Process control technology

Process Control Supporting Ever-changing Manufacturing

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Abstract

This article reports on the advancement of process control technology that has been supporting the stable operation and efficiency improvement of production facilities, processes, and plant products within the KOBELCO Group to accurately respond to the new needs of customers and changes in products and processes. Specifically, it provides an overview of process control technology, touching upon its historical background and introduces several recent cases. It also discusses the relationship between this technology and KOBELCO Group's materiality, "Contributing to a green society," and offers insights into the contributions to a future carbon-neutral society.

Introduction

The KOBELCO Group maintains efficient, stable, high-throughput production operations in each of its various businesses to manufacture products in a way that responds to customers' needs expeditiously. This necessitates a wide variety of processes including reduction, combustion, heat treatment, and forming. Suitable process control technologies and combinations of these processes are additional critical elements. The steel industry has been a notable pioneer in the use of computers and the advancement of control functions. Kobe Steel develops and uses optimal control and robust control and has amassed a list of achievements in big data analytics and AI. Advancements in process control technology will become increasingly important alongside the evolution of industrial processes such as waste-to-energy and low-CO_2 blast furnace technologies. Such innovations are crucial to contribute to a green society and to production technology supporting a future with a reduced population. This paper introduces the KOBELCO Group's process control technologies refined over the course of many years.

1. Overview of process control

Process control technology enables efficient and stable operation by quickly detecting and reacting to changes in conditions in process manufacturing. It thus supports the foundation of manufacturing through its essential role in large-scale operations and steel production. The needs of manufacturing change over time, with theories of operation including mass production, quality over quantity, difficult-to-manufacture products, and high-mix, low-volume production. The KOBELCO Group has responded to changes in customer and internal needs by altering manufacturing conditions and introducing new processes through the advancement of process control technology.

The 1980s were an era shaped by mass production. During this period, the KOBELCO Group was one of many steel manufacturers pioneering the use of computers and automation (PID controller technology) on the production line. Such systems enabled the stable operation of processes and equipment, high-yield production, and ultimately the ability to provide products in large volumes. In particular, rolling control technologies in the form of plate thickness control and temperature control were applied to actual operations through optimal control technology that uses simulations of the physical phenomena to be controlled.[1)]

When the late 1990s introduced a shift from quantity to quality, Kobe Steel responded by incorporating the latest technologies into process control. Specifically, we developed adaptive and robust control technologies that have enabled the attainment of various material properties.[2)] We have also developed new machine learning functions and improved the accuracy of initial computational models to minimize losses associated with lot changeovers involving different materials. These developments enable the production of difficult-to-manufacture products arising from diversifying customer needs, and they support the shift to high-mix, low-/variable-volume production. In addition, we are improving technology for managing and clustering large volumes of complex operational data such as time series data. We have furthermore improved steel quality and expanded our portfolio through our converter auxiliary material charging system and waste incinerator temperature prediction control technology.[3)]

The trends of high-mix, low-volume production and difficult-to-manufacture products have boosted the demand for advanced manufacturing technology. This in turn drove the KOBELCO Group to set goals of further stabilizing production and increasing the accuracy of control technology. Stipulations attached to these goals were to capitalize on the expertise of senior operators and to strike a balance between automation and technical skill. Kobe Steel's JIT (just-in-time) modeling technology has enhanced converter auxiliary material charging system technology through the use of reliable, accurate sensor technology and large-capacity data storage equipment. We have enabled operators to make decisions based on the simulated expertise of senior operators that draws on statistical similarities within historical operational data. Incorporating human reasoning into the automated control loop enables the coexistence of automation and technical skill, yielding manufacturing practices that capitalize on the expertise of senior operators. This methodology makes it possible to produce a variety of products by overcoming challenges that conventional automation approaches cannot handle, such as temperature prediction in steelmaking and initial computational models for the hot rolling process.[4)] By extending this concept to more challenging blast furnace operations, we established technologies for visualizing permeability and predicting temperature changes in the furnace. Our company was the first to use these technologies in actual processes.

We are industry leaders in the incorporation of machine learning into real-time process control. Our forthcoming machine learning technology will be suitable for use in actual operations and will advance process control technology. Kobe Steel will pursue technological development related to customers' needs in new products and plant characteristics. Technological development related to changes within the sphere of raw materials such as steel qualities and hot briquetted iron (HBI) will be a further area of focus. Our process control technology will support carbon neutrality through the precision management of large-scale operations and processes to minimize the waste of material and energy.

