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Development of Utilization of Digital Data in JFE Steel

KAZAMA Akira[*1] KAWAMURA Kazuo[*2] TSUDA Kazuro[*3] SUGIOKA Shingo[*4] MIYATA Jun[*5]

Abstract:

Utilization of digital data on steel works in JFE Steel started at the middle of 20th century with introducing only several dozens of computers. It was a top level challenge for automation. Recently, installing IoT into production lines, applications and R&D on data science, AI and corresponding technologies are being proceeded to utilize big data. In this paper, history of utilization of digital data in JFE Steel is overviewed. Then, direction and challenges in steel production on recent technological innovation with state-of-the-art concept 'Cyber Physical System' is discussed.

1. Introduction

After the Second World War, the Japanese steel industry recovered its prewar level of crude steel production in 1955 and has been achieved large growth until now. The driving force for this success was the world's most modernized steel works of the time, which were constructed in various locations of the country. These works featured highly efficient plant layouts and introduced state-of-the-art production equipment, as well as many proprietary developed technologies. Steel works that boasted the world's highest level of performance, as measured by indexes such as quality, productivity and energy saving, were completed in various locations and supported Japan's economic growth. Because one common technology that formed the core of this development was automation by the introduction of computer systems in manufacturing process, it can be said this period was the dawn of digital data utilization in the Japanese steel industry. In the period that followed up to the present day, remarkable progress in IT was achieved centering on information infrastructure, computer systems and application software. In step with this progress, JFE Steel has also consistently promoted the utilization of digital data in production processes. The first half of this paper presents an overview of this history, which spans the past half-century.

With the start of the 21st century, the volume of data increased exponentially thanks to the development of information infrastructure. Data science (DS) was in the spotlight as a method of problem-solving by sophisticated data analysis techniques, and AI transitioned to a stage of explosive implementation after several breakthroughs. Moreover, industry as a whole has truly embarked upon the 4th Industrial Revolution. The distinctive features of DS and AI, which include advanced machine learning, recognition and predictive techniques, make it possible to maximize efficiency and achieve other benefits without major equipment modifications. And even more importantly, depending on the method of use, these techniques are also expected to provide solutions to problems that greatly exceed human intelligence, namely, simultaneously achieving multiple goals such as stability, energy conservation, cost reduction and quality. While referring to other papers in this Special Issue of JFE Technical Report, the second half of this paper describes the current efforts, future development and challenges in connec-

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*1 Dr. Eng.,
Vice President,
JFE Steel

*2 Executive Assistant,
General Manager,
Data Science Project Dept.,
JFE Steel

*3 Staff General Manager,
Data Science Project Dept.,
JFE Steel

*4 Staff General Manager,
Data Science Project Dept.,
(currently, Manager, Plant Control Technology Sec.,
Plant Control Dept., West Japan Works (Kurashiki))
JFE Steel

*5 Staff General Manager,
Technology Planning Dept.,
JFE Steel

tion with the application of these innovative technologies in JFE Steel.

2. History of DS Utilization in JFE Steel

2.1 Dawn of Introduction of Process Computers

The spread of administrative-type business computers and plant operation-type computers started in the 1950s, and with the introduction of OA, application to automation of production planning using acquired data also began. On the other hand, because speed is required in process control computers, implementation dates from the mid-20th century. According to a reference from 1973[1), in 1969 Japan's five integrated steel makers of the time had introduced a total of 137 process computers[1)]. Since the country's annual crude steel production was about 90 million tons, which is almost the same as today, this is a miniscule number in comparison with the present, when a single production line uses innumerable control-related computers and microprocessors. Although JFE Steel's West Japan Works Fukuyama District and Kurashiki District had a combined total of only 59 digital computers, installation proceeded rapidly after that time. The same reference[1)] notes that "The number of units introduced increased by 250 % in comparison with 4 years earlier... and together with demonstrating the effectiveness of computer control, computers have been applied almost without exception to the new equipment and new steel works constructed during this period." In other words, although the effectiveness of process control by computers was still unknown, steel makers promoted installation as an essential technology. However, at this point in time, digitization was limited to implementation of the minimum necessary control loop or digitization of manual or analog computer operations, and data utilization was still limited only in host computer level.

