG_{\underset{boiler}{\min}} \; || \; Q_{LDG_{TE}} == 0 \; \forall \; t \; in \; [0.23] \quad (12)$$

$$Q_{COG}[t] \geq GOC_{\underset{boiler}{\min}} \; || \; Q_{GOC} == 0 \; \forall \; t \; in \; [0.23] \quad (13)$$

$$Q_{NG}[t] \geq NG_{\underset{boiler}{\min}} \; || \; Q_{NG} == 0 \; \forall \; t \; in \; [0.23] \quad (14)$$

As a singularity, Equation (12) assigns all LDG consumption for thermal use. Although in the present case study, the boilers were the same manufacturer and model. These expressions can be dimensioned and modulated according to the technical characteristics of each boiler.

Equivalently, the boilers cannot exceed the upper technical limit of the burner for each fuel. This is developed according to Equations (15)–(17):

$$Q_{LDG\_TE}[t] \leq LDG_{\max\_boiler} \; \forall \; t \; in \; [0.23] \quad (15)$$

$$Q_{COG}[t] \leq GOC_{\max\_boiler} \; \forall \; t \; in \; [0.23] \quad (16)$$

$$Q_{NG}[t] \leq NG_{\max\_boiler} \; \forall \; t \; in \; [0.23] \quad (17)$$

5.2.5. Engine Constraints

The engines also have their technical consumption limitations, as shown in Equations (18) and (19):

$$Q_{LDG\_EE}[t] \geq LDG_{\min\_engine} \; || \; Q_{LDG_{EE}} == 0 \; \forall \; t \; in \; [0.23] \quad (18)$$

$$Q_{LDG\_EE}[t] \leq LDG_{\max\_engine} \; \forall \; t \; in \; [0.23] \quad (19)$$

5.3. Scenario Description

The study considered a time window of 24 h with real and representative data obtained from the operation in the SGCP. The study considered the time scale of 1 h, due to it corresponding to the real unit of measurement used in the process. The data evaluated for the preparation of the work corresponded to normal operating cycles, without incidents or off-design conditions. This was carried out with the objective of evaluating the potential of optimization against the actual operating conditions of the plant.

Table 2 represents the average amounts of income from steam production and the cost of purchasing gas for the period studied. Penalty values for objective function are shown in Table 3. Regarding the price of CO_2 emissions, the market value of the emissions rights was established during the reference period, specifically the year 2014. Whose amount was around 5.96 €/t CO_2.

Table 2. Cost for gas and revenue for steam.

	Units	COG	LDG	NG
Cost for gas purchasing	(€/m^3)	0.0288	0	0.2574
Revenue for steam production	(€/t)	3.6	3.6	2.4

Table 3. Penalty value for the objective function.

Penalty	Values (€)
Mg CO_2 Emissions	5.96

Table 4 Exposes the values of the upper and lower restriction coefficients for each of the SGCP equipment. The *i-j* pairs indicate pipelines connecting the *i-th* producer with de *j-th* consumer.

Table 4. Constraints coefficients flowrates per consumer.

Fuel	*i*	Equipment	*j*	Constraints	
				B*ij*	**m*ij***
COG	1	Boiler	3	5000	1200
		Plant	1	15,000	1200
LDG	2	Boiler	3	15,000	2000
		Engine	12	2000	1100
		Plant	1	45,000	2000
NG	3	Boiler	3	4000	400
		Plant	1	12,000	400
LDG GH	4	Gasometer	1	61,000	10,000

Figures 3–5 present the available steel gas flow rates, the steam demand for the steel process, and the electricity market price, respectively, during the analyzed period.

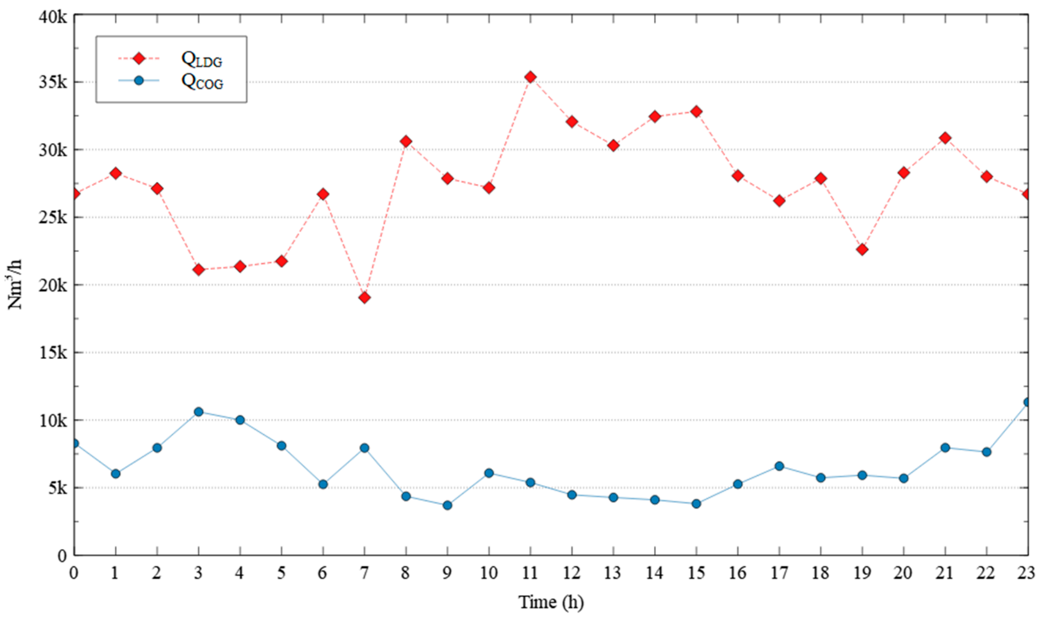

Figure 3. Availability of steel waste gases.

