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Development and Future Prospects of Instrument, Control and System Technology at JFE Steel

YAMAGUCHI Osamu[*1] IIZUKA Yukinori[*2]

Abstract:

In this paper, we review the progress in the fields of measurement, control and system at JFE Steel over the past decade, along with the background and technological trends. In response to increasingly important needs such as the production of high-performance steel products, high-efficiency manufacturing, and the stable operation with aging facilities, we have incorporated and put into practical use technologies that have been developed in the 21st century, such as AI and machine learning. The technologies developed with numerous specific examples are outlined in this paper.

1. Introduction

In the 2010s, Germany introduced the concept of the Fourth Industrial Revolution known as Industrie 4.0, while a similar initiative called Society 5.0 has long been advocated in Japan. In recent years, efforts to utilize data and automate operations and tasks with the aim of transforming business have been made under the keyword Digital Transformation (DX). Technologically, the development of generative AI using Large Language Models (LLMs) and robotics has been remarkable. At the Consumer Electronics Show (CES) 2025 held in Las Vegas, examples of Agentic AI, which acts as an autonomous agent in making decisions and performing tasks in a human-like manner, and application of AI to autonomous driving and robotics were introduced, indicating that technological development enabling automation of corporate operations in the near future is underway.

In measurement and control in the steelmaking process, the optimum state-of-the art digital technologies for challenges and implementation at the time have also been introduced with the aim of stable production of high-quality products. Ten years have now passed since the last Special Issue on Instrument and Control Engineering[1)], and the technological progress during this period has been remarkable. This paper outlines the technical trends in measurement, control, and system technologies over the past decade, along with specific examples.

2. Trends in Measurement, Control, and System Technologies

2.1 Intelligent Steel Works

JFE Steel aims to realize an intelligent steel works which is capable of autonomous learning and autonomous optimal automatic operation[2)], as illustrated in **Fig. 1**. The core technology for achieving this is the Cyber-Physical System (CPS), which links physical/statistical models established in virtual space (cyberspace) and the actual steel works (physical space). The aims of this initiative are to prevent trouble, improve product yield and quality, accelerate product development, enhance labor productivity, and respond to the challenge of a declining population of skilled workers by applying the optimal operational strategies derived from simulations in the virtual space to the real steel works.

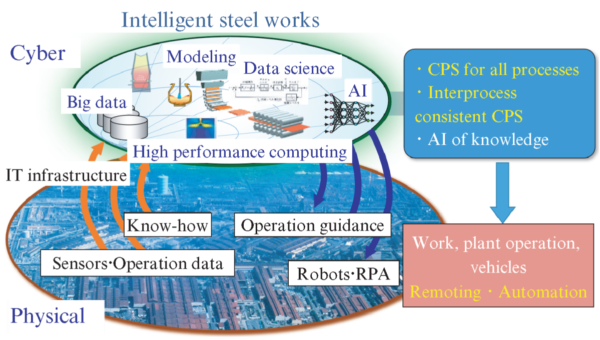

Fig. 1 Intelligent steel works

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*1 Manager, Digital Transformation Planning Dept., Digital Transformation Strategy Headquarters, JFE Steel