2.2 Progress of Digital Data Utilization Technologies

With the progress of computer control, implementation of networks and digital storage also advanced, making it possible to accumulate large amounts of data of various types. JFE Steel has utilized raw digital process data since the 1980s, and carried out full-scale development and practical application of technologies using what are now called DS techniques. The following is an overview of this history.

A history of efforts related to DS and AI technologies at JFE Steel is presented in the **Chronology** at the end of this paper, where the horizontal axis shows the period, the vertical axis shows the fields of application, the boxes with the white background show the purpose and items in blue letter are element technologies. For indispensable items, the Chronology also shows the brief paper titles or excerpts of the contents, together with numbers of the related items in **References**.

Until the mid-1970s, JFE Steel was engaged in efforts related to automation and optimization of production planning by the upper level (host) computer, and in efforts for introduction of DS techniques in process control in upstream production processes such as the blast furnace (control of raw material charging from the furnace top) and control of continuous casting[2)]. When spread of microcomputers began in the 1980s, technologies utilizing data analysis techniques were finally deployed in all processes[3)]. One topic from the second half of the 1980s until the first half of the 1990s was implementation of AI, represented by expert systems. Because AI makes it possible to digitize the knowledge of highly skilled operators, such as process planning, large expectations were placed on this technology, including application to conventional physical model-based process control. While a number of developmental-level implementation efforts were carried out[4–8)], beginning with the blast furnace, few of knowledge rule-based AI systems were long-lived, as they did not have adequate capabilities or adaptability for increasingly complex process control environments. On the other hand, process modeling technologies have developed to be applied to tasks other than control, as exemplified by a case-based reasoning technology for blast furnace burden distribution control[9)] and a molten steel flow optimization technique employing a locally weighted regression model[10)]. The locally weighted regression technique has also been applied to tasks other than control. This technique is an important element technology of DS which has been used in a variety of applications to date, including reduction of product quality dispersion[11)], and has been deployed company-wide[12)] until now. From the second half of the 1990s, advanced search algorithms in the form of a genetic algorithms for optimization of logistics[13)] and constraint programming for operation control[14)] were developed and implemented[15–17)], and these systems have demonstrated considerable effectiveness. As mentioned at the outset, because DS techniques are mainly implemented in the form of software, the investment cost is frequently small in comparison with the expected economic effect. Considering the enormous number of items with potential adaptability, research and development investment in DS technologies greatly surpassed the allocation of resources to conventional control technologies around the year 2000. However, conventional control problems have also been solved by the development of multivariate optimization, dynamic control, disturbance observer and other leading-edge control technologies by incorporating DS elements[18, 19].

From the beginning of the 21st century, many new theoretical approaches and hardware and software products that accelerated the evolution of DS appeared on the scene, including further progress in ICT (Information and Communication Technology), new development such as Bayesian estimation, deep learning and other breakthroughs in AI, and GPGPU (General Purpose Graphic Processing Unit). Actively utilizing these new tools, JFE Steel undertook the challenges of automation or development of guidance systems for the work that had depended on experienced operators by developing and implementing a process simulator[20], a scheduling engine using metaheuristic search and other technologies which had previously been considered impossible due to the limitations of computational capabilities.

Utilization of DS in sensing also entered the stage of practical application. Here, too, JFE Steel began an attempt to automate the construction of a surface defect judgment logic, which had depended on experienced operators, by using DS techniques[22, 23], and quickly implemented a method using CART (Classification and Regression Trees), which was then developed to all of the company's steel works[24]. Facility diagnosis by principal component analysis (PCA)[25], enhanced accuracy of radiation thermometer technology[26] and other DS based technologies made it possible to improve sensing accuracy without modifying the existing hardware. Anomaly detection technologies by applying DS to sensor data also evolved, as seen in blast furnace anomaly diagnosis by Q-statistics and other DS techniques[27, 28] and strip breakage prediction by canonical correlation analysis[29], and many other technologies applying DS have also been developed and implemented in recent years.

