Data driven science and AI application technology

Application Technologies of Data-driven Science and AI that Evolve Alongside Humans

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Abstract

The steel and metal processing industries, which demand precision manufacturing in harsh, high-temperature environments, have a rich history of actively exploring advanced model-based control, sensing technology, and communication technology. In recent years, the rapid progress in information and communication technology has enabled the learning of extensive performance data and has advanced inference capability. This has paved the way for the practical implementation of data-driven science, contributing to the development of AI systems capable of accumulating both physical and operational knowledge and presenting it to individuals. As a result, these AI mechanisms are now making their way into the manufacturing field. This paper delves into the recent and remarkable transformations in the use of data-driven science and AI application technology at Kobe Steel, shedding light on the collaborative relationship that has evolved between individuals and AI through these applications.

Introduction

The steel and metal processing industries, which demand precision manufacturing in harsh, high-temperature environments, have a rich history of actively exploring automation in production. Rolling process control technology is one area of focus. Kobe Steel has been promoting advanced model-based control, sensing, and communication technologies in manufacturing, as these are necessary controlling forming processes.

Information and communication technology (ICT) has made it possible to gather large amounts of data. Application of this technology has evolved from model-based control to learning-based control. As such, it is now possible to incorporate operators' knowledge rather than relying solely on physical models.[1)] Data-driven science enables advanced reasoning by learning from large amounts of data accumulated in people's minds. Data-driven models are now being applied to areas with a paucity of data, such as development and design. AI can be defined as a system with mechanisms for input, output, and the incorporation of existing knowledge into a data-driven scientific model, alongside the model itself created as a result of the learning process. AI can hence be implemented to solve a variety of industrial challenges, supporting manufacturing by serving as a mechanism that can learn and present rulesets and operational knowledge. This paper introduces Kobe Steel's approach to using ICT in industry. Particularly in focus are data-driven science and AI application technology, which have recently undergone remarkable change, and our latest efforts to foster the mutual growth of humans and AI.

1. Kobe Steel's vision of data-driven science and AI application technology

Kobe Steel's spheres of activity include materials (e.g., steel, aluminum, copper), machinery (e.g., compressors, industrial machinery), and electric power. We provide precision on-site manufacturing and ensure the dependable supply of products to customers' supply chains. Alongside automation, staff knowledge has played an important role in all of these areas. Automation to the fullest extent practicable is of course important. However, Kobe Steel's objective in developing data-driven science and AI application technology in manufacturing is to support the mutual growth of humans AI, and systems. As depicted in **Fig. 1**, this objective is met not only by developing physical models, but also by learning from people's operational knowledge and combining it with modeling technology, thereby advancing operations. The concept of mutual growth between people and AI has two implications. One is that AI will rapidly gain operational knowledge as people reveal it, freeing people to engage in tasks with higher added value. The second is that, although it is believed that AI will not achieve humans' degree of capacity for adaptation and creativity for some time, AI will supplement these two skills, fostering the mutual growth of people and AI. Beyond this collaboration, our solutions will continue connecting humans and technology and ensuring safety and security in community development and manufacturing.

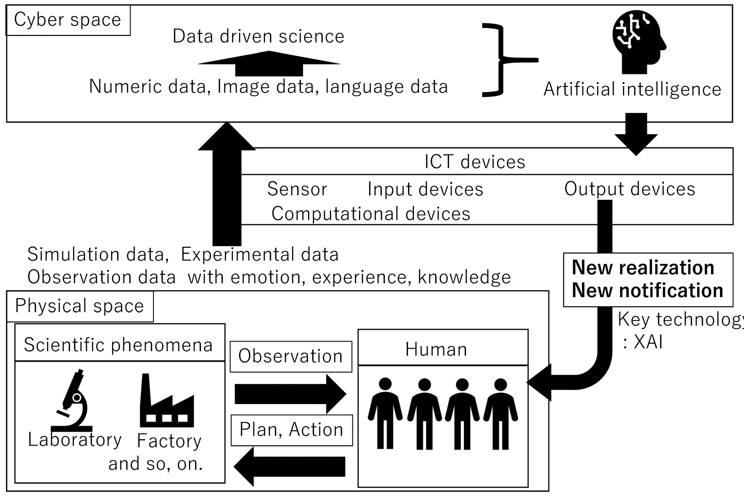

Fig. 1 Human-AI interaction through various data

Table 1 Changes in ICT application and our manufacturing

era	1980-1990	1990-2000	2000-2010	2010-2020
Key word of ICT	Computer communications Internet	Mobile phone Digital camera	Broadband	Smart phone Cloud system Bigdata, deep learning
Key word of manufacturing at our company	Mass production	High quality	High quality and multi-product low-volume manufacturing	Diversified added-value product
ICT applierd to our manufacturing and product	Process computer	IT(Information technology) Signal processing Wireless communications	Data cooperation system Image processing	IoT, AI Analysis bigdata

2. How ICT supports data-driven science and AI application technology

Kobe Steel's areas of focus regarding ICT have shifted in tandem with the field's development, as shown in **Table 1**.

