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CPS-Based Smart Manufacturing: Integration of Sawing and Punching for Aluminum Profile

L-B. Lin[1*], R. Yang[2], D-B. Zhang[2], H. Qin[2], D-W. Wu[2]

[1] Guangdong University of Technology, Guangzhou, China
996232780@qq.com

[2] Institute of Intelligent Manufacturing, Guangdong Academy of Sciences, Guangzhou, China
{R.Yang , DB.Zhang , H.Qin , DW.Wu}@Giim.Ac.Cn

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Abstract. The work aims to put forward an intelligent manufacturing based on CPS (Cyber-Physical Systems), in order to realize the goal of digitization, networking, high efficiency and fewer people in the integrated sawing and punching production of aluminum profile, improve product quality, and promote the intelligent transformation and upgrading of enterprises. In this paper, firstly by building a smart industry with three-tier architecture: physical devices, network and applications, we proposed a solution based on CPS for aluminum profile production. This solution allows the smart factory to be integrated with other systems, and industrial data information coming from different kinds of industrial control system to be collected together, so as to integrate, exchange and share multi-source heterogeneous data in a closed-loop system. Then, aiming at the sawing machine, we analyze the quality of production process based on data association rule, then we find and control the key factors which cause quality fluctuation, so as to improve the quality in the production process of sawing machine. Then, we use OEE (Overall Equipment Effectiveness) method to calculate the production efficiency and do the experiment. the experimental results are used to verify whether the efficiency of the proposed system and the practicability satisfy the requirements. Finally, the production line capacity efficiency increased by 48.5% and product qualification rate was 99%

Keywords: CPS (Cyber-Physical Systems), smart factory, association rule, OEE (Overall Equipment Effectiveness), quality control

1 Introduction

Under the guidance of "Made in China 2025" strategy, intelligent manufacturing and intelligent factory have become the trend of technology development in the industry. The Cyber-Physical System (CPS) integrates deeply computing, control and communication technology, realizes the deep integration of information system and physical system of production line, creates the information connection between enterprise management and production line, guarantees the production of a "data flow" and realizes the goal of digitization, networking and intelligence in the production of enterprise. It improves the production efficiency and market competitiveness of enterprises [1-2].

Regarding the application of CPS in industry, Chen, Yang, Zhou and Xiang constructed the CPS model of CNC working process according to the massive electronic control data generated in the CNC system during the working process. With this model, intelligent applications such as optimization of CNC processing parameters and health assurance of CNC machine tools are carried out [3]. However, the completeness and the accuracy of the CPS model of NC machine tools constructed by this CPS modeling method based on large data are not high. Chen, Chang and Feng proposed an industrial robot system based on CPS method. The system was divided into physical layer, network layer, control layer and

* Corresponding Author

application layer. It realized data acquisition, communication and control of equipment, task extraction, simulation, optimization and monitoring of robot [4]. However, Chen only built a unit-level CPS to control a single device. They did not realize a system-level CPS composed of multiple unit-level CPS and non-CPS unit equipment to control the entire intelligent factory and to optimize the allocation of resources for the production line [5].

At present, in the process of analysis of production quality of equipment, the key factors causing quality fluctuations are found out and controlled mainly through the experience of engineers. The method of product quality control is determined by sampling for the finished product. These methods lead to low rate of good products and high production cost. Therefore, in the manufacturing process of products, the key problem to be solved urgently for enterprises is to adopt on-line monitoring, diagnosis and optimization methods for parameters and quality indicators in all processes instead of making samplings of finished product [6].

Xu, Zhang, Li and Xu embedded the process control system with CPS quality control module in each manufacturing process of automobile steel and studied the online control system architecture and the control model based on embedded CPS of the product quality [7]. They proposed a data-driven quality anomaly judgment model and an analysis method of quality anomaly causes based on contribution graph to realize on-line dynamic control and optimization of product quality in the whole process. Qu, Lu and Chen designed the discrete manufacturing process based on quality rule mining and analyzed the method to mine the association rules between the processing procedures according to the accumulated quality data of manufacturing process. A monitoring model of discrete manufacturing process based on quality data fusion and rule mining is established to realize intelligent monitoring of manufacturing process [8]. Zhang and Zhou applied the improved AMPHP-SON algorithm to mining association rules of EMU (Electric Multiple Units) operation and maintenance efficiency, and found the important factors affecting the operation and maintenance efficiency of EMU. Furthermore, it supports the optimization of EMU repair system, improves operation and maintenance efficiency, and reduces operation and maintenance costs [9].

In order to realize the goal of digitization, networking, high efficiency and fewer people in the integrated sawing and punching production of aluminum profile. Base on the application researches of CPS method and mining method, in order to establish a high-quality, low-cost and high-output production line for aluminum profile manufacturing enterprises, this paper proposes an integrated sawing and punching production of aluminum profile based on CPS method, and builds smart factory with three-tier architecture: physical layer, network layer and application. Aiming at the sawing machine, we analyze the quality of production process based on data association rule, then we find and control the key factors which cause quality fluctuation, so as to improve the quality in the production process of sawing machine.

