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Review

Planning and Scheduling with Uncertainty in the Steel Sector: A Review

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Received: 22 May 2019; Accepted: 1 July 2019; Published: 2 July 2019

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Featured Application: The current paper presents a review about solutions dealing with uncertainty in planning and scheduling problems for the steel industry which could be useful for researchers on similar topics.

Abstract: The following paper proposes a study about the existing solutions for dealing with uncertainty while solving the planning and scheduling problem at steel industry manufacturing processes. The different techniques designed to cope with uncertainty in manufacturing scheduling are discussed, along with the main uncertainty factors affecting the scheduling. The paper proposes a classification for the main uncertainties affecting the steelmaking process and analyzes the existing literature about solutions for the scheduling with uncertainty in the steel sector in terms of approaches followed and uncertainty types considered. Finally, the main remarks and future challenges within this field are presented.

Keywords: steel industry; scheduling; uncertainty; review

1. Introduction

Steel process is a complex chain of transformation processes, from raw materials (iron ore, coal, scrap, etc.) to finished products (coils, plates, rails, tubes, etc.). As in many other transformation industries, planning and scheduling plays a capital role in the steel sector. For this reason, the topic has been well covered by the literature [1,2]. However, lately it has been identified that the classical deterministic approach on steel manufacturing scheduling presents difficulties when applied to the real world production conditions where uncertainties of different nature (order cancellations, rush jobs, etc.) and production disturbances (equipment breakdowns, deviation in product specifications, etc.) continuously modify the initial plans and schedules, forcing the operators to change and readapt to these new situations [3]. New ways of incorporating these elements have motivated researchers to propose new approaches to tackle with the uncertainty problem in industrial sectors, such as multistage stochastic programming, robust optimization, or fuzzy programming [4–6].

The purpose of this paper is to analyze the most notable contributions in the literature to address the planning and scheduling under uncertainty problem in the steel industry and discuss the future challenges that the community will face to close the gap between the real needs of the steelmaking industry and the scheduling models used within it. The rest of the paper is organized in the following structure. Section 2 introduces a definition of the general problem of scheduling under uncertainty and the different techniques that can be applied to deal with it. Section 3 presents how the uncertainties in the steel process have been identified in the existing literature and proposes a classification. Section 4 presents a detailed analysis of the solutions and how they deal with the uncertainty. Section 5 concludes with the main remarks and the future challenges identified.

2. Uncertainty in Scheduling: Definition and Approaches

The steel industry involves different production steps, each one with their own characteristics and problematics which translates into specific planning and scheduling procedures. However, in most cases they can be considered to be a complex Hybrid Flow Shop (HFS) scheduling problem with hard constraints. This problem is based on the necessity to process a given set of jobs through various processing stages, with one or more parallel machines on each stage optimizing an established objective function. All the jobs must follow the same stages processing route [7]. The HFS scheduling problem can be expressed as a mixed integer linear programming (MILP) problem. Let x denote the continuous variables that represent the starting and finishing times (or processing times) of the jobs and let y denote the binary variables referring to the selection of tasks to be processed and the machines in which they are allocated. Considering c and d as the correspondent coefficient vectors for the decision variables x and y, the HFS can be formulated in the following way:

$$\mathrm{Min}\ (c^T x + d^T y) \tag{1}$$

Subject to $Ax + By \leq p \,\middle|\, x \geq 0;\ y \in \{0, 1\};\ x \in \mathrm{R}^n,\ y \in \mathrm{R}^m$ where the constraints ($Ax + By \leq p$) are time limitations due to tasks durations, sequence requirements and other process-related restrictions. The parameters A and B represent the constraint matrixes associated with decision variables x and y respectively. The parameter p corresponds to the maximum threshold.

Ben-Tal and Nevirovski [8] state that slight modifications in the nominal values of this type of model may lead to infeasible solutions. The uncertainties responsible for these modifications can be of very different nature, like disruptions in the processing times, unexpected equipment stoppages or non-fulfillment of target specifications of the order. Hence, the presence of uncertainty becomes one of the main factors impacting the correct realization of schedules in steel manufacturing processes.

There are many studies in the literature that analyze and classify the approaches in the scheduling uncertainty across different sectors [3,6,9]. Most of the authors agree that there are two main groups in which these techniques can be divided: proactive scheduling solutions and reactive scheduling solutions.

2.1. Proactive Scheduling

Proactive schedules try to estimate and anticipate the effect that potential uncertainties could have in the production schedules. To this meaning, historical data analysis and forecasting techniques are used to model the uncertainty inherent to the process and propose schedules to reduce the potential impact that future disturbances could provoke in the production phase. There are several reviews that analyze the main proactive scheduling solutions [3,4,10,11]. The most common approaches identified in the literature for the proactive scheduling, can be considered inside the following groups: stochastic programming, robust optimization and fuzzy programming.

