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Review

Recent Innovations in Computer and Automation Engineering for Performance Improvement in the Steel Industry Production Chain: A Review

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Abstract: The steel industry is a hard-to-abate sector; it involves many energy-intensive and complex processes. Continuous performance improvement is a fundamental requirement. Efficiency enhancement of the involved sub-processes can serve as the basis of an effective roadmap for the industry's decarbonization. Efficiency and performance can be investigated in terms of whole plants, parts of a plant, individual machines, or individual devices; in addition, efficiency and performance can be associated with different topics, e.g., energy, CO_2 emissions, sustainability, and product quality. In this context, computer and automation engineering innovations could have a massive impact due to both their specificity and their potential to contaminate other crucial disciplines in the field. This review paper aims to research and provide an update on state-of-the-art innovations (e.g., emerging technologies and best practices) for performance improvement in the steel industry production chain, focusing on Industry 4.0, digitalization, data, and key performance indicators. In addition, emphasis is placed on the reheating furnaces employed in hot rolling mills, due to their significant role in decarbonization and the creation of sustainability pathways.

Keywords: steel industry production chain; computer and automation engineering; performance improvement; efficiency; digitalization; Industry 4.0; data; key performance indicator; reheating furnace

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1. Introduction

Performance improvements in large production facilities—in terms of energy efficiency and, more generally, in terms of the efficiency of whole plants, parts of a plant, machines, and devices—are gaining major attention within the framework of efforts to limit air pollution and decrease resource waste. In this context, certain industries remain particularly challenging to transition due to their high energy consumption, reliance on fossil fuels, and demand for high-temperature heat [1,2]. These "hard-to-abate" sectors include heavy industries such as steel, cement, chemicals, and transportation (aviation, shipping, and long-haul trucking). Achieving energy efficiency (and, more generally, decarbonization) in these sectors is crucial for reducing greenhouse gas (GHG) emissions and ensuring a sustainable industrial future. While significant challenges remain, a combination of process optimization, electrification, alternative fuels, and carbon capture, utilization, and storage (CCUS) could enable industries to reduce their emissions and enhance their sustainability [3–6].

Among the "hard-to-abate" sectors is the steel industry, which provides crucial materials for modern society. Global development often triggers an increase in the annual consumption of steel. At present, fossil fuels still play a central role in steelmaking; for this reason, the CO_2 emissions from this industry are huge (about 7% of all anthropogenic CO_2 emissions) [7,8]. In addition to decarbonization and sustainability objectives, product quality must be maintained in the steel industry production chain. In this context, performance improvement in terms of the efficiency of the processes in the production chain is a challenging target. In particular, the evaluation and improvement of efficiency in the steel industry can refer to a whole plant, to parts of a plant, to individual machines, or to individual devices [9–11].

Figure 1 displays an example of a steel industry production chain, while Figure 2 depicts some typical features of a steel industry production chain and some of the systems that could be installed within it. In the given examples, scrap materials represent the material input. These materials are supplied to furnaces, e.g., an electric arc furnace (EAF), a blast furnace, or a basic oxygen furnace (BOF); these furnaces, together with other components located downstream (e.g., ladle furnaces (LFs)), prepare materials for continuous casting processes. The obtained semi-finished products, e.g., billets, blooms, and slabs, can supply warehouses or can be immediately forwarded to subsequent processes, e.g., reheating furnaces within a hot rolling mill. Here, the semi-finished products are reheated in order to be prepared for the subsequent hot rolling phase. Subsequently, the final products are obtained, e.g., tube rounds [12,13].

In the last decade, the efficiency of the steel industry production chain has been increased by Industry 4.0 and the digitalization of monitoring, maintenance, control, and optimization applications [14–20]. Monitoring, maintenance, control, and optimization systems are described in Figure 2, together with some of the typical information they exchange within the steel industry production chain. As can be seen in Figure 2, Information and Communication Technology (ICT) is also present in the steel industry production chain.

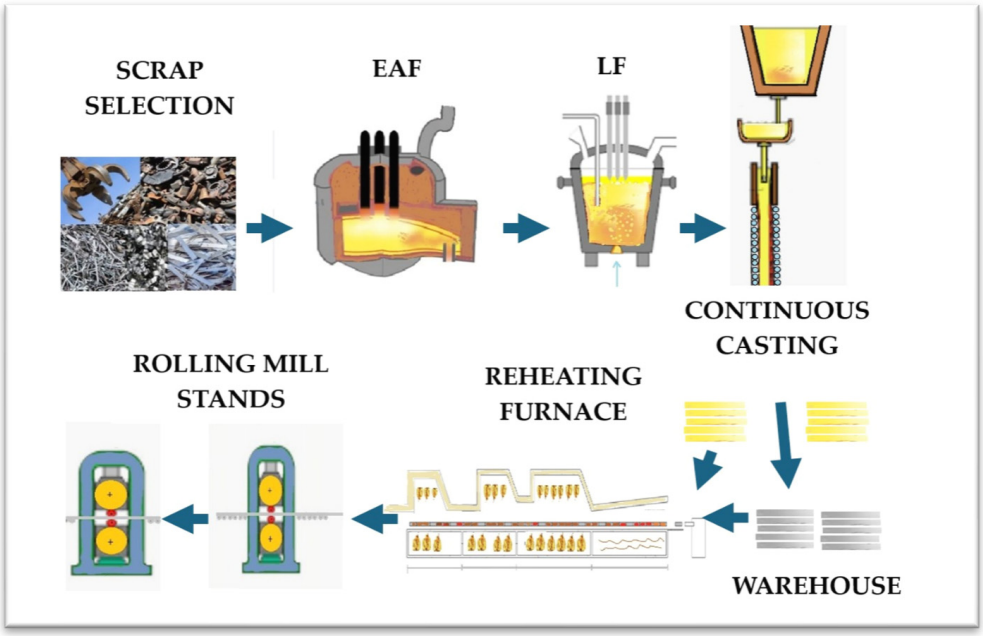


Figure 1. Example of a steel industry production chain.

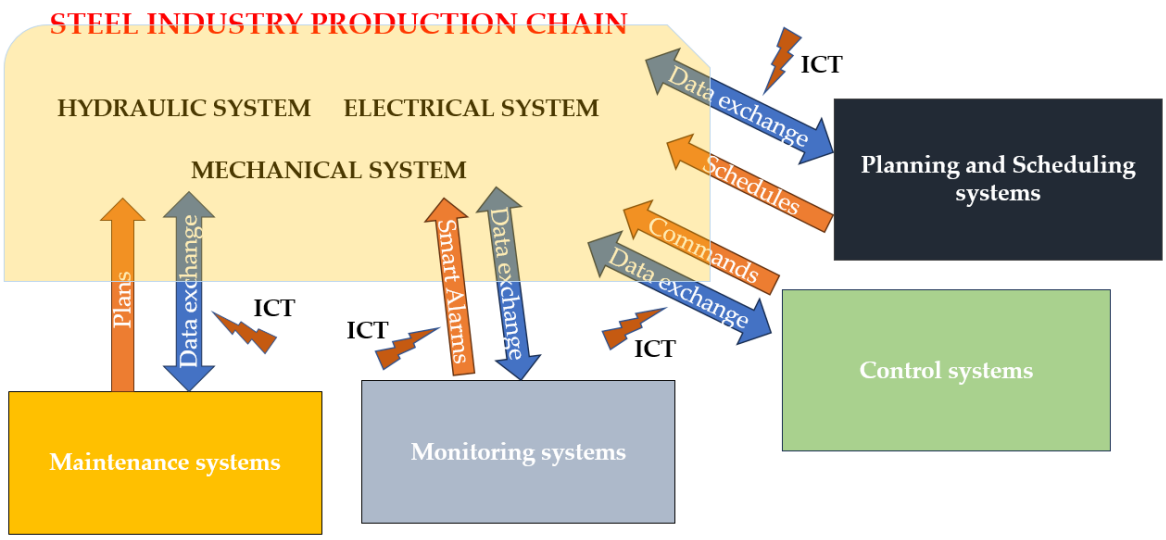


Figure 2. Overview of the general features of a steel industry production chain and the different systems which are present or which could be installed.

The assets of the steel industry often have long lifespans. The design, manufacture, and installation of steel industry production chains require a large initial investment. In addition, retrofitting or replacing infrastructure with energy-efficient alternatives requires significant investments, posing financial challenges. Energy efficiency, and efficiency more generally, are crucial targets in the management of steel industry production chains. Efficiency can be associated to a single component of a plant and/or parts of that plant. Ad hoc Key Performance Indicators (KPIs) must be formulated and used for efficiency certification. In fact, KPIs represent unbiased tools used for efficiency evaluations. In order to optimize different aspects of plant management, tailored monitoring, maintenance, control, and optimization procedures must be applied. In this field, computer and automation engineering can have a massive impact on innovations intended to improve the performance of the steel industry production chain, e.g., in terms of efficiency.

Different review papers are present in the current literature on steel industry production chains. Some of their topics are as follows:

- Assessment of the problems associated to the transition to Steelworks 4.0 and identification of technologies (e.g., artificial intelligence (AI) and virtual reality (VR)) that can enable digitalization [21];
- Digital transformation and digitalization [22–27];
- GHG control, with focus on emissions data [28];
- Sustainability assessment [26,29];
- Decarbonization transition [27,30–32];
- Industry 4.0 [23,32–36];
- Supervisory Control and Data Acquisition (SCADA) systems [37];
- Instrumentation technology for automation [38];
- Production and operation decision optimization [36];
- Machine learning (ML) and deep learning (DL) [39–42];
- Assessment and perspectives for steel industry reheating furnaces [26,43].

Table 1 summarizes the topic, providing a description, and the main findings of the previously mentioned review papers. As can be observed in the previous bullet list and in Table 1, digitalization, digital transformation, Industry 4.0, sustainability, decarbonization, GHG control, production and operation, SCADA, instrumentation technology, AI, and reheating furnaces represent the primary subjects of the analyzed review papers. The

transition to Steelworks 4.0 represents a crucial challenge [21–27], since it involves different milestones, e.g., digitalization and digital transformation. Different technologies and methods can help to reach these milestones, e.g., full automatization and the use of industrial robots. Another crucial aspect in this context is represented by the skills required to conduct such a transition, e.g., soft and digital skills. The different milestones, e.g., digitalization and decarbonization ("twin challenges"), can be reached through coordinated efforts associated to the social and technological aspects [27–32]. Industry 4.0 represented, represents, and will continue to represent a strategic paradigm for effective and efficient technology implementation aimed at improving production and operation features [32–36]. In order to implement technologies, tailored systems are needed (e.g., SCADA systems), together with specific instruments [37,38]. The impact of AI in the steel industry production chain may be massive, e.g., AI can generate environmental Decision Support Systems (DSSs) and can give insights regarding manufacturing processes and steel industry performance [39–42]. As previously described, different furnaces may be present in a steel industry production chain, e.g., reheating furnaces. The digitization and greening of these processes can speed up the overall shift to fulfilling the "twin challenges" [26,43].

Table 1. Main features of some review papers focusing on the steel industry production chain.

