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Influencing Factors of Machine Utilization Based on Industrial Internet of Things

Xiaobo Fang[1*], Fangxin Zhang[2], Minoo Ghoreishi[3]
[1]School of Business, Xinyang Normal University, Xinyang, Henan,China.
[2] School of Traditional Chiness Medicine, Beijing University of Chinese Medicine, Beijing, China.
[3] Department of Management and Marketing Lombardo College of Business, Millersville University of Pennsylvania, Lancaster, PA, USA.
*Corresponding Author.

Abstract:

The influencing factors of machine utilization in manufacturing companies have attracted more and more attention from scholars and practitioners. Based on the literature of intelligent manufacturing and industrial Internet of Things, this study monitors the accurate time of machine downtime by installing data acquisition modules on 11 gear hobbing machines in the same series, so as to reduce the influence of human factors. Synchronize the data to the computer host of the company’s management information system, so as to improve the real-time performance of production information. Taking the number of downtime caused by various main reasons as the independent variables and the machine utilization as the dependent variable, this study establishes a regression model, and uses multiple regression analysis to explore the relationship between the number of downtime and the machine utilization. The model was tested on 1120 sets of data collected continuously for 121 days. The survey results show that lack of manpower, personnel rest, machine setting and development of new products are the main reasons that affect the machine utilization, and reveal the influence of the various main factors on the machine utilization.

Keywords: *Industrial Internet of Things, Intelligent Manufacturing, Machine Utilization, Multiple Regression Analysis.*

I. INTRODUCTION

Machine utilization (MU) is an important factor affecting production efficiency. How to improve machine utilization has become the main problem faced by enterprise managers. This paper takes a gear manufacturing company (AB Company) in China as the research object. Due to the high purchase cost of gear hobbing machines as the main production equipment and no redundant equipment, the company implements a 24 hours a day, 7 days a week mode of production, and operators take shifts to rest. However, in actual operation, there are many situations where the gear hobbing machine stops production, and there are many reasons for the gear hobbing machine to stop production. Judging from the operation record of the company’s gear hobbing machine in the past 5 years, there are several reasons for stopping production. The first is the human aspect: lack of manpower, personnel rest, and personnel training. The second is the

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aspect of the machine: troubleshooting, tool wear and tear, equipment maintenance. The third is raw materials; material quality problems, the arrival time of raw materials or spare parts are postponed to the agreed time. Fourth, the working methods: changes in the production process, etc.

The feature of smart factory is to use the Industrial Internet of Things (IIoT) to connect the main production equipment to the network, and obtain real-time production data as the basis for analysis and decision-making [1]. AB Company installed data acquisition modules on 11 gear hobbing machines and used the IIoT to connect the machines to monitor the exact time of machine downtime. In addition to saving manpower, the obtained data can be obtained in real time and analyzed in time to avoid untimely information processing. After obtaining the big data of the operation of the gear hobbing machine, the items that can be analyzed have increased a lot without increasing the time and cost of the analysis.

AB Company uses the industrial Internet to synchronously transmit the operation data of the gear hobbing machine to the computer host of the company's management information system to increase the real-time nature of production information. After the gear hobbing machine is connected to the Internet, information sharing can also be achieved between various departments within the company through the ERP enterprise resource management software, which improves the overall intelligence level of the factory.

The purpose of this paper is to collect the big data of production equipment operation as the research basis, combine with intelligent manufacturing theory, and apply regression analysis method to improve MU by big data analysis. This paper studies the time length of the main downtime reasons as the independent variable and the machine utilization as the dependent variable, establishes a regression model, and uses the complex regression analysis to analyze the relationship between the downtime caused by various reasons and the machine utilization rate, and establishes a set of Reduce the factors that cause downtime, shorten the downtime to improve the predictive model of MU. This paper is divided into six sections. The next section provides a literature review. This is followed by research methods, data collection and processing, and the conclusion.

II. THEORETICAL BACKGROUND

2.1 Smart Manufacturing

Smart Manufacturing is a complex system engineering, including the following subsystems: Manufacturing Execution System (MES), I I oT system that integrates virtual production and real production, automated production lines that use intelligent robots to replace traditional manual operations, highly intelligent production line control system, etc. [1]. Smart Manufacturing can shorten the manufacturing time of new products, reduce costs, improve production efficiency and improve product quality.

The manufacturing execution system is the core of smart manufacturing. It applies the Internet of Things technology to provide real-time information on equipment operation, quality management,

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inventory, etc. of the factory. It can effectively meet the needs of customer customization, and timely transmit on-site information in the production process to management information. The system can better control production activities, effectively improve product yield, shorten delivery time, and reduce inventory. It is the best tool for companies to achieve Industry 4.0[2].

The main purpose of intelligent manufacturing is also to strengthen the integration of production data of various units (such as materials, production management, manufacturing, quality control, warehouse management, etc.) between production lines, so as to quickly and correctly grasp the production status. Through the perfect Web network mechanism, the company allows remote decision-makers and on-site managers to synchronize, more effectively monitor production status, quality control and delivery processes, real-time control of production capacity and improve product yield, to achieve production efficiency and customer satisfaction, reduce management costs [3].

The application of big data technology is a key factor for the success of smart manufacturing. The data structure of smart manufacturing is divided into three levels, namely the sensor control layer Connection, the communication layer Commucotion and the decision-making layer Decision. The sensory control layer is the physical production equipment or measuring instrument, through the physical characteristics generated by the equipment or instrument, such as physical changes such as counting, pressure, temperature, flow, etc., the track of the change is recorded through the sensor. The communication layer receives and transmits the signals of the sensor control layer to the database through the WIFI wireless network. The decision-making layer builds and analyzes the collected big data models, and the results serve as the basis for decision-making [4].

There are great differences between smart manufacturing and automatic production. In the past, industrial production emphasized mass production on a large scale and reduced production costs by increasing scale. Therefore, an automated continuous production model was adopted, using single-function equipment and employees with low technical ability to produce standardized products. However, it has encountered the impact of diversified market demand. Therefore, the manufacturing mode has changed to customized, multi-variety production, emphasizing the collection and analysis of equipment operation big data, and carrying out preventive maintenance based on real-time monitoring of equipment status, replacing the past in equipment. Maintenance depends on the operator's experience and judgment, and the equipment is repaired only after the equipment fails and shuts down [5].

2.2 Industrial Internet of Things

The Industrial Internet Of Things (I I of T) is the integration of various acquisition and control sensors with sensing and monitoring functions, combined with mobile communication, intelligent computing analysis and other technologies, and applied to every link in the industrial production process, so as to greatly improve the production efficiency. At the same time, it can also improve product quality; reduce production costs and resource consumption, to achieve the ultimate goal of making traditional industries move towards a new stage of intelligent industry [6].

