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Preventive Maintenance Decision Model of Urban Transportation System Equipment Based on Multi-Control Units

HUAN-YAN LI[1], WEI XU[1], YANJUAN CUI[2], ZHOU WANG[1], MENG XIAO[1], AND ZHI-XIAO SUN[1]

[1]School of Management, Shenyang University of Technology, Shenyang 110870, China
[2]School of Finance, Dongbei University of Finance and Economics, Dalian 116025, China

Corresponding authors: Wei Xu (369252882@qq.com) and Yanjuan Cui (cuiyanjuan_dl@163.com)

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ABSTRACT This paper studies the fault prediction of equipment and the decision of joint equipment maintenance in urban traffic system based on Internet of Things and big data as the background of multiple control units, and proposes a joint equipment monitoring model for multi-equipment systems composed of intelligent control units. The network method predicts the fault of the equipment and gives the equipment fault prediction process. Combining the multi-equipment system attributes of intelligent control unit, aiming at minimizing the total maintenance cost of control unit system, and taking the reliability of the whole system and the availability of equipment as constraints, a preventive maintenance decision model for joint equipment maintenance is established. Finally, the optimal preventive maintenance interval of the entire system is solved.

INDEX TERMS Combined traffic control equipment maintenance, fault prediction, intelligent control unit, PHM theory, preventive maintenance.

I. INTRODUCTION

With the continuous development of social economic technology, intelligent control units have become the trend of manufacturing enterprises. Complete equipment maintenance management is one of the important factors to ensure the smooth completion of production by the manufacturing enterprises. Therefore, the fault prediction and joint equipment maintenance decision of the equipment in the intelligent control unit multi-equipment system are the demands of today's manufacturing enterprises. The manufacturing enterprises should reform and adjust the enterprise in a timely manner. Production mode, the establishment of intelligent control units, under the premise of ensuring the safety and reliability of the operation of the multi-equipment system of the control unit, realize the efficient control of the operation state of the equipment in the multi-equipment system of the intelligent control unit, and establishes a set of cost-effective. The equipment maintenance guarantee system is a key issue for current manufacturing companies.

Fault prediction is the basis for implementing CBM conditional maintenance, and the problem of uncertainty is ubiquitous in fault prediction problems. Shu *et al.* [1] proposed a slowly variable equipment fault prediction method, which combines AR sequence analysis and multivariate statistics (MPCA) to achieve the prediction of slowly varying faults in the intermittent process of hydraulic experiments. Hu *et al.* [2] considered the characteristics of uncertainty, randomness and complexity of fault propagation, and proposed a dynamic prediction model based on dynamic Bayes. Yun *et al.* [3] systematically analyzed the application of HMM-based fault prediction methods in mechanical

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equipment, and summarized the future development trend based on HMM fault prediction model. Hu *et al.* [4] proposed a fault prediction method based on Grey Theory and expert system for track circuit. The original grey model was improved by using the equal dimension dynamic prediction model. The validity of this fault prediction maintenance mechanism based on equipment condition was proved by data.

At present, according to the composition and structure of the production equipment system, the maintenance decision is divided into the maintenance decision of the single equipment system and the maintenance decision of the multi-equipment system. Zhijie *et al.* [5] considered that the preventive maintenance cost is changed with the times of equipment maintenance, and the optimal maintenance strategy of the equipment is studied. Grall and Dieulle [6] considered the degradation state of the device as a continuous Gamma process to propose a visual maintenance strategy for a single device system. Dekker *et al.* [7] systematically analyzed and classified the maintenance decision model considering system economic relevance, and divided the maintenance model into two categories, namely, Stationary Grouping and Dynamic Grouping. Gang *et al.* [8] considered the economic correlation and performance-related factors between equipment components,and proposed a decision-making method based on the opportunity maintenance theory.

In this paper, the factors influencing the fault prediction and maintenance decision of urban traffic control equipment are analyzed. The data source of intelligent control unit for fault prediction is presented in the background of Internet of Things and big data technology. The idea of joint equipment fault monitoring is put forward and the fault monitoring model of joint equipment is established based on Bayesian theory. The network model is used to predict the failure of traffic control equipment. Finally, combined with the results of fault prediction, a preventive maintenance decision-making model for combined equipment of control unit and multi-equipment transportation system based on CBM is established by using group maintenance theory, which improves the availability of the system. On the basis of ensuring the reliability and safety of the system operation, lean implementation is carried out to save cost and time. The economy of the system is realized [9].

II. ANALYSIS OF FACTORS AFFECTING FAULT PREDICTION AND MAINTENANCE DECISION OF CONTROL UNIT TRAFFIC EQUIPMENT

A. ANALYSIS OF FACTORS AFFECTING FAILURE PREDICTION OF CONTROL UNIT TRAFFIC EQUIPMENT

1) DATA INTEGRITY

For fault prediction of intelligent control unit traffic equipment, the most important thing is to have complete and effective historical data, and the choice of parameters also affects the accuracy of equipment failure prediction.

2) CHOICE OF FAULT PREDICTION METHOD

The choice of fault prediction method will directly affect the accuracy of the forecast, which will affect the choice of maintenance methods, and ultimately have a huge impact on the implementation of maintenance support.

B. ANALYSIS OF FACTORS AFFECTING MAINTENANCE DECISION OF CONTROL UNIT TRAFFIC EQUIPMENT

1) MAINTENANCE COST FACTORS

The cost of maintenance of traffic control equipment is divided into unexpected failure maintenance cost and preventive maintenance cost. The former is usually used to minor repairs on equipment, and the maintenance cost is low. The latter is to determine the maintenance time of the equipment by predicting the failure of the equipment before the failure of the equipment, so as to minimize the maintenance cost [10]. The shutdown of equipment caused by minor repairs and preventive maintenance will force the whole production to stop. For the maintenance of traffic control equipment, the economy of maintenance is the primary consideration of manufacturing enterprises. When the unit maintenance cost is considered, the optimal maintenance cost and maintenance time can be found [11].

2) EQUIPMENT EFFECTIVENESS FACTORS

The effectiveness of traffic control equipment is mainly divided into the inherent effectiveness, reachability and usability of the equipment. The usability of the traffic control equipment refers to the effective use of the equipment that is continuously running. It refers to the probability that certain equipment can work well when it is used under certain conditions in the actual operating environment. It is the ratio of the time when the device is operational to the time when the device has been running. The main consideration in this paper is the usability of the traffic control equipment.

3) EQUIPMENT RELIABILITY FACTORS

The reliability of traffic control equipment is mainly divided into two types: the inherent reliability of the equipment and the reliability of the equipment. The reliability of a device is often used to measure the reliability of the system, or the probability that the system or device will be able to maintain normal operational operation under certain conditions and for a specific period of time. The indicators that measure the reliability of the traffic control equipment usually include the failure rate of the equipment, the average failure time interval, and the mean time between failures.

4) EQUIPMENT MAINTAINABILITY

The maintainability of the traffic control equipment indicates the degree of repairability and ease of repair of the equipment. The indicators that measure the maintainability of the traffic control equipment include maintenance, maintenance density, average repair time, and repair rate.

5) EQUIPMENT SAFETY / RISK

The safety of the traffic control equipment is the prerequisite for ensuring smooth production. This paper predicts the failure of traffic control equipment, prompts production personnel and equipment management personnel to discover the potential safety hazards of traffic control equipment in time, and makes corresponding measures in time, and finally judges the corresponding dangers.

III. DATA DRIVEN CONTROL UNIT TRAFFIC EQUIPMENT FAILURE PREDICTION

Fault prediction is based on the current state of use of the equipment, taking into account the operating environment, structural characteristics and historical data of the operation, using reasonable models and algorithms to effectively predict the possible failure of the equipment [12], [13].

A. DESCRIPTION OF THE PROBLEM

This section is based on data-driven fault prediction of control unit traffic equipment. It effectively combines model and data to realize fault prediction of control unit traffic equipment. This paper studies traffic equipment maintenance management in intelligent control unit by using PHM theory and technology for reference. Fault prediction is one of the core contents of PHM. To predict traffic control equipment faults, first of all, it is necessary to identify the data sources of equipment fault prediction, and at the same time, select appropriate fault prediction methods to predict equipment faults. It is also very important to say that it directly affects the accuracy of fault prediction results. According to the result of fault prediction, it can directly or indirectly refer to and guide the decision-making of the next traffic control equipment maintenance, that is, according to the operation status of the equipment, the condition monitoring and fault diagnosis of the equipment are the basis of fault prediction, and the result of fault prediction is the judgment basis of equipment maintenance decision-making. According to the results of maintenance decision-making, the final requirements of maintenance activities are obtained.

B. CONTROL UNIT TRAFFIC EQUIPMENT FAILURE PREDICTION DATA SOURCE

The advanced technology of the Internet of Things (such as sensors, RFID, etc.) is introduced into the intelligent control units of the manufacturing enterprises, thereby realizing the monitoring of the operating state of the traffic control equipment and the collection of various related information. Enterprises build and process information for production equipment failure prediction in intelligent control units by building a foundation for data collection. Currently widely used data acquisition systems are SIEMENS and FANUC [14]. The device status information is mainly divided into the internal status information of the traffic control device and the external status information of the device for the devices in the control unit. The internal information of the traffic control device is obtained by collecting various sensors in the device itself, thereby realizing the collection of device operation information data, but some state information such as the temperature of the component cannot be obtained through the built-in sensor. This method is usually adopted by adding an external sensor device to perform periodic or continuous monitoring of the operating state of the device. The data sensed by the traffic control device usually includes information such as equipment pressure, temperature, and vibration.