Topic	Topic Description	Main Findings	Ref.
Digitalization	Transition to Steelworks 4.0	Analysis of the main problems associated with the transition to Steelworks 4.0 (e.g., digitalization). Identification of the technologies and the methods that can enable digitalization (e.g., drones, AI, VR, industrial robots, full automatization).	[21]
Digitalization and digital transformation	Digital transformation in the European steel industry	Description of the current state of technological transformation in the steel sector. Provision and discussion of the results of a questionnaire tailored to European steel companies.	[22]
Digitalization and digital transformation Industry 4.0	Digitalization and innovation in the steel industry in Poland	Presentation of the tools used in the steel industry in Poland to achieve adequate digitalization for Industry 4.0.	[23]
Digitalization and digital transformation	Digital transformation in the steel industry	Ecosystem analysis in the German Rhein/Ruhr Area. Investigation on the skills required to enable the digital transformation (e.g., digital skills and soft skills).	[24]
Digitalization and digital transformation	Digitalization in the steel sector	Introduction of the digitalization context. Description of the current technological transformation. Analysis of the main developments funded by European Research Programs. Analysis of the impact of the digitalization on the steel industry workforce and on economic developments.	[25]
Digitalization and digital transformation Sustainability Reheating furnaces	Digitization and greening of the industrial reheating furnaces	Review on mathematical models, heating patterns, control systems, and energy analyses.	[26]
Digitalization and digital transformation Decarbonization	Decarbonization and digitalization in the European steel industry	Discussion on social and technological innovations associated to the steel sector in Europe. Analysis of the "twin challenges" of digitalization (Industry 4.0) and decarbonization.	[27]

Table 1. *Cont.*

Topic	Topic Description	Main Findings	Ref.
GHG control	GHG control in the steel manufacturing	Review on the current methodologies for GHG accounting in the steel sector, focusing on the critical role of emissions data.	[28]
Sustainability	Sustainability assessment of steel manufacturing companies	Review on decision-making methods for sustainability assessments in steel manufacturing companies.	[29]
Decarbonization	Decarbonization pathways in steelmaking industries	Review on current steel production processes, assessing their environmental impact in terms of the CO_2 emissions at a global level.	[30]
Decarbonization	Steel industry decarbonization transition	Analysis of the socio-technical impact of Key Enabling Technologies for the transition to decarbonization in the steel industry. Assessment of the impact of AI on decarbonization in the steel industry.	[31]
Decarbonization Industry 4.0	Adoption of Industry 4.0 technologies for steel industry decarbonization	Identification of barriers to Industry 4.0 technologies based on technological, organizational, and environmental theory.	[32]
Industry 4.0	Energy efficiency trends for the Polish steel industry in the context of Industry 4.0	Analysis of the issues associated to the energy efficiency and Industry 4.0 in the Polish steel sector. Provision of an econometric model to highlight the relationship between investment in new technologies and energy efficiency in steel production.	[33]
Industry 4.0	Implementation of Industry 4.0 in Bangladesh's steel sector	Identification of the current state of the affairs and barriers (e.g., high capital investment and a lack of government support) associated to the implementation of Industry 4.0.	[34]
Industry 4.0	Industry 4.0 strategies in the steel supply chain	Identification and evaluation of the most effective policies to implement Industry 4.0 strategies. Analysis of the gap based on the current condition in Iran (e.g., associated to the infrastructure and to the supply chain balancing).	[35]
Industry 4.0 Production and operation	Production and operation decision optimization in smart steel plants under Industry 4.0 and human-CPS (Cyber Physical System)	Analysis of crucial features of the steel manufacturing process and related implications for the optimization of decisions about production and operations.	[36]
SCADA systems	SCADA systems in the steel industry	Survey on architectures, standards, challenges, and Industry 5.0 with a focus on interoperability and interconnectivity.	[37]
Instrumentation technology	Instrumentation technology for automation in the steel industry	Review on development trends and future prospects, focusing on the main challenges associated to the sustainability (e.g., GHG emission reduction and fulfilment of the required quality specifications).	[38]

Table 1. *Cont.*

Topic	Topic Description	Main Findings	Ref.
AI	Implementation of digitalization and ML in the steel industry	Provision of a vision from the steel industry on how environmental DSSs can be defined and developed in order to improve the environmental footprint of production processes while preserving specifications regarding product quality and process operation.	[39]
AI	DL for the iron and steel making field	Review on the current trends associated to the application of DL techniques in the iron and steel making field, with a focus on the type of processes and analytical methodologies.	[40]
AI	ML application in steel manufacturing processes	Review on ML methods for the steel industry, focusing on methodologies that are able to establish complex relationships between manufacturing processes and steel industry performance.	[41]
AI	ML in steelmaking process modelling	Overview of applications of ML in steelmaking process modeling for hot metal pretreatment, primary steelmaking, and secondary refining.	[42]
Reheating furnaces	Assessment and perspectives for steel industry reheating furnaces	Review on energy efficiency assessments, waste heat recovery potential, heating process characteristics, and new perspectives.	[43]

The aforementioned review papers [21–43] focus on digitalization, digital transformation, Industry 4.0, sustainability, decarbonization, GHG control, production and operation, SCADA systems, instrumentation technology, AI, and reheating furnaces, but no details are provided about recent innovations in computer and automation engineering for performance improvement in these fields.

This review paper provides a comprehensive review of state-of-the-art innovations in computer and automation engineering (e.g., best practices and emerging technologies) aimed at improving performance in the steel industry production chain. Industry 4.0, digitalization, data, and KPIs are considered due to their significance as fundamental elements for the design of innovation roadmaps. In fact, these elements represent the necessary background to build complex strategies, e.g., aimed at performance improvement in terms of decarbonization, sustainability, and required product quality fulfillment. In addition, a focus—from computer and automation engineering points of view—on steel industry reheating furnaces installed in hot rolling mills is proposed, due to their significant roles in decarbonization and sustainability pathways. In fact, steel industry reheating furnaces are critical elements due to their location in the steel industry production chain (see Figure 1) and because they are energy intensive and can significantly affect the quality of the products. Based on the authors' knowledge and on the literature analysis of the review papers reported in Table 1, it was noted that a thorough overview of the proposed topics is not present in existing literature.

Figure 3 is a word cloud containing key words. The size of a word is associated to the specificity of that word in the context of the paper. The words that express more general concepts (e.g., production and energy) are larger than those associated to more specific concepts (e.g., control level and platform).



Figure 3. Word cloud containing the most important words in this review paper.

This paper is organized as follows: the methodology applied for the literature analysis is reported in Section 2, while the topics of Industry 4.0 and digitalization in the steel industry production chain are described in Section 3. Data and KPIs are tackled in Section 4, while Section 5 focuses on steel industry reheating furnaces installed in hot rolling mills. Discussion and insights regarding recent innovations in computer and automation engineering for the steel industry production chain are reported in Section 6. Finally, Section 7 presents the conclusions and future research directions.

2. Methodology for the Literature Analysis

Different databases were consulted in order to retrieve documents to be analyzed, i.e., Scopus, Web of Science, IEEE Xplore, Springer Link, and Google Scholar. In addition, different publishers and editorial groups were considered, e.g., IEEE and MDPI. Furthermore, Google search was used. Different search strings were used to identify significant documents. The general structure of these search strings was "steel" AND "industry" AND "word", where "word" was replaced by the topic to be investigated, i.e., "Industry 4.0", "Digitalization", "Data", "Key Performance Indicator", "Reheating Furnace".

The applied methodology is reported in Figure 4. Three main tasks were executed: the identification of review documents, the identification of technical documents, and the identification of support documents. The review documents comprised previous review papers; the technical documents comprised technical papers; the support documents comprised documents (e.g., papers and books) that theoretically/technically supported the conducted analysis. Generally, for each task, one or more phases were included, i.e., initial selection, evaluation based on the defined eligibility criteria, and final selection. With regard to the identification of review documents, previous review documents present in the current literature on steel industry production chains were identified from databases, publishers, and editorial groups. Subsequently, after eliminating duplicates, two eligibility criteria were defined: a range associated to the year of publication (2020–2025) and the relevance to/impact on the considered field. Twenty-three review papers were obtained from this procedure (see Table 1). These review papers support the subsequent identification of technical documents, i.e., they allowed us to select the topics to be tackled in the present review paper. Based on the selected topics, technical papers in the current literature were identified from databases, publishers, and editorial groups. Subsequently, after eliminating

duplicates, two eligibility criteria were defined: a range associated to the year of publication (2020–2025) and relevance to/impact on the considered field. In this way, 110 technical papers were obtained. Finally, 30 support documents were selected and added to the references. A total of 163 references were considered.

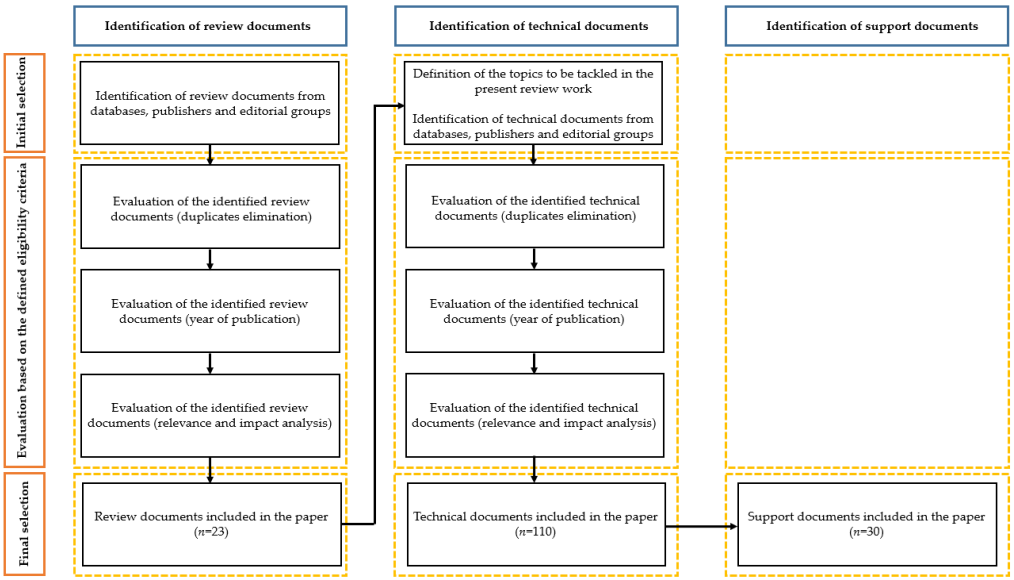


Figure 4. Methodology of the literature analysis.

Figure 5 reports the number of investigated documents on previous review works associated to the steel industry production chain (see Table 1) based on the year of publication (2020–2025).

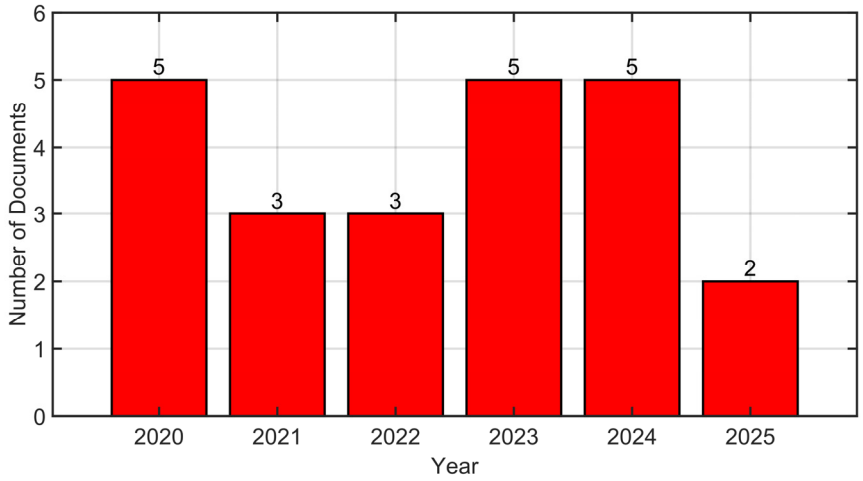


Figure 5. Bar graph showing the number of investigated documents (previous review works) based on the year of publication.

Among the 163 references, 110 technical documents (with a focus on computer and automation engineering) served for the technical core of the present paper (Sections 3–5). The number of the investigated technical documents, based on the year of publication (2020–2025), is reported in Figure 6. A distinction based on the topic is provided in Figure 7 (note that because some technical documents were associated to more than one topic, those documents are presented more than once in Figure 7). Finally, Table 2 reports all references (technical and support documents) considered for each topic.

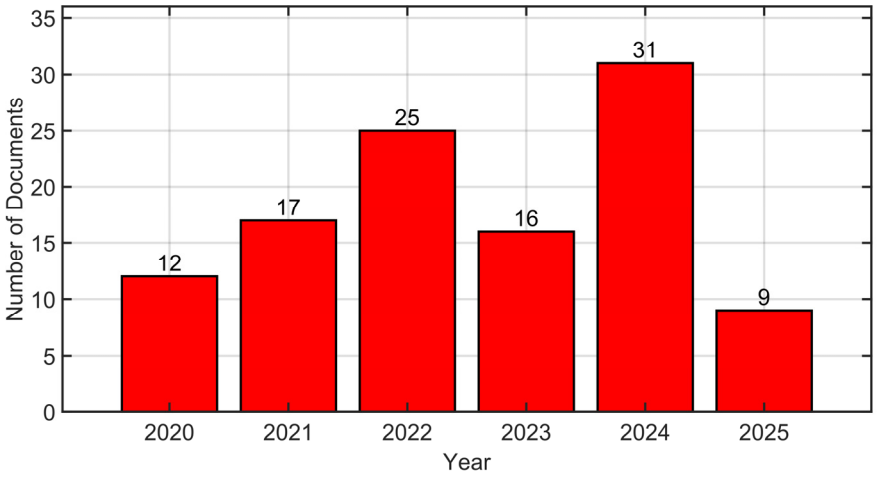


Figure 6. Bar graph showing the number of investigated technical documents (computer and automation engineering for steel industry production chain) based on the year of publication.

