A Study on Cyber-physical System Architecture to Predict Cutting Tool Condition in Machining

Yasuo Kondo
Yamagata University/Department of Mechanical System Engineering, 4-3-16 Jhonan Yonezawa, Japan
Email: kondo@yz.yamagata-u.ac.jp

Mitsugu Yamaguchi, Satoshi Sakamoto and Kenji Yamaguchi
University of Tokyo/Institute of Industrial Science, Kashiwanoha Kashiwa Chiba, Japan
Email:ymitsugu@iis.u-tokyo.ac.jp
Yokohama National University/Department of Education and Human Science, Tokiwadai Yokohama, Japan
E mail: ssatoshi@ynu.ac.jp E-mail:yama@yonago-k.ac.jp

***Abstract*— This article illustrates a systematic approach for predicting tool wear in machining process through Cyber-Physical System (CPS) architecture using simple electronic components such as personal computers and low-cost sensors. The proposed Cyber-Physical structure consists of 5 steps; smart connection, data to information, feature extraction, awareness of issues and self-adjustment. We tried to install a big data analysis technology into CPS architecture to catch the usual/unusual state of the cutting tool from the spindle power consumption changes. The excessive repetitions of grooving would bring the trend changing of power consumption. To facilitate the statistical analysis, the correlation coefficient R was calculated from the single regression analysis between two different cycles of time-series power consumption. The correlation coefficient R also had a strong relation with the condition changes of tool wear and would become a powerful tool to catch the usual/unusual state of the cutting tool in the proposed CPS architecture. The health information obtained from the system can be used for higher level of management of cutting tool based on the condition monitoring free from the schedule-based maintenance.**

***Index Terms*—cyber-physical system, industry 4.0, Society 5.0, big data analytics, tool wear, predictive maintenance**

I. Introduction

Due to the increased digital networking of machines and systems in the production area, large datasets are generated. In addition, it is possible that more external sensors are installed at production systems to acquire data for production and maintenance optimization purposes. Therefore, data analytics and interpretation is one of the challenges in Society 5.0 in Japan [1] and Industry 4.0 in Germany [2] applications.

According to a study by McKinsey [3], predictive maintenance is one of the main application fields of the IoT (Internet of Things). The development of new sensor technologies such as sensor – IoT system Pi offer great potential to enable production machine for condition-based monitoring using low-cost sensors [4,5,6].

Integrating advanced analytic with communication technologies in close conjunction with the physical machinery has been named Cyber-Physical Systems (CPS) by American government since 2007 as a new developments strategy [7, 8]. Currently, the CPS concept is still under development. The implementation of predictive analytics as part of the CPS flamework enables the assets to continuously track their own performance and health status and predict potential failures. By implementing the predictive analytics along with a decision support system, proper services could be requested and actions taken to maximize the uptime, productivity and efficiency of the industrial systems. CPS facilitates the systematic transformation of massive data into information, which makes the invisible patterns of degradations and inefficiencies visible and yields to optimal decision-making. This paper briefly discusses a systematic architecture for applying CPS in manufacturing. Then, a case study for predicting tool wear in machining process through CPS architecture is presented.

II. Concept

A. Society 5.0 or Industry 4.0 Factory

Table I represents the difference between a today's factory and Society 5.0 (Industry 4.0) factory. In current industry environment, providing high-end quality service or product with the least cost is the key to success and industrial factories are trying to achieve as much performance as possible to increase their profit as well as their reputation. In contrast, in the Society 5.0 industry, in addition to condition monitoring and fault diagnosis, components and systems are able to gain self-awareness and self-predictiveness, which will provide management with more insight on the status of the factory. The peer-to-peer comparison and fusion of health information from various components also provides a precise health prediction in component and system levels.

Manuscript received April 5, 2019; revised January 21, 2020.

doi: 10.18178/ijmerr.9.4.565-569

TABLE I. COMPARISON OF TODAY'S FACTORY AND SOCIETY 5.0 FACTORY

Data source		Today's Factory		Society 5.0 (Industry 4.0) Factory	
		Key attributes	Key technologies	Key attributes	Key technologies
Component	Internal sensor External sensor	Precision	Smart Sensors Fault Detection	Self-awear Self-predict	Degradation Monitoring Remaining Useful Life Prediction
Machine	Controller	Producibility & Performance (Quality & throughput)	Schedule-based Monitoring & Disgnostics	Self-awear Self-predict Self-compare	Up Time with Predictive Health Monitoring
Production System	Networked Manufacturing System	Productivity & Overall Equipment Efficiency	Lean Operations: Work and Waste Reduction	Self-configure Self-Maintain Self-Organize	Worry-free Productivity