2.1.1. Stochastic Programming

Stochastic programming consists on optimization models where the main variables are represented by discrete or continuous probabilistic distributions. The most relevant example within this category is the two-stage stochastic programming. In the first stage, the main driver decisions are taken before the incorporation of any uncertainty parameter, while in the second stage the infeasibilities raised by the realization of the uncertainty can be compensated by corrective recourse actions.

Let $Q(x, y, \xi)$ be the optimal solution of the stochastic model of the second stage, with ξ being the vector of uncertain parameters associated with the problem. These uncertain parameters can be represented by random variables with known distributions. The first stage model can be formulated incorporating the mathematical expectation (E) of $Q(x, y, \xi)$ to the equation expressed in (1):

$$\mathrm{Min}\left\{c^T x + d^T y + \mathrm{E}[Q(x, y, \xi)]\right\} \tag{2}$$

Let z denote the decision variables for the second-stage problem, with the random variable $q(\xi)$ representing the corresponding coefficient vectors. The second-stage model can be defined as:

$$\text{Min } q(\xi)^T z \tag{3}$$

Subject to: $T(\xi)x + V(\xi)y + W(\xi)z \leq h(\xi) \mid z \geq 0$, where T, V, W correspond to random variables representing the constraint matrixes for the second stage problem associated with the decision variables x, y, z respectively. The maximum threshold for these constraints is established by the random variable h.

2.1.2. Robust Optimization

Preventive schedules are considered robust schedules when they are built minimizing the effects of potential uncertainties and ensuring small deviations from the executed manufacturing schedules. This approach assumes proactive suboptimal schedules that ensure the feasibility of the solutions and provide near optimal results under the manifestation of disturbances during their execution. Based on the problem formulated in (1), the model will be a robust schedule if the constraints $Ax + By \leq p$ can be satisfied for the worst case of $(A, B) \epsilon P$, with P being a subset of R^{nxm}.

2.1.3. Fuzzy Programming

Fuzzy programming follows a similar approach to the stochastic programming but, in this case, the main variables and parameters are considered to be fuzzy numbers and the constraints are treated as fuzzy sets. The partial violation of constraints is permitted, with the degree of satisfaction of a constraint being defined as its membership function. Finally, the objective functions can have lower and upper bounds defined by the expected goal levels for the user. Based on the model in (1), for a constraint $Ax + By \leq p$ in which the right-side parameter p can take values belonging to the interval $[b, b + d]$ with $d > 0$, the membership function of the constraint, $\mu(x, y)$, can be defined as:

$$\mu(x, y) \begin{cases} 1 & Ax + By \leq b \\ 1 - \frac{Ax + By - b}{d} & b < Ax + By \leq b + d \\ 0 & Ax + By > b + d \end{cases} \tag{4}$$

2.2. *Reactive Scheduling*

Techniques based on the reactive scheduling approach are mainly used in those scenarios in which there is not enough information to allow a preventive action which would avoid the uncertainty from occurring. Hence a change in the schedule must be proposed to readapt to the new scenario whenever an unexpected event appears [3]. Ouelhadj and Petrovic [12] propose four main categories to classify dynamic scheduling solutions, one being the robust scheduling, which refers to proactive scheduling approach, and the other three representing the reactive approaches:

- Completely reactive: Tasks are directly scheduled in real time, applying mainly dispatching rules or heuristics that evaluate the status of the scenario, considering aspects like process priority or processing time.
- Predictive reactive: A basic preventive schedule is generated for a deterministic scenario. According to different rescheduling strategies (on a periodic basis, each time a new job arrives or a disturbance appears) the model can propose modifications to the initial schedule or generate a completely new schedule.
- Robust predictive reactive: In this approach, the reactive schedules proposed whenever an unexpected event appears try to minimize the effect of the disruption upon the initial schedule. This is done by considering not only the schedule efficiency criteria, but also the deviation from the original preventive schedule (stability).

Chaari et al. [6] propose additional criteria to classify these models differentiating between distributed solutions and centralized approaches and according to the usage of priority rules for the reassignment of the tasks after the disturbance: they can be static (they do not depend on the time) or dynamic (they depend on the time and the status of the system).