2 System Architecture of Smart Factory for Aluminum Profile

CPS integrates the information world and the physical world. The system of smart factory system for aluminum profile based on CPS method consists of physical layer, network layer and application layer, as shown in Fig. 1.

2.1 Physical Layer

Physical layer is the practical operation part of physical process which includes physical entities such as human, machine and objects and devices such as sensors, actuators, interactive device and so on. Machine mainly includes robot unit, sawing machine, punching machine, conveyor belt and AGV (Automated Guided Vehicle) [10]. The sensor mainly includes encoder, photoelectric sensor, cylinder magnetic ring sensor, current sensor and voltage sensor. The controller system mainly includes embedded control system, PLC controller, servo control system and frequency converter control system.

2.2 Network Layer

The network layer connects the physical world and the information world and also establishes the information connection between the application layer and the physical layer. Based on OPC UA (unified

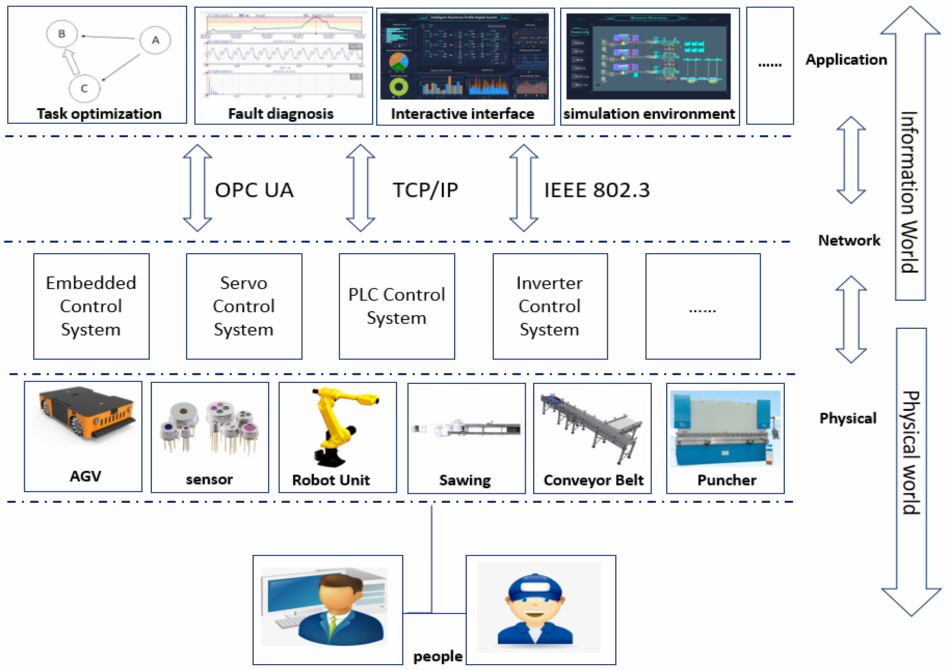

Fig. 1. Three-tier architecture: physical devices, network and applications

architecture), this paper uses industrial Ethernet to realize the interconnection, interoperability and interoperability of systems and platforms, and to integrate, exchange and share multi-source heterogeneous data in a closed-loop system [11].

2.3 Application Layer

The application layer provides system simulation, fault diagnosis, task optimization and decision-making. This paper constructs an intelligent production management system, which can grasp the changes of personnel, equipment, materials, process quality, energy and environment, the real-time implementation and completion rate of production plan, and the life cycle of production equipment.

3 Quality Analysis Based on Association Rules Mining

Association rule mining can extract hidden relationships that affect product quality from the data of equipment in operational processes. Therefore, firstly, we monitor several sawing machines, and record the running status (sensors and parameters of equipment) when this equipment produces unqualified products and we save them to the database. Then, we use Apriori algorithm to mine the important factors affecting product quality from these the database. Finally, the key factors causing quality fluctuations are identified and controlled to improve the level of quality control in the product manufacturing process.

3.1 Data Preprocessing

The method of equal-width (distance) partitioning divide the data of sensors and equipment into four zones. The zoon's width of data is decided according to the data type and corresponding numeric range [12]. For example, the range of federate of sawing machine is 0-20m/min, and the zoon's width of data width is equal. They were divided into four grades. Grade 1: $0 < V < 5m$ / min, grade 2: $5 < V < 10m$ / min, grade 3: $10 < V < 15m$ / min, grade 4: $15 < V < 20m$ / min.

3.2 Frequent Item Set Mining

Apriori algorithm uses an iteration method of searching database layer by layer. Firstly, the counts of each item are accumulated by scanning the database. Then, it collects items that meet minimum support threshold and finds out L1, the item set of frequent item 1. Then, L1 is used to find L2 the frequent item

2, L2 is used to find L3, and iterates in turn until frequent item K cannot be found again. In order to improve the efficiency of generating frequent item sets layer by layer, we use Apriori property to compress the search range by two steps: connection step and pruning step [13].