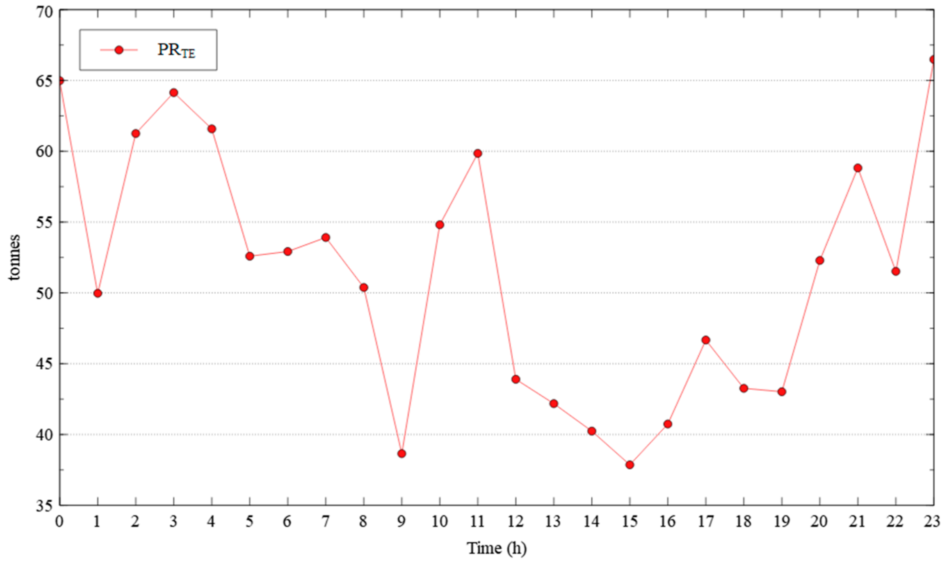

Figure 4. Process steam demand.

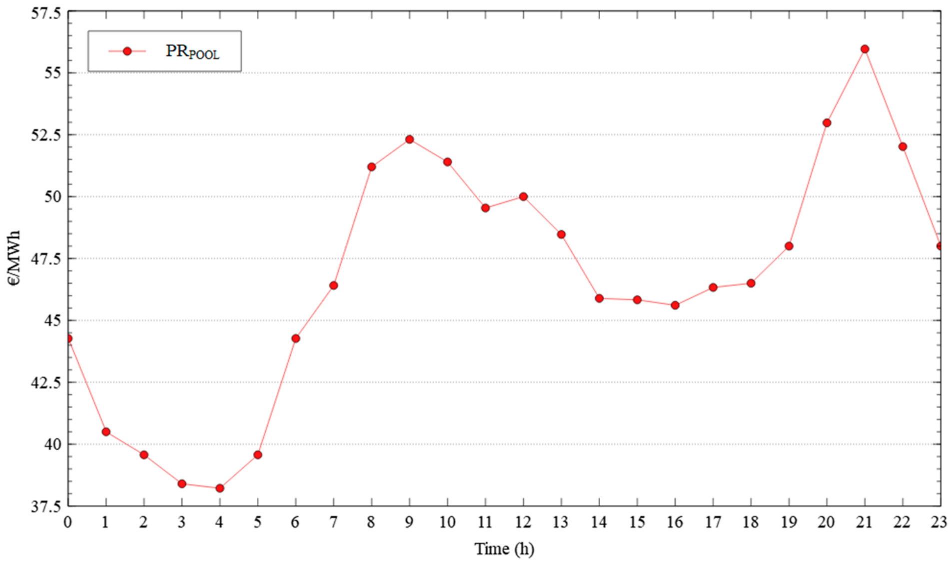

Figure 5. Electricity market price.

6. Results and Discussion

At first, the problem is modeled with CPLEX as a mono-objective optimization for the optimization (maximize) of the profit, as described in Step 3 of the method. Then, CO_2 emissions are turned into a variable that is varied through its valid range, stepping *ε-times* each iteration, as described in Step 4. In this case, CO_2 was studied in the range of 1000–1205 tons, with a step size of 5 tons. The Pareto front was subsequently built, as presented in Figure 6. Under these conditions, the ε-constraint algorithm presents a range for profit starting at 6734 € and reaching the maximum value at 15,020 €/day. As expected, the tons of CO_2 produced was a monotonic increasing sequence, but a remarkable point was found in the inflection of 1145 t.

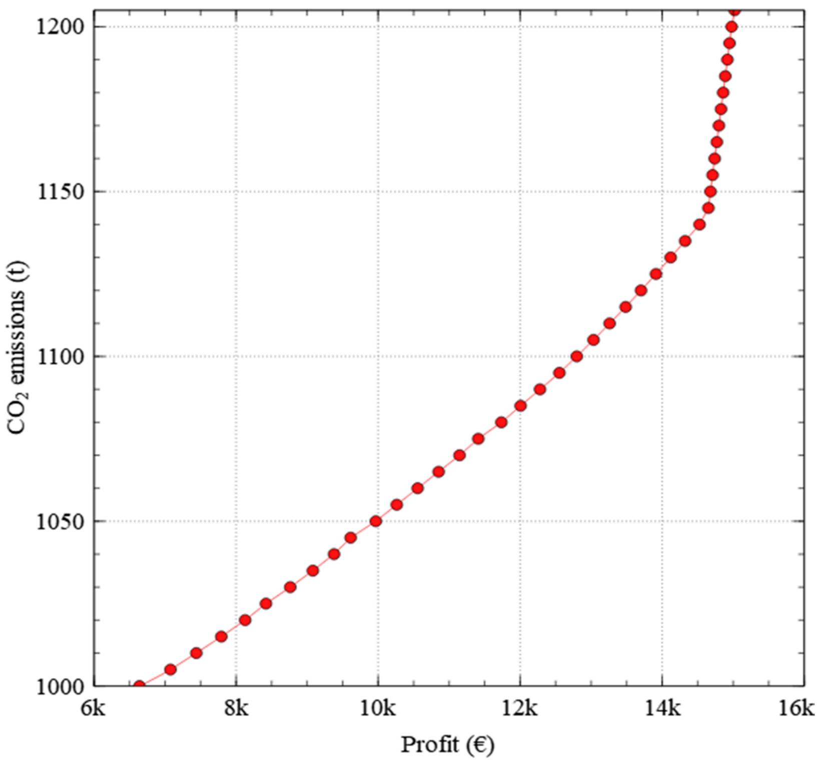

Figure 6. Pareto frontier solutions obtained with the ε-constraint method.