2.3 Challenges Spanning a Half-Century

Reviewing the history of process computer introduction and DS technology, the level and scale of challenges has clearly increased, and progress can also be seen in the technical level of solutions. In recent years, achievements have increased in spite of a decrease in the number of engineers and researchers. Nevertheless, many fundamental challenges to digital data utilization still remain. The following quotes an excerpt concerning technical challenges from the reference[1] from half-a-century ago cited at the beginning of this paper.

1) Many constraints exist in the area of process computers, and the inheritability of software assets is a challenge.
2) Because the most suitable type of computer model is introduced in terms of utilization, connectivity with the network in a multi-vendor environment is a challenge. (Development for connectivity between different systems is carried out by the user.)
3) Many fields which have not been automated still exist, including non-routine tasks such as ore leak handling and ground metal picking, etc., and the planning and design fields that have not been adequately systematized.
4) In addition to inadequate CPU power, the inability of software to respond quickly and flexibly to policy changes is also a problem.

Among these items, 1) is more or less continuing to be overcome by the evolution of middleware, and the second part of 3) and 4) have also been solved. On the contrary, however, 2) has become a serious issue in data utilization at the process level recently.

3. Future Outlook

3.1 Data Driven Architecture

The "3Vs" (Volume, Variety, Velocity) are considered to be the three attributes of big data processed by IoT, high speed, large volume data infrastructure and HPC (High Performance Computing). However, big data analysis is fundamentally different from the past, in that the values of the 3Vs are overwhelmingly larger, the data are not representative or intentionally selected, and the raw data population itself is analyzed directly for use in operation of the target system. If all the data concerning operation, sensors, products, etc. are analyzed impartially by DS or AI, this type of big data analysis has the potential to reveal causal relations between events, unknown phenomena and signs of anomalies that were unknown until now, and this kind of data driven operation also becomes increasingly effective and necessary as the scale of production systems and plants becomes larger[30].

As of 2019, approximately 4000 computers for process control were in operation in JFE Steel, and if DCSs that operate 10 CPUs each are also considered, the actual number of computers is in the several tens of 1000s. Although a large volume of data is exchanged between computers, big data analysis of the entire process at once was not originally assumed when the systems were implemented, resulting in a complex architecture which has been repeatedly upgraded and expanded, and this is an obstacle to the use of the 3Vs of big data. Other issues also exist, including an inconsistency of the data structure and temporal axis, but first of all, it is necessary to improve the data collection method to a data driven architecture.

In the conventional steel manufacturing process, sensor signals are transmitted to higher levels after being aggregated to lower level computers such as sequencers, as illustrated on the left side of **Fig. 1**. In this process, the sequencers aggregate the signals for the host computer through the logical operations, threshold processing, etc. of multiple sensors, and many data are unavoidably discarded. Since analysis and utilization of the 3Vs of big data are impossible with this kind of architecture, a system that can collect and analyze all data impartially, like that on the right side of Fig. 1, is required. In this type of system, the sensors, etc. are configured as IoT devices, as has been widely advocated in recent years, and all data can be collected efficiently, including legacy data. This method of promoting data utilization while structurally standardizing the data aggregated by an edge server, etc. in order from the priority data groups is considered to be an efficient and realistic solution to the above-mentioned problem of multi-vendor environments. Many steel works in other countries have already implemented this kind of data driven infrastructure, and JFE Steel is also constructing a data driven system by utilizing state-of-the-art data conversion and high speed communication technologies, while continuing to make the best use of the existing system.

3.2 Cyber-Physical Systems

Collected data is analyzed for various purposes. The general method of use is to derive the factors which are corresponding to process efficiency or product quality from the data, and then work out appropriate countermeasures. Although this is a conventional methodology, in many cases hidden insights can be discovered by increasing the number of data and applying DS. However, the concept of a Cyber Physical System (CPS) has been proposed as an approach that makes more skillful use of the entire body of data, and thus supports the evolution of the target system as a whole[31, 32]. Steel making involves a large number of dynamic processes, and the hurdles to maximizing the use of diverse types of big data are high, but as a data utilization method for this type of system, CPS is an excellent concept.