In terms of the techniques employed to solve the reactive scheduling problem, the solutions can be sorted by [12]:

- Dispatching rules and simulation: Dispatching rules for dynamic environments are usually combined with simulation techniques to evaluate and select the best suited rule for the current scenario. Most of the completely reactive approaches rely on this technique.
- Heuristics: They are mainly employed to define the schedule repairing strategies for the initial schedules according to the type of disturbance produced.
- Metaheuristics: In recent years, metaheuristics have developed an increasing presence in the scheduling literature. Some of the most common include: genetic algorithms (GA), ant colony optimization (ACO), particle swarm optimization (PSO), artificial bee colonies (ABC), differential evolution (DE) or tabu search (TS).
- Multi-agents and other Artificial Intelligence techniques: A multi-agent framework is used for distributed approaches where the manufacturing system is split into separate agents that negotiate to achieve global optimal results. Other Artificial Intelligence-based techniques also employed are knowledge-based-systems, neural networks, case-based reasoning.

2.3. Hybrid Approaches

In some situations, the difference between reactive and proactive methods is not so clear. Some authors consider hybrid approaches that combine simplified proactive methods to define the preventive schedule and afterwards define a reactive approach to deal with uncertainties not covered by the proactive initial stage [6,9]. However, there are still few works that could be included within this category, due to the novelty of the proactive scheduling solutions [9]. Figure 1 represents the behavior of the different approaches in terms of uncertainty analysis and rescheduling capabilities.

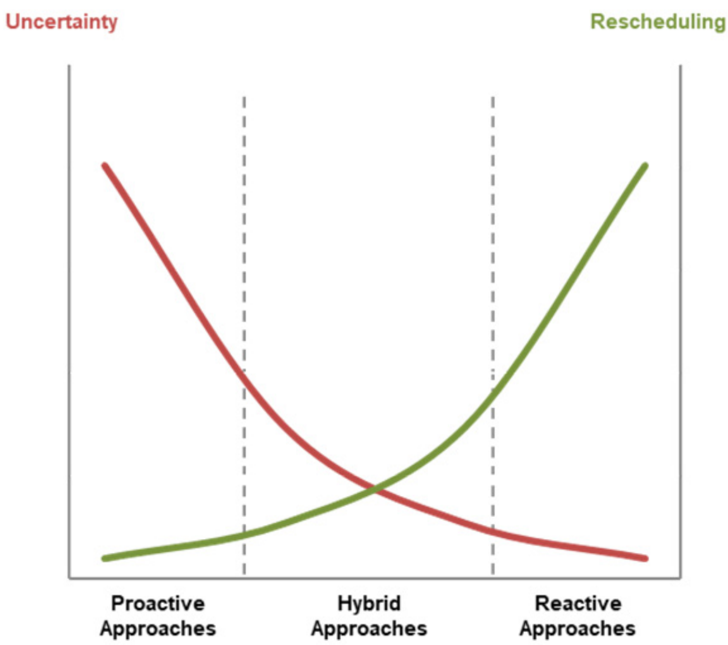

Figure 1. Classification according to uncertainty and rescheduling capabilities.

3. Classification of Uncertainties in the Steel Sector

3.1. General Manufacturing Uncertainty Factors

Two main levels of classification for the uncertainty factors affecting the manufacturing process scheduling can be considered [5]. The first level of classification consists on distinguishing those who are external to the process from those who are internal to the process. The other level of classification proposes to sort these factors according to the time horizon of the uncertainty. In the case of the scheduling, the most relevant are the short-term uncertainties. Vieira et al. [13] propose a summary of the most common factors identified by the existing rescheduling studies in the manufacturing process which can be grouped in two main groups:

- Job related: Urgent (rush) job arrival, job cancellation, due date change (delay or advance), change in job priority.
- Resource related: Machine failure, delay in the arrival or shortage of materials, over or underestimation of process time, rework or quality problems, operator absenteeism.

3.2. Steelmaking Uncertainty Factors

Different authors have elaborated several studies with the purpose of analyzing and classifying the main factors contributing to the uncertainty in the steel industry, most of them focused on the steelmaking process. Hao et al. [14] establish a general classification for the continuous casting process, differentiating the possible disturbances according to the impact caused to the scheduling between critical and non-critical events. Roy et al. [15] present a list of the main disruptions that can appear in the steelmaking process such as steel composition being out of specification, steel temperature not according to process specifications, lack of hot metal supply or ladle gate failure. Hou and Li [16] study the different disturbance events that can arise in the steelmaking process classifying them attending to the origin of the event: internal to the steelshop (machine breakdowns, steel grade variations) and external to the steelshop (urgent orders, unavailability of slabs). Worapradya and Thanakijkasem [17] divide the main daily disruptions events that can happen in this environment into 4 groups: machine failure, rush orders, excessive defects during an operation and order cancellations. Tang et al. [18] consider the differentiation of real-time events affecting the steel making phase between resource-related and job-related but propose also a third category, which are the quality-related (processing time changes, steel grade changes, process route changes).

