Key Technologies of Real-time Visualization System for Intelligent Manufacturing Equipment Operating State under IIOT Environment

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Abstract

In the context of Industry 4.0, real-time fine-grained visualization and fault prediction of intelligent manufacturing equipment is critical for adopting optimal maintenance strategies to reduce total production cost and avoid unnecessary downtime and even casualties. Based on the analysis of the electrocardiogram (ECG) principle of intelligent manufacturing equipment, this paper profoundly studies the key technologies of the Real-time Visualization System (RVS) of intelligent manufacturing equipment operating state. Firstly, the operating state of intelligent manufacturing equipment is the standard to determine the health condition of the equipment, so we define the tolerance value to make real-time judgment on the operating state of the equipment. Secondly, aiming at the outliers in the original data, an improved Rheinda criterion is proposed to eliminate the gross errors in the data. Thirdly, the Baseline value of the intelligent manufacturing equipment operation is the premise of judging the equipment running condition. The correlation analysis is carried out on the processed data, the Baseline model is established and the model robustness is tested. Finally, the robot of vehicle side welding line is taken as an application case to verify the reliability and effectiveness of the system, which provides a new method for monitoring the real-time fine-grained operation and active operation and maintenance of intelligent manufacturing equipment.

Keywords: Real-time Visualization System, Intelligent manufacturing equipment, Fine-grained visualization, Fault diagnosis

1 Introduction

The digitization of the production process is of great significance for improving the industrial ecosystem. Industrial Internet of Things (IIOT) utilizes smart sensors and actuators to enhance manufacturing and industrial processes. Modern factory production automotive welding lines have a large number of intelligent manufacturing equipment. How to manage this equipment and ensure them to perform production tasks safely and reliably is one of the key issues that managers must solve. The advanced state monitoring technology assures timely and accurate acquisition of the information on intelligent manufacturing equipment operation state, and further fault diagnosis [1], providing an important technical method to ensure safe and reliable operation of manufacturing equipment. Intelligent manufacturing equipment is based on the integration of advanced manufacturing technology, information technology, artificial intelligence technology, and other innovative technologies, which reflects the development characteristics of intelligent, digital, and networked manufacturing [2-4]. In the context of smart manufacturing, intelligent manufacturing systems need to meet the requirements of mixed-flow manufacturing mode with small batches, individualization and customization [5]. At present, the operational data collection, analysis and visualization of intelligent manufacturing equipment can effectively reflect the health status of intelligent manufacturing equipment, provide a basis for active operation and maintenance of mixed-flow manufacturing equipment points, and promote the development of a new-generation of intelligent manufacturing system.

In the era of IIOT, production equipment used in the modern automobile assembly industry is developing in the direction of high precision, high efficiency and intelligence. Even a slight performance degradation or security risk in smart manufacturing equipment can have serious consequences. Condition monitoring is an important part of modern equipment maintenance. In general, the performance of a machine or a component will gradually degrade before it fails. Therefore, advanced analysis and prediction techniques can be used to detect and correct incorrectness before a machine or component failure occurs. In recent years,

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scholars at home and abroad have studied intelligent manufacturing equipment from different perspective, and made a lot of science research achievements. In the study of intelligent manufacturing equipment operation visualization, Liu et al. [6] realized a plug-and-play sensor platform for popularization and monitoring of traditional industrial machines using wireless sensors and open source edge devices and software. Few works like [7] proposed a real-time monitoring system based on the production process was. This system had good configurability and scalability and could monitor the process information of various devices in real time. A virtual reality system to study the establishment of 3D models and dynamic monitoring of equipment was proposed in [8]. A general-purpose, three-dimensional text file-driven visualization system was developed in [9], which can display the products of the construction process and evolution in three-dimensional (3D). Since the decision-making process of traditional mechanical equipment fault diagnosis method is not visible, Sand et al. [10] proposed a new 3D visualization technology to analyze and evaluate the assembly process and quality measurement data in the actuator manufacturing process, revealing the correlation between process, energy and quality data to identify events that affect the quality of the final product. A visual monitoring system based on the Internet of Things (IoT) to address the dynamic visualization monitoring problem of a discrete manufacturing process was proposed in [11]. Ren et al. [12] proposed a model-driven interactive information visualization development method - Dasiy, and studied its core technology. In [13], the author proposed a visual classification technique for production and logistics simulation, and outlined how to use this classification technique as the basis for decision support to select an appropriate visualization technology for a specific target group. A visualization method that can monitor the production schedule and equipment status in real time was proposed in [14], which makes production process transparent and facilitating production improvement.

