Monozukuri Navigation System to Deliver Outstanding Quality and Efficiency

● Eiji Takada ● Taizan Kobayashi ● Hidetoshi Matsuoka ● Takeshi Soeda
● Masatomo Maida

Fujitsu strives to offer "smart Monozukuri" services that help to achieve efficient quality and product management applying information and communications technology (ICT) to Monozukuri (Japanese way of manufacturing). One of the systems being developed as part of this is Monozukuri Navigation System, based on technology to realize virtualization/integration at manufacturing sites. The system allows the users to fully leverage sensing technology, analytical tools, artificial intelligence (AI), and other ICT from the upstream of product development, helping them to utilize all production-related data, and it offers solutions that best suit the requirements for a particular production site. It is important for manufacturing practice to incorporate data regarding design assets, experience amount and capabilities of the production site, and operational status of the production facilities, as required, at the development and manufacturing sites and to develop the product to achieve an appropriate quality level. We focus on developing a system that reviews in-house practices and creates data relating to the conditions specific to the production site. The system analyzes them and provides a basis for models that predict manufacturing status, which are then used to optimize the site's manufacturing conditions. This paper outlines Monozukuri Navigation System, and explains its features. The paper also presents the real-time navigation, which is designed to prompt people to make the best plans based on comparisons between actual and predicted operational statuses.

1. Introduction

To dominate the global market, the Japanese manufacturing industry should implement a specific and effective strategy, in terms of efficiency in development and production, enhancement of product quality, and creation of attractive products for customers. In order to accomplish these challenges, Fujitsu strives to offer "smart Monozukuri" services that help to achieve efficient quality and product management applying information and communications technology (ICT) to Monozukuri (Japanese way of manufacturing).[1)]

One example is our internal initiative Monozukuri Navigation System, which is based on technology to realize virtualization/integration for manufacturing sites by fully leveraging sensing technology, analytical tools, artificial intelligence (AI), and other ICT. Based on the virtualization and integration of production sites by those technologies, the system can connect all production-related data and offers solutions that best suit the requirements for a production site. This system makes it possible to optimize the use of available data in manufacturing, from conventional Monozukuri statistics to unique circumstances specific to certain sites, and knowledge on design.

2. Issues at manufacturing sites

Fujitsu pursues smart Monozukuri while closely working with its in-house factories. Issues in the field are diverse, and we have found that a mere comparison between manufacturing conditions and product quality data at any given time is not sufficient to achieve optimal manufacturing. It is true that sometimes, insights into solutions may be found by visualizing causal relationships between different segments of data and/or arranging data in a chronological order. However, it is more often the case that problems in the field are related to a multiple number of factors, which make it difficult to identify the exact causes. Thus, conventional

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data analyses alone are insufficient to find effective measures. We need to integrate all production-related information, in addition to the existing data on manufacturing conditions and facility uptime log, to build up a rich database in terms of quality and quantity. For example, specific conditions in a factory, such as know-how of particular tasks and criteria for in-field decision-making, may be turned into data sets. It is also possible to convert equipment maintenance data into a data set to know the equipment conditions.

Many customers in the manufacturing industry are interested in conducting preventive maintenance on their production lines,[2)] and also there is a growing expectation that ICT-based data analysis technologies will be able to bolster product development.[3)]

For products like our communication products that require the highest-possible performance, the finished product does not necessarily guarantee the desired level of performance even if the variance in the characteristics of individual parts is kept within the tolerance range. In the field, it is often the case that such variance of parts characteristics has no clear explanation or known mechanism. Certain products are also easily influenced by the line workers' skill levels. In such a case, it is difficult to identify a causal relationship accurately based only on the manufacturing conditions and data sets of test results. The behavior models built mainly on statistical computing are basically a black box, so that the mechanism of their behaviors cannot be fully explained. To better cope with this problem, we need to incorporate into the models the design knowledge and principles, as well as the circumstances in the field, if necessary.

