Integrated Management of Machining Factory Using IoT Platform

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Abstract

In a processing plant with a multiple-variety mixed-flow production system, a single worker handles multiple machine tools. The traditional human-dependent management method, however, is facing difficulty in efficiently operating the entire factory. As an attempt to solve such issues using process data obtained from machine tools, an IoT platform has been constructed to monitor the status of the machine tools by utilizing IoT technology. This paper details the construction of a system that analyzes process data from machine tools in real-time and detects abnormalities for automation, including the machine-stop command. It also discusses the implementation of this system on machine tools and provides examples of analysis and utilization by combining worker position information with machine operation information.

Introduction

Although manufacturing is becoming more advanced, Japan is experiencing a major issue of a severe labor shortage. The early years of the 21st century are seeing the practical application of digital technologies such as AI, IoT, and robotics, advancing automation and efficiency in numerous fields. However, there are still many manufacturing processes that rely on skilled labor, with technologies to overcome this challenge still to be desired.

The machining factory at Kobe Steel's Takasago Works runs multiple-variety mixed-flow production. Each part undergoes a large number of processes on its way to becoming a finished good, with pitch times for each process ranging widely, from a few hours to several hundred hours. In addition, the operation is made more complex because of each customer's highly specific requirements, which entails many parts with similar geometries yet few that are identical. The conventional method of improving productivity has been to automate machinery and employ a system in which each operator is responsible for multiple machine tools (hereafter, multi-machine operation). However, monitoring production operations is a challenging task because the products vary and have demanding machining needs in terms of shape, workpiece material, and tolerances. As the combination of machine operation status and worker status becomes more complex, it becomes more difficult for the supervisor to grasp the overall status of the operation, which is a major impediment to improving productivity on the shop floor.

As part of recent progress in IoT, production facilities are outfitting machine tools with communication functions to acquire real-time data. These endeavors are intended to overcome the aforementioned issues by supporting an IoT platform (hereinafter, PF) that grasps the status of the entire machine tool, or multiple machine tools, to enable data utilization.

Many attempts have been made to quantify the effects of improvement and value added in production using industrial engineering techniques, mainly in terms of increased throughput in tasks performed by humans[1]. Recent developments in sensor technologies have also driven attempts to analyze operations based on worker position information and imaging.[2] Furthermore, the field of machine tools has seen remarkable progress in terms of IoT. Computer Numerical Control systems (CNCs) and Programmable Logic Controllers (PLCs) can now provide detailed information regarding operating status. In the machining sector, for example, MTConnect has become a proven standardized protocol for obtaining operating information.[3]

These developments have led to attempts to visualize the value added behind operations incorporating people and equipment by combining worker position information with machine operation information.[4]

The PF presented in this paper supports the management of production status in a machining factory in a manner that integrates the statuses of workers and equipment.

Section 1 describes the machine tool PF central to this initiative. Section 2 provides examples of the use of process data acquired from machine tools using the PF. Finally, we report the results of evaluating the productivity of operations incorporating people and equipment by combining machine operation information acquired by the PF with worker position information.

1. Machine tool IoT platform

Kobe Steel's machine tools come from many different manufacturers, necessitating a versatile data acquisition system that can interface with a wide variety of machine tools. Many of our machine tools use FANUC CORPORATION's control panels. Because communication with other manufacturers' control panels and robots is also possible, we adopted FANUC's factory operation management software MT-LINKi. We chose MotionBoard Cloud (BI dashboard made by WingArc1st Inc.) for our visualization tool because of its high degree of flexibility and customization. The PF developed in collaboration with KOBELCO SYSTEMS CORPORATION makes it possible to run iterative cycles of data collection, visualization, analysis, and optimization.

1.1 System configuration

Fig. 1 shows the system configuration. MT-LINKi can collect equipment information not only from machine tools with FANUC CNC systems, but also from FANUC robot controllers, PLCs supporting OPC UA (open platform communications unified architecture), and machine tools compatible with MTConnect. Machine tools made by other manufacturers, such as the Yamazaki Mazak Corporation and Okuma Corporation tools in our plants, interface with MT-LINKi via MTConnect. With this system configuration, data from machines with FANUC control panels can be acquired every 0.5 seconds, and data from equipment using MTConnect can be acquired every 2.0 seconds.

