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ORIGINAL ARTICLE

The Sensor Network for Multi-agent System Approach in Smart Factory of Industry 4.0

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ABSTRACT – This research was developed to plan, monitor, and control the production in a modern manufacturing system model with heterogeneous production facilities, consisting of several automatic machine tools and conventional machine tools. Therefore, it proposed, a smart factory concept that utilises computer technology, internet networks and sensors so that the production process can be monitored. The sensor network monitors the condition of the machine tools and the status of the job. The temperature sensors, the vibration sensors, the electrical energy sensors are used to check tool conditions in machine tools. Meanwhile, the radio frequency identification (RFiD) system is used to check the status of the workpiece whether it has been completed, work in progress, or is waiting in a buffer or a pallet stocker. The information relating to the performance of the machine tools is sent using the IoT application so that through the web. The machine performance data are collected, and their status can be monitored. Likewise, job status is visible on the shop-floor control system. The sensor network model at the prototype scale had been built and tested on a laboratory scale. The test results showed that the performance of machine tools and job status were monitored properly.

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INTRODUCTION

This research focuses on the sensor network model in the smart factory, which consists of computerised production machinery and non-computerised equipment. The problem raised in a company that utilises the Flexible Manufacturing Systems (FMS) and the conventional machine tools in the production system. The information of job status and the machinery components status have not been monitored so that production control cannot make any decisions for rescheduling due to the status of machinery components, in this case, the condition of the cutting tools. The design of the sensor network model is important when the company use the Internet of Things (IoT) technology as one of the advantages of Industrial 4.0. The outline of this paper begins with the background of this research. Section 2 presents related work and studies of the sensor networks in smart factories. The system description in section 3 describes the detailed scope of problems to be developed. The system consists of the FMS, the monitoring system for machine tool components and the shop floor control. Section 4 explains the model of the sensor network, the monitoring system and the application system that has been built. Section 5 presents the test results and analysis, while section 6 concludes the research.

The advanced digital technology such as the IoT, sensor networks, artificial intelligence have been utilised in manufacturing environments that implement Industry 4.0. Integration plays an important role in the implementation. Wang et al. [1] explained that integration in manufacturing systems could be classified into three types, which are vertical integration, horizontal integration, and end-to-end engineering integration. Vertical integration facilitates the flow of information from sensors on the production floor to the monitor system. Horizontal integration provides to flow the information, materials, and finance between divisions in a company. End-to-end engineering integration provides the infrastructure to add value creation, for example, the customer requirements to production, service, and maintenance division. Kusiak in 2017 [2] explained that automatic factories that use the smart manufacturing concept could be evaluated based on six pillars, that are materials, data, predictive engineering, sustainability, resource sharing and networking as well as technology and manufacturing processes. Rossit et al. [3] explained that the implementation of industry 4.0 also includes smart scheduling and production planning, which is called Cyber-Physical Production Systems (CPPS).

Kang et al. [4] reported smart manufacturing has been used in several industries. His research shows the development of smart manufacturing implementation in the past, present and the direction of research in three countries, namely Germany, United States of America, and Korea. To realise smart manufacturing in various fields, cyber-physical systems, cloud manufacturing, big data analytics, IoT, and smart sensors are being used. Wang et al. [5] developed a self-organised multi-agent system for coordination in industrial networks using smart shop floor control. Decision making can be done independently (autonomous) and distributed on each object consisting of machine tools, conveyors, and products. The

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simulated model shows that the smart shop floor control coordination provides high efficiency. The multi-agent system is a heterogeneous set of objects with different abilities, tasks, and goals. Objects can coordinate with each other and exchange information to make the best decisions when conflicts arise as described by Tripathi et al. [6].

Savaglio et al. [7] conducted a survey explaining the state of the art and research challenges for agent-based, which utilised IoT technology, which is called Agent-based Computing (ABC). Technologies integrated with ABC including Edge Computing, Cloud Computing, Semantic Technology, Machine Learning, Blockchain Technology, and Wireless Sensor Network (WSN). WSN is used at a low level, which is placed on the components of the manufacturing system to get production data, such as job status and machine tool status. Meanwhile, Chen et al. [8] emphasised the importance of smart factories to upgrade the manufacturing industry. The main goal of this paper is proposing the design in the physical layer, data application layer and network layer. Chen designed the industrial wireless network (IWSNs) for the cyber-physical production system (CPPS). Lee et al. [9] examined in more detail, which explain the design and implementation of a wireless sensor-based monitoring system for a smart factory of supporting utility machines for a real-time environment using a wireless sensor network architecture. The purpose of this research is to extend lifetime of the utility machines like motors, water-pumps, and compressor machines by checking the white noise, illegal vibration, and high temperature. Meanwhile, Iqbal et al. [10] examined reliable decision making using a wireless sensor network (WSN) for the Factory Condition Monitoring process. Performance analysis is presented to calculate the error rate. Ud Din et al. [11] designed a multi-agent system framework for small to medium-size enterprises which implement Industry 4.0 by utilising the Enterprise Resource Planning System (ERP).

