Changes in Data Analysis Technology in the Manufacturing Industry in the Midst of the Third Artificial Intelligence Boom

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The arrival of the third artificial intelligence boom has been announced recently. As a background, parts of human intelligence are being replicated by processing big data thanks to the improvement of data infrastructure such as networks and cloud environment, and the advancement of data analysis technologies including statistics, pattern recognition and machine learning. This new IT trend is gradually changing the ways of utilizing data in the manufacturing industry. This paper introduces recent major IT trends and shows that they depend on big data and advanced data analysis technologies. The paper then describes the transition of industrial data analysis in the manufacturing industry affected by the IT trends, and discusses its future.

INTRODUCTION

The first artificial intelligence (AI) boom started at the Dartmouth Conference in 1956. The conference showed the possibility that computers can prove mathematical theorems, which was thought to be an intellectual feat that only human beings could perform, and thus expectations of artificial intelligence grew greatly. However, the boom soon vanished as it gradually became clear that the theories and computers of those days were able to handle only simple problems.

The second AI boom emerged in the 1980s. Its focus was an expert system that imitated the decision-making by specialists and made deductions based on knowledge. In this system, humans build a knowledge base, and computers make deductions based on predicate logic. However, people gradually realized that it is difficult for the system to imitate sophisticated judgments by specialists because the knowledge base could be inconsistent and imperfect while the actual environment contains various exceptions.

Some people now say that the third AI boom has come. There are reports that parts of human intelligence are being replicated by processing big data thanks to improved data infrastructure such as networks and cloud computing, as well as advanced data analysis technologies including statistics, pattern recognition, and machine learning. This IT trend is steadily affecting the manufacturing industry.

This paper first clarifies that big data and advanced data analysis technology play a key role in the third AI boom, referring to major cases in recent years. Second, we describe changes in data analysis in the manufacturing industry which is being influenced by the IT trend, and then discuss the future of data analysis in the manufacturing industry. Finally, we will draw some conclusions.

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IT TREND IN THE THIRD AI BOOM

This chapter discusses the current IT trend referring to three major cases in recent years.

The first case is Watson[1], IBM's question-answering computer system. This system performs multiple tasks such as analyzing question statements, and generating, verifying, and selecting candidate solutions in real time. This sophisticated system consists of 2,880 processor cores, a database containing tens of gigabytes of various information, text analysis technology, and multiple machine learning technologies. Watson astonished people by beating human champions in a quiz show in 2011.

The second case is ImageNet Large Scale Visual Recognition Challenge (ILSVRC)[2], a competition in which various systems compete at automatic recognition of objects by using a large amount of images. In 2012, one system overwhelmed the others with a lead of more than 10 points (others were within 1 point of each other). This system used machine learning technology with a deeply connected neural network, called deep learning. Other participants had created discrimination algorithms based on each feature of images. In contrast, the winning system used deep learning to learn features of images while adjusting discrimination functions.

The third case is AlphaGo[3], a computer system developed by DeepMind for Go, a Japanese board game. The game-tree complexity of chess is 10^{120} and that of Shogi, another Japanese board game, is 10^{220}, while that of Go is 10^{360}. In view of the vast search space, it had been expected to take a long time for computers to beat human Go players. However, AlphaGo learned good moves of great professional Go players from vast archives of recorded games and learned more through its own match-up simulations. Following this strategy, this system beat a professional Go player. As in the second case, deep learning was used to analyze the big data of recorded games.

It is worth noting that no one created algorithms to achieve the objectives in these three cases. Each system analyzed big data (AlphaGo contained data generated by the system itself) by using machine learning technology, and autonomously found the optimum algorithm.

Although these successful cases applied to limited situations, it was a big breakthrough that tasks that require sophisticated recognition and judgment by human beings can be reproduced by data analysis.

CHANGES IN DATA ANALYSIS TECHNOLOGY IN THE MANUFACTURING INDUSTRY

Now, let's take a look at the manufacturing industry. The manufacturing industry has been working on data analysis to use limited energy, resources, and facilities in order to manufacture products safely while maximizing efficiency. However, it is hard to apply conventional methods to some situations because systems and operations are becoming more complicated due to external factors and other reasons. In this situation, advanced analysis technology, mainly machine learning as described above, is gradually being used. This chapter looks at this trend.

Main Tools for Data Analysis in the Manufacturing Industry

The main data analysis technologies in the manufacturing industry are regression analysis and multivariate analysis, both of which assume linearity among variables (Figure 1).