The main purpose of collecting data such as the operating state of the control unit traffic equipment is to realize real-time sensing of the operating state of the running equipment in the control unit, thereby effectively controlling these equipments. Collect various data such as the running status of the traffic control device and historical faults. Signal analysis and processing techniques are typically used to denoise and further resolve the signal to obtain a characteristic sensitivity factor that characterizes the state of the sensor. The appropriate feature extraction and state recognition algorithms are used to extract the feature quantity of the device, select the appropriate feature quantity, and use data processing technology to filter and fuse the data, and then perform fault diagnosis and fault prediction for the subsequent equipment. Data support is provided based on preventive maintenance decisions based on condition-based maintenance (CBM). A complete production equipment data acquisition system based on the control unit of the Internet of Things can complete the collection of operational data of the control unit traffic control equipment. Figure 1 is the structural function of the control unit equipment system based on PHM theory. It can be seen from the figure that the operational data collection of the equipment is obtained through the production equipment data acquisition system. The data acquired from these data is used as the basis for fault prediction and maintenance decision-making of equipment.

C. CONTROL UNIT JOINT TRAFFIC EQUIPMENT MONITORING MODEL

Considering the characteristics of control unit traffic equipment, as well as the structural and functional similarities between components, the key components of the traffic control equipment are identified and classified first. Then adopting the same or similar monitoring technology for the structural similar components and functionally similar components of the device, thereby achieving unified management and unified monitoring of the devices in the multi-device traffic control system of the control unit, and selecting similar feature quantities, which can be extreme. This can greatly reduce the workload of monitoring and fault prediction of control unit equipment. Figure 2 shows the joint traffic control equipment failure monitoring model.

D. BAYESIAN NETWORK BASED TRAFFIC CONTROL EQUIPMENT FAILURE PREDICTION

In this paper, the Bayesian network method is used to predict the fault of the traffic control equipment. The Bayesian

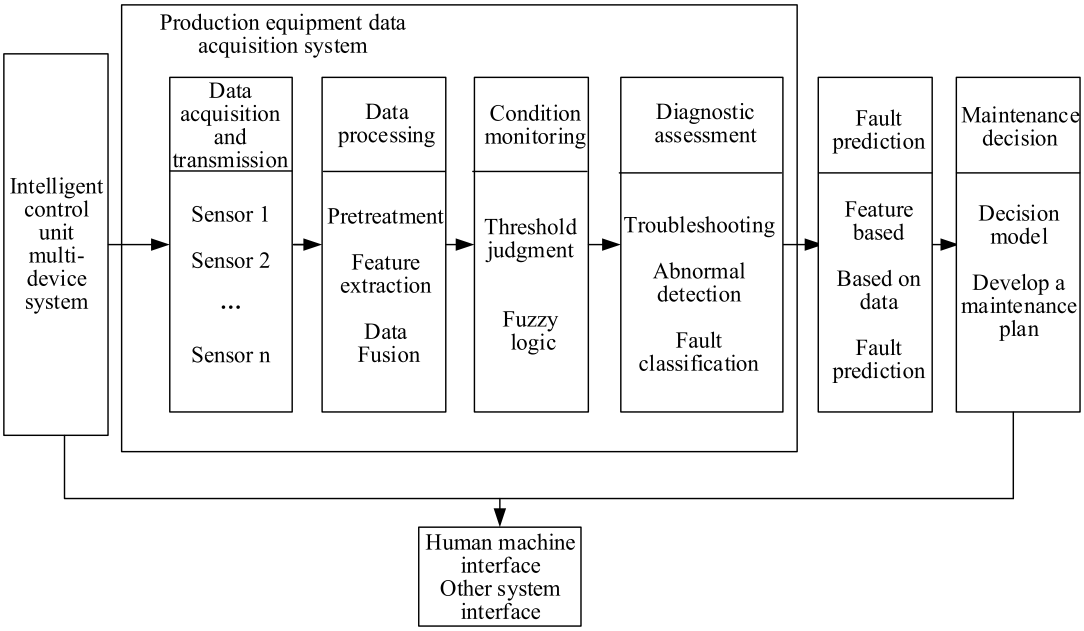

FIGURE 1. Maintenance management of intelligent control unit equipment based on PHM theory.

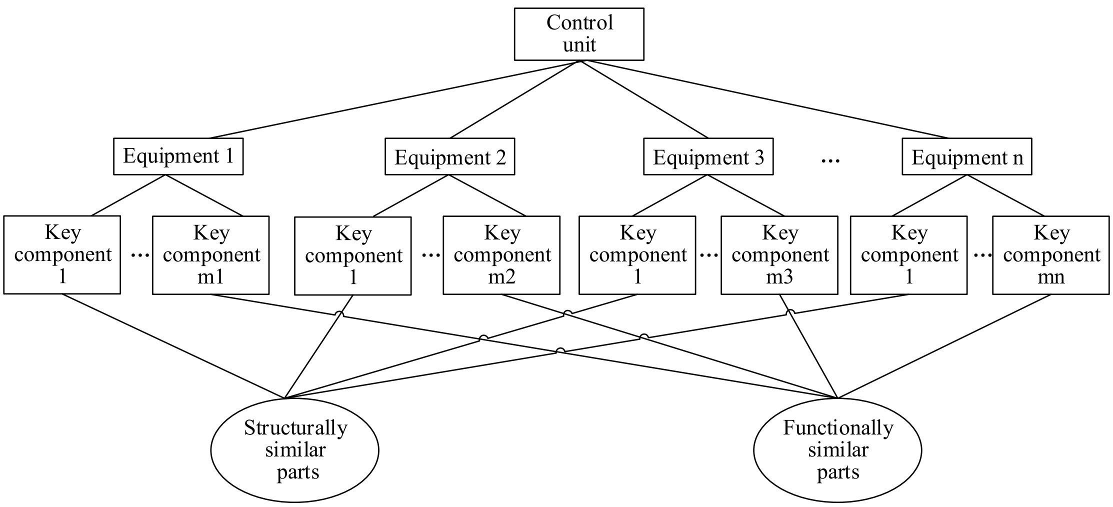

FIGURE 2. Fault monitoring model of combined traffic control equipment.

network prediction method is different from the traditional prediction method. Traditional prediction methods usually use only two kinds of information for prediction in the process of prediction, that is, according to the information of the model and the information of the sample data, while the Bayesian prediction method can not only utilize the model information and samples in the process of traffic control equipment failure prediction. The data information, this method also uses the information of prior probability, that is, the subjective consciousness of the decision makers who make the prediction. Therefore, this paper chooses Bayesian network prediction method to predict the fault condition of the traffic control equipment. Because the Bayesian Network (BN) method has unique capabilities for dealing with uncertain events, it plays a very important role in the field of prediction [15], [16].

1) TRAFFIC CONTROL EQUIPMENT DEGRADATION STATUS DESCRIPTION

Fault prediction of the traffic control equipment first requires an understanding of the degradation process of the equipment. As shown in Figure 3, the degradation process of the device is mainly divided into three phases, namely, device normal state, device degradation state, and device fault state. The time when the device is running corresponds to the abscissa t, and the health index of the device corresponds to the ordinate H. The curve describes the normal operating state of the traffic control device. At this stage, the device

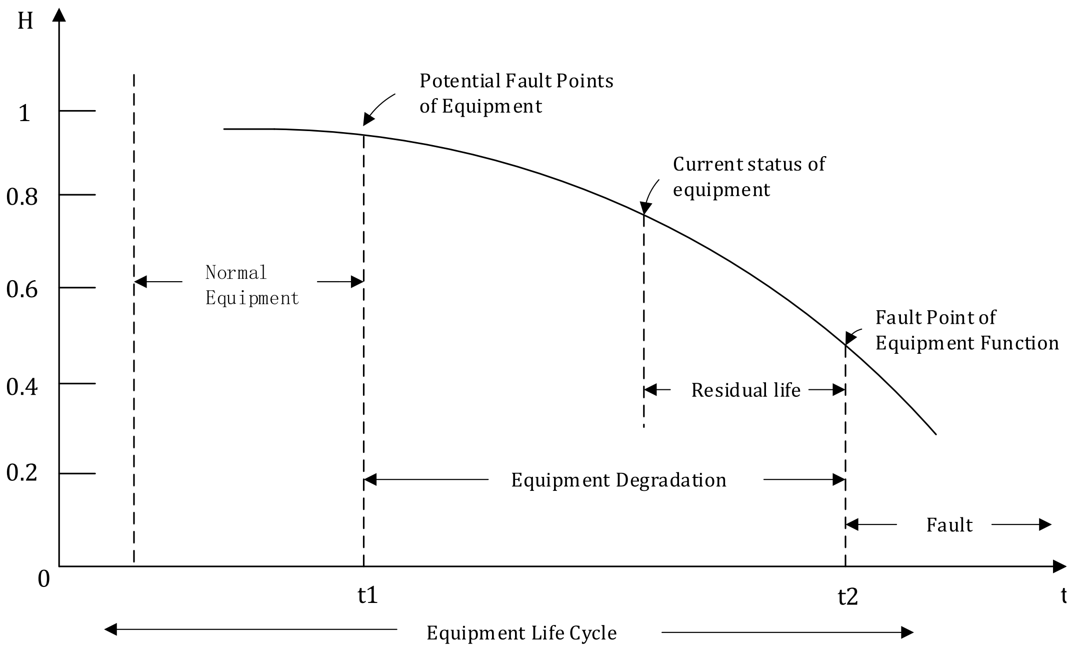

FIGURE 3. The degradation curve of the traffic control equipment health.