In the following sections, we describe the Monozukuri Navigation System, which introduces high-quality solutions into manufacturing by utilizing both Monozukuri statistics and other information such as unique circumstances and knowledge of design from the field.

3. Configuration of the Monozukuri Navigation System

Various activities have been carried out in the scenes of Monozukuri to make improvements, such as visualization and analysis of production plans, plant/equipment performance, and results of manufacturing/testing. The Monozukuri Navigation System is based on these activities with added features of leveraging data, and the system makes it easier to create new values such as by solving complex problems, identifying signs of errors and predicting future manufacturing quality, all of which have been difficult to achieve before.[4)] The system has the following four functions in the main (**Figure 1**):

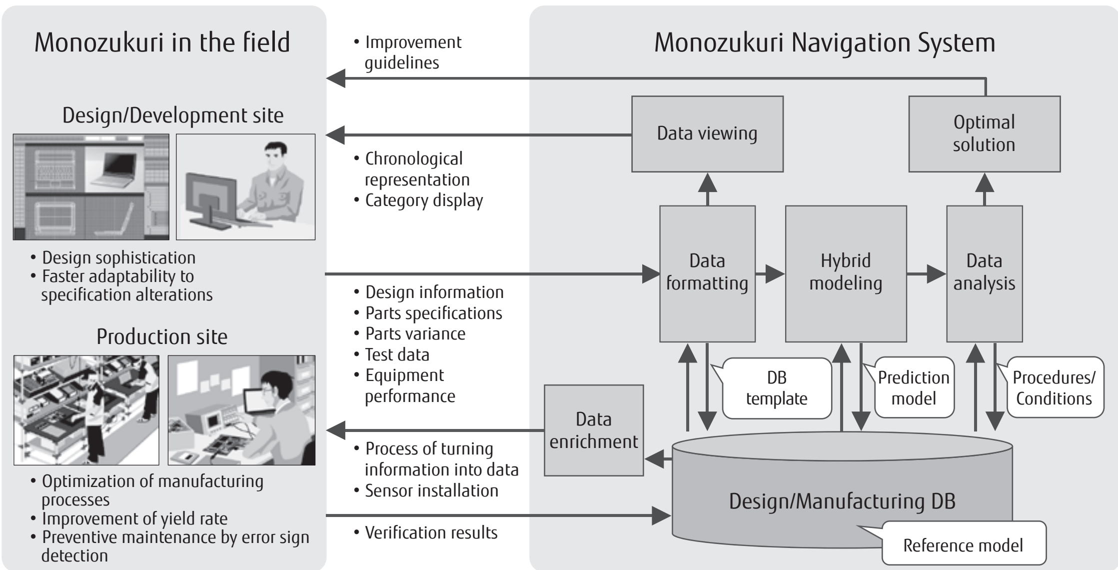

Figure 1
Overview of Monozukuri Navigation System.

1) Data enrichment

To add in-field know-how, workers' movements etc. that have been turned into data to existing data such as equipment uptime performance, and categorize them according to specific problems to deal with.

2) Data formatting

To convert raw data of various forms such as production information, equipment operation status, parts variance, and know-how to create a database.

3) Data viewing

To make data viewable and draw workers' attention by displaying the energy used by equipment and production status in chronological order, or fault occurrences shown by category. Experienced workers can often find solutions merely from this.

4) Hybrid modeling

To turn in-field information such as know-how possessed by experienced workers or design knowledge such as operating mechanism into models, and integrate them into a statistical model.

5) Data analysis

To build analytical processes and obtain optimal solutions by making the best use of statistical analysis, machine learning, data mining, and other tools. The analytical processes are registered in a knowledge database so that they can be easily reapplied to similar cases.

6) Optimal solution output

To process and display data so that on-site workers can understand the analysis results easily, such as cost-equivalents and movements, while some data are directly shown (adjustment values, control values, etc.).

4. Results from the application

This section explains the results from applying this system to manufacturing sites.