*2 Dr. Eng., Principal Researcher, Steel Res. Lab., JFE Steel

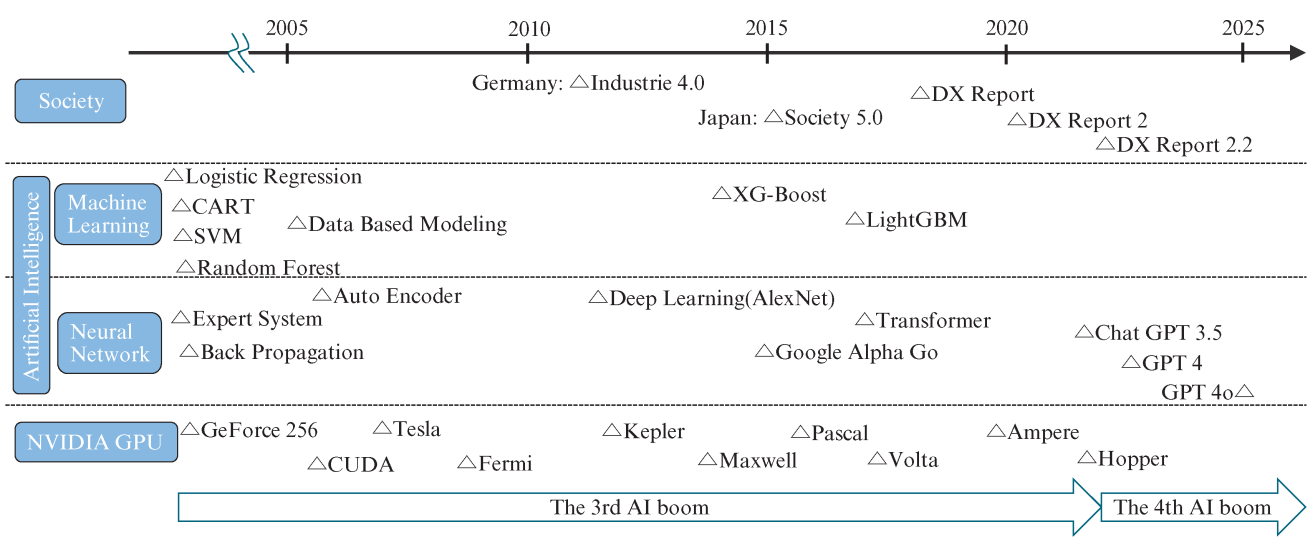

Fig. 2 Progress of technologies related to AI

To build CPS, it is essential to integrate measurement technologies for acquiring physical data, control technologies based on models (digital twins) in cyberspace, and the system technologies that compose these elements.

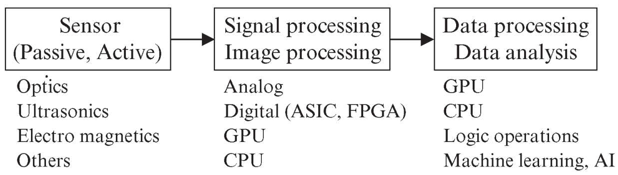

Fig. 3 Elements of instrumentation technology

2.2 Trends Surrounding the Measurement, Control, and System Fields

Figure 2 summarizes the societal initiatives and trends in machine learning, AI-related technologies, and particularly GPUs (Graphics Processing Units) since 2005, which have significantly contributed to the advancement of AI and have all influenced the fields of measurement, control, and systems.

Industrie 4.0 was proposed in Germany in 2011, and Japan has been promoting similar efforts under the concept of Society 5.0 since 2016. In 2018, the Ministry of Economy, Trade and Industry (METI) issued the DX Report, highlighting the need to renew legacy systems and realize a transformation to digital industry. Technologies that support this transformation have advanced rapidly, especially in the United States.

From the 2000s, the world entered the third AI boom. This era is characterized by the construction and utilization of models that perform classification and regression through machine learning based on large volumes of data. Although a series of machine learning algorithms had been proposed before 2000, the accumulation of training data and acceleration of computational speed have also accelerated implementation of machine learning. Algorithms such as XG-Boost and LightGBM, which reduce prediction error, have been devised, and have demonstrated their superiority in platforms such as Kaggle.

In the field of neural networks, the release of AlexNet in 2012 marked the beginning of the deep learning era. Subsequently, the development of GPUs by NVIDIA and remarkable progress in algorithms have led to the emergence of generative AI technologies, exemplified by ChatGPT.

3. Measurement Technologies

3.1 Trends in Measurement Technology Development

Measurement technologies evolved from early research and development of radiation thermometry and radiology, and then expanded to techniques in optical imaging, ultrasound, electromagnetics and electromagnetic waves. In response to the construction of new steel works in the 1980s, applications such as dimensional shape measurement, surface inspection, and non-destructive testing were developed[3]. Since the 1990s, the need for quality measurement for production and quality assurance of high-grade steels and process measurement for efficient, stable operation has driven advances in various measurement technologies against the background of innovation in digital technologies. With intensifying global competition in recent years, increasingly stringent requirements have been placed on these needs, and in addition, needs such as automatic measurement for labor-saving in response to the decline in the manufacturing labor force and measure-