The concept and approach of energy management in production based on the IoT were developed by Shrouf et al. [12] at a smart factory in Industry 4.0. The control technique is to collect energy consumption data from the shop floor. Then this data is processed to reduce the wastes and enable energy-aware decision-making at the production management level. Meanwhile, Wang et al. [13] implemented a smart factory that utilises sensors and actuators with machine tools that use EtherCAT as a substitute for ethernet as network infrastructure. Gao et al. 2019 [14] emphasise the connectivity of highly dynamic wireless sensor networks in smart factory. For implementation in the manufacturing industry in Korea, there are several important factors that must be considered, namely organisational support, informatisation capabilities, IT personnel, qualifications, and scale; are seen in other technologies and innovation acceptances [15]. Pagnon et al. [16] conducted research that focuses more on how production equipment can be maintained by utilising interconnectivity between the data and the central office. The data collected is related to online ordering, order processing, raw material processing, product manufacturing, product shipment, and smart factory maintenance. Based on the analysis of his research, Sjödin et al. in 2018 [17] offer a model for smart factory implementation, which built by three principles to achieve the benefits in the management aspect. Those principles are the cultivating digital people, introducing agile processes, and configuring modular technologies. It integrates data flow horizontally between partners, suppliers, and customers. The data also integrates vertically within the organisations from the product development to the final product. The future smart factory will also integrate with the new technologies, such as artificial intelligence (AI), data science, and virtual reality. Therefore, implementing the smart factory is complex because of not only traditional fields such as the mechanical, electronic, and its automation, but also involves the emerging technologies which are data science, AI, and virtual reality [18].

Referring to the research of Wang et at. [1], the proposed research focuses on vertical integration and horizontal integration in a smart factory that utilised FMS integrated with conventional manufacturing systems. The FMS is a manufacturing system consisting of an automatic material handling system and several automatic machine tools controlled by a computer. The computer is a part of the controller on the production floor that can be connected to the company's ERP system. Several modern manufacturing companies that have taken advantage of FMS, also still operate manufacturing systems that use conventional machines. For example, conventional lathes and milling machines are used for the preparation of raw materials that will be processed by the FMS. This conventional equipment is located in the warehouse and material preparation division. The information data, the material, and the value creation from this division need to be monitored and controlled.

The problem in this research is how to integrate the planning and production control in a cyber-physical system model which consists of equipment controlled by computer, and some are not controlled by computer. The example of the controlled computer machines is the computerised numerical control (CNC) machines, while the non-controlled equipment is the conventional milling machine. Setiawan et al. [19] proposed three types of sensor, which are the temperature sensor, vibration sensor, and electrical current sensor to monitor the cutting tool condition in the machining process. For further research, Setiawan developed a sensor network in the shop floor to monitor the status of material and work in process. The FMS and the conventional machine require additional sensors, processors and application that can integrate with a smart manufacturing system to interact with other system elements. The application to integrate the system is the Shop Floor Control System (SFCS). The SFCS model in the smart manufacturing system is shown by Zheng et al. [20], which connects the cyber-physical system, local control system and cloud. In his research, Zheng explained that sensor and actuator deployment is needed to retrieve data which is then processed into decision making by big data-driven.

DESCRIPTION OF SYSTEM

The manufacturing system in this study consists of two sub-manufacturing systems, which are the FMS sub-system and the conventional machinery sub-system. Those sub-systems are integrated by a shop floor control system.

The Flexible Manufacturing System (FMS)

The FMS used in this study corresponds to the FMS in Setiawan et al. [21]. The FMS consists of four CNC-horizontal milling machines, a stacker crane, a pallet stocker and two loading-unloading stations. The CNC-horizontal milling machine is equipped with an automatic tool changer (ATC) which has the capacity to store 90 tools. CNC machines are also equipped with an automatic pallet changer (APC), a tool used to take workpiece from the CNC machine buffer to the machining room. Pallet stocker is storage of workpiece on a pallet with a capacity for 60 pallets. The workpiece is mounted on a pallet according to the fixture to be used. To setting up material in the fixture, it is done at the loading/unloading station. FMS construction is reported in Figure 1.