Japan played a major role in the global steel industry in the 1980s and 1990s. Early digital technology was adopted in process control technology for the efficient mass production of steel, with positive results.[2)]

In the 1990s and 2000s, as steel production in emerging economies increased, Japan focused on efficiently producing and developing many different products, including high-grade steel. Differing products across industries presented barriers to automation and efficiency. As such, manufacturing operators became highly skilled by necessity.

The advent of the internet in the 1990s made it possible to amalgamate data previously confined to individual computers.[3)] The increasing capacity of data storage media and enhancements in wireless communication technology (e.g., widespread use of cellphones) in the 2000s and 2010s improved the practicability of using large amounts of data to automate operations.[4), 5)] Advances in information infrastructure have enabled automation challenges to be overcome by modeling production. For instance, multivariable model predictive control based on operational data has been used to automate plants that are difficult to represent via purely physical models, such as waste incineration plants.[6)]

Hardware that can acquire data in the adverse environments of metals manufacturing presents a competitive advantage. The same is true of sensing technology, which supports communication between people and processes. Sensing technology has evolved alongside advances in digital technology, such as in the use of wireless sensors[7)] designed for the harsh environment of heat treatment furnaces.[8)]

The 2010s, and particularly the past decade, have seen the commoditization of hardware for cloud systems and the communication speed, storage density, and processing power that support ICT infrastructure.[9)] In turn, demand for products that support the use of data in manufacturing has grown, as in the case of Kobe Steel's industrial machinery products[10)] and welding system products.[11)] Many companies including Kobe Steel have shifted their competitive focus to big data and data-driven science. Kobe Steel began using data-driven science techniques such as machine learning and statistical modeling, which we have cultivated through process control and operations research, to develop AI that can use the operational knowledge hidden behind data and can develop alongside operators.

3. AI that combines data-driven science and domain expertise

The expanded application of data-driven science has made it possible to incorporate valuable information into data-driven models, including experiences stored in the human mind and data that can be expressed mathematically, such as in the form of physical models. AI incorporates domain knowledge from scientific processes such as forming and heat transfer prediction into data-driven science to extract the more effective methodologies people reveal. This section clarifies this concept through examples of AI application in plant operations and materials development. Values measured by sensors and data input by humans essentially represent two different realities, resulting in a factor of uncertainty. Furthermore, because plants operate under a variety of conditions, the volume of data collected is sometimes insufficient for accurate analysis. Kobe Steel has developed technology to bridge the gap between actual operations and what is to be expected based on the laws of nature. Specifically, we use physical models to ensure accuracy and data-driven models to meld the human experience with the laws of nature, or domain knowledge. **Fig. 2** exemplifies these concepts. The lower part of the figure depicts how each element's strengths are used. While data-driven models incorporate real-world fluctuations that are difficult to represent in physical models, physical models stabilize data that were extrapolated rather than learned. The weight given to physical versus data-driven models in AI is based on the ease of reproducing the knowledge of subject-matter experts (SMEs). The resulting model yields an output that enables people to understand multidimensional data, which they can validate and evaluate the integrity of through comparison with their own knowledge and experiences.

A strong example lies in the advanced temperature prediction technology we have developed for steelmaking. It is based on people's estimation of temperatures based on operating experience. We weighted groups of similar operational data based on the deviation between data collected and temperature prediction values from a physical model. In this way, temperature predictions were aligned with operator knowledge to yield exceptional accuracy.[12)]

Materials integration, or materials informatics (MI), describes the use of information science in materials design. MI uses machine learning to predict material properties from a database of experimental values. Such techniques open up capabilities similar to those made possible by the use of data-driven science in plant operations. Examples include the prediction of properties that are challenging to predict from physical models, the development of AI that can determine the process conditions necessary to achieve desired properties, and the development of multi-scale predictive models that link the prediction of component performance with the prediction of material properties. Unlike plant operational data, however, data used in materials development are characterized by small volumes and high complexity. This is because there are few opportunities for experiments per type of material, and because experiments have a broad spectrum of objectives. The wide variety of experimental conditions and types of data make it challenging to standardize database structures at the outset. As such, this is one of the most difficult fields for the application of data-driven science.

