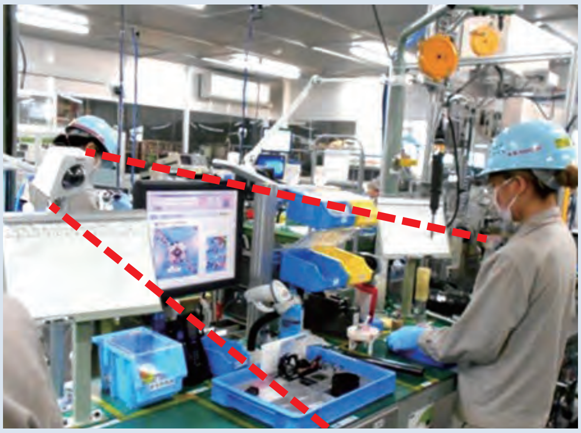
Utilization of AI and Optimization Technologies for Productivity Enhancement with Manufacturing Data



Uncertainty in business is increasing. In order to survive as a manufacturer, we are required to have manufacturing floors that can respond promptly and flexibly to changes in the social environment. AI (artificial intelligence) and optimization technologies have enabled us to make decisions based on on-site conditions, such as optimizing work sequences and boosting work quality. By applying these technologies, we have successfully eliminated dependence on skilled workers and have raised productivity, including reducing lead times, through reforming work processes.

Introduction

Recently, uncertainty in business has been increasing due to rapid changes in the social environment. Given such circumstances, our manufacturing floors must be competitive and enable us to enhance productivity while responding promptly and flexibly to these changes.

1 Background

Thanks to improvements in infrastructure, an environment facilitating the accumulation of big data is being put into place. In addition, AI and data analysis technologies have advanced rapidly and can enable more sophisticated decision making. Many cases of utilizing such technologies to enhance productivity on the manufacturing floor have been reported[1)]. Data collection and accumulation are underway on our own manufacturing floor as well as those of other companies, and systems for visualization and work automation are being put into place.

2 Productivity enhancement with data utilization

Recently, we have become able to adopt data utilization technologies more easily thanks to improved, more affordable data analysis environments. However, there is no single data analysis technique that can be applied to solve every type of challenge on the manufacturing floor, so data analysts with a general knowledge of data analysis, including of topics such as statistics and machine learning, must propose solutions.

At the same time, to enhance productivity through data utilization, we must not only implement new systems but also deeply understand the current challenges, define the ideal work processes, and carry out reforms to realize such processes. To this end, the data analysts must have the ability not only to understand data science technology but also to work with manufacturing personnel to deepen our understandings of their work, to identify the actual challenges, and to propose solutions for the identified challenges.

In our company, for example, data analysts are working closely with manufacturing personnel to identify challenges and to use data to find solutions to such challenges in order to propose factory layouts and to optimize production plans[2)]. In addition, we are making various efforts to enhance productivity.

3 Examples of our efforts

As examples of our recent efforts to enhance productivity through data utilization, the following describes a detection system for preventing deviations from work standards in real time; a planning system for automatically optimizing the sequence in which different products are fed into an assembly line, and a production management technique for shortening lead times in large factories.

(1) Real-time prevention of deviation from work standards

(i) Challenge

Our Precision Machinery Business Division manufactures hydraulic equipment used mainly for construction machinery. On the manufacturing floor, we are working to enhance productivity while ensuring safety and quality by thorough work standardization. However, workers have been frequently shuffled in order to change the number of workers in response to rapidly fluctuating demand. As a result, new, inexperienced workers deviated from the work standards (abnormal work) in some cases, which caused accidents and quality issues; these in turn reduced productivity.

To prevent such deviation, we adopted foolproof systems on the manufacturing floor and installed cameras to record work. However, foolproof systems cannot be applied to work in which tools that cannot output signals are used. As for recording, abnormal work, which causes accidents and quality issues, cannot be detected in real time; instead, it can be addressed only after the fact.