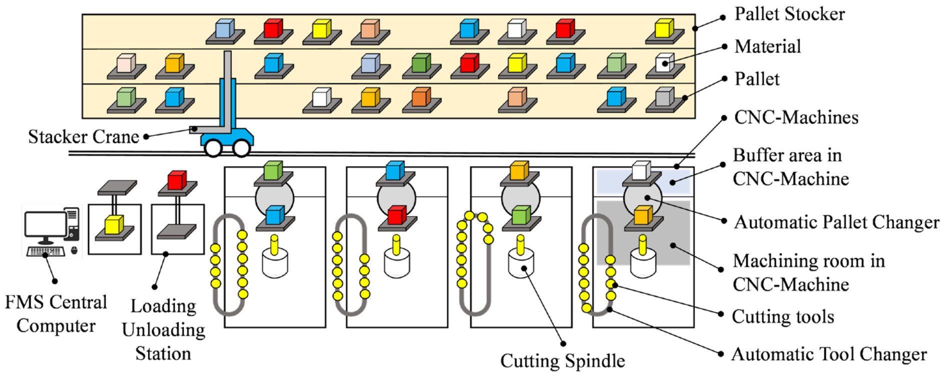


Figure 1. The FMS construction.

In the previous research, the FMS was not equipped with a system to monitor the status of the workpiece. If there is an interference or breakdown in the FMS component, rescheduling was done. Therefore, FMS requires a system that collects information on the workpiece status, whether it is completed, is being machined on or waiting. The other important information is the location of the workpiece, whether it is in the CNC-machine buffer, in the CNC-machined machining room, at the loading/unloading station, on the stacker crane or in the pallet stocker, as described in this problem [22]. For this reason, a Radio Frequency Identification (RFiD) sensor network is needed to detect the work status and location of a workpiece. In the research of Setiawan et al. [21], [22], the production rescheduling should not wait too long for maintenance. The objective function was developed to minimise the makespan, in this case, completion time (C) as explained in the following equations:

$$\text{Min } C_{\max} = \sum_{j=1}^{J} d_{j,m} \quad , \ \forall j, \forall m \tag{1}$$

Equation (1) explains the objective function, to maximise the makespan (C_{max}) in minutes. The makespan is the time, when the latest job (j) in a machine (m) in a batch, as shown in Figure 2. The makespan is the maximum of the total processing time ($d_{j,m}$) of the jobs in a machine (m), where the indices:

j, j' : index for job, where $1 \leq j \leq J$.

m : index for machine, where $1 \leq m \leq M$.

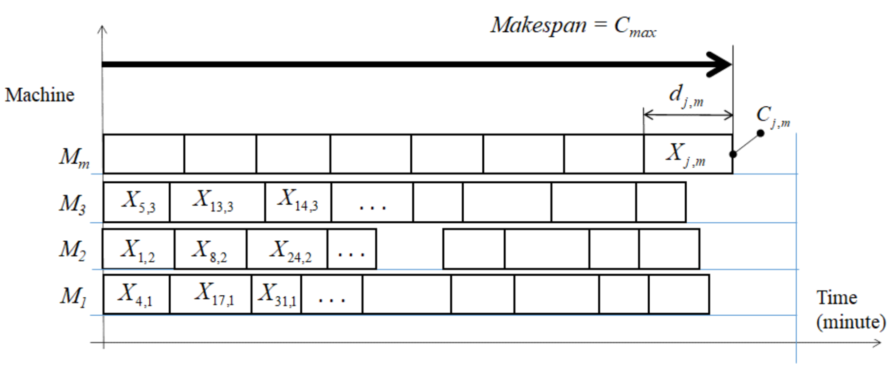


Figure 2. The makespan C_{max} in the production scheduling gantt-chart.

Constraints:

$$\sum_{m=1}^{M} X_{j,m} = 1 \quad , \ \forall j, \forall m \tag{2}$$

Equation (2), explains that only a job (*j*) is processed in a machine (*m*) at the same time, for all job and all machine.

$$S_{j,m} + C_{j,m} \leq X_{j,m} \cdot L \ , \ \forall j, \forall m \tag{3}$$

The constraint in Eq. (3) explains that the starting time (*S*) of a job (*j*) at a machine (*m*) and the completion time *C* of the job (*j*) at the same machine (*m*), must be smaller or equal to the big number *L*, for all job and all machine.

$$C_{j,m} \geq S_{j,m} + d_{j,m} - (1 - X_{j,m}) \ , \ \forall j, \forall m \tag{4}$$

Equation (4) explains that the completion time (*C*) of the job (*j*) at the machine (*m*), must be more or equal to the starting time (*S*) of the job (*j*) at the same machine (*m*) plus the processing time (*d*) of the job (*j*) at the machine (*m*), for all job and all machine.

$$S_{j,m} \geq C_{j',m} - \left(Y_{j,j',m}\right) \cdot L \ , \ \forall j, \forall m \tag{5}$$

$$S_{j',m} \geq C_{j,m} - \left(1 - Y_{j,j',m}\right) \cdot L \ , \ \forall j, \forall m \tag{6}$$

