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UTILISATION OF IoT AND SENSING FOR MACHINE TOOLS

Strong requirements for automation in the production processes using machine tools have been increasing due to lack of high-skilled machining engineers. Automation used to be utilised in mass production, but it is also necessary in medium- to low-volume production recently. Next requirements will be monitoring or sensing functions to make the following possible: prompt service when the machine stops; detection of abnormality before the machine breaks down; and compensation of thermal displacement to ensure machining accuracy. These now need to be performed automatically in place of operators so that abnormality can be detected during machining operation. In this paper core technologies to support automation system will be discussed which are operation monitoring, predictive maintenance, sensing interface and thermal displacement compensation as a sensing application.

1. INTRODUCTION

The external environment of the machine tool business has reached a transitional point. With keywords such as the shift to EV (Electric Vehicle), aging population, IoT (semiconductor) and AM (Additive Manufacturing), the technological development trend is shifting from machining of mass-production parts, as represented by automobiles, to consolidation of parts, complex-shaped dies and molds, and new materials and techniques. Due to a worldwide shortage of machining engineers and an increasing demand for automation to stay cost competitive in developed countries with high labor costs, machine tool manufactures are now faced with one of the most challenging issues, the development of automation systems which include 5-axis control machines, mill-turn centres, and AM machines; and IoT and sensing technologies supporting those systems. Automation used to be utilised in mass production, but it is also necessary in medium- to low-volume production recently [1].

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The development of key components of a machine tool, which are the spindle and the feeding axes, has achieved quite a high level of technological sophistication. While the continued advancement is needed, more focus now needs to be placed on automation of workpiece loading/unloading to tackle the shortage of machining operators, and automation of machine operation which was conventionally done by operators, such as measurement of workpiece accuracy and compensation, monitoring of machining abnormality, and tool changes. High reliability is required of devices for collecting chips and coolant to prevent machine stoppage caused by failure during long-hour, no-man operation. It is also required to predict failure in advance to prevent machine stoppage and to recover promptly in case of failure.

In the meantime, innovative production technologies using IoT technologies, as represented by Industry 4.0 in Europe, have been rapidly developed and deployed in recent years. This paper reports the development of key technologies necessary for machine tools for automation, using IoT and sensing technologies.

2. REMOTE MONITORING

Remote monitoring is the fundamental function of the machine tool IoT technology.Remote monitoring is now capable of analysing causes of machine stoppage, in addition to serving as the fundamental function such as remote monitoring of machine operation status, acquisition of the past statistical data including operation rates, and management of tool usage status. This can be achieved by monitoring the number of actuator operation times, operation hours and sensing information as well as machine operation status and alarm history at the same time. Research on predictive maintenance is also being conducted by storing information of multiple machines in the DB to analyse the data [2]. There is a prac-tical example which DMG MORI has offered operation monitoring/analysis systems since 2004 [3]. Today, approximately 7,000 machines are connected to this system. The system is capable of visualising the operation status by automatically collecting the operation status data of the machines. In other words, the system serves as a tool that helps operators to analyse the machine operation status and to find problems. Using this system, operators can identify and solve problems effectively, which makes it possible to prevent or minimise a machine stoppage. In the system, the machine operation status data are stored in the buffer of the HMI (PC) unit. The encrypted data are sent to the server of the machine- tool manufacturer by e-mail. Then, the data are stored by the machine, they are processed for statistics, and they are provided to the customers. In the conventional system, the available machine information was the operation status and the alarm history. Despite the limited information, some customers have increased machine operation rates by analysing the cause of the stoppage from the alarm and by eliminating the cause of the repeated alarm. In order to improve the system efficiency, the new system has certain additional monitoring items designed for lifetime simulation of parts and components of mass-production machines that inevitably operate for long hours and long periods. The monitoring of the operation status of the main actuators has been added to the new system. Table 1 shows lists of the main actuator which are monitored by this system. Figure 1 shows a system structure for collecting machine operation data. In the structure, multiple machines are connected to a PC via Ethernet. MTconnect [4] is used as the interface between the machines and the PC to allow the system to flexibly accommodate the future addition of new machines from any manufacture.