In the workplace for assembling the joystick-type electric remote control unit (electric joystick) shown in **Fig. 1**, we have adopted the mixed production system, where multiple workers repeat a series of steps of standardized work, including mounting and screwing parts and applying grease, on the work stage. This process makes use of a work instruction system linked with tools [3], whereby each worker executes, step-by-step, the standardized work specified in the work procedure presented by the system. However, in the grease application and adhesive application work, for which work completion cannot be detected mechanically, it is confirmed by pushing a button. Therefore, with this system, human error, such as omission of a necessary step or application of too much grease or adhesive, cannot be completely prevented.

(ii) Solution policy

We developed an automatic detection technology with AI that automatically detects deviations from work standards in real time based on videos taken by cameras placed on the manufacturing floor and output alarms.

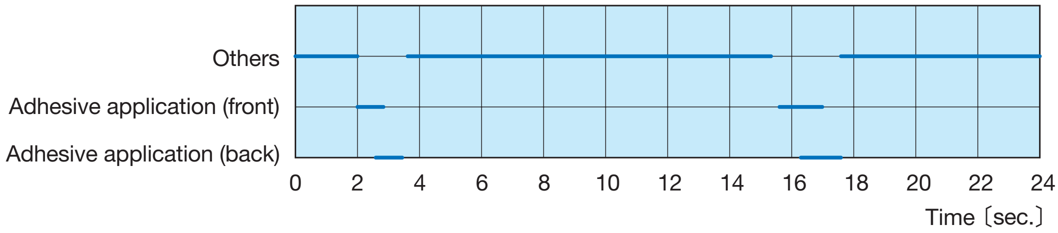
We extracted images from the video data; labeled them as "Adhesive application work (front)," "Adhesive application work (back)," and "Other work" to prepare training data; and created an AI model for image classification using a model trained in advance. We then sampled images from the work videos at 0.1-second intervals and classified them by work type with the developed model. **Figure 2** shows the time-series graph of the classification results. Based on the results, we found that it is possible to detect abnormal work in real time by performing a series of steps of standardized work in advance, defining trends by type of work (standard sequence), and monitoring whether the judgment result conforms to the standard sequence.

Next, we conducted a preliminary study and tuned the training data and model to improve the judgment accuracy. As a result, we achieved a false negative rate of 0% (the rate at which abnormal work is judged to be normal work) and a false positive rate of 5% or less (the rate at which normal work is judged to be abnormal work) for videos showing the handling by multiple workers of over 1,000 workpieces.

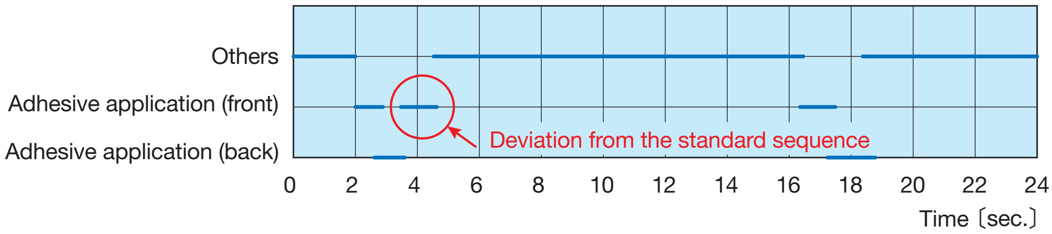
(iii) Results

We systematized this technology in April 2021, and it has now been in operation for more than a year. The system enables us to plan workpiece feeding sequences quickly even in the absence of experienced personnel, thereby contributing to stable production. In addition to

Fig. 1 Assembly of Electric Remote Control Unit



(a) Normal work



(b) Abnormal work

Fig. 2 Work classification by AI

enhancing quality through the detection of operational errors, this system is expected to improve the manufacturing floor by detecting deviations from standard work times, identifying causes, and facilitating response. Tests are underway for improvements. This system can be applied relatively easily to any standardized repetitive work. We are making efforts to apply this system to other divisions within the company.