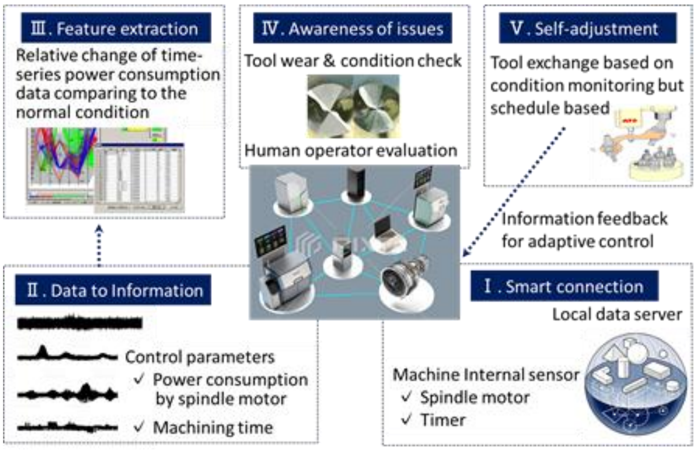

Figure 1. Overall cyber-physical system setup for predicting tool wear in machining

B. *Outline of Communication Architecture*

"Fig. 1" shows the overall CPS setup for predicting tool wear in grooving. The structure consists of 5 steps; smart connection, data to information, feature extraction, awareness of issues and self-adjustment.

1) Smart-connection

In the connection level, a time-series data is acquired from machines through the timer signals and the electric power meter in spindle motor. The electric power monitoring is a popular fault detection method for monitoring health condition of cutting tool [9, 10,11]. The data is now processed in the desk-top computer connected to a CNC machine.

2) Data-to information conversion

In the 2nd level, data to information level, the worthwhile information is extracted from the pool of collected time-series data and normalizes it for further analysis [9, 10, 11].

3) Feature extraction

After the data conversion, the computer further performs feature extraction. The feature extraction consists of identification of cutting time domain to be managed, where the changing pattern of time-series data shows a difference according to the health condition of cutting tool, and measuring the similarity of time-series data between the usual and reference health conditions.

4) Awareness of issues

In the 4th level, awareness of issues, the computer performs an adaptive clustering method to segment the health condition of cutting tool into soundness, need to be exchanged and damaged based on the relative change of time-series data. the adaptive clustering method compares current features with the usual features. In addition to the condition data, the cyber-physical model obtains the information on shape and abrasion loss of cutting edge from production line. These configuration parameters help the core of model to standardize and adaptively cluster the operation data for more accurate processing.

5) Self-adjustment

The health stages can be further utilized in the 5th level, self-adjustment, for optimization purposes. For example, after a certain amount of tool wear has been detected, a more moderate cutting should be applied to ensure quality including the exchange of cutting tool. To help such decision making process, ideally Web and iOS-based user interface should be developed so that the health information of each connected machine tool can be accessed in real time.

III. CASE STUDY

A. *Experimental Setup*

The experimental setup for measuring the power consumption is shown in "Fig. 2". Only electric power consumed by the spindle motor $P_{measure}$ was measured at

0.2 seconds interval by using a power tester. Then the net power consumption in the cutting P_{cut} was estimated by subtract the power consumption at idle running P_{idle} from the measured spindle power. The evolution of P_{cut} is evolution of cutting force and a fairly accurate measure of the deterioration of tool condition.

$$P_{cut} = F_c \cdot V / (60 \times 1000 \times \eta) \qquad (1)$$

where, P [kW] is net effective power, F_{c} [N] is principal cutting force, V [m/min] is cutting speed and η is mechanical efficiency. A grooving of 0.1mm depth was conducted on a vertical CNC with an AC spindle motor by using a Φ2mm of two-flute end mill under the conditions in "Fig. 3". The workpiece was a commercial brass plate (JIS C3604) and the shape of groove consisted on a straight section and two curved sections with curvature radius of 10mm and 40mm.