The constraint in (5) express that the starting time (*S*) of the job (*j*) at the machine (*m*) must be started after the completion time (*C*) of previous job (*j*') at the same machine, for all job and all machine. While the constraint in (6) explains that the job (*j*) and the previous job (*j'*) on the same machine (*m*) are processed in sequence and cannot be done at the same time, where *C* is completion time (minute), and *S* is starting time (minute)

$$C_{\max} \geq C_j \ , \ \forall j \tag{7}$$

Equation (7) explains that the maximum completion time (*C*) of the jobs (*j*) does not exceed or equal to the makespan (C_{max}).

$$X_{j,m} \in \{0,1\} \ , \ \forall j, \forall m \tag{8}$$

$$Y_{j,j',m} \in \{0,1\} \ , \ \forall j, \forall j', \forall m \tag{9}$$

where *X* and *Y* variables are the binary number. $X = 1$ means that job-*j*, is allocated on machine-*m*, $Y = 1$ means that job-*j*, is precedes job-*j'* on machine-*m*.

The Cutting Tool Condition Monitoring System

Another sub-manufacturing system is a conventional machine tool to prepare the raw material for FMS. The conventional machine, which is the manual lathe was in different building and the information of material status should be reported. Not only the material status needs to be reported, but the cutting tool condition status must be reported. Therefore Setiawan et al. [19] proposed a model to monitor cutting tool which consist of a temperature sensor, a vibration sensor, and an electric power measuring sensor. The relationship between the data from the sensors and the cutting tool condition is shown in the following equation:

$$R(t) = f\left(T(t), V(t), P(t)\right) \tag{10}$$

where $R(t)$ is the cutting tools reliability function at time *t*. Equation (10) explains the reliability of a cutting tool at time (*t*) has the function of the temperature (*T*), vibration (*V*) and power consumption (*P*) at time (*t*). While the reliability function is related to the Weibull distribution, which is related to the shape parameter (β) and scale parameter (θ); as explained in Eq. (11). If we have the shape parameter (β) and scale parameter (θ), then we could find the mean time to failure (MTTF). The MTTF has relation with gamma function (Γ).

$$R(t) = e^{-\left(\frac{t}{\theta}\right)^{\beta}} \tag{11}$$

$$MTTF = \theta \cdot \Gamma\left(1 + \frac{1}{\beta}\right) \tag{12}$$

While the reliability on cutting tool is related with flank, W_f, and crater wear, W_c,

$$R(t) = f(W_f, W_c) \tag{13}$$

Taylor formulated the cutting tools lifetime, U, as the maximum use of the cutting tool, although it depends on the cutting speed, v_c.

$$v_c \cdot MTTF^n = U \tag{14}$$

where $MTTF$ is mean time to failure of cutting tools which is cutting tool lifetime, and n is a constant.

The Shop Floor Control

The SFCS collects data from the sensors and processed into feedback for production. The collected information is the status of the workpiece and status of the machinery components. Then the SFCS provide the decision for the production scheduling in the real-time. If problems raised, for the example, the cutting tools wear already to the limit or even break, then the SFCS propose a rescheduling. Therefore, the sensor network is necessary for the SFCS. The cutting tool monitor described in the next section of this paper.

MODEL DEVELOPMENT

The manufacturing systems consist of computerised controlled machinery, which is the FMS, and the non-computerised controlled machine, which are the conventional lathes. The data from the shop floor is sent to the SFCS and reported via desktop and handphone. Therefore, the managers and board directors could also monitor the comprehensive status.

To assist quick and accurate decisions making, the operation on the system needs to be processed with an Object-Oriented Modeling (OOM) approach. All elements in a manufacturing system can be considered as objects. Objects that have the same properties are categorised as a class. In this system, there are five main classes, which are the product-class, the machines-class, the cutting tools-class, the loading/unloading stations-class, and the pallet-stockers-class. The product-class has seven attributes, which are the job, stage, operation, the allocated machine, the machine status, the allocated cutting tools in the machines. Whereas, the machine-class, the loading/unloading-class, and the pallet-stocker-class have only one attribute, which is the identity or their respective location. The cutting-tool-class has the attribute estimated cutting tool condition. The classes and attributes of the objects are shown in Figure 3.

To implement a shop floor control system with an object-oriented modelling approach, it requires the software and hardware design. The software or the application should register and save all scheduled products (workpiece) into the database. The information includes the operations of the products, the completing and status of jobs, the RFiD identity numbers, the allocated machines, the queues in scheduled machines. Each operation of the product requires a type of cutting tool and the machining duration time. In the model, we put some RFiDs and microprocessors, which transmit the data by Wi-Fi to the cloud. The data processing is done on the server and partly done on the cloud (cloud computing) by exploiting artificial intelligence methods and machine learning. The locations for the RFiD and microprocessor in the shop floor are described in Figure 4.

