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Integration of Health Monitoring of Cutting Tools and Production Scheduling in Smart Factory

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ABSTRACT

Smart factory evolves by adding new functions or upgrading existing functions to meet the needs of manufacturers in the use stage of the life cycle. To reduce complexity of smart factory, these functions must be carefully designed considering interactions with other functions. This study analyzes integration of functions situated in the different layers in the functional hierarchy of smart factory. In this study, a health monitoring system for cutting tools in a shop floor, which offers a function to manage the lifetime of cutting tools, is presented. The system is integrated with a production scheduling system, which offers a function to schedule machining processes considering efficient usage of machines as well as cutting tools, while maintaining the quality machining processes. Primary evaluation of the functional integration shows that activities in the shop floor regarding selection and replacement of cutting tools are considered in defining production schedules. It also shows that such functional integration results in increase in complexity regarding the behavioral model of humans in smart factory.

1. INTRODUCTION

Smart factory evolves by adding new functions or upgrading existing functions to meet the needs of manufacturers in the use stage of the life cycle (Komoto et al. 2020). For instance, production engineers and operators expect smart factory to support more advanced decision makings as a large amount of operational data of assets becomes available. To meet such needs and expectations, these functions must be carefully designed considering interactions with other functions realizing smart factory.

Functions constituting smart factory are situated in various layers on the functional hierarchy of smart factory (IEC 2013). Integration of functions in smart factory is not a trivial task due to several reasons. First, each function must be executed with operational data collected at the right time. Second, interfaces among the functions must be clearly defined. A premise of functional integration is interfaces for information transfer among the systems implementing functions. Standardization of such interfaces is useful to effectively develop systems rather than ad-hoc system development with specific interfaces (IEC 2013). The present study analyzes capabilities and limitations in integrating functions situated in different layers of the functional hierarchy by conducting a use case.

Health monitoring is a typical function to observe the state of smart factory to maintain its availability as well as the quality of manufactured products. Health monitoring is crucial for effective usages of manufacturing resources such as cutting tools, as the monitored data can be used to improve machining operation parameters to decrease resource consumption and increase resource lifetime. As a result of health monitoring, preventive maintenance and repair of manufacturing assets, and replacement of consumables are planned and executed. In practice, operators and production engineers perform health monitoring in smart factory by observation of the operational data of machine tools, robots with specific analysis tools.

Production scheduling is a crucial function for operational management of smart factory. Production engineers and managers define production schedules including the assignment of operators and manufacturing assets to specific tasks for minimizing the delay of task completion. In defining a production schedule, needed maintenance activities identified by health monitoring must be considered.

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Integration of health monitoring and production scheduling in smart factory is challenging. It is because of that interfaces between two functions are not well defined, as these tasks are done by experts in charge of the different layers in the functional hierarchy of smart factory.

This study describes research in integration of a health monitoring system and a production scheduling system for smart factory. The structure of the paper is as follows. Section 2 briefly explains the research environment, and a health monitoring system of cutting tools and a production scheduling system build on the environment. To illustrate the approach of this research, Section 3 describes a prototype system to support advanced production scheduling considering efficient usage of cutting tools by means of integration of two functions. Section 4 summarizes the study and describes its outlook.

2. THE RESEARCH ENVIRONMENT

To explain the smart factory discussed in the context of this study, this section describes the research environment of smart factory developed by the authors (Komoto and Masui 2018; Komoto et al. 2020; Komoto & Furukawa 2022). Figure 1 shows the overview of the research environment. The shop floor consists of machines for a variety of machining processes (e.g., turning, milling, and servopressing). Among these machines, each machine is equipped with a tool exchanger, on which multiple cutting tools are set. Furthermore, a simulator of the shop floor is used to model the digital representation of the shop floor.



Figure 1. Smart factory research environment

In the research environment, OPC-UA (IEC 2020) is used as a communication interface between the shop floor and the simulator. An OPC-UA server makes the states of these machines accessible from OPC-UA clients in the same network. The simulation model includes another OPC-UA server, which communicates the machines in the shop floor through an OPC-UA client. With this OPC-UA connection, the bidirectional exchange of the values of the attributes of the machines in the shop floor and those in the simulator is possible.

2.1. Health monitoring of cutting tools in smart factory

In this study, cutting tools (such as end-mills for milling processes) attached to the machines in Figure 1 are the objects of health monitoring. As described in Section 1, health monitoring data can be used to improve the operational parameters (e.g., feed rate, number of revolutions per second) so that the lifetime of cutting tools increase. Cutting tools are regarded as expensive consumables in executing machining operations, thus the impact of health monitoring is higher than that of other consumables. The contact surface of a cutting tool is damaged during the respective machining processes (e.g., drilling, milling, etc.), which results in creation of wear on the tool frank and increases in the surface roughness of the work piece machined by the cutting tool. Figure 2 shows a cutting tool and the progress of wear on the tool flank.



Figure 2. Tool flank wear of a cutting tool

Tool wear of cutting tools is evaluated in terms of the width and length of the damaged area on the surfaces of cutting tool under physical contact with workpieces during machining. Due to difficulty in monitoring of the wear of a cutting tool mounted in the machine, other measured data are used to estimate the degree of tool flank wear. For this reason, the authors investigate various types of sensors such as dynamometer, accelerometer, microphone, camera, and current, and power meters in context of quantitative estimation of tool wear (Herwan et al. 2022). As a result of health monitoring of cutting tools in this setup, the level of surface quality of work pieces machined with cutting tools and remaining lifetime of cutting tools is obtained.