1.2 Information and visualization screens

Table 1 shows a sample of the data that can be obtained from a machine tool. Information that can be collected includes machine operating status, program information, command and actual speed and feed rate, spindle load, servo load by axis, and position deviation.

We designed our visualization screen to facilitate the use of information collected from the machine tools and have begun trial operation. The following is an explanation of the visualization screen and how it is used.

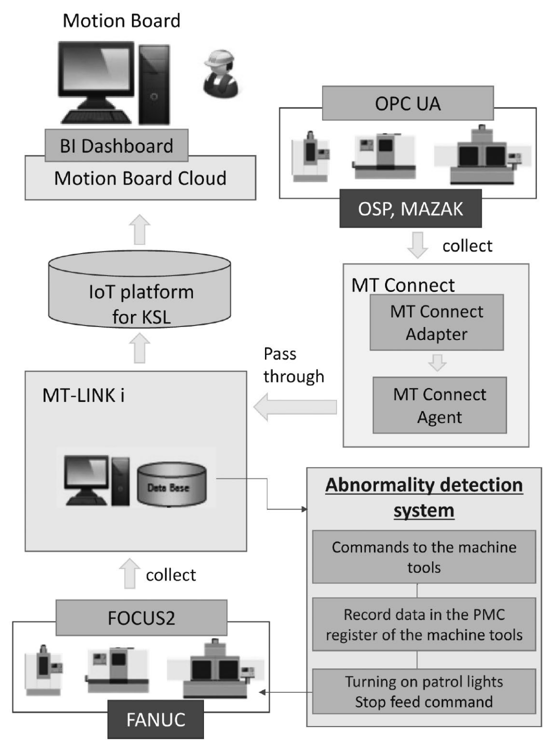


Fig. 1 System configuration

Table 1 Signal data from a machine tool

No	Signal data	Description	No	Signal data	Description
1	SigOP	Automatic operation signal	31	Override	Override of feed rate
2	SigSTL	Automatic operation starting signal	32	SigNP	In-position signal
3	SigSPL	Automatic operation stop signal	33	AbsPos	Absolute position
4	SigAL	Alarm signal	34	RelPos	Relative position
5	EMG	Emergency stop signal	35	McnPos	Machine position
6	Mode	Mode	36	SpindleLoad	Spindle load
7	MainProgram	Main program	37	SigENB	Operating spindle load signal
8	ActProgram	Running program	38	SpindleSpeed	Spindle speed
9	Sequence	Sequence no	39	SpindleTemp	Spindle motor temperature
10	MainComment	Main program comment	40	ServoSpeed	Servo speed
11	ActComment	Running program comment	41	ServoTemp	Servo temperature
12	ActS	Actual revolutions	42	ServoError	Servo position deviation amount
13	ActF	Actual feed rate	43	ServoLoad	Servo load
14	ActFdec	Measured feed rate	44	ServoCurrent	Servo current
15	ModalS	Command value of revolutions	45	ServoCurrentPer	Servo current rate
16	ModalF	Command feed rate	46	PulseCodeTemp	Servo pulse code temperatuire
	…	…		…	…

Fig. 2 shows the operation status visualization screen. The operator can use this screen to check the real-time operating status of the machines they are responsible for with a mobile device such as a smartphone. The screen also helps the operator determine which machine to attend to next, reducing machine downtime. Machines in green are in automatic operation and do not require attention. If a machine is yellow, this indicates that the programmed operation has stopped and human intervention is required. A red machine is stopped in the alarm state and requires immediate confirmation of machine status.

Fig. 2 Operation status visualization screen

Fig. 3 shows the automatic measurement result visualization screen. Specifically, in the machining process of mass production operations, a touch sensor can automatically measure workpiece dimensions after machining. The results can be viewed in chronological order, with the vertical axis containing the automatic measurement results. Entering the upper and lower tolerance limits in advance makes it possible to see at a glance whether the measurement result is within tolerance. This feature can be used to enhance traceability and manage trends in dimensional stability.