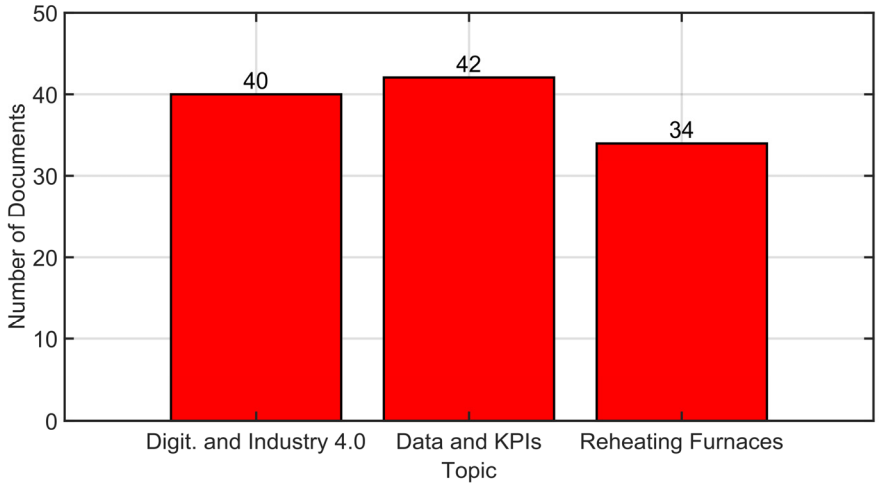


Figure 7. Bar graph showing the number of investigated technical documents (computer and automation engineering for steel industry production chain) based on the topic.

Table 2. References (technical and support documents) associated to each topic.

Topic	Associated References
Digitalization and Industry 4.0	[14–17,20,44–84]
Data and KPIs	[44,85–127]
Reheating Furnaces in Hot Rolling Mills	[9–13,110,117,119,121,122,124,125,128–157]

3. Industry 4.0 and Digitalization in the Steel Industry Production Chain

In the present section, Industry 4.0 and digitalization in the steel industry production chain are analyzed. In particular, the present section reports on selected research works in this context, focusing on the main topic, on the scope, and on the main findings.

The concept of Industry 4.0 was born in the fourth industrial revolution. Digitalization strictly depends on the Industry 4.0 paradigm. The Industry 4.0 paradigm refers to the application of the "digital industry" concept in several industrial sectors. Conventional plants can be converted into smart plants by exploiting and implementing the Industry 4.0 paradigm. Industry 4.0 technologies, e.g., simulation, robotics, the Internet of Things (IoT), augmented reality (AR), cloud computing, cybersecurity, blockchains, big data analytics,

CPSs, AI, and ML can contribute to the improvement of industrial and non-industrial processes [14–17,20].

In the Industry 4.0 context, ML can be used to provide benchmarks associated to different crucial topics, e.g., energy efficiency. The final objective can be represented by modelling in order to assess the consumption of various critical processes or the parameters that significantly affect their behavior. Challenges concerning the implementation of ML-based technologies in the steel industry represent a significant theme, e.g., data specifications must be defined in order to provide significant datasets for algorithm design and tuning [44,45]. In order to predict and/or monitor the behavior of significant process variables or key features, Digital Twin (DT) and/or Digital Shadows (DS) can be applied. For example, the tracking of material properties along the production chain can be achieved using DT/DS-based architectures [46]. Another example of the application of DTs is the temperature prediction of critical processes, e.g., heating furnaces. In order to design DTs, first principles and/or ML methods can be used, considering the pros and cons of each method with respect to the specific objective to be pursued [47]. DTs can also be applied for operation optimization; one example of this is the modelling and optimization of waste heat recovery processes in green steel production in order to obtain optimized production plans [48]. In the design and implementation of DTs, a test phase is crucial in order to assess the reliability of the developed tools. In this context, tailored architectures must be designed based on the specific needs of the analyzed process; a demonstrative example in the forging industry is given in [49]. In addition, DT can be combined with other technologies, e.g., VR, in order to support smart operators [50]. DT can also be exploited for zero defect production objectives, e.g., in forging lines. In this field, deep reinforcement learning (RL) can be applied in order to optimize the heating processes [51,52]. Table 3 reports the cited research works on Industry 4.0 and digitalization in the steel industry production chain (with a focus on modelling, DT, and DS), summarizing the main topic, the scope, and the main findings of each work.

Table 3. Main features of the selected papers regarding digitalization and Industry 4.0 in the steel industry production chain (with a focus on modelling, DT, and DS).

Main Topic	Scope	Main Findings	Ref.
Predictive modelling for steel manufacturing industry high energy consumption processes within an Industry 4.0 context	Use of ML to achieve relevant energy efficiency benchmarks	Identification of the gaps in steel mills (e.g., data to be collected for each energy intensive process)	[44]
Digitalization in the steel industry	Develop an industrial scale virtual rolling model for the hot rolling industry	Virtual models can be used to identify the crucial parameters that affect the warming of a work roll surface	[45]
Description of the material properties along the process chain based on databases	Provide a concept based on Material DT and Material DS.	Two concepts are applied for the implementation of materials into digital representations of production processes: an integrated digital description of the materials and their properties and an extended Material DT for material information retrieval.	[46]
DT for steel industry processes	Develop a DT on a heating furnace for cast billet temperature prediction	Pros and cons associated to the application of first principles and ML methods to process modelling	[47]

Table 3. *Cont.*

Main Topic	Scope	Main Findings	Ref.
Waste heat recovery in green steel production	Application of DT for operation optimization	DT approaches can be used to model and optimize the involved energy systems (e.g., in the production operation planning) in an adaptive way	[48]
DT for steel industry processes	Design of an architecture for DT testing on a production line in the forging industry	Snapshot creation methods and testing agent architecture can be applied to quickly test DT, improving its reliability	[49]
Support the steel industry smart operator in Industry 4.0	Propose an architecture that is able to support a smart operator	Development of an ontology-based, general-purpose, and Industry 4.0-ready architecture for a smart operator, based on VR (KNOW4I) and DT	[50]
Zero defect production	Exploitation of a DT-based optimization strategy for the heating process in a forging line	Deep RL can be used to automate the traditional heating process	[51]

Predictive maintenance, fault diagnosis, surface defect recognition [53], and inspection represent additional key challenges where AI, e.g., based on ML and DL, could be successfully applied.

With regard to predictive maintenance, ML can be applied combined with reliable sensors, e.g., vibration sensors, which can provide significant measurements for pattern recognition [54]. Data-driven predictive maintenance can be effectively applied, but real world datasets can be large and complex, so tailored methods, e.g., data cleaning, must be used [55]. In addition, data analysis can be combined with expert knowledge to tackle health assessments of critical assets [56]. Predictive maintenance can also support equipment prognostics. Software analytics algorithms can be developed in order to predict the behavior of key process variables [57].

Fault diagnosis in the steel industry represents another key challenge. Steel industry processes are often characterized by complex dynamics, nonlinearities, and nonstationary characteristics. In order to address these problems, data-driven multivariate statistical analysis could be applied and, if needed by a specific application, hybrid methods could also be exploited; an example of an application on a blast furnace is given in [58]. Fault diagnosis can be combined with condition monitoring in order to determine machine status. In this field, unsupervised approaches can be used, e.g., based on signal processing and/or anomaly detection; performance and the efficiency can be improved based on operator experience, which can provide qualitative information about abnormal behaviors that can occur [59].

Robust and efficient inspection methods must be designed in order to improve steel manufacturing, evolving toward intelligent steel manufacturing [60]. For example, convolutional neural networks (CNNs) can be used for hot rolled steel surface defects recognition. Different CNNs-based architectures exist, and smart manufacturing can be obtained in an Industry 4.0 context [61]. Automatic defect recognition can be targeted to achieve product quality enhancement; in this regard, explainable artificial intelligence (XAI)-based semantic segmentation can play a useful role in possible effective methods [62].

Table 4 reports the cited research works on Industry 4.0 and digitalization in the steel industry production chain (with a focus on predictive maintenance, fault diagnosis, surface defect recognition, and inspection), summarizing the main topics, the scope, and the main findings of each paper.

Table 4. Main features of the selected papers regarding digitalization and Industry 4.0 in the steel industry production chain (with a focus on predictive maintenance, fault diagnosis, surface defect recognition, and inspection).

Main Topic	Scope	Main Findings	Ref.
Surface defect recognition of products in the steel manufacturing industry	To improve defect recognition	Application of a hybrid model for efficient and robust inspections of the steel surface during the manufacturing process	[53]
Digital transformation through Industry 4.0 for the steel industry	To design predictive maintenance algorithms through the use of vibration sensors and ML	The travel distance can be detected by vibration sensors	[54]
Predictive bearing wear maintenance in the steel industry	To show the potential of using incomplete sensor data to improve predictive maintenance algorithm performance	Comparison of data-driven methods for predictive maintenance and proofing of techniques for data cleaning in large and complex datasets in the real world	[55]
Maintenance of steel industry machinery in the context of Industry 4.0	Proposes an Industry 4.0-based approach aimed at health assessment of critical assets	Development of a model based on expert knowledge and real time data	[56]
Predictive maintenance in the steel industry	To sustain turbo blower equipment prognostics	Application of a multi-step time prediction process using software analytics algorithms	[57]
Fault diagnosis in the steel industry	To overcome the limitations of data-driven multivariate statistical analyses due to complex dynamics, nonlinearities, and nonstationary characteristics	A mixed kernel-aided canonical stationary variate analysis method is proposed and tested on a blast furnace process	[58]
Fault diagnosis and condition monitoring of Industry 4.0 manufacturing processes, considering steelmaking plants	Classification of machine status through unsupervised approaches (e.g., anomaly detection and signal processing)	Application of diagnostic algorithms together with operator experience (qualitative information) to identify abnormal behaviors	[59]
Intelligent manufacturing in the steel industry	Intelligent steel surface defect management and prediction	Provision and implementation of a framework/ecosystem based on microservice architecture concepts that exploit ML and DL	[60]
Smart manufacturing and Industry 4.0 in the steel industry	Identification of hot rolled steel surface defects	Development of an ensemble methodology based on different CNN-based architectures	[61]
Guaranteeing quality in the steel manufacturing process	Implementation of automated defect detection systems for product quality enhancement	Evaluation and use of different semantic segmentation approaches based on XAI	[62]

In order to shift toward digitalization and Industry 4.0 in the steel industry, assessments of the changes to be implemented, the potential technologies to be applied, and the obtained effects, represent key milestones. With regard to the changes to be implemented, the organizational structure may be significantly involved [63]. In addition, smart retrofitting techniques, e.g., based on Design Thinking, can be applied in existing plants in order to migrate toward the Industry 4.0 paradigm [64]. Migration to digitalization and

to the Industry 4.0 paradigm could provide process innovation, resulting in an increase in product quality and reliability, together with an improvement of flexibility and productivity [65]. In addition, continuous planning and scheduling can be digitalized through automated models included in tailored, multi-criteria, decision-making algorithms. These algorithms can be characterized by different ingredients, e.g., encompassing economic, environmental, and social factors [66]. Smart operating roadmaps must be created within the Industry 4.0 environment; these maps must include the integration of different levels, e.g., Enterprise Resource Planning (ERP) and Manufacturing Execution System (MES). In this way, strategic business plans can be generated through the integration of tools, functions, and methods [67]. In order to effectively conduct, conclude, and maintain effective projects, strategic project management guidelines must be provided and put into practice. Reporting and communication rules can assume a key role in the digitalization of steel manufacturing [68].

System integration and industrial internet represent significant changes that can be introduced in Industry 4.0 migration. Conventional industrial communication systems are characterized by different shortcomings, e.g., inflexibility and lack of scalability. Migration to Industry 4.0 can solve these issues [69]. In addition, the development of the industrial internet can be achieved through integration services in order to tackle different problems associated to the current industrial internet, e.g., increasing demand for AI computing [70].

Assessments of the Industry 4.0 technologies to be applied and the associated prospects and potential represent another key theme to be tackled with regard to automation, ICT, and digitalization within the steel industry. Correct assessments are needed, especially in cases characterized by limited financial opportunities [71,72].

Dynamic Life Cycle Assessment (LCA) can be exploited in investigations into the effects of steel industry digitalization. In particular, economic costs and global warming impact evaluations can be provided [73]. Digitalization migration, if driven by reliable pathways, can generate energy efficiency improvements [74]. For example, the energy consumption of a steel industry can be optimized through hardware and/or software interventions, e.g., the installation of high-efficiency devices and/or advanced process control (APC) systems [75]. In this context, digital tools and energy efficient equipment can be successfully combined to reduce CO_2 emissions [76]. Due to the key roles of heat and energy consumption in the steel industry, tailored econometric models could be developed thanks to data collected within an Industry 4.0 context [77]. In addition, electricity can represent a significant variable to be monitored and considered in critical processes of the steel industry production chain, e.g., EAFs and BOFs [78].

Computer engineering tools, e.g., databases, can be used to investigate the effect of the Industry 4.0 revolution on the steel workforce. In fact, Industry 4.0 and digitalization require and will continue to require the adaptation of skills in the steel sector; this adaptation is triggering and will continue to trigger technological and organizational changes [79].