1. Connection step. Connection step: In order to find L_k, we connect frequent itemset L_{k-1} with itself and find out the itemset C_k which contains candidate item k. We suppose that l_1 and l_2 are the item of the itemset L_{k-1} $l_i[j]$ is the item j of l_i which satisfies $l_i[1] < l_i[2] < \ldots < l_i[k-1]$. The connection L_{k-1} & L_{k-1} is executed. If $(l_1[1]=l_2[1]) \wedge (l_1[2]=l_2[2]) \wedge \cdots \wedge (l_1[k-2]=l_2[k-2]) \wedge (l_1[k-1]=l_2[k-1])$ is satisfied, l_1 and l_2 are considered connectable, and the result item set is: $\{l_1[1], l_2[2], l_1[k-1], l_2[k-1]\}$.

2. Pruning step: C_k is the superset of L_k. To simplify the pruning process by using the Apriori property, any infrequent itemset k-1 is not a subset of the frequent itemset K. Therefore, if the subset of items k-1 of a candidate itemset k is not in L_{k-1}, then the candidate itemset k is not frequent and we can delete it from C_k.

3.3 Generate association rules

After mining all frequent items, association rules are calculated by setting minimum support threshold and minimum confidence thresholds to generate strong association rules. Conditional probability is expressed by item set support degree count, then the confidence degree is calculated as follows:

$$confidence(A \Rightarrow B) = P(B \mid A) = \frac{support\_count(A \cup B)}{support\_count(A)} \quad \textbf{(1)}$$

$support\_count(A)$ is the number of transactions that contain item set A in the quality database.

If condition is satisfied:

$$\frac{support\_count(l)}{support\_count(s)} \geq \min\_conf \quad \textbf{(2)}$$

Then the rule is $s \Rightarrow (1-s)$, $\min\_conf$ is the minimum confidence threshold.

4 Design Realization and Analysis of Result

4.1 Design of Integration of sawing and punching for Aluminum Profile Production Line

4.1.1 Process Flow

The working process of the aluminum profile production line is as follow: aluminum profile raw materials are manually placed on the conveyor line, and steel straps are removed and packages are cleaned manually. After the transvers conveyor detects that the raw materials are in place, the raw materials are conveyed to the feeding area by lifting the conveyor. The gripper of the robot flips the raw materials 180 degrees, and places uniformly the raw materials in turn upward on the high-altitude conveyor. The distributing arm on the high-altitude conveyor places the raw materials on the feeding frame of the sawing machine. The feeding frame automatically locates and tightens the raw materials. The sawing machine automatically conveys the raw materials to the sawing area and completes the sawing of raw materials, and the waste is conveyed to the waste bin through two conveyors. The finished product is transferred to the platform of the length detection machine by the manipulator arm. The length detection machine first locates the product, and then the servo motor to detect the product with distance mode and position mode. If the product is qualified, the next process will be carried out. If the product is unqualified, the mechanical arm will stack the product to the designated bad product stacking area. If three pieces of unqualified products are detected continuously, the sawing machine stops, and alarm signals will be sent to prompt the staff to check and repair it. Qualified products reach the punching zone. First, the product is positioned by the side, and then the robot automatically grabs the product and feeds it into the punching machine for the first punching. After the first punching, the robot places the product on the rotating platform. The rotating platform automatically rotates to change the direction of the product. The robot grabs the product again for the second punching. The waste of the punching machine is conveyed to the waste bin by the conveyor. Finally, the finished product is put into the hole spacing detection platform which uses CCD image recognition to detect product hole spacing. If the product is qualified, the gantry manipulator will stack the product to the good product area, while the unqualified gantry manipulator will stack the product to the bad product area. After the product stacking is completed, the AGV system transmits the product to the corresponding warehouse [14, 16]. The overall working process is shown in Fig. 2.

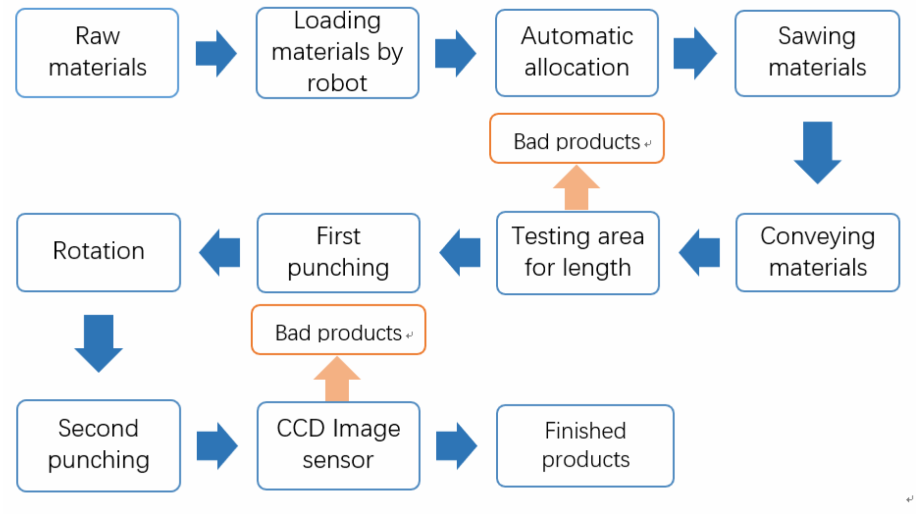

Fig. 2. Process flow chart of aluminum profile automatic production line

4.1.2 Composition of Mechanical Structure

This automatic production line consists of automatic sorting area of raw materials, single robot loading area, double-row conveyor at high altitude, upper and lower distribution arm, automatic sawing machine, automatic aluminum scrap recovery system, detection area of product's length, automatic rotation mechanism, automatic punching machine, automatic double-plate punching robot, CCD hole distance detection equipment and gantry manipulator arm, etc. The whole structure is shown in Fig. 3.