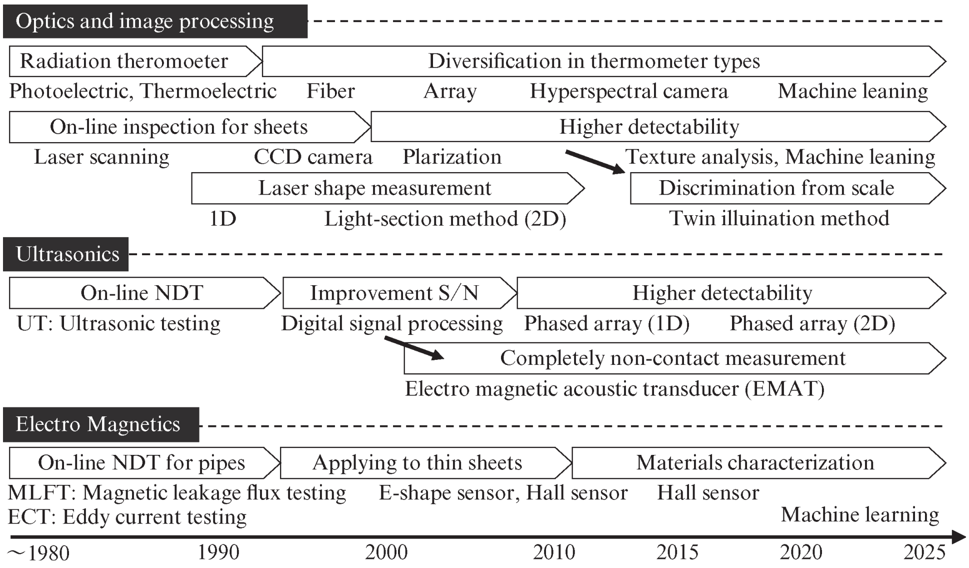

Fig. 4 Trends in major instrumentation technologies

ment technologies for plant management have also become challenges.

As shown in **Fig. 3**, measurement technologies consist of sensors, signal processing, and data processing. Each of these seed technologies benefits from advances in electronics and machine learning. Therefore, we have also enhanced our ability to meet emerging needs by quickly adopting the latest seed technologies.

Looking back over the past decade since the previous Special Issue on Instrument and Control Engineering[1], the trends of higher resolution sensors, faster signal processing, and versatile/low-cost peripheral devices remain largely unchanged, and have in fact accelerated, making it easier to handle large volumes of data. The rise of big data has also led to a surge in the application of AI and machine learning as a major trend. Furthermore, practical methods for estimating quantities that cannot be measured directly have been developed based on models using observable measurements. Significant evolution of AI-integrated and model-based measurement technologies is also expected to continue in the future.

3.2 Key Measurement Technologies and Development Examples

Measurement technologies vary depending on the seed technology used, such as the principles, frequencies, and wavelengths of sensors. **Figure 4** presents an outline of the technological trends of the major measurement technologies of optical imaging, ultrasound, and electromagnetics. These technologies are explained in detail in the following sections.

3.2.1 Optical Imaging Measurement

In the measurement of steel products, where the targets are often high-temperature materials moving at high speed, optical methods ranging from radiation thermometry to surface inspection are widely applied, as these methods allow non-contact remote measurement. These technologies are also used in various other industries, not limited to steel, enabling the use of advanced and versatile sensors, and because imaging is comparatively easy, various image processing technologies can also be used.

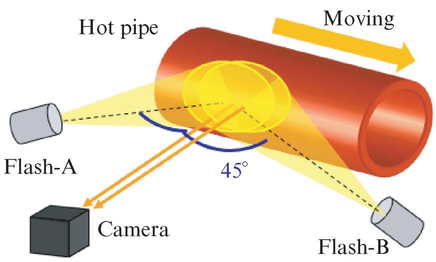

Fig. 5 Surface inspection using twin-illumination and subtraction technique[4]

A representative example is the surface inspection system using JFE Steel's twin-illumination and subtraction technique[4]. Initially, laser-based methods were common, but since 2000, linear cameras and area cameras have become the main stream, with practical application progressing from the thin sheet field, where products are characterized by a uniform surface. On the other hand, because the surface of hot-rolled products such as steel pipes and plates is covered with mill scale (iron oxide), distinguishing between surface patterns and actual defects was a challenge. The twin-illumination and subtraction technique overcomes this problem by illuminating the object from two directions, as shown in **Fig. 5**, and using the difference in the shadow appearance to emphasize dents defects. The signal-to-noise ratio (SNR) is also improved by capturing two area images with a 1/10 000 second interval using strobe lighting and applying differential processing. Combining this technology with machine learning enhances the ability to distinguish patterns from defects, enabling automated surface inspection of hot-rolled steels. As additional advantages, inexpensive general-purpose hardware can be used, and modern computing power has dramatically improved performance.