Figure 7 presents part of the different solutions obtained by applying the scalarization technique described above, in this case, stepping 50 t. For greater ease of visualization of the results, part of the solutions of the Pareto front has been represented for different values of CO_2 emissions from the industrial process. The benefits and distribution of steel gases are plotted. As can be seen, the hours of greatest benefit coincide with the peak hours of the electricity market, and, therefore, the LDG is used mainly to produce electricity. However, as the restriction of CO_2 emissions increases, the profits are much more continuous and stable during all hours, with an approximate value of 700 €/h. The consumption of COG increases and displaces the consumption of LDG to guarantee the supply of thermal energy. This also explains the behavior of the graph at the inflection point, caused by the increase in fuel costs due to the contribution of COG as the main fuel for the production of thermal energy and the consequent drastic decrease in profits.

Figures 8–10 present the distribution proposed for $LDG_{\_TE}$, $LDG_{\_EE}$ y $COG_{\_TE}$ during the analyzed period for each of the restrictions imposed on the value of CO_2 emissions. Figures 8 and 10 are practically complementary, when $LDG_{\_TE}$ consumption increases, $COG_{\_TE}$ decreases, and vice versa. Between both fuels, they must produce the steam required by the steel factory. In both illustrations, the relevant parameters are the calorific value and the emission factor of the COG with respect to the LDG, two times higher and four times lower, respectively. Referring to Figure 9, $LDG_{\_EE}$ consumption is distributed to optimize sales. Therefore, the important factor is the hourly price of the electricity market.

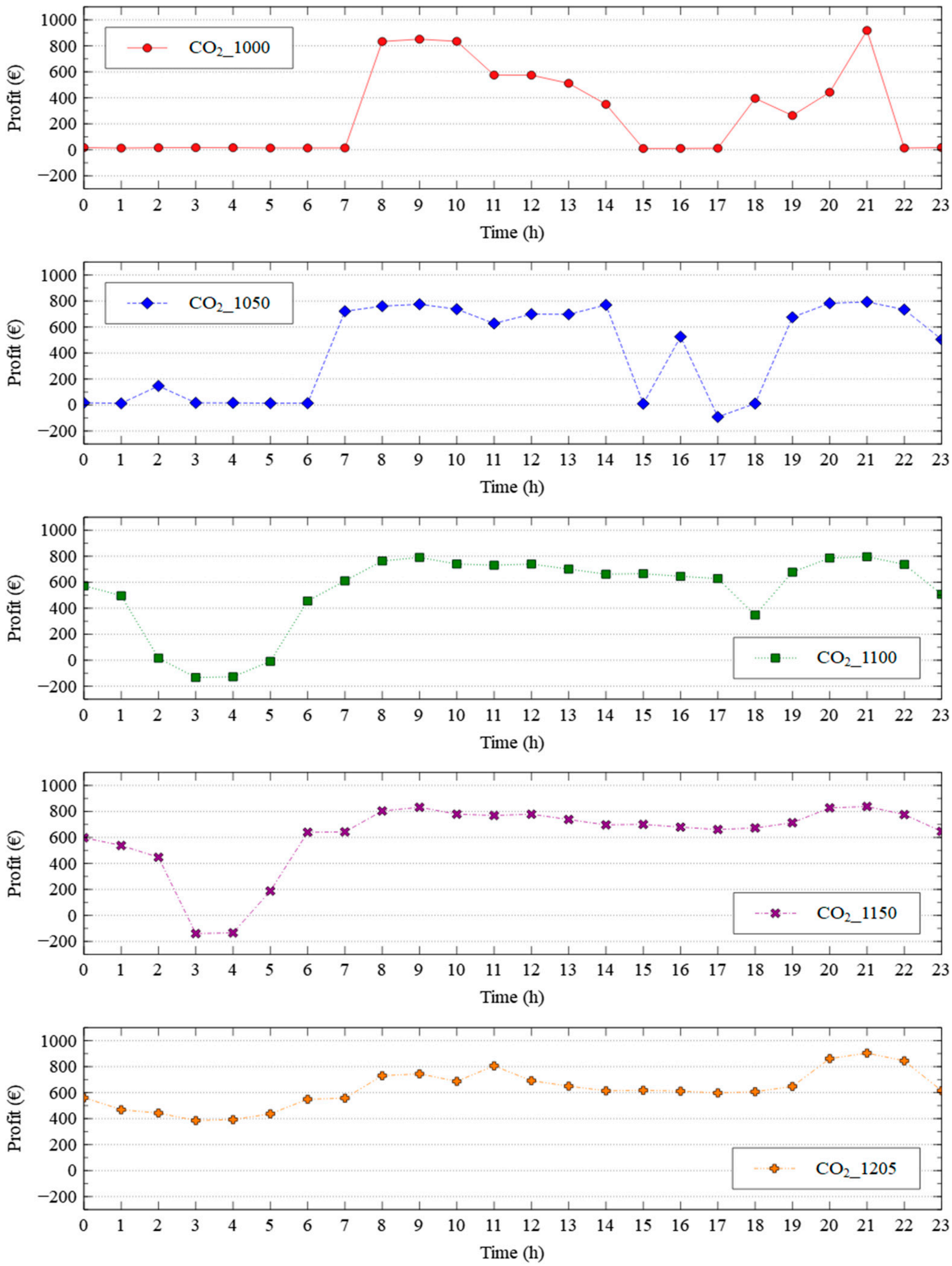

Figure 7. Profits and ε-constraint CO_2 emissions in the considered period.

