Featured Articles

Utilization of AI in the Manufacturing Sector

Case Studies and Outlook for Linked Factories

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OVERVIEW: Utilization of the IoT is steadily advancing in the manufacturing sector. In response to this trend, Hitachi is working to provide new industry solutions based on the symbiotic autonomous decentralization concept for achieving overall optimization of activities and for creating new business by linking various systems and stakeholders together. To make new industry solutions a reality, it will be necessary to have on-site sensing, to provide an infrastructure for collecting and archiving big data, to analyze and plan countermeasures, and to give feedback to sites. This article describes advanced on-site sensing, integrated analysis of a variety of on-site data for analyzing and planning countermeasures, and the utilization of AI technology for them.

INTRODUCTION

IN recent years, utilization of the Internet of Things (IoT) has resulted in increasingly active trend towards a new evolution of the manufacturing industry. The Industrial Internet Consortium (IIC), which includes General Electric Company (GE) as one of its founders, and the government-led Industrie 4.0 were established in the USA and Germany, respectively. Both of these organizations are engaged in the formation and standardization of a new ecosystem that involves the manufacturing industry and information technology (IT) industry.

Hitachi has a track record for building large-scale control systems in diverse fields, such as energy, transportation, and water supply and sewerage, in addition to production management systems and control systems designed for various manufacturing industries including steelmaking, automobiles, and medicine. Hitachi is leveraging its knowledge of systems such as these to link diverse systems. It is advocating the "symbiotic autonomous decentralization" concept[1] to provide value gained from this to the manufacturing industry and the social infrastructure sector, and to promote new growth.

Symbiotic autonomous decentralization allows sensing of a site's various statuses (Sensing), analysis of issues and planning of countermeasures based on various collected and archived information (Thinking), and feed back of the results obtained to the site (Acting), thus enabling the optimization of value chains inside and outside of the factory.

This article describes new industry solutions that will be achieved by such symbiotic autonomous decentralization, and the machine learning technology and artificial intelligence (AI) that form the core of these systems.

LINKED FACTORIES AND NEW INDUSTRY SOLUTIONS ACHIEVED BY SYMBIOTIC AUTONOMOUS DECENTRALIZATION

Conventional optimization at production sites is limited to analysis at the individual system level and improvement of each site based on this, and the effectiveness of such improvements is becoming saturated. This is why symbiotic autonomous decentralization is being applied to achieve linked factories with a view toward optimizing activities across multiple systems and the creation of new value chains. To make this a reality, Hitachi is collecting and archiving information from other related systems in addition to the information gained from manufacturing systems, and is also further analyzing the information of other factories that are being expanded globally, planning countermeasures, and giving feedback to sites with the aim of optimizing activities overall (see Fig. 1).