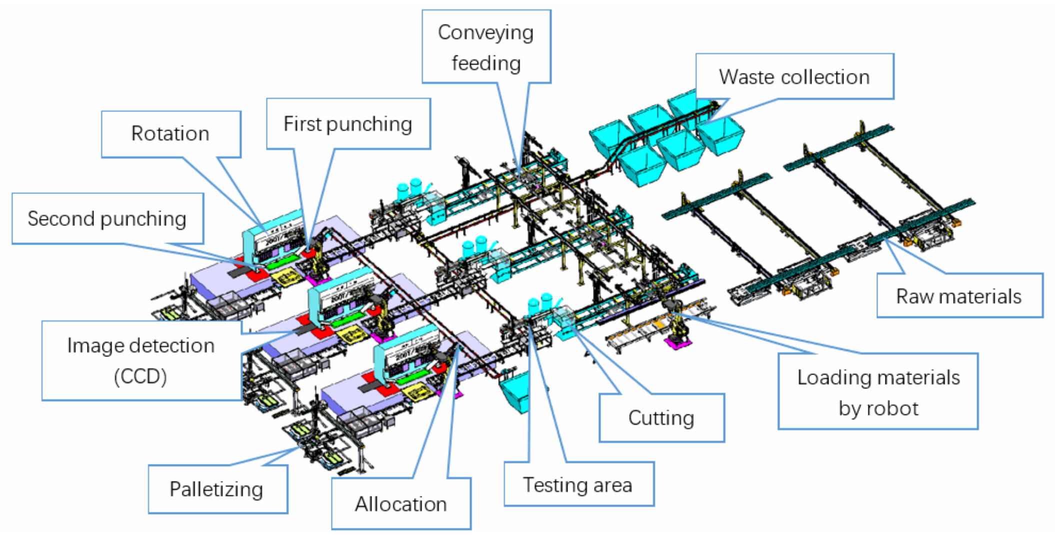

Fig. 3. Overall mechanical design of aluminum profile automatic production line

4.1.3 Design of Electrical Control

Punching and sawing machines are provided by factory. In order to meet the requirements of control, this paper designs a control cabinet for conveying raw materials automatically and three control cabinets for sawing and punching machines of aluminum profile. Mitsubishi Fx5U-80MT/ES PLC is selected as the controller of the control cabinet for conveying raw materials automatically. Five frequency conversion motors, one CC-Link module, one remote IO hybrid module and several cylinders are also selected to realize the function of conveying raw materials automatically to the feeding area. The cabinet for sawing and punching machines of aluminum profile integrates a touch screen of GS2110-WTBD. The controller adopts Mitsubishi Fx5U-80MT/ES PLC to control 8 frequency conversion motors, a 485 communication module, a CC-Link module, seven servo drivers, a remote IO hybrid module, a remote input module, a remote output module and several cylinders. It realized the control function of integrated production of aluminum profile sawing and punching [17, 20]. The principle of control system is shown in Fig. 4.