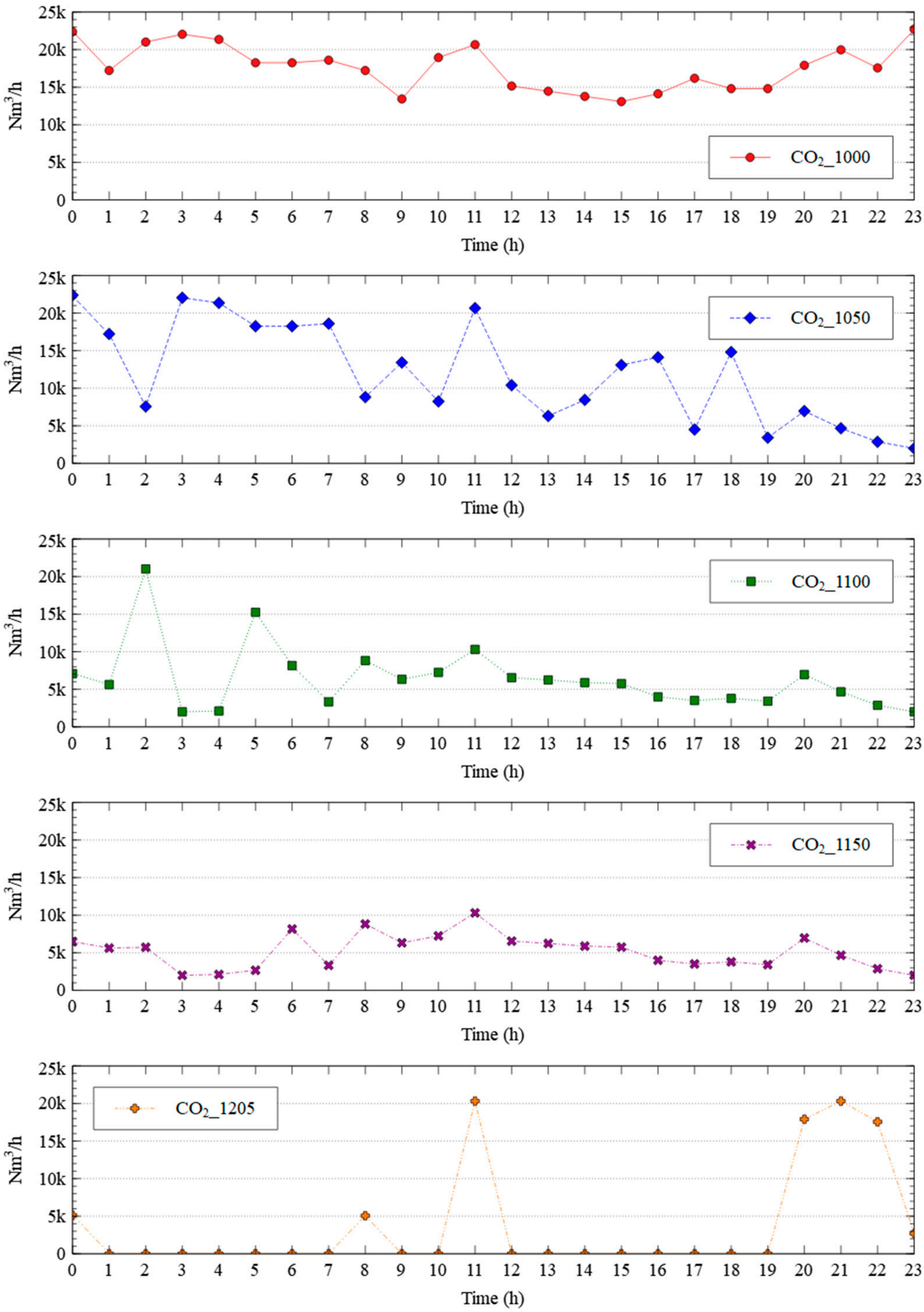

Figure 8. LDG thermal distribution and ε-constraint CO_2 emissions in the considered period.

