

Methods and Tools of Improving Steel Manufacturing Processes: Current State and Future Methods

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Abstract: The steel industry is continuously looking for new ways to improve resource efficiency and sustainability due to high dependence on resources and increasing demand for more sustainable production. There are general tools and methodologies available and applicable for a wide range of production processes. The general tools and methodologies have similar characteristics as the domain specific tools needed or already utilized in the steel industry. However, there is still clear need for integration, further development, domain specific modelling, utilizing artificial intelligence and machine learning. This paper reviews the current state and recent developments of plant coordination & control, raw materials & energy optimization and quality management in steel industry and discusses the future methods and developments.

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Keywords: Steel industry, plants, process systems, co-ordination, control, optimization, quality

1. INTRODUCTION

In large-scale production, even small changes in using raw materials and in energy can significantly improve process efficiency. The steel industry is continuously looking for new ways to improve resource efficiency and sustainability due to high dependence on resources like energy, raw materials and utilities. There are general tools and methodologies available and applicable for a wide range of production processes. The general tools and methodologies have similar characteristics as the domain specific tools needed or already utilized in the steel industry.

This paper overviews the current state and recent developments of plant coordination & control, raw materials & energy optimization and quality management in steel industry. The review shows that there is plenty of solutions and tools for managing different process steps. However, they do not provide overall view of the whole process.

This paper is a starting point to present the work on Morse project (Model-based optimisation for efficient use of resources and energy). Morse project is developing tools and methods for managing through process integration in steel industry.

The paper is organized as follows. At first, the classification of process systems are presented in order to clarify the diversity of used systems. Chapter 3 focuses on raw

materials and energy optimization solutions. In chapter 4, solutions and methods for improving, controlling and monitoring product quality are reviewed. Finally, chapter 5 discusses about current situation overall and future methods and developments.

2. PROCESS SYSTEMS IN STEELMAKING

Process systems are complex entities, involving raw materials, products, energy, processes, automation systems and people. Their efficient operation involves numerous functions and tasks. A commonly used classification for process systems includes Planning, Scheduling, Real-time optimization, and Control. (Daoutidis et al. 2018)

2.1 Planning and Scheduling

It is necessary to combine different techniques, like operations research, artificial intelligence (AI) and coordinated visualization, to achieve adaptive, flexible, and optimal planning and scheduling systems (Tang et al. 2001). For example, multi-agent systems have been overviewed for production planning (Caridi & Cavalieri, 2005). Li and Shang have proposed an integrated model for production planning in a large iron and steel manufacturing environment based on input-output (I-O) model (Li & Shang, 2001). There have been also a case study from the steel making industry about a

scheduling system in the steelmaking-continuous casting process of a steel plant in Austria (Missbauer et al. 2009).

Also, key decision-making problems referring to the integrated production planning for the steelmaking continuous casting - hot rolling process in the steel industry have been investigated. A concept “order-set” is proposed for modelling and a multi-objective optimization model to optimize the throughput of each process, the hot charge ratio of slabs, the utilization rate of tundishes and the additional cost of technical operations (Lin et al. 2016).

Since classic optimization methods might fail to obtain optimal solutions for steelmaking continuous casting scheduling problem the Hybrid Ant Colony and Classic Optimization method utilizing simultaneously meta-heuristic algorithms and non-linear optimization methods has been also proposed (Atighehchian et al. 2009).

A new trend is also rising in scheduling of manufacturing and production. It is called robust scheduling and it is seen as a solution to production process disruption and uncertainty. For example, intelligent job scheduling system based on predictive and reactive scheduling have been presented. (Sobaszek et al. 2018)

A plant-wide optimization method and its application to hydrometallurgy process have been proposed. The hydrometallurgy process consists of a series of unit processes with coupling relationships between them. The proposed method decomposes the complicated optimization problem into several easier solvable sub-problems based on the coupling relationships between unit processes. The global optimum will be found by solving the sub-problems. (Yuan et al. 2016)

2.2 Real-time Optimization

Real-time optimization (RTO) is a model based upper-level optimization system that is operated iteratively in closed loop and provides set-points to the lower-level regulatory control system in order to maintain the process operation as close as possible to the economic optimum (Gao et al. 2017). RTO improves the performance of processes by adjusting their inputs in response to disturbances and process variations (Gros 2017). Usually process optimization includes following steps: process modelling, numerical optimization using the process model and application of the model-based optimal inputs to the plant (Marchetti et al. 2017).