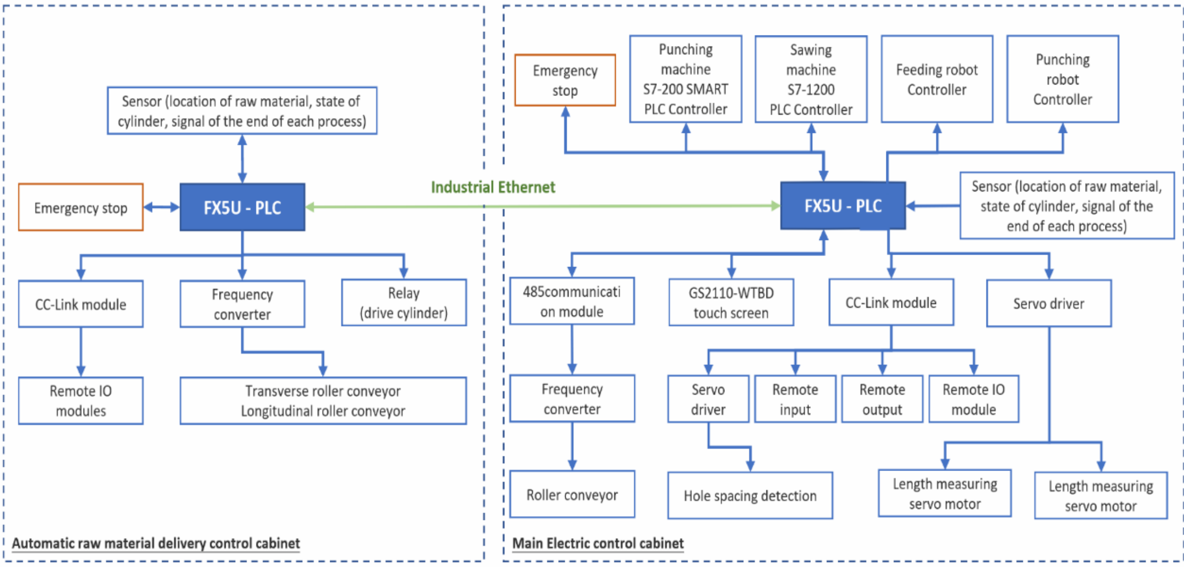

Fig. 4. Diagram of control system

4.2 Design of Integration of Sawing and Punching for Aluminum Profile Production Line

OPC UA provides a comprehensive interaction of information platform which is independent of network facilities (including transmission protocol, information publishing and network services). It could enable efficient communication, collaboration and solve parallel problem among heterogeneous control systems. Based on OPC UA, we use industrial Ethernet to realize the interconnection, interoperability and interoperability of systems and platforms, and to integrate, exchange and share multi-source heterogeneous data in a closed-loop system.

The workshop's main optical fiber network is designed as a separate optical fiber ring network. The three production lines are independent of each other and have no influence on each other. Each fiber-optic ring network is connected to the cloud server in the network center. The structure of optical fiber ring network has the reliability of bidirectional redundancy, so as the main network of network communication. Each production line is regarded as a network node of the main network. The network node of the production line is designed as a star network structure to connect all the equipment in the production line. Each node uses a routing firewall to ensure the safety and reliability of the field network. The network schematic of the factory is shown in Fig. 5.

In order to realize standard communication and semantic interoperability of machine, and to publicly display the complex parameters of machine structure to users, we establish the information model of machine based on the concept of information model of OPC UA, according to the relevant standards and specifications in the field of IoT for manufacturing and automation control, and the requirement of the application scenarios of actual objects. Taking the sawing machine as an example, this paper establishes the information model of sawing machine based on OPC UA [21, 23].