4.1 Preventive maintenance of production lines

The patterns of faults in production equipment are predefined based on the data such as uptime operation, records on maintenance, fault correction, and sensor data. These are used to monitor the real-time operational data, and the system issues alerts if there are potential needs for parts replacement or if other attention is required.

Take the case shown in **Figure 2** as an example of maintenance operation. Certain production equipment has downtime every 12 weeks. Whenever there is major equipment trouble, the production is halted for several hours. If the fault patterns and causal factors are known in advance, it will be possible to detect early signs of such faults, enabling the manufacturer to prepare measures such as providing replacement parts and arranging maintenance engineers before the equipment stops operating, thereby minimizing the downtime.

Errors and faults in the field may vary, and so does the response time required. It is thus best to consider and prioritize the fault patterns in terms of the levels of urgency before implementing this system on site, so that decisions can be made, for example, to focus on those errors that take longer to recover.

4.2 Enhancing the manufacturing efficiency

Multi-product low-volume production lines with complex and constantly changing manufacturing conditions involve numerous production processes, as well as diverging and converging of production flows, entailing much preparatory work for setup. For this reason, it is crucial to carefully make production plans so as to minimize the time for working and waiting, and thus make the production lines more efficient.

The system we propose can generate highly productive plans by optimizing the orders in which items go into production lines. The system analyzes the past manufacturing data in terms of the in-process lead time against the product types (product drawing numbers) and equipment that are involved. Then it proposes the

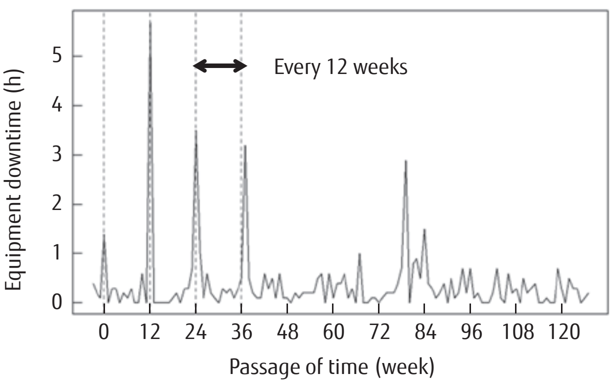

Figure 2
Output of downtime patterns for production equipment.

best manufacturing plan, while considering minimum equipment parts replacement and changes of settings required to maximize the productivity (**Figure 3**).

The steps of optimizing parts allocation (to the certain machine) and determining manufacturing sequence by product type are one of the combinatorial optimization problems. However, the calculation for this task is so complex that even the most high-performing optimization solver cannot find exact solution. Thus, we have developed a method to divide up the problem and obtain quasi-optimum solution.

More specifically, we grouped several products by the parts used in them, and determined the sequence of products that go into manufacturing to minimize the equipment idling time, while considering the in-line equipment load balance, in order to minimize the time for setup. By optimizing each component of this process hierarchically, this method can find solutions in a realistically acceptable time. It has thus reduced offline setup time by 15% compared with calculations done by conventional optimization programs.

Also, the task of supplying parts from warehouses to work areas adds little value, so is required to eliminate mutual interference between workers picking up parts in this limited space. The system has successfully leveled out the numbers of pickers' trips to parts shelves (to avoid concentration of pickers in one shelf), and optimized the layout of the shelves to minimize the total length of the picking trip.

The system is also equipped with a simulation tool that can evaluate a planned layout change in terms of the picking trip in a virtual space before it is implemented on site. Through these efforts, the interference between pickers is reduced while the storage space is economized by 35% in one revision of a parts shelf layout. Furthermore, the system can analyze whether the optimal shelf layouts are maintained or not based on the past picking performance data regardless of a change of production items.