2. Development of AI Souro[5)]

A blast furnace is a large countercurrent-exchange reaction vessel that produces molten iron. Iron ore and coke are alternately charged into the top of the furnace, and hot air and pulverized coal are blown in through tuyeres at the bottom to heat and reduce the iron ore. Stable blast furnace operation requires a constant permeability of the packed bed, (countercurrent moving bed) and a constant furnace temperature (hot metal temperature, HMT). Blast furnace operators play a key role in controlling furnace temperature. They use a vast amount of measurement data and indications alongside the experience to predict furnace conditions several hours in advance, making adjustments accordingly to keep HMT within specifications (**Fig. 1**). Operators must have advanced judgment capabilities for low coke rate operation of large blast furnaces. This is because the large time constant caused by thermal inertia can lead to serious malfunction if actions are delayed.

This issue drove us to develop AI Souro. This technology combines AI, mathematical models, and measured data to predict furnace temperature and permeability and to perform advanced furnace control. The objective of this technology is to reduce CO_2 emissions from blast furnaces and achieve fully stable operation (zero cooling, zero gas channeling). Next, we introduce one of our main AI technologies: furnace temperature (HMT) prediction technology.

The HMT estimation model is based a model of the transient response in furnace temperature that derives the change in molten iron temperature $\varDelta T$pig from the total change in heat consumption $\varDelta Q$ in the lower part of the furnace. Inputs to the model are actions affecting operating conditions, changes in heat consumption related to in-furnace parameters, the amount of molten iron remaining in the furnace, and historical HMT data. The change in heat consumption is reflected in the change in HMT, thereby accounting for transient response; the parameter θ of the transient response curve is iteratively optimized using AI.

Fig. 2 shows sample results of HMT prediction five hours in advance. (1) At time zero, the model predicted a sudden drop in HMT over the next five hours. (2) The furnace operator initiated

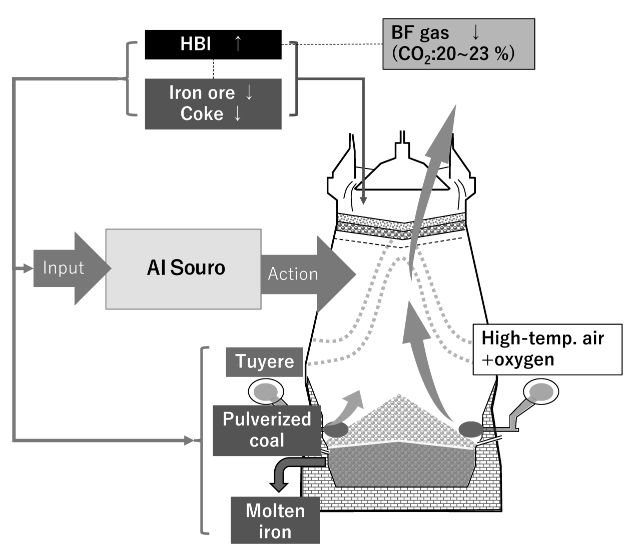


Fig. 1 Outline of AI Souro

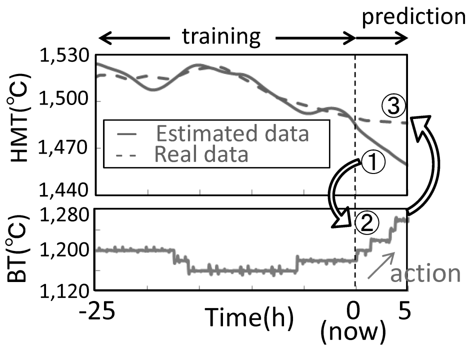


Fig. 2 Result of HMT (hot metal temperature) prediction

countermeasures to increase blast temperature (BT) at time zero. (3) HMT was maintained within the setpoint range, validating the prediction model. Initial data to train the system came from discrete HMT measurements via a conventional immersion thermocouple. However, we developed technology to continuously determine HMT based on the brightness of imaging from a camera pointed at the tapping stream. Using these data as input drastically improved prediction accuracy.

This prediction technology was tested alongside high-volume charging of HBI in the No.3 blast furnace at Kakogawa Works, demonstrating the practicality of the technology in low-CO_2 blast furnace operation using an actual machine. We are developing enhanced functions toward AI Souro that will enable CO_2 reduction through high-volume HBI charging in blast furnaces around the world.

3. Development of waste management plant automation[6)]

The KOBELCO Group's product portfolio covers the waste incineration process. The KOBELCO Group has developed numerous process control technologies that support stable operation, minimize the concentration of substances in the exhaust that carry an environmental burden (CO, NOx), and automate operations. One such example is the company's automation technology for reducing CO and NOx in exhaust gas.