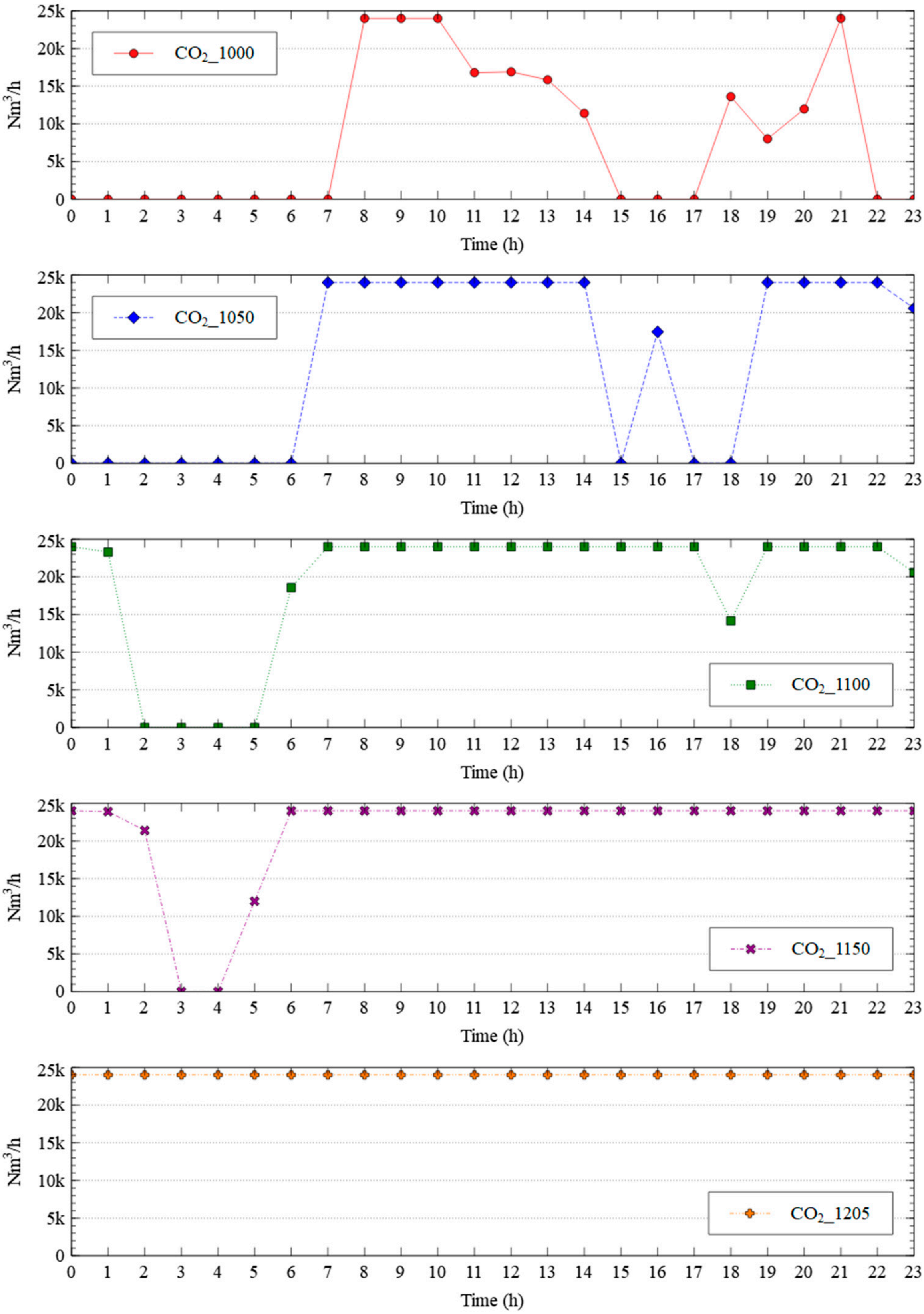

Figure 9. LDG electricity distribution and ε-constraint CO_2 emissions in the considered period.