In 1963, computer control was realized for the first time in the Japanese steel industry at the LD converter at Keihin Works of today's JFE Steel Corporation[1]. Human operation of the LD converter was more difficult than operation of the conventional open hearth furnace, and this provided the motive for using state-of-the-art computer (at the time). Although this was the first automatic control system using only a control model in an iron or steel manufacturing process in Japan, computer control systems were widely developed in the following decades. If a complete control model can be developed, quantitative prediction of the movements of the process becomes possible. In other words, a complete virtual (Cyber) process is implemented in the computer, making it possible to predict future states and detect unexpected anomalies. Then, a system in which the physical process and its virtual model operate in parallel can be created by providing an expanded range of elements such as structural, thermodynamic and statistical elements, chemical reactions, etc. in the model and linking sensor information concerning the actual (Physical) process to the model. This is the fundamental concept of CPS[30]. In CPS, the aim is to realize mainly the following functions applying its features of visualization (sensing) and automation (modeling).

i) Visualization of the past, present and future

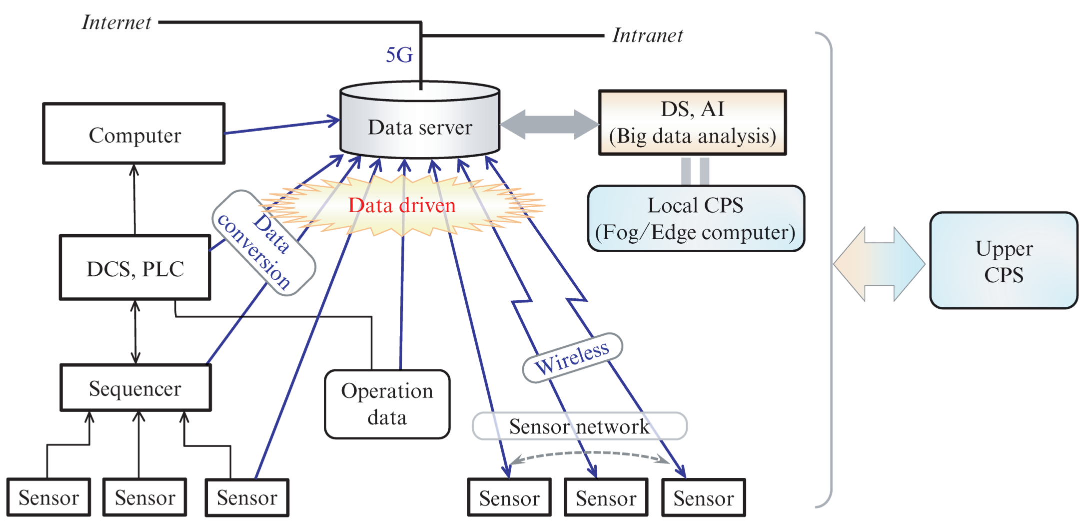

Fig. 1 Schematic of Data-Driven Architecture and Cyber Physical Systems

states of the process (health monitoring, anomaly detection and prediction)

ii) Automatic operation and advanced remote operation (identical operation of the actual process and the virtual process: operator can operate the process via the internet)

iii) Simultaneous optimization of stable operation, improved productivity, reduced energy consumption, etc.

iv) Virtual experiments (substantial improvement in process development efficiency by highly accurate simulations of new operating parameters, new equipment, etc.)

Figure 2 shows an example of the concept of CPS. The total cyber process is made to function organically by incorporating multiple elemental models and linking the data from the physical process to the respective models. It can also be said that the model side is a real-time version of coupled numerical analysis, and high performance, advanced HPC (High Performance Computing) is increasingly required as the system becomes more complex. JFE Steel has constructed and begun operation of CPS systems for blast furnace operational guidance, prediction of energy supply-and-demand in the steel works and reproduction of the state of ferro-coke furnace. (Articles on these three topics can be found in this Special Issue of JFE Technical Report.) Because CPS is extremely large-scale and complex in comparison with the systems of 50 years ago, which were limited to offline control models, many CPS systems are still in the local CPS stage shown in the center of Fig. 1. However, development of a higher level CPS to the total process level is on the way by utilizing AI, etc. to include human knowledge and experience. Additionally actuators are also indispensable elements in feedback/feed-forward of the physical process in CPS. By integrating robotics technologies such as material handling and transportation, we aim to realize a comprehensive CPS for advanced plant integration in steelworks..