The Shop Floor Control (SFC) Model has been developed in a laboratory-scale by utilising the RFiD-readers, which is connected to the microprocessors that could send the data through the internet to the data base. The type of RFiD-reader that has been used is the RC-522, connected with the NodeMCU-ESP8266 microprocessor. The SFC-Model requires many RFiD-readers, which are located on the loading/unloading station, the CNC machines, the conventional machines, and the stacker crane. Another important device is the RFiD-tag to store data, which are the product name and identity, the number in batch, the requirement of cutting tools and the machining duration time, and the allocated machine. The RFiD-tag is mounted on the pallet. Therefore, wherever the pallet goes and detected by the RFiD-reader, the system is known by the SFC-Model. The SFC-Model was built using the Laravel software as the interface and SQL as the database. The design of the interface of the proposed application of the Online Monitoring System is described in the following figures. After logging into the application, the main menu displays several sub-menus, which are:

- the sub-menu to create product data by the RFiD-tag Code,
- the job listings and information,
- the product production schedule on cutting machines and tools,
- the product location information on the FMS,
- the finished product information, and
- the interruption information and rescheduling process.

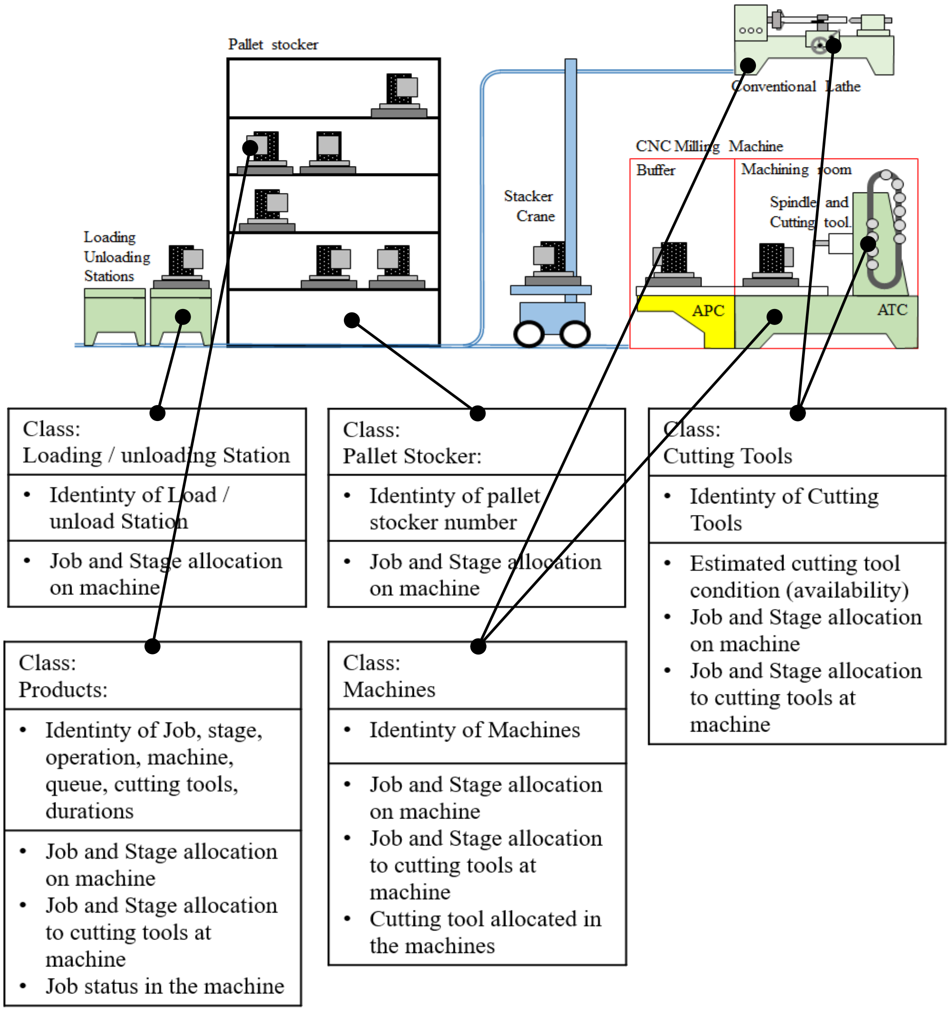


Figure 3. The classes in object-oriented modelling in the shop floor control.