Fig. 4 shows the program operation status screen. Previously, we could only determine operating status via indicator lights for three modes: automatic operation, stop, and alarm. With this screen, we can now see not only the operating status, but also the percentage of time each mode is active. EDIT applies during program editing; HANDLE, JOG, and MDI involve different types of operator intervention; and MEMORY is an automatic operation. It is possible to increase the automatic operation ratio by first analyzing the proportion of each mode per NC program and then reducing the duration of modes other than automatic operation. In addition, comparing NC programs for similar parts makes it possible to compare automatic operation ratios by NC programmer to determine whether a program lends itself well to automatic operation.

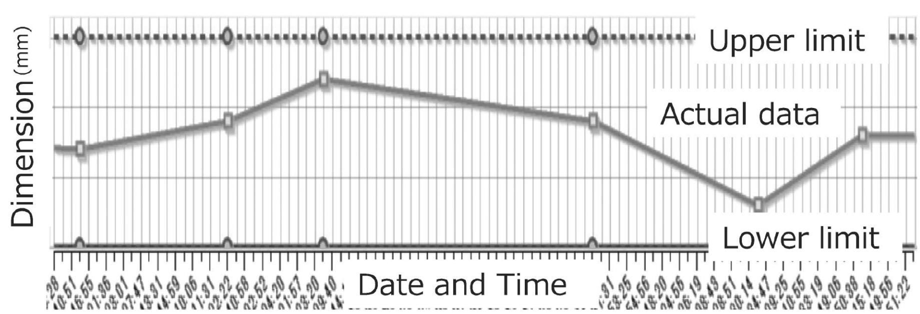


Fig. 3 Automatic measurement result visualization screen

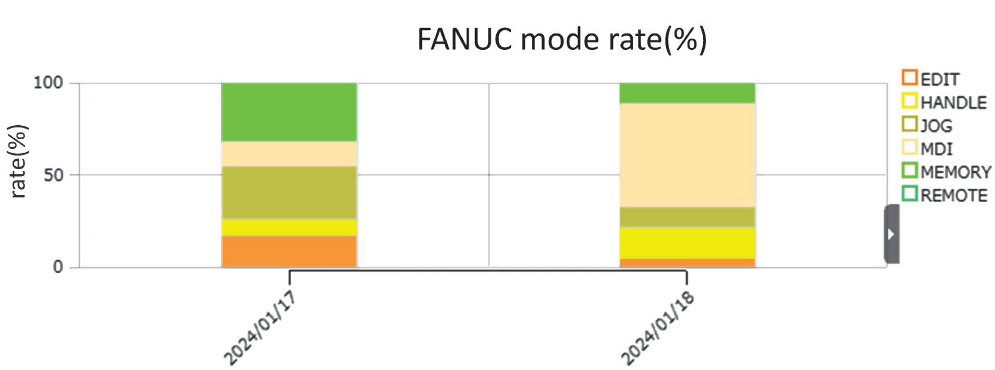


Fig. 4 Program operation status screen

2. Prediction and detection of tool abnormalities using process data

The machining process for Part A includes the cutting of a deep pocket with an end mill. The required tool has a long projection relative to the tool diameter, increasing the likelihood of tool abnormalities due to machining vibration and tool deflection. This hinders the ability to increase throughput, reduce manpower, or automate the process. To prevent tool abnormalities, Kobe Steel has developed and deployed tool abnormality prediction and detection technology and an adaptive control system using IoT-powered machining technology.

2.1 Target workpiece and machining process

Major tool damage could occur during machining, as shown in **Fig. 5**. In some cases, the workpiece must be scrapped. This led us to begin developing a system that prevents tool breakage by detecting fractures or adhesion. The system analyzes process data collected from machine tools and stops the equipment before the tool breaks completely.