The information is stored in the server of the machine-tool manufacturer and is analysed for predictive maintenance. Figure 2 presents an example of the machine operation history of the main components for the purpose of estimating the lifecycle time. Figure 3 shows a Pareto chart of the alarm history by frequency of occurrence. The bars show the number of alarms and the blue points indicate the accumulated probability of alarms, starting from the leftmost alarm. In this case the “Lift up/down” alarm, which is indicated in red, was generated when the duration of the upward or downward movement exceeded the specified time; hereafter, this will be referred to as the time-over alarm.

Table 1. Actuators list for monitoring

Monitoring	Item	Unit
Cycle time	ATC shutter open/close	s
	Lifter up/down	s
	A axis clump/unclamp	s
	Transfer shutter open close	s
	Fixture open/close	s
Accumulated Operation number	ATC	
	Table index	
Accumulated Operation time	Spindle rotation	min

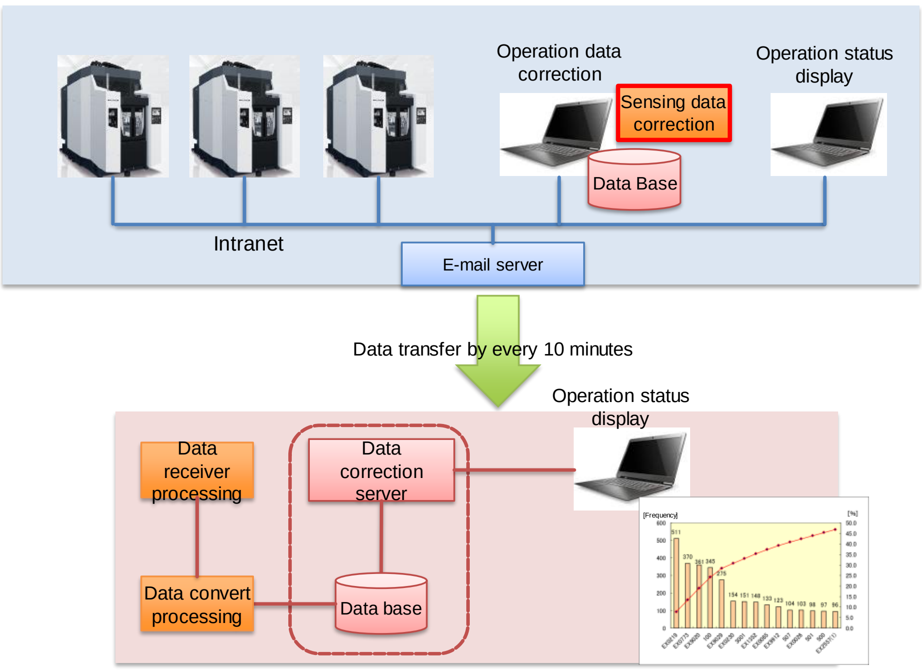


Fig. 1. System structure

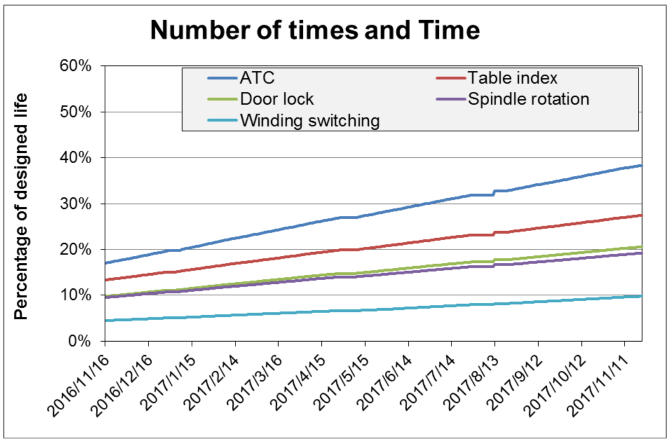


Fig. 2. Operation history

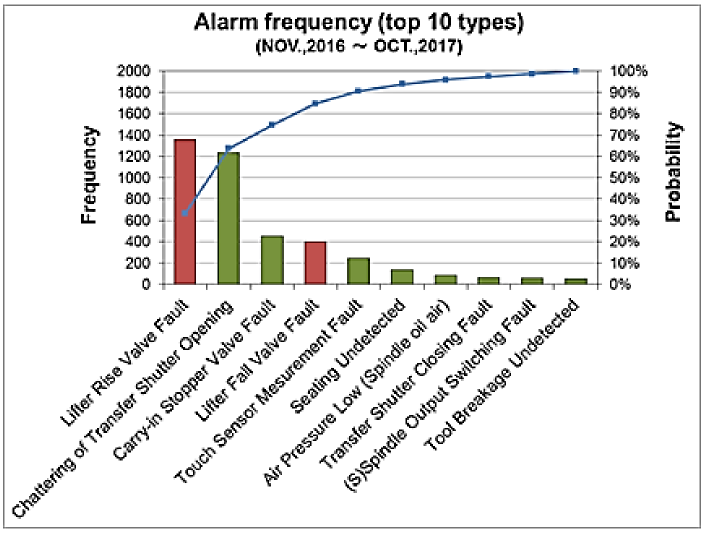


Fig. 3. Pareto chart by alarm frequency