(2) Automatic optimization of the sequence in which different products are fed into an assembly line

(i) Challenge

Our Robot Business Division offers a product lineup consisting of several hundreds of items to meet various market needs. Its assembly lines produce small quantities of various products through mixed production. On these mixed production lines, if workpieces are not fed in an appropriate order, the necessary equipment or jigs may not be available, and workers will be forced to wait until they become available, which causes delivery delays or leads to overtime work. Therefore, each day the optimal workpiece feeding sequence is planned by experienced planning personnel. However, planning the optimal workpiece feeding sequence requires consideration of various factors—including the workload, equipment configuration, and number of jigs—for each model to be produced on each production line. For this reason, at present only a limited number of personnel are capable of planning the workpiece feeding sequence, making such planning dependent on individuals, and many hours are spent each day to plan the workpiece feeding sequence.

(ii) Solution policy

To empower inexperienced personnel to plan the workpiece feeding sequence quickly so as to ensure stable production, we employed optimization technology to automate workpiece feeding sequence planning. This time, we achieved such automation in an assembly workplace where general-purpose large robots are used and mixed production is performed by connecting an assembly line and an operational inspection line in series as shown in **Fig. 3**.

The option configurations and specifications of the models handled in this workplace vary greatly depending on customer requirements; therefore, it is difficult to maintain or adjust the standard work time for individual models and tasks. Completing the work as fast as possible is not always the best approach, and the optimal solution cannot be calculated mathematically based on the standard work time master. Therefore, we studied a method that does not require meticulous maintenance of master data.

We conducted interviews with experienced planning personnel regarding the workpiece feeding sequence planning method and found that they had defined rules that must be observed in their heads in order to evaluate workpiece feeding sequences. We then made a list of these rules for workpiece feeding sequences (hereinafter, "feeding rules") and quantified the importance of each rule so that they could be processed by computer. In addition, we used a genetic algorithm to impose penalty points for violations of each feeding rule and to determine the workpiece feeding sequence that minimized the sum of the penalty points. This helped us reflect the ideas of the experienced planning personnel in the system's logic, enabling workpiece feeding sequences to be planned automatically based on experienced planning personnel's

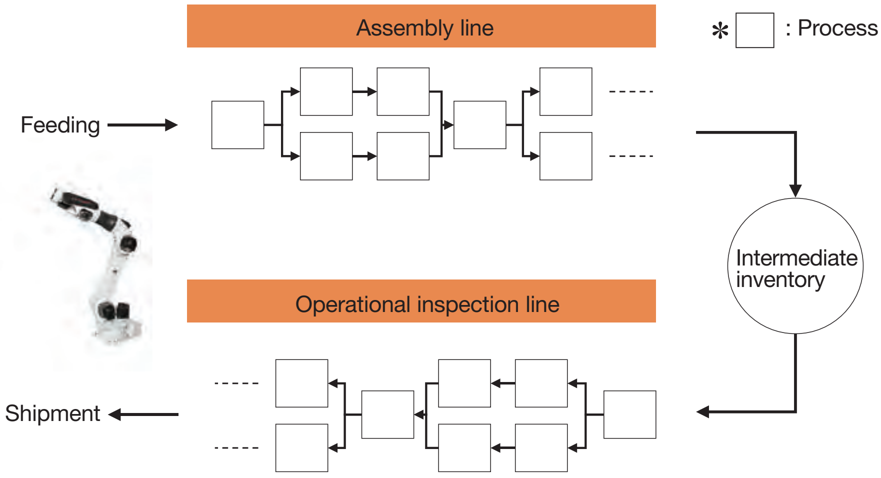


Fig. 3 Production line configuration using robots

ways of thinking.

At first, the calculated workpiece feeding sequence differed greatly from the workpiece feeding sequence planned by the experienced planning personnel, so we worked with the experienced planning personnel to set and review the feeding rules. As a result, we became able to calculate a workpiece feeding sequence that did not differ from that planned by the experienced personnel within five minutes, whereas such a sequence took the personnel one hour to prepare.

After establishing the system's logic, the experienced planning personnel modified the feeding rules according to changes in model specifications and other conditions. For systemization, we needed high flexibility to respond to changes in these conditions. Therefore, we again sorted out the feeding rules and found that the feeding rules could be classified into specific patterns, each of which could be represented in terms of parameters. We then abstracted the feeding rules and developed a product feeding sequence optimization system that enables flexible addition and correction of feeding rules by configuring settings on-screen. An overview of this system is shown in **Fig. 4**.