In the study of intelligent manufacturing equipment fault diagnosis, Xia et al. [15] proposed a new two-stage method based on deep neural network to estimate the remaining service life of the bearing automatically. In [16], the author designed a new framework for online monitoring and diagnosis of large-scale systems optimized for plant performance. Aiming at the problem that data fusion method in the traditional fault diagnosis was not accurate enough, and it was difficult to distinguish the fault type with the dimensionless index, a data fusion method based on mutual dimensionless was proposed in [17]. In [18-19], a fault diagnosis method based on the localization of a vibration signal wavelet packet was proposed. Authors [20] proposed and implemented a big data solution for proactive preventive maintenance in manufacturing environment. In [21], the author integrated the proposed intelligent system into the machine's architecture to detect the occurrence of equipment failures and generate corrective actions.

The emergence of the IoT has increased industrial production efficiency and reduced product costs and resource consumption. Since the traditional fault diagnosis method based on signal processing and feature extraction and classifier is no longer applicable to the "big data" in the IoT, Ning et al. [22] designed an intelligent diagnostic architecture for industrial IoT devices, and based on this basis, proposed a fault diagnosis method applicable to IIOT. Cao et al. [23] introduced an image transformation preprocessing method for converting time-domain signals of fault diagnosis into two-dimensional images, and a convolutional neural network (CNN)-based adversarial network structure was designed for faults classification.

Most of the above-mentioned equipment monitoring and fault diagnosis methods are coarse-grained and depend on expert system. In this paper, inspired by human ECG technology, a sub-process of the device operation status in the workshop production process is carefully monitored using the device ECG technology to realize a fine-grained visualization of the current equipment operation state. Also, it is determined whether various functions of the plant equipment are operating normally, is there a risk of downtime, and should certain special actuators (such as cylinders, motors, sensors, and the like.) be replaced. Based on the above characteristics, a real-time, accurate and efficient monitoring and control of the manufacturing process are realized.

The contributions of this paper are as follows. (1) Inspired by human ECG technology, in the aspect of monitoring the operation status and active operation and maintenance of intelligent manufacturing equipment, this paper deeply studies the core motor technology of intelligent manufacturing equipment and the key technology to realize the real-time visualization system of production process. (2) Data preprocessing is a basis for studying the key technologies of the RVS. The original data in the database is grouped according to the baseline value, and the distribution of each data group is analyzed. The improved Rheinda criterion is proposed, and outliers are detected by mathematical statistics. (3) Applying RVS to the body-in-white side welding line, a real-time fine-grained visualization of the welding robot operating conditions is used to demonstrate the reliability and effectiveness of the system.

The framework of this paper is as follows: Section 2 introduces the RVS and its architecture in detail. Section 3 studies the key issues of the RVS, including the data acquisition of intelligent manufacturing equipment operation status, the definition of manufacturing equipment working status, the processing of abnormal values of operation status data, baseline modeling and model test of intelligent manufacturing equipment operation. Section 4 presents the white body side wall welding line which is used as an application case and provides the real-time fine-grained visualization of the welding robot operation status. Section 5 summarizes the conclusions and gives the guidelines for our future work.

2 RVS Architecture

Equipment ECG is inspired by human ECG technology, doctors use an electrocardiograph to detect the corresponding ECG. According to the ECG trends and changes, doctors can effectively determine whether the body organs are in their normal state and whether there is a risk of some disease. Similarly, there is an inherent machine ECG intended for intelligent manufacturing equipment state monitoring [24]. Through the accurate detection and real-time interpretation of this ECG, it can be judged whether the various functions of the equipment are running normally, whether there is a risk of downtime, and whether some special actuators (such as cylinders, motors, and sensors.) need to be replaced in time. The ECG of a smart manufacturing equipment displayed by the RVS is presented in Figure 1.

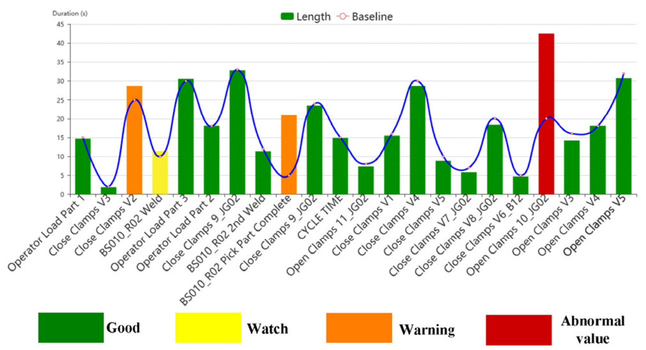


Figure 1. The ECG of the smart manufacturing equipment displayed by the RVS

The blue envelope in the Figure 1 denotes the action timing diagram of the device point. The duration of sub-actions of intelligent manufacturing equipment in each cycle is displayed in the form of a histogram and marked with green, yellow, orange or red, respectively representing good operation, gengeral, warning and failure of the equipent. The histograms are displayed in a sequential view in the ECG, represented a set of loop operations. The abscissa in the ECG indicates the order of device sub-actions, and the ordinate represents the duration of each sub-action. The orange event is the main reason for the elongated beat. When we solve the orange histogram, we can improve the working beat of the device. The red event indicates that the device is faulty or there is a problem with the data collection. In that case, the system issues a warning and needs to immediately check the related equipment to eliminate the fault and reduce the production loss.