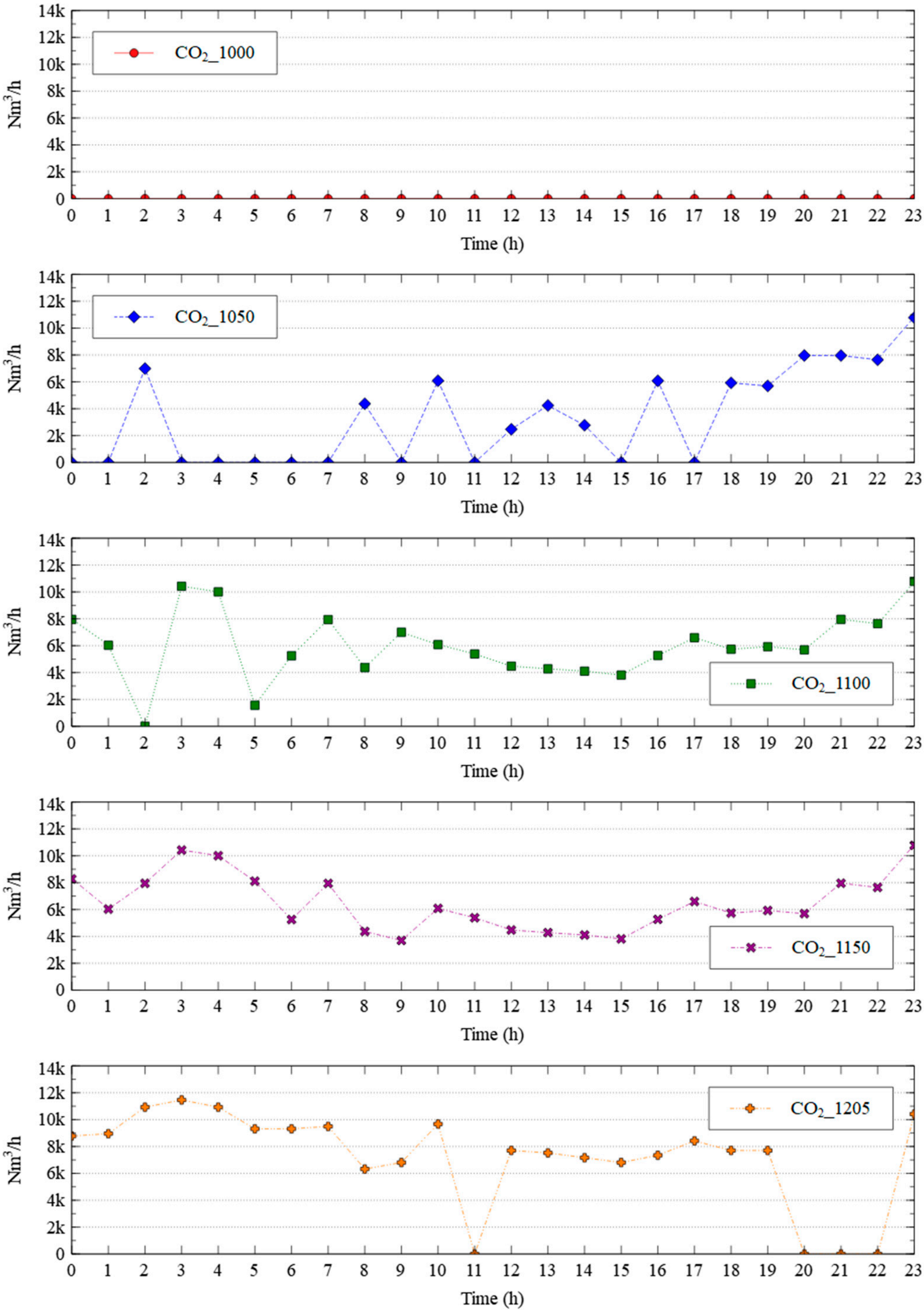

Figure 10. COG thermal distribution and ε-constraint CO_2 emissions in the considered period.

Figure 8 shows how in the limitations with a lower level of CO_2 emission, the consumption of $LDG_{\_TE}$ increases. It translates into lower fuel costs but also lower revenues by prioritizing thermal energy production over electrical production.

Figure 9 details for limitations below 1050 t of CO_2, $LDG_{\_EE}$ is used only during peak hours. On the contrary, in the other scenarios, they only restrict consumption in some valley hours, the rest of the hours keep consumption at maximum.

Figure 10 presents that as CO_2 emission levels increase, $COG_{\_TE}$ consumption increases. Therefore, a greater amount of LDG is available for the production of electrical energy with the consequent maximization of sales. As $COG_{\_TE}$ consumption increases, so do fuel costs. However, because $COG_{\_TE}$ is less polluting than $LDG_{\_TE}$, the costs associated with emissions decrease.

The solution over the period analyzed brings about a considerable increase in terms of energy sales. The decisions proposed by the optimization model are compared against the fuel consumption derived from the plant managers' commands, hereinafter referred to as the base case. The consumption of each gas is depicted in Figure 11.

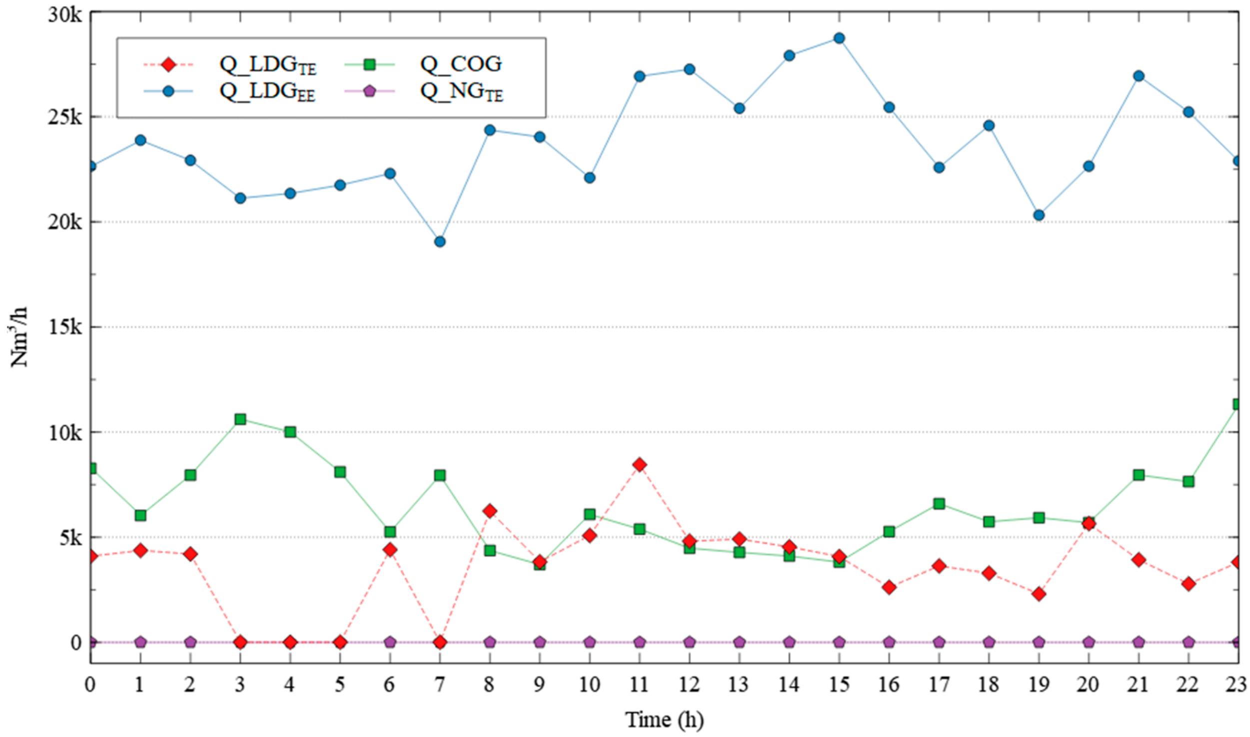

Figure 11. Distribution of gases in a base case.

Considering as reference the inflection point for the comparison, the proposed model emits 3% less CO_2 than the base case (Figure 12), mainly due to greater use of both gases, especially COG, to produce thermal energy, and thus the allocation of the largest amount of LDG to the production of electrical energy, as can be seen in Figures 12 and 13.

Regarding the profit side, the results obtained by the method are detailed in Figure 13. The ε-constraint optimization allows higher values to be reached (the difference is 14.86%) with respect to the base case. In this case, the proposed optimization shows an improvement in the performance of the plant operations. They were originated by a more efficient distribution of available gases.