(iii) Results

We put this system into practical use in April 2021, and it has now been in operation for more than a year. The system enables us to plan workpiece feeding sequences even in the absence of experienced personnel, thereby contributing to stable production. In addition, we have improved the system so that feeding rules can be flexibly added and modified, which enables even personnel without specialized knowledge of programming to respond flexibly to changes, and moreover facilitates application of the system to the production lines of other divisions. We are now applying the system to other workplaces.

(3) Production management technique for shortening lead times in large factories

(i) Challenge

Our Aerospace Business Division produces various parts ranging from mass-produced parts to specialty parts

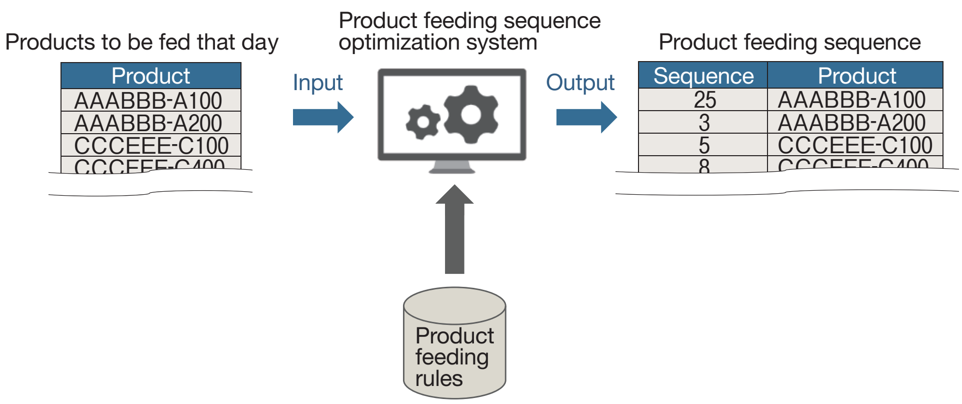


Fig. 4 Production sequence optimization system

produced in quantities of a few pieces a year. Various parts of various sizes and quantities are manufactured using multiple processes, including machining, manual work, surface treatment, and coating; for this reason, it is difficult to build dedicated production lines. Under the job-shop production system, parts are manufactured by passing them between various workplaces as shown in **Fig. 5**. Parts pass through several hundreds of workplaces along several tens of thousands of routes annually, with over a hundred thousand production requirements during normal times, thus necessitating an extremely large, complex system. Therefore, we could not prepare detailed production plans that took into consideration the available resources, and we made daily work plans for individual workplaces by referring to an overall plan determined based on standard lead times that assumed unlimited capacity. However, we had insufficient or excessive intermediate inventory between workplaces, mainly because mass-produced parts, which have some repeatability, and made-to-order parts, which do not have repeatability, co-existed and because trouble and urgent orders frequently occurred.

(ii) Solution policy

A relatively easy method for shortening lead times and for ensuring delivery times are met in a large factory is to control parts feeding by controlling the amount of raw materials fed into the factory and specifying the priority for adjusting delivery lead times [4]. One such method is to set an upper limit on the number of workpieces in the factory (WIP: Work In Process) as shown in **Fig. 6** so as to limit the amount of raw materials fed into the factory; such an approach is known as the CONWIP (CONstant WIP) method. However, this method can be applied to mass-produced parts only. Thus, we improved the method. Parts are classified into a limited number of groups, and the amount of raw materials to be fed is controlled on a group