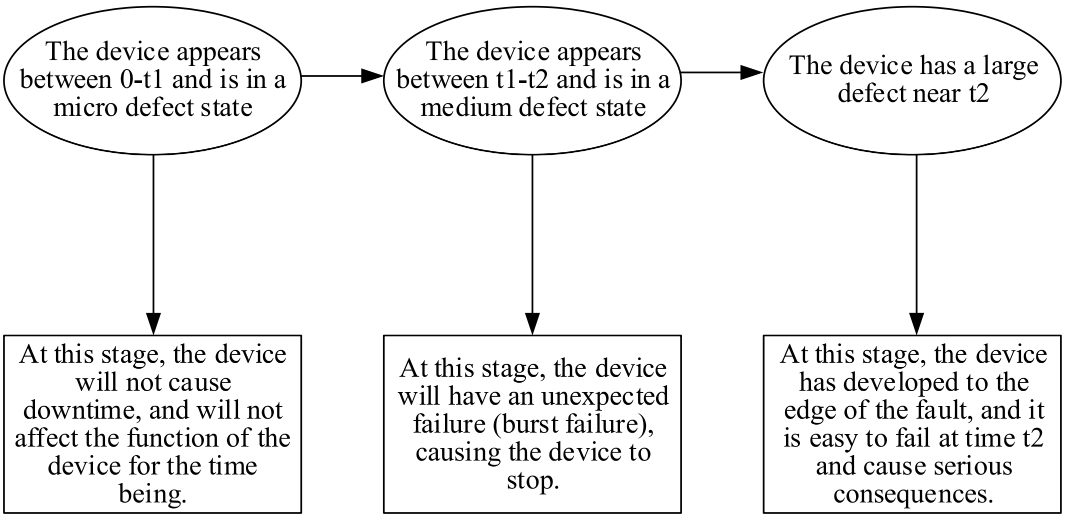

FIGURE 4. Gradual process of traffic control equipment performance degradation.

is in good condition in all respects. The failure degree of the device has not yet appeared to cause abnormal operation of the device. The detection device cannot monitor the information of the device failure. At this time, the health index of the device is set to 1; the defect occurs in the device and enters the degradation phase of the device. At this stage, the device enters the potential failure point, and a minor fault at the potential failure point can be monitored and predicted, and the failure prediction of the device is at this stage, it is judged whether the preventive maintenance strategy is adopted according to the fault prediction result. At this time, the health index of the equipment is also reduced synchronously with the degradation of the equipment; as the working time of the equipment increases, the deterioration state of the equipment continues to increase, and the fault continues. The degree is deepening, which eventually leads to equipment failure, and the equipment enters a fault state. At this stage, the equipment fails and cannot work normally.

The process of the traffic control equipment performance degradation is not a one-step process. It is a process from quantitative change to qualitative change. There are many reasons for the continuous deterioration of equipment performance, which may be caused by a single factor or by many factors. Figure 4 is a gradual process of traffic control device

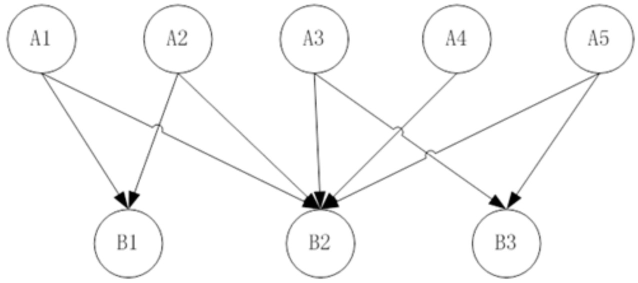

FIGURE 5. Bayesian network structure prediction model.

performance degradation, corresponding to the three stages of device normality, device degradation, and device failure in the device health state degradation curve in Figure 3.The traffic control equipment failure prediction is mainly in the equipment degradation stage, corresponding to the *t1-t2* stage in Figure 3, corresponding to the medium defect status in Figure 4.

2) BAYESIAN NETWORK-BASED TRAFFIC CONTROL EQUIPMENT FAILURE PREDICTION

Using Bayesian network to predict the fault of the traffic control equipment is to use the historical data of the operation of the equipment before the fault, and combine the expert knowledge to establish a Bayesian network based on data prediction. The model predicts the probability of equipment failure through joint reasoning. The Bayesian network structure represents device qualitative information, and the quantitative information is reflected by the joint probability density between nodes in the Bayesian network structure. The following are the steps to predict traffic control equipment failure using a Bayesian network:

Selection of node variables: There are many factors that cause traffic control equipment failure. According to historical data of traffic control equipment operation and failure, combined with expert experience, the final node variables are selected and determined.

Determination of Bayesian network structure for traffic control equipment failure: Assuming that the traffic control device network topology is known, a Bayesian network structure diagram is constructed, in which the nodes are outputted by the directed edges refer to them as root nodes (also called parent nodes), and the nodes that are input to the directed edges refer to them. It is a leaf node (also called a child node), and it is defined that there is no connection between nodes belonging to the same layer. As shown in Figure 5, A_i ($i = 1, 2, 3, 4, 5$) is the network root node. That is, the parent node set, B_j is the network leaf node, that is, the child node set.

Determination of the prior probability of the root node variable: After the Bayes network structure is established, the next is the determination of the probability of failure of each root node A_i, that is, the value of $p\,(A_i = f)$, where f is used to indicate the state of failure between the nodes. In this paper, the method of fuzzy membership function is used to determine the a priori failure probability of the root node A_i:

$$\theta_i = p\,(A_i = f|S) = \alpha \cdot \mu\,(H\,(A_i)) + (1-\alpha) \cdot Q\,(A_i) \quad (1)$$

where θ_i is used to represent the parameter variable of the prior probability of the node, and S is used to represent the Bayesian network structure of the device, where $\mu(\cdot)$ is used to represent the fuzzy membership function of the device, and $H(A_i)$ is used to represent each root node A_i. The degree of health $Q(A_i)$ is used to indicate the information of the running trend of each root node A_i, and α represents the weighting coefficient. Since the failure rate of the traffic control device increases as the health of the device decreases, $\mu(\cdot)$ selects a low-level membership function with a specified lower limit fault indication. The device membership function is determined based on the degradation characteristics of the health of the device components to determine the membership function distribution, and then the sample data is used to fit the membership function distribution parameters and the parameters are estimated to determine a suitable fuzzy membership function. In the following section 3.5, by calculating the health degree of each device and fitting the fuzzy membership function using sample data, a fuzzy membership function $\mu(t)$ suitable for the device is obtained.

The health function $H(A_i)$ of the root node A_i is:

$$H\,(A_i) = \Phi\left(F_f\,(A_i)\,, F_e\,(A_i)\right) \quad (2)$$

$F_f(A_i)$ is the frequency of the historical failure of node A_i, $F_e(A_i)$ is the degree of failure of node A_i, and Φ is a weighting function.

The running trend information of the root node A_i is determined by qualitative trend analysis [17]. This method divides the signal frequency band into seven types, and the qualitative trend (Q) value corresponding to each type is shown in Table 1. The first one is a constant value signal (I), and the corresponding Q value is 0; the second is a signal that deviates from the normal area (II), and the corresponding Q value is 1; the third is the signal returning to the normal region (III), and the corresponding Q value is -1; the fourth is the step deviation signal (IV), and the corresponding Q value is 0.3; the fifth is the step regression signal (V), and the corresponding Q value is -0.3; the sixth is the deviation/regression transient signal (VI), and the corresponding Q value is -0.5; the seventh is the regression/deviation transient signal (VII), and the corresponding Q value is 0.5.

Determination of conditional probability of variable nodes: The conditional probability of a variable node represents the extent to which the operating state of the root node affects the operational state of the leaf node. The parameter learning algorithm is used to determine the conditional probability of the variable node. Since the object of research is a traffic control device in an intelligent control unit, which has a complete data acquisition system, its sample data (ie, historical data of device operation) is sufficient, but the obtained data may be complete or missing. In different situations, the algorithms applied are different.

TABLE 1. Types of signal frequency bands and corresponding qualitative trend values.

Fragment Interval	Normal	Normal	Normal	Normal	Normal	Normal	Normal
Types	I	II	III	IV	V	VI	VII
Q	0	1	-1	0.3	-0.3	-0.5	0.5

Parameter learning algorithm used when data is missing: For traffic control devices with missing data, an iterative algorithm is usually adopted, that is, the expectation maximization algorithm, also known as the EM algorithm, calculates the maximum likelihood probability of the Bayes network, and alternately uses the expectation (E) and the maximum during the use (M) step. The central idea of the EM algorithm is to give the initial value θ^0 of a parameter, and then to continually correct it, and finally maximize its maximum likelihood probability value, namely:

$$\text{Max}\ E\left\{\ln p\left(X \mid \theta^l\right)\right\} \tag{3}$$

Among them, X is the complete sample after repair, from the current estimate of θ^l to the next value θ^t.Where the (E) step is: the known observable sample Z and the current estimated value θ^1, the probability distribution of the complete sample X of the calculated data is expected to be:

$$\begin{aligned} p\left(\theta^{\mathrm{t}} \mid \theta^{\mathrm{l}}\right) &= E\left\{\ln p\left(X \mid \theta^t\right) \mid \theta^l, D\right\} \\ &= \sum\nolimits_l \sum\nolimits_t \ln p\left(Z_l, D_l \mid \theta^t\right) p(D_t|Z_t, \theta^t) \end{aligned} \tag{4}$$

where Z is used to represent the observable data set, and D is used to represent the missing data set, ie the unobserved data set, the complete sample data set $X = Z \cup D$. The (M) step is to further calculate the maximum likelihood estimate θ^t of θ based on the previous step, that is:

$$\theta^t = \arg Max\ p\left(\theta^t \mid \theta^l\right) \tag{5}$$

Parameter learning algorithm used when data is complete: Bayesian estimation is often used for data-complete parameter learning methods. This method takes all possible values of the parameter θ into consideration and determines the given Bayesian network structure S and the observable sample Z. The Yes rule can be obtained:

$$p\left(\theta \mid Z, S\right) = \frac{p\left(Z \mid \theta, S\right) \cdot p(\theta|S)}{p(Z|S)} \tag{6}$$

Calculation formula for traffic control equipment failure prediction: According to the state of the root node failure of the known traffic control device, the probability of the device failure can be predicted. Taking the Bayesian network structure shown in Figure 5 as an example, the calculation formula of the device failure probability prediction is (7), as shown at the bottom of this page.

According to the historical data of the traffic control equipment operation, the equipment is predicted to be faulty, and then the fault prediction result is analyzed and compared with the actual data actual fault condition, and the model is further adjusted and optimized according to the actual situation, so that the predicted result is closer to the actual situation. The situation is more accurate and effective.

E. ANALYSIS OF THE CASE

There are many factors that cause traffic control equipment failure. In order to provide a more reliable and effective equipment failure analysis, it can provide a certain degree of failure warning for the manufacturing workshop of the manufacturing enterprises to some extent, reference and support for equipment maintenance personnel to choose and adopt appropriate maintenance methods. In this case, the fault prediction of traffic control equipment is carried out by using Bayesian network-based data prediction method. It is proved that the model is effective for traffic control equipment fault prediction by running in MATLAB.