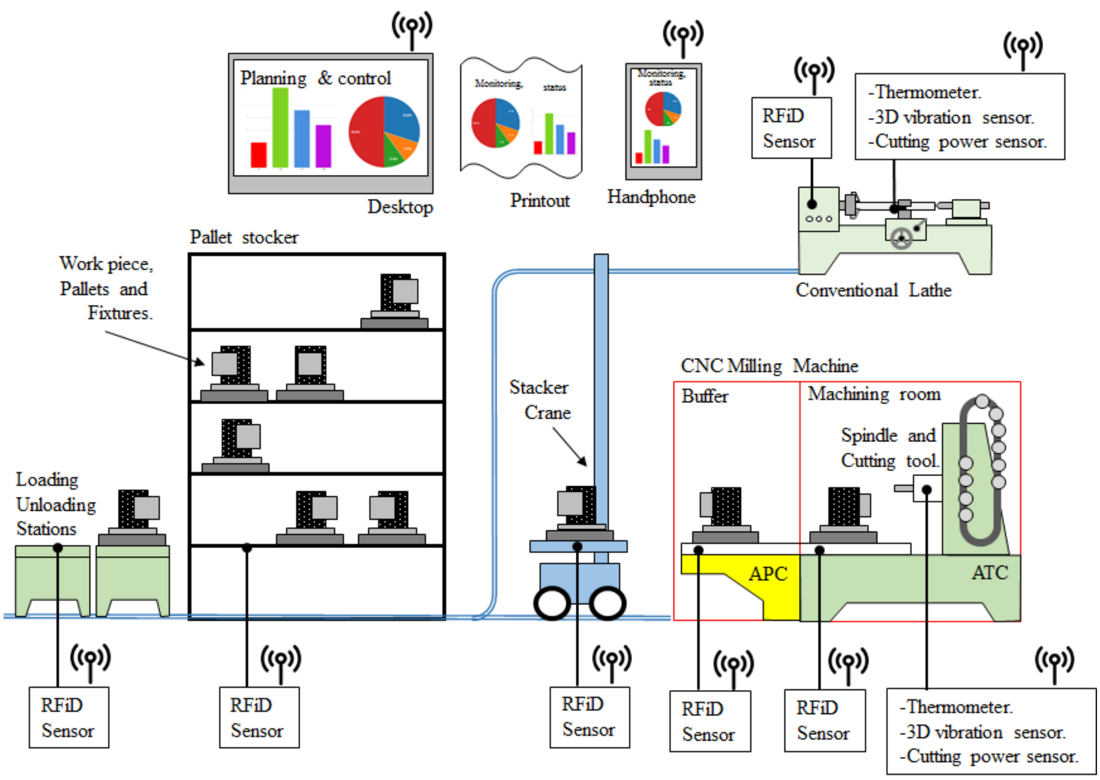


Figure 4. The sensor network in the manufacturing systems.

In addition the product location data, the cutting tool conditions are also provided in the user monitoring system, (in Figure 5 and Figure 6), the graph database, the sensor data table (in Figure 7) and the gauge that shows the condition of the turning tool. The initial production schedule is calculated, referring to Eq. (1) to Eq. (10), as proposed by Setiawan et al. [21], [22]. The next menu is the machine data table that displays the MySQL database such as temperature, vibration sensor in X-axis, Y-axis and Z-axis, energy consumption, log time, and IP address.

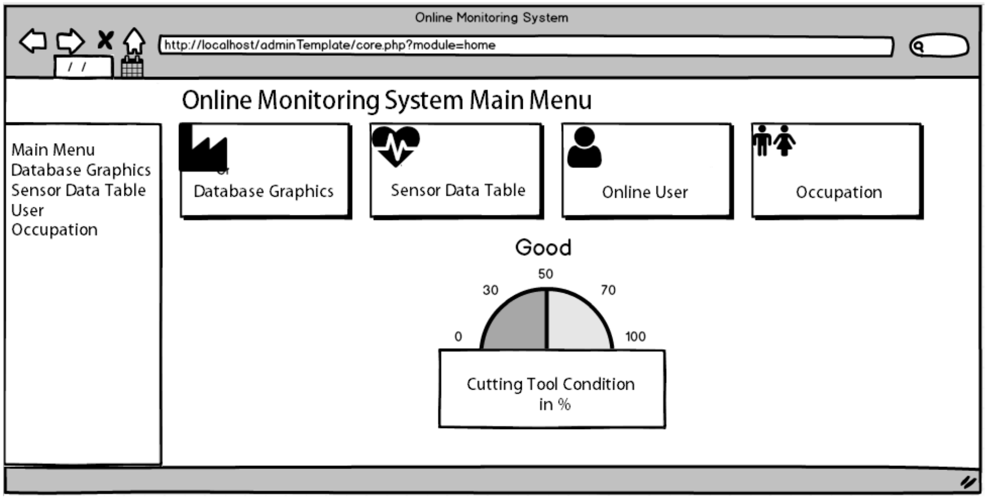


Figure 5. Display of four main menu buttons.