For surface inspection of thin sheets, polarization techniques have been used to distinguish oil stains and glossy areas. However, detecting low-contrast defects remained a challenge. To solve this, a surface inspection method using texture analysis was developed by applying spatial filters based on the defect orientation and statistically extracting differences from sound areas[5]. In this example, real-time image processing is achieved by using GPUs.

New devices such as hyperspectral cameras capable of imaging spectroscopy are also being adopted. In radiation thermometry, variations in emissivity affect radiance and introduce errors. As a measure for this problem, a technique utilizing principal component analysis of spectral data to perform radiation thermometry using components unaffected by emissivity changes was developed[6] and has been implemented in annealing lines for stainless steel sheets, where the thickness of the oxide film affects emissivity.

Other developments introduced in this Special Issue include laser-based 2D rangefinders and CCD-based 2D thermometers applied using versatile devices[7,8]. Increasing use of smartphones in measurement applications[9] is also another notable trend over the past decade.

3.2.2 Ultrasonic Measurement

Ultrasonic measurement has long been a mainstream technology in non-destructive testing because of its excellent penetration into materials and ease of use compared to radiation. By the 1980s, ultrasound was established as an online automatic flaw detection technology. Since the ultrasonic frequencies are in the MHz range, digital signal processing became applicable in the 1990s, enabling practical application of SNR improvement techniques such as synchronous averaging and chirp pulse compression. Initially, dedicated LSIs were required, but the desired signal processing can now be implemented easily using FPGAs (Field Programmable Gate Arrays). This has led to the proliferation of phased array technology and reduction of equipment costs, making industrial application feasible since the 2000s.

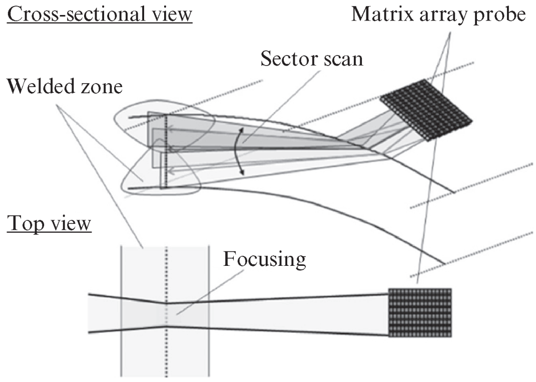

Fig. 6 Ultrasonic inspection of weld for UOE pipe using matrix array probe[10]

Phased array technology allows flexible focusing, deflection, and scanning of ultrasonic waves. JFE Steel has utilized this feature to upgrade ultrasonic flaw detection. The previous Special Issue introduced 1D array-based weld quality inspection for ERW (Electric Resistance Welded) steel pipes[1], and 2D matrix arrays are now feasible at an industrially acceptable cost. As shown in **Fig. 6**, this technology has been applied to weld inspections of UOE steel pipe[10], resulting in highly sensitive, highly reproducible flaw detection.

Synthetic aperture methods, which use multiple signals from a single probe to achieve effects similar to phased arrays, have also become feasible in real-time operation by applying GPUs, and their effectiveness in enhancing sensitivity has been confirmed[11].

In electromagnetic ultrasonic methods, which previously required contact due to low sensitivity, completely non-contact hot measurement has been achieved by applying digital signal processing[12]. This technology, combined with sensor and engineering innovations, makes it possible to measure the final solidification position (crater end) in continuous casting machines[13], contributing to improved internal quality of slabs.