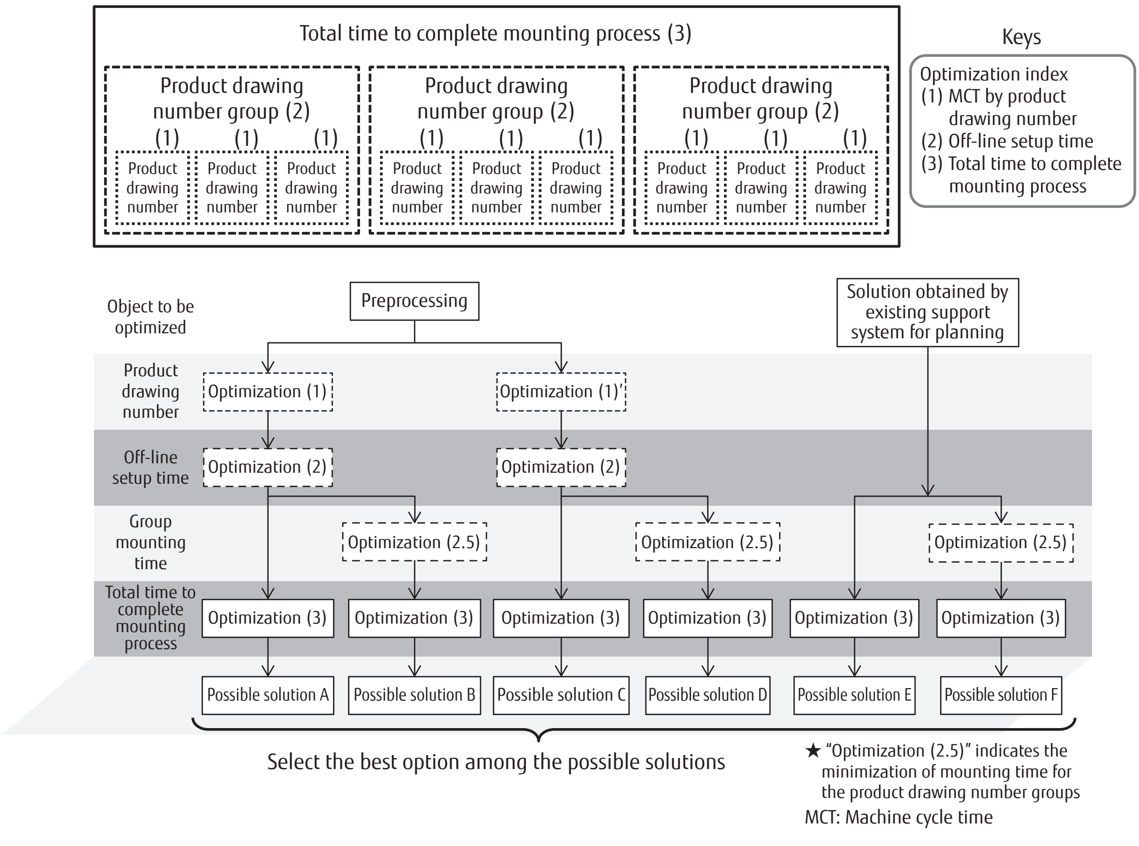

Figure 3
Optimization of production line plans.

4.3 Improvement on quality

Products must be able to perform in a real operational environment. However, the environment for real use may be different from that which is envisaged at the product design stage. It is also possible that a variance in parts characteristics supposed at the design phase turns out to be different in reality. Parts with a small variance will lead to increased procurement cost, while those with a large variance will lower production efficiency as they extend the scope of tuning tasks.

The system is capable of very accurately predicting quality by incorporating a gray box model, with which a known mechanism of product behavior is physically interpreted while the rest is statistically estimated.[5] The physical interpretation is conducted by means of, for example, a computer-aided engineering (CAE) model or an equivalent circuit model, against which measured values are verified to obtain parameters. Meanwhile, statistical estimation is conducted by using the maximum likelihood estimation[note)] of a mathematical model based on actual measurements of the characteristics unexplained by a physical model, or a distribution model that statistically estimates the individual parts variance that is difficult to measure.