Table 5 reports the cited research works on Industry 4.0 and digitalization in the steel industry production chain (with a focus on changes, technologies, and effects), summarizing the main topic, the scope, and the main findings of each work.

Table 5. Main features of the selected papers regarding digitalization and Industry 4.0 in the steel industry production chain (with a focus on changes, technologies, and effects).

Main Topic	Scope	Main Findings	Ref.
Industry 4.0 in the steel industry	Practical application of the Industry 4.0 paradigm in a steel company	Investigation into the changes to be implemented in organizational structures in order to allow an Industry 4.0-based digitization process aimed at improving efficiency	[63]
Smart retrofitting in the steel industry	Industry 4.0 migration process in a steel mill plant	Application of a retrofitting methodology based on Design Thinking aimed at Industry 4.0 migration	[64]
Digital transformation, digitalization, and Industry 4.0 in the steel industry	Achieving digitally enabled process innovation	Contributions to the theory of process innovation in steel industries and to strategic management through the development of a specific framework	[65]
Industry 4.0 and automation in the steel industry	Use of automated models for the digitization of continuous planning and scheduling	Multi-criteria decision-making techniques can be used based on economic, environmental and social factors	[66]
Planning and control of a steel group in an Industry 4.0 environment	Creation of a smart operating roadmap and integration of ERP and MES under an Industry 4.0 environment	A strategic business plan can be obtained integrating functions, methods, and tools	[67]
Project management for steel manufacturing in the digitalization era	Provide guidelines for the generation of project plans	Reporting and communications rules are crucial to devise a good project plan in order to improve profitability and productivity	[68]
System integration for steel plants in the context of Industry 4.0	Provide a solution to rigidness, inflexibility and lack of scalability associated to conventional industrial communication systems	Development of a message-bus-based communication architecture that does not depend on its position in the functional hierarchy of the plant	[69]
Current industrial internet considering steel manufacturing scenarios	Analysis of the problems associated to the current industrial internet (e.g., uncertainty of network performance and increase of AI computing demand)	Provision of integrated services aimed at the high-quality development of industrial internet	[70]
Industry 4.0 in the steel industry	Reveals prospects and potential associated to the use of Industry 4.0 technologies in the steel industry (e.g., AI and robotics)	Recommendations for the implementation of Industry 4.0 technologies in enterprises with limited financial means	[71]
Automation and digitalization of the steel industry	Investigates potential technologies for product identification and traceability over the supply chain	Evaluation criteria and methodology related to ICT approaches for small and medium-sized enterprises (SMEs)	[72]
Evaluation of the effects of steel industry digitalization	Use dynamic LCA for evaluations, minimizing losses during casting	Quantifications of economic costs and global warming impact using LCA	[73]
Digitalization in the steel industry	Pathways for efficiency improvement in the steel industry through digitalization	Investigation into the background required for energy efficiency improvement (equipment availability improvement, yield increase, optimized production schedules)	[74]

Table 5. *Cont.*

Main Topic	Scope	Main Findings	Ref.
Energy efficiency and digitalization of production in the steel industry	Creation of industry development scenarios	Proposal of integrated solutions to optimize energy consumption in the steel industry (e.g., high-efficiency furnaces, waste heat recovery systems, and advanced control systems)	[75]
CO_2 emission reduction in the steel industry	Presentation of a framework for energy intensive industries based on the introduction of digitalization and energy efficient equipment in the production line	Combine digital tools and energy efficient equipment through innovation absorption and digitalization	[76]
Process heat and energy consumption in the Polish steel industry within an Industry 4.0 context	Establish a relationship between heat and energy management in the steel production process	Development of an econometric model for the Polish steel industry based on data (e.g., electricity prices and intensity of heat consumption)	[77]
Electricity and heat demand in the steel industry within an Industry 4.0 context	Characterization of electricity and heat demand for EAFs and BOFs	Trends associated to electricity and heat consumption in EAFs and BOFs	[78]
Effects of Industry 4.0 on the steel workforce	Identification of current and future skill requirements within the steel sector	Development of a sectorial occupational database that would serve the steel industry as a tool for all future technological and organizational changes	[79]

Together with innovations in the Industry 4.0 and digitalization contexts, additional innovations have been proposed in recent years, e.g., agent-based technology [80], raw material provider selection considering digitalization, circular economy and resilience dimensions [81], optimum processing parameter determination in complex processes using ML [82], CPS framework definition [83], and the application of machine vision technology to enhance accuracy requirements [84]. Table 6 reports the cited research works regarding Industry 4.0 and digitalization in the steel industry production chain (with a focus on examples of novel innovations), summarizing the main topic, the scope, and the main findings of each work.

Table 6. Main features of the selected papers regarding digitalization and Industry 4.0 in the steel industry production chain (with a focus on examples of peculiar innovations).

Main Topic	Scope	Main Findings	Ref.
Multi-agent systems in a steelwork plant	Reports multi-agent system applications in the steel sector	Description of the benefits of agent-based technology to improve process efficiency and to valorize specific byproducts	[80]
Raw material provider selection in the steel industry	Evaluation of potential raw material providers	Digitalization, circular economy, and resilience dimensions represent important factors/indicators	[81]
Advanced high strength steel in an Industry 4.0 context	Determination of the optimum processing parameters for coiling process	Unsupervised ML approaches (e.g., self-organizing maps) can be applied to reveal correlations and patterns in production datasets	[82]

Table 6. *Cont.*

Main Topic	Scope	Main Findings	Ref.
Converter intelligent steelmaking	Determination of molten steel carbon content	Development of a CPS framework for steelmaking plants in order to design a non-contact intelligent prediction model	[83]
Intelligent, efficient, and sustainable manufacturing in the steel industry	To improve the positioning accuracy requirement of bars	Application of machine vision technologies for unmanned warehouse areas used for bars, through the use of a binocular vision-based measurement method	[84]

4. Data and KPIs in the Steel Industry Production Chain

In this section, the role of data and KPIs in the steel industry production chain is analyzed. In particular, some research works about these themes are reported, with a focus on the main topic, on the scope, and on the main findings of each work.

Digitalization and Industry 4.0 are highlighting the role of data selection and acquisition and storage methodologies in the steel industry production chain. The overall steel industry production chain is receiving huge benefits from data gathering and analysis in a metallurgical data science context [85].

The development of ICT in the steel industry production chain resulted in abundant data resources, heralding the steel industry big data era. In this context, big data analytics can play a crucial role at all levels through the harnessing of data for proactive decision-making and monitoring associated to key indicators, e.g., carbon emissions [86]. In order to acquire data, tailored acquisition systems must be suitably designed and programmed; in this way, they can facilitate the selection of the desired configuration of measurement elements and technical parameters to customize the acquisition and storage of measurement data [87]. In this context, missing data represents an important issue to be addressed. Missing data patterns must be accurately identified, and the associated causes must be investigated in order to select the optimal imputation technique [88]. For the management of missing values, generative adversarial networks (GANs) can be used [89], also in combination with deep convolution [90].

Table 7 reports the cited research works focusing on data and KPIs in the steel industry production chain (with a focus on data science and ICT), summarizing the main topic, the scope, and the main findings of each paper.

Table 7. Main features of the selected papers regarding data and KPIs in the steel industry production chain (with a focus on data science and ICT).

Main Topic	Scope	Main Findings	Ref.
Metallurgical data science for the steel industry	Provides a method for the prediction of final product composition and quality in a BOF	Combination of ML with fundamental knowledge and first-principal calculation	[85]
Carbon emissions in the steel industry	Provides a correlation analysis and a monitoring method based on big data	An entropy weight-grey correlation-TOPSIS analysis method is inferred to determine the correlation between carbon emissions and influencing factors	[86]

Table 7. *Cont.*

Main Topic	Scope	Main Findings	Ref.
Acquisition and analysis of measurement data in the steel industry	Design of a computer system to analyze measurement data for a skew rolling mill used to produce steel balls	Enabling the configuration of measurement elements and technical parameters in order to customize the acquisition and storage of measurement data	[87]
Steel industry data analysis	Theory and application of missing data research in the steel industry	Identification of missing data patterns, understanding the causes thereof and the selection of an imputation technique	[88]
Steel industry data analysis	Management of missing values	Introduction of a GAN-based framework for the generation of synthetic data pertaining to data imputation	[89]
Steel industry data analysis	Management of missing values associated to datasets for a blast furnace	Introduction of a Deep-Convolution-GAN-based data filling method	[90]

As previously mentioned, the monitoring and investigation of carbon emissions in the steel industry are enabled by steel industry data science. Tailored correlation analyses can be provided with regard to the carbon emissions and several influencing factors [86]. In order to predict the carbon emissions in the steel industry, data-driven ensemble learning modelling can be applied based on suitable data preprocessing techniques [91]. Energy consumption represents another parameter to be monitored, together with carbon emissions. Suitable regression models (e.g., CatBoost) represent valuable tools for energy management and conservation in a sustainability pathway [92]. In addition, the forecasting of the power demands of the steel industry retains an important role in a decision-making context; in this regard, different types of models can be applied, e.g., Random Forest [93]. In order to enhance the sustainability of the steel industry supply chain and to implement a circular economy, data can be used for clusterization purposes in order to provide data-driven optimization models which are able to face uncertainties [94]. Sustainability can also refer to the selection of sustainable suppliers for steel manufacturing through tailored assessment methods [95]. Finally, data can enable data-based LCA in the steel industry, using primary manufacturing data in order to assess the emissions associated to critical processes, e.g., blast furnaces, BOFs, and casting rolling [96]. Table 8 reports the cited research works on the application of data and KPIs in the steel industry production chain (with a focus on carbon emissions, energy consumption, power demand, and sustainability), summarizing the main topic, the scope, and the main findings of each paper.

Table 8. Main features of the selected papers regarding data and KPIs in the steel industry production chain (with a focus on carbon emissions, energy consumption, power demand, and sustainability).

Main Topic	Scope	Main Findings	Ref.
Carbon emissions in the steel industry	Provides a correlation analysis and a monitoring method based on big data	An entropy weight-grey correlation-TOPSIS analysis method is inferred to assess the correlation between carbon emissions and influencing factors	[86]
Data-driven carbon emission prediction in the steel industry	Use of data-driven ensemble learning modelling	Data preprocessing and design of a stacking ensemble learning model	[91]

Table 8. *Cont.*

Main Topic	Scope	Main Findings	Ref.
Predictive modelling of energy consumption in the steel industry	Proposes a data-driven approach to sustainable energy management	Highlights the potential of CatBoost regression as a valuable tool for energy management and conservation	[92]
Daily load forecasting in the steel industry	Designs a power demand management system for the iron and steel industry	Development of a module based on Random Forest Modeling	[93]
Design of a sustainable steel supply chain network to achieve a circular economy	Data-driven, robust optimization	Support vector-based clustering applied to historical data to address uncertainties and for the design of data-driven robust optimization models	[94]
Sustainable supplier selection in the steel industry	Provides an approach for multi-criteria decision-making problems associated to the supply chain sustainability	Integration of data envelopment analysis (DEA), spherical fuzzy analytic hierarchy process (SF-AHP), and spherical fuzzy weighted aggregated sum product assessment (SF-WASPAS) to identify a sustainable supplier for the steel manufacturing industry in Vietnam	[95]
LCA in the steel industry	Use of primary manufacturing data for LCA	Provision of an assessment of the emissions associated to blast furnaces, BOFs and casting rolling	[96]

One field where big data analysis can represent a powerful solution is quality control in an Industry 4.0 context. Through multivariate monitoring, huge benefits for fault diagnosis and for reducing manual work can be obtained [97]. In addition, ML techniques can be applied for real-time quality control, together with non-invasive data acquisition [98] in the steel industry. Together with quality control, quality assessment also represents an important field in the steel industry production chain. Product quality prediction plays a key role in this context. In this regard, multiobjective ensemble learning can be used, together with data fusion [99]. Tailored DSSs can be implemented for product quality assessment, e.g., exploiting data mining techniques [100]. In addition, data fusion techniques can provide benefits in terms of valuable knowledge and quality improvement [101]. Table 9 reports the cited research works on data and KPIs in the steel industry production chain (with a focus on product quality control and assessment), summarizing the main topic, the scope, and the main findings of each paper.

Table 9. Main features of the selected papers regarding data and KPIs in the steel industry production chain (with a focus on product quality control and assessment).