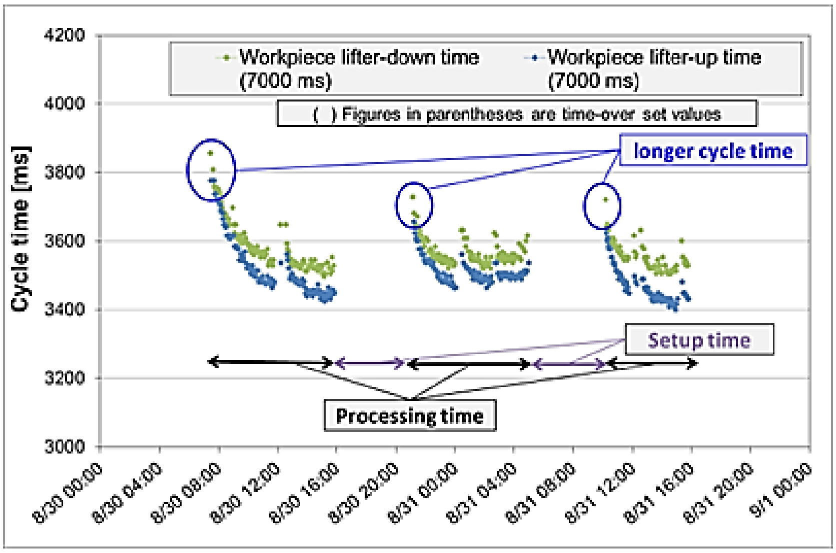


Fig. 4. Cycle time transition of lifter up/down

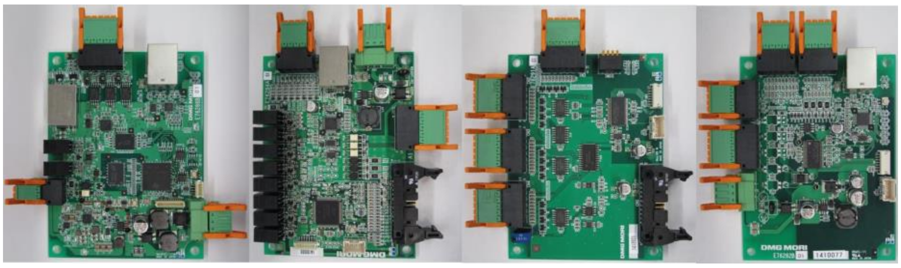
To investigate the cause of the movement delay, the time for the lifter up/down operation was analysed. Figure 4 shows the cycle time transition of the lifter up/down operation. The horizontal axis is the date and time and the vertical axis is the cycle time. In the analysis of the operation time of each actuator, signs of failure were detected, and the lifter up/down movement was found to have lasted 10% longer when the machine stopped its operation for a long time before coming to a complete stop. According to the operation result checked by the remote monitoring system, it was also demonstrated that the power was shut off during the set-up operation.

The cause of this was estimated to be the following: when the temperature of the hydraulic oil – which is the power source of the lifter – is low, the time required for the lifter to perform the up/down movement is near the time-over alarm, thus indicating a narrow margin. This analysis proves that recording the cycle time of an actuator is useful for analysing intermittent problems for maintenance purposes.