3.2.3 Electromagnetic Measurement

Methods based on electromagnetic phenomena, such as eddy current and magnetic flux leakage testing, have long been also mainstream technologies in non-destructive testing. Initially applied to automatic flaw detection of steel pipes, their scope of application expanded in the 1990s to include inspections for inclusions in thin steel sheets and scab inspections using Hall elements or E-type sensors. Recently, attention has shifted to new applications that take advantage of sensitivity to material properties and integration with machine learning.

Magnetic flux leakage methods have achieved detection of minute surface irregularities on the micrometer

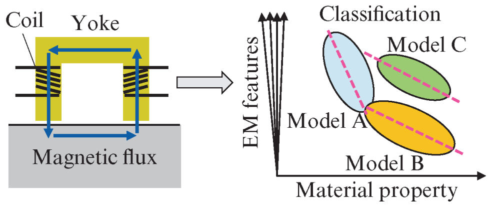

Fig. 7 Hard spot inspection of plate surface using eddy current testing with machine learning

order in thin steel sheets. These defects typically require partial visual inspection with grinding to visualize the defect. While the development of optical detection techniques for some inspection targets had been attempted from any early date, detection was extremely difficult. Recognizing that these defects are caused by roll-induced indentations, application of the magnetic flux leakage method was conceived, focusing on the point that the magnetic properties of the material appear to change depending on strain. Practical implementation has been achieved by adding synchronous averaging based on the roll period to improve SNR[14].

Differences in electromagnetic properties due to the material structure have also enabled inspection for hard spots in plates using the eddy current method. As shown in **Fig. 7**, application of machine learning to the results of measurements of multiple electromagnetic features has resulted in higher measurement accuracy and successful implementation[15].

Other applications of machine learning include reduction of the over-detection rate in eddy current scab sensor signal waveforms by using logistic regression with E-type sensors[16]. Ongoing expansion of the use of machine learning in this field is expected.

4. Control and System Technologies

4.1 Trends in Control and System Technology Development

The concept of automatic control is said to have originated with James Watt, who is famous as the inventor of the steam engine. Watt invented a centrifugal governor to maintain a constant rotational speed in steam engines using the outward movement of weights around a rotating shaft due to centrifugal force. In a steam engine, the outward movement of the weights acts to close the valve that supplies steam to the cylinder. When output increases and rotation speeds up, the weights move outward, closing the valve and reducing output. Conversely, when output decreases, the weights return inward, opening the valve and increasing output. This delicate balance of reverse-direction control, which is called negative feedback, allows the engine to maintain a constant rotational speed.

Control methods have evolved from such simple single-input, single-output systems to modern control theories represented by optimal control (1950s) and H∞ control (1980s), which model the target plant using linear ordinary differential equations and handle multiple inputs and outputs.

Compared to these simple linear time-invariant examples, recent control targets have become more complex, requiring careful selection of the control method and system construction. Since around 2005, data-driven modeling using sensor data has been widely applied. JFE Steel utilized the latest technologies of the time, starting with Data-Based Modeling (DBM), and also including techniques such as XG-Boost and LightGBM, to reduce prediction error by gradient boosting. More recently, application of third-generation AI, represented by deep learning, to control systems has been actively researched.

Like autonomous driving in automobiles, collaboration between operators and control systems in the steel works has become a critical issue, leading to the emergence of the concept of shared control[17]. As mentioned previously, JFE Steel aims to realize intelligent steel works[2]. The core technology is the Cyber-Physical System (CPS, **Fig. 8**), and construction of virtual models represented by mathematical and/or statistical models is the key to control. Representative control and system technologies are explained in the next section. Recently, the use of GPUs has enabled high-speed computation of nonlinear thermal-fluid models, making CPS implementation possible in various processes.

4.2 Key Control and System Technologies and Development Examples

4.2.1 Model Predictive Control

Model Predictive Control (MPC) refers to a general class of algorithms that precisely model a control target using physical or statistical models, predict the future behavior of the plant, and determine control actions so that the predicted values satisfy the target. **Figure 9** illustrates the concept of MPC. Initially applied to chemical processes with long time constants, the development of MPC dates back to the 1960s. Originally, control parameters were calculated offline and implemented manually, but with remarkable advances in computers, real-time control was first implemented in 1997[18]. By combining MPC with data assimilation (discussed in the following section), model parameters can be adjusted to match sensor data, improving prediction accuracy and making the method practical.