Main Topic	Scope	Main Findings	Ref.
Quality control in a steel Industry 4.0 context based on big data analysis	Upgrade to intelligent manufacturing in a steel plant	Big data can be exploited to migrate from univariate to multivariate monitoring in steel industry process operations, improving fault diagnosis accuracy and reducing manual work	[97]
Real-time quality control in the steel industry	Application of ML on non-invasive data	Development of a contactless, non-invasive, electromagnetic sensor to measure materials during production in real-time. The data provided by the sensor were used to design a ML-based model.	[98]

Table 9. *Cont.*

Main Topic	Scope	Main Findings	Ref.
Product quality prediction in the iron and steel industry	Use of a multiobjective ensemble learning method	Development of multiobjective CNN-based ensemble learning methods with multiscale data fusion	[99]
DSSs for quality assessment in the steel industry	Evaluation of quality management practices in Industry 4.0 for steel manufacturing	Formulation of semantic data mining techniques	[100]
Manufacturing data fusion	Use of data fusion methods in steel rolling processes	Summary of case studies on steel rolling processes where valuable knowledge and quality improvement are obtained through data fusion	[101]

Fault diagnosis and isolation, anomaly detection, and predictive maintenance represent other fields that are crucial for the steel industry production chain. DTs can be used in these contexts; in particular, physics-enhanced DTs can support downtime prediction and stoppage cost management [102]. In addition, anomaly detection can use data quality analyses to provide reliable prediction analyses and operation scheduling for energy systems in the steel industry [103]. Finally, in order to manage large volumes of data in predictive maintenance applications, change point detection algorithms can be used to select the key parameters [104]. Table 10 reports the cited research works about data and KPIs in the steel industry production chain (with a focus on fault diagnosis and isolation, anomaly detection, and predictive maintenance), summarizing the main topic, the scope, and the main findings of each work.

Table 10. Main features of the selected papers regarding data and KPIs in the steel industry production chain (with a focus on fault diagnosis and isolation, anomaly detection, and predictive maintenance).

Main Topic	Scope	Main Findings	Ref.
Process state control in a steel manufacturing plant	Use of physics-enhanced DTs	Data-driven modelling can be applied for correlation analyses among features in order to predict downtime and manage stoppages costs	[102]
Anomaly detection in the steel industry	Assessment of the quality of data from acquired energy systems for prediction analysis and operation scheduling	Development of a method based on varying-scale hypercube accelerated density-based spatial clustering for applications with noise (VHCA-DBSCAN)	[103]
Predictive maintenance in the steel industry	Tests the usability of change point detection algorithms to implement large data volumes	Design of a parameter selection method for defect diagnosis using time-series vibration data from critical assets	[104]

In a metallurgical data science context, ML is playing an important role in current and future applications. Product composition and quality prediction can benefit from ML methods, also in combination with fundamental knowledge and first-principal calculations [85]. Energy consumption can be also assessed through ML techniques in order to enhance production sustainability in energy-intensive processes, e.g., EAFs [105]. In this context, regression learner-based models can be used for predictive modelling [44]. ML techniques can also be applied for process optimization, e.g., in a rolling mill [106]. In order to effectively migrate to data-driven manufacturing in the steelmaking industry,

ML algorithms can be applied based on data provided from different stages (e.g., EAF, LF, continuous casting, hot rolling) [107]. ML algorithms can benefit from data clustering methods that can be combined with supervised learning techniques in order to mitigate prediction problems in steel industry processes, e.g., plate rolling [108]. Table 11 reports the cited research works on data and KPIs in the steel industry production chain (with a focus on ML), summarizing the main topic, the scope, and the main findings of each work.

Table 11. Main features of the selected papers regarding data and KPIs in the steel industry production chain (with a focus on ML).

Main Topic	Scope	Main Findings	Ref.
Metallurgical data science for the steel industry	Provides a method for the prediction of the final product composition and quality in a BOF	Combination of ML with fundamental knowledge and first-principal calculation	[85]
Energy consumption analysis in the steel industry production chain	Provide a data-driven model for energy consumption analysis along with sustainable production in the steel industry	Investigation into the electricity consumption of an EAF via data-driven models based on ML	[105]
Process optimization	Development of a ML-based model for the rolling mill process	Provision of an engineering strategy based on the collected data in order to obtain multiple models	[106]
Data-driven manufacturing in steelmaking	Application of ML algorithms for the prediction of the strength of steel rods manufactured in an EAF	Datasets provided from different stages (EAF, LF, continuous casting, hot rolling) can be used to design ML-based models	[107]
Prediction for manufacturing factors in a steel plate rolling smart factory	Use of data clustering-based ML in order to improve thickness estimation	Clustering algorithms and supervised learning algorithms can be combined to mitigate prediction problems in steel plate rolling processes	[108]

In order to devise sustainability roadmaps, investigations into inefficiency in the steel industry are of crucial importance. To this end, KPIs can be used. Energy-based KPIs can be formulated and applied for quantitative assessments of inefficiency [109]. In this context, the efficiency of energy-intensive processes in the steel industry can be evaluated, e.g., gas-fueled reheating furnaces. In such a setting, influential variables must be taken into account, e.g., average byproduct weights, number of processed byproducts, and gas consumption [110]. In addition, sustainability indicators can be formulated and evaluated using data associated to social, economic, and environmental factors [111]. These assessments can provide indications on steel companies' performance and efficiency in an environmental sustainability structure [112]. Based on the obtained results, ad hoc policies can be designed and implemented in order to promote sustainable development based on cleaner production and green factories [113]. In addition, the potential of innovative technologies, e.g., waste heat recovery, can be assessed through KPIs, e.g., specific heat input and heat utilization rate [114]. Another innovative field in the steel industry involves the optimization of water consumption, which can be investigated through KPI definition. In this field, KPI definition must be evaluated together with barriers in order to provide a holistic overview [115]. As mentioned above, Industry 4.0 provides drivers with which to devise sustainability and decarbonization roadmaps. Here, in order to assess Industry 4.0 maturity, multi-dimensional analytical indicators can be used [116]. Table 12 reports the cited research works on data and KPIs in the steel industry production chain (with a focus on KPIs), summarizing the main topic, the scope, and the main findings of each work.

Table 12. Main features of the selected papers regarding data and KPIs in the steel industry production chain (with a focus on KPIs).

Main Topic	Scope	Main Findings	Ref.
Inefficiency investigation in the steel industry	Quantitative assessment of machine- and line-level inefficiency in the steel industry	Formulation of an energy-based KPI	[109]
Enhancement of the efficiency of reheating furnaces in the steelmaking industry	Evaluation of the efficiency of a Brazilian steelmaking company's hot rolling mill reheating process	Estimation of the efficiency, identification of the crucial variables to be considered, simulated analysis	[110]
Sustainable development in the steel industry	Presentation of an analysis of the indicators of steel companies based on data provided by the World Steel Association	Evaluation of the sustainability indicators associated to steel industry, taking into account social, economic, and environmental factors	[111]
Environmental sustainability in the steel sector	Structuring and measuring environmental sustainability	Exploration of the implications of strategic environmental sustainability indicators in order to assess company performance	[112]
Sustainable development in iron and steel production in China	Design of new environmental policy instruments to promote sustainable development	Investigation of indicators of cleaner production and a green factory	[113]
Evaluation of waste heat recovery potential in energy-intensive sectors (e.g., the steel industry)	Design of methodologies oriented toward the quantification of waste heat recovery potential, taking into account economic production conditions	Provision of different KPIs (e.g., specific heat input and heat utilization rate)	[114]
Optimization of water consumption in steelmaking processes	Investigation into barriers, with an analysis and KPI definition	Holistic combination of on-line monitoring and optimization and innovative water treatment technologies	[115]
Industry 4.0 maturity assessment in the steel industry	Development of a multi-dimensional analytical indicator methodology	Design of a weighted average method to assess Industry 4.0 readiness which applies a multi-dimensional analytical indicator	[116]

Data selection, acquisition, storage, and analysis play crucial roles in feasibility studies and performance assessments of control systems in the steel industry. These control systems can be located at different levels of the automation hierarchy and can be oriented to guarantee a trade-off between decarbonization objectives and product quality. Data analyses can reveal key relationships between crucial process variables in energy-intensive processes, e.g., billet reheating furnaces. These relationships can be used to provide static and/or dynamic models; such models can be used in controller performance assessments. In this case, the models refer to KPIs, e.g., specific fuel consumption. On the other hand, these models can be used in the design of model-based control systems, e.g., model predictive control (MPC)-based ones [117–125]. In addition, data analysis can reveal the optimal position to be assigned to critical measurement devices in order to provide reliable measurements, e.g., in a rolling mill [120]. Rolling mill management could benefit from data analysis, because data can be applied to achieve reliable static modellization. In this context, data processing methods that are able to mitigate the effect of noise on modellization results should be

proposed [126]. Another application with data-based modelling is end-point parameter prediction for converter steelmaking [127].

With regard to the control systems for steel industry reheating furnaces, Level 2 control systems can benefit from data analysis for their design, testing, and implementation. In particular, the use of data potential makes it possible to detect furnace conditions, to design reliable models, and to adapt control actions based on the current furnace conditions in terms of plant conduction and/or configuration [121,122].

Table 13 reports the cited research works on data and KPIs in the steel industry production chain (with a focus on data analysis, modellization, and control systems), summarizing the main topic, the scope, and the main findings of each work.

Table 13. Main features of the selected papers regarding data and KPIs in the steel industry production chain (with a focus on data analysis, modellization, and control systems).

Main Topic	Scope	Main Findings	Ref.
Data analysis and control of a steel industry reheating furnace	Design of a control system for the considered reheating furnace, also applying data potential	By applying data analysis methodologies, crucial relationships among key process variables can be inferred	[117]
Data analysis and modelling for billet temperature in steel industry reheating furnaces	Design of temperature models based on data analysis	By applying data analysis techniques, key relationships can be inferred among crucial process variables, taking into account different plant configurations	[118]
Steel industry pusher type billet reheating furnace control	Design of an MPC system	KPIs, e.g., specific fuel consumption, are used to assess controller performance	[119]
Data analysis and modelling of billet features in the steel industry	Design of models associated to billet features based on data analysis	Data analysis can modify the plant hardware configuration in order to enhance the reliability of measurements	[120]
Level 2 control of steel industry reheating furnaces	Design of an APC system that is able to manage all process conditions	Use of data for the design and implementation of an APC system based on different control modes which is able to optimize all furnace conditions (production, planned/unplanned shutdowns/downtimes, and restarts)	[121]
Level 2 control of steel industry reheating furnaces	Design of an APC system that is able to manage all process conditions and different configurations of plant hardware	Application of data to obtain a synergic combination of hardware and software for energy efficiency and process control improvement	[122]
Energy usage simulation in the steel industry	Provides an information-based energy usage simulation method for an energy-intensive steel casting process	KPIs (energy usage, production, and product quality) are investigated under different operating conditions in order to provide a baseline assessment of specific energy consumption	[123]
Static modellization	Static model identification for a Sendzimir Rolling Mill	Provision of a data processing method using multiple valid sets of operation data in order to mitigate the impact of measurement noise on the modellization results	[126]

Table 13. *Cont.*

Main Topic	Scope	Main Findings	Ref.
Modelling through the use of process data	Analysis of time-series data associated to converter steelmaking in order to propose methodologies for data processing and transforming	Use of time-series data and primary static process data to infer the influence of different process parameters on the end-point parameters of converter steelmaking	[127]

5. Focus on Steel Industry Reheating Furnaces in Hot Rolling Mills

In this section, a focus on recent innovations in computer and automation engineering for performance improvement of steel industry reheating furnaces in hot rolling mills is proposed. In particular, some research works focusing on these themes are reported, including the main topic, on the scope, and the main findings of each work.

5.1. Reheating Furnaces Description

An example of a steel industry reheating furnace is shown in Figure 8 [12,13]. A reheating furnace can process different types of semi-finished products, e.g., billets, slabs, and blooms. Plant configurations that could involve continuous casting, sorting lines, stock lines, and stands in a rolling mill are often considered. Different geometries and steel compositions can characterize the semi-finished products, together with different furnace inlet temperatures.

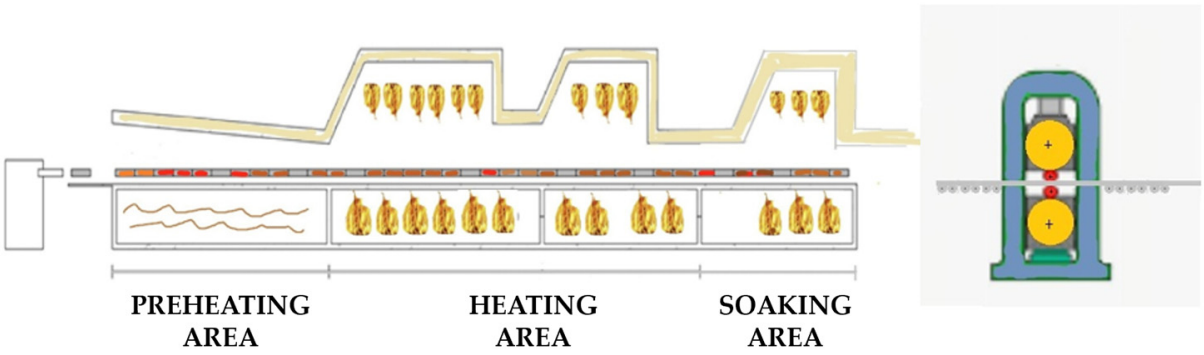


Figure 8. Example of a steel industry reheating furnace and a rolling mill stand.