Effective and sufficient historical data of traffic control equipment operation is the basis and prerequisite for equipment failure prediction. This paper takes the traffic equipment M in the H enterprise intelligent control unit as an example. The company specializes in the development and production of urban transportation system equipments. Since the intelligent control unit installs a complete data acquisition system for the traffic control device from the start of production, the data of the device is complete. From the expert knowledge and the historical data of the operation

$$\begin{cases} p\left(B_1 = f|S, Z\right) = \sum\limits_{A_1, A_2} p\left(B_1 = f|\left(A_1, A_2\right)\right) p\left(A_1, A_2\right) \\ p\left(B_2 = f|S, Z\right) = \sum\limits_{A_1, A_2, A_3, A_4, A_5} p\left(B_2 = f|\left(A_1, A_2, A_3, A_4, A_5\right)\right) p\left(A_1, A_2, A_3, A_4, A_5\right) \\ p\left(B_3 = f|S, Z\right) = \sum\limits_{A_3, A_4, A_5} p\left(B_3 = f|\left(A_3, A_4, A_5\right)\right) p\left(A_3, A_4, A_5\right) \end{cases} \tag{7}$$

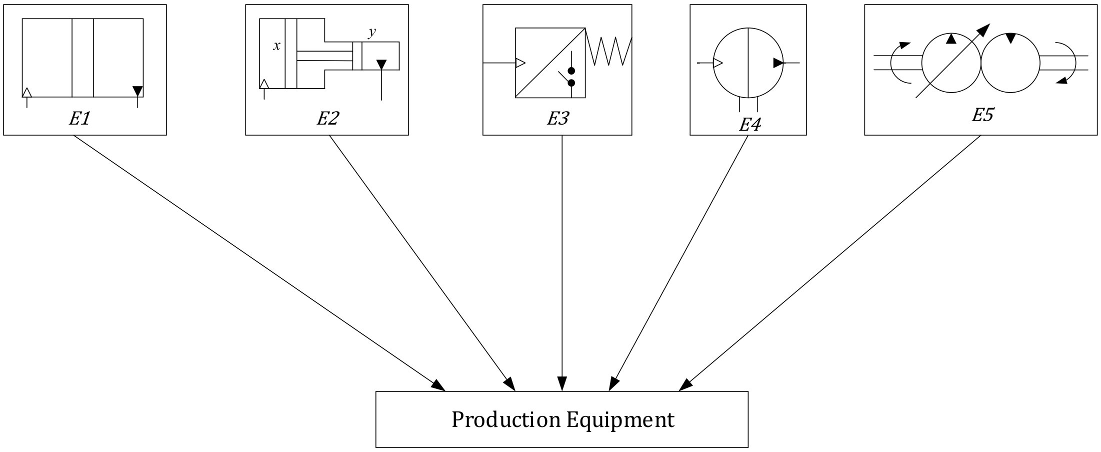

FIGURE 6. Bayesian network model diagram of device M.

of the equipment, there are five main factors causing the failure of the equipment M, including the transmission of the equipment, the supercharger, the sensor, the electric motor and the drive unit. Figure 6 is given by expert experience. The device is based on a Bayesian network model map. Where E_1 is the transmission, E_2 is the supercharger, E_3 is the sensor, E_4 is the motor, and E_5 is the drive unit.

It can be seen from Figure 6 that there are five factors causing traffic control equipment failure that need to be quantified. The sample information is based on the equipment information collected by the production equipment collection system of the enterprise urban transportation system equipment control unit (including the information of previous equipment failure, the information of equipment operation status, and the information of equipment historical maintenance, etc.).

Firstly, the health of each device is calculated according to formula (2), and the fuzzy membership function is used to fit the sample data, so that the fuzzy membership function is suitable for the device is obtained:

$$\mu(t) = \begin{cases} 0, & t > 1 \\ (1-t)^{3.25}, & 0 \leq t \leq 1 \\ 1, & t > 0 \end{cases} \tag{8}$$

In this paper, 100 sets of training data are selected and run in MATLAB. The fault prediction process based on Bayesian network mentioned in the previous section finally predicts the fault of the traffic control equipment. According to the running trend analysis method, the Q value corresponding to the different sampling segments is determined, and the failure probability $p(E_i = f)$ of the root node variable E_i in the 100 sets of data is calculated according to the formula (1), where $i = 1, 2, \ldots, 5$. Take the average of 100 sets of failure probabilities as the failure probability of the four root nodes of the device. At the same time, the probability $p(M = f)$ of the failure of the device M in the 100 sets of data is counted.

The historical data of the operation of the traffic control device M is used as a training sample for parameter learning, and a Bayesian estimation algorithm is used to calculate a conditional probability table of the leaf node, that is, the device M. The parameter training results of M is shown in Table 2, where f indicates that the node is faulty and u indicates that the node is operating normally.

According to the formula (7), the probability calculation formula (9) for the failure of the device M can be obtained:

$$p(M=f|S,Z) = \sum_{E_1,E_2,E_3,E_4,E_5} p(M=f \mid E_1,E_2,E_3,E_4,E_5) \cdot p(E_1,E_2,E_3,\mathrm{E}_4,E_5) \tag{9}$$

As can be seen from Figure 7 and Figure 8, the actual failure rate of the training sample data (that is, the traffic control equipment operation data collected by the production equipment acquisition system) can be in good agreement with the actual data, which can basically match the original data and prediction. The error is small, and for the data to be detected, it can be seen from Figure 8 that the Bayesian network prediction method can preserve the trend of the data, and the data positioning prediction can also be accurately obtained. The inspection process provides a more reliable basis. Therefore, the Bayesian network prediction method has a good application in traffic control equipment fault prediction. By judging the predicted result and the fault threshold given by the expert, when the result of the fault prediction is less than the equipment fault threshold, no maintenance measures are required for the equipment; however, when the equipment fault prediction occurs, the result is larger than the equipment fault threshold. When it is necessary, preventive maintenance is required on the equipment.

IV. CBM-BASED CONTROL UNIT COMBINED WITH PREVENTIVE MAINTENANCE DECISION FOR TRANSPORTATION EQUIPMENT

A. DESCRIPTION OF THE PROBLEM

1) DESCRIPTION OF THE PROBLEM

To maintain and manage the traffic equipment in the intelligent control unit, firstly, the data collected by the intelligent

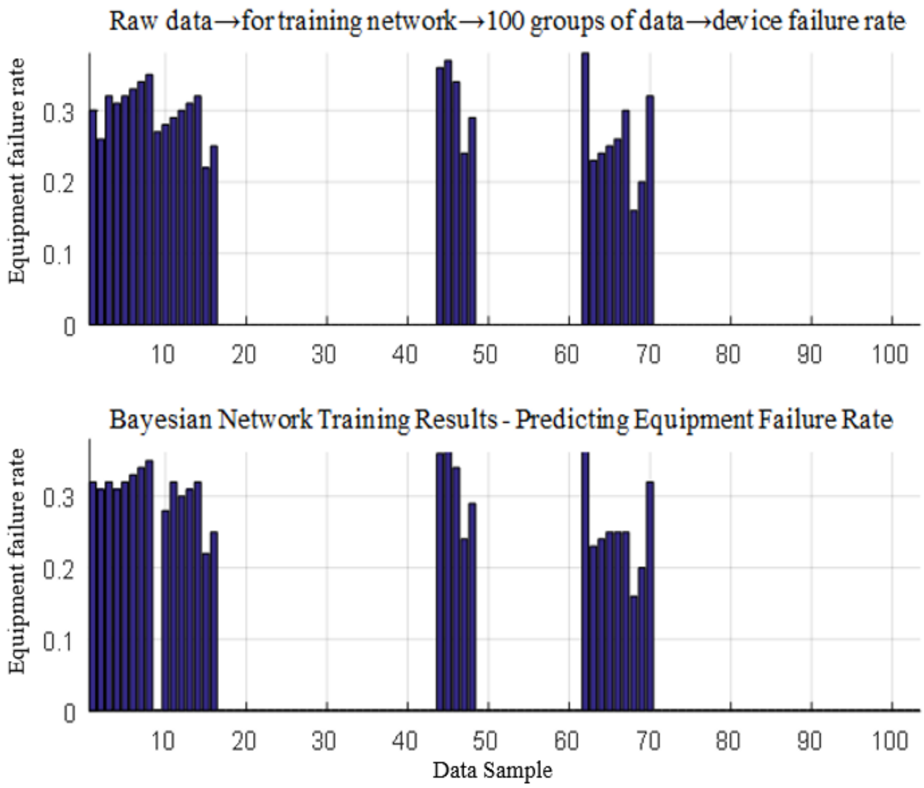

FIGURE 7. Actual failure of the traffic control equipment.