As an example from steel industry, an advisory system that employs a first-principles electric arc furnace (EAF) model to support the operator decision making in real-time for economically optimal process operation. A dynamic optimization calculation can be triggered by the operator. The advisory system computes estimates of the process states based on current and past inputs and measurements. End-point constraints and possible batch duration extension handled by optimization algorithm. (Shyamal & Swartz, 2018)

2.3 Control

According to the Daoutidis et al. (2018), process control is responsible for meeting the production goals, taking into account process dynamics and disturbances. Plant-wide control in particular refers to meeting these goals for entire plants, rather than single process units.

There are monitoring systems presented (Vannocci et al. 2015) to be utilized to get a clear and updated picture of the ongoing process and also model-based dynamic monitoring and end-point control of oxygen converter processes (Schlautmann et al. 2011).

The process can be also controlled by the help of predictions. New BOF process control devices were installed a steel plant with the purpose to investigate the possibility for a dynamic system for slopping prediction (Brämning et al. 2016).

A model for the composition adjustment by sealed argon bubbling-oxygen blowing (CAS-OB) process has been also revised and converted for online estimation and Nonlinear Model Predictive Control (NMPC). The model calculates and predicts metal temperature and composition. In addition, model predictive control was implemented and tested. (Rotevatn et al. 2015)

Zheng et al. (2013) have implemented hot-rolled strip laminar cooling process plant-wide temperature monitoring and control. A modified extended kalman filter (EKF) with trade-off feedback coefficient is implemented to reconstruct the spatial distribution of strip temperature. In addition, a control strategy based on the designed EKF and model predictive control (MPC) is proposed for high strength low carbon steel (HSLC) to improve the precision of coiling temperature (CT). (Zheng et al. 2013)

2.4 Decision-making

Typical hierarchical structure of decision-making in process operations and control in traditional industries includes planning, scheduling, optimization, supervisory control and process. (Daoutidis et al. 2018)

Decision support systems have been applied also for example steel hot rolling mill scheduling. In several steel plants throughout the world, decision support system gives better results than a manual planning system. Cowling (2003) have discussed the features of the system, qualitative and quantitative improvements and other issues arising from decision support system implementation. Use of a semi-automatic scheduling system may yield substantial benefits, mainly saving scheduler time. (Cowling, 2003)

3. STEELMAKING RAW MATERIALS AND ENERGY OPTIMIZATION

The steels are produced with Blast Furnace (BF), Basic Oxygen Furnace (BOF), Electric Arc Furnace (EAF), Ladle Furnace (LF), degasser and continuous casting systems. Optimization of these systems is essential to maximize yield and productivity, and at the same time to minimize carbon

dioxide (CO₂) emissions, waste, raw material and energy consumption, and production cost. (Emi 2014)

Process optimization and Process Integration paradigms and recent works relating to sustainability have been overviewed and the progress noticed to have been made in energy, water efficiency, waste management, waste-to-energy, pollution prevention and remediation. The three pillars for sustainability improvement have been stated: Minimizing waste of energy and materials, maximizing the use of the renewable resources, and sustainable and efficient processing. (Fan et al. 2017)

Future aspects of steelmaking have been researched to increase sustainability of the industrial domain. Emerging blast furnace operation technologies combined with carbon capturing and utilization units and integration with a poly generation system producing district heat, electricity and methanol have been researched. A mathematical model of the suggested approach have been developed to optimize the use of residual gases minimizing the internal energy demand under specified operating costs, simultaneously considering investment costs for new process units. (Ghanbari et al. 2015)

3.1 Energy

Reacting to rapid changes in operating conditions creates a need for short-term energy planning and optimization. Planning processes from production to energy management must operate seamlessly integrated on top of real-time data. An energy management system must be integrated with production management and mill control systems. This enables the forecasts and optimizations to be performed with up-to-date operative data. (Merkert et al. 2015)