At JFE Steel, MPC has been applied to hot metal temperature control in blast furnaces[19,20], fuel and

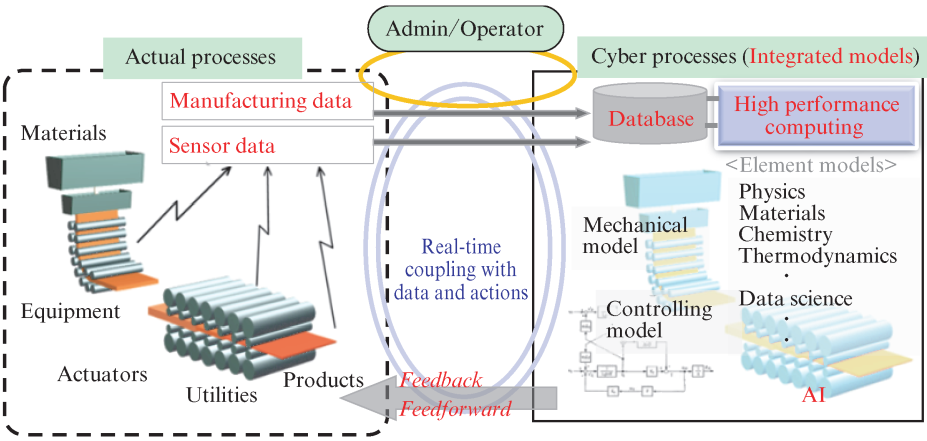

Fig. 8 Concept of Cyber Physical Systems

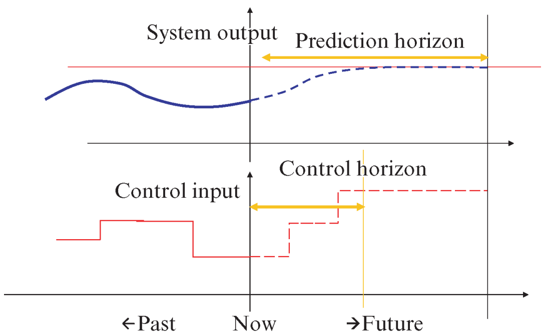

Fig. 9 Concept of model prediction control

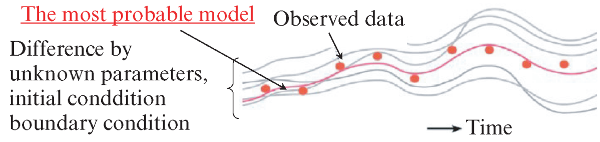

Fig. 10 Concept of data assimilation

power operation guidance in steel works[21], and intelligent skinpass mills[22]. In converter refining control, models combining the physical and material balance approaches are used for precise, real-time estimation of internal states (composition, temperature)[23].

4.2.2 Data Assimilation

Data assimilation refers to techniques that enhance the accuracy of model calculations by integrating sensor data and model calculations. As shown in **Fig. 10**, data assimilation involves searching for models that match current measurement values, a technique that has been used in weather forecasting since the 1950s[24].

At JFE Steel, examples include Moving Horizon Estimation for blast furnace hot metal temperature control[20] and particle filters for ferro-coke dry distillation control[25]. In real-time estimation models for the internal state of the converter, the parameters are tuned to correct each of the models so that the values of the exhaust gas predicted by the physical model and the measured values by the material balance model match[23].

4.2.3 AI and Machine Learning

Numerous cases in which models trained on large volumes of data from manufacturing processes are used for setup, anomaly detection, and guidance have been reported. Examples include load prediction for plates using DBM[26], reading charts visually checked by blast furnace operators using convolutional neural networks for control and stable operation[20], predictive monitoring of equipment anomalies (J-dscom®)[27,28], and a control maintenance support system using AI (J-mAIster®)[29].

This Special Issue also introduces an example in which a neural network was applied to tandem cold mill (TCM) schedule calculations[30]. Specifically, machine learning was used to automate the rolling schedule settings (reduction rates and tension settings for each TCM stand), which were previously set manually by the operators. In this case, a shared control system was constructed to achieve efficient operation by selectively training the neural network on schedules with recognized high efficiency.