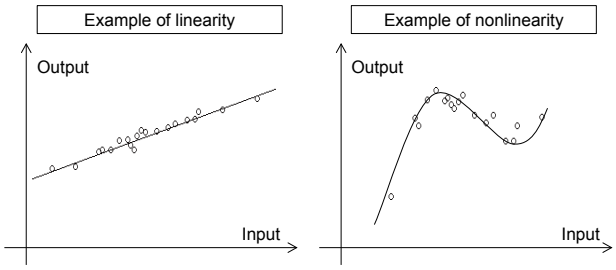

Figure 1 Example of linearity or nonlinearity

For example, multiple regression analysis is used to predict product quality based on operating conditions, linear discriminant analysis analyzes factors of conformity/non-conformity, principal component analysis identifies the characteristics of a system with many sensors/inputs, and statistical process control is useful for quality control. The paper "Data Analysis for Stabilizing Product Quality and the Mahalanobis Taguchi (MT) Method" in this issue describes an analysis method that assumes linearity among variables and quantifies the deviation from normal data samples.

Although linearity seems to be too simple an assumption for data generated from actual systems, it is well accepted for the reasons outlined below.

- Easy interpretation, implementation and maintenance because basic linear algebra is enough to describe analytic models
- Empirically, characteristics of systems can be approximated linearly (for example, a single operating condition)
- Mature analysis technology with a wealth of research and application

These mathematical analysis technologies have been successfully applied thanks to engineers' various know-how. They include the setting and pretreatment of a suitable analysis scope based on sufficient knowledge about the system; sufficient knowledge for using the above analysis technology; and the integration ability to use analysis results effectively in the system.

Such know-how beyond mathematics is expected to continuously play an important role in data analysis in the manufacturing industry. The examples in the paper "Quality Stabilization of Formulation Process by Using Mahalanobis Taguchi (MT) Method and Applications to Continuous Drug Production" in this issue show a high integration of such data analysis technology and engineers' know-how.

Complex Objects for Analysis

In contrast, there are many cases in which the assumption of linearity is not appropriate because of the complexity of data. They include:

- Cases with strong non-linearity, such as reaction processes that have exponential characteristics like the Arrhenius equation
- Cases to which local linear approximation is not applicable, such as analyses for total optimization of multiple processes
- Cases with uneven data distribution, which is caused by frequent changes in operation recipes in multi-product manufacturing, or by changes in characteristics due to the deterioration of equipment

Since the premises for the analysis substantially differ from those for these cases, conventional methods do not yield satisfactory results in analyzing data. Theoretically, it is possible to handle these cases by engineering efforts such as searching for an appropriate model equation from many references, or clustering the data samples into a similar group and analyzing each case individually. However, such efforts would require considerable time and cost.

Fortunately, many studies have been carried out in various areas because mathematically similar problems occur not only in the manufacturing industry but also in all other fields. Engineering can give only limited solutions to cases with complex data especially in the areas of natural language, image processing, and voice processing. As a result, technologies for advanced, automatic analyses have been studied including machine learning. Such studies led to the explosive development of the third AI boom.

In the past, advanced data analysis technologies including machine learning were not popular in those sectors of the manufacturing industry that require mission-critical systems because parts of the analyses were like a black box to users. This situation is changing due to the increasing engineering cost for complex analysis. At the same time, advanced data analysis technologies have been increasingly applied to various areas, and know-how has been accumulating. As a result, engineers have come to understand parts of the black box. This is another cause of the changing situation.

Data analysis technologies and peripheral technologies are introduced below, with a focus on the increasingly popular machine learning.

Latest Approaches to Data Analysis in the Manufacturing Industry

The Kernel method[4] is a popular non-linear analysis method, which maps data onto a feature space whose dimension is higher than that of the data and performs non-linear analyses in the framework of linear data analysis. A technique called the Kernel trick eliminates the need to calculate the high-dimension feature value and enables efficient non-linear analysis by simply defining inner products in the feature space. By combining the regularization method to the Kernel trick, non-linear analysis methods can be applied to intrinsically high-dimension data or data from a relatively small number of samples that have strong non-linearity. The radial basis function (RBF) model used in a system described in reference[5] is closely related to the Kernel method.