The architecture of the RVS is shown in Figure 2. The system is divided into physical layer, data transmission layer, functional business layer and user interface layer. In the physical layer, the device information acquisition module obtains the real-time status data of the workshop site, including the equipment status and processing parameters, the barcode system collects the completion information of the processing task and the status information of the work in process, the manufacturing execution system (MES) pushes production task instructions and logistics instructions in real time, thus forming a real-time and efficient workshop production status information flow. The data transmission layer is responsible for information transfer and data storage. The information transmission is mainly based on Ethernet and Internet, and it combines technologies such as OPC UA (OPC Unified Architecture) to efficiently and securely transfer data in the production process to the functional business layer. In the functional business layer, the information visualization preprocessing module mainly completes the information visualization mapping, including the data link update module, the tree directory acceptance module, and the data analysis module. The production efficiency evaluation module mainly analyzes the theoretical production plan output by the MES system based on the information about field equipment status, work-in-process, and task completion progress, thus evaluating the production status and real-time scheduling optimization of production resources. The user interface layer is for enterprise managers, team leaders, operators, and so on. Users interact with the platform through browser, client and mobile terminals to monitor and manage the entire production process.

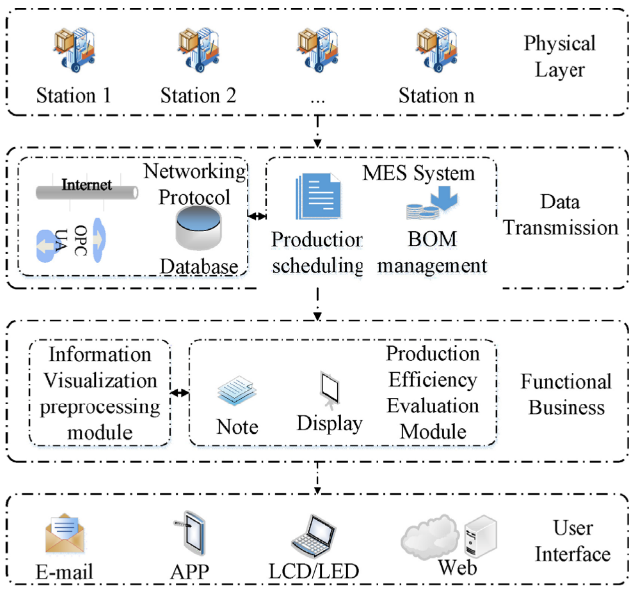


Figure 2. The RVS architecture

Traditional equipment health monitoring techniques require the installation of additional sensors [25-30], and the monitoring status is coarse-grained [31]. This coarse-grained detection can identify a fault only after it has occurred, which means that no signs of device degradation are detected until a critical problem occurs. RVS retrieves the information on each device or operator level from the programmable logic controller (PLC) timely, saving a large number of sensor installations. In addition, the RVS displays various parameters of intelligent manufacturing equipment in a graphical form, visually displaying the operating conditions of the equipment, thus realizing the early warning function.

3 RVS Key Technologies

By monitoring the sub-processes of intelligent manufacturing equipment operation status, RVS can visualize its current running process state or historical data to determine whether the functional modules of intelligent manufacturing equipment are operating normally and whether there is a risk of downtime, some special executive functions (such as cylinders, motors, sensors, and others) need to be replaced in time.

In this section, we study and analyze the real-time visualization system of automobile production process from four aspects: data acquisition of intelligent manufacturing equipment, definition of operating state of manufacturing equipment, data pre-processing and the establishment of Baseline model, and then profoundly analyze the ECG mechanism of intelligent manufacturing equipment.

3.1 ECG Data Acquisition Based on OPC UA and SDN in IIOT Environment

The data acquisition system mainly collects the intelligent manufacturing equipment data in real time, and this information realizes data exchange and information update through a serial interface. Industrial data related to the manufacturing line includes equipment status data, product data, process data, and other data, which includes periodic signals, real-time alarms, device logs, and the like. The assembly data received by each data collection terminal is stored in the database of the data acquisition system, and the enterprise manager can timely access the real-time assembly data of the assembly line site, so as to timely make corresponding task scheduling for the assembly plan. The OPC UA server is applied to the intelligent manufacturing equipment and connected to PLC. Using OPC UA technology, a unified data interface is built to process and transmit device status data through hypertext transport protocol (HTTP), so as to realize a high-speed and reliable acquisition of device detection data. In the C/S mode of OPC UA, the client can obtain information on similar devices in different places and automatically integrate the data provided by the OPC UA server.