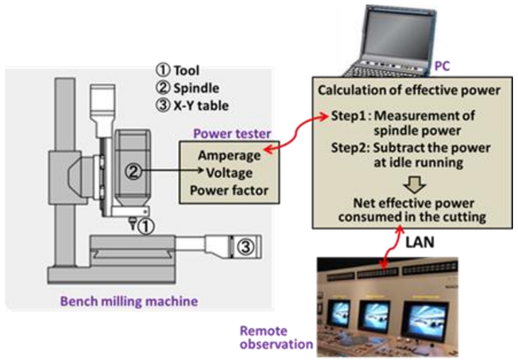

Figure2. Experimental setup for material cutting

Machining tool	CNC milling machine
Groove shape	See Fig.1
Cutting tool	φ2mm of two-flute end mill High speed tool steel
Workpiece	JIS C3604
Work feed speed	1200 mm/min
Revolution of tool	7000 rpm
Cutting depth	0.1 mm
Lubrication	Insoluble cutting oil
Measuring interval	Input power 0.2 s Acceleration 0.2 ms

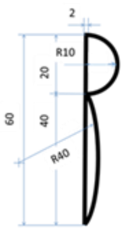

Figure 3. Summary of cutting conditions

B. Statistical Analysis

To acquire a large volume sensor data, input power consumption supplied to the spindle were measured at 0.2s interval by using a power meter. The grooving with 0.1mm of cutting depth had been repeated 1000 times and the tool wear was measured every 100 times grooving by using a digital microscope.

To analyze the time-series data, the concepts called cycle is set. The one "cycle" corresponds to one round of grooving from the straight section to the curved sections with curvature radius of 40mm via the curved sections with curvature radius of 10mm. To facilitate the statistical analysis, the time-series data obtained from the one cycle of grooving were divided at a second interval. Then the average power consumption, zone average power consumption, were calculated every one second as shown in "Fig. 4". Finally, the correlation coefficient R was calculated from the single regression analysis between two different cycles of time-series zone average power consumption. As the correlation coefficient R is closer to 1.0, the time-series sensing data in the two different cycles have a more similar power consumption changes over times with each other.

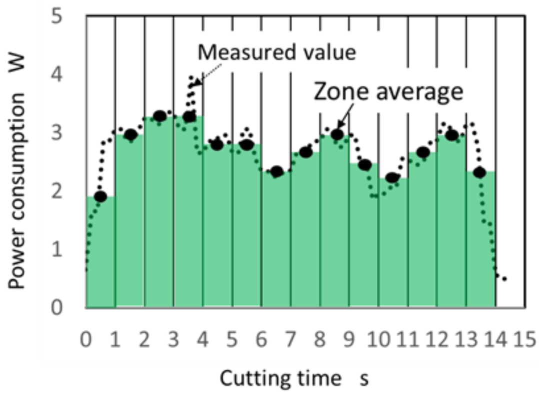

Figure 4. Calculation model of zone average value

C. Predicting Tool Wear through CPS Architecture

1) Smart connection and Data to information

"Fig. 5" shows the time-series data obtained from the 30, 91, 249, 498, 616, 752, 851, 985 and 1000th cycles of grooving. The absolute value of power consumption tended to increase with the number of cutting cycles, but the changing trends of power consumption are similar with each other. "Fig. 6" shows the detailed comparison of power consumption trends among the 91, 249 and 752th cycles of grooving. Although the changing trends of the 91 and 249th cycles are quite similar over the entire of grooving, the changing trend of the 752th cycle showed the opposite trend of 91 and 249th cycles at the first parts of curved section with curvature radius of 10mm and 40mm. This means that the excessive repetitions of grooving would bring the trend changing of power consumption as well as the increasing of its absolute value.

2) Feature extraction and Awareness of issues

"Fig. 7" shows the correlation coefficient R calculated from the single regression analysis between 91th and 249th cycles and 91th and 752th cycles of time-series zone average power consumption. Where the time-series zone average power consumption in the 91th cycle is considered as the usual (soundness) data set which represents the typical power consumption changing trend in the usual cutting condition because there is no apparent tool wear after 91th cycle of grooving as shown in "Fig. 8". The correlation coefficient between 91th and 249th and 91th and 752th are 0.88 and 0.75 respectively. As mentioned above, the power consumption changing trends in the 91th and 249th cycles are quite similar while the changing trend at the 752th cycle showed the opposite trend of 91th cycles at the first parts of curved section. This means that as the changing trends of power consumption in sample cycle (249th, 752th) are more similar to that of usual state (91th), the correlation coefficient R is closer to 1.0 as supposed.