Based on the previous studies and in order to analyze uncertainty scheduling solutions in the existing literature, we propose to use the following classification of uncertainty factors:

- Orders: Uncertainties related to order cancellations, rush orders, changed priority.
- Machines: Disturbances affecting machines and equipment like breakdowns, unplanned repairs, etc.
- Product specifications: Disruptions of the schedule caused by the failure in the achievement of the order's target specifications.
- Processing times: Uncertainties increasing or decreasing the initially estimated processing time of the scheduled tasks.

4. Scheduling Solutions in Steel Sector Considering Uncertainty: Literature Review

The analysis of the existing literature in the current topic shows that the study of uncertainty in scheduling in the steel sector has become a topic of interest in recent years. Prior to that, scheduling systems used to avoid addressing the reactive scheduling problem, leaving the reaction to the unexpected events to the responsibility of the human schedulers [19]. Table 1 summarizes the main contributions from the literature to the problem of planning and scheduling with uncertainty in the steel sector. The papers analyzed are organized according to the steel production process steps in which they are applied, and the main approach followed to deal with uncertainty (proactive or reactive).

Table 1. Planning and scheduling models dealing with uncertainty in steel production.

Reference	Process Step					Approach	
	EAF/BOF	Refining	Continuous Caster	Hot Rolling	Finishing Mills	Reactive Schedule	Proactive Scheduling
Suh et al. 1998 [19]				X		X	
Cowling et al. 2004 [20]			X	X		X	
Oueldhadj et al. 2004 [21]			X	X		X	
Roy et al. 2004 [15]			X			X	
Guo and Li 2007 [22]			X	X		X	
Pang et al. 2008 [23]	X	X	X			X	
Rong and Lahdelma 2008 [24]	X						X
Tang and Wang 2008 [25]					X	X	
Ozoe and Konishi 2009 [26]	X	X	X			X	
Worapradya and Buranathiti 2009 [27]	X	X	X			X	
Yu et al. 2009 [28]	X	X	X				X
Chen et al. 2010 [29]	X	X	X			X	
Worapradya and Thanakijkasem 2010 [17]	X	X	X				X
Zhu et al. 2010 [30]			X			X	
He et al. 2011 [31]	X	X	X			X	
Luo et al. 2011 [32]			X			X	
Slotnick 2011 [33]			X				X
Wang et al. 2011 [34]					X	X	
Yu et al. 2011 [35]	X	X	X			X	
Hou and Li 2012 [16]			X	X		X	
Luo et al. 2012 [36]			X			X	
Yu and Pan 2012 [37]			X			X	
Fazel and Azad 2013 [38]						X	
Gerardi et al. 2013 [39]	X						X
Tang et al. 2013 [40]			X			X	
Yu 2013 [41]			X			X	X
Krumeich et al. 2014 [42]			X				X
Mao et al. 2014 [43]	X	X	X			X	
Tang et al. 2014 [18]	X	X	X			X	
Ye et al. 2014 [44]	X		X				X
Yue and Xianpeng 2014 [45]					X		X
Hao et al. 2015 [14]			X			X	
Li et al. 2015 [46]	X	X	X			X	
Long et al. 2015 [47]	X	X	X			X	
Luo et al. 2015 [48]	X						X
Mori and Mahalec 2015 [49]					X		X
Nastasi et al. 2015 [50]					X		X
Sun et al. 2015 [51]		X					X
Bo et al. 2016 [52]			X			X	
Jiang et al. 2016 [53]	X	X	X			X	X
Lin et al. 2016 [54]			X	X			X
Yu et al. 2016 [55]	X	X	X			X	
Guirong and Qiqiang 2017 [56]	X	X	X				X
Jiang et al. 2017 [57]	X	X	X			X	
Jiang et al. 2017 (b) [58]	X	X	X				X
Long et al. 2017 [59]			X			X	
Noshadravan et al. 2017 [60]	X						X
Pang et al. 2017 [61]	X	X	X			X	
Sun et al. 2017 [62]	X	X	X			X	
Sun et al. 2017 (b) [63]	X	X	X			X	
Wang et al. 2017 [64]				X			X
Zheng et al. 2017 [65]	X	X	X			X	
Kammammettu et al. 2018 [66]			X				X
Long et al. 2018 [67]			X				X
Niu et al. 2018 [68]			X				X
Peng et al. 2018 [69]	X					X	
Yang et al. 2018 [70]	X	X	X				X
Yang et al. 2018 (b) [71]	X	X	X				X
Guo et al. 2019 [72]	X	X	X	X	X	X	

Most of the studies (53/59) are focused on the upstream steel production sector (especially in the steelshop scheduling) and only five papers are focused on downstream processes (specifically, two for cold rolling mill, one for color coating mill, one for plate mill and one for all the finishing mills).