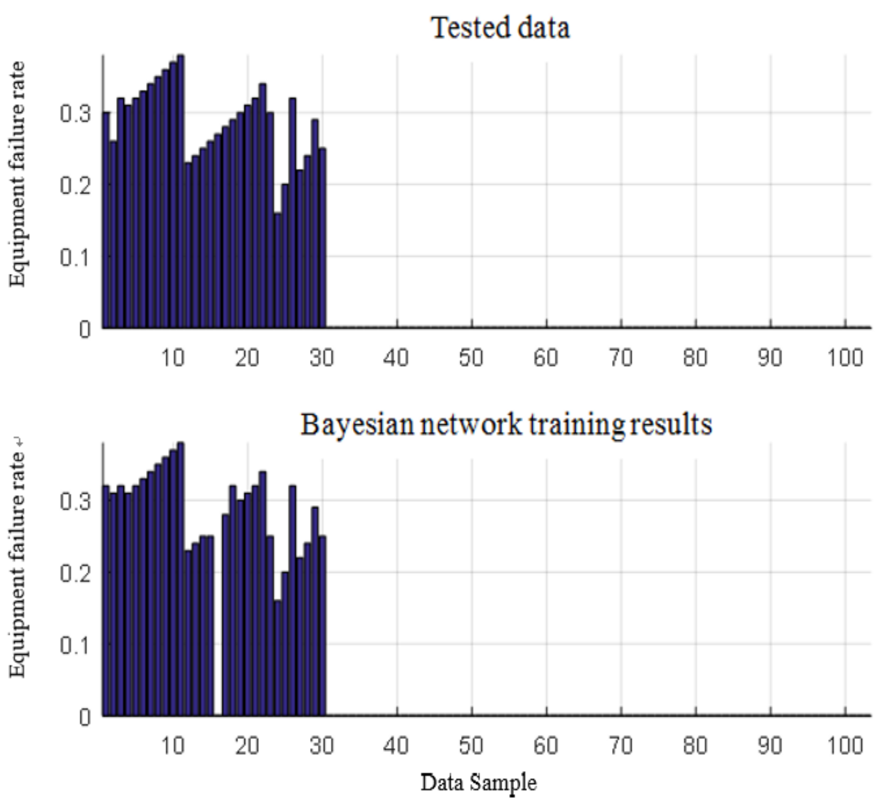

FIGURE 8. Prediction of data to be tested.

acquisition system are used to predict the failure of the traffic control equipment, and then the joint preventive maintenance strategy of the traffic equipment in the control unit is formulated according to the predicted results, so as to implement

TABLE 2. Conditional probability table of parameter learning M.

Conditional Probability	Probability
$P(M{=}f\vert E_1{=}u,E_2{=}u,E_3{=}u,E_4{=}u,E_5{=}u)$	0
$p(M{=}f\vert E_1{=}u,E_2{=}f,E_3{=}u,E_4{=}u,E_5{=}u)$	0.250
$p(M{=}f\vert E_1{=}u,E_2{=}u,E_3{=}u,E_4{=}f,E_5{=}u)$	0.315
$p(M{=}f\vert E_1{=}f,E_2{=}f,E_3{=}u,E_4{=}u,E_5{=}u)$	0.325
$p(M{=}f\vert E_1{=}f,E_2{=}u,E_3{=}u,E_4{=}f,E_5{=}u)$	0.325
$p(M{=}f\vert E_1{=}u,E_2{=}f,E_3{=}f,E_4{=}u,E_5{=}u)$	0.275
$p(M{=}f\vert E_1{=}u,E_2{=}f,E_3{=}u,E_4{=}u,E_5{=}f)$	0.423
$p(M{=}f\vert E_1{=}u,E_2{=}u,E_3{=}f,E_4{=}u,E_5{=}f)$	0.420
$p(M{=}f\vert E_1{=}f,E_2{=}f,E_3{=}f,E_4{=}u,E_5{=}u)$	0.404
$p(M{=}f\vert E_1{=}f,E_2{=}f,E_3{=}u,E_4{=}u,E_5{=}f)$	0.340
$p(M{=}f\vert E_1{=}f,E_2{=}u,E_3{=}f,E_4{=}u,E_5{=}f)$	0.375
$p(M{=}f\vert E_1{=}u,E_2{=}f,E_3{=}f,E_4{=}f,E_5{=}u)$	0.257
$p(M{=}f\vert E_1{=}u,E_2{=}u,E_3{=}f,E_4{=}f,E_5{=}f)$	0.255
$p(M{=}f\vert E_1{=}f,E_2{=}f,E_3{=}f,E_4{=}f,E_5{=}u)$	0.277
$p(M{=}f\vert E_1{=}f,E_2{=}f,E_3{=}u,E_4{=}f,E_5{=}f)$	0.396
$p(M{=}f\vert E_1{=}f,E_2{=}u,E_3{=}u,E_4{=}u,E_5{=}u)$	0.250
$p(M{=}f\vert E_1{=}u,E_2{=}u,E_3{=}f,E_4{=}u,E_5{=}u)$	0.312
$p(M{=}f\vert E_1{=}u,E_2{=}u,E_3{=}u,E_4{=}u,E_5{=}f)$	0.315
$p(M{=}f\vert E_1{=}f,E_2{=}u,E_3{=}f,E_4{=}u,E_5{=}u)$	0.380
$p(M{=}f\vert E_1{=}f,E_2{=}u,E_3{=}u,E_4{=}u,E_5{=}f)$	0.381
$p(M{=}f\vert E_1{=}u,E_2{=}f,E_3{=}u,E_4{=}f,E_5{=}u)$	0.275
$p(M{=}f\vert E_1{=}u,E_2{=}u,E_3{=}f,E_4{=}f,E_5{=}u)$	0.260
$p(M{=}f\vert E_1{=}u,E_2{=}u,E_3{=}u,E_4{=}f,E_5{=}f)$	0.420
$p(M{=}f\vert E_1{=}f,E_2{=}f,E_3{=}u,E_4{=}f,E_5{=}u)$	0.340
$p(M{=}f\vert E_1{=}f,E_2{=}u,E_3{=}f,E_4{=}f,E_5{=}u)$	0.424
$p(M{=}f\vert E_1{=}f,E_2{=}u,E_3{=}u,E_4{=}f,E_5{=}f)$	0.257
$p(M{=}f\vert E_1{=}u,E_2{=}f,E_3{=}u,E_4{=}f,E_5{=}f)$	0.641
$p(M{=}f\vert E_1{=}u,E_2{=}u,E_3{=}f,E_4{=}f,E_5{=}f)$	0.434
$p(M{=}f\vert E_1{=}f,E_2{=}f,E_3{=}f,E_4{=}u,E_5{=}f)$	0.396
$p(M{=}f\vert E_1{=}f,E_2{=}u,E_3{=}f,E_4{=}f,E_5{=}f)$	0.384
$p(M{=}f\vert E_1{=}f,E_2{=}f,E_3{=}f,E_4{=}f,E_5{=}f)$	0.670

preventive maintenance measures of the combined equipment in the control unit based on CBM.

When considering how to determine the optimal interval time for joint maintenance of control unit multi-equipment traffic system, the time length of preventive maintenance should be considered [18]. If the interval of maintenance of traffic control equipment is extended, it will probably cause frequent failure of the equipment, that is, the phenomenon of insufficient maintenance appears. The service life of equipment is quite disadvantageous, which will seriously shorten the service life of equipment. At the same time, it is also considered that when the maintenance interval of the equipment is too short, it is easy to cause over-maintenance problems. This increases the total maintenance cost and maintenance time of the control unit system. Therefore, a reasonable and effective preventive maintenance interval is set for the control unit traffic system, thereby achieving the problem of being able to effectively reduce or avoid insufficient maintenance or over-maintenance of the system, and ultimately achieve the economical purpose of maintenance. This section considers the relationship between the economic and structural correlations of the equipment in the multi-equipment traffic system of control unit. Based on this, a preventive maintenance decision-making model of the combined traffic equipment of control unit based on CBM is established to obtain the optimal maintenance interval when the maintenance cost of the system is minimized.

2) MODEL SYMBOL DEFINITION AND PARAMETER DESCRIPTION

The relevant symbols used in this model are defined as follows:

T_i— preventive maintenance intervals for multi-equipment traffic systems in control units;

$\lambda_{ij}(t)$ — the failure rate of device j before and after its i-th preventive maintenance;

θ_i— is the failure rate increment factor;

δ_i— is the ageing factor;

$R_{ij}(t)$ — the reliability of equipment j in its i-th preventive maintenance facility;

ST_i— the maintenance interval for the i-th preventive maintenance of a single unit;

L_{ij}— the effective age of the equipment during the maintenance interval for the i-th preventive maintenance;

n_{ij}— the number of unexpected failures that device j has experienced during the i-th preventive maintenance interval;

W_i—CBM-based preventive maintenance time point, where $i = 1, 2, \ldots, N$;

P_{ij}— device j at the point in time of its i-th preventive maintenance;

C_{mj}— equipment j an unexpected failure repair cost is minor repair cost;

C_{mij}— the minor repair cost of equipment j during its i-th preventive maintenance interval T_i;

TC_{mj}—the total minor repair cost of equipment j in the first N preventive maintenance;

t_{mj}— equipment j an unexpected fault repair time is a minor repair time;

Tt_{mj}— the total time required for minor repairs in equipment j during its first N preventive repairs;

C_{pmij}— preventive maintenance costs for equipment j during its i-th preventive maintenance, this is, interval T_i;

TC_{pmij}— the total maintenance cost of equipment j during the first N preventive maintenance;

t_{pmij}— the time required for preventive maintenance of equipment j during its i-th preventive maintenance interval T_i;

Tt_{pmij}— the cost of total preventive maintenance of equipment j during the first N preventive maintenance;

t_{parkj}— the total downtime of equipment j during the first N preventive repairs;

Tt_{parkj}— the total downtime of equipment j during the first N preventive repairs;

TC_{park}— the total downtime cost of the multi-equipment system of the control unit during the first N preventive repairs;

C— the total maintenance cost of the multi-equipment system of the control unit;

C_{pr}— the cost of preventive replacement of equipment;

TL—the time the system is running;

A_j— the validity of device j;

A_{j0}— the threshold of the efficiency of device j;

R_{ij}— the reliability of the i-th preventive maintenance of equipment j;

R_{i0}— the reliability threshold for the i-th preventive maintenance of the multiequipment system of the control unit;

Among the above parameters, $i = 1, 2, \ldots, N$; $j = 1, 2, \ldots, n$.