In this way, the gray box model considers the actual variance of parts characteristics and combinations of each parts, to calculate the impact of these characteristics or the environment, and make optimal selections of parts that pass the criteria. For units that already have mounted parts, the system obtains the parameters to focus on, or guideline values for tuning, by measuring the behavioral conditions and characteristics of the given units and verifying the results against the past tuning pattern data. Once the guidelines are determined, they are passed onto the subsequent processes. By applying the same guidelines to key processes to conduct tuning, we can expect efficient quality management and improvement.

By finding combinations of parts with variable characteristics or the tuning guidelines based on past operational data, the system helps to reduce the cost with quality improvement and optimal parts selection while leveraging the field know-how.

This system also comes with options to archive past performance data so that solutions can be directly derived, and to visualize production statuses and changes in circumstances so that on-site workers can easily recognize them.

In the next section, we will describe real-time navigation, which is the highlight of this system's development.

5. Real-time navigation

Real-time navigation is a feature to predict the production status in the immediate future based on the production site data, and support workers and equipment for countermeasures. There are three components in this feature: optimization, error prediction, and text systems (**Figure 4**).

The optimization system is used to quickly optimize parameters in the behavior model formula, and provide them to workers and equipment. Two examples of optimization concerning resource distribution are presented below.

First is a case in which many errors occur simultaneously in a production line. Lines to mount electronic parts have many pieces of equipment attached, such as solder printers and mounters. The number of such pieces of equipment becomes great in major factories. While factories are increasingly automated, there are not necessarily enough equipment maintenance staff, so that some pieces must be put on a waiting list while maintainers are fixing other equipment. The system calculates the cycle time and the time required for responding to errors based on production performance data, then it generates several scenarios for the multiple errors and predicts future production status from the current point in time. The production time will be prolonged when concurrent errors occur, and thus the system will select the best scenario to minimize the delay. At the same time, solutions for bottleneck problems, such as dependency of equipment on product types or positional relationship between equipment and workers, are required depending on the real situation. While not all of the data regarding the bottleneck have been integrated into the system yet, we are deploying cameras and beacon systems as sensors to obtain data on worker movement flow. By enriching data in this way, we aim to facilitate more precise development of scenarios.

The second example is about flexible production planning. In a production site, sudden specification

note) In statistics, this is a method of estimating the parameters of probability distribution from given data.

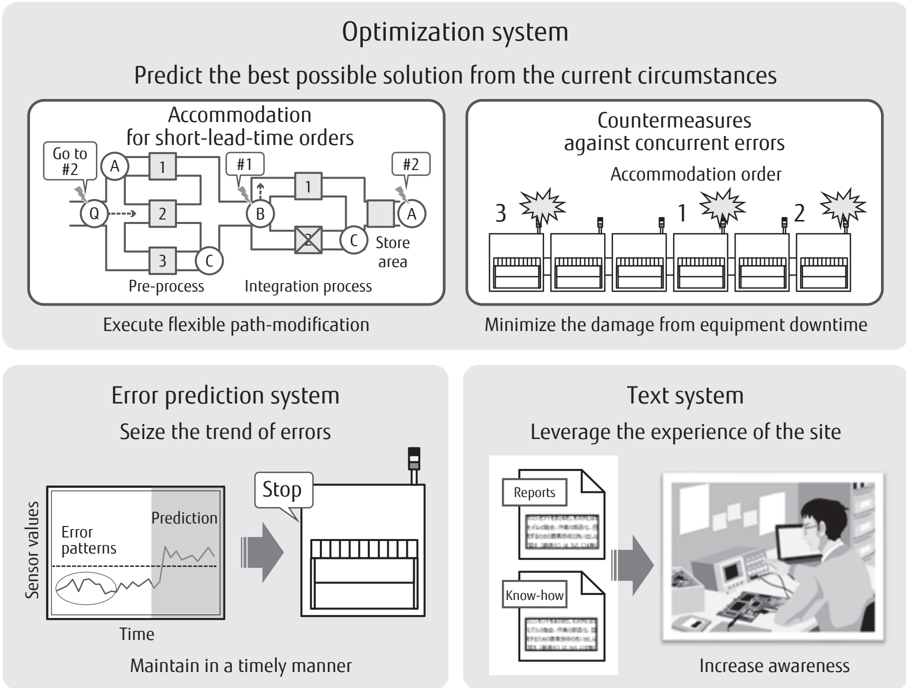

Figure 4
Application of real-time navigation (example).