There are two special cases: the solution proposed by Guo et al. 2019 which covers all the processing units within the steel process and Fazel and Azad [38] who developed a generic multi-agent framework for steel production scheduling, without associating it to a specific process step. Inside the upstream segment proposals, almost all of them (45/53) include the continuous casting process, while half of them (24/53) deal with the whole steelshop problem (steel making + refining + casting). There are a few approaches (5/53) that consider the combined scheduling of casting and hot strip mill processes. In terms of the uncertainty scheduling approach, there is a greater number of authors (37/59) who have proposed reactive scheduling solutions against a lesser number (24/59) who have studied and developed proactive scheduling approaches. However, proactive studies seem to be a more recent approach, starting on 2008 and growing in frequency during the following years, while reactive scheduling solutions are present during the whole period covered by this review. Only a few authors consider the possibility of combining both approaches in their works (hybrid approaches), such as Jiang et al. [53], Worapradya et al. [17,27] or Yu et al. [41]. This can be explained by the focus in recent years on the application of metaheuristics and simulation solutions to reactive approaches (see Table 2) which could be motivated by the necessity of improving the solutions to be executed dynamically in real production environments.

Table 2. Reactive scheduling models in steel production.

Reference	Approach			Technique			
	Completely Reactive	**Predictive Reactive**	**Robust Predictive Reactive**	**Dispatching Rules and Simulation**	**Heuristics**	**Metaheuristics**	**Multiagent and other AI**
Suh et al. 1998 [19]	X				X		
Cowling et al. 2004 [20]			X				X
Oueldhadj et al. 2004 [21]			X				X
Roy et al. 2004 [15]		X					X
Guo and Li 2007 [22]			X		X		
Pang et al. 2008 [23]		X			X		
Tang and Wang 2008 [25]		X			X	TS	
Ozoe and Konishi 2009 [26]		X					X
Worapradya and Buranathiti 2009 [27]			X			GA	
Chen et al. 2010 [29]		X		X		GA	
Zhu et al. 2010 [30]			X			GA	
He et al. 2011 [31]		X		X		GA	
Luo et al. 2011 [32]		X		X			
Wang et al. 2011 [34]		X				ACO	X
Yu et al. 2011 [35]		X			X		
Hou and Li 2012 [16]	X				X		
Luo et al. 2012 [36]		X				GA	
Yu and Pan 2012 [37]		X			X		
Fazel and Azad 2013 [38]			X				X
Tang et al. 2013 [40]		X			X	TS	
Yu 2013 [41]		X		X			
Tang et al. 2014 [18]		X				DE	
Mao et al. 2014 [43]		X			X		
Hao et al. 2015 [14]		X			X	PSO	
Li et al. 2015 [46]			X			FOA	
Long et al. 2015 [47]	X			X			
Bo et al. 2016 [52]		X				PSO	
Jiang et al. 2016 [53]			X	X	X		
Yu et al. 2016 [55]		X			X		
Jiang et al. 2017 [57]		X		X		DE	
Long et al. 2017 [59]		X				GA + VNS	
Pang et al. 2017 [61]		X		X	X		
Sun et al. 2017 [62]		X			X		
Sun et al. 2017 (b) [63]		X					X
Zheng et al. 2017 [65]		X			X	GA	
Peng et al. 2018 [69]		X			X	ABC	
Guo et al. 2019 [72]		X				MILP + DE	

Table 2 presents the studies considered to be using a reactive approach. The solutions analyzed are mainly distributed between predictive reactive (26/37) and robust predictive reactive (8/37).

The category with fewest studies corresponds to the completely reactive, which only contains three studies: Suh et al. [19] present an heuristic to propose repair solutions for disturbances in the hot strip mill scheduling, Hou and Li [16] define a set of repair strategies to tackle with the uncertainties as they occur in the steelshop, while Long et al. [47] propose a simulation framework in which dispatching rules are used to schedule the jobs in the different machines within the steelshop according to an established matching decision algorithm. Regarding the techniques employed, heuristics (16/37) and metaheuristics (16/37) are developed in most of the papers, while the rest of solutions are based either on dispatching rules and simulation (8/37) or on multiagent systems and other Artificial Intelligence techniques (7/37).