3.3 DS Utilization for Other Fields

JFE Steel is also expanding the scope of DS utilization to various problems outside of the manufacturing process. In particular, the practicality of the new generation of AI in applications in fields that had been difficult to model by mathematical expressions is steadily increasing as a result of inputting appropriate data and laborious learning. For example, in electrical maintenance, JFE Steel introduced a system in which records of past trouble and action were learned by AI and guidance on appropriate action is given when new trouble occurs throughout the company (also discussed in an article in this Special Issue). In support for safety, a system in which AI automatically recognizes video images and stops the production line when a worker enters a hazardous zone in a plant has reached partially practical application.

Regarding the purpose utilizing DS, it is steadily becoming a general methodology for various types of innovation in society, spanning a diverse range from individual equipment to human systems. Of course, DS is not omnipotent, but there are actually many situations where DS techniques can discover some type of solution for problems that had reached an impasse with the conventional methods. Recognizing this potential, JFE Steel has adopted a policy of expanding the fields of DS application and actively introducing DS in the

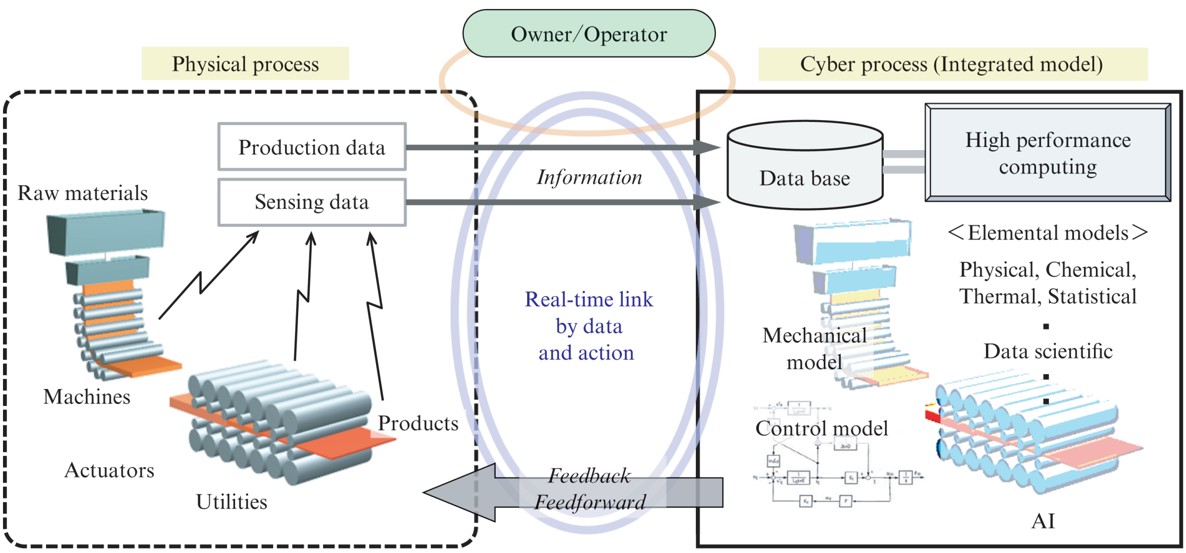

Fig. 2 Conceptual schematic of Cyber Physical System

future as well.

3.4 Challenges for DS Utilization

Japan's 5^{th} Science and Technology Basic Plan, which was adopted by the Cabinet Office in January of 2016, proposed "Society 5.0" as a vision for the future of Japanese society, and also mentioned CPS as a method for solving social problems and supporting economic growth. Active use of DS, AI, ICT and robotics is not limited to the manufacturing industries, but is also a trend in society as a whole. The issues that arise when implementing these policies including raising the awareness of people who are unacquainted with the potential of technology, investment cost and manpower requirements, and a shortage of data scientists. Here, however, the reference[1)] by our predecessors contains a passage which states that the purpose of introducing computers is "to free managers and engineers from everyday regular jobs and provide the opportunity for a higher order of human-oriented work." This is precisely the same as the main purpose of introducing DS and AI today, when "work-style reform" is so widely advocated in society. In other words, over the past half-century, we have realized various types of automation (although routine or non-routine work is another matter), but by successively creating work which cannot be computerized, we have reached a point, today, where we are unable to reform our own situation.