As an example of integrated production and energy management is implementation of an integrated production and electricity optimization system in melt shop. Integrated system enables the melt shop to adjust its production schedule to changing electricity prices and lower costs. An existing production scheduling optimization system based on a continuous-time mixed-integer linear programming model was also further developed to account for electricity costs. (Gajic et al. 2017)

There are also several other researches and studies performed relating to energy optimization and consumption in steel industry. For example: A power quality (PQ) knowledge discovery and modelling framework for both temporal and spatial PQ event data collected from transformer substations supplying iron and steel plants (Guder et al. 2015), Integration of environmental indicators in the optimization of industrial energy management using phase change materials. (Ferreira et al. 2015), Development of a model for optimal exploitation of energy resources in integrated steelworks, through multi-objective optimization (Maddaloni et al. 2015), and an energy intensity optimization model for production system in iron and steel industry (Lu et al. 2016).

3.2 Emissions

In manufacturing domain iron and steel production is consuming most energy in the world and due to that it emits about 4-5 percent of total carbon dioxide (CO₂). The use of iron and steel products is increasing constantly and this leads to the fact that also CO₂ emissions are increasing. Developing and implementing energy-efficient and low-carbon technologies and solutions is necessary in the iron and steel making. The researched technologies are for example waste heat energy recovering combined with carbon capture and storage (CCS). The implementation of CCS technology in coal-based integrated steel plant have been seen efficient for more sustainable iron and steel manufacturing. (Qader et al. 2015) For example, Arasto et al. (2012) have modelled carbon capture processes and utilized the results for estimating CO₂ emissions reduction potential of integrated steel mill from a plant operator's point of view. (Arasto et al. 2012)

In addition to utilizing waste heat and capturing carbon directly, there are also indirect means to affect emissions. These means are for example process optimization via process integration methods. Process Integration methods could be applied to the integrated steelmaking route for CO₂ reduction by optimizing material and energy systems (Maddaloni et al. 2015). According to Manan et al. (2017), process integration methodologies and frameworks for CO₂ emission planning have been most researched topics when aiming for cleaner production. Most of the previous works focus mostly on energy and CO₂ emission reduction strategies, but some researches have been extended towards economics and profitability as key decision-making criteria. (Manan et al. 2017)

Porzio et al. (2013) have implemented a tool for monitoring plant energy and CO₂ performances that helps to reduce costs and emissions. On the other hand, optimizing processes and plants may have conflicting objectives when emissions should be reduced but for example, profitability increased. Porzio et al. (2014a) addressed multi-optimization problem by modelling first the main sub-plants and calculating mass and energy balances in different scenarios of operation. The scenarios were exploited to minimize both cost and CO₂ emissions at the same time. The results of the extended research show that multi-objective optimization is an efficient solution with 4% CO₂ emissions reduction and 20% profit increase compared to the pre-existing situation (Porzio et al. 2014b).

4. THE QUALITY OF STEEL

The quality of metallurgical products is usually qualified from physical attributes like chemical composition and properties, physical properties, precision, functionality and so on. Certain properties of the products must fulfil production standards and customer orders' requirements. The products are quality controlled in the plant. Despite the fact that quality control is nowadays usually computerised, process depends on the precision of measurements. The validity of product quality evaluation depends on accuracy of measurements and employees. (Gajdzik & Sitko, 2014)

4.1 Quality Monitoring and Control

In order to achieve high quality process it is important to understand process quality status, detect deviations from normal state and find root causes for process errors. Quality monitoring tool is a framework for analysing process quality status. Tool reads process data measurements from plant data sources and turns it to quality information using calculation models. Calculation models can also output visual information that can be presented in tool. Process layout with different process phases is modelled to tool and calculation models are set for different parts of the process. (Tamminen et al. 2018)

In addition to monitoring and visualizing quality via measurements and calculation models, quality monitoring enhancing research have been performed. Network based online system helps in predicting mechanical properties of interstitial free (IF) steel strip and also elaborates how this models can help in capturing various metallurgical phenomena during rolling (Mohanty et al. 2014). In addition, integration of a new data acquisition/processing scheme in Split-Hopkinson Pressure Bar (SHPB) test and characterization of the dynamic material properties of high-strength steels using the optional form of Johnson-Cook model have been utilized (Tuazon et al. 2014). There is also available an approach to monitor quality in manufacturing using supervised machine learning on product state data to achieve the goal of improved quality monitoring. (Wuest et al. 2014)

Also new measurement/detection methods have been developed. For example, Atzlesberger et al. (2013) have utilized magnetic method combined with a new sensor concept sub-surface defect detection in a steel sheet. Prats-Montalbán et al. (2014) have proposed statistical process control based on Multivariate Image Analysis for monitoring and defect detection.