Different types of charging can happen on a reheating furnace, e.g., in pairs or individually. Tailored kick-in pushers are installed to execute the charging phase. Different procedures associated to the movement of semi-finished products can be observed. For example, in a *pusher-type* furnace, they are moved by means of kick-in pushers, whereby no empty spaces are present between the semi-finished products in the furnace. In other types of furnaces, e.g., *walking beam*, the semi-finished products do not come into contact with each other during their path along the furnace, and there could be empty spaces between them.

Different areas can be present in furnace (see Figure 8) that the semi-finished products pass through; one or more zones characterize each reheating furnace area. As can be observed in Figure 8, preheating, heating and soaking areas are noteworthy. Radiation, convection, and conduction heat transfer phenomena take place in the furnace, and semi-finished products are subjected to increasing temperatures. Hot gasses from downstream areas and burners (if present) make a preheating phase possible. Major combustions

reactions take place in the heating area, and an equalization phase is performed in the soaking area.

The semi-finished products can be moved continuously at a time varying/fixed production rate; in addition, unplanned/planned downtimes/shutdowns, and restarts can take place. For this reason, the production rate and the associated furnace movement time may not be constant; rather, they are subject to scheduling/planning decisions. Suitable discharge devices are responsible for the discharge of semi-finished products from the furnace; having exited the furnace, semi-finished reheated products start their path to the rolling mill. Usually, a descaling device is present in order to decrease the amount of scale on the product's surface. Subsequently, the semi-fished products enter the rolling mill stands (see Figure 8) and plastic/forming deformation takes place in order to obtain the final product, e.g., tube rounds or rods. Plastic/forming deformation takes place by means of the action of cylinders.

The reheating furnace in a hot rolling mill is a critical piece of equipment in steel industry, because it is energy intensive and, in addition, it can significantly affect the quality of the product.

With regard to the automation level hierarchy for a steel industry reheating furnace, Level 0, Level 1, Level 2, and higher levels can be distinguished (see Figure 9) [9–11]. Level 0 is associated to the process. Level 1 and Level 2 are associated to the controllers. The scope of Level 1 controllers is to calculate, for each furnace zone equipped with burners, the power to be injected. For example, the power can be expressed in terms of gas demand to be provided and in terms of the associated air flow rate for stoichiometry specification fulfillment. The calculation involves the required temperature setpoint associated to the considered zone (provided by Level 2). With regard to Level 1 controllers, some challenging objectives have to be addressed, e.g., the fulfillment of the desired time response in terms of the selected indicators and metrics, and robustness to disturbances. Level 2 controllers often compute the temperature setpoint for each zone equipped with burners. In this computation, product scheduling (in terms of production rate and of furnace movement time) and temperature specification along the path within the furnace and at furnace discharge must be taken into account, together with the thermal behavior and conditions of the furnace itself. With regard to Level 2, many variables and parameters must be considered and investigated; a challenging problem is represented by the absence of direct real-time temperature measurements associated to the semi-finished products. In fact, in real-time operations, only zone temperature is measured. In addition, the presence of nonlinear dynamics and significant disturbances, as well as constraints on the process variables involved, raise the complexity of the design of Level 2 controllers. Finally, higher levels refer to planning and scheduling; an example of data exchange from higher levels to Level 2 is the desired temperature profile for each semi-finished product to be processed.

For each level in the automation hierarchy (see Figure 9), a characterization in terms of automation and computer devices can be obtained. Usually, Level 1 controllers are implemented in the form of programmable logic controllers (PLCs), while SCADA systems are used for Level 2 controllers. Often, a MES is present for the higher levels [128].

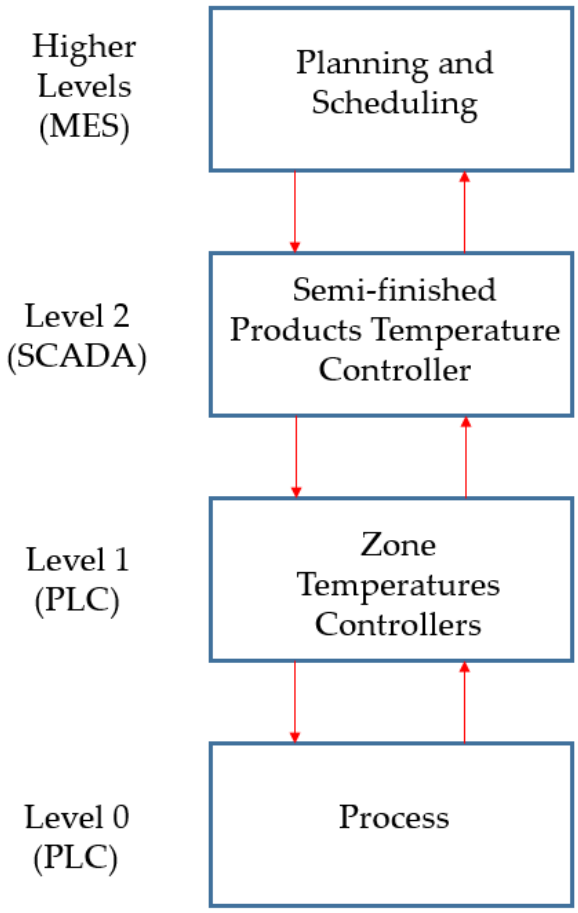


Figure 9. Hierarchy of automation levels for a steel industry reheating furnace.

5.2. Research Works on Selected Reheating Furnaces

The evaluation of the efficiency of reheating furnaces associated to hot rolling mills is a crucial step. Data analysis can support this challenging task because, thanks to data potential, the most significant process variables to be considered can be identified and used in simulated analyses [110]. The efficiency is also related to CO_2 emissions; renewable energy sources (RESs), e.g., H_2, can support the path toward a CO_2-neutral process of heat generation [129]. Other parameters to be monitored in a reheating furnace are electricity consumption and natural gas consumption; these tasks can be supported by AI and can be functional for an effective technologic decision making process with regard to planning and long-term activities [130]. In this context, retrofit and design activities can also play an important role. For example, structural modifications (e.g., associated to refractories) on existent reheating furnaces can support energy saving [131]. Additional examples include the design of the burners to be installed, e.g., hydrogen-fueled regenerative burners show the potential of the hydrogen use to avoid carbon emissions [132]. In order to assess and prove the associated optimization margins, mathematical simulation methodologies should be implemented [133].

Table 14 reports the cited research works on recent innovations in computer and automation engineering for performance improvements in steel industry reheating furnaces (with a focus on efficiency, emissions, and decision making), summarizing the main topic, the scope, and the main findings of each paper.

Table 14. Main features of the selected papers regarding reheating furnaces of the steel industry production chain (with a focus on efficiency, emissions, and decision making).

Main Topic	Scope	Main Findings	Ref.
Enhancement of the efficiency of reheating furnaces in the steelmaking industry	Evaluation of the efficiency of a Brazilian steelmaking company's hot rolling mill reheating process	Estimation of the efficiency, identification of the crucial variables to be considered, simulated analysis	[110]
Case study for the investigation of pathways toward achieving CO_2-neutral process heat generation	Investigation of the impact of reheating furnaces on CO_2 emissions and on alternative solutions	RES (e.g., H_2) application can achieve lower primary energy consumption and lower CO_2 emissions	[129]
Modelling of electricity and of natural gas consumption	Use of AI and simulation methods	Design of an algorithm to make effective technological decisions regarding planning and long-term activities	[130]
Retrofitting reheating furnaces	Study of energy savings under different structural modifications	Implementation of structural modifications and analysis of optimal location for oxygen-enriched combustion and optimal oxygen-enriched concentration	[131]
Design of burners	Evaluation of hydrogen-fueled regenerative burners	Comparison between traditional and regenerative burners with methane and hydrogen as fuel in order to show the potential of hydrogen to avoid carbon emissions	[132]
Design of burners	Use of swirl and diffusion burners	Development of a mathematical simulation methodology to show energy optimization	[133]

As highlighted in the previous subsection, measurements in real-time are not available for the semi-finished product temperature. In order to evaluate critical process features, e.g., uniformity of the temperature and total exchange factors, different tests can be applied to provide data to be used offline, e.g., for modelling. Non-contact measurement approaches can be applied, e.g., infrared thermal imaging [134]; in addition, a semi-finished product can be instrumented to obtain significant temperature data [135].

Modelling procedures can be associated to different crucial variables, e.g., zone temperatures, semi-finished product temperature, and scale formation. Modelling results can be used for efficiency enhancement in the operation and maintenance of reheating furnaces, e.g., in terms of emission reductions and product quality specifications fulfillment. With regard to the zone temperatures, the temperature field can be modelled taking into account the flow parameters. The obtained models can then be implemented to detect problems, e.g., over-burning, insufficient burning, or overheating [136]. In order to take disturbances into account, e.g., unknown dynamics or unmeasurable energy losses, disturbance observers can be designed. For this purpose, an immersion and invariance (I&I) approach can be used [137]. Alternative approaches for the temperature modellization of different zones could be based on AI techniques; in particular, recurrent neural network (RNN), long short-term memory (LSTM), gated recurrent unit (GRU) and temporal convolutional networks (TCN) approaches can be applied [138,139]. With regard to the temperature of semi-finished products, investigations into heat transfer coefficients can be useful to mitigate uncertainties [140]. In this context, the design of models that are detailed and tractable at the same time represents a significant challenge. In order to validate models that guarantee a trade-off between these two conflicting requirements, more complex

computational fluid dynamics (CFD) models can be used [141], also taking into account dynamic mesh to model the movement of semi-finished products [142]. In addition, in order to replace the measurements, simulation frameworks based on meshless methods can be applied [143]. For the accurate modelling of the temperature of semi-finished products, the consideration of different charging conditions is advantageous in the workflow, because semi-finished products with different charging conditions may require different modellization parameters [144]. Soft sensors associated to the temperature of semi-finished products can also be designed using AI techniques, e.g., data-driven models and transfer learning, combined with traditional mechanism knowledge [145,146]. With regard to scale formation, "scale" represents an oxide layer that causes a loss of product quality and steel yield. In order to perform process analyses for scale formation, oxidation, discharge temperature, and residence time should be considered as parameters in a regression analysis and to obtain functional relationships [147]. Table 15 reports the cited research works about recent innovations in computer and automation engineering for performance improvement of steel industry reheating furnaces (with a focus on measuring approaches and modelling), summarizing the main topic, the scope, and the main findings of each paper.

Table 15. Main features of the selected papers regarding reheating furnaces of the steel industry production chain (with a focus on measuring approaches and modelling).

Main Topic	Scope	Main Findings	Ref.
Non-contact measuring approach	Design of a method for the quantitative uniformity evaluation of steel slab heating temperature based on a non-contact measuring approach	Use of an infrared thermal imager, steel slab analog, and industrial image acquisition to reveal potential enhancement of quality, scrap rate reduction, and economic efficiency improvement margins	[134]
Modelling and determination of the total heat exchange	Accurate knowledge of the total heat exchange factor of a regenerative heating furnace	Use of the zonal method and the Monte Carlo method together with instrumented slabs trials	[135]
Modelling of the temperature field	Modelling and simulation of the influence of the flow parameters on the temperature field	The formulated model overcomes some problems, e.g., insufficient burning, over-burning, and overheating	[136]
Modelling and identification of furnace temperatures	Dynamical modellization of the zone temperatures	Use of a disturbance observer to estimate disturbances (unmeasurable energy losses and effects of unknown dynamics) based on an I&I approach	[137]
Zones temperature modelling	Zone temperature prediction through the use of neural models	Consideration of RNN, LSTM, GRU, and TCN approaches	[138]
Zones temperature modelling	Zone temperature prediction through the use of DL	Consideration of RNN, LSTM, GRU, and TCN approaches	[139]
Modelling of non-stationary heat exchange (heating) process of steel billets	Mitigate the uncertainties due to the need to adapt the thermophysical parameters	Consideration of heating environment parameters, taking into account a varying heat transfer coefficient	[140]
Modellization of radiative heat transfer phenomena	Design of a model that is detailed and computationally tractable	Development of a two-dimensional state-space model using a finite volume method and comparison with more complex CFD models	[141]

Table 15. *Cont.*

Main Topic	Scope	Main Findings	Ref.
Modelling through a CFD approach	Modelling and numerical analysis	Use of dynamic mesh to model slab movement and a comparison between a CFD-based model and real measurements	[142]
Simulation of the temperature field of steel billets	Provides simulation methods which are able to replace the measurements	Design of a simulation framework based on a meshless method	[143]
Modellization of the energy consumption and of slab heating quality	Design of a model that is able to take into account different charging conditions	Development of a model that integrates dynamic control and tracks the heat load demand and the slab energy in the furnace	[144]
Soft sensor model design for billet temperature	Formulation of a soft sensor to predict billet temperature	Application of transfer learning and knowledge distillation	[145]
Billet temperature modelling	Billet temperature prediction through a combination of different types of models	Combination of data-driven models and traditional mechanism knowledge	[146]
Scale formation modelling	Investigation of scale formation	Consideration of oxidation, discharge temperature, and residence time	[147]

As described in Section 5.1, Level 1, Level 2, and higher levels can be distinguished within the automation hierarchy of a reheating furnace. Different recent innovation pathways associated to computer and automation engineering have been proposed by practitioners, researchers, and engineers in these fields.