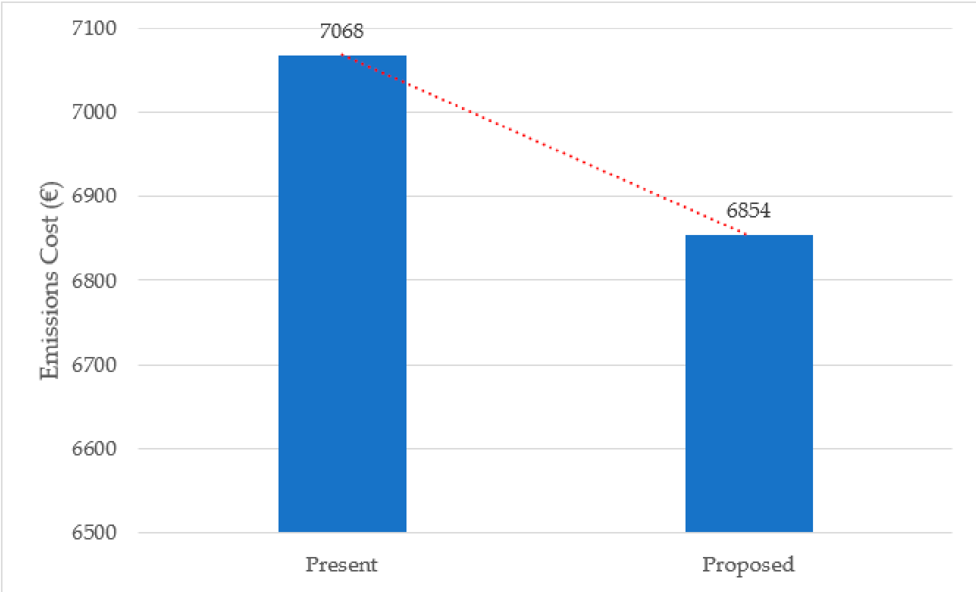

Figure 12. CO_2 emission decrease during the analyzed period case.

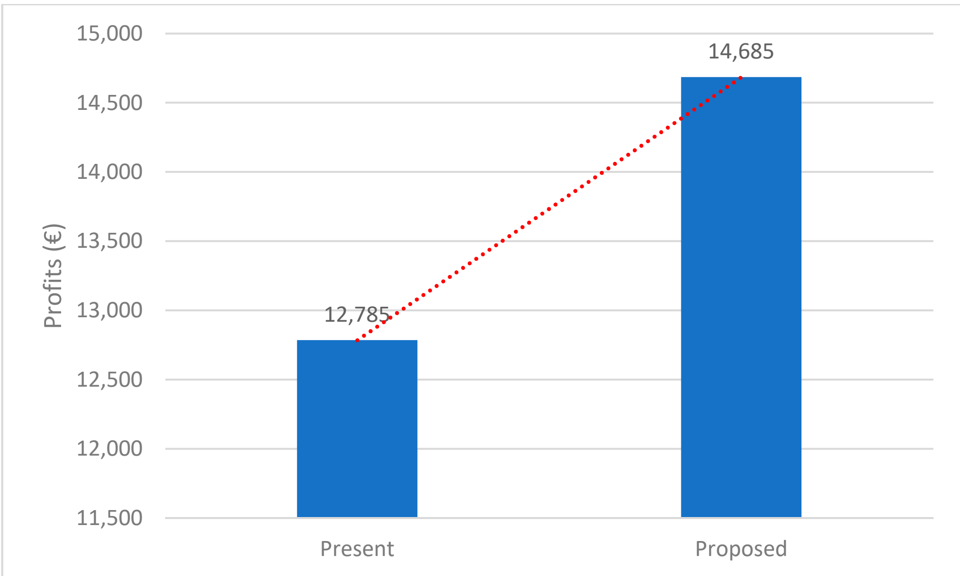

Figure 13. Profits increase during the analyzed period.

Sensitivity Analysis of the CO_2 Price and CO_2 Constraints

Within the challenge of companies to improve efficiency, competitiveness, and sustainability, the trade of CO_2 emissions is increasingly relevant. Market forecasts suggest that the price of CO_2 will continue to rise. In this context, it is especially important to perform a sensitivity analysis by increasing P_{CO2} and comparing it with the ε-constraint CO_2 emission parameters used in the application of the MOO of the process. Its influence on profits as can be seen in Table 5.

Table 5. Sensitivity analysis of the CO_2 constraint and CO_2 prices.

Profit [€]		**CO_2 Price (€/t)**					
		5	**10**	**15**	**20**	**25**	**30**
CO_2 Constraint (t)	1000	7597	2599	−2400	−7401	−12,400	−17,398
	1050	10,947	5697	447	−4802	−10,052	−15,302
	1100	13,749	8249	2749	−2750	−8250	−13,750
	1150	14,952	9202	3452	−2297	−7976	−13,529
	1200	15,555	9595	3650	−2280	−7976	−13,529

Figure 14 shows how profits change with different suppositions of CO_2 prices and CO_2 constraints; from 20 €/t, the SGCP is not economically viable. Likewise, for the three least restrictive coefficients of CO_2 emissions, the trend of each of the lines with CO_2 above 20 €/t practically overlaps. However, for the two most restrictive coefficients, the lines have parallel trajectories throughout the price range of CO_2.