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The application of the I I o T is to improve the existing infrastructure of the enterprise, the purpose is to improve the intelligence of the equipment, not to replace the original industrial equipment of the enterprise. In September 2017, the "Industrial Internet of Things White Paper" issued by the China Electronics Standardization Institute and others explained the definition of the I I o T as follows. The I I o T is the network interconnection, data interconnection and system interoperability of industrial resources. To achieve flexible configuration of manufacturing raw materials, on-demand execution of manufacturing processes, rational optimization of manufacturing processes and rapid adaptation of manufacturing environments [7].

Tong et al. proposed an industrial Internet of Things architecture based on cloud computing, and designed a system for remote automatic monitoring of the operation status of industrial boilers [8]. With the continuous development of technologies such as 5G, NB-IoT, eMTC and uRLLC, it has brought new technical support to the I I of T [9]. The Mercedes-Benz factory transformed a smart assembly line using the I I o T, hoping to obtain real-time data and information flow for data feedback for quality control and improve the quality of vehicle assembly production [10]. Shuxing developed and designed a motorcycle endurance test intelligent control and management system using the I I o T, providing remote real-time monitoring of the entire test process, timely prediction of control deviations, instant fault perception, fast intelligent processing, automatic recording, storage and statistical equipment various functions such as operating data and fault data [11].

In the machinery manufacturing industry, production efficiency can be improved through the I I o T. GB Corporation, a Chinese automobile manufacturing corporation, produces performance through a series of value processes. The higher the degree of informatization, the better the efficiency of the process. Through the degree of intelligence, sensors are added to the production equipment, and the production process is optimized through the collection of production data, and the sore points are analyzed for improvement. 10 years ago, GB Corporation used a lot of automated production equipment, which can produce 24 hours a day. When the production scale continued to expand 5 years ago, it began to introduce an intelligent production model, install sensors to collect machine operation data in real time, and use the I I o T. The data is transmitted to the company's management information system for analysis, and the results are used as a reference for decision-making [12].

III. RESEARCH METHODS

3.1 Research Process

The research is mainly divided into three steps. (1) The digital transformation of the gear hobbing machine is to install a data acquisition module in the machine and connect it with the computer of the company's management information system through the Internet of Things to obtain the real-time and accurate operation information of the gear hobbing machine. (2) According to the rules of the company's previous shutdown records, organize and classify the read data. (3) A mathematical model is established, and the model parameters obtained by the complex regression analysis are used as indicators of the impact of downtime. (Maheswari, et al., 2020) [7]. (4) Compare and analyze the regression model results with the downtime results manually recorded before the equipment retrofit.

3.2 Data Acquisition

Before the digital transformation of AB Company, when the gear hobbing machine failed and stopped, it could only rely on the on-site operators to manually remove the fault, and after the fault was eliminated, the total time of the downtime was reported to the company's management information system by manual input. Through the management system of manual input information, it is impossible to accurately record the time of each machine downtime and the number of downtimes per day. Therefore, the original management information system cannot analyze the cause of downtime.

3.2.1 Data acquisition module

In this paper, the same series of gear hobbing machines are selected for data collection. We have made substantial changes to the internal circuits of these machines, as shown in Fig 1. To get a more accurate picture of downtime, we installed a data acquisition I/O module (WF-2051) on the machine. WF-2051 is a 16-channel digital input module with a 32-bit counter. Its wireless connection is compatible with IEEE820.11b/g. Compared with the wired connection to read the signal; the method of wireless transmission is relatively comparable.

It is simple and can effectively save space and avoid over-complex physical lines. With the popularization of 802.11 network facilities, the WF-2051 module can monitor the operation of the machine more effectively.

Fig 1: Internal wiring of gear hobbing machine

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After we installed the data acquisition I/O module (WF-2051) on the gear hobbing machine, the module continuously receives the signal from the machine to monitor the operation of the machine. We connect a wire from the hobbing machine to the module. When the machine is turned on, it will continue to output 24 volts of current to the module, as shown in Fig 2 and Fig 3; when it stops, the machine will stop outputting 24 volts of current; When the machine restarts, it will re-output 24 volts to the module. We determined that when the module receives 24 volts of output current continuously, it means the gear hobbing machine is running; on the contrary, when the module does not receive 24 volts of output current, it means that the gear hobbing machine stops. We also use the same principle to connect an external wire to the clamping jaw of the hobbing machine, so whenever the clamping jaw moves, the hobbing machine will output 24 volts of current to the module, and we use this signal source as a record of the workpiece processed by the hobbing machine data. Because the hobbing machine can be in an idling state, that is, running without machining parts, two signals are needed to confirm the working state of the hobbing machine.