Kobe Steel initiated a solution by developing a

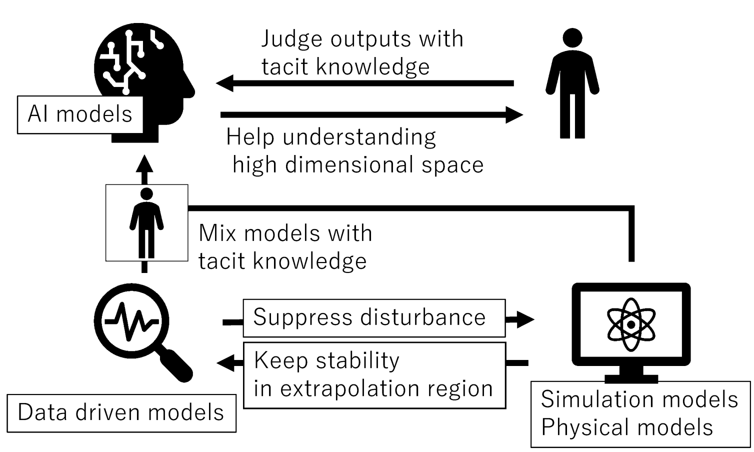

Fig. 2 Complementary relationship between AI and humans

database system to link and store data accumulated by researchers for various purposes and structure it in a manner conducive to MI. The resulting platform, DataLab®, aggregates data once maintained only by individual researchers. Unlike ordinary databases, DataLab®'s core strength is that it does not require the strict definition of a structure in advance, making it possible for experimental data to handle complex relationships such as branching and recombination during analysis. In one particular materials development project, a machine learning model derived from experimental data was used to achieve conflicting performance characteristics in welding consumables.[13)]

Additive models and Gaussian process regression have been used to construct data-driven models that integrate knowledge of actual parameters and data characteristics as mentioned above. Experts can account for conditions and phenomena for which data do not exist by selecting materials proposed by the resulting model. This enables efficient progression through the prototyping stage and improved performance over conventional materials.[13)]

Kobe Steel has established a complementary relationship between humans and AI through MI. These efforts constitute the use of computational and data-driven science to achieve new heights in information for R&D and design, fields in which small and complex datasets are a barrier to model development. Moreover, these efforts are a foundational element of collaboration between humans and AI.

4. Mutual understanding between people and AI to support next-generation manufacturing

CCD and CMOS cameras alongside the advent of deep learning have dramatically improved the usability of data from imaging. Accordingly, such technologies are beginning to replace sensory evaluation in manufacturing. The models with a physical context described to this point differ from data-driven scientific models used in sensory evaluation on a fundamental level. The latter, especially models using deep learning for image discrimination, have no strict guidelines, have simplistic outputs, and are easily evaluated even by non-SMEs because of the abundance of tools available. These characteristics yield a broad scope of application of such models. The relationship between data-driven science and people has recently started shifting toward one of cooperation. This is observed in the creation of digital art by generative AI based on deep learning, in which AI creates art based on instructions provided by a person.

However, the cooperative relationship between AI and people is more complex for sensory evaluation than it is for the creation of generative AI images. Specifically, sensory evaluation requires the ability to explain good and bad results as well as deviations. This in turn necessitates technology that enables people to comprehend or control AI. Our focus hence turned to the rapidly growing technology of XAI (explainable AI), which cultivates a better understanding of AI models.

Developments in XAI generally have one of two objectives: improving the accuracy of models with high explainability, or creating technology to understand models with low explainability. Kobe Steel's focus is on the latter to support technological development in the use of deep learning with low explainability to replace sensory evaluation.

Fig. 3 depicts Kobe Steel's work in fostering the understanding of AI models with low explainability. In Case 1, a person checks the direct output of the AI and controls the AI's loss function and hyperparameters to make it behave as desired. In