3) Self-adjustment

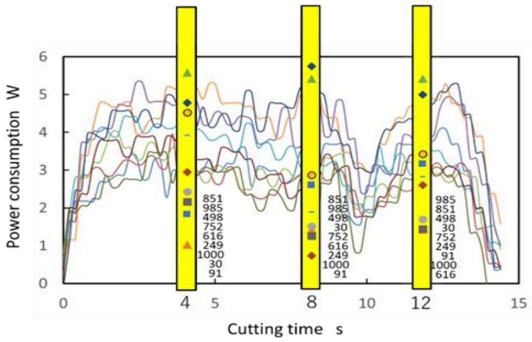

Figure 5. Time-series power consumption data

"Fig. 9" shows the correlation coefficient R of 30, 249, 498, 616, 752, 851, 985 and 1000th cycles of grooving when the changing trend of 91th cycle is set as the reference data set. A sharp drop and increase of correlation coefficient R are seen near the 700~800th and 1000th cycles respectively. These changes in correlation coefficient had a relation with the condition changes of tool wear. The tool abrasion loss rapidly increased between 700th and 800th cycles and the cutting tool was worn out near the 1000th cycle as shown in "Fig.9".

These facts indicate that the correlation coefficient R would become an influential tool for catching the usual/unusual state of the cutting tool from the spindle power consumption changes.

The proposed architecture covers all necessary steps from acquiring data, processing the information, presenting users and supporting decision making. Furthermore, the health information obtained from the system can be used for higher level of management of cutting tool based on the condition monitoring free from the schedule-based maintenance.