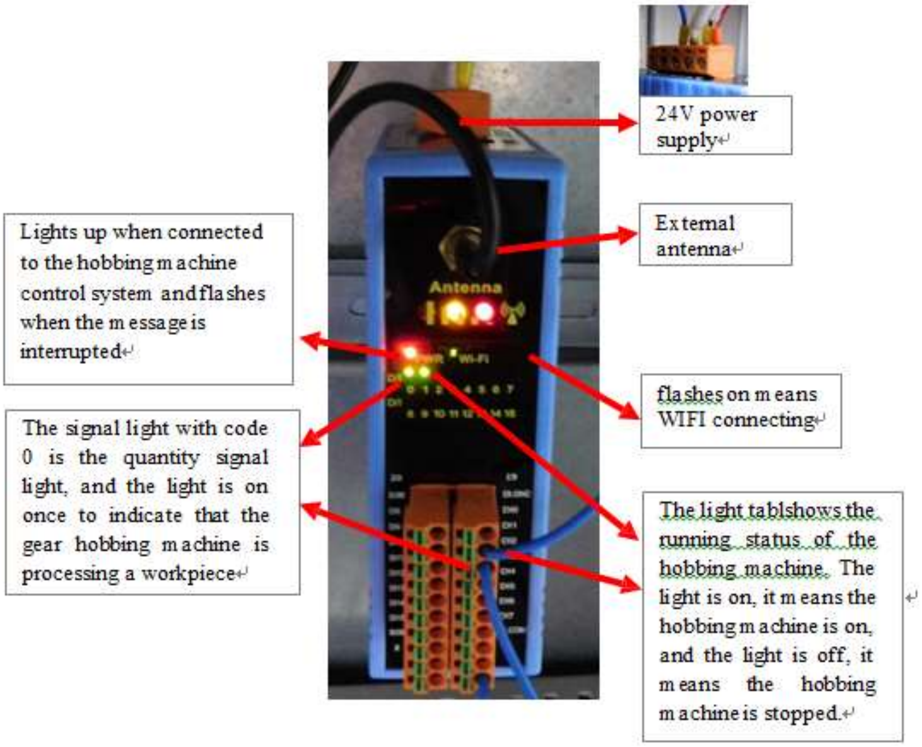

Fig 2: WF-2051 module and machine connection

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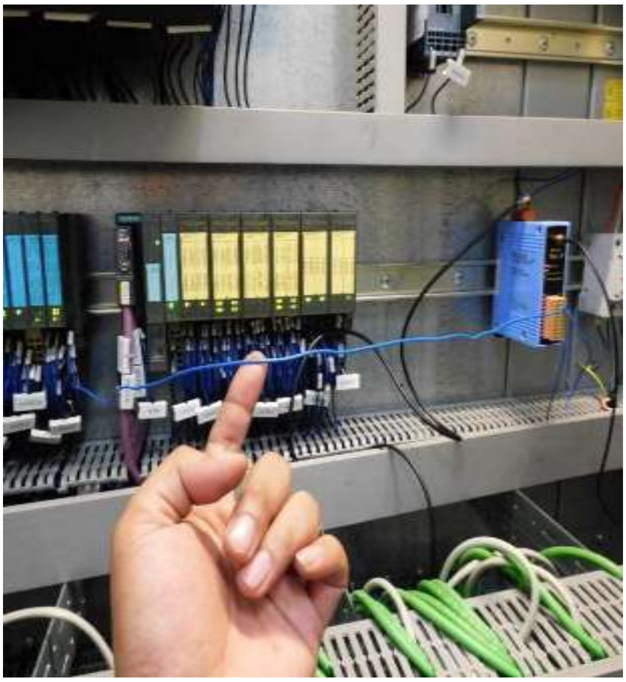

Fig 3: External wiring from the internal I/O module of the machine to the WF-2051 module

3.2.2 Data transmission and reading

After the WF-2051 module effectively receives the signal from the machine, we transmit the signal collected by the module to the company host in real time through the wireless network (Wi-Fi) to realize the transmission of Machine to Machine (M2M), and the machine The information produced by the station is directly transmitted to the computer host of the company's management information system, which greatly reduces the impact caused by human factors during data collection and transmission. How it works is shown in Fig 4.

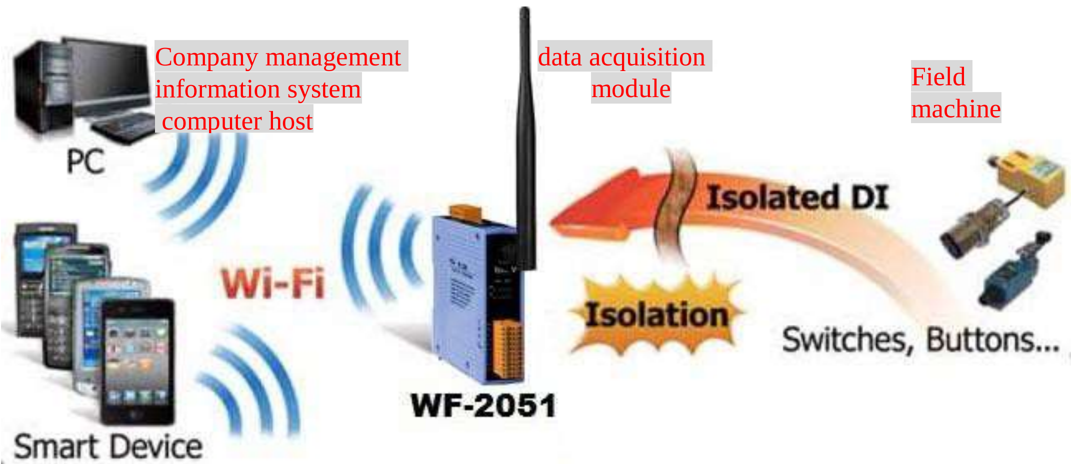

Fig 4: Module Operation Flow

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On the computer host interface of the company's management information system, we use AdVieW software to connect with the WF-2051 module. When the gear hobbing machine sends a signal and outputs it to the WF-2051 module, the module uses the WiFi router to transmit the read signal data to AdVieW, and then assists us in summarizing the machine's signal by setting the AdVieW receiving method.

After entering the interface of AdVieW, we use the communication channel to set the IP address of the target hobbing machine and the receiving host. The interface is set as shown in Fig 5. First Alias is the name of the target gear hobbing machine, and Driver Name and Port are using Modbus communication protocol, and then set Timeout: 500ms, Retry: 1, Sleep: 1sec means that if the system is offline within 500ms, it will automatically Reconnect once, if you can't connect, wait for a second and then reconnect again. Finally, the Remote IP is the IP address of the target hobbing machine and the WF-2051 module corresponds to each other, and the Local IP is the IP of the host receiving the signal.

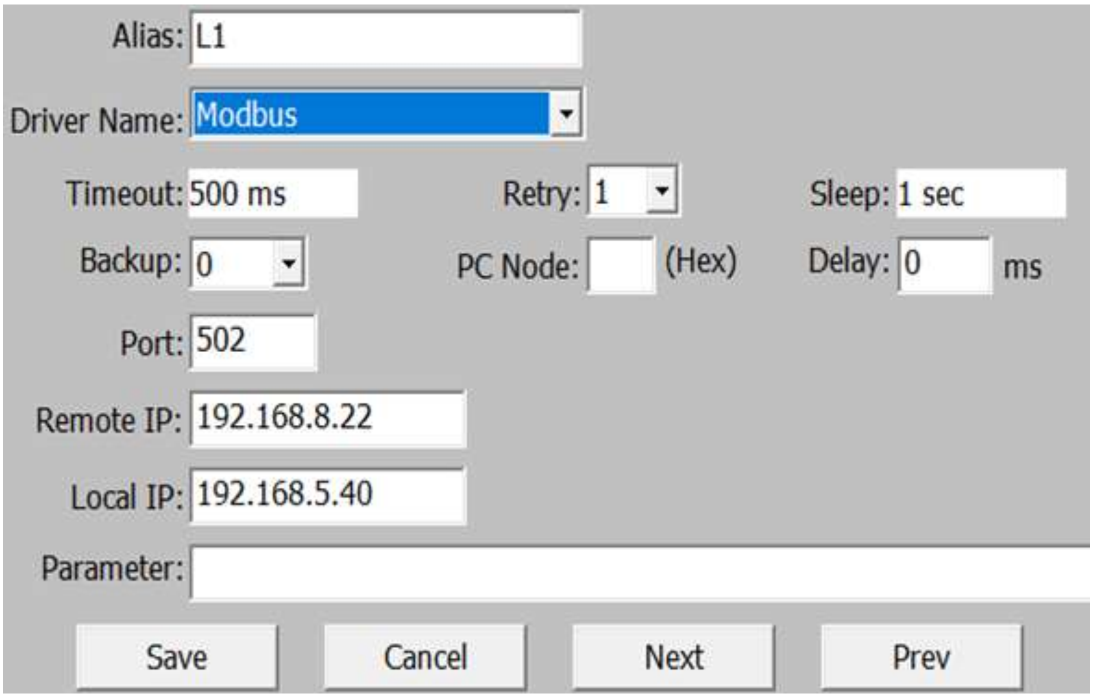

Fig 5: AdVieW initial setting interface

Then we set the received signal, as shown in Fig 6. First, enter the name of the hobbing machine in the Unit Name, after entering the channel in the Channel, then we refer to the DI Address given by the WF-2051 module to set the I/O Address, and finally we set 400ms in the Scan Time, which means that every 400ms will be received Once the signal of the WF-2051 module, and add a DI input point.