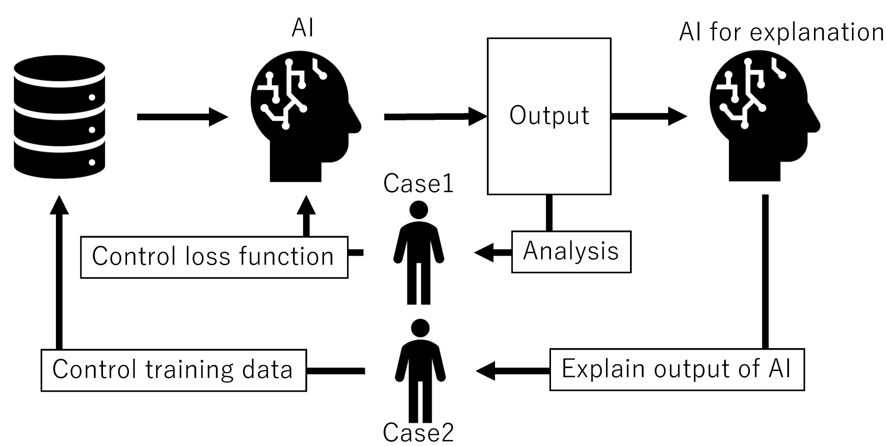

Fig. 3 How to create highly explainable AI

Case 2, a person controls the training data and then observes how the output changes, based on how an XAI algorithm explains the output of the AI model developed.

An example of understanding AI behavior by controlling training data through XAI lies in the development of image recognition technology for welding automation. We created an AI model designed to recognize the features of the molten pool (the area where the welding torch and base metal meet). However, accuracy declined as we trained the AI using specific data. To overcome this challenge, we developed a technique to understand the behavior of deep learning models via the following procedure. First, we used XAI in conjunction with a deep learning model with encoder-decoder architecture, like U-Net, to create fixation maps that visualize regions of interest. Maps are then ranked by importance based on the change in the AI model's performance as areas of each map are sequentially omitted. We used this ranking to track how the model's accuracy changed based on which areas of the image were omitted. This interactive understanding of which areas the model considered important improved the accuracy of the model.[14] This method resembles the way in which people communicate inspection results by pointing at images and explaining what to look for. Thus, developments in this field progress by communicating intention between people and AI via data.

Our construction of an AI model that controls omissions serves as an example of AI model development in which the loss function is controlled directly. Discriminative models of deep learning algorithms are supposed to learn to improve accuracy when evaluating products as conforming or nonconforming based on sensory criteria. However, cases such as ours at Kobe Steel necessitate certain requirements related to missed nonconformances, as a miss will negatively impact downstream processes and customers. Both misses and over-detection (misidentification of acceptable and nonconforming goods) must be limited to a certain percentage. This is why Kobe Steel developed a method to optimize the loss function by including the confidence threshold itself as a hyperparameter of the machine learning model. This development validated that models can be more accurate when given constraints than when adjusted based on general accuracy evaluations.[15] Although this method is still experimental and not yet ready for application in complex models, it already has a very wide range of applications.

Expanding the use of data-driven science in manufacturing, a human-dependent field, requires mutual understanding between people and models as well as the embedding of intention in models. XAI will continue to develop to suit these needs, particularly in industry. Much is left to be learned about XAI, and the orientation of its development is not yet clear. However, Kobe Steel will keep its focus on this technology as an essential means to apply data-driven science to manufacturing.

5. The future of data-driven science and AI application technology

The ability to collect more types of data and the advancement of data-driven science make it possible to model human knowledge, phenomena that are challenging to verbalize, and concepts that are challenging to represent as physical models. Kobe Steel has already begun using data-driven scientific models to connect various domains. Data-driven science and AI technologies have expanded and evolved to a remarkable degree. Large-scale generative AI services have opened the ability for laypersons to accomplish what was recently possible only for specialized researchers simply by feeding data to applications on the internet. There is no doubt that the use of AI will continue to spread across the industrial sector. As we apply AI to conventional process models and MI, we will also increase our ability to use data-driven science by establishing a foundation for human resource development, using data, and sharing knowledge and experience regarding the core technologies of data-driven science and AI application.

Conclusions

Goods must now be evaluated beyond their inherent characteristics because of new standards in areas such as carbon neutrality; data related to raw materials and production methods must be part of the evaluation. This means it is necessary to link goods and information in an exceptionally accurate manner. Furthermore, the application data-driven science, which is now becoming intertwined with humankind, will become even more important in manufacturing. Because manufacturing relies on people, this sector will face challenges in passing on technology owing to the shrinking workforce. Additionally, many companies are struggling with a lack of experience in the complexities and expansion of industrial infrastructure alongside a shortage of human resources to use such infrastructure. Kobe Steel is focused on supporting mutual growth between people and AI in industry, creating new value by combining data with human knowledge. Kobe Steel's technologies support the general capabilities of manufacturing and a broad spectrum of industrial domains. Our objective in providing these developments is to foster a safe, secure, and prosperous society for the next 100 years.

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