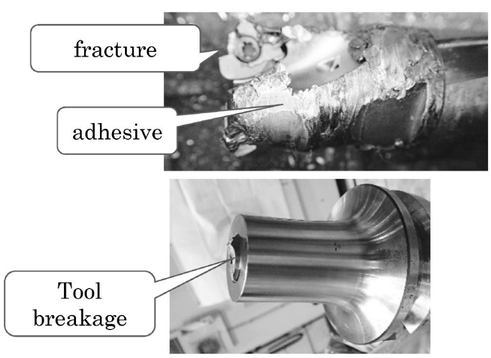


Fig. 5 Pictures of damaged tools

There is potential in techniques to detect tool abnormalities via comparison with simulations[5] and via discernment of abnormalities based only on data occurring under normal conditions, such as machining sounds, acoustic emissions, and spindle current.[6), 7)] However, the need to collect simulation data or normal data under similar machining conditions prior to actual production was an impediment to the practical application of these techniques. Therefore, we pursued a method that uses only load data collected from machines without requiring prior data for learning. We studied past tool abnormalities, as shown in **Fig. 6**, focusing on the fact that a sudden increase in spindle load (load on the spindle motor) or an increase in the vibration of the spindle and Z-axis servo motors (load swing - absolute value of the difference between data points) occurs before an abnormality. As such, we developed an abnormality detection algorithm that detects load and load fluctuations to recognize precursors to a machining abnormality. Note that spindle load and changes in load are shown as a percentage of the rated output of the drive motor of each axis.

2.2 Abnormality detection algorithm

The abnormality detection algorithm based on the spindle load data in **Fig. 7** is described next. The first 40 seconds of machining are excluded from the target of detection, as large changes in load are likely to occur before and after the start of tool rotation and before and after the start of machining during this period. Furthermore, averaging the data from the most recent 20 seconds of abnormality judgment time (hereafter, smoothed value) suppresses false positives due to sudden changes in machining load outside of intended tool