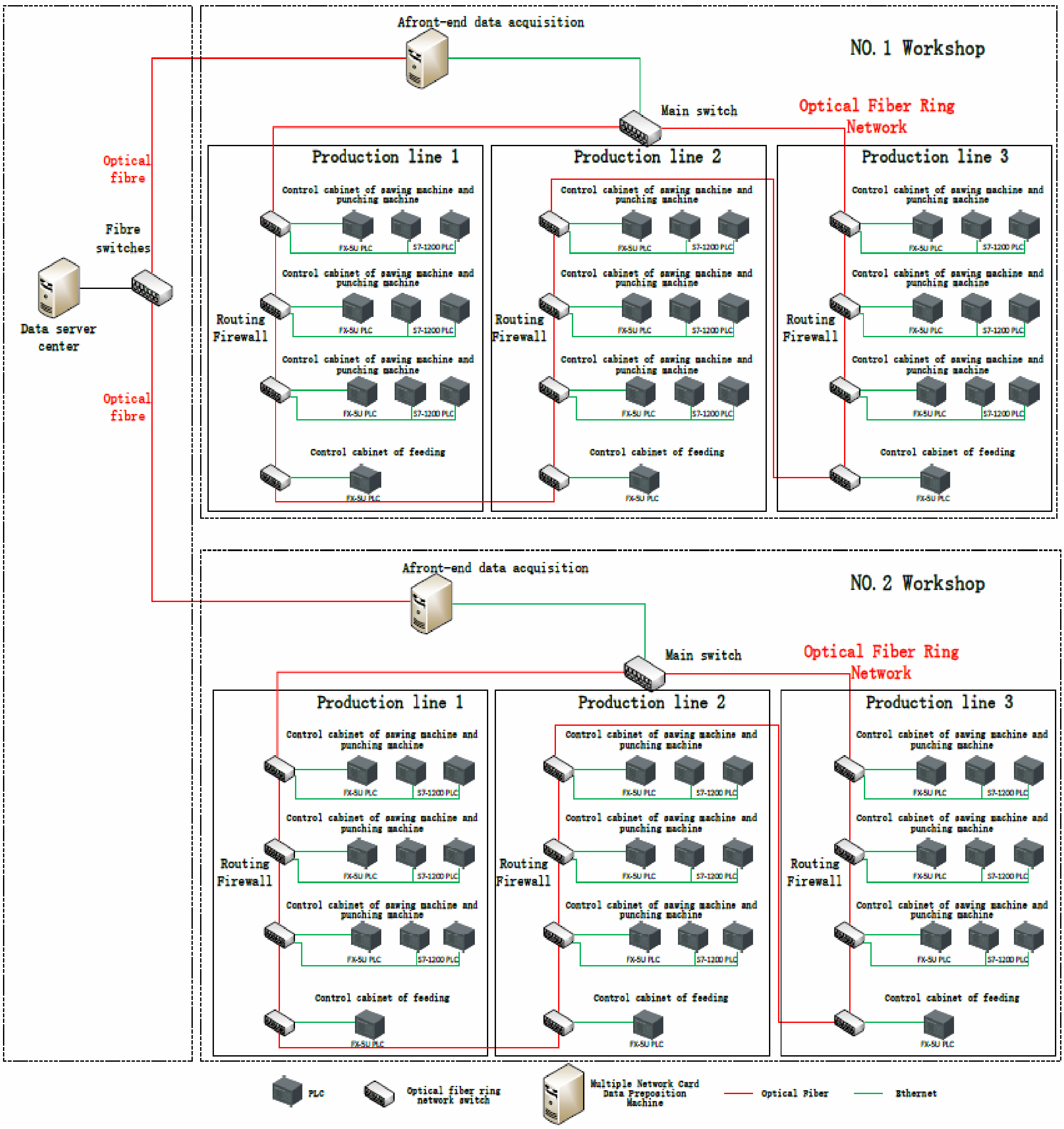

Fig. 5. Network schematic of the factory

Fig. 6 shows the main structure of information model of sawing machine, which mainly includes machine information type, machine status type, power unit type, user information type, job information type and logbook event type. Machine basic information types mainly include basic information such as machine manufacturer, controller type, working voltage, working pressure and equipment size. Machine status types mainly include machine connection status and operation mode. Power unit types mainly include information such as power unit type, speed, power, operation direction and real-time temperature. User information type mainly includes basic information of operating machine employees. Job information type mainly includes basic information of product production and dataset of setting parameters of machine operation process, such as product name, product outline, customer name, cutting length, cutting speed, cutting quantity and so on. The logbook event type mainly includes production parameters, changes of production status and the status of related alarm of sawing machine [24]. The definition of sawing machine information model is shown in Table 1.