In RVS, PLC accesses and summarizes the data collected by each sensor as the OPC UA client, and provides the total operating data of the device to the data processing layer as the OPC UA server. The technical characteristics of software defined network (SDN) transfer control separation meet the requirements of cloud platform-based manufacturing data center server for centralized network control, and enhance the actual configurability and operational flexibility of the data center. The schematic diagram of the SDN interface [32] is displayed in Figure 3.

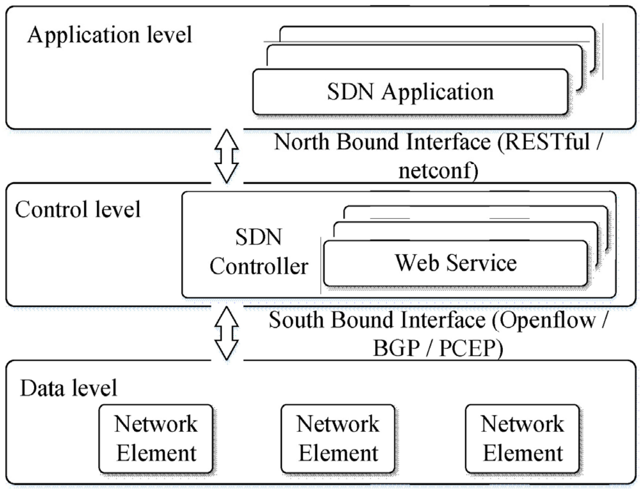


Figure 3. The schematic diagram of the SDN (Software Defined Networks) interface

Representational State Transfer (REST) is a style of distributed system architecture design. In the REST, the entire Web is treated as a set of resources, and the resources are identified by a uniform resource identifier (URI). The operation of the resources is implemented by a combination of the URI and HTTP protocol specified by the client. The cumbersome response process when accessing device resources reduces coupling with other distributed components, making the acquisition system addressable and connected. The RESTful interface is the interface between the controller and the upper application (APP). By using the RESTful standard syntax to represent resources uniformly to simplify the system architecture, which can realize the cross-platform data collection function independent of manufacturing equipment, and the standardized integration of manufacturing systems can be realized quickly. The Openflow interface is a chip-based interface protocol between the controller and the lower transponder [33]. The Open Flow protocol is based on TCP/IP protocol, which is used for the communication between the controller and the transponder. The controller can directly access and manipulate the forwarding plane network device through the Open Flow protocol, which not only reduces the complexity of the control plane, but also increases the programmability and scalability of the network configuration.

Figure 4 shows the RVS data acquisition architecture. The architecture is divided into three layers, namely the application layer, data layer, and mechanical layer. The mechanical layer denotes the device layer, and the data acquisition source includes PLC, distributed control system (DCS), control center, and the like. The middle layer is the data layer, and OPC UA is the general data acquisition module. Its main function is to build the full information model of the device on the manufacturing equipment, and support the embedded information transmission protocol (such as HTTP). The configured data acquisition can be realized through the confrigruation of equipment controllers, field instrumentsand sensors. The top layer of the architecture is the data application layer, and the collected data can be distributed online real-time visual reports.

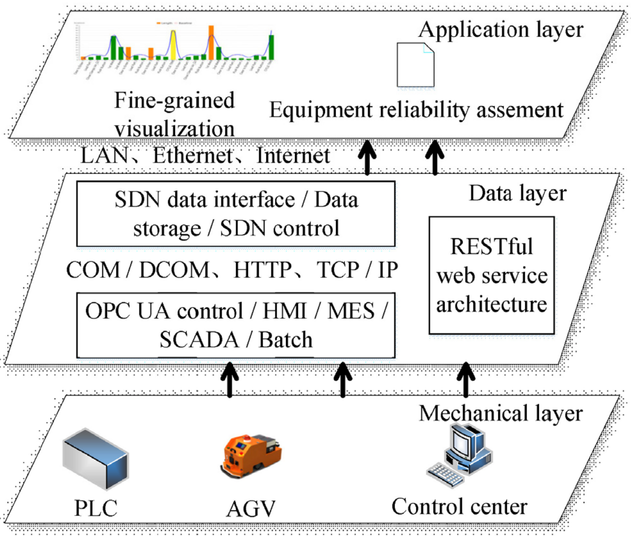


Figure 4. Data acquisition architecture of the RVS

The data acquisition system terminal is installed on each device of the assembly line, and then the network serial port structure is used to realize the information transmission between the data acquisition system and the data acquisition terminal of the assembly line. The collected real-time data is sent to the local area network of an enterprise, thereby realizing data exchange with the MES. The data collection node supports the RESTful web service protocol. On the one hand, the collected I/O information can be captured in real time for data development through polling process; on the other hand, the data stored in the database can be applied to the secondary development through the Restful protocol, or it can be integrated into the MES for production management.