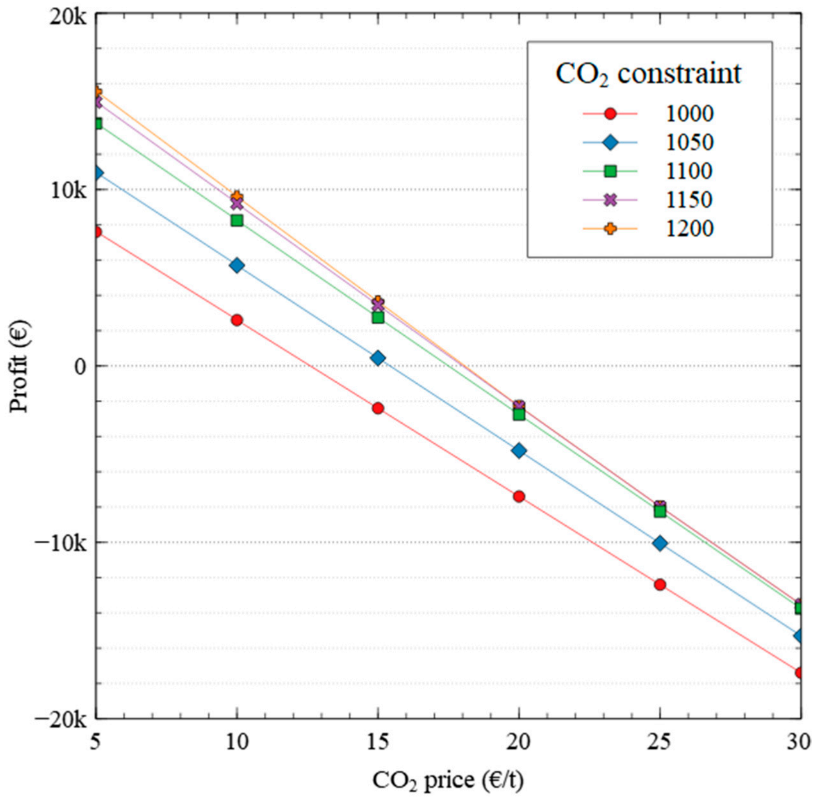

Figure 14. Sensitivity analysis of the CO_2 constraint and CO_2 prices.

7. Conclusions

A new approach for the optimization of profit and CO_2 emissions of an SGCP based on the ε-constraint combined with a MILP optimization case was presented in this paper. The method was simpler to apply compared with other MOO methods such as evolutionary algorithms. The proposed method was useful and provides management of processes with important information for byproduct gas scheduling. The results are reliable and practical in the plant and can constitute an effective decision support tool for the process operator. Compared with the current operation of the plant, the proposed model may increase profit by up to 14.8% and reduce CO_2 emissions by up to 3%. The case study was based on a typical operation day from data captured on the site.

The model makes it possible to identify inflection points from which the level of emissions would increase disproportionately. In the case studied, an inflection point was found when the CO_2 emissions reach 1145 t. The identification of these points is key in the decision-making process.

A sensitivity analysis of the behavior of profits according to changes in the price of CO_2 and CO_2 constraints was also conducted. We can conclude from the sensitivity analysis that with CO_2 emission prices above 20 €/t, a plant would not be profitable and would have very limited viability, especially in the case of LDG, due to its low calorific value and its high emission factor.

Although the limitation of this study is that the results are particular to a specific case of operation, the results can be generalized because the case is representative.

The presented model also has good potential to be applied to other multi-fuel processes, such as the oil refinery process or biogas treatment plants. It would simply be necessary to adapt the properties of the new fuels to the model. One of the challenges of this work is the low storage capacity of the gasometer. The model makes it possible to make the most of the temporary store of gases, adapting to the hourly price of the electricity market. Therefore, it can be considered as a very useful tool for making decisions in the very short term, no more than 2 or 3 h.

As the penalties for CO_2 emissions are expected to increase continually, the proposed model will play a more and more important role in the power management of the grid in the future. The model can be applied not only to improve the management of an existing process but also simulations with virtual processes can be performed. It would also be useful to assess the feasibility of possible changes in the operating conditions of a process, which may be posed by future needs or for future extension of the plant model, including additional system components or constraints. As a result, further research is needed to apply this model to other plants to verify its validity and to find its limitations.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/en14102741/s1, model.mod and data.dat.

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Nomenclature

C_{FUELS}	Fuel costs (€)
C_{CO2}	Emissions CO_2 costs (€)
D_{TE}	Demanded thermic energy (t)
F_{LDG}	LDG flow (Nm^3/h)
H_{LDG}	Heat value of LDG (kJ/Nm^3)
H_{COG}	Heat value of COG (kJ/Nm^3)
H_{NG}	Heat value of NG (kJ/Nm^3)
L_{LDG}	Gasometer level (Nm^3)
te_{ti}	Thermal energy boiler I at time t (t)
P_{POOL}	Electricity market price (€/MW)
P_{TE}	Thermal energy price (€/t)
P_{LDG}	LDG price (€/Nm^3)
P_{COG}	GOG price (€/Nm^3)
P_{NG}	NG price (€/Nm^3)
P_{CO2}	CO_2 price (€/t)
PR_{EE}	Electric power production (MW)
PR_{TE}	Thermal energy production (t)
Q_{COG}	Allocated amount of COG (Nm^3/h)
Q_{LDG}	Allocated amount of LDG (Nm^3/h)
Q_{NG}	Allocated amount of NG (Nm^3/h)

R	Revenue (€)
R_{EE}	Electric power revenue (€)
R_{TE}	Thermal energy revenue (€)
$stock_{LDG}$	Stocked LDG in the gasometer
μ_{LDG}	Emission factor LDG (t/Nm^3)
μ_{COG}	Emission factor COG (t/Nm^3)
μ_{NG}	Emission factor NG (t/Nm^3)
V_{LDG_MIN}	Min. LDG gasometer threshold (Nm^3)
V_{LDG_MAX}	Max. LDG gasometer threshold (Nm^3)
Subscript	
NG	Natural gas
LDG	Linz-Donawitz gas
COG	Coke oven gas
GEN	Generate
PLANT	Steel Cogeneration Plant
POOL	Daily electricity market
STEAM	Steam
EE	Electric energy
TE	Thermal energy

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