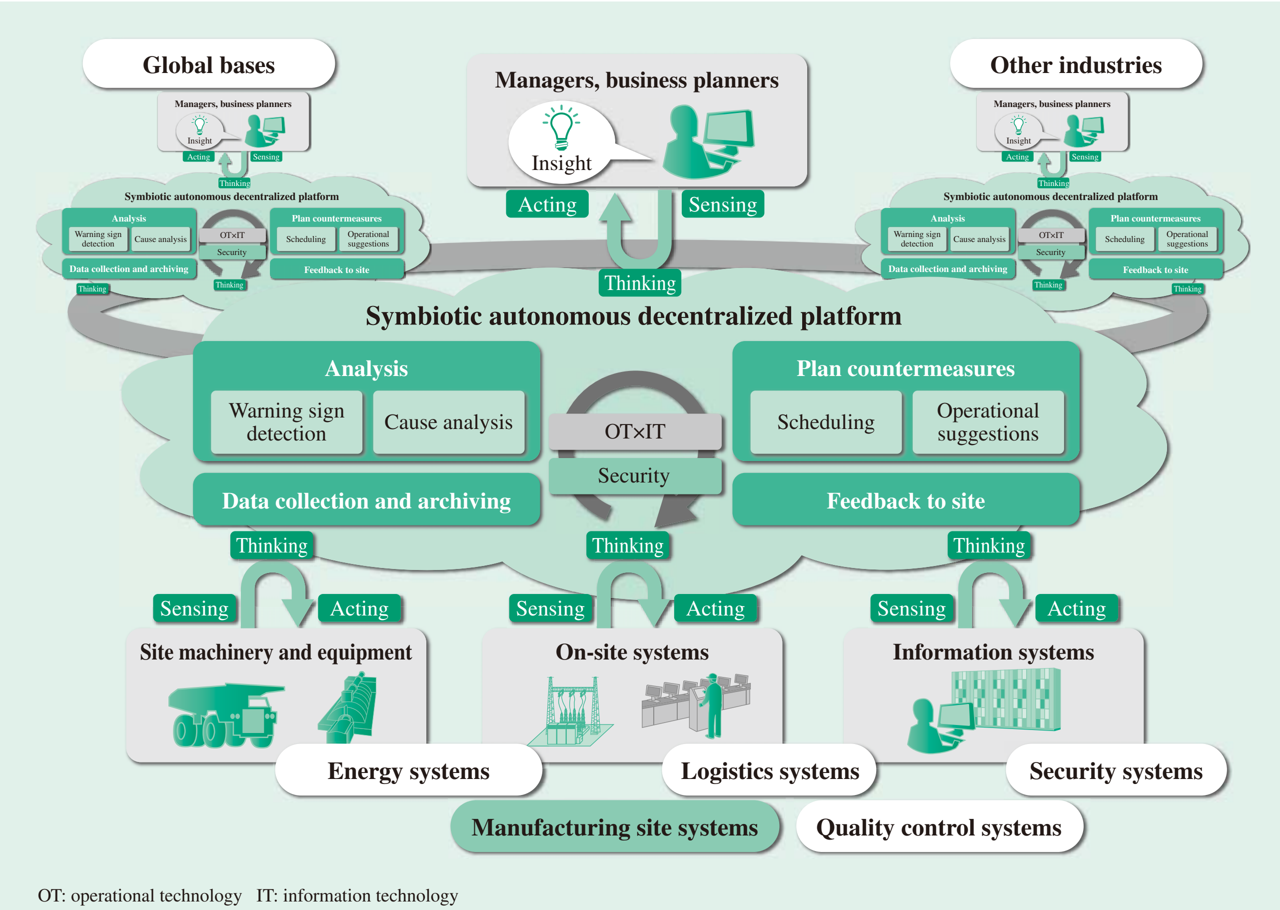

Fig. 1—Symbiotic Autonomous Decentralization Concept.
Activities can be optimized in terms of management considerations and new value chains created by collecting and archiving data from a variety of on-site systems, analyzing it and planning countermeasures, and providing information back to the site as feedback.

Depending on the information to be combined, the following types of solutions are possible.

(1) Improved energy productivity

It is predicted that energy costs will fluctuate considerably as a result of the liberalization of electric power, violent fluctuation of the crude oil price, utilization of renewable energy, and other factors, and improvements in productivity to correspond with this fluctuation will be required. For this reason, Hitachi is collecting data on the status of energy consumption in addition to detailed production site information from sources such as manufacturing execution systems (MESs) and points of production (POPs), is conducting analysis regarding the relation between energy and productivity, and is formulating energy procurement plans and production plans that will lead to the reduction of overall energy costs and peak shaving. Formulated plans are fed back to an MES and the optimum production plan is executed so that renewable energy in the factory is used effectively and energy costs are reduced.

(2) Supply Chain Management (SCM) coordination

To achieve optimum operation of factories that are expanding globally, site information from MESs and inventory control systems is analyzed, and high-precision management indicators are evaluated by a business value simulation tool that factors in the logistical status of each region. These indicators are then used to determine the optimum production plan for each site, distribution routes, stock quantities, etc., and the production plan is then executed based on these parameters. Also, since on-site information is analyzed in real time, production capacity and inventory is adjusted to accommodate unforeseen circumstances.

(3) Global quality management/improvement

Ensuring consistent quality at a high level between factories that are expanding globally not only results in cost reductions but also reduces the risk of product recalls. To accommodate this, worker actions are sensed by video analysis as well as detailed manufacturing information from MES and POP. The information that is gained is archived and analyzed so that factors that degrade quality can be extracted and countermeasures can be planned. Hitachi will introduce new analytical methods such as AI since the factors that affect quality are complex and are predicted to be wide-ranging. Obtained countermeasures will be fed back to workers using augmented reality (AR) as well as MESs and other control systems.