3.2 Intelligent Manufacturing Equipment Working Status Judgment

The operation state of intelligent manufacturing equipment depends on its operation time. Taking the welding robot as an example, the measurement of the working time of a welding robot is related to the task and joint of the robot. Robot movement in three-dimensional space requires not only the ability to track a specified pose, but also to be as smooth as possible, which can not only improve the quality of welding, spraying and other operations, but also prevent the impact of joints and mechanical parts caused by the discontinuous changes of the robot's overall posture.

The robot is programmed and experimented in the simulation software. Under the conditions of satisfying the requirements of welding speed, welding precision, and weld quality, and reasonable settings of the interference zone, the working time standard of the robot welding line robot station is obtained.

In the ECG of intelligent manufacturing equipment displayed by the RVS, the minimum value labeled as DurationMin of the green bar graph and the duration minimum labeled as DurationMax of the orange bar graph were found. By correlating the two columns of data and referring to methods in [34,35], we defined the tolerance ∇ as follows:

$$\vartheta = DuratioMax / DurationMin \tag{1}$$

By a large amount of data analysis and engineering experience, when $\vartheta < 1.05$, the intelligent manufacturing equipment is in good condition, and the corresponding action bar graph of the RVS displays as green (Good); when $1.05 < \vartheta \le 1.15$, RVS action bar graph displays as a yellow (Watch); when $1.15 < \vartheta \le 2.1$, RVS displays the sub-action bar graph as orange (Warning) and needs to check the portion displayed in orange; when $\vartheta > 2.1$, the bar graph of the sub-action in the ECG displays as red (Abnormal value), indicates that the device is faulty or there is a problem related to data acquisition. In this case, system issues an alarm, and the staff needs to check the red event to address the cause immediately. During the running process of the equipment, the fine-grained action diagram displayed by RVS can be used to clearly understand the running condition of the device, saving time for troubleshooting problems. The definition of the operating state of intelligent manufacturing equipment is the key events shown in orange and red bars, which is essential to discover the occurrence law of key events and obtain the relationship model between the key events and equipment failures.

3.3 Preprocessing of Intelligent Manufacturing Equipment Status Data

Data preprocessing is to analyze the existence and causes of "dirty data" within the obtained data, and the theoretical methods are used to transform "dirty data" into "clean data" to meet the data quality standards and application requirements. The main tasks of data preprocessing include the processing of redundant data, the processing of missing values and the detection and processing of outliers. Since the amount of missing data in our dataset is small, we delete records containing "#NAN#" and duplicate redundancy. Outliers affect the statistics results and statistical inferences to different degrees [36]. Some statistical methods are very sensitive to outliers, and individual outliers can result in large changes in statistics and statistical inference results, leading to unreasonable or even completely erroneous results [37]. The use of mathematical statistics to identify anomalous data is mainly based on the assumption of a small probability principle and the measurement error obeying the normal distribution. Common criteria for discriminating anomalous data include the Rheinda criterion, the Grubbs criterion, the Dixon criterion and the Schweiler criterion.

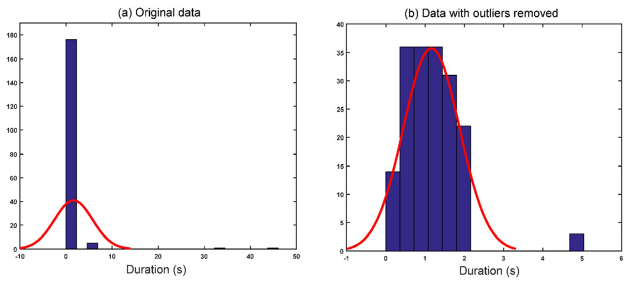
The baseline of intelligent manufacturing equipment vary from one task to another, and the baselines have a large span. Therefore, before detecting outliers, we group the data in the database according to the Baseline, and then analyzed the distribution of each data group. The SPSS (statistical product and service solutions) test results show that the classification data belongs to the positive partial distribution. Therefore, the abnormal value detection is performed by using the mathematical statistics method, so as to avoid the problem that a normal value was detected as abnormal value or an abnormal value was detected as a normal value can be avoided. Since the data samples are sufficient and the number of selected data measurements is much greater than 50 times, the Rheinda criterion is selected to identify outliers in the raw data [38].