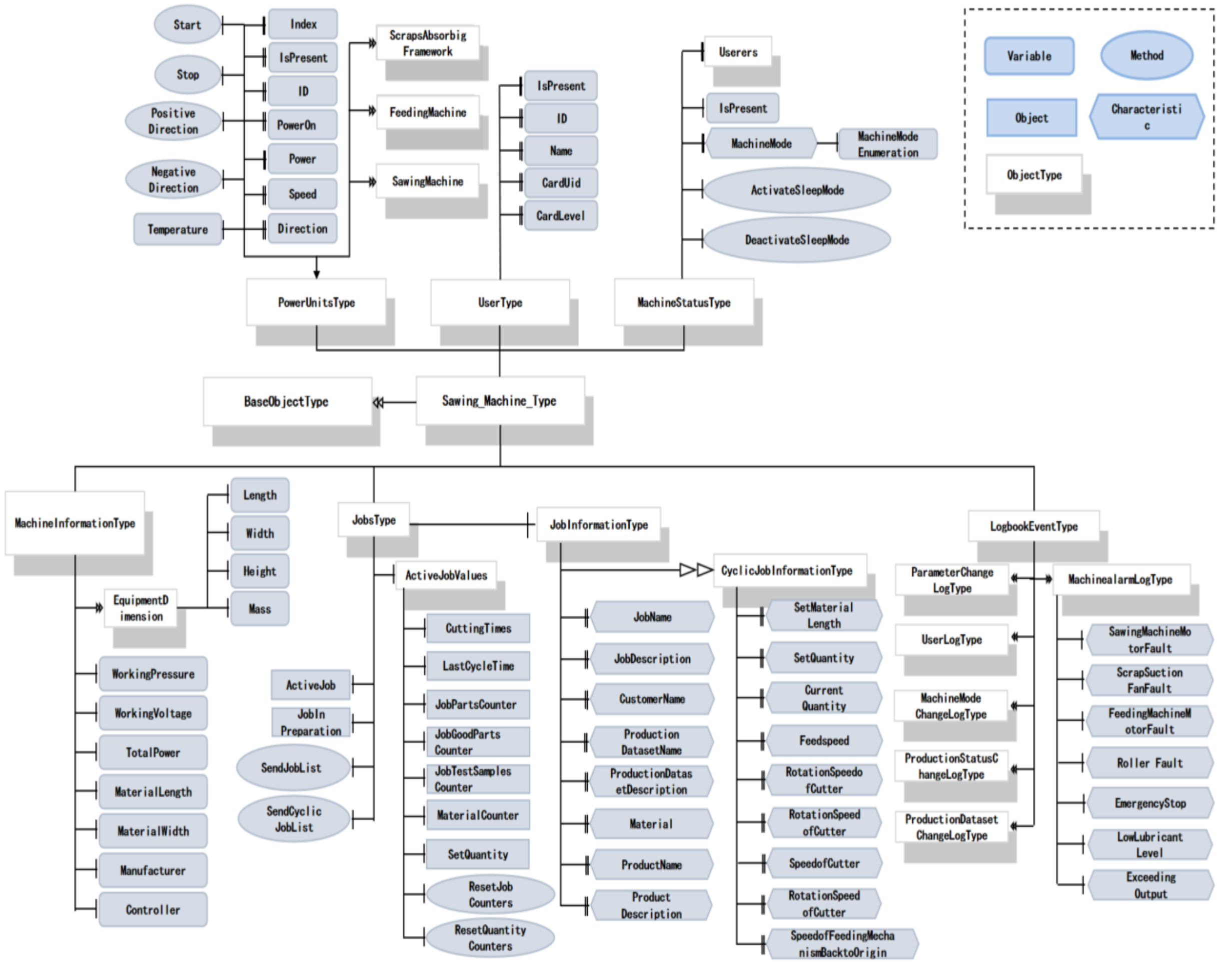

Fig. 6. Sawing Machine Information Model

Table 1. Definition of Information Model of Sawing Machine

Attribute			Value		
BrowseName			Sawing_Machine_Type		
IsAbstract			False		
References	Node Class	BrowseName	DataType	TypeDefinition	Modelling Rule
Subtype of *BaseObjectType* defined in OPC UA Part 5					
HasSubtype	ObjectType	MachineInformationType		Defined in 6.2	
HasSubtype	ObjectType	MachineStatusType		Defined in 6.3	
HasSubtype	ObjectType	PowerUnitsType		Defined in 6.4	
HasSubtype	ObjectType	UserType		Defined in 6.5	
HasSubtype	ObjectType	JobsType		Defined in 6.6	
HasSubtype	ObjectType	LogbookEventType		Defined in 6.10	

4.3 Design of Interface

We use Visual Studio developed by Microsoft to develop a 3D monitoring platform for factory. By integrating ERP (Enterprise Resource Planning) system, production automation system, WMS (Warehouse Management System) and other systems, we realized the visualization and digitalization of product order/batch, material status, production progress, production efficiency, quality information, logistics information, equipment operation and other processes of management. The software interface is shown in the Fig. 7.