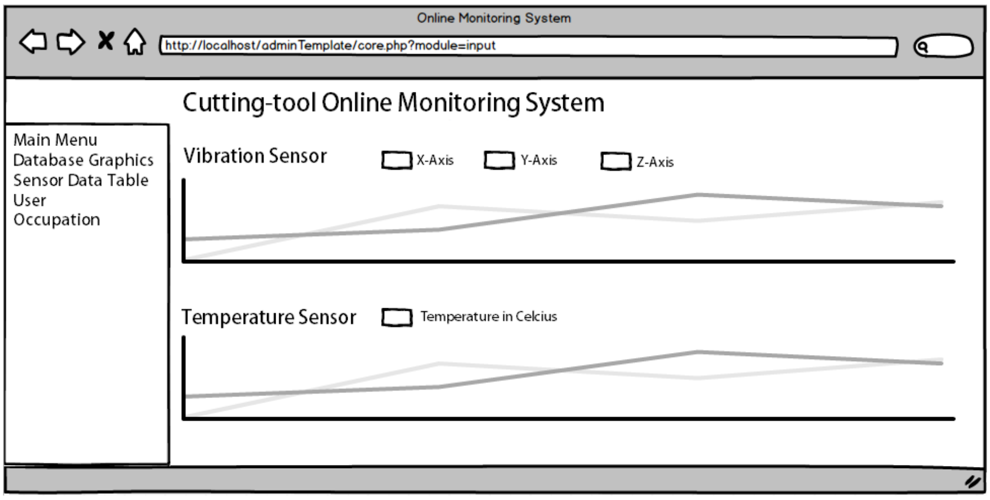


Figure 6. Display of the database graph menu.

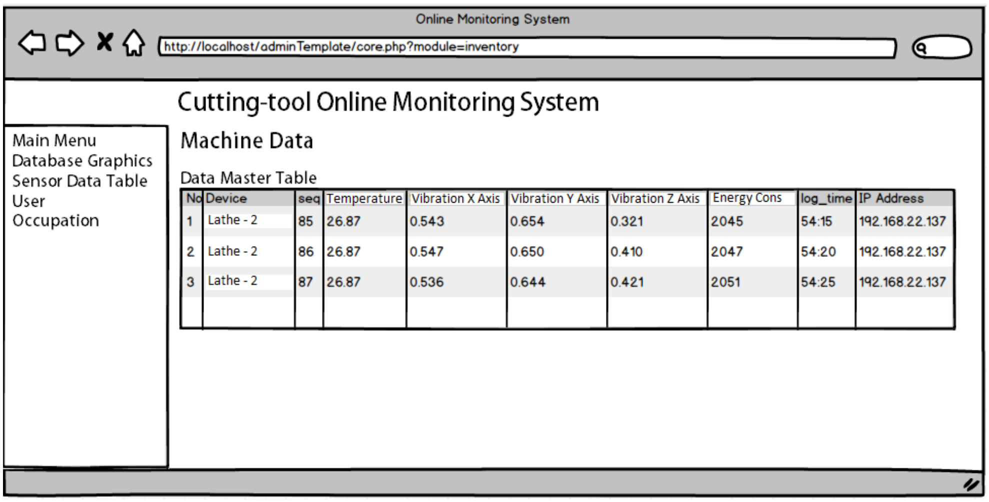
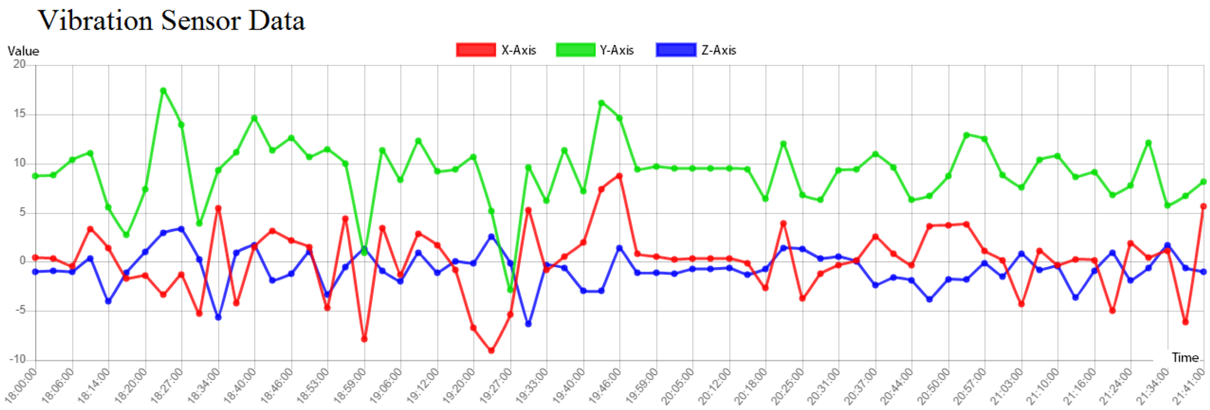