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Fig 6: Receive signal setting interface

Then we set the newly added DI input point, as shown in Fig 7 and Fig 8. According to the settings of the data acquisition module in the previous section, we set the No. 1 signal source as the processing number (WorkPiece), and the No. 2 signal source as the gear hobbing machine operation (RedLight). In the setting interface of WorkPiece, since the Level of Off Label is set to 0, the light off does not mean any meaning, and when the system receives an On signal, it means that the light is on once, and it also means that the hobbing machine has completed a processing. On the other hand, in the interface set by RedLight, the Level settings of On Label and Off Label are both 1, which means that the system receives both On and Off signals. When the light is on, it means that the hobbing machine resumes operation, and when the light is off, it means that the hobbing machine has stopped.

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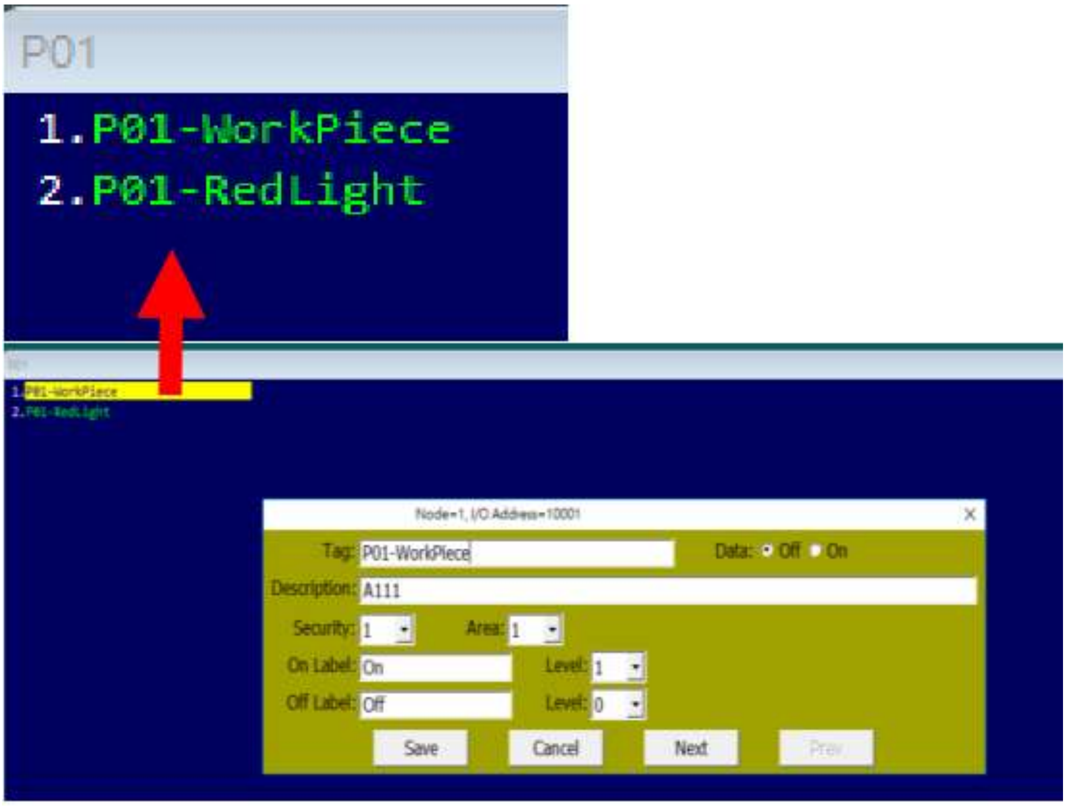

Fig 7: Analog signal input setting

Fig 8: Machine operation signal setting(On once to start operation, Off once to stop operation)

Finally, let the machine work and enter the AdVieW page to observe whether the machine signal is received. The result is as shown in Fig 9. As shown in the Fig 9, the system is continuously receiving the information collected by the module according to our settings, which means that the data collection and receiving settings have been completed.

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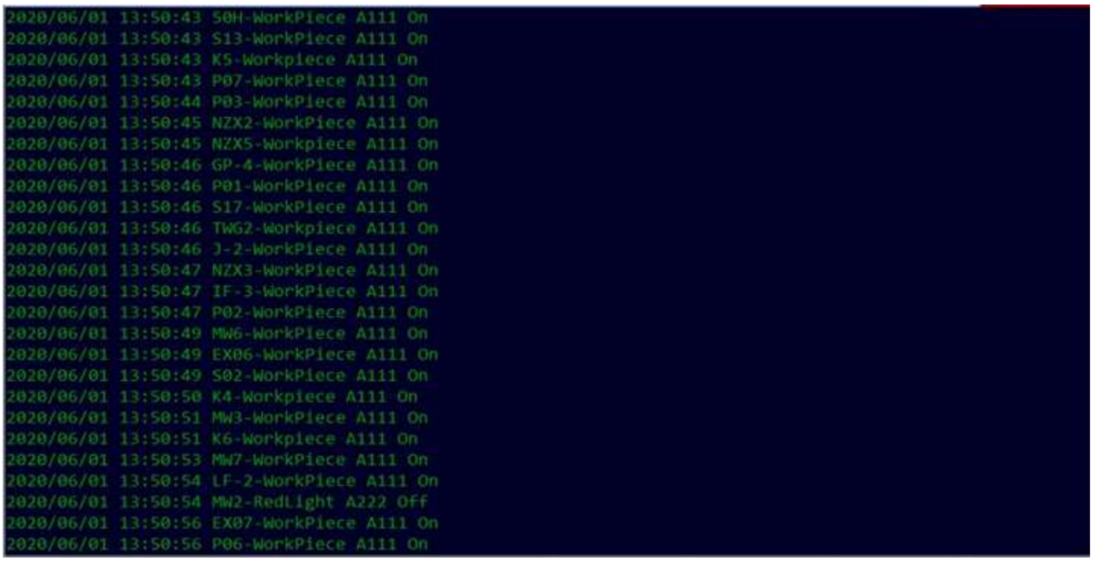

Fig 9: AdVieW Receive Data Result

After installing the data acquisition module, compared with the reasons for downtime previously recorded manually, we can not only obtain more accurate downtime by using this module, but also record the time point and frequency of each downtime. The data form is more detailed and precise.