Several automatic surface-inspection systems are utilized in the steel industry to detect defects and to help operators in decision-making: accept, reroute, or downgrade the material. In addition, an advanced predictive quality control strategy involving different facilities have been proposed. The strategy focuses on considering defects in an integrated fashion, managing the uncertainty about the exact position of a defect due to different process conditions by means of Gaussian additive influence functions. The prediction is provided to technical operators to help them in their decision-making process. (Ordieres-Meré et al. 2013)

4.2 Quality Management

Nowadays many kinds of quality control tools, solutions and instruments are utilized in enterprises for controlling quality of the products. Still there are complaints about product quality and major causes for these are material, mechanical and human factors. Enterprises are forced to implement product quality management systems according to ISO 9001 standard. Product quality management system is a component

of the company's management system. (Gajdzik & Sitko 2014)

Product quality can be seen as a key aim of enterprise management and WCM standard (World Class Manufacturing). Due to this, many companies have certified quality management systems. Enterprises have developed and implemented several quality management instruments and methods like 5S (tidiness, orderliness, cleanliness, standardization, discipline), Six Sigma (a standard deviation of a variable), FMEA (Failure Mode and Effects Analysis), SMED (Single Minute Exchange of Die), TMP (Total Productive Maintenance), SPC (Statistical Process Control), FMS (Flexibility Manufacturing System), LM (Lean Management), BSC (Balanced Scorecard) and Kaizen. (Gajdzik & Sitko 2014)

5. DISCUSSION AND CONCLUSIONS

Linear, dynamic models for various processes in the process industry are available from a large number of commercial vendors. In the oil refining and petrochemical industries, they are already widely used in Model Predictive Control applications. Linear process models are not applicable for highly nonlinear processes and (semi-)batch processes.

In steel industry, the available individual process models generally consider the prediction of selected process and quality parameters. Process control is done by monitoring plant settings (process, quality) through dedicated applications. Set points are mostly defined and modified by models that are tuned by research and development engineers, and generally, set-point calculations for energy and resource inputs are straightforward and dedicated to the single processes.

Nonlinear model predictive control (NMPC) is provided by a few commercial vendors, and some larger companies (e.g. Borealis and ExxonMobil Chemicals) have, or have commercialized, their own in-house software.

Plant-wide steady-state optimization is widely used in the petrochemical industry. However, these industries are unique application area, and the methods used there are not generally applicable to other process industries. Some dynamic, plant-wide optimization tools using mechanistic, grey-box and black box models already exist. However, there is no industry consistency between the individual predictive process models and optimization methods is currently ensured.

Some holistic plant-wide control systems implemented at small scale or as prototypes exploit measures coming from the production lines and perform multi-objective optimization by tuning different process and operational parameters.

The use of artificial intelligence and machine learning technologies are clearly future also in steel industry. Already in the beginning of this millennium, hundreds neural networks were installed in steel mills worldwide running in the process control and improve the quality and accuracy of rolling processes. Already then, neural networks and other methods from artificial intelligence were seen beneficial next step at all higher automation levels, including scheduling and

management systems. These approaches were seen potential in creating integrated production techniques to improve efficiency and competitiveness of entire industrial facilities. (Schlang et al. 2001)

Machine learning have been recently utilized in steel industry for example to detect anomalies in press-hardening (Lejon et al. 2018). Time series classification have been utilized in machine and deep learning for example to predict scrap rate in transfer molding (Mándli et al. 2017), and to detect the quality of the semi-finished products and to predict the next production process step (Mehdiyev et al. 2017).

There are general tools and methodologies available and applicable for a wide range of production processes with similar characteristics, as can be found in the process and steel industry. Further improvements can be achieved by new artificial intelligence and machine learning methodologies and optimizing whole chain of production process by integrating needed tools together.

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