In the previous section, it was mentioned that when $1.15 < \vartheta \leq 2.1$, the sub-action bar graph of the RVS was displayed as orange (Warning). The traditional rheinda criterion is to calculate the standard deviation of all the data in an array, and then determine an interval according to a certain probability. The error beyond this interval is the gross error, and the data containing this error should be eliminated. The improvement of the Rheinda criterion is that for $Duration(X_1, X_2, \ldots, X_n)$, the data was grouped based on Baseline value, the mean and standard deviation of each group should be subject to the ceiling of 2.1*Baseline. That is, when calculating the average and standard deviation of each group, the value ≥ 2.1*Baseline shoud be excluded from this array. This will eliminate most of the coarse errors, making the data normally distributed and convenient for future research. Programming in Matlab [39], where ans = find (Duration(:) < 2.1*Baseline), the mean and standard deviation of the arithmetic of ans were calculated as $\overline{X} = mean(ans)$, $u = std(a)$, respectively, and then the root mean square deviation was found by using the Bessel method as $\sigma = (\Sigma v_i^{\,2} / n-1)^{1/2}$. Assuming that v_i conformed to the positive distribution, i.e., the measurement column conformed to positive distribution, the modified Rheinda criterion was based on the following:

$|X_i - \overline{X}| > 3\sigma, X_i$ denotes the gross error and should be abandoned, **(2)**

$|X_i - \overline{X}| \leq 3\sigma, X_i$ denotes the normal data and should be kept.

According to mathematical statistics, when the Rheinda criterion is used to discriminate the outliers and when an error obeyes positive distribution, the occurrence probability of the observation data containing an error greater than 3σ is less than 0.003, that is, the occurrence probability is greater than one in more than 300 observations. When the Rheinda criterion is used for gross error rejection, the confidence is 95%, and the probability of abandonment is small. The proposed Rheinda criterion limits the calculation of the Duration standard deviation and the arithmetic mean to the range (0, 2.1*Baseline), excluding the coarse errors in the original data that do not meet the improved Rheinda criteria. The original data of Baseline 2 and the data processed by the outliers are tested, and the obtained results were shown in Figure 5.



(a) Raw data containing the gross errors

(b) The data after gross errors elimination by the improved Rheinda criteria

Figure 5.

The distribution diagram of the original data is presented in Figure 5(a), and the distribution of the abnormal data obtained by the modified Rheinda criterion is presented in Figure 5(b). The modified Rheinda criterion eliminates the coarse error that does not conform to the rule, verifies the rule validity, and facilitates future data analysis.

3.4 Intelligent Manufacturing Equipment Action Duration Baseline Modeling

Intelligent manufacturing equipment status warning plays an extremely important role in monitoring diagnostic technology to promote enterprises and development of predictive maintenance systems. Reliable warnings can not only ensure the equipment safety, but also reduce the cost of equipment state monitoring diagnostics. A proper setting of the Baseline can improve the working efficiency of operators and ensure the safe and stable operation of industrial production processes.

During an action cycle of a smart device, the device action map displayed by the RVS will display different colors when the device action exceeds the set threshold. The setting of the performance Baseline of intelligent manufacturing equipment needs to be obtained through a large number of mathematical statistics and engineering experience analysis. Inductive statistics are performed on the data after pre-processing, for instance, as for the 2nd weld of the BS10L station on the side wall welding line of the car, the logo completed by the 2nd weld action is weld completed, and the weld completed in the database collected in a certain period of time is performed. Then, we find the minimum value of DurationMin in the green bar and the minimum duration DurationMax in the orange bar. Do the same process for other actions in the same loop. The data with dimensions of DurationMax, DurationMin, and Baseline is obtained. Our goal is to find out the relationship between Baseline, DurationMax, and DurationMin, that is, to accurately fit the Baseline using the values of DurationMax and DurationMin. The OPC UA server is directly connected to PLC, can obtain a large number of device motion data samples, which is beneficial to improve the accuracy of the Baseline model.

The correlation analysis was conducted on the preprocessed data. Pearson correlation coefficient correlation test shows that in the triples DurationMax, DurationMin, and Baseline, the two dominant correlation coefficients are 0.18, 0.09 and 0.114, respectively, indicating that the three columns of data were almost irrelevant. The data of the dimensions of DurationMax, DurationMin and Baseline are nonlinearly fitted, and the DurationMax and DurationMin are the independent variables, and the dependent variable is the nonlinear function relationship of Baseline, which is the mathematical model of Baseline. The fitting results are shown in Figure 6.

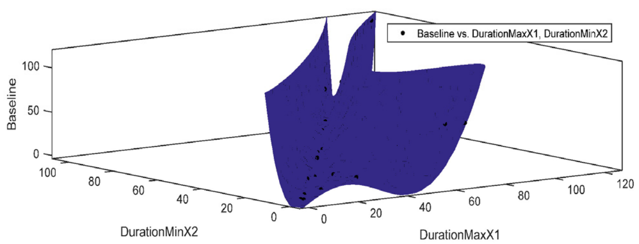


Figure 6. The fitting results of the Baseline model

The Baseline model was defined by:

$$f(x, y) = p_{00} + p_{10} * y + p_{20} * x^2 + p_{11} * x * y + \\ p_{02} * y^2 + p_{30} * x^3 + p_{21} * x^2 * y + \\ p_{12} * x * y^2 + p_{03} * y^3 + p_{40} * y^4 \quad (3)$$

The values of the model parameters are given in Table 1.