3.3 Classification of Downtime Reasons

Below we will categorize the various reasons for downtime. Since the data acquisition system itself can only judge whether the hobbing machine is running or not, it cannot judge the reason for the shutdown, so manual analysis and judgment are still required for the reasons for the shutdown. The reasons for machine downtime may vary from company to company. Therefore, we will examine the classification of the main reasons for the downtime of various machines at AB Company over the past 20 years. According to the previous data and the analysis of senior engineers, the reasons for downtime can be mainly divided into 9 types: (1) Shortage of Manpower, (2) Fixture Adjustment/Adjustment, (3) Personnel Breaks, (4) Tool Monitoring/Check tool, (5) First product confirmation/first article measurement, (6) Tool replacement, (7) Troubleshooting, (8) Machine setup (Set up)/shakedown test, (9) Manufacture of New Products (including the use of new materials). We analyze the frequency of these 9 reasons.

3.3.1 Reasons for downtime

Shortage of Manpower(SM): lack of operators matching the full load production of the machine.

Fixture Adjustment/Adjustment (FA): the fixture used in the machine needs to be checked and adjusted in time after running for a period of time.

Personnel Breaks (PB): 10-minute breaks each day during lunch and dinner periods, as well as in the

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morning, afternoon, and evening.

Tool Monitoring/Check tool（TM）: check the tool wear condition in time.

First product Confirmation/First product Measurement（FC）: the first product manufactured by the machine in each shift needs to be inspected by the operator using a suitable measuring tool, and the product quality inspector confirms whether the production can be started.

Tool Replacement (TR): the tool installed on the machine needs to be replaced in time due to wear after a period of use.

Troubleshooting (TS): if the machine fails, it needs to be eliminated to make it run normally.

Machine Setting /calibration (MS): different jigs, tools, processing programs, etc. are required for the hobbing machine to process different products. This requires setting the parameters of the hobbing machine according to the technical requirements.

Manufacture of New Products (NP): new products are processed for the first time, and it takes a long time to adjust the machine.

3.3.2 Model construction

We use “machine utilization” (MU) as the dependent variable Y. We used the method of multiple regressions to analyze the relationship between independent and dependent variables.

All of the hobbing machines we studied were 24-hour machines, so they were all scheduled to work 24 hours. In addition, the operating status of the gear hobbing machine may be divided into red light time, green light time and warm-up time. The red light time is the time when the gear hobbing machine breaks down, solves technical problems, sets machine parameters, and checks the machine. Time; warm-up time is the time that the hobbing machine has no faults and remains on, but no product is produced. This may be due to insufficient number of operators or personnel breaks. Therefore, in this paper, the MU is defined as follows:

$$MU = \left(\text{green light time} - \text{warmup time}\right) / \text{total planned work time} \tag{1}$$

In order to explore the correlation between the number of downtimes caused by different reasons and the MU, this paper is classified according to the 9 main reasons mentioned above. The independent variables of the linear regression model in this paper are the number of downtimes caused by these 9 reasons. TABLE I shows the comparison of the independent variable and the number of shutdowns.

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TABLE I. Comparison of Independent Variables and Downtime Reasons

Independent variable	Reason for downtime (number of times)	Independent variable	Reason for downtime (number of times)
X_1	SM	X_6	TR
X_2	FA	X_7	TS
X_3	PB	X_8	MS
X_4	TM	X_9	NP
X_5	FC		

3.3.3 Stepwise estimation

Although the above has summarized and inferred 9 independent variables that may mainly affect MU, we still need to find out the magnitude of the correlation between each independent variable and MU through quantitative research. In the following, we will analyze the explanatory power of each independent variable using individual explanatory power. This article will use the change in R2 to find the individual explanatory power of each independent variable.

Because in regression analysis, the independent variable that is put into the model for analysis first.There is no influence of other independent variables, its R^2 change is usually the highest. Therefore, we first perform regression analysis on Y and X_2, and then directly add X_1 for analysis. The second increase in R^2 change is the single explanatory power of X_1. We will “usePartial and Partial Correlation” in SPSS software for analysis.We put the independent variable with the highest independent explanatory power into the model first, and then select the independent variables with higher independent explanatory power from other independent variables to join the model in sequence, and each time we put a new independent variables into the model , delete the independent variables that did not reach the significant level in the previous model, until each independent variable in the model reaches the significant level or above, the best model in the current independent variables selection can be obtained.

3.4 Comparison of Results

After obtaining the best model, this paper compares the results of the study with data on the causes of previous downtimes. In the past, the total time of downtime was directly used to analyze MU. This article will analyze MU from different reasons that affect downtime.

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IV. DATA COLLECTION AND PROCESSING

This paper takes the automatic gear hobbing machine of AB Company as the research object.The company's technicians have many years of experience in operating gear hobbing machines. The company's multiple automated gear hobbing machines can help us obtain more accurate and real-time data.

4.1 Data Collection and Analysis

4.1.1 Machine classification

The reasons for the downtime of different series of machines may be quite different. Therefore, 11 gear hobbing machines belonging to the P series in the same workshop of AB Company were analyzed as the research objects to avoid the difference in downtime caused by different models from affecting the research results.

4.1.2 Data range

We integrate the data of the P series gear hobbing machine, and use the data acquisition module to collect the MU rate of each machine every day, as well as the downtime and reason of each machine, so every day can be 11 sample data were generated, and finally all the data were unified for multiple regression analysis. For example: First, we collect the number of downtimes caused by "insufficient manpower" on February 1, and then collect the number of downtimes caused by "fixture adjustment/adjustment" for each hobbing machine on February 1, and so on. Until the number of shutdowns caused by each cause of each hobbing machine is collected. So far, we have obtained the number of downtimes caused by each cause of the 11 gear hobbing machines on February 1, which is the independent variable value of these 11 data. Then, through the downtime data of the specific gear hobbing machine stored in the computer of the company's management information system, the MU rate of each gear hobbing machine of the P series per day can be calculated, and the dependent variable of each group of data can be obtained.

This article will perform regression analysis on the data collected by the module from February 1, 2020 to May 31, 2020. Due to unpredictable factors such as factory power outages and signal interruptions occasionally, some of the collected data are not in line with common sense, so we screened out some abnormal data. Finally, in these 4 months, a total of 1120 data of 11 gear hobbing machines of the P series were collected, and the multiple regression analysis was carried out.