(4) Business Continuity Plan (BCP) support

In recent years, cyber-attacks have increased the risk of factory operations being shut down. As a result, the impact on business when an incident occurs must be minimized. Monitoring information, detected illegal access to control systems, and detected viruses, as well as detailed information collected from manufacturing systems, is collected from each base. When an incident such as a virus infection is reported by the security monitoring center, the impact of the virus itself, the scope of impact from the viewpoint of control system configuration, and the impact on business operations from the viewpoint of production status are judged as a whole, and plans, for example, for setting the system offline, eradicating the virus, or adjusting production capacity are formulated.

UTILIZING AI TO ACHIEVE NEW INDUSTRY SOLUTIONS

Technology for (1) conducting advanced sensing of site information and (2) analyzing a variety of data to plan countermeasures will be the keys to achieving the solutions described above. With regard to advanced sensing, video analysis technology is gradually being put to use in obtaining birds-eye-view like information such as people's movements, and learning functions, AI, or the like for comprehending the meaning of captured video are anticipated.

For the analysis and planning of countermeasures, it is strongly desirable to utilize AI from the viewpoint of analyzing diverse data in an inter-disciplinary manner to obtain new knowledge.

The following describes actual case studies where AI was utilized.

Application of Machine Learning to the Recognition of Work Activities

Hitachi is developing a sensing technology for recognizing the movements of factory workers and for detecting worker movements that deviate from a predetermined standard range (i.e. abnormal operation) for the purpose of improving product quality. The following describes the machine learning that forms the core of this sensing technology.

First, a motion camera is used to recognize worker movements. This allows joint position information (e.g. wrists, elbows, shoulders) to be obtained from a worker's 3D shape. Machine learning is then used based on the obtained joint position information to recognize the worker's movements.

Fig. 2 shows an overview of the abnormal operation detection algorithm. In the preprocessor, noise in the joint information is removed by smoothing, and information that is not directly related to work, such as arm length or leg length, is canceled out through normalization. The feature value extractor extracts feature values, which are pieces of information that represent movements. In the classifier, combinations of feature values are selected according to the kind of work in which abnormal operation is to be detected.

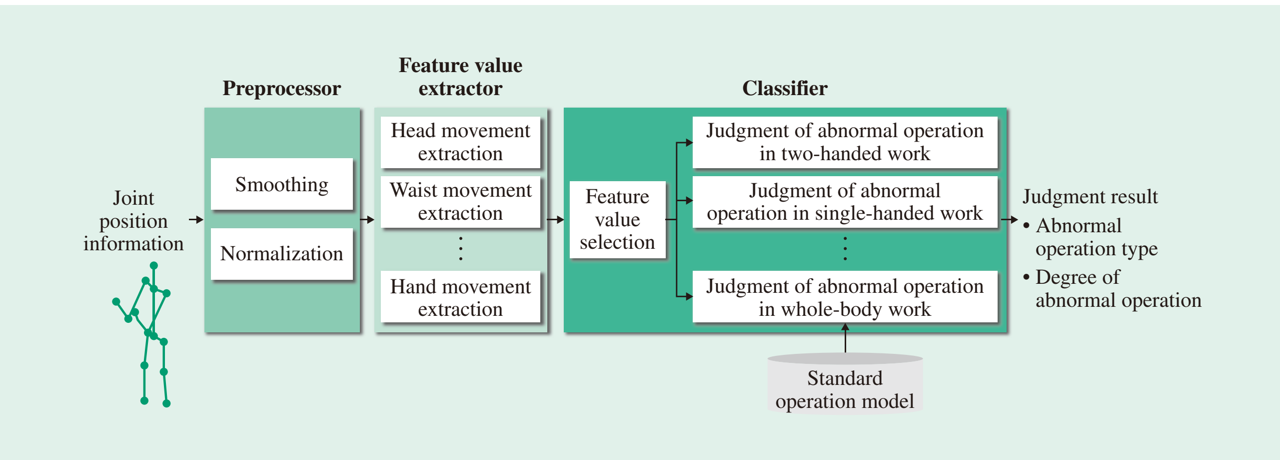

Fig. 2—Overview of the Abnormal Operation Detection Algorithm.
Machine learning is applied in each of the abnormal operation judgment processes in the classifier.