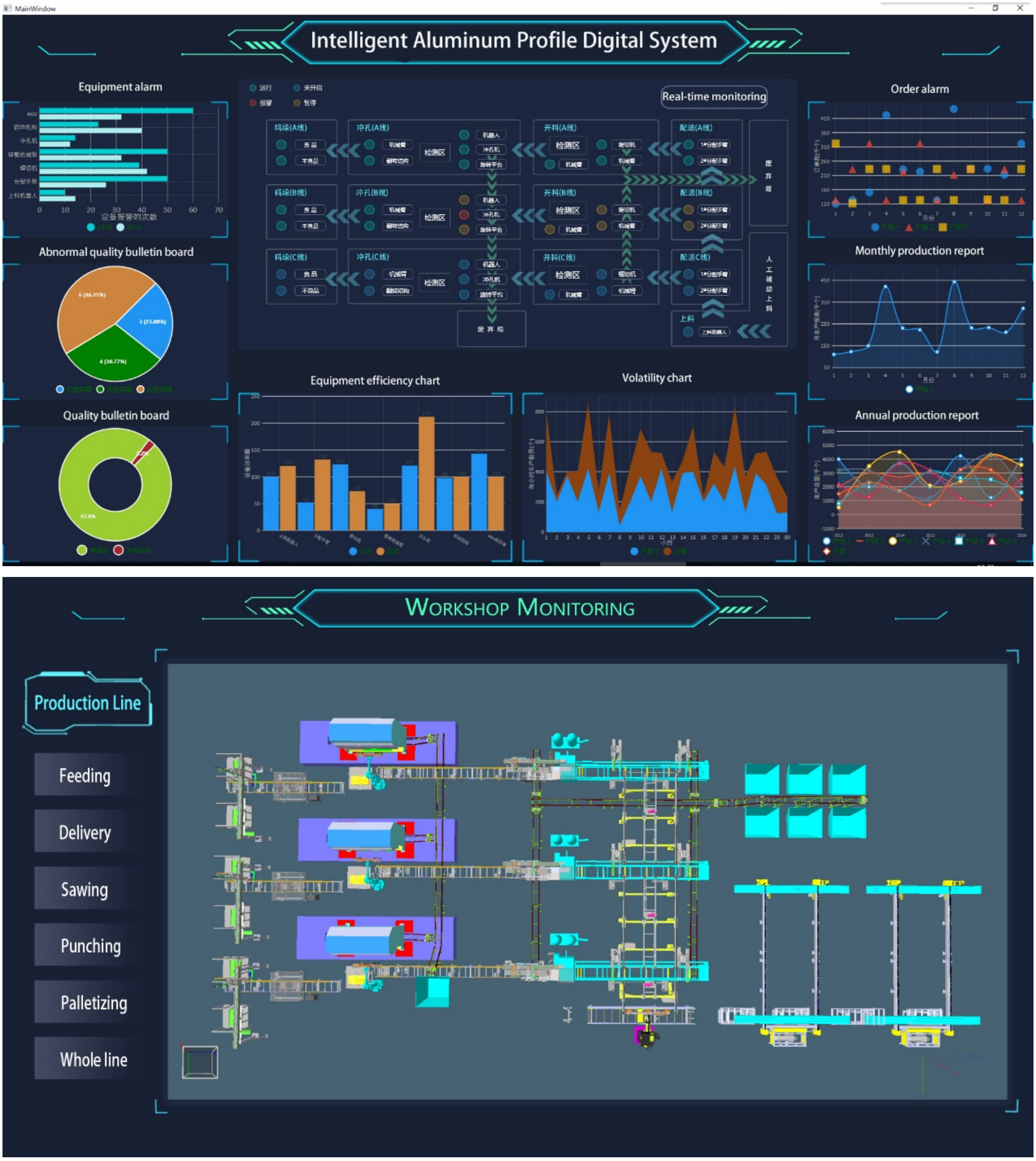

Fig. 7. Design of interface

4.4 Analysis of Quality Relation of Sawing Machine

Experiments were carried out on a PC with a CPU clock speed of 2.8 GHz and a RAM of 8 GB in the period of Nov.2018-Apr.2019. The data including sensor and parameter setting device, came from 12 sawing machines those who produced unqualified products. Minimum support counting threshold min_sup is 5% and minimum confidence threshold min_conf is 70%. Using Apriori algorithm to mine association rules from these data, it is concluded that some association rules affecting product quality are shown in Table 2.

Table 2. The following rules can be obtained

Association rules	Support	Confidence (%)
Sawing blade: using time: level 3; speed of main motor: level 2→ product qualification rate↓	0.072	80.9
Feeding mechanism: feeding rate: level 4; working time: level 3→ product qualification rate↓	0. 055	71.5

(1) When the using time of sawing blade is grade 3 and the speed of main driving motor driving sawing blade is grade 2 in the process of sawing, the qualified rate of products will be reduced. The occurrence rate of samples is 7.2% and the confidence level is 80.9%. The pass rate of products is in line with the practical significance of the rule. When the sawing blade is used for too long, the wear degree of the sawing blade increases, the sharpness degree of the saw blade decreases, the resistance of the saw blade increases when cutting aluminum profile, therefore the speed of the spindle motor driving the saw blade to rotate decreases, which ultimately leads to the reduction of the accuracy of the cutting products, so the qualified rate of the products decreases. The rule indicates that when the sawing time is longer, the sawing blade should be replaced in advance, so as to improve the product quality.

(2) When the feed speed level of the feeding mechanism of the sawing machine is 4 and the level of working time the machine is 3, the qualified rate of the product will be reduced. The occurrence rate of the samples is 5.5% and the confidence level is 71.5%. This rule also conforms to the practical significance, that is, the feeding speed of the feeding mechanism of the machine is faster, and the working time of the machine is longer. As a result, the positioning accuracy of the feeding mechanism is reduced, and the qualified rate of the product is finally reduced. According to the above rules, instruct the equipment operator to set a reasonable speed of feeding mechanism in order to improve product quality.

4.5 The Results of Efficiency of Equipment

After the construction of the intelligent factory for aluminum profile based on CPS method, the intelligent production management system developed is used to visualize and digitalize the production process of the intelligent factory. The factors causing the quality fluctuation of the sawing machine are found out and controlled by the analysis of the production process quality of the sawing machine based on association rules mining, and a six-month experiment is carried out. We record relevant parameters every day, use OEE method to calculate the overall equipment efficiency, and take the average value as the monthly value. As shown in Fig. 6. According to the figure, the efficiency of this intelligent production line is on the rise, and all of them remain above 70%. This shows the effectiveness and practicability of the solution which is based on CPS method.

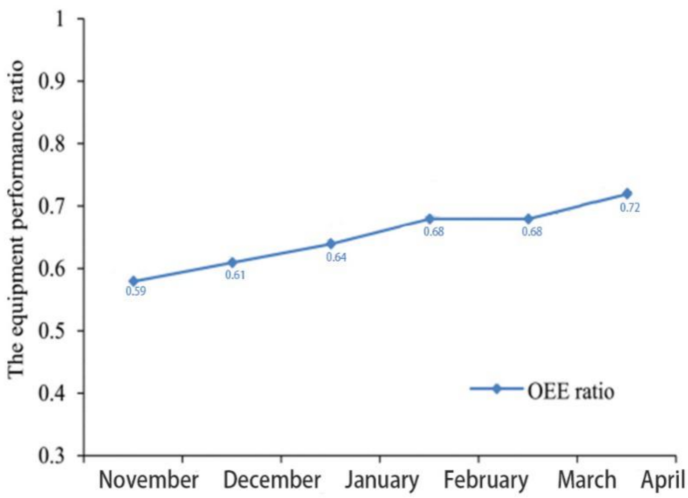

Fig. 8. Design of interface

5 Conclusion

This paper presents an intelligent manufacturing solution based on CPS method. It builds a smart factory with three layers of architecture: physical layer, network layer and application layer. It also builds an intelligent management system of production, which can connect the data flow of each part of the intelligent factory and integrate, exchange and share multi-source heterogeneous data in a closed-loop system. The factors causing quality fluctuation are found out and controlled, and the quality control level in the production process of sawing machine equipment is improved. Based on the theoretical analysis, the production efficiency of equipment is calculated by OEE method, and a six-month experiment is carried out. The final experimental results verify the effectiveness and practicability of the solution and provide an advanced solution for smart factory. Finally, the production line capacity efficiency increased by 48.5% and product qualification rate was 99%.

Acknowledgements

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