Heuristics are mainly used in predictive reactive approaches to model the required decisions to adapt the initial predictive schedule to the disruptions that have originated the rescheduling. Most of the metaheuristics mentioned in Table 2 can be considered within the category of evolutionary algorithms, especially Genetic Algorithms (GA), considered by seven of the authors. Worapradya and Buranathiti [27] define a two-level genetic algorithm to find robust schedule for continuous casting: an outer loop to find optimal schedule and the inner loop to find worst case scenario schedule, using this last one as fitness function for the outer loop. Chen et al. [29] present a hybrid GA adapted for real time scheduling which remains listening for new orders and disturbances as soon as they are registered by the system. Luo et al. [36] propose also a GA to generate a modified schedule after any change on the processing times of the charges. Zhu et al. [30] combine the GA with a parallel backward inferring algorithm for the construction of caster schedules and uses a simulation based on cellular automata to validate and adjust the results obtained. He et al. [31] uses a GA to generate a static initial schedule, which is combined with scheduling rules to adapt to potential disturbances, introducing also the possibility of generating a complete reschedule using the GA. Long et al. [59] develop a GA combined with variable neighborhood search (VNS) for a dynamic schedule model to reallocate pending production orders under potential caster breakdown events. Zheng et al. [65] define a rescheduling framework based on GA and heuristics, considering connection problems between adjacent schedules and the matching between the created schedule and the available production material. Other evolutionary algorithms include Wang et al. [34] who introduce the possibility of applying an Ant Colony Optimization (ACO) for cold rolling scheduling with rebalance of process flow on a dynamic environment in combination with a multiagent framework. Tang et al. present three approaches based on metaheuristics: a solution combining a rescheduling heuristic with Tabu Search for the reactive scheduling in color-coating lines [25], a Tabu Search to reallocate slabs scheduled in the continuous caster to a different order after an event invalidated the current assignment [40] and a solution for rescheduling of continuous casting process using a Differential Evolution (DE) algorithm [18]. Jiang et al. [57] apply also DE technique, in this case a dynamic multi-stage DE, combining a Multi Objective DE to perform the global scheduling considering the values of waiting time cost and cast break penalty for the worst scenario, and a Knowledge Based DE to perform the local scheduling considering interval values for waiting time cost and cast break penalty. Other metaheuristics studied include Particle Swarm Optimization (PSO) [14,52], Fruit Fly Optimization (FOA) [46] and Artificial Bee Colony (ABC) [69].

In the case of multiagents, the first proposal for the rescheduling of continuous casters and hot strip mill was proposed by Cowling et al. [20] and Ouelhadj et al. [21]. Specific agents are defined for each process step, capable of generating local schedules and use a negotiation protocol to obtain global near optimal solutions. Fazel et al. [38] used multiagent systems for steel dynamic scheduling. Ozoe and Konishi. [26] consider a solution based on three types of agents: a scheduling agent that creates the basic schedules, a temperature evaluation agent that calculates the temperature of the molten steel, and the evaluation agent that combines results from the other agents to evaluate the viability of the schedule. Sun et al. [63] present a framework of intelligent agents that detect changes in the dynamic environment and communicate the virtual system developed with the existing real production scheduling systems. Different artificial intelligence approaches include Roy et al. [15] who created a knowledge-based model that tries to replicate the expert knowledge used in the rescheduling of the steelshop operations in the presence of disturbances.

References summarized in Table 3 cover the proactive scheduling solutions focused on modeling the uncertainty in the steelmaking process.

Table 3. Proactive scheduling models in steel production.

Reference	Modeling Techniques				Uncertainty Factor			
	Stochastic	Robust	Fuzzy	Others	Orders	Machine	Product Specification	Operation Time
Rong and Lahdelma 2008 [24]			X				X	
Yu et al. 2009 [28]			X					X
Worapradya and Thanakijkasem 2010 [17]	X	X		Montecarlo	X	X	X	X
Slotnick 2011 [33]	X			Heuristic	X			X
Gerardi et al. 2013 [39]	X						X	
Yu 2013 [41]				Prediction				X
Krumeich et al. 2014 [42]	X			Forecasting		X		X
Ye et al. 2014 [44]	X	X			X			X
Yue and Xianpeng 2014 [45]		X					X	
Luo et al. 2015 [48]				MILP	X			
Mori and Mahalec 2015 [49]				BN				X
Nastasi et al. 2015 [50]				Prediction + MOEA			X	
Sun et al. 2015 [51]	X						X	X
Jiang et al. 2016 [53]				GPR		X		X
Lin et al. 2016 [54]				IP-MOEA				X
Guirong and Qiqiang 2017 [56]				2-layer CE				
Jiang et al. 2017 (b) [58]				EDA				
Noshadravan et al. 2017 [60]			X				X	
Wang et al. 2017 [64]				NSGA-II		X		
Kammammettu et al. 2018 [66]	X							X
Long et al. 2018 [67]		X		Forecasting				X
Niu et al. 2018 [68]		X						X
Yang et al. 2018 [70]		X					X	
Yang et al. 2018 (b) [71]				TR-MOEA				X

The uncertainty factor most studied is the disturbance of the process time, due to the huge impact that it has on the final makespan of the scheduling, which is considered by most of the objective functions in the analyzed papers. Machine and equipment events, along with deviation from product specifications are also considered by several authors, while only four works [17,33,44,48] analyze the uncertainty associated directly with the orderbook and demand.