And, the presence of each abnormal operation is judged (abnormal operation judgment) by making a statistical comparison with a standard operation model.

Machine learning can be put to effective use by the feature value extractor and classifier. In particular, when there is a large amount of data, both can be optimized using a technology called “deep learning,” in other words, automatic design is now becoming possible. However, when a large amount of data cannot be obtained, prior human knowledge is used to execute optimization up to the feature value extractor and to design the combinations of feature values. With the proposed techniques, work movements were decomposed down to their motion elements based on the observation and investigation of on-site work, and those elements were taken as prior knowledge in the design of the feature value extractor and combinations. Up to this point, the process is qualitative design, which can be understood by humans.

On the other hand, with abnormal operation classification, the question is: what kind of judgments are to be made about the feature values, namely, quantitative design is required. Machine learning is generally excellent for quantitative design.

There are two types of machine learning, supervised and unsupervised. With supervised machine learning, two types of training samples are used, normal operation samples and abnormal operation samples. When a training sample is input, the abnormal operation classifier is optimized so that the correct judgment is made. However, collecting abnormal operation samples is difficult, for two reasons: there are few abnormal operations and there are countless variations.

For this reason, unsupervised training, which uses only normal operation samples to perform learning, is used. As a result, the standard operation model can be estimated as a probability distribution.

Fig. 3 shows a conceptual diagram of a probability distribution. Judgment results are expressed by single points within this distribution, and the further the judgment is from the center of the distribution, the stronger the degree of abnormal operation is going to be. For example, the center is the operation that is taken as the model, and the peripheral area around the center is a normal operation. If we move further away from the center, operations that require caution or abnormal operations can be demarcated as caution or abnormal, respectively. It has been demonstrated that operations that different from the norm can be actually extracted by using the standard operation model that has been learned.

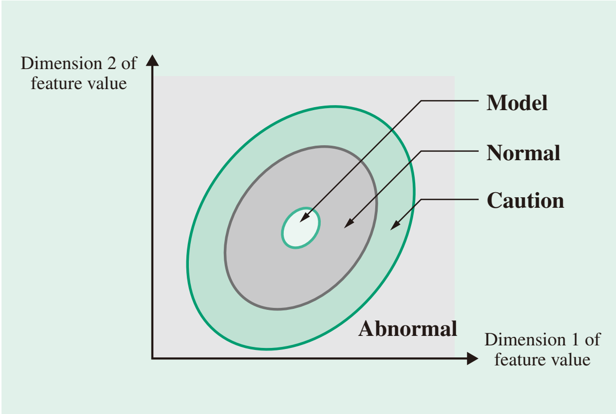

Fig. 3—Conceptual Diagram of Probability Distribution Showing a Standard Operation Model.
A standard operation model is estimated as a probability distribution. Judgment results are expressed by single points within this distribution, and the further the judgment is from the center of the distribution, the stronger the degree of deviation will be.

Utilizing AI for Analyzing Site Data

Generally, distributed control systems (DCSs), which are in charge of the direct control of facilities, and MESs, which are in charge of production and quality management, are installed at productions sites. These systems collect enormous volumes of data relating to manufacturing facilities, production processes, and product quality every day. This data is mainly archived as numerical values and have been analyzed and utilized by statistical quality control techniques up to now. However, the rapid increase in the volume of archived data has made it humanly difficult to search for relationships between that data and key performance indicators (KPIs), such as quality and non-defective product ratio at production sites, and identify causes.

For this reason, Hitachi has been implementing analysis using Hitachi AI Technology/H (hereafter referred to as H), its own proprietary artificial intelligence technology[2]. When a KPI and data potentially related to the KPI (explanatory parameters) are input, H automatically generates feature values from the explanatory parameters, comprehensively calculates the correlation with KPI, and outputs statistically significant feature values (see Fig. 4). The characteristic of H here is that it generates combinations of explanatory parameters as feature values.