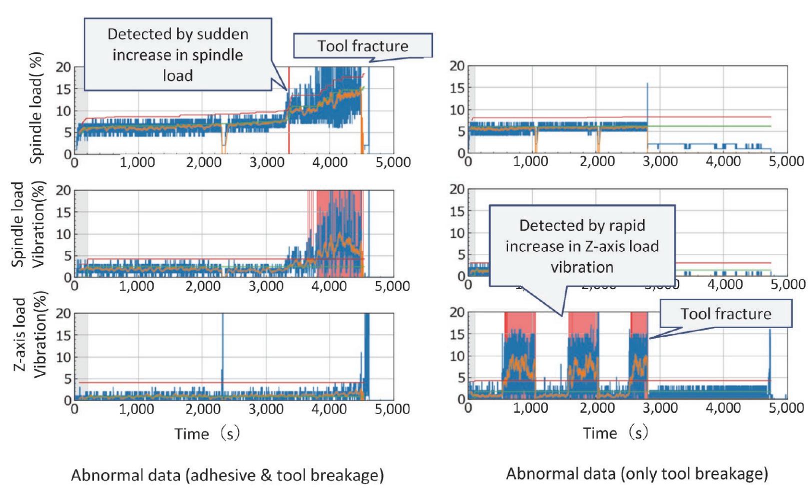


Fig. 6 Process data when an abnormality occurs

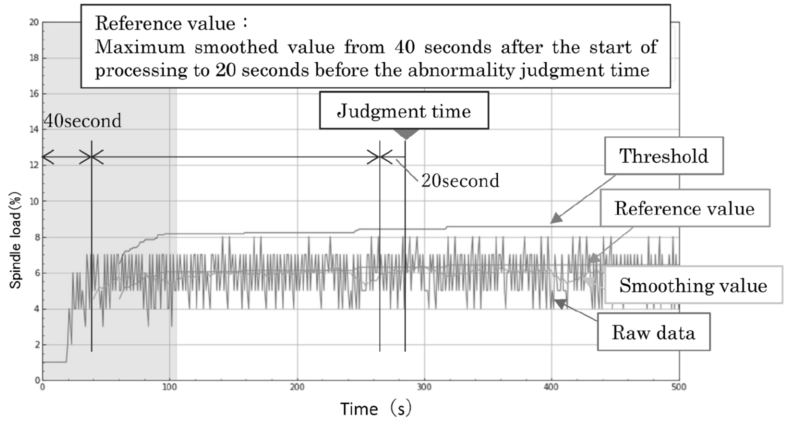


Fig. 7 Features for abnormality detection related to spindle load

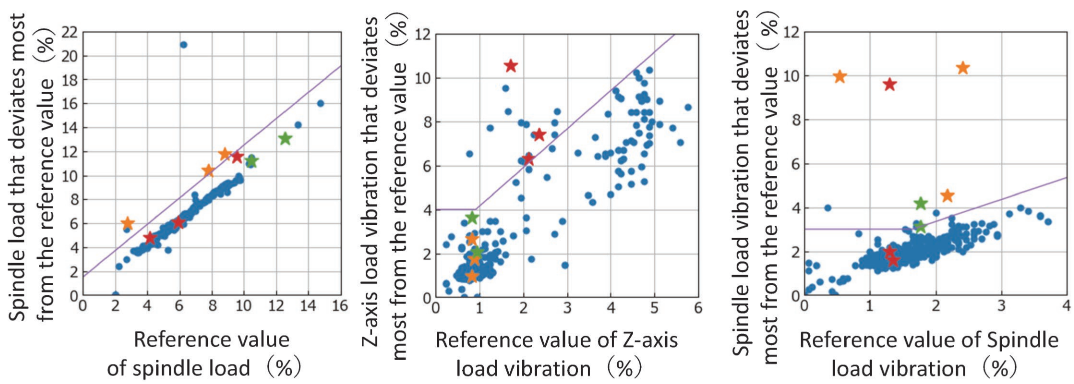


Fig. 8 Detection simulation results for past abnormal conditions

abnormalities. The maximum value of the smoothed load in each interval from 40 seconds after the start of machining to 20 seconds before the abnormality judgment time serves as the reference value per Equation 1. If the smoothed value exceeds the threshold value, obtained by adding an offset to the reference value multiplied by a coefficient based on historical results, it is judged that an abnormality is impending.

Equation 1: Smoothed value > threshold (= coefficient × reference value + offset)

To validate this abnormality detection method, its detection performance was verified using two years of historical process data. **Fig. 8** contains the results. Each graph in Fig. 8 shows the smoothed value and reference value when the ratio of the former to the latter is at its maximum, calculated sequentially for all historical machining orders (data with the highest risk of abnormality for a given machining order). The system determines that an abnormality has occurred when there is a value above the purple line, which is the threshold value. The graph on the left shows the results of discrimination by spindle load, with orange stars indicating the points detected within the abnormal machining process. The graph in the center shows the results of discrimination by Z-axis load vibration, with red stars indicating the points detected within the abnormal machining process. The graph on the right shows the results of discrimination based on the spindle load vibration. Among the plots that were not detected by the two aforementioned criteria, those detected here are indicated by green stars.

The results show that by indicating the presence of an abnormality when any of the three criteria are met, all types of machining abnormalities are flagged in the historical data without being overlooked. However, several points were detected in processes without an abnormality. But although the applicable parts were machined without issue, it appears that an abnormality nearly occurred in quite a few of these instances. Therefore, this detection method is beneficial in terms of ensuring that parts are not scrapped due to tool breakage.

When used in an actual machining process, this system must prevent tool breakage and the subsequent substantial damage. As a result of this project, we have constructed and implemented a system that automatically stops the machine tool safely when any sign of abnormality is detected, and we have enabled continuous monitoring for tool abnormalities without requiring an operator near the machine.

3. Productivity analysis by combining machine operation information with worker position information

Progress in the automation of machines has increased the prevalence of multi-machine operation, wherein one operator is in charge of multiple machines. In the case of multiple-variety mixed-flow production, such as at Kobe Steel, setup work before and after machining and inspections during the machining of new or complex parts are processes that occur at irregular intervals. How to weave human intervention into multi-machine operation is a defining factor affecting productivity. However, there was previously no mechanism for a comprehensive and continuous analysis of this concept.

Therefore, we developed a system to visualize productivity (wasted time) by combining machine operation information with worker position information.