In relation to the modeling techniques used in these solutions, about half of them (13/24) apply classic approaches like stochastic and robust programming or fuzzy systems, explained in Section 2 of this review. Some of these solutions are also combined with other techniques. Worapradya and Thanakijkasem [17] use Montecarlo simulation with historical data to model the stochastic variables for the potential uncertainties, proposing afterwards a robust approach to solve the worst-case scenario. Krumeich et al. [42] propose a model based on Big Data, in which Complex Event Processing (CEP) techniques are applied to improve the stochastic forecasting methods by providing more information from the real environment, introducing event-based forecasting which reduce the generation of potential invalid production plans.

Yu [41] creates a prediction model to analyze the potential disturbance delays affecting operational time of steelmaking charges and propose a prediction method to estimate abnormal conditions which reduces the frequency of the reschedules and the modifications performed to the initial schedule when readjusts are required. Luo et al. [48] consider a model based on historical data to estimate the raw material demand and establish a purchasing model using on MILP. Mori and Mahalec [49] use Bayesian Networks (BN) to predict the distribution variables for production loads and production times at the different stages of a plate mill process. Guirong and Qiqiang [56] apply the Cross Entropy (CE) algorithm in a two-layer approach to solve the steelmaking scheduling problem, with an outer layer to calculate the basic processing times and the start casting times, and an inner layer to calculate the machine assignment of the charges. Jiang et al. [53] introduce a combined proactive and reactive solution for steelmaking scheduling, combining rescheduling capabilities with Gaussian Process Regression (GPR) procedure to predict the characteristic indexes (slack ratios) aiming to enhance the robustness of the initial schedule of their model against uncertainties. On a similar problem they also propose a continuous Estimation Distribution Algorithm (EDA) [58] applied in two phases: the first EDA calculates the slack ratios as characteristic indexes while a second phase EDA combined with Local Search optimizes the schedule of the jobs at the continuous casting stage.

Other authors have relied on multi-objective evolutionary algorithms to deal with the proactive scheduling in steel production. Wang et al. [64] present an Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II) to solve the rolling process scheduling under machine breakdown uncertainty, where the breakdown probability is known from historical data analysis. To reduce the duration of the fitness evaluation phase, NSGA-II is combined with a Support Vector Regression (SVR) model. Yang et al. [71] introduce a Target-Ranking Multi-objective Evolutionary Algorithm (TR-MOEA) to solve the charge planning problem tackling the objectives of due date difference within each charge and the minimization of the total weight of open orders. Lin et al. [54] solve the integrated planning of continuous caster and hot rolling processes, considering the throughput uncertainties as interval variables and using a modified Imprecision-propagating Multi-Objective Evolutionary algorithm (MI-MOEA) which is more suitable to work with interval valued objectives. Nastasi et al. [50] propose a solution based on Multi-objective Evolutionary algorithms for the route planning of the orders through all the finishing mills, considering the impact that the selected route will have on the quality of the final product. To measure this quality impact, they propose to develop prediction models based on neural networks or fuzzy systems.

5. Discussion and Future Research

Planning and scheduling under uncertainty in the steel industry has been a topic of interest in recent years. Reactive approaches have been researched along the past 15 years, while proactive solutions have gained more attention during the latest period (2013 onwards). Due to the relative novelty of the application of proactive techniques in this sector, hybrid solutions which integrate aspects from both approaches are not quite common yet.

Considering which part of the complete steel industry production has been more studied by the different authors, most of the papers reviewed in the present work are focused on the primary segment of steelmaking (specially the casting process). There can be several reasons that explain this:

- Primary steelmaking is the process in which disruptions and uncertainty have a greater impact on the scheduling operations. Any disruption in the planning will affect not only the installation or machine subject to the uncertainty, but also all the following downstream processes required for the job delayed or cancelled.
- Due to the nature and the complexity of the primary steel making process itself, the number of uncertainty factors that are present in this step is higher than in other finishing processes. This situation causes the need to propose more robust scheduling solutions.

In terms of uncertainty factors, most of the studies focus on the disturbances affecting processing times, while paying less attention to other elements such as machine related events and deviations from product specifications. There can be a couple of reasons to explain this interest in the literature to focus on this factor:

- Many of the papers analyzed use the minimization of the makespan as the objective function to optimize the scheduling. Not being capable of properly represent the process time of the different jobs used to calculate this makespan objective will have an important impact on the realization of the calculated scheduling.