B. DETERMINATION OF PREVENTIVE MAINTENANCE CYCLE OF TRAFFIC CONTROL EQUIPMENT BASED ON CBM

1) DETERMINATION OF PREVENTIVE MAINTENANCE CYCLE FOR A SINGLE TRAFFIC CONTROL DEVICE BASED ON CBM

Determine the failure rate of the traffic control equipment: It is necessary to establish the failure rate evolution rule for the prediction of the failure rate function in CBM-based non-periodic preventive maintenance. In this paper, the failure rate increment factor and the service age fallback factor are introduced in the failure rate function of the traffic control equipment and the two are combined. The failure rate function of the equipment before and after preventive maintenance is:

$$\lambda_{i+1}(t) = \theta_i \lambda_i (t_i + \delta_i T_i) \tag{10}$$

where t_i is the moment of the i-th preventive maintenance of the equipment, where $t_i = \sum_{s=1}^{i} t_s$, i represents the number of preventive maintenance of the equipment, $i = 1, 2, \ldots, N$; where $\lambda_i(t)$ is used to indicate the failure rate distribution function of the equipment before the i-th preventive maintenance of the equipment, $\lambda_0(t)$ represents the initial failure rate distribution function of the equipment; δ_i represents the equipment age return factor, and θ_i represents the equipment failure Rate increment factor, where $0 < \delta_i < 1, \theta_i > 1$.

The value of δ_i is:

$$\delta_i = \left(a \cdot \frac{C_{pmi}}{C_{pr}} \right)^{\tau \cdot i \cdot i^{\sigma}} \tag{11}$$

where α is the equipment maintenance cost adjustment coefficient; τ represents the time adjustment coefficient; σ represents the learning effect adjustment coefficient, $\sigma = \ln \psi / \ln 2$; ψ is the percentage of the empirical curve given by experts based on empirical judgment or estimation. The value of θ_i can be taken according to the historical data of the device operation and the actual situation.

Determine the maintenance interval of a single traffic control device: The preventive maintenance cycle of a single traffic control device in this paper is determined according to the reliability of the components that make up the device. Firstly, according to the characteristics of equipment j, experts usually pre-set the reliability threshold R_{j0} of equipment. When the reliability of equipment reaches and exceeds the pre-set reliability threshold R_{j0}, preventive maintenance measures are implemented for the equipment.

According to the reliability function of a single device j:

$$R_{ij}(t) = \exp\left(- \int_0^{ST_i} \lambda_{ij}(t)\, dt \right) \tag{12}$$

When the device reaches its reliability threshold, it has:

$$\exp\left(- \int_0^{ST_1} \lambda_{1j}(t)\, dt \right) = \exp\left(- \int_0^{ST_2} \lambda_{2j}(t)\, dt \right) = \ldots = \exp\left(- \int_0^{ST_i} \lambda_{ij}(t)\, dt \right) = R_{j0} \tag{13}$$

Equation (13) can be rewritten as:

$$\int_0^{ST_1} \lambda_{1j}(t)\, dt = \int_0^{ST_2} \lambda_{2j}(t)\, dt = \ldots = \int_0^{ST_i} \lambda_{ij}(t)\, dt = -\ln R_0 \tag{14}$$

The simultaneous (10) and (14) methods result in a preventive maintenance cycle ST_i for a single traffic control device in the system, where $i = 1, 2, \ldots, N$.

Determine the effective age of the traffic control equipment.

After prophylactic maintenance of the traffic control equipment, it will make its age less. The age-return factor is related to the number of preventive maintenance performed by the equipment and the effectiveness of preventive maintenance.

The effective age before and after the first preventive maintenance of the equipment is:

$$L_1^- = T_1 \quad L_1^+ = (1 - \delta_1) T_1 \tag{15}$$

The effective age before and after the second preventive maintenance of the equipment is:

$$L_2^- = L_1^+ + T_2 = (1 - \delta_2) T_1 + T_2 \tag{16}$$

$$L_2^+ = (1 - \delta_2) L_2^- = (1 - \delta_1)(1 - \delta_2) T_1 + (1 - \delta_2) T_2 \tag{17}$$

According to this type of evidence, the effective age before and after the i-th preventive maintenance of the equipment

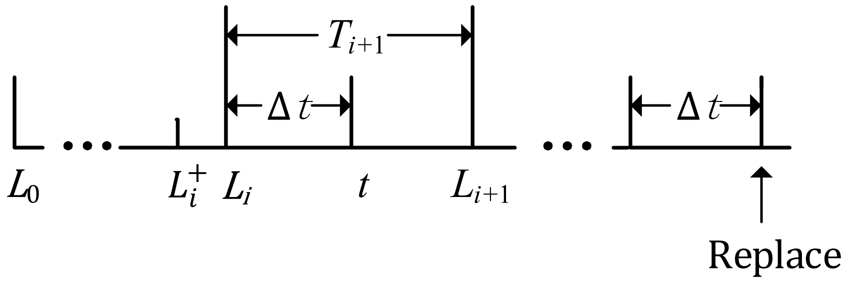

FIGURE 9. Equipment age changes in equipment during its life cycle.

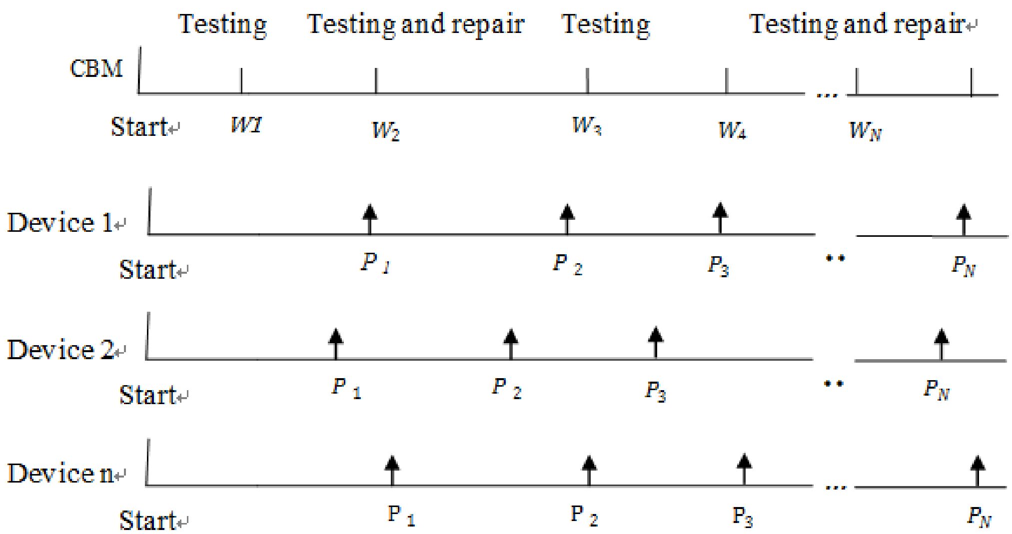

FIGURE 10. Preventive maintenance of unadjusted multi-device system.

can be obtained:

$$\begin{aligned} L_i^- &= L_{i-1}^+ + T_i \\ &= \prod\nolimits_{l=1}^{i-1}(1-\delta_l)\,T_1 + \prod\nolimits_{l=2}^{i-1}(1-\delta_l)\,T_2 \\ &\quad + \ldots + (1-\delta_{i-1})\,T_{i-1} + T_i \end{aligned} \tag{18}$$

$$\begin{aligned} L_i^+ &= (1-\delta_i)\,L_i^- \\ &= \prod\nolimits_{l=1}^{i}(1-\delta_l)\,T_1 + \prod\nolimits_{l=2}^{i}(1-\delta_l)\,T_2 \\ &\quad + \ldots + \prod\nolimits_{l=i-1}^{i}(1-\delta_l)\,T_{i-1} + (1-\delta_i)\,T_i \end{aligned} \tag{19}$$

As shown in Fig. 9, according to the analysis, it can be seen that the effective service life of equipment j during the maintenance interval of the i-th preventive maintenance is as follows:

$$\begin{aligned} L_{ij}(t) &= L_i^+ + \Delta t = L_i^+ + \left(t - \sum_{s=1}^{i} T_s\right) \\ &= t + \left[\prod_{l=1}^{i}(1-\delta_{lj}) - 1\right]T_1 + \left[\prod_{l=2}^{i}(1-\delta_{lj}) - 1\right]T_2 \\ &\quad + \ldots + \left[\prod_{l=i-1}^{i}(1-\delta_{lj}) - 1\right]T_{i-1} - \delta_{ij}T_i \end{aligned} \tag{20}$$

The number of times that equipment j is minorly repaired during the i-th preventive maintenance interval is the number of unexpected failures:

$$n_{ij} = \int_{L_{i-1}^+}^{L_i^-} \lambda_{ij}(t)\,dt \quad j = 1, 2, \ldots, n \tag{21}$$

2) DETERMINATION OF PREVENTIVE MAINTENANCE CYCLE FOR JOINT TRAFFIC EQUIPMENT OF CONTROL UNITS BASED ON CBM

For control unit traffic systems, there are some differences in the preventive maintenance intervals of the traffic control equipment that make up the system. If the maintenance is performed according to the optimal preventive maintenance interval of the each traffic control equipment, the system will be shut down frequently, resulting in an increase in the cost of preventive maintenance of the system and a reduction in the utilization of the system.

In this paper, the equipment in the control unit traffic system is taken as the research object, and the preventive maintenance interval of the equipment in the system is analyzed. Figure 10 is the CBM-based maintenance that the control unit system has not adjusted.