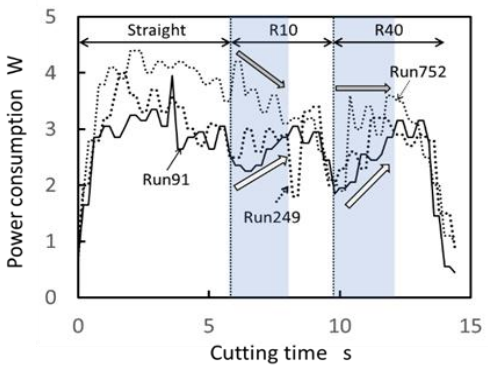

Figure 6. Detailed comparison of power consumption trends

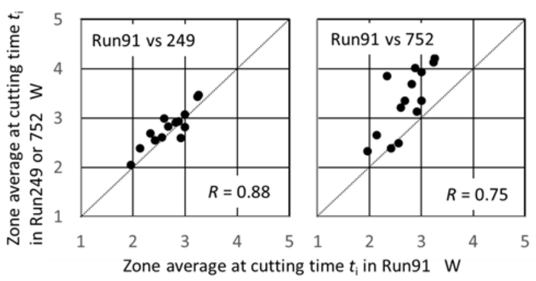

Figure 7. Correlation coefficient obtained from single regression analysis

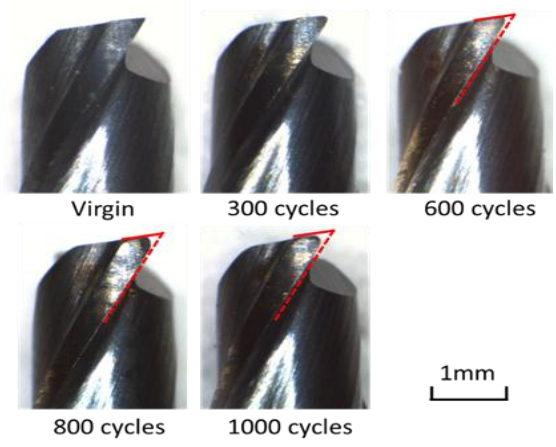

Figure 8. Progress of tool wear with grooving cycles

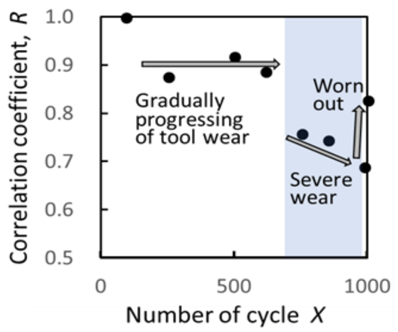

Figure 9. Relation between correlation coefficient and grooving cycle

IV. Conclusions

We tried to install a big data analysis technology into Cyber-Physical System (CPS) architecture to catch the usual/unusual state of the cutting tool from the spindle power consumption changes. The proposed Cyber-Physical structure consists of 5 steps; smart connection, data to information, feature extraction, awareness of issues and self-adjustment. The spindle power change strongly reflects the cutting force change because the spindle provides the mechanical force necessary to remove material from the part. To acquire a large volume sensor data, input power consumption supplied to the spindle were measured at 0.2s interval by using a power meter. The excessive repetitions of grooving would bring the trend changing of power consumption as well as the increasing of its absolute value. To facilitate the statistical analysis, the correlation coefficient R was calculated from the single regression analysis between two different cycles of time-series power consumption. The correlation coefficient R is closer to 1.0 if the changing trends of power consumption is similar between the usual and reference cycles. The correlation coefficient R also had a strong relation with the condition changes of tool wear. This means that the correlation coefficient R would become a powerful tool to catch the usual/unusual state of the cutting tool in the proposed CPS architecture and the health information obtained from the system can be used for higher level of management of cutting tool based on the condition monitoring free from the schedule-based maintenance.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Y. Kondo conducted the research; M. Yamaguchi, S. Sakamoto and K. Yamaguchi analyzed the data; all authors had approved the final version.

REFERENCES

[1] M. Hermann, T. Pentek, B. Otto, "Design principles for industrie 4.0 scenarios," in *Proc. of 2016 49th Hawaii International Conference on System Sciences (HICSS)*, (2016).
[2] N. Yamada, Y. Takashima, Y. Kimura, "Towards realizing "super smart society" 8Society 5.0)," *J. of Information Processing and Managrement*, vol. 60, pp. 325-334, 2017.
[3] J. Manyika, M. Chui, P. Bisson, J. Woetzel, R. Dobbs, J. Bughin, D. Aharon, "The Internet of Things; Mapping the Value Beyond the Hype," McKinsey Global Institute, (2015).
[4] E. Uhlmann, A. Laghmouchi, E. Hohwieler, C. Geisert, "Condition monitoring in the cloud," in *Proc. of the 4th Inter. Conf. on Through-life Engineering Services Cranfield, Procedia CIRP*, vol. 38, p. 53-57, 2015.
[5] A. Albaebar, S. Mekid, A. Staar, R. Pietruszkiewiez, "Suitability o fMEMS accelerometers for condition-monitoring: An experimental study," *Sensors*, vol. 8, no. 2, pp. 784-799, 2016.
[6] S. B. Chashury, M. Sengupta, K. Mukherijee, "Vibration monitoring of rotating machines using MEMS accelerometer," *Int. J. of Scientific Engineering and Research*, vol. 2, no. 9, pp. 5-11, 2014.
[7] J. J. Shi, H. Wan, H. Yan, H. Suo, "A Survey of Cyber-phisical systems," *International Conference on IEEE Wireless Communications and Single Processing*, 2011.
[8] "Cyber-Physical Systems," *IEEE Control System Society*, 2011.
[9] Y. Kondo, Y. Higashimoto, S. Sakamoto, T. Fujita, K. Yamaguchi, "Feature extraction from sensor data streams for optimizing grinding condition," *Materials Science and Engineering*, vol. 229, 2017, pp. 1-6.
[10] Y. Kondo, S. Mizunoya, S. Sakamoto, K. Yamaguchi, T. Fujita, M. Yamaguchi, "A utilization method of big sensor data to detect tool anomaly in achining process," *Key Engineering Materials*, vol. 719, 2016, pp. 122-126.
[11] Y. Kondo, M. Yamaguchi, S. Sakamoto, "A big data analysis technology for catching usual/unusual state of cutting tool," in *Proc. of 3rd IC3MT, CD-ROM*, (2018).

Yasuo Kondo received his Ph.D Degree in 1994 from Osaka University. Now he is a professor of Graduate School of Science and Engineering, Yamagata University. His research interests include manufacturing system, On-line monitoring system for machining operation and Engineering education. Yuko Itoh is a senior student in Yasuo Kondo's laboratory of Yamagata University.

Mitsugu Yamaguchi received the Dr. Eng. degree in 2016 from Ibaraki University. He is currently an rsearcher with the Institute of Industrial Science, University of Tokyo. His current research interests include laser sintering of metal nanoparticles for metal substrates.

Satoshi Sakamoto received his doctorate from Kanazawa University, Japan in 1997. Now he is a professor of Education at Yokohama National University. His current research interests include precision machining of hard and brittle materials. He is a member of the Japan society for precision engineering, the Japan society of mechanical engineers, and the Japan society for abrasive

Kenji Yamaguchi received the ph.D degree in 2002 from Tottori University. His current position is a professor of the Department of Mechanical Engineering, Yonago National College of Technology. His research interests include an effective succession of technicians' skill and a monitoring system for cutting fluids condition.