For example, with product manufacturing in a discrete system, assume manufacturing equipment X and Y, for which the processing values fall roughly within the ranges 1.0 to 4.0 and 5.0 to 10.0, respectively.

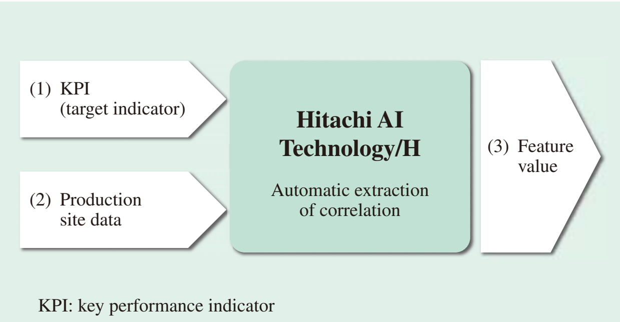

Fig. 4—Diagram Illustrating Input/Output of H.
When (1) KPI and (2) KPI-related production site data are input, then (3) multiple correlated feature values are output.

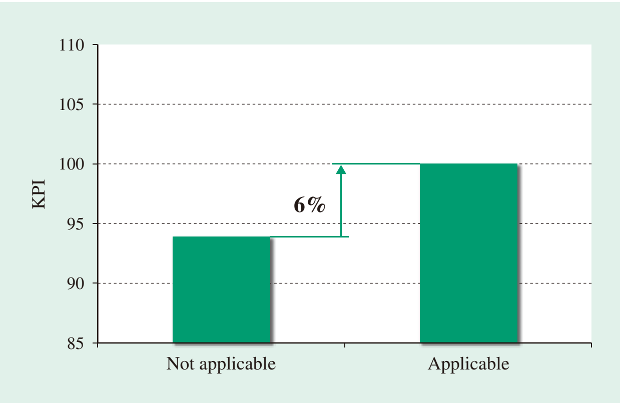

Fig. 5—Example of Results Discovered by H (Relative Values taking Applicable to be 100).
"Applicable" indicates a group that satisfies the discovered feature values, and "Not applicable" shows a group that does not.

When the data from manufacturing equipment X and Y and the KPI (here: production volume) are input to H, an enormous volume of feature values is generated, the correlation with KPI is comprehensively analyzed, and statistically significant feature values are extracted.

Fig. 5 shows an example of the analysis. The product group that satisfies the feature value (X: 1.0 to 1.5 and Y: 9.5 to 10.0) discovered by H is shown as Applicable, and the average value of that KPI (production volume) was 100 (relative value). Whereas, the product group that does not satisfy the feature value (where either X: 1.0 to 1.5 or Y: 9.5 to 10.0 deviate outside this range) is shown as "Not applicable," and the average value of that KPI (production volume) is 94. It can be seen that there is a difference of 6% in production volume between when product manufacturing satisfies the feature value and when it does not. In other words, an improvement in production volume of 6% can be anticipated by controlling manufacturing equipment X and Y so that the feature value is satisfied.

With production in a continuous system, each piece of equipment and each process generally has designed control values, and as long as these control values fall within the control ranges at each step of production there is no problem. However, production processes fluctuate on a daily basis, and appropriate operating conditions for the production processes keep changing because of the wearing and degradation of parts, and before and after facility maintenance. Furthermore, operating conditions and control conditions must be reviewed when production is switched over to new products. H is effective for discovering the appropriate operating conditions for responding to changes such as these and for gaining new awareness based on large amounts of data. For example, in processes that are comprised of a total of ten steps, combinations of data across processing in the first and third steps can be analyzed. The ability to analyze a wide breadth of data across steps and processes in this way is an advantage of H, and this can be used as an opportunity to make workers and managers at production sites, who tend to focus on the management of facilities and processes, more aware.

CONCLUSIONS

This article described linked factories and new industry solutions based on the symbiotic autonomous decentralization concept, as well as the utilization of AI that will be key in achieving this.

Although the article dealt mainly with utilization of AI geared towards improving quality, in the future, Hitachi intends to increase the number of case studies where AI is utilized in other solutions, and to apply AI technology to production and engineering sites while advancing the verification of its effectiveness with a view to supporting manufacturing innovation.

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