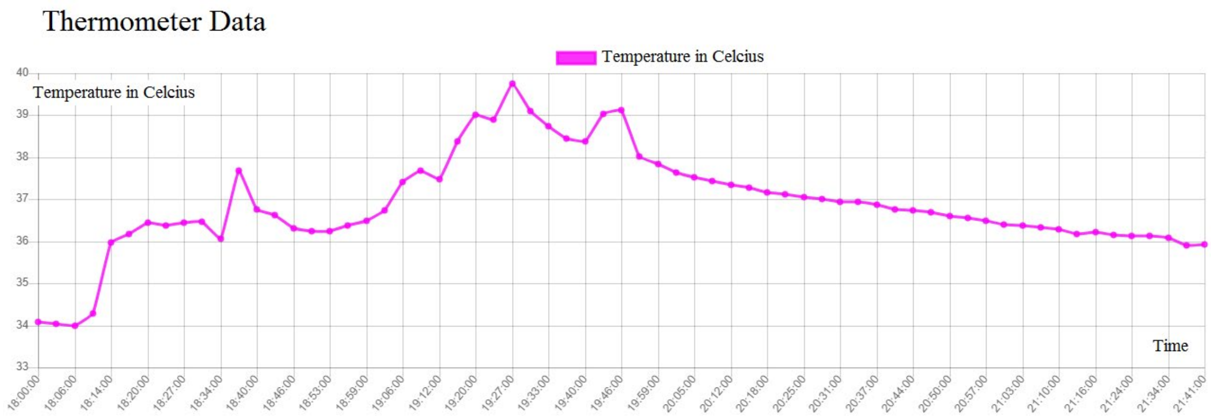
Figure 7. Display of sensor data table.

RESULTS AND DISCUSSION

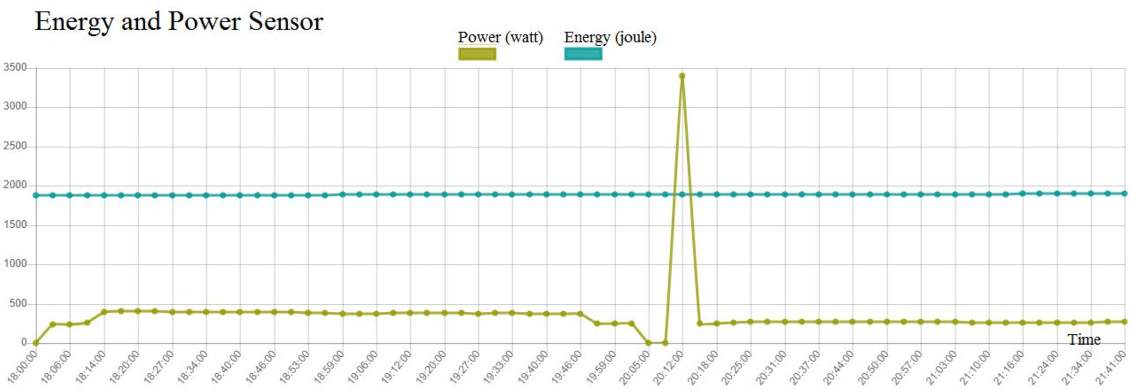
A series of experiments have been carried out, with the first experiment was carried out using wood as a workpiece and high-speed steel (HSS) as a cutting tool material in the turning process. The cutting condition uses deep depth of cut, high cutting speed and medium feed rate. Therefore, the cutting tool gets high vibration, high temperature and require high electrical power consumption. The graphical data is described in Figure 8(a) for cutting tool vibration data. Figure 8(b) describes the cutting tool temperature, and Figure 8(c) describes the energy consumption data.



(a)



(b)



(c)

Figure 8. Graphical data of (a) vibration sensor, in X-axis, Y-axis and Z-axis, (b) temperature and (c) energy consumption.

The test was carried out for six minutes, and the wear that occurs is approximately 0.1 mm. By using Eq. (10) and (14), the increase in the temperature, vibration, and consumption of electrical energy, is correlated to the increase in cutting tool wear, as explained in Setiawan et al. [19].

CONCLUSION AND FURTHER RESEARCH

Based on the analysis of the experiments, it can be concluded that the shop floor control system model could operate properly and has been tested to monitor the location of the workpiece in real time for integrated manufacturing systems. To integrate the planning and production control in a Cyber-Physical System model, it requires sensor network.

i. In this research, the sensor consists of temperature sensor, vibration sensor, energy sensor, and RFiD network sensor.
ii. Those sensors are connected to the microprocessor that provides IoT.
iii. The data is saved in the database and processed by multi-agent approach.

Further research direction in term data processing is provided. The data of vibration, temperature and energy consumption need to process to estimate the cutting tool or the machine components conditions. In addition, the product data and workpiece status data need to be processed into production rescheduling if there is a disturbance in production equipment. This will be proposed for the approach of artificial intelligence and machine learning.

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