- The existing techniques (such as forecasting) and the available data from the process environments can be better suited to model an accurate estimation of the process times, instead of detecting potential disruptions on machines availability or product composition.

Considering the time horizon of the problem solved, most of the papers analyzed are focused on short and mid-term scheduling scenarios, while a very small number propose a solution for long term planning problems. This could be explained by the high quantity of reactive approach solutions and the huge impact that uncertainty has on short and mid-term scenarios, making this type of problems more appealing for the research community.

Future research in this field should focus on increasing the efficiency of the reaction capacity of the industry to provide realistic schedules. Real production environments require fast solutions to readapt to the disturbances in their operations. This increase in the scheduling efficiency should come from several sources:

- Growing implementation of Industry 4.0 and digitalization paradigms in the steel industry shall improve the level of control over the manufacturing process [42]. This will provide access to additional new data and information not available before that should lead to a better understanding of the potential disruptions. New techniques based on new trends like Big Data and the Internet of Things will create better models to predict uncertainties, providing the opportunity for better proactive solutions.
- Evolution of techniques used in rescheduling solutions (specially metaheuristics) should allow for faster time response on the search of an improved reschedule upon the apparition of a disruption.
- Integration of both proactive and reactive solutions into hybrid solutions. The combination of both approaches should allow not only to provide feasible reschedules on reasonable times but also to reduce the number of times that the schedules need to be readapted to face uncertainties through the improvement of the proactive techniques used to create the initial schedules.

6. Conclusions

A review of the recent studies dealing with the planning and scheduling problem in steel industry under uncertainty has been presented in this paper. The most commonly used techniques to model potential uncertainties or to react to disruption have been exposed. We have discussed the potential uncertainty factors and proposed a classification to be used in the analysis on the solutions present in the literature for this problem. The most relevant studies have been classified and discussed. Finally, the main findings and some conclusions about future research lines have been presented.

Author Contributions: Conceptualization, M.I.-E. and F.O.-F.; Methodology, J.V.-B.; Formal Analysis, V.R.-M.; Investigation, M.I.-E.; Writing—Original Draft Preparation, M.I.-E. and F.O.-F.; Writing—Review & Editing, M.I.-E. and J.V.-B.; Supervision, V.R.-M.; Funding Acquisition, F.O.-F.

Funding: This work was funded by the Science, Technology and Innovation Plan of the Principality of Asturias (Spain) Ref: FC-GRUPIN-IDI/2018/000225, which is part-funded by the European Regional Development Fund (ERDF).

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

Parameter	Explanation
x	Decision variable for processing times of the jobs
y	Decision variable for selection of tasks and machines
c	Coefficient vector for decision variable x
d	Coefficient vector for decision variable y
A	Constraint matrix associated with decision variable x
B	Constraint matrix associated with decision variable y
p	Constraints maximum threshold

ξ	Vector containing the scenario information for the second-stage problem
$Q\,(x, y, \xi)$	Solution with optimal values for stochastic model of second-stage problem
$\mathrm{E}\,[Q\,(x, y, \xi)]$	Mathematical expectation for the solution of the second-stage problem
$q\,(\xi)$	Random variable for the coefficients of objective function z
z	Decision variable for the second-stage problem
$T\,(\xi)$	Random variable for constraints associated with objective function x in second-stage problem
$V\,(\xi)$	Random variable for constraints associated with objective function y in second-stage problem
$W\,(\xi)$	Random variable for constraints associated with objective function z
$h\,(\xi)$	Random variable for constraint maximum threshold
μ	Membership function of a constraint
b	Lower bound for parameter p
d	Used in the calculation of the upper bound for parameter p

Abbreviations

Abbreviation	Full Name
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AI	Artificial Intelligence
BN	Bayesian Networks
BOF	Basic Oxygen Furnace
CE	Cross Entropy
CEP	Complex Event Processing
DE	Differential Evolution
EAF	Electric Arc Furnace
EDA	Estimation Distribution Algorithm
FOA	Fruit Fly Optimization Algorithm
GA	Genetic Algorithm
GPR	Gaussian Process Regression
HFS	Hybrid Flow Shop
IP-MOEA	Imprecision-propagating Multi-objective Evolutionary Algorithm
MILP	Mixed integer linear programming
MOEA	Multi-objective Evolutionary Algorithm
NSGA-II	Elitist Non-Dominated Sorting Genetic Algorithm
PSO	Particle Swarm Optimization
SVR	Support Vector Regression
TR-MOEA	Target-Ranking Multi-objective Evolutionary Algorithm
TS	Tabu Search
VNS	Variable Neighborhood Search

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