4.1.3 Independent variable selection

First, we use SPSS software to perform partial correlation analysis, and the results are shown in Table II. The individual explanatory power of the independent variables is obtained by calculating the amount of

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change in R^2. For example, according to the SPSS analysis results, the zero-order correlation of "SM" is -0.364, the partial correlation value is -0.371, and its independent explanatory power is the square of -0.371, which is equal to 0.138, and so on, to obtain the independent explanatory power of each variable , as shown in Table III. From this, it can be seen that the independent explanatory power of the independent variable is at most "MS" (the independent explanatory power is 0.223), so first put the reason for this shutdown into the model, conduct a regression analysis, and then use In the successive estimation in the sequential search method, other independent variables are added successively according to the magnitude of the individual explanatory power. Therefore, we add the independent variables in the order of MS (0.223), SM (0.138), TR (0.024), PB (0.023), TS (0.023), and NP (0.017)), FA (0.015), TM (0.004), FC (0.001), the independent variables and the reasons for shutdown are shown in Table II.

Table II. Zero-Order Correlation and Partial Correlation of Downtime Causes

	Zero-Order Correlation	Partial Correlation
SM	-0.364	-0.371
FA	-0.181	-0.124
PB	-0.038	-0.152
TM	0.188	0.066
FC	-0.152	-0.033
TR	-0.117	-0.154
TS	-0.213	-0.150
MS	-0.532	-0.472
NP	-0.172	-0.132

Table III. Partial correlation and individual explanatory power of downtime reasons

Downtime reasons	**Partial correlation**	**Individual explanatory power**
SM	-0.371	0.138
FA	-0.124	0.015
PB	-0.152	0.023
TM	0.066	0.004
FC	-0.033	0.001
TR	-0.154	0.024
TS	-0.150	0.023
MS	-0.472	0.223
NP	-0.132	0.017

Next, we added the second-ranked"SM" (individual explanatory power of 0.138) into the model, and performed another regression analysis to delete the variables below the significant

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level (P-value > 0.05), and use And so on, until all the independent variables in the model are above the significant level (P-value<0.05), the selection of independent variables is completed.

After adding all the independent variables to the multiple regression model and observing the significant level after the above steps, the results are shown in the Table IV. As shown in Table IV, only the "FC" shutdown reason did not reach a significant level (P-value > 0.05), so we removed this independent variable and performed another multiple regression analysis. Finally, according to the analysis results, the remaining independent variables all reached the significant level (P-value < 0.05).

Table IV. Independent Variable Significance Results

coefficient[a]						
Unstandardized coefficients				standardized coefficient		
Model		B	standard error	β	T	Significance
1	(Constant)	86.357	.662		130.452	.000
	SM	-6.099	.342	-.374	-17.836	.000
	FA	-.099	.017	-.125	-5.955	.000
	PB	-.799	.109	-.154	-7.308	.000
	TM	.317	.100	.067	3.158	.002
	FC	-.079	.050	-.034	-1.575	.116
	TR	-.087	.012	-.156	-7.419	.000
	TS	-.069	.010	-.153	-7.203	.000
	MS	-.134	.006	-.496	-22.702	.000
	NP	-.130	.021	-.133	-6.331	.000
a. Dependent variable: MU						

4.2 Analysis results of Gear Hobbing Machine

4.2.1 Regression model significance test (F test)

We use SPSS software to input the selected independent variables and dependent variables, and then perform multiple regression analysis to obtain the analysis results, as shown in Table V. The calculated F-value is 149.901, and its significance P-value is less than 0.001, rejecting the null hypothesis, thus proving that this regression model is significant and has predictive power.

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Table V. Regression Model Significance Results

Analysis of Variance [a]						
Model		Sum of Squares	Degrees of Freedom	Mean Square	F	Significance
1	Regression	107863.910	8	13482.989	149.901	.000[b]
	Residual	99929.971	1111	89.946		
	Statistics	207793.881	1119			
a. Dependent variable: MU						
b. Independent variables: NP, SM, FA, TR, PB, TM, TS, MS						

4.2.2 Marginal test of regression coefficients (T test)

After verifying the significance of the regression model, we use the marginal test to test whether the coefficient of each independent variable is zero, because when β coefficient of an independent variable is zero, it means that the independent variable has no explanatory power. Therefore, we assume that the null hypothesis H_0 is when β coefficient is zero, and the opposite hypothesis H_α is when β coefficient is not zero. Since there are 8 independent variables screened at the end of this paper, and these 8 independent variables all require marginal tests, a total of 8 tests are required. The test results are shown in Table VI. The significant P-values of these 8 reasons for downtime (independent variables) are all less than 0.001, which rejects the null hypothesis, which means that this independent variable has a certain effect on the dependent variables of this regression model.

Table VI. Analysis results of multiple regression model

Unstandardized coefficients				standardized coefficient		
Model		B	SE	β	T	Sig
1	Constant	86.299	.661		130.482	.000
	SM	-6.094	.342	-.374	-17.812	.000
	FA	-.099	.017	-.126	-5.972	.000
	PB	-.798	.109	-.154	-7.292	.000
	TM	.320	.100	.068	3.189	.001
	FC	-.089	.012	-.158	-7.555	.000
	TR	-.069	.010	-.153	-7.175	.000
	TS	-.136	.006	-.503	-23.558	.000
	MS	-.129	.021	-.132	-6.293	.000
	NP	86.299	.661		130.482	.000

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4.2.3 Adjusted r-square

In regression analysis, R^2 can be used as the basis for judging the proportion that the model can explain. The larger R^2 is, the higher the proportion of the relationship between variables that can be explained by the regression model, and the higher the model fit will be. However, since R^2 does not take into account the relationship between the degrees of freedom of the model, as the number of samples increases, the fitness of the model will get better and better, but some independent variables and dependent variables may not be related to each other at all, resulting in high estimated situation. In order to avoid the overestimation of the coefficient of determination R^2, we use the adjusted R^2 (Adjusted R-square) as the explanatory power of the regression model. The analysis results are shown in Table VII, R^2 is 0.519, and the corrected R^2 after considering the degree of freedom of the model is 0.516, which means that in this complex regression model, the screened 8 reasons for downtime (independent variables) can be Explain 51.6% of the equipment utilization (dependent variable) in the data.