The properties of waste change constantly throughout the waste management process. Concentrations of substances in the exhaust that carry an environmental burden fluctuate, meaning there is a need to dampen fluctuations and introduce automation. The KOBELCO Group developed technology that uses machine learning to incorporate wide-ranging variables into the accurate prediction of CO and NOx emissions from process data. This paper covers our automation technology that uses this technology's predictions to optimize the

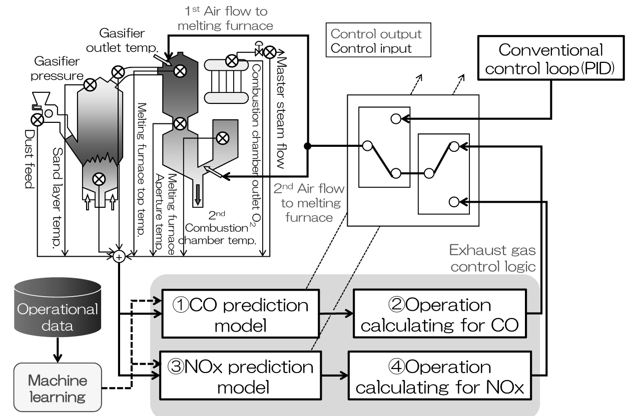


Fig. 3 Outline of developed CO/NOx emission control system

combustion air flow rate and thus control CO and NOx in exhaust gas (**Fig. 3**).

The technologies are linked together as follows.

(1) Modeling of exhaust gas characteristics using machine learning: A decision tree was used to construct logic that predicts sudden changes in CO and NOx based on historical operating data. This enables the operator to decide whether manual intervention is necessary.

(2) Need-based air flow rate control:
The logic predicts increases in CO and NOx so the necessary exhaust gas control operations (adjustment of the first and second air flow rates in the melting furnace) can be executed in advance. Interventions are implemented only when necessary, ensuring stable operation and minimizing impact on parameters.

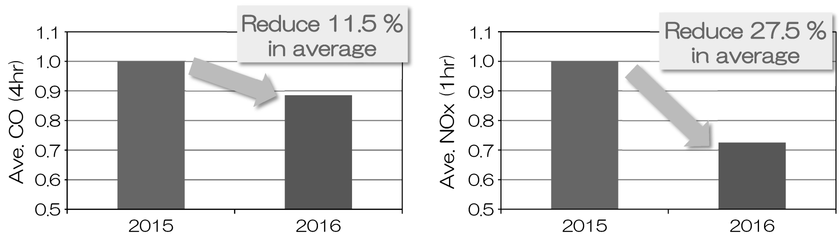
The CO and NOx prediction logic uses known reaction and combustion mechanisms to achieve high accuracy. It calculates characteristic values from process information such as sand layer temperature, furnace pressure, and oxygen concentration at the furnace outlet.

We deployed our control system in the fluidized-bed gasification and melting furnace of the facility represented in **Table 1**, after which we conducted performance validation. We compared the operating data from the one-month evaluation period of September 2016 to data from September 2015. NOx suppression was based on readings from the analyzer at the inlet of the catalytic reaction tower.

Fig. 4 compares the September 2015 and September 2016 4-hour-average concentrations of CO and 1-hour-average concentrations of NOx. CO and NOx concentrations were reduced by 11.5% and 27.5%, respectively. Additionally, the number of manual operator interventions during the evaluation period was zero for CO and about half that of the benchmark period for NOx, achieving

Table 1 Outline of target plant

Disposal method	Fluidized-bed gasification and melting furnace
Disposal capacity	143 t/day (71.5 t/day * 2 Furnaces)
Exhaust gas cooling system	Waste heat boiler + Water spray
Steam conditions	350 °C * 4 MPa
Exhaust gas treatment method	Non-catalytic denitration + Bag filter + Catalytic reaction tower
Wastewater treatment equipment	Flocculation precipitation/Sand filtration + Membrane treatment equipment
Power generation	1,970 kW



(a)Results of CO emission case (b)Results of NOx emission case

Fig. 4 Results of CO/NOx emissions control by control system developed

the other objective of reducing manual intervention. Our system has both flow rate control functionality and selective non-catalytic reduction technology for NOx. The combination of these features will eliminate manual intervention in the future.

By developing this technology, the KOBELCO Group is ensuring the stable operation of its waste incineration plants and reducing the environmental burden.

4. Development of a deep learning temperature prediction model for coiling temperature control (CTC) in hot strip mill[7)]

We developed technology that uses deep learning to predict steel strip temperature in order to control coiling temperature (CT) in the hot strip rolling process. This makes steel strip temperature control substantially more precise compared with conventional technologies based on thermal conduction formulas.

CT greatly influences the characteristics of steel strip; precise temperatures are essential for quality improvement. In addition, the development of high-tensile strength materials with good workability requires the design of new compositions and flexible responses to cooling conditions. However, if the conventional control model based on thermal conduction formulas cannot process the cooling conditions of a new material, the model must be adapted accordingly, which is time consuming. Furthermore, the limited processing power of computers integrated into the process necessitates the simplification of computations for real-time control. This simplification sacrifices some degree of accuracy. In addition, operator input was a factor in the parameters for fine-tuning the model, creating a challenge in terms of stabilizing quality.