3.1 System overview

Our system visualizes the status of a machine based on the machine's operating status and worker position. Machine operation information is acquired from sources including MT-LINKi and the operating status visualization system. Worker position information is obtained from BLE (Bluetooth low energy) beacons on the control panel and in the setup area of the machine. The operator carries a smartphone, and worker position is estimated based on the strength of the BLE beacon signal received.

The site of the experiment is shown in **Fig. 9**. 27 beacons were installed around 12 machines in an area of about 1,800 m^2 (32 m east/west × 56 m north/south). Data were collected from nine total operators with smartphones on the day and night shifts.

3.2 Analytical methods and experiment results

Fig.10 shows a example of operational status visualization. The machine's status is organized based on the combination of machine operation status ("operation," "stop," and "abnormality") and worker position status ("absence," "control panel," and "setup location"). For example, when a worker is absent and the machine is stopped, the situation status is defined as "waiting for worker," which means that the equipment may be ready for machining if a worker arrives, and therefore that there could be potential for improvement. As another example, when a worker is absent and the machine is running, the situation is defined as "automatic operating," which means productivity is at its maximum. **Fig.11** shows the results of the visualization experiment. Machines A and B have high automatic operation rates and are usually either operating automatically or waiting for human operators. Improving the throughput of these machines likely lies in how to keep them running without interruption. Machines C and D require significant operator attention for operation and setup, so the challenge here is clearly to optimize the manual processes.

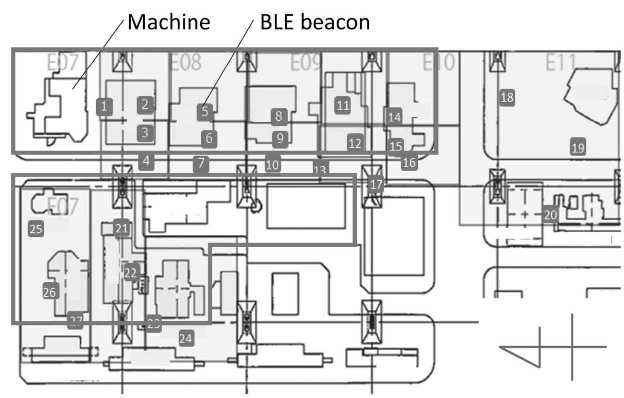
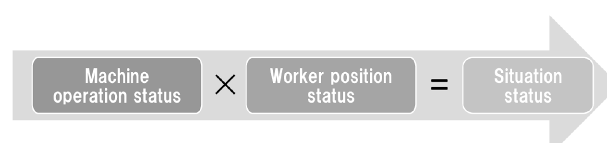


Fig. 9 Experiment site



Machine operation status	Worker position status	Situation status
Stop	Absence	00_Waiting for worker
Operation	Absence	01_Automatic Operating
Operation	Control panel	02_Operating while Control
Operation	Setup location	03_Operating while Setup
Stop	Control panel	04_Waiting for control
Stop	Setup location	05_Waiting for setup

Fig.10 Example of visualizing operational status

Machine	Operating rate	(Automatic op. rate)	Worker waiting rate	Other (setup, etc.)
A	76%	(100%)	21%	3%
B	59%	(100%)	41%	0%
C	28%	(66%)	48%	24%
D	72%	(21%)	7%	21%

Fig.11 Example of visualization experiment

Conclusions

This paper introduced the challenge of multi-machine operation necessary for multiple-variety mixed-flow production at Kobe Steel. It presented an example of how we successfully addressed this challenge by using IoT technology to develop and implement an adaptive control system that uses data from machine tools to detect abnormalities and automatically stop machine tools. We have shown that a more detailed analysis into the productivity of multi-machine operation is possible by combining machine operation information with worker position information, although a future improvement is to provide timely information to operators. Multiple-variety mixed-flow production will become increasingly prevalent alongside an increasing difficulty in securing labor. The issue of how to ensure the stable operation of a large number of machines with a small number of workers is therefore expected to gain importance. As such, we intend to broaden the scope of application of this PF to yield an integrated system that provides a holistic view of the production line, including personnel and equipment. This system will be able to guide workers regarding the optimal next steps in a timely manner, with the aim of achieving DX (systematization = D, workflow transformation = X) that will transform manufacturing.

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