Currently, the authors develop a predictive health model for cutting tools. Figure 3 shows the usage of the predictive model. The predictive model takes the description of new machining process (e.g., machining program, machining conditions), which will be scheduled in the production plan and executed in the shop floor. The information is then used in a machining process simulator to simulate the force during the planed machining process. The simulated force and the historical data related to operation and health monitoring is used to predict the physical deterioration of cutting tool wear.



Figure 3. A predictive health model for cutting tools

2.2. Production scheduling in smart factory

In the research environment, the simulator shown in Figure 4 is used to search for production schedules with efficient usage of machines in the shop floor. The simulation model consists of machines, operators, and other assets and consumables (e.g., fixtures and work pieces). Cutting tools are either stored in the tool holder of these machines or tool holders situated in the shop floor. The simulator is developed in principle of agent-based simulation, which enables modeling of rational actions of operators (e.g., setting up a fixture on a machine, transporting a workpiece to a machine) considering the dynamic state of the shop floor. Figure 5 shows possible sequences of such actions of operators defined in the simulator. The executed actions and the timing of execution is diverse according to the state of the shopfloor and the operators.

Production scheduling in smart factory studied in the research environment is distinguished from traditional production scheduling in two aspects. First, production scheduling is executed considering the real-time state of shop floor. The latest state of shop floor is obtained from a variety of sensor data (incl. the data obtained through communication based on OPC-UA). Second, production scheduling algorithm is aligned with the heuristics of production scheduling experts.



Figure 4. Factory simulation used for production scheduling



3. FUNCTIONAL INTEGRATION

Having described the health monitoring of cutting tools and the production scheduling for the shop floor in the research environment, this section introduces the integration of these two functions

This functional integration has two objectives. First, it is enhancement of the functions of production scheduler to be able to schedule health monitoring, maintenance, and replacement of cutting tools as a part of actions scheduled in the shop floor. The second objective is to generate production schedules with efficient utilization of cutting tools, as cutting tools are relatively expensive among the consumables of machining processes. In this study, the executable workflow of the operators in the simulator has been updated so that the workflow includes a sequence of processes to decide and execute the replacement of cutting tools. Furthermore, the expected remaining lifetime and the decree of wear was defined as a property of cutting tools. The predictive health model is used for incremental change of the degree of tool wear as a function of the condition of machining processes and process time.

Figure 6 shows an example output of the prototype of a production scheduler taking the predictive health model of cutting tools into account. It shows simulated activities of two operators with respect to time. In simulating operations of machines as well as the activities of operators (incl. transportation and setup of workpieces), the simulator inserts tool setup, transportation, and replacement activities considering the degree of tool wear.



Figure 6. Simulated activities of operators

As it stands, some functions have not been implemented in the prototype including (1) advanced decision-making model of operators regarding selection of cutting tools considering the specified quality of machining, and (2) initial set up of cutting tools set in the tool holders.

The functional integration resulted in increase in complexity of the model of operators in the simulator regarding decision-makings and operations. For instance, in the model, when operators recognize wear of cutting tools, they immediately update production schedules considering productivity in the shop floor, the quality of workpieces, and the efficient usage of cutting tools. In practice, the actions of such operators are distributed by operators, production engineers, and managers with different roles.

4. SUMMARY AND OUTLOOK

This paper presents integration of two functions to support operations in smart factory developed at the research environment at the site of the authors. One is a predictive health monitoring of cutting tools and the other is a simulator for production scheduling. This paper describes integration of these applications to support scheduling of activities related to the efficient usage of cutting tools, in which functional integration resulted in increase in complexity of decision-making and execution activities of operators and their digital representation in the shop floor. A future work includes analysis of the effectiveness of such integration based on use cases, and comparison of the implementation with other alternative ones with different architectural views.

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REFERENCES

- Herwan, J., Misaka, T., Furukawa, Y., & Komoto, H., (2022). A proposal for improving production efficiency of existing machining line through a hybrid monitoring and optimization process. *International Journal of Production Research*, pp.1-19, doi:10.1080/00207543.2022.2101403
- International Electrotechnical Commission (IEC), (2013). Enterprise-control system integration part 2: Objects and attributes for enterprise-control system integration. In IEC, *IEC 62264-2:2015*
- International Electrotechnical Commission (IEC) (2020): OPC Unified Architecture part 1: Overview and concepts. In IEC, *IEC TR 62541-1:2020*
- Komoto, H., & Masui, K., (2018). Model-based design and simulation of smart factory from usage and functional aspects. *CIRP Annals*, vol.67, no.1, pp.133-136, doi:10.1016/j.cirp.2018.04.025
- Komoto, H., Herrera, G., & Herwan, J., (2020). An evolvable model of machine tool behavior applied to energy usage prediction. *CIRP Annals*, vol.69, no.1, pp.129-132, doi:10.1016/j.cirp.2020.04.082
- Komoto, H., & Furukawa, Y., (2022), Modeling environmental performance evaluation of manufacturing systems from semantic and computational aspects, *Procedia CIRP*, vol.107, issue.1, pp.1011-1016, doi:10.1016/j.procir.2022.05.100

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