3. SENSING TECHNOLOGIES FOR MACHINE TOOL

It is very important to improve service efficiency for machine tool manufactures because machine tools are used for very long term and need to dispatch service engineers at customer site. Many researches are being done to realize preventive maintenance and predictive maintenance to solve this issue [5, 6]. In order to estimate cutting condition and machine tool status like thermal displacement, cutting vibration, tool wear, power consumption and so on, internal and external sensors' information are utilised. These functions are key to support autonomous machine tools to monitor machine tool on behalf of machine operator. Process monitoring was developed by using sensory machine tool integrating a sensing fixture and an adaptive sensory milling spindle [7]. A comprehensive survey of machining monitoring, innovative signal processing, sensor fusion and related applications was reported by CIRP key note paper [8]. The sensing board was developed to monitor analogue sensors signal by the industrial computer for machine tools [9]. Acceleration sensors were installed in the spindle unit were used to measure chatter vibration, collision impact, and abnormal bearing vibration. Temperature sensors were installed in the spindle unit and table were used to compensate thermal displacement or diagnose spindle bearings. High speed sampling rate were required for acceleration sensors exceeds several kHz in order to monitor chatter vibration.

The sensing network was structured with the 100BASE-TX Ethernet because sensors cannot be connected to the Ethernet directly, four types of interface boards for sensor signal inputs and Ethernet outputs were developed. The Data Acquisition FFT Board (DAQF) has three acceleration sensor interfaces and two temperature sensor interfaces. The Data Acquisition Temperature Board (DAQT) is a A/D converter board to monitor maximum eight temperature sensors. The Electrical Power Monitor Board (EPM) is connected to electrical current sensors and voltage sensors, which were placed at three-phase. Figure 5 shows developed sensing interface board. Figure 6 shows sensing items on machining centre [10].