Table VII. Results of regression analysis coefficient of determination R^2

Model summary[b]					
Model	R	R-squared	Adjusted R-squared	Standard Error	Durbin-Watson
1	.720[a]	.519	.516	9.48398	2.048
a. Independent variables: （Constant）NP, SM, FA, TR, PB, TM, TS, MS					
b. Dependent variable: MU					

4.2.4 Collinearity test

In multiple regression analysis, if the independent variables are not independent of each other, collinearity is likely to occur. If the collinearity problem occurs between the independent variables, it will greatly affect the accuracy of the regression model. Therefore, this paper will use the variation inflation factor (VIF) as the basis for judging the collinearity between independent variables. The variation inflation factor is the reciprocal of the tolerance value (tolerance), so the smaller the variation inflation factor, the less collinearity problem. After we use SPSS for collinearity diagnostic analysis, the results are shown in Table VIII. Among the 8 reasons for downtime analyzed in this paper, the variation expansion factor of each item is less than 10, indicating that these reasons for downtime are not serious of collinearity.

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Table VIII. Collinearity diagnosis

coefficient[a]								
Unstandardized coefficients				Standardized coefficient			Collinearity Statistics	
Model		B	SE	β	T	Sig	Tolerance	VIF
1	C	86.299	.661		130.482	.000		
	SM	-6.094	.342	-.374	-17.812	.000	.983	1.017
	FA	-.099	.017	-.126	-5.972	.000	.976	1.024
	PB	-.798	.109	-.154	-7.292	.000	.970	1.031
	TM	.320	.100	.068	3.189	.001	.959	1.043
	FC	-.089	.012	-.158	-7.555	.000	.985	1.015
	TR	-.069	.010	-.153	-7.175	.000	.952	1.050
	TS	-.136	.006	-.503	-23.558	.000	.948	1.054
	MS	-.129	.021	-.132	-6.293	.000	.987	1.013
	NP	86.299	.661		130.482	.000		
a. Dependent variable: MU C: Constant SE: standard error Sig: Significance								

4.2.5 Complex regression model equation results

After the above inspection, it can be found that there is a significant correlation between the equipment utilization of the gear hobbing machine and the number of downtime reasons. This paper uses MS SM TR MS TR NP FA and TM, a total of 8 reasons for downtime as the independent variables of the complex regression model, Taking the equipment utilization rate of the gear hobbing machine as the dependent variable, the regression analysis is carried out through SPSS, and the analysis results are shown in Table VI. According to the unstandardized coefficients in Table VI, the final complex regression equation established in this paper is shown in Equation 2:

$$Y = 86.299 - 6.094X_1 - 0.099X_2 - 0.798X_3 + 0.320X_4 - 0.089X_6 - 0.069X_7 - 0.136X_8 - 0.129X_9 \quad (2)$$

Among them, Y is the equipment utilization rate of the gear hobbing machine, and X_i (i=1,2,3,4,6,7,8,9) is the number of gear hobbing machines caused by different reasons, as described in TABLE I. Among them, because the "first product confirmation/first piece measurement" has been deleted from the independent variable screening in the previous section, the independent variable X_5 is missing from the model.

From the results of the regression model, most of the coefficients of the independent variables are negative, which is in line with the actual situation. Because when downtime occurs, equipment utilization also decreases. In addition, according to the size of the independent variable coefficient, the influence of

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individual shutdown reasons on equipment utilization can be judged. First of all, the most significant factor affecting the utilization rate of machine equipment is”SM”. Whenever there is a shortage of manpower, the equipment utilization rate of the machine will be reduced by 6.094%; then the secondary reason for downtime that affects the utilization rate of equipment is”PB”, the equipment utilization rate of the gear hobbing machine will be reduced by 0.798% every time the operator takes a rest, and so on, we can see that the reason for the downtime is in the order of decreasing equipment utilization rate and then”MS” “ NP” “FA”“TR”“TS” and “TM”.

The coefficient of”TM”is a positive value, which means that every time”TM” occurs, the equipment utilization rate does not decrease but increases, which is not in line with common sense, and we will discuss it in the error analysis below.

4.3 Validation of Regression analysis Results

According to the above analysis results, the model designed in this paper can effectively reflect that the number of downtime reasons does have a significant negative correlation with the equipment utilization of the machine. In other words, as the number of downtimes increases, equipment utilization decreases. In addition, using this complex regression model, it can also be judged that individual downtime causes have different effects on equipment utilization. Although the results of the multiple regression model show that there is a significant correlation between the variables, the analysis results still need to pass the three assumptions when the model is established, that is, the error term must meet (1) normality, (2) independence, and (3) isomorphism of variance, and this section discusses whether the results of this multiple regression model analysis meet these three assumptions.

Therefore, the analysis results of the multiple regression models in this study were tested for the normality of the error term, the independence of the error term and the homogeneity of the variance. After we bring the sample data into the model, we compare the predicted equipment utilization rate with the actual equipment utilization rate, and integrate the difference between the two values into error data. After performing regression standardization on this group of error data, a regression standardized residual is obtained. A histogram of difference versus frequency. It can be seen from the histogram that the residuals of the results predicted by the regression model show a standard bell shape, which roughly conforms to a normal distribution, indicating that the error term of the regression model conforms to a normal distribution. We can also use SPSS to make a normal probability plot of the residuals to determine whether the errors are normal. The horizontal axis is the cumulative probability of the observed value (the actual equipment utilization rate), and the vertical axis is the cumulative probability of the prediction (the equipment utilization rate predicted by the model), so when the data distribution is closer to the 45-degree oblique line, the residuals of this model are more normal. And the graph presented by this model does roughly show a 45-degree sloping line, which is in line with the normality of residuals. The results of regression analysis in this study show that the Durbin-Watson statistic is 2.048, and we refer to the Durbin-Watson Table with a significant level of 0.01 (α=0.01) to judge whether the residuals in this paper are independent or not. The complex regression model in this paper finally collected 1120 pieces of data and used eight independent variables for regression, so we query the Dubin-Watson statistic scale, when

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n=1120 and k=8, its DL value is about 1.847 , the DU value is about 1.876, and the 4-DU value is 2.124, while the complex regression analysis results in this paper show that the DW value is 2.048, which is greater than the DU value and less than 4-DU. The null hypothesis is accepted, so it is proved that the residual term of this complex regression model is independent. To test whether the variables have isomorphisms, we use a plot of regression-standardized predicted values versus regression-standardized residuals. When the data points jump evenly up and down the horizontal line where the regression-standardized residuals are 0, we can judge that the variance is isomorphic. The results were analyzed according to the regression model. We found that although a few data points deviate far from the horizontal line where the regression-standardized residuals are 0, most of the data points are densely distributed along this horizontal line, so the multiple regression model of this study conforms to the variance isomorphism type.