Mixture modeling that uses multiple elemental models for modeling an object is also used widely. This category includes the piecewise linear model (Figure 2), which makes up a regression function with more than one multiple regression model, and the mixed Gaussian model[6], which expresses the complex shape of data with multiple Gaussian distributions. Since the model from which each sample is obtained is not obvious, the model is deduced by using machine learning such as the expectation maximization (EM) algorithm or the Markov Chain Monte Carlo (MCMC) method. As a result, data are sorted into groups, each of which is expressed by respective models. In the case of the mixed Gaussian distribution, traditional multivariate analysis methods can be used to analyze each group. Thanks to this characteristic, data can be sorted automatically for subsequent analyses even if production systems have implicit modes such as changes in internal states of facilities. The paper "Modeling Technology for Optimizing Energy Consumption and Product Quality, and Example Applications" in this issue describes application examples of such complex analyses to system modeling for energy optimization. In addition, references[7][8] report methods of identifying a dynamic model for advanced control and modeling of soft sensors to estimate product characteristics.

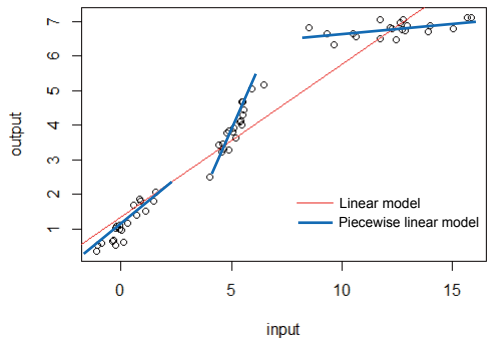

Figure 2 Piecewise linear model

Deep learning[9], described in the previous chapter, is also a notable machine learning technology. Deep learning is a set of technologies that have solved problems associated with deep neural networks and have brought neural networks to a practical level (problems of deep neural networks include over-fitting to data and poor learning due to network terminals being out of reach of learned information). Deep learning generates a neural network whose processing is equivalent to a human's primary analysis (feature extraction). Thus, this is called feature learning. Thanks to this function, deep learning can semi-automatically analyze high-dimensional data such as images, sounds, spectral data, and data obtained from sensor networks. The paper "Machine Learning Applied to Sensor Data Analysis" in this issue reports on how to apply deep learning to sensor data analysis.

Progress in analysis technologies has been brought about by progress in data infrastructure. As reported in the paper "Evolution of Exaquantum to Accelerate Effective Use of Plant Data" in this issue, Yokogawa's Exaquantum plant information management system can now accumulate and use big data while satisfying the requirements for a mission-critical manufacturing system, such as real-time operation and robustness. The paper "Real-Time Data Extraction Technology for Effectively Supporting Work Improvement Cycles" in this issue introduces bases for quickly consolidating data from multiple manufacturing entities and using these data. The paper "A Method for Quickly Searching Similar Waveform Patterns in Historical Process Data" in this issue introduces technologies for searching necessary data efficiently among accumulated data.

FUTURE OF DATA ANALYSIS IN THE MANUFACTURING INDUSTRY

The previous chapter described how new IT trends affect and change data analysis in the manufacturing industry. This chapter discusses the three possibilities of changes in manufacturing sites.

First, know-how about organoleptic tests and equipment inspections is expected to be systematized. In the discrete manufacturing industry, human workers visually inspect final products, and in both the process and discrete industries, human staff routinely patrol sites. Experts in these areas have a great ability to sense anomalies and detect subtle differences in surroundings. However, the number of experts is dwindling, and thus it is becoming difficult to deploy experts in many sites or hand their know-how down to the next generation. One solution is to record their operations in the form of images and sounds and use these big data to establish systematized operations.

Second, heterogeneous systems will be interconnected. For example, a huge amount of information is being accumulated as big data in different departments, offices, or companies in the same supply chain, and these organizations have different situations but influence each other. If any problem occurs across these organizations, it is not practical for engineering alone to analyze all data. It is necessary to make full use of machine learning and other technologies, and to detect correlations and anomalies semi-automatically. This solution will be crucial for companies to strengthen their competitiveness.

Third, manufacturing strategies will be drawn up including control and operation. Big data and advanced technologies for analyzing them help create a precise model of manufacturing systems, and such models enable effective what-if analysis. This solution is expected to significantly enhance manufacturing strategies for optimizing control and operation and improving production efficiency.

CONCLUSION

This paper described several examples of the third AI boom and showed that this boom depends on big data and advanced data analysis technologies. The paper also showed that data analysis in the manufacturing industry is changing, and discussed possible changes in manufacturing triggered by new IT trends.

As seen, big data and advanced technologies for analyzing them have created a new IT trend, which is establishing the position of innovation creators. Meanwhile, Yokogawa has been providing customers with operational technology that supports mission-critical manufacturing systems today. Our challenge is how to incorporate this new IT trend with high potential into our operational technology and help the manufacturing industry continue to create value.

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