Table 1. Model parameters

Par. label	p_{00}	p_{10}	p_{20}	p_{11}	p_{02}
Par. value	-0.51	0.72	0.08	-0.4	0.31
Par. label	p_{30}	p_{21}	p_{12}	p_{03}	p_{40}
Par. value	-0.004	0.027	-0.04	4.9e-05	-0.0004

The goodness of fit test was performed on the Baseline model. The statistic for measuring the goodness of fit is the determinable coefficient R^2, which is also called the coefficient of determination. The closer R^2 is to 1, the better the fit of the regression line to the observation is, and vice versa. At $R^2 = 0.9999$, test results indicate that the model could explain almost all dependent variables. After adjusting the degrees of freedom, the residual squared adjusted $R^2 = 0.9997$, which is close to 1, indicating that the model fitting effect is good.

4 Application of RVS to Automobile Siding Production Line

The side wall is a part of the body-in-white composition and plays an important role in the overall bending rigidity of the body. The Side Frame Line completes the combination of the inner and outer panels of the side wall. On the side wall assembly line, there are inter-station transfer mechanisms, welding fixtures, robot spot welding systems, gluing equipment, automatic conveying machinery, and others [40]. To ensure the synchronization of the production efficiency of the whole vehicle, the left and right sides are welded on the same production line. Figure 7 shows the layout of the left assembly line and the same on the right.

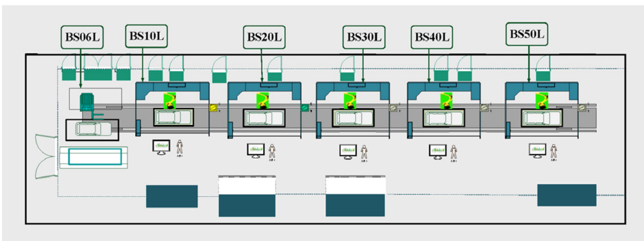


Figure 7. Side body welding line linear technology layout

There are five assembly welding stations (BS10L station, BS20L station, BS30L station, BS40L station, and BS50L station) and one lower line station on the left sideline (BS06L station). The robot station is used as an example to demonstrate the application of the

RVS to the side welding line of the automobile. Each time the robot complets an action, the corresponding action completion logo is written to the controller. The PLC read the robot's logo and its corresponding time from the controller and stores the data in the database. The RVS reads the data from the database and display it in a fine-grained manner.

The real-time visualization of the BS10L and BS20L robot stations movements are respectively presented in Figure 8 and Figure 9. From the figure, it can be seen that the longest sub-action of the BS10L station are Clear to Enter 1, Clear to Enter 2, Clear to Enter 3, and 1st Weld. The most time-consuming action of the BS20L station is Cycle Time. Addressing the orange part in Figure 8 to Figure 9 could improve the production cycle of the production line. The real-time fine-grained visualization effect of BS30L, BS40L, and BS50L stations is the same as the above two stations, so they are not presented here due to the space reasons.

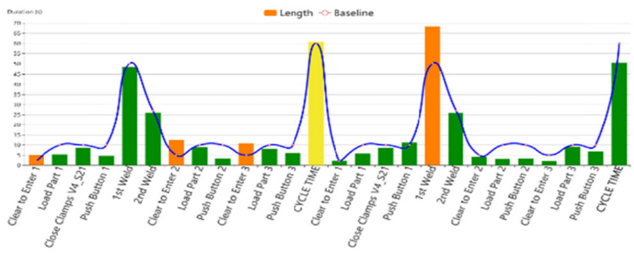


Figure 8. A visual map of the BS10L station

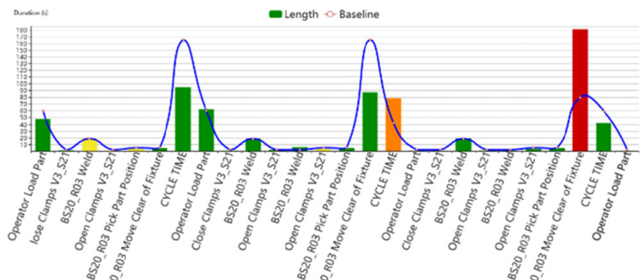


Figure 9. A visual map of the BS20L station

Through RVS, it is found that the beat bottleneck is mainly concentrated in the time of waiting for the EMS in BS10L, BS20L, BS40L, and BS50L stations. The results of the visual analysis of the five stations of the side welding line are given in Table 2.