Another example involves using deep learning for real-time shape control in cluster rolling mills. This technology has demonstrated control performance equivalent to skilled operators, leading to actual implementation[31]. Expanded use of deep learning in plant control is expected to continue.

4.2.4 Optimization Technologies

Smooth operation of a steel works requires appropriate decisions on manufacturing sequences and material placement from raw material transport to product delivery. These are formulated as optimization problems with objective functions such as minimizing production costs or maximizing the on-time delivery rate, under constraints such as quality assurance and equipment capacity. Although commercial high-speed linear programming solvers exist, creative approaches are needed to obtain near-optimal solutions within a realistic computation time. For example, in determining the blend of sintered ore to be charged into a blast furnace, a hybrid method combining particle swarm optimization and linear programming was proposed, and successfully achieved highly precise solutions within the required computation time[32].

5. Conclusion

This paper has summarized the progress achieved in measurement, control, and system technologies at JFE Steel over the past decade. The progress of computing power and AI technologies, represented by machine learning and deep neural networks, has had a significant impact on the development of measurement and control systems, resulting in improved detection and control performance.

Under conditions that are accelerating the decline of Japan's labor population, both society and companies are moving toward autonomy and automation through the use of AI. Measurement, control, and system technologies are the key seed technologies driving this transformation. Going forward, we will continue to actively adopt cutting-edge technologies and pursue practical development to promote digital transformation (DX).