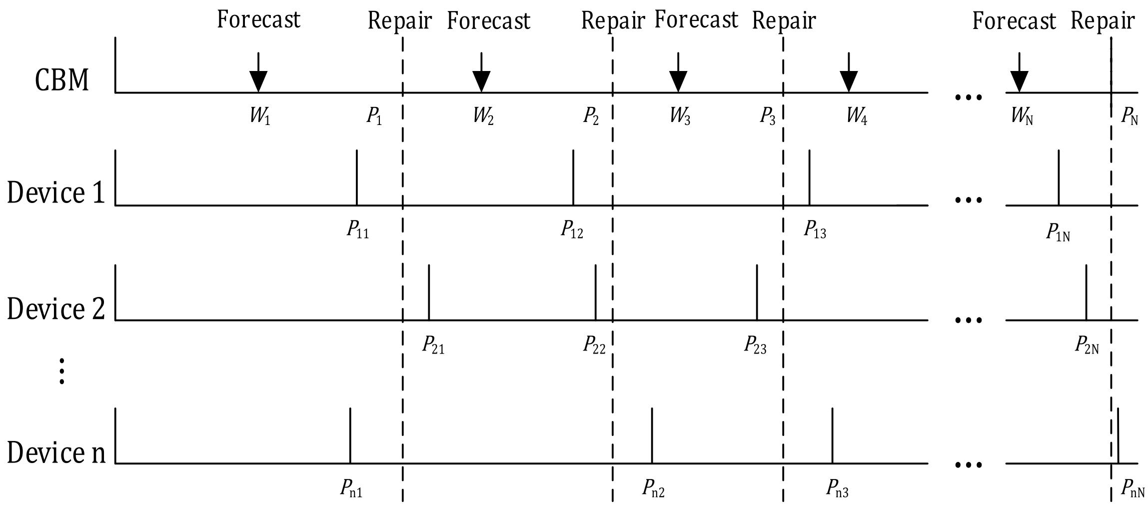

FIGURE 11. **Preventive maintenance of adjusted multi-device system.**

Control unit multi-device traffic system consists of n different devices. The optimal preventive interval W_i for a single device (where $i = 1, 2, \ldots, N$) can be derived from the formula (10). It is calculated in parallel with the formula (14), and the corresponding time is indicated by "↑". In a certain time interval, if the preventive cycle is not adjusted, the optimal preventive maintenance time for each traffic control device is at a different time; if the optimal preventive interval is based on each device in the control unit, the time for preventive maintenance will result in continuous downtime of the entire control unit traffic system, which will ultimately have a very negative impact on the execution of the manufacturing system, the control of maintenance costs, and the utilization of the system. Since system production must respond quickly to fluctuations in demand [19], we need to adjust the preventive maintenance plan of the traffic control system, that is, to prevent or delay the preventive maintenance interval of traffic control equipment in the system, and use group maintenance. The theory is adjusted to reduce the total downtime of the control unit multi-equipment transportation system, reduce system maintenance costs, and increase overall system utilization. Figure 11 shows a preventive maintenance plan for an adjusted multi-equipment traffic control system.

Figure 11 provides a uniform adjustment of the preventive maintenance intervals for equipment in a fault-free control unit traffic system compared to Figure 10, implementing the first preventive maintenance of the system. In the case, it can be seen from Fig. 11 that the preventive maintenance time P_{11}, P_{n1} of the device 1 and the device n are advanced to the time P_1, and the preventive maintenance time of the device 2 is delayed to the time P_1, thereby avoiding the entire control unit before the time W_2. Multi-device systems require down 3 times, increasing traffic control equipment utilization.

In order to achieve the joint maintenance of the traffic equipment in the control unit, that is, the overall maintenance optimization, in the preventive maintenance decision of the joint equipment of the control unit traffic system, the actual use of the each traffic control equipment should be combined, and the traffic control equipment in the system should be considered. The correlation feature exists to adjust the preventive maintenance interval of each device to obtain the optimal preventive maintenance interval for the multi-equipment traffic system of the control unit.

C. ESTABLISHMENT OF JOINT TRAFFIC EQUIPMENT MAINTENANCE DECISION MODEL FOR CONTROL UNIT

1) DETERMINATION OF RELIABILITY OF MULTI-EQUIPMENT TRAFFIC SYSTEM IN CONTROL UNIT

In the control unit production system, the reliability of the traffic control system equipment and the structure of the multi-equipment traffic system of the control unit determine the reliability of the entire production system. The main considerations in this paper are the control units of the tandem structure. It is assumed that the reliability of each device in the multi-device traffic system of the tandem control unit is $R_{ij}(t)$, where $j = 1, 2, \ldots, n$, based on the definition of device reliability and the characteristics of the multi-device system in series, the system can be obtained. Overall reliability $R_i(t)$:

$$R_i(t) = R_{i1}(t) \cdot R_{i2}(t) \ldots R_{in}(t) = \prod_{j=1}^{n} R_{ij}(t) \tag{22}$$

It can be seen from the formula (22) that in the multi-device traffic system of the control unit, the number of traffic control devices in the system has a direct influence on the reliability of the control unit traffic system. The relationship between the reliability of the control unit system and the reliability of a single device constituting the system is shown in Fig. 12, where n is expressed as the number of devices that make up the control unit system. As can be seen from Fig. 12, when the reliability R_j of a single device in the control unit traffic system is fixed, the reliability of the system is continuously reduced as the number of devices in the system increases.

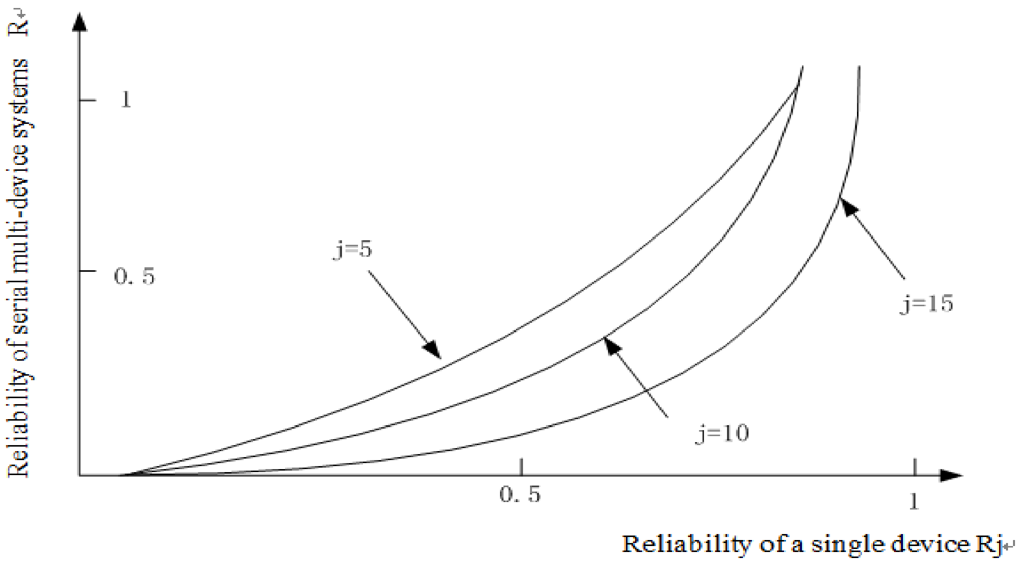

FIGURE 12. Relationship between reliability of control unit series system and reliability of single equipment.

2) DETERMINATION OF DYNAMIC MAINTENANCE COSTS AND EQUIPMENT AVAILABILITY OF EQUIPMENT

Determination of traffic control equipment maintenance cost:

Minor repair and maintenance costs for unexpected failures: Assume that traffic control equipment j is repaired in the first preventive maintenance interval T_i with unexpected maintenance. The minor repair cost is C_{mj}, and the repair time of one minor repair is t_{mj}, i minor repair costs in the maintenance interval T_i are:

$$C_{mij} = C_{mj} \cdot n_{ij} \tag{23}$$

The total minor repair cost in equipment j in its first i preventive maintenance:

$$TC_{mj} = \sum_{i=1}^{N} C_{mj} \cdot n_{ij} = C_{mj} \cdot \sum_{i=1}^{N} \int_{L_{i-1}^{+}}^{L_i^{-}} \lambda_{ij}(t)\, dt \tag{24}$$

The time required for the minor repairs of equipment j in its first i preventive maintenance:

$$Tt_{mj} = \sum_{i=1}^{N} t_{mj} \cdot n_{ij} = t_{mj} \cdot \sum_{i=1}^{N} \int_{L_{i-1}^{+}}^{L_i^{-}} \lambda_{ij}(t)\, dt \tag{25}$$

Non-periodic preventive maintenance costs: According to the actual situation, when the traffic control equipment reaches the reliability threshold, the equipment is subjected to non-periodic preventive maintenance. Considering that the preventive maintenance cost of the equipment is dynamic, the cost of equipment i in its i-th preventive maintenance is:

$$C_{pmij} = C_{fj} + i \cdot C_{vj} \tag{26}$$

The total preventive maintenance cost of equipment j in the first i preventive maintenance is:

$$TC_{pmj} = \sum_{i=1}^{N} C_{pmij} = \sum_{i=1}^{N} (C_{fj} + i \cdot C_{vj}) \tag{27}$$

Equipment j at the time required for its i-th preventive maintenance:

$$t_{pmij} = \tau \cdot i \cdot T_i \tag{28}$$

The time required for the total preventive maintenance of equipment j in its first i preventive maintenance is:

$$Tt_{pmj} = \sum_{i=1}^{N} T_{pmij} = \sum_{i=1}^{N} \tau \cdot i \cdot T_i, \quad j = 1, 2, \ldots, n \tag{29}$$

where C_{fj} is used to indicate the fixed cost of implementing preventive maintenance for equipment j, C_{vj} is the variable cost for preventive maintenance of equipment j; τ is the time adjustment factor for preventive maintenance, which indicates the equipment with the running time. It is getting longer and longer, and the equipment wears out continuously and makes the equipment take longer and longer for preventive maintenance.