4.4 Comparison of Research Results

Let's explore the differences between previous rankings based on downtime and our results. First, we obtained the data for the same time frame as this paper, and then calculated using the methods that previously affected the ranking of device utilization, and the result will be shown in Table IX. According to Table IX, the longest total downtime from P1 to P11 in these three months is " PB" followed by "MS" "TS" and " TR" " FA""TM"" SM" and "NP". The regression results of this paper are shown in Table IX.

It can be seen from the comparison of Table IX that the results of previous discussions on the reasons for downtime on equipment utilization are significantly different from those of this paper. Using past data, it is impossible to determine the impact of the number of downtimes on equipment utilization. The downtime caused by "SM" actually has little effect on the utilization rate of machine equipment. However, according to the data in this article, as long as there is a shortage of manpower, it has the greatest impact on equipment utilization, and it is obvious Higher than other reasons for downtime, it means that although the number of "SM" is small, each downtime is long, which will have a great impact on the utilization of machines and equipment. Next, except for the ranking of "PB" and "MS", which are consistent with the original calculation results, other reasons for downtime are due to the addition of accurate downtime analysis, which has caused its influence to be the same as in the past. Calculating the model results differently, plant managers and engineers can use these results to improve management and technology, eliminate or mitigate causes that have a high impact on equipment utilization, and thereby reduce downtime.

Table IX. Total time of each downtime cause and Regression Analysis Results

Reason for downtime	**Total downtime (hours)**	**Reason for downtime**	**Regression coefficient (hours/times)**
PB	3,901.83	SM	6.094
MS	1,478.28	PB	0.798
TS	1,123.33	MS	0.136

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TR	510.07	NP	0.129
FA	211.52	FA	0.099
TM	166.29	TR	0.089
SM	155.90	TS	0.069
NP	109.23	TM	-0.23

V. CONCLUSION

5.1 Research Results

According to the above research results, as the most influential cause of downtime, there is a very large gap between “SM” and “PB”, which ranks second in influence, which is in line with the reality. Because according to previous data, when the company has a shortage of manpower, the gear hobbing machine will be shut down for more than 1 hour each time. Especially during traditional festivals, the lack of manpower often makes the machine downtime for more than ten hours, resulting in a sharp drop in machine utilization. On the contrary, the time of machine downtime due to rest is very fixed every day, and there are about two to three hours of rest time every day. Therefore, after the analysis of this paper, the company needs to recruit more employees to make up for the shortage of manpower, so as to improve the equipment utilization rate of the machine.

However, compared with “SM” and “PB”, which are factors that are difficult for the company to control and change, the company can reduce the decline in equipment utilization due to other reasons for downtime by training operators in skills. The third-ranked “MS” and the fourth-ranked “NP” are also important influencing factors. The company can strengthen the training of employees in machine setting and new product development, so that it will encounter similar problems in the future. In the event of downtime problems, the number of machine settings and new product development can be reduced to reduce the impact on equipment utilization.

Finally, although “FA” “TR” and “TS” have a certain impact on equipment utilization, compared with “MS” and “NP”, the impact of the first three on the company’s overall equipment utilization is not very large, you can wait until the two problems of “MS” and “NP” have been effectively improved, and then reduce other reasons for downtime.

In this paper, a large amount of data with high accuracy is obtained through the data acquisition module. Regression analysis is carried out based on these data to provide AB Company managers with a more credible gear hobbing machine work evaluation method, so that public managers can understand the improvement effect at any time and change the company’s operation strategy in real time. Therefore, this paper uses the complex regression model to analyze the real-time collection of gear hobbing machine operation big data, and provides a well-founded and effective improvement plan for the decision makers of AB Company, which has high value for the company to improve production efficiency.

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5.2 Discussion of Error

This section mainly discusses the errors in this paper. There are two large errors in this paper. One is that in the analysis results, the correlation coefficient of the shutdown cause such as “TM” is a positive value; when the number of cause occurrences is 0, the equipment utilization rate should be 100%. However, in the analysis result, the model constant term is only 86.299. Therefore, this section will discuss these two research errors.

5.2.1 The correlation coefficient is positive

First of all, according to the actual situation, no matter what the cause of downtime is, when the number of occurrences increases, the utilization rate of machine equipment should decrease accordingly. However, the correlation coefficient of “TM” in this paper is positive; we think it should be related to the number of “TM” and the downtime of each time. Because in the overall collected data, the number and time of “TM” are relatively small, usually no more than 10 times a day, and each TM does not exceed 5 minutes. In this case, the impact of “TM” on the reduction of equipment utilization can be said to be very small, and the impact of other reasons for downtime is too large, so when other reasons for downtime do not occur or do not occur frequently, the machine The utilization rate of the equipment will be very high, resulting in a positive correlation coefficient of “TM” in the regression results.

5.2.2 The constant term is not 100

According to the actual situation, when there is no reason for downtime, the equipment utilization should be 100%, but the model analysis result of this study is only 86.299. The possible reason for this error is that we did not list all the reasons for the downtime of the gear hobbing machine in the establishment of this regression model, but only selected the more common and obvious reasons for downtime after analyzing with the field engineer. Therefore, in the data collected in this paper, these 9 reasons cannot completely affect the equipment utilization rate of the machine, and it is necessary to consider the influence of some rare but more influential downtime reasons on the equipment utilization rate.

5.3 Research Deficiencies and Prospects

In this paper, in order to increase the number of data, 11 gear hobbing machines of the same series are subjected to regression analysis at the same time. Although gear hobbing machines of the same series have similar performance and reasons for downtime, there may be some differences in functional details. Therefore, we can discuss the direction of future research in this paper.

5.3.1 Add data of different series of machines

The regression analysis is only performed on the P-series gear hobbing machines, and the company still has several different series of gear hobbing machines. In the future, different series of gear hobbing machines can be added for individual analysis, and the differences between the factors affecting the equipment utilization of different types of machines can be explored. In addition, the impact of these different performance machines on the company's overall operations can be explored more broadly.

5.3.2 Establish the criteria for identifying the cause of downtime

In this paper, the identification of the cause of downtime is judged by the on-site engineer; however, the identification of the cause of downtime by different engineers will be different due to subjective judgment. In the same situation, some engineers think it is a fault repair, while others think it is Machine parameter setting. Therefore, establishing a set of unified identification standards will help to improve the accuracy of regression models.

5.3.3 Add other reasons for downtime or amend the equipment utilization formula

In this paper, only 9 main reasons for machine downtime are analyzed, but in fact there are other reasons for downtime that have not been added to the model analysis, and these unexplored reasons may cause the analysis error of the model. On the other hand, if some downtime causes with very few occurrences are added to the model analysis, not only the impact of the downtime causes cannot be accurately analyzed, but also the accuracy of the model may be reduced. Therefore, when these rare downtime reasons occur, we can also design a new equipment utilization correction formula to reduce the errors caused by these downtime reasons that are not considered in the model.

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