Deep learning uses a relatively simple network structure. It requires low computational power to predict temperature, making it suitable for real-time control. However, machine learning methods such as deep learning are generally weak in extrapolation areas where there is no training data. They have mostly been used in combination with a physical reference model only to find and correct errors. In contrast, our technology represents cooling equipment processes as a network structure, as shown in **Fig. 5**, and incorporates the state of phase transformation as an intermediate feature. We applied data augmentation, an effective technique in the field of imaging, by using a virtual thermometer to indicate the temperature of the steel strip during cooling. In this way, we generated a large volume of training data from the limited physical models and operations data, thereby constructing a prediction model with high generalization performance.

As shown in **Fig. 6**, this technology ensures highly accurate control even when the target temperature changes during coiling, improving flexibility in responding to cooling conditions. Moreover, the model does not need to be adapted for new materials or accuracy enhancements. Rather, the model learns from actual operational data to eliminate subjectivity. This mode of continuous improvement safeguards quality and reduces the

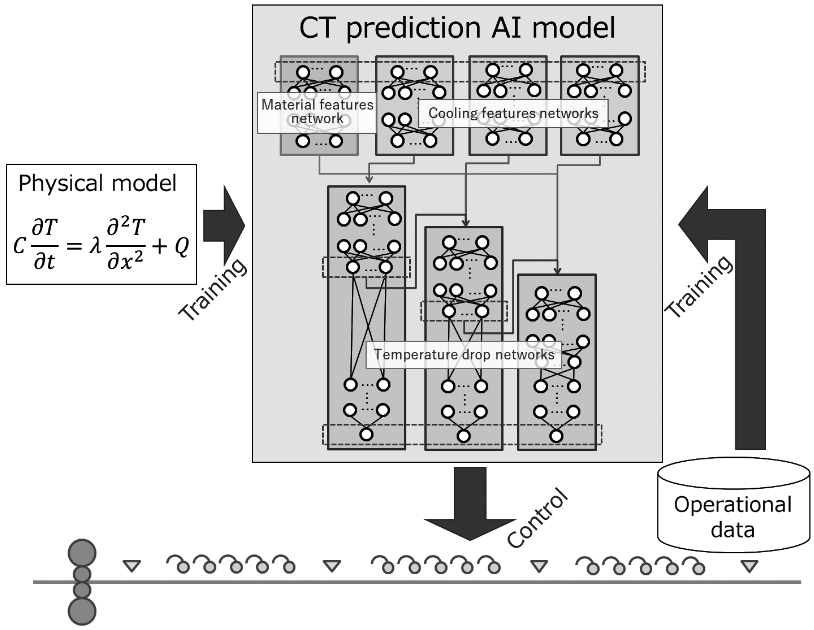


Fig. 5 AI-based coiling temperature control

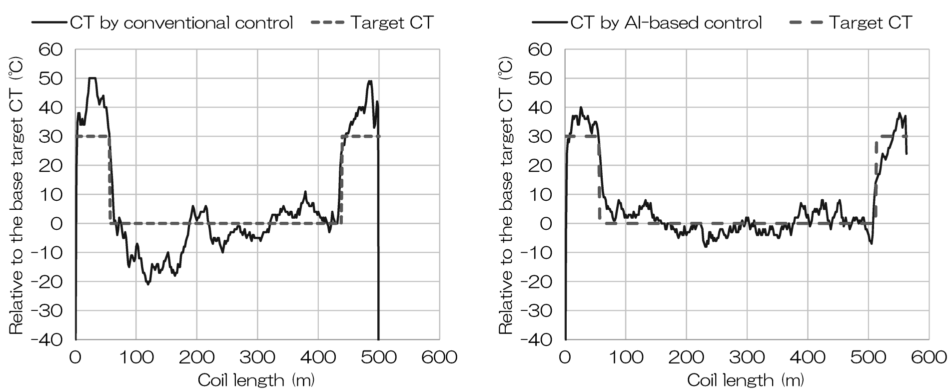


Fig. 6 Coiling temperature when using conventional and AI-based control

time required to develop high-performance steel strips, which is difficult to produce.

In addition to CTC, we will apply deep learning and AI extensively to control non-steady-state areas that do not respond effectively to process control technologies based on conventional theory and knowledge alone.

Conclusions

This paper introduced the process control technologies that support the KOBELCO Group's unparalleled manufacturing performance, including specific examples of developments and future trends. The technologies introduced here contribute to stable and efficient operation, enabling us to provide high-quality products and contribute to a green society. The KOBELCO Group will further enhance its process control technology by incorporating state-of-the-art technologies from fields such as sensing technology and data analysis. In this way, the company will continue meeting the ever-changing needs of customers and supporting manufacturing in the forthcoming carbon-neutral society.

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