changes are common. It is important to have a level of flexibility in the production system so that such eventualities can be handled. When accommodating the manufacturing of products for orders with a short lead time (express items), it is necessary both to meet the short lead time production and to minimize the delay in the normal production. The equipment is determined according to the product types (product drawing numbers). Therefore, the system looks for the best possible production route for the express items according to equipment conditions and current status of scheduled production items. The system makes adjustments to the production of scheduled products to run/halt or avoid the stoppage of the line, according to the equipment availability. After the express items have passed, the system replans and suggests the production schedule for normal items to minimize the effects of the delay. In the future, with added features of bolstered traceability, the system will be capable of more flexible production planning.

The error prediction system helps workers to operate the aforementioned preventive maintenance function on a real-time basis. Sensors installed inside and outside the equipment capture slight deviations, and the system predicts the probability of error patterns, which are obtained from the chronological pattern analysis, to be realized. In this way, the system can suggest countermeasures for the most likely equipment trouble.

Finally, the text system provides solutions on the spot for workers to the challenges they are faced with, leveraging the experience of the site. For example, by analyzing the relationships between keywords based on past error response records, certain keywords are identified through strong associations with particular errors. Also, the system can visualize the process that leads to the error, drawing on the difference in the strengths of the keyword associations. This feature is useful in that, upon detecting certain deviations, we can predict possible major errors (i.e., keywords that signify them) waiting to happen by tracing the keywords found in the descriptions of the identified deviations. Generally, the error response records contain countermeasures. Therefore, the system can suggest the countermeasures for various cases of error.

We are planning to develop the system further in the future by analyzing the keywords, sensing, and strengthening the coordination with the aforementioned error prediction system. Currently, the solutions provided by the text system development draw on data such as existing reports and interviews with skilled workers. In the future, however, we hope to improve the system performance by using voice recognition technology to achieve more complete and richer work records and thus suggest more accurate countermeasures.

6. Conclusion

This paper described the Monozukuri Navigation System in terms of its features and applications—a system for assisting Monozukuri in development and manufacturing through prediction and suggestion of improvements.

As the world is seeing the Internet of Things (IoT) progress, Monozukuri is also embracing this technology, facilitating a mass collection of diverse data from the field. The use of big data renders the Monozukuri data more valuable, which in turn drives Monozukuri itself to a new level. Fujitsu is an ICT vendor that engages in this very Monozukuri, and will therefore strive to offer solutions to its customers' challenges by making full use of the big data. Leveraging our expertise gained from Monozukuri innovations, which we have pursued as a manufacturer, we will boost Monozukuri further by providing our customers with our reference models built upon in-house practices.

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Eiji Takada
Fujitsu Ltd.
Mr. Takada is currently engaged in the development and application of Monozukuri ICT.

Taizan Kobayashi
Fujitsu Ltd.
Mr. Kobayashi is currently engaged in the development and application of Monozukuri ICT.

Hidetoshi Matsuoka
Fujitsu Laboratories Ltd.
Mr. Matsuoka is currently engaged in the research and development of modeling, optimization and know-how management for Monozukuri.

Takeshi Soeda
Fujitsu Laboratories Ltd.
Mr. Soeda is engaged currently in the research and development of Monozukuri IoT.

Masatomo Maida
Fujitsu Telecom Networks Limited
Mr. Maida is currently engaged in next-generation Monozukuri.