With regard to Level 1 control, different solutions were developed in order to reduce the fluctuations in furnace zone temperatures. In this regard, stable and fluctuating working conditions must be distinguished. The detection of these conditions can be used in the design of intelligent control systems [148]. Another crucial issue to address to improve temperature response is the different load conditions that can take place in a reheating furnace. In this regard, cascade controllers can be designed based on the Taguchi method [149]. In this field, alternative algorithms can also be tested, e.g., particle swarm optimization (PSO) [150]. While satisfying the desired specifications concerning temperature response, a Level 1 controller must be oriented toward the optimization of fuel consumption; for this purpose, APC techniques, e.g., generalized predictive control (GPC), can be used. In addition, comparisons between different control techniques, e.g., GPC, Smith Predictor and Fuzzy Control, can provide insights [151]. In addition to GPC, other model-based control solutions have been proposed, e.g., based on AI and, in particular, on GRU approaches; these approaches have been employed to identify a model to be used in combination with a feedforward controller [152]. Table 16 reports the cited research works about recent innovations in computer and automation engineering for performance improvement of steel industry reheating furnaces (with a focus on Level 1 control), summarizing the main topic, the scope, and the main findings of each work.

Table 16. Main features of the selected papers regarding reheating furnaces of the steel industry production chain (with a focus on Level 1 control).

Main Topic	Scope	Main Findings	Ref.
Level 1 control associated to the furnace temperature	Design of an intelligent control system which is able to mitigate large fluctuations in furnace temperature	Design of a hybrid intelligent control system which is able to adapt based on stable and fluctuating working conditions	[148]
Level 1 control associated to the temperatures of different furnace zones	Improve the temperature response and increase the temperature stability under different load conditions	Design of a cascade controller through the Taguchi method	[149]
Level 1 control associated to the furnace temperature	Design of a control system which is able to improve furnace temperature stability	Design of an optimization strategy based on PSO	[150]
Level 1 temperature control	Design of an improved Level 1 control system which is able to optimize fuel consumption	Application of GPC and comparisons with Smith Predictor and Fuzzy Control	[151]
Level 1 control associated to the inside temperature of the furnace	Design of a model-based control system	Application of a GRU-based approach for temperature forecasting. Combination of the developed model with a feedforward controller in order to improve the stability of the control system.	[152]

With regard to Level 2 control systems, data analysis can be applied to infer relationships between the process variables associated to Level 2 control. These relationships can be associated to process variables that are considered in the control matrix and/or variables that would be monitored as KPIs (e.g., specific fuel consumption). In order to design control systems that can adapt to different working conditions (production, planned/unplanned shutdowns/downtimes, and restarts), different control modes may be needed. Different control modes can use different APC strategies, e.g., MPC [117,119,121,122,124,125]. MPC represents a reliable Level 2 control technique for reheating furnaces, because it can take mixed loading and delayed operations into account. Under certain conditions, the weighting factors of the formulated optimization problem may need to be adapted online; for this purpose, adaptive entropy-TOPSIS methods can be applied [153]. As in the Level 1 case, alternative controllers can also be used on Level 2, e.g., based on neural networks models [154] or on the PSO algorithm [155]. Table 17 reports the cited research works on recent innovations in computer and automation engineering for performance improvement of steel industry reheating furnaces (with a focus on the Level 2 control), summarizing the main topic, the scope, and the main findings of each work.

Table 17. Main features of the selected papers regarding reheating furnaces of the steel industry production chain (with a focus on Level 2 control).

Main Topic	Scope	Main Findings	Ref.
Data analysis and Level 2 control of a steel industry reheating furnace	Design of a control system for a reheating furnace, also applying data potential	Applying data analysis methodologies, crucial relationships among the key process variables can be inferred and used for the design of a control system	[117]
Level 2 control of a steel industry pusher type billet reheating furnace	Design of an MPC system	KPIs, e.g., specific fuel consumption, are used to assess controller performance	[119]

Table 17. *Cont.*

Main Topic	Scope	Main Findings	Ref.
Level 2 control of steel industry reheating furnaces	Design of an APC system which is able to manage all process conditions and all plant hardware configurations	Design and implementation of an APC system based on different control modes which is able to optimize all furnace conditions (production, planned/unplanned shutdowns/downtimes, and restarts)	[121]
Level 2 control of steel industry reheating furnaces	Design of an APC system that is able to manage all process conditions and all plant hardware configurations	Combination of a control system (software) with hardware modifications (installation of an insulated tunnel at the end of the reheating furnace) for energy efficiency and process control improvement	[122]
Level 2 control of steel industry reheating furnaces	Design of a control strategy that is able to take into account mixed loading and delay operations	Combination of MPC with an adaptive entropy-TOPSIS method which is able to suggest real-time modifications to the weighting factors of the optimization problem	[153]
Level 2 control	Design of a Level 2 controller based on heat transfer characteristics	Development of a controller based on a neural network model which is able to predict the temperature field and exergy loss	[154]
Level 2 control	Design of a Level 2 control system that is able to avoid too high heating process temperatures	Development of a multi-objective optimization method based on the PSO algorithm	[155]

As noted in the previous subsection, higher levels and high-level optimization refer to scheduling and planning. The major challenge in this field is to design solutions which are able to take the practical connections between consecutive stages of the steel industry production chain into account. In this way, the limitations of disjointed planning/scheduling decision-making processes can be overcome. In this context, integrated multi-objective optimization algorithms can be applied [156], as well as particular optimization techniques, e.g., ant colony-based approaches, in order to take uncertainty into account [157]. Table 18 reports the cited research works on recent innovations in computer and automation engineering for performance improvement of steel industry reheating furnaces (with a focus on higher levels and high-level optimization), summarizing the main topic, the scope, and the main findings of each work.

Table 18. Main features of the selected papers regarding reheating furnaces of the steel industry production chain (with a focus on higher levels and high-level optimization).

Main Topic	Scope	Main Findings	Ref.
High-level optimization for reheating furnaces and hot rolling processes	Considers the practical connections between consecutive stages	Design of an integrated multi-objective optimization algorithm for a reheating furnace and rolling plan	[156]
High-level optimization in hot rolling production	Overcoming the limitations of a disjointed decision-making process associated to planning and scheduling decisions	Development of a learning-enhanced ant colony optimization algorithm which takes uncertainty into account	[157]

6. Discussion

Performance improvement in the steel industry production chain represents a crucial objective in the current energy transition and digital transition scenarios. Performance can be associated to different systems, e.g., a whole plant, some parts of a plant, specific machines, and specific devices, and can be interpreted in terms of different objectives, e.g., energy efficiency, sustainability, decarbonization, product quality, and operation and maintenance (O&M) optimization.

The processes that characterize the steel industry production chain are very complex and challenging to optimize due to economic, environmental, and process details. Economic details refer to the investments needed for the design, installation, start-up, and retrofitting. Environmental details are associated to the regulations that must be observed and the challenges that should be tackled in the current energy transition and digital transition scenarios. Process details refer to electrical, mechanical, and hydraulic systems that interact with each other and with the surrounding control, monitoring, planning and scheduling, and maintenance systems, that can be installed based on suitable ICT tools.

The customization of O&M practices refers to control, optimization, maintenance, and monitoring, together with the customization of design and retrofitting; these are fundamental requirements due to the high variability of the elements that characterize the steel industry production chain. In this context, performance improvement is not a trivial task. Different disciplines can occupy key positions in performance improvement efforts; computer and automation engineering are playing a crucial role in this field, because they contribute to empowering performance through basic elements and concepts that can serve the development of complex strategies. These basic elements and concepts are represented by Industry 4.0, digitalization, data, and KPIs. The robustness level associated to the incorporation, embedding, and application of these topics in the steel industry production chain from a computer and automation engineering point of view can ensure smoother pathways toward performance improvements, e.g., devoted to decarbonization targets, sustainability assessment, and product quality fulfillment.

Industry 4.0 and digitalization pathways are fundamental in the steel industry production chain. They can provide process innovation through supporting the creation of smart operating roadmaps. Industry 4.0 is a driver for digitalization. In a digitalization context, the convergence between operation technology (OT) and information technology (IT) can be ensured; this convergence, together with the mutual influence between computer and automation engineering, make it possible to implement performance improvement projects, e.g., digital and green transitions. In addition, performance improvement in terms of efficiency can successfully draw upon Industry 4.0 tools, e.g., simulation, robotics, IoT, AR, cloud computing, cybersecurity, blockchain, big data analytics, CPSs, AI, and ML. These tools can trigger the evolution of conventional/traditional plants into smart plants. For example, thanks to IoT, and in particular to Industrial IoT (IIoT), connected smart actuators, sensors, and other types of devices can be used to collect and exchange data.

The significance of data is being increased through Industry 4.0 and digitalization. Criticalities do not rely only on data analysis, but also on data selection, acquisition, storage, and visualization. In many case studies, relevant results can be obtained by merging data science and expert knowledge. In this context, the definitions of specifications are a critical factor, because they massively affect the data reliability for the selected context, e.g., algorithm tuning and model parameter identification. Steelworks 4.0 and steel industry production chain CPSs make it possible to collect big data. The associated information must be inferred; it can empower design, retrofitting, O&M, and business level practices. As previously mentioned, data can support modellization; in particular, DT and DS architectures can make it possible to track material properties along the steel industry

production chain. In addition, they can be used to monitor the behavior of key features and critical process variables. In this context, reliable models used in the field represent the DTs of their physical counterparts. For the development of models, different methods can be applied, e.g., first principles-based and AI-based ones. Each method is characterized by pros and cons, and specific customization is needed based on the considered process variables and the final goal. For example, models characterized by high accuracy can be used to design reliable process simulators, but these may not be tractable enough to be embedded within a model-based control strategy. Generally, DTs can support different practices, e.g., O&M. The objectives can be different, e.g., optimization of the processes, predictive maintenance, fault diagnosis, and defect recognition.

In order to involve all the automation hierarchy levels in migration toward Industry 4.0 and digitalization, suitable integration strategies must be implemented at the process level and at the system level. The different levels must be integrated from different points of views, e.g., functions and methods. Suitable platforms and tools must be applied to support this digital transition, e.g., databases. In addition, strategic steps must be implemented to take full advantage of available data, e.g., data mining, data classification, and data reliability/quality assessment. At all levels, DSSs can be developed and installed for the enhancement of decision-making and command computation. These procedures can be interpreted as a shift to data-driven strategies and can shrink the time horizon associated to decision making.

Another crucial keyword in analyses of the impact of automation and computer engineering on performance improvement policies associated to the steel industry production chain is KPI. KPIs can refer to O&M, sustainability, decarbonization, and other challenging critical topics related to efficiency. An (semi-)automatic assessment of KPIs can be interpreted as an additional, dominant strategy aimed at optimizing the decision-making time horizon and the optimality of the decisions. KPI computation is based on two main aspects: data availability and modellization. To compute KPIs, data associated to the involved process variables must be available; in addition, in order to formulate significant KPIs, tailored modellization techniques must be adopted. As mentioned above, O&M policies can be supported by data and KPIs within an Industry 4.0 and digitalization context. In this context, the acceptance of projects aimed at the installation of APC systems in the steel industry production chain can be improved thanks to the ability of KPIs to provide unbiased certification of performance.

A summary of some important results associated to Industry 4.0, digitalization, KPIs, and data in the steel industry production chain is reported in Figure 10.

Different complex processes characterize the steel industry production chain (see Figures 1 and 2). One energy intensive process is the reheating furnace in a hot rolling mill (see Section 5). From a computer and automation engineering point of view, the complexity of this process is related to data, automation hierarchy, and the process variables involved. For example, with regard to data, no direct real-time temperature measurements associated to the semi-finished products are available.

The available data can be used to assess evaluations of the efficiency of a reheating furnace. Efficiency and performance can be related to different aspects, e.g., energy and CO_2 emissions. In this context, AI can provide massive support. In addition, data can support the execution of reliable simulations based on tailored models. In this field, offline data can be used for the execution of specific experiments, e.g., experiments that investigate the real temperature of semi-finished products along their path in the reheating furnace. These experiments can be dedicated to different tasks, e.g., the identification of uncertain parameters in the developed models. On the other hand, data that can always be acquired can support both modellization and O&M strategies.