Thus, it appears that the greatest challenge may be a reform of our own consciousness of the intrinsic purpose of utilizing DS, AI and CPS, which is to achieve complete automation, truly change how we work, and improve labor productivity without creating unnecessary work. Since FY 2018, JFE Steel has adopted a policy of promoting the development of data scientists and education in AI literacy divided by organizational levels, and enlightenment not only in the technical aspects of these technologies, but also in light of their intrinsic purpose.

4. Conclusion

This paper has described the utilization of DS, AI and other ICT and digital data in JFE Steel Corporation. However, compared to the enormous number of processes and equipment in the steel works and plants, application of these technologies is still small, and there remains much manual work and data handling in paper form at the job sites. Although introduction of DS utilization on a company-wide basis is predicted to be time-consuming and costly, we believe that continuing to introduce DS will gradually create a positive spiral that will generate synergistic effects.

Chronology Digital Data Utilization Efforts in JFE Steel

Legend
Red: Classification of purpose
Black: Individual task
Blue italics: Element technology

	～1989	1990～	2000～	2010～2019
Infrastructure, etc.			OA/IT infrastructure →	OA/IT infrastructure → FA/OT infrastructure (IoT) → DS/AI tools → Data scientist training program →
Sensing/Diagnosis/Prediction			Early attempts with DS/AI Steel sheet defect classification [22] *Support vector machine* Nonlinear separation of defect feature quantities [23] *Gaussian mixture model* *EM (expectation-maximization) algorithm*	DS/AI fusion type Steel sheet surface defect judgment logic [24] *Decision tree* Hot rolling equipment condition monitoring [25] High accuracy radiation temperature measurement (multivariate analysis of spectral radiation) [26] Blast furnace anomaly detection using tuyere images [27] Blast furnace shaft pressure anomaly detection [28] CAL strip break prediction by canonical correlation [29] Blast furnace cohesive zone shape estimation *Principal component analysis, Q statistics and other statistical/DS analysis* Hydraulic system anomaly detection *Data-driven modeling* Cyber Physical System
Modeling/Automation	Application of classical controls *Feedback, Feed-forward PID control* Ship auto-pilot *Adaptive control*	Operation automation and optimization Blast furnace operation control [5] Plate cooling bed control [6] Converter blowing end-point control [7] Burden distribution control [8] *Expert systems* Burden distribution control [9] *Case-based reasoning* Hot stove gas control *Fuzzy control* Plate width control Hot metal flow optimization *Local regression model*	High accuracy control of complex objects *Modern control model, estimation theory, AI* Hot strip threading simulation [20] Hot rolling mill pacing Automatic planning of heating furnace charging sequence Plate mill pacing *Simulator*	High Performance Computing Reduction of product quality dispersion [11] Company-wide development of the above [12] *Local regression analysis* Multivariate optimal control for hot skin pass mill [18] Hot-rolling finishing mill control Cold-rolling strip thickness/tension model control Coke oven combustion control method *Model predictive control* Hot-rolling finish rolling temperature control Temper rolling flatness/elongation control [19] CC mold level stabilization (constant pressure wave model) Work roll eccentricity control (periodic disturbance estimation) *Observer*
Optimization	Production planning Automation/Optimization *Simulation*	Integrated coastal logistics planning Coal blend planning [4] Product shipment planning Pipe production control *Logistics general-purpose simulator* Scheduling for tapping sequence [13] *Genetic algorithm* Raw material operation planning system [14] *Constraint programming*	Planning automation/optimization *Mathematical optimization, advanced search algorithm* Automatic planning of tapping sequence Coil vehicle logistics planning [21] *Metaheuristics* Plate production control *Mixed integer programming*	East Area production control Ore carrier ship allocation *Automatic scheduling* Material design, steel sheet logistics and cargo handling planning Planning for barge navigation in Tokyo Bay Width prioritized search algorithm for steel ladle assignment [15] Guidance for plate heating furnace extraction sequence [16] Mathematical programming methods for ore blending [17] Production logistics *Application of congestion studies and various other techniques*

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