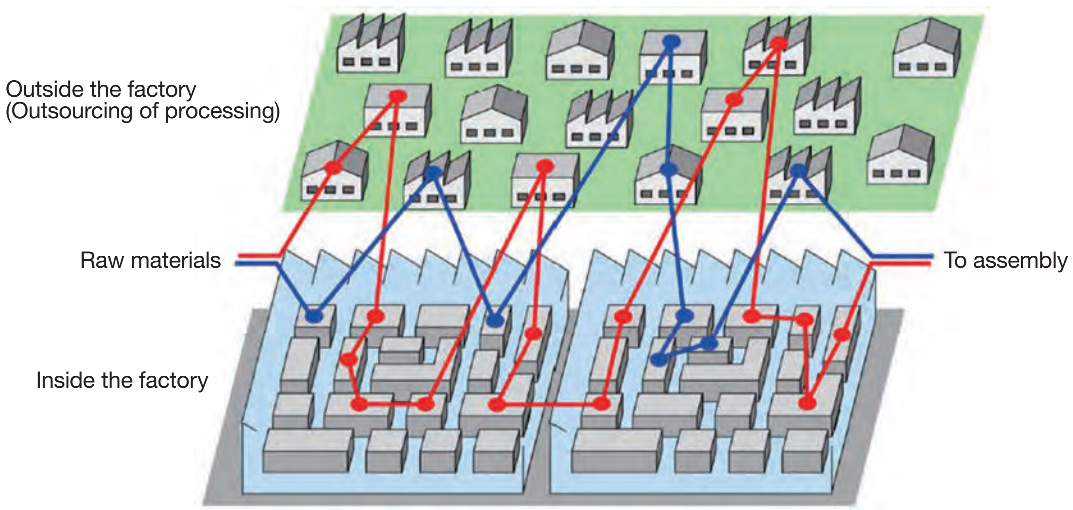


Fig. 5 Production system for aircraft parts

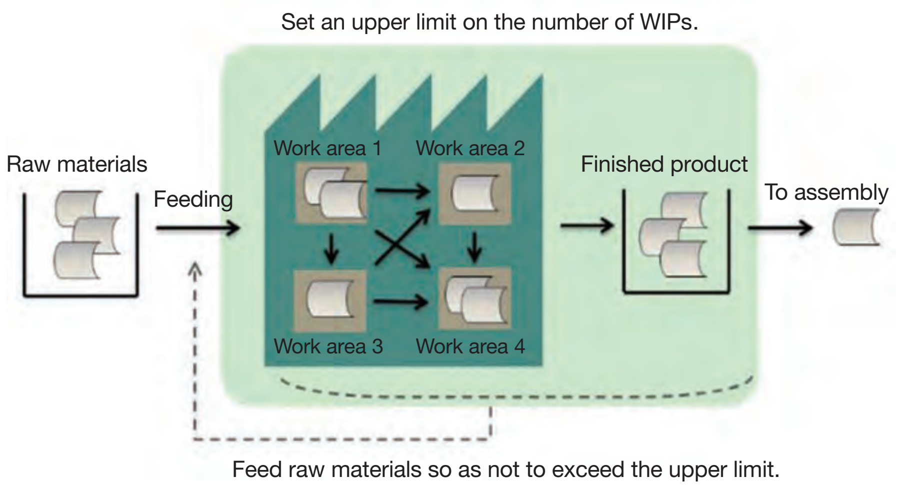


Fig. 6 CONWIP production method

basis. Priority is calculated based on the number of WIPs for mass-produced parts, and on lead times for made-to-order parts. In this way, we have successfully built a feeding logic that enables us to determine the feeding timing while handling mass-produced parts and made-to-order parts in the same manner.

(iii) Verification of effectiveness

We conducted a simulation with the logic we built and verified its effectiveness. We confirmed that when we decreased the number of WIPs by 20%, lead times could be shortened by 15% while output was maintained at the same level. We now plan to apply this logic to some factories on a trial basis in fiscal 2022 and to further verify its effectiveness.

As part of the Smart-K Project, our Aerospace Business Division is working to integrate work processes in the engineering chain and supply chain through digitalization and has realized Smart Factories, where various manufacturing floor data can be obtained. In the future, we will apply this feeding control based on such data to contribute to management through reduced lead times.

Conclusion

The waves of DX (digital transformation) are expected to propagate further and to digitalize every inch of manufacturing floors. To solve the challenges we face on the manufacturing floor with data utilization for reforming work processes and creating new value, we need to develop data utilization personnel who can appropriately apply data analysis technologies to the manufacturing floor. Therefore, we will continue to work with manufacturing personnel to tackle these challenges to develop data utilization ability. In addition, to make maximum use of data utilization, we should not merely make case studies out of successful cases but rather standardize them so that they can be applied to other areas. Thus, we will make full use of our knowledge for standardization and further development.

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