References

1) Asano, K.; Iizuka, Y. Progress of Instrumentation and Control Technology in JFE Steel. JFE Technical Report. 2016, no. 21, p. 91–98.
2) JFE Holdings DX Report 2021, p. 6.
3) Kazama, A.; Nagata, Y.; Morimoto, T.; Koshihara, T. Progress in Process Measurement Technologies for the Last 100 Years, and the Future. Tetsu-to-Hagané. 2014, vol. 100, no. 10, p. 1220–1228.
4) Ono, H.; Ogawa, A.; Yamasaki, T.; Koshihara, T.; Kodama, T.; Iizuka, Y.; Oshige, T. Twin-illumination and Subtraction Technique for Detection of Concave and Convex Defects on Steel Pipes in Hot Condition. ISIJ International. 2019, vol. 59, no. 10, p. 1820–1827.
5) Umegaki, Y.; Koshihara, T.; Kemmochi, M. Detection Technique for Defects on Steel Sheet Surface by Texture Analysis Using Gabor Filters with Sub-band Decomposition Considering Defect Orientation. Transactions of the Society of Instrument and Control Engineers. 2024, vol. 60, no. 10, p. 545–554.
6) Kenmochi, M.; Oshige, T.; Tsuda, K. Emissivity-Free Thermometer Using Principal Component Analysis and Its Application. JFE Technical Report. 2021, no. 26, p. 9–14.
7) Tanaka, Y. Development of Bloom Marking Reading Device. JFE Technical Report. 2026, no. 35, p. 50–54.
8) Takada, H.; Watanabe, K.; Sasaki, T. Development of Welding Condition Monitoring System in Cold Steel Sheet Process Line. JFE Technical Report. 2026, no. 35, p. 60–66.
9) Tsukamoto, Y.; Matsui, Y.; Haga, S. The measurement method of welding misalignments of steel pipes using AR markers and a smartphone. CAMP-ISIJ. 2023, vol. 36, no. 2, p. 531.
10) Matsui, Y; Iizuka, Y. Development of New Inspection Method for LSAW Pipes Using Matrix Phased Array UT. ISIJ International. 2022, vol. 62, no. 1, p. 165–172.
11) Terada, K.; Matsui, Y. The high sensitivity inspection technique for round billet using synthetic aperture focusing technique. CAMP-ISIJ. 2021, vol. 34, no. 2, p. 377.
12) Iizuka Y.; Awajiya, Y. High Sensitivity EMAT System using Chirp Pulse Compression and Its Application to Crater End Detection in Continuous Casting. Journal of Physics. Conference Series. 2014, 520, 012011.
13) Nishizawa, Y.; Toishi, K.; Tanaka, T.; Iizuka, Y. Crater End Detection in Continuous Casting by Longitudinal and Shear Wave Hybrid Technique with High Sensitivity EMAT. JFE Technical Report. 2025, no. 34, p. 25–32.
14) Koshihara, T.; Kato, H.; Nagamune, A. Development of Concave and Convex Defects Inspection on Steel Sheets by Magnetic Flux Leakage Testing Method. Tetsu-to-Hagané. 2014, vol. 100, no. 11, p. 1380–1385.
15) Terada, K.; Matsui, Y.; Izumi, D.; Imanaka, H.; Fujiwara, T. Development of Non-destructive hardness evaluation technique for surface of TMCP steel plates. 2024, AMPP 3rd Conference.
16) Shigefuji, Y. Improvement Detection Performance of Pickling Scab Sensor. JFE Technical Report. 2026, no. 35, p. 55–59.
17) Kitamura, A.; Kishi, M. Shared control of human and systems to achieve high efficiency and stable rolling. CAMP-ISIJ. 2022, vol. 35, no. 2, p. 326.
18) Otsuka, T. Research Trends in Nonlinear Model Predictive Control. Journal of Systems, Control and Information. 2017, vol. 61, no. 2, p. 42–50.
19) Hashimoto, Y.; Kitamura, Y.; Nishino, T.; Okamoto, Y.; Kaise, T. Operation guidance on thermal control of blast furnace. CAMP-ISIJ. 2019, vol. 32, no. 2, p. 608.
20) Masuda, R.; Hashimoto, Y.; Saito, R.; Hirahara, T.; Dokko, H. Improvement of Blast Furnace Operation with Cyber-Physical System. CAMP-ISIJ. 2024, vol. 37, no. 2, p. 497.
21) Suzuki, K. Development of Guidance System for Fuel and Power Management in Steel Works. CAMP-ISIJ. 2024, vol. 37, no. 2, p. 313.
22) Ogasahara, T.; Tateno, J.; Asano, K. Development of Intelligent Multivariable Optimal Control for No. 4 Skin Pass Mill in Fukuyama District, West Japan Works. JFE Technical Report. 2019, no. 24, p. 115–121.
23) Kase, H.; Tomiyama, S.; Sato, S. Real-Time State Estimation Model for Converter Steelmaking. JFE Technical Report. 2026, no. 35, p. 9–16.
24) Ishibashi, T. Background Error Covariance Matrix Factorization in Variational Data Assimilation for Atmospheric State Analysis. Proceedings of the Institute of Statistical Mathematics. 2022, vol. 70, no. 2, p. 181–193.
25) Hashimoto, Y.; Annyashiki, T.; Fujimoto, H.; Tsuda, K. Online Heat Pattern Control of Ferro-coke Furnace Based on Data Assimilation. JFE Technical Report. 2021, no. 26, p. 35–41.
26) Shigemori, H. High-Precision Process Control Technology for Steel Plant through Just-In-Time Modeling: Recent Developments and Applications. JFE Technical Report. 2016, no. 21, p. 99–106.
27) Matsushita, M.; Hirata, T.; Suzuki, N.; Sue, T.; Tsuji, H.; Iizuka, Y. Development of anomaly detection system for hot strip mills. CAMP-ISIJ. 2020, vol. 33, no. 1, p. 189.
28) Harada, Y.; Hirata, T.; Matsushita, M. Anomaly-sign detection techniques for hot strip mills utilizing data science. CAMP-ISIJ. 2022, vol. 35, no. 2, p. 375.
29) Eto, A.; Morooka, N.; Tominaga, F. Development of Control Maintenance Support System. JFE Technical Report. 2021, no. 26, p. 57–61.
30) Yamazaki, T.; Mukaiyama, A.; Yajima, M. Development of AI for Tandem Cold Mill Pass Schedule Setup. JFE Technical Report. 2026, no. 35, p. 17–22.

31) Kitamura, T.; Ueno, M.; Saito, S. Development of shape control technology based on data science for 12Hi cluster rolling mill. CAMP-ISIJ. 2023, vol. 36, no. 2, p. 565.

32) Kumano, A.; Yamamoto, S.; Ishigaki, Y. Utilization of DS-CPS Technology in Raw Material Logistics & Yard Operation and Maintenance. JFE Technical Report. 2022, no. 28, p. 52–58.