(a) DAQF (b) DAQT (c) DAQL (d) EPM

Fig. 5. Sensor Interface Boards

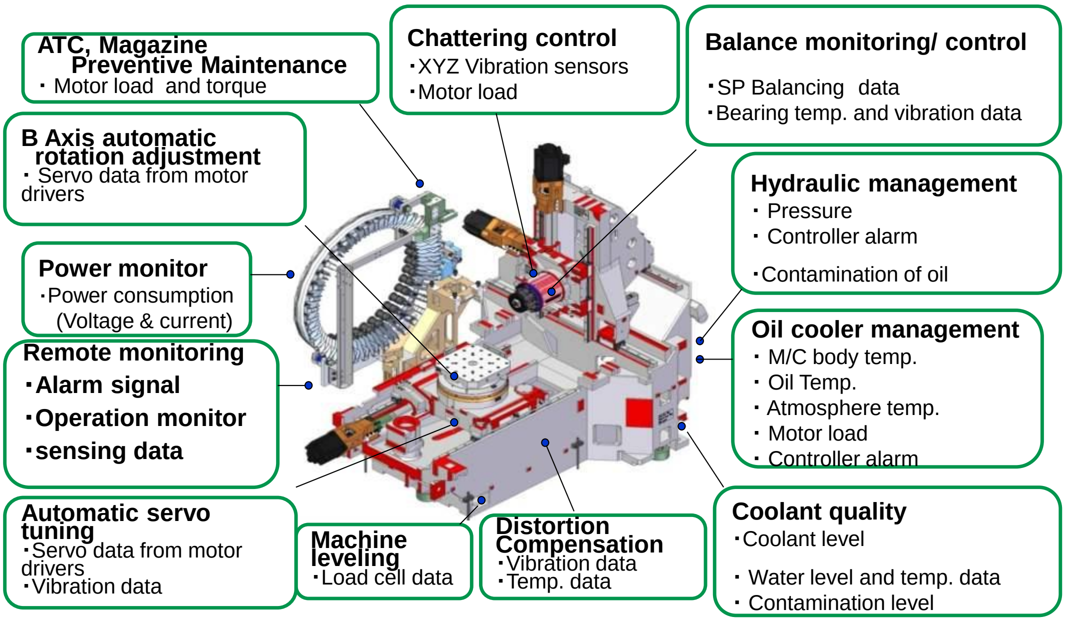


Fig. 6. Sensing items on machining centre

4. THERMAL DISPLACEMENT COMPENSATION

Thermal deformation is one of the biggest causes of accuracy deterioration. It is affected by Machine structure, Ambient temperature, State of heat sources and Coolant usage so that it is very difficult to estimate thermal displacement accurately. In recent years, due to lack of labour force in the manufacturing industry, automation systems have been required in order to reduce manual handling at the factory. For continuous operation, it is important to suppress the deterioration of accuracy due to thermal deformation because manual adjustment by measurement is difficult due to unmanned operation. Against this issue, various thermal displacement control technics by cooling and compensation have been developed [11, 12]. Although so many researches have been done, thermal displacement is still one of the most important issue in order to improve machining accuracy. Because it is very difficult to absorb to individual machine characteristic difference of individual machines or individual environment of customers' factory or machining condition by conventional mathematical method. In order to make an accurate thermal displacement prediction model, deep-learning was used. Deep-learning is a technique which has made remarkable achievements in various fields in recent years, particularly in the fields of image recognition and speech recognition. CNN (convolutional neural network) is applied to temperature data, it is feature extraction of temperature variation and information compression can be performed and features of temperature variation can be captured abstractly. A conceptual diagram of CNN used in deep-learning is shown in Fig. 7. It is a model that the temperature data from past fixed time period are given as input to predict the thermal displacement at that time. The performance of CNN was verified using actual temperature data. In order to determine the thermal sensor position, thermal sensitivity analysis was applied to a turning centre. The relationship between load pT generated by temperature variation Δt can be expressed as the temperature-load transformation matrix H:

$$pT = H\Delta t \tag{1}$$

The temperature variation Δt and the displacement u is expressed by Equation 2:

$$u = K^{-1}H\Delta t = W\Delta t \tag{2}$$

The transfer function between the displacement and the temperature variation is obtained as Equation 3 from the stiffness matrix and the temperature-load transformation matrix [13–15]. Thermal sensitivity W can be described by inverse stiffness matrix and temperature-load transformation matrix as:

$$W = K^{-1}H \tag{3}$$

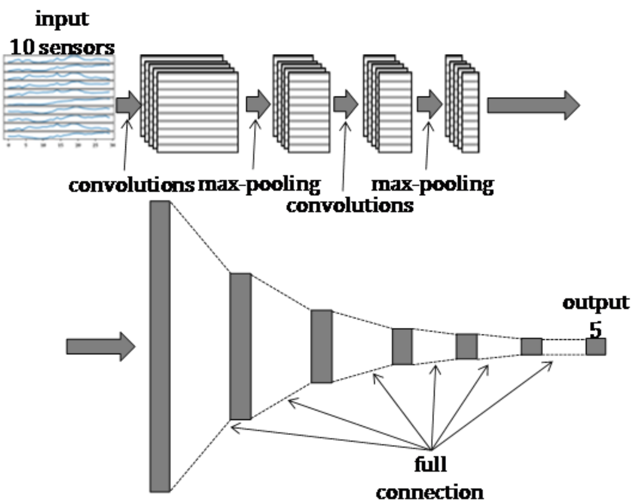


Fig. 7. Conceptual diagram of the CNN used

The stiffness matrix K is normally calculated from the finite element model. Nastran was applied to calculate K. The temperature-load transformation matrix H was calculated based on Nastran's thermal load generation algorithm of solid element. Based on these, the thermal sensitivity W can be obtained. The overview of this method is shown in the Fig. 8.

Using the information of the 10 temperature sensors attached to the turning centre, models of "ridge regression", "non-convolutional NN" and "CNN" were created and learning was carried out. The results of displacement error comparison are shown in the Fig. 9. The CNN error is 59.5% smaller in peak-to-peak than ridge regression and 71.6% smaller than non-convolutional NN. CNN has the best performance.