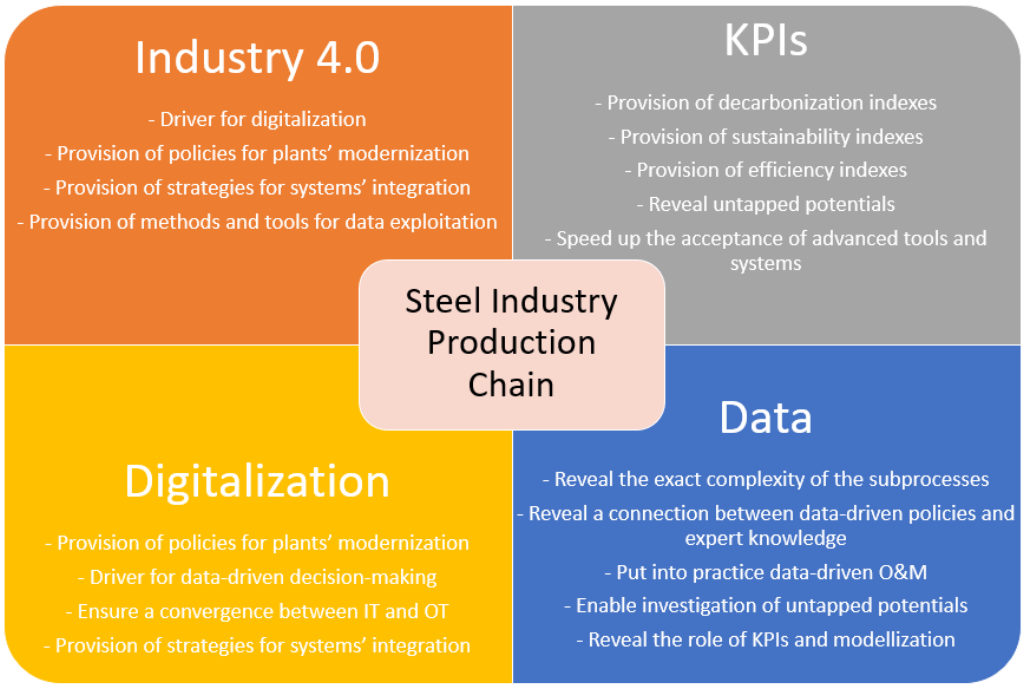


Figure 10. Summary of important results that Industry 4.0, digitalization, KPIs, and data can provide in the steel industry production chain.

Modelling strategies can refer to different process variables, e.g., furnace zone temperatures and semi-finished products temperature. In addition, specific features of semi-finished products can be investigated, e.g., scale formation. Based on the variable to be modelled/predicted, tailored process variable sets must be defined. For example, the flow parameters associated to the combustion reactions that are triggered in the reheating furnaces can be considered for the provision of zone temperature models. Different techniques can be used in this field, e.g., AI-based ones. With regard to the modellization of semi-finished product temperature, heat transfer coefficient estimation must be performed in order to develop reliable soft sensors. The model validation phase plays a key role. In this context, CFD-based complex models can be used. In all cases, a crucial aspect in modellization is to design methods which are able to mitigate the detrimental effects associated to unmodelled dynamics and/or unmeasurable effects.

The automation hierarchy plays a key role in steel industry reheating furnace control and optimization. Level 1, Level 2, and higher levels can be distinguished with regard to this topic. Recent trends associated to Level 1 aim to reduce fluctuations in the zone temperatures to be controlled. Different techniques can be combined for this purpose, e.g., AI and predictive control. With regard to Level 2, the different working conditions (production, planned/unplanned shutdowns/downtimes, and restarts) of the furnace must be taken into account in the design of reliable solutions. For Level 2 controllers, different strategies can also be combined, e.g., MPC and neural networks. Finally, with regard to higher levels, multi-objective optimization algorithms are advantageous because of their ability to overcome disjointed planning/scheduling decision-making solutions.

A summary of some important results associated to data, modelling and simulation, and automation hierarchy for the reheating furnaces in a hot rolling mill is reported in Figure 11.

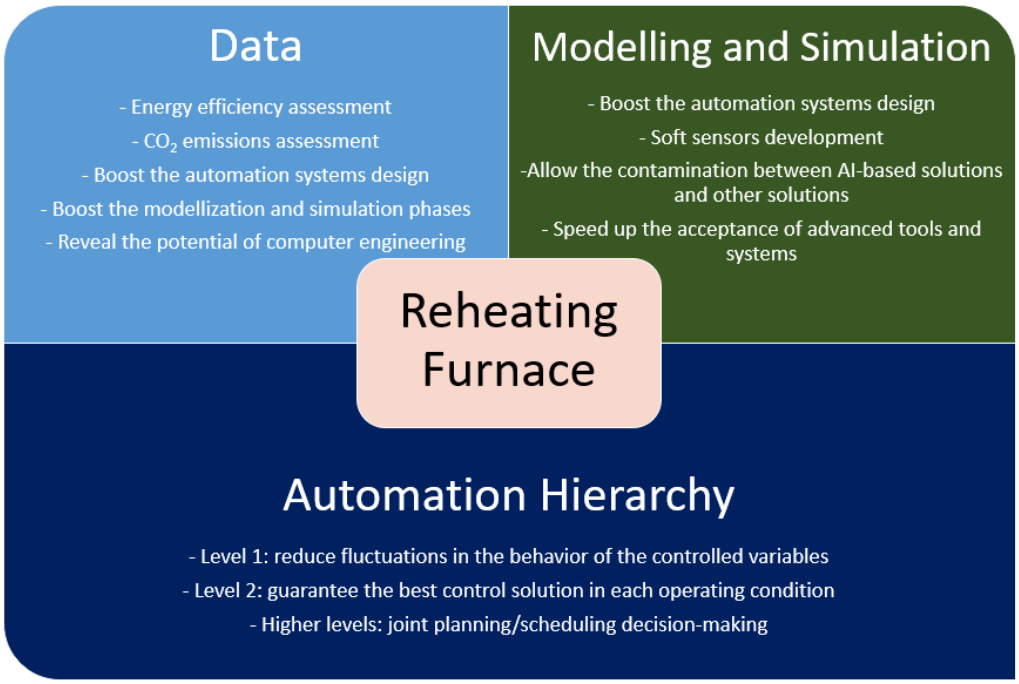


Figure 11. Summary of important results associated to data, modelling and simulation, and automation hierarchy for steel industry reheating furnaces in a hot rolling mill.

The previous discussion pointed out the main aspects associated to recent data, KPI, digitalization, and Industry 4.0 trends in computer and automation engineering for performance improvements in the steel industry production chain. In addition, interactions among the various topics have been highlighted. A focus on steel industry reheating furnaces in hot rolling mills was presented due to the significance of this process in terms of emissions, energy consumption, and product quality.

In the authors' opinion, in order to further enhance and assess the potential and impact of the considered topics in the steel industry production chain (and in reheating furnaces), the following principles must be applied:

- Keep creating teams with computer and automation skills combined with other skills, e.g., energetics, for the development of tailored projects. The steel industry production chain involves very complex processes that are interconnected; knowledge fusion and skill sharing are fundamental requirements in order to evaluate significant variables the right way and at the right time.
- Keep reducing the gap between public and private entities in order to implement policy support, technological innovation, and collaborative efforts. In this way, roadmaps toward energy-efficiency and environmental sustainability can be enhanced and accelerated.
- Keep reducing the gap between facilities and universities with regard to computer and automation engineering. Facilities can provide expert knowledge on different aspects, e.g., current O&M procedures and critical issues to be addressed. Universities can provide state-of-the-art scientific and theoretical approaches.
- Increase the number of small-scale laboratories. Small-scale laboratories can support and speed up the development of optimized O&M practices through the small-scale implementation of parts of real plants.
- Increase the amount of open access information. Open access data can trigger the cross-fertilization of existent algorithms (e.g., those implemented in other sectors) within the steel industry production chain at all process and system levels, further speeding up performance improvement processes.

- Effectively apply scientific results associated to the steel industry production chain, and, in particular, with computer and automation engineering. The present paper highlights the huge benefits that can be obtained by properly applying the potential of data, KPIs, Industry 4.0, and digitalization in the steel industry production chain. In addition, the focus of this paper on reheating furnaces in hot rolling mills provides a zoomed-in view of a critical process which has crucial implications for emissions, energy consumption, and product quality.
- Keep exploring the connections among different processes in order to provide high-level analyses that consider all possible interconnections among different production chain stages.
- Use the mentioned trends in order to enhance the effectiveness of the monitoring/control (remote and onsite) of the different processes of the steel industry production chain.
- Keep customizing computer and automation solutions based on the target to be reached at each level.
- Keep sharing expert and data-driven knowledge in order to design computer and automation solutions which are able to untap hidden performance improvement margins.

7. Conclusions and Future Research Directions

The present paper provides a comprehensive literature review of recent innovations in computer and automation engineering for performance improvement in the steel industry production chain. In particular, the topics of Industry 4.0, digitalization, data, and key performance indicators topics were analyzed. In addition, a focus on advanced solutions associated to the reheating furnaces in hot rolling mills was presented. Furthermore, the authors proposed a set of insights regarding methods and concepts that can be used for the further enhancement and assessment of computer and automation engineering potential in the steel industry production chain.

Future research directions should be associated with the following concepts:

- An overall assessment of Industry 5.0 for the steel industry production chain. In this context, a thorough shift to a "value-driven" approach (Industry 5.0, 2017) is required, starting from the Industry 4.0 "technology-driven" concept (born in 2011). Investigations into the coexistence of Industry 4.0 and Industry 5.0 and of the benefits that could be obtained thereof should be performed [158–160]. Industry 5.0 is based on sustainability, resiliency, and human-centricity. As mentioned in this paper, sustainability pathways are being proposed and tracked; on the other hand, additional efforts are required to achieve resilience and human-centricity. For example, with regard to human-centricity, operators of monitoring/control rooms (remote and onsite) could be placed out of the lower-level loops in order to gain crucial supervisory roles. In this context, XAI could support Industry 5.0 pathways [159,161,162]. The same rationale could be extended to higher levels of the automation hierarchy, where engineers could apply advanced decision making technologies.
- Industry 6.0 overall assessment for the steel industry production chains. Digital Twins must continue to show their potential and be implemented within industrial plants, while AR/VR concepts must acquire major diffusion [163].
- Overall assessment of opportunities to obtain challenging and strategic certifications (e.g., for Industry 5.0).
- Continue to shrink the gap between field implementation and simulation. Computer and automation engineering projects that are tailored to steel industry production chains, characterized by lasting field implementation, could be used to effectively highlight the potential of these disciplines in the field. The real implementation of

a system requires in-depth evaluation of its robustness and reliability against the requirements of a system, as tested through simulations in a virtual environment.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
APC	Advanced Process Control
AR	Augmented Reality
BOF	Basic Oxygen Furnace
CCUS	Carbon Capture, Utilization, and Storage
CFD	Computational Fluid Dynamics
CNN	Convolutional Neural Network
CO_2	Carbon Dioxide
CPS	Cyber Physical System
DEA	Data Envelopment Analysis
DL	Deep Learning
DS	Digital Shadow
DSS	Decision Support System
DT	Digital Twin
EAF	Electric Arc Furnace
ERP	Enterprise Resource Planning
GAN	Generative Adversarial Network
GHG	Greenhouse Gas
GPC	Generalized Predictive Control
GRU	Gated Recurrent Unit
ICT	Information and Communication Technology
I&I	Immersion and Invariance
IIoT	Industrial Internet of Things
IoT	Internet of Things
IT	Information Technology
KPI	Key Performance Indicator
LCA	Life Cycle Assessment
LF	Ladle Furnace
LSTM	Long Short-Term Memory
MES	Manufacturing Execution System
ML	Machine Learning
MPC	Model Predictive Control
O&M	Operation and Maintenance
OT	Operation Technology
PLC	Programmable Logic Controller
PSO	Particle Swarm Optimization
RES	Renewable Energy Source

RL	Reinforcement Learning
RNN	Recurrent Neural Network
SCADA	Supervisory Control And Data Acquisition
SF-AHP	Spherical Fuzzy Analytic Hierarchy Process
SF-WASPAS	Spherical Fuzzy Weighted Aggregated Sum Product Assessment
SME	Small- and Medium-sized Enterprise
TCN	Temporal Convolutional Network
VHCA-DBSCAN	Varying-scale Hypercube Accelerated Density Based Spatial Clustering for Applications with Noise
VR	Virtual Reality
XAI	Explainable Artificial Intelligence

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