Table 2. Equipment action statistics

Station (L)	Beat minimum (s)	Beat mean (s)	Metronome standard deviation	Effective count
BS10	131.9	172.5	31.4	1716
BS20	120.4	165.7	32.6	1731
BS30	109.6	114.2	17.9	1731
BS40	121.4	166.3	31.1	1728
BS50	128.5	139.3	17.6	1726
Wait for EMS	-	53.45	94.66	1673

After data analysis, it was found that the minimum value of the beat was ideal, but the average value was too large. Such results were caused by the following: ① robot grabbing parts; ② welding stability; ③ manual upper parts; ④ single cylinder stability; ⑤ cylinder group synchronization. The possible reasons for the instability of the robot catching and dropping parts are as follows: the scraping pin when the workpiece was placed down, the interference zone setting was unreasonable, the gripper chuck opening and closing was not smooth, and the slow response of the sensor on the robot after the workplace was placed. When the robot did not enter the weld in synchronism, there might be an interference zone waiting which was inconsistent with expectation. For the cylinders of the same road gas, it can be adjusted appropriately according to the actual situation to synchronize the movement of all cylinders. The optimization results are given in Table 3.

Table 3. Optimization results

Station (L)	Ori. beat aver(s)	Adjust the pick & place (s)	Upper part optimization (s)	Estimated beat (s)
BS10	172.5	0.5	10	149.8
BS20	165.7	1.5	0	148.4
BS30	114.2	1	0	111.2
BS40	166.3	1.5	0	148.9
BS50	139.3	1	0	136.3
Wait for MES	53.4	0	0	28.5

Simulation was performed on the optimized production line by Flexsim, without adding any hardware points, it is expected that the entire line of Cycle would be upgraded from 172.46 s to 149.76 s, with an improvement rate of 13%; thus, the reliability and effectiveness of the RVS are verified.

By marking the key events which are displayed in orange and red by the RVS, we can get an evolution of the warning component and identify the source of the problem. Figure 10 shows the performance degradation trend of certain intelligent manufacturing equipment displayed by the ECG of the device during a certain period of time. The sub-actions at *Baseline=18* are selected to be displayed in it. As for the other sub-actions, the fractal theory [41] showed that the performance attenuation law of intelligent manufacturing equipment was the same as that at Baseline=18. In Figure 10, the law of the occurrence of key events can be observed, namely, it can be seen that it was possible to carry out effective pre-judgment before the equipment fails and maintain the equipment in advance, thereby reducing industrial losses.

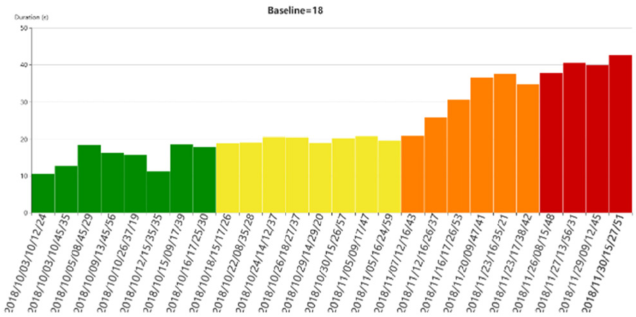


Figure 10. Equipment manufacturing ECG showing the performance degradation trend of intelligent manufacturing equipment

5 Conclusion

In this paper, key issues of active operation and maintenance of intelligent manufacturing equipment, that is how to carry out the real-time fine-grained monitoring of intelligent manufacturing equipment operation status and implement fault diagnosis to reduce industrial losses and even casualties caused by equipment failure, are studied. We introduce the architecture of RVS, compared RVS with traditional monitoring system, and point out the advantages of RVS. Taking the robot station on the side wall welding line of the body-in-white as an example, RVS visualizes 6 stations on the left circumvention welding line with fine granularity. The orange and red events in the ECG of the device need our close attention. The orange event is the main reason for the extension of the production line beat. Therefore, by addressing the orange event, the production cycle of the car sideline can be significantly improved. In addition, red events indicate equipment failure or data acquisition problems, so the relevant equipment needs to be inspected immediately to eliminate faults and reduce industrial losses. The fine-grained visualization of the robot station verifies the reliability and effectiveness of the real-time visualization system in automotive production processes.

The next step is to find out the rules of key events, determine the relationship model between key events and equipment faults, predict the potential faults of intelligent manufacturing equipment with artificial intelligence technology, and characterize the performance degradation process of manufacturing equipment. In this way, preventive maintenance of intelligent manufacturing equipment is carried out to reduce the failure rate of intelligent manufacturing equipment and promote the development of the new generation of intelligent manufacturing system.

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