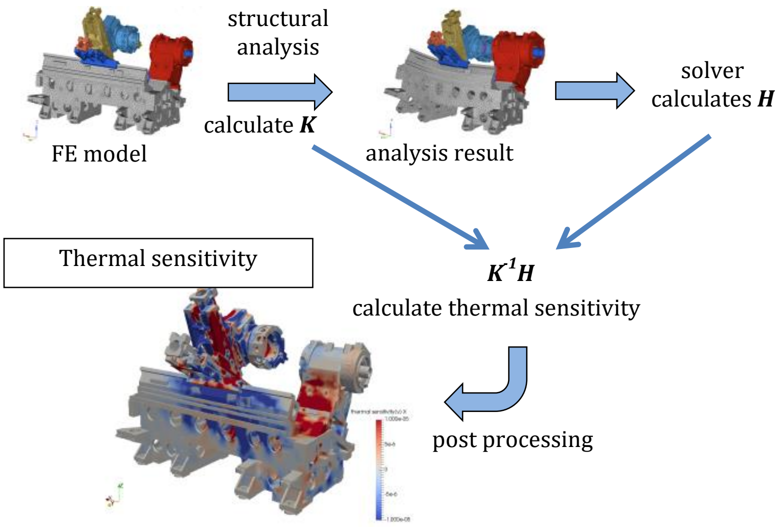


Fig. 8. Calculation method for thermal sensitivity

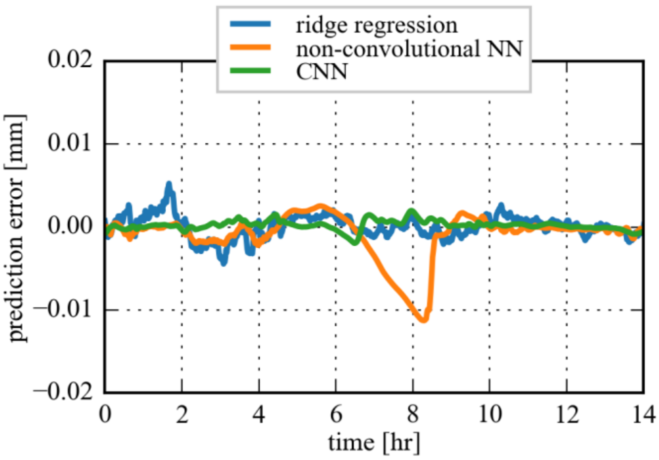


Fig. 9. Comparison between CNN and other methods

To realise more robust and accurate prediction model, we obtained large data for learning. Portable temperature variable booth was manufactured to change ambient temperature for the mass production turning centre at the assemble factory of DMGMORI. The temperature variation of each part of the machine structure and the thermal displacement was measured. The measurements were taken from multiple turning centres in the same model in a portable temperature variable booth and air conditioner as shown in Fig. 10.

Fig. 10. Portable temperature variable booth and air conditioner

1st step target was achieved by this algorism to realise 5 μm accuracy against ambient temperature change. We are utilising temperature data at the customer's machine as a next step to reproduce actual customers' environment at the DMGMORI factory. Remote monitoring function is used to obtain the temperature sensor data and measurement data (Fig. 11).

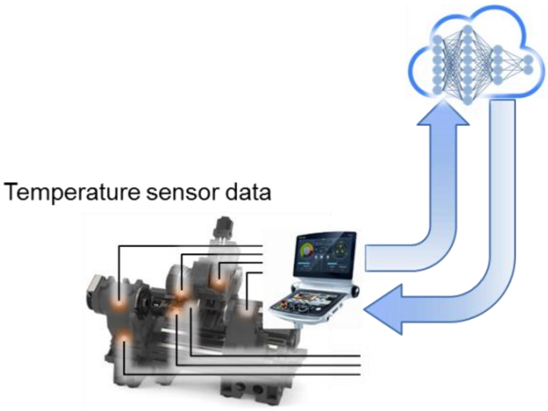


Fig. 11. Remote monitoring of temperature sensor data at customer site

5. CONCLUSION

This paper presents utilisation of IoT and sensing technologies for machine tools. Operation monitoring and analysis are effective tools for analysing the cause of failure that hinders the improvement of operation rates. In order to estimate thermal displacement, cutting vibration, power consumption and so on, sensing interface board was developed. As a typical application, high performance thermal displacement compensation function was developed by sensing technology and CNN method.

1. By adding the cycle time and operation number of actuators on the remote monitoring function, basic function of predictive maintenance was developed.
2. To adopt CNN algorism for thermal temperature displacement, it is possible to absorb individual difference of individual machines or individual environment.

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