Loss of downtime costs: The total downtime of equipment j during its first i preventive maintenance interval is:

$$\begin{aligned} Tt_{parkj} &= Tt_{mj} + Max\left[Tt_{pmj}\right] \\ &= t_{mj} \cdot \sum_{i=1}^{N} \int_{L_{i-1}^{+}}^{L_i^{-}} \lambda_{ij}(t)\, dt + Max\left[\sum_{i=1}^{N} \tau \cdot i \cdot T_i\right] \end{aligned} \tag{30}$$

Due to the relatively small time of minor repair (repairable maintenance), the minor repair of one traffic control equipment will not affect the downtime of the entire multi-equipment system, so the downtime of the whole system does not count the minor repair time, then the total downtime of the control unit multi-equipment transportation system in its first preventive maintenance is:

$$\begin{aligned} Tt_{park} &= Max\left[Tt_{pmj}\right] \\ &= Max\left[\sum_{i=1}^{N} \tau \cdot i \cdot T_i\right] \end{aligned} \tag{31}$$

The total downtime cost of the control unit multi-equipment traffic system in the first i time is:

$$TC_{park} = C_{park/h} \cdot Tt_{park} \tag{32}$$

The total maintenance cost of the control unit multi-equipment system in the first i preventive maintenance of the system is:

$$\begin{aligned} C &= \sum_{j=1}^{n} \left[TC_{mj} + TC_{pmj}\right] + TC_{park} \\ &= \sum_{j=1}^{n} \left[C_{mj} \cdot \sum_{i=1}^{N+1} \int_{L_{i-1}^{+}}^{L_i^{-}} \lambda_{ij}(t)\, dt + \sum_{i=1}^{N} \left(C_{fj} + i \cdot C_{vj}\right) \right] \\ &\quad + C_{park/h} \cdot Tt_{park} \end{aligned} \tag{33}$$

Determination of the effectiveness of the traffic control equipment:

The validity of a device is the probability that the traffic control device is in a usable state during its lifetime. The expression of the device's validity is:

$$A = lim_{n\to\infty} \frac{A(t)}{T} \tag{34}$$

Then the validity of device j is:

$$\begin{aligned} A_j &= \frac{TL - Tt_{parkj}}{TL} \\ &= \frac{\sum_{i=1}^{N} T_i - t_{mj} \cdot \sum_{i=1}^{N} \int_{L_{i-1}^{+}}^{L_i^{-}} \lambda_{ij}(t)\, dt - Max\left[\sum_{i=1}^{N} \tau \cdot i \cdot T_i\right]}{\sum_{i=1}^{N} T_i} \end{aligned} \tag{35}$$

3) CBM-BASED CONTROL UNIT JOINT TRAFFIC EQUIPMENT PREVENTIVE MAINTENANCE DECISION MODEL

With the goal of minimizing the dynamic maintenance cost of the control unit traffic system and taking the effectiveness of the each traffic equipment in the control unit and the reliability of the system as constraints, a preventive maintenance decision model for the control unit joint traffic equipment is established. The model is as follows:

$$\begin{cases} min\ C = \sum_{j=1}^{n} \left[TC_{mj} + TC_{pmj}\right] + TC_{park} \\ s.t\ A_j = \dfrac{TL - Tt_{parkj}}{TL} \geq A_{j0} \\ R_i(t) = R_{i1}(t) \cdot R_{i2}(t) \ldots R_{in}(t) = \prod_{j=1}^{n} R_{ij}(t) \geq R_{i0} \\ N > 0, \quad i = 1, 2, \ldots, N;\ j = 1, 2, \ldots n \end{cases} \tag{36}$$

The cost of various maintenances of the traffic control equipment during its life cycle and its loss can be obtained through the relevant historical data of the equipment and the experience of the maintenance personnel. The time range T of the equipment is usually specified by the maintenance decision-makers. In a month, it can also be a year or even a few years.

4) MODEL SOLVING

Solution Steps:

Firstly, the traffic control equipment is analyzed based on the historical operation data of the equipment, thereby determining the failure rate increment factor θ_i of the equipment, and determining the service age back factor δ_i of the equipment according to the formula (11), and finally calculating the failure rate of device j according to the formula (10).

According to the formula (12), it can be judged whether the reliability of the device j reaches its reliability threshold R_{j0}, and when it reaches its reliability threshold R_{j0}, the device is subjected to preventive maintenance. The simultaneous maintenance intervals ST_i for a single device can be obtained for the simultaneous (10) and (14) versions.

Calculate the effective age of the device j before and after the implementation of the i-th preventive maintenance according to equations (18) and (19), and calculate the device j at its i-th of the effective age of the preventive maintenance interval and the number of unexpected failures n_{ij} according to equations (20) and (21).

Objective function. According to formula (24), the total minor repair cost TC_{mj} of equipment j in N preventive maintenance is calculated. The cost TC_{pmj} of the total preventive maintenance of the device j in the first i preventive maintenance is calculated according to the formula (27). Calculate the total downtime Tt_{park} of the control unit multi-equipment system in its previous i-preventive maintenance according to equation (31). Calculate the total TC_{park} cost of equipment j in the first i time preventive maintenance according to equation (32). Then, according to formula (33), the total maintenance cost C of the control unit system of the control unit multi-equipment system during the pre-prevention maintenance time is calculated.

Constraints. The validity threshold A_{0j} of the traffic control device j in the control unit is respectively determined according to the actual situation of the device, and the validity degree A_j of the n devices is respectively determined to be higher than the effective threshold of the device according to the formula (35). Calculate the reliability R_{ij} of the nth preventive maintenance of the i-th equipment according to the formula (12), calculate the reliability of the system according to (22) and ensure the reliability of the traffic control system is higher than the reliability threshold of the system.

Using the genetic algorithm to solve the model and programming in MATLAB to achieve the computational formula (36) optimization problem and finally with the change of the number of preventive maintenance of traffic control equipment, through calculation, an optimal maintenance strategy combination can be found, and the optimal cbm-based maintenance interval T_i of the control unit multi-equipment traffic system can be determined, so as to minimize the total maintenance cost of the traffic control system.

D. ANALYSIS OF EXAMPLES

In order to verify the established mathematical model, the following example is analyzed. Taking the H-enterprise

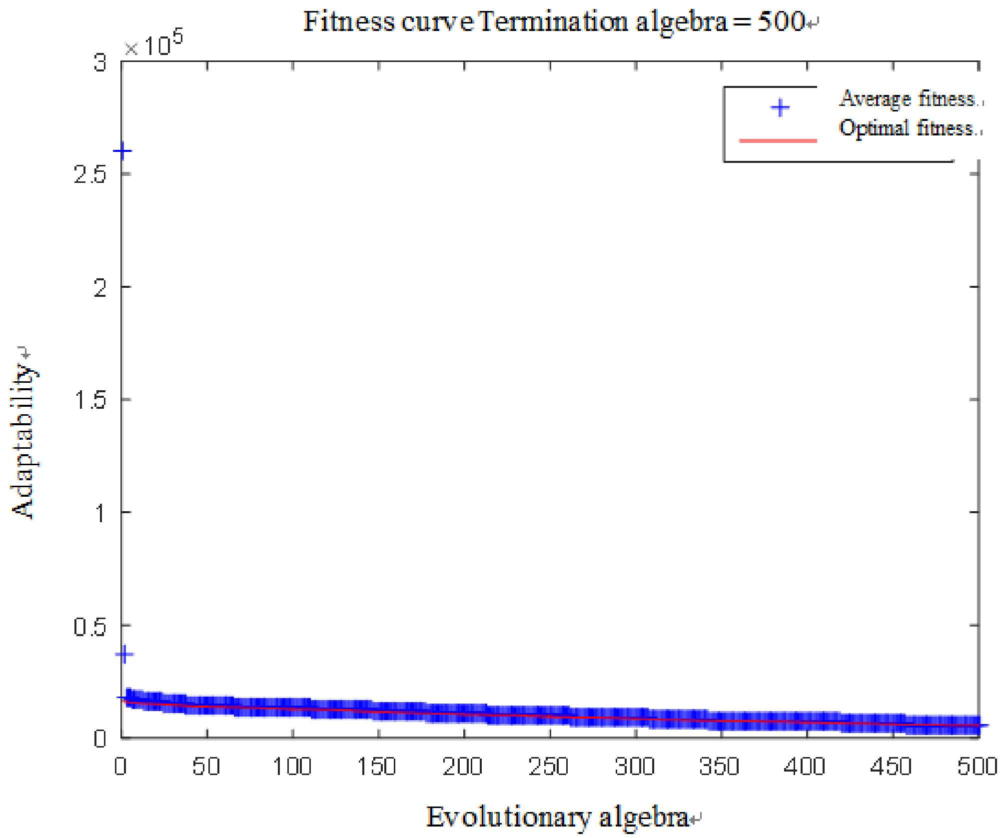

FIGURE 13. The relationship between the number of iterations and the value of the objective function.

intelligent control unit multi-equipment transportation system engaged in the R&D and production of urban transportation system equipment in above as an example, it consists of 5 traffic control equipments connected in series. Composition, based on historical data on equipment operations, combined with expert experience, in the limited interval T =[0,1000] (unit, h), the values of the parameters of the five intelligent devices are as follows: the equipment maintenance cost adjustment coefficient $\alpha = 1$, the initial equipment failure The rate $\lambda_0 = 0.1$, the equipment shutdown cost is $C_{park/h} = 5000$ (unit, yuan), the number of preventive maintenance is $i = [1,20]$ and the time t_{mj} of a minor repair of the equipment is 50. The values of the parameters of the remaining devices are shown in Table 3.

The model is programmed in MATLAB 2015b, and the relationship between the decision variable i, the number of preventive maintenance, and its objective function is counted. The iterative process of the model when $R_0 = 0.6$ is shown in Figure 13.

Among them, the parameters of the genetic algorithm used are set as follows: the size of the population is set to 50, wherein the mutation probability is set to 0.3, the crossover probability is 0.8, the crossover operator and the mutation operator parameters are 20, and the number of system iterations is 500. As can be seen from Figure 13, as the number of iterations increases, the target value C begins to gradually decrease and eventually gradually stabilizes. When the number of iterations is 480 generations, the target value exhibits a convergence trend. It can be seen that the algorithm used in this section has good convergence for solving the model established in this paper.

By changing the value of the number of preventive maintenance i and running the program, the interval between preventive maintenance of the traffic control system at each stage, that is, the preventive maintenance corresponding to 10 preventive maintenance of the system can be obtained. The interval time is shown in Table 4. As can be seen from Table 4, with the increase in the number of preventive maintenance i of the control unit multi-equipment traffic system, the maintenance interval T_i for preventive maintenance of the control unit traffic system is continuously shortened, which is related to the control unit traffic system. The running time of the traffic control equipment increases, the equipment is degraded due to abrasion. When the equipment degrades to the potential failure point and enters the equipment degradation stage, as the number of equipment maintenance increases, the frequency of equipment failure increases. The frequency of each device failure is inconsistent, resulting in an increase in the frequency of the multi-device system of the control unit, which is consistent with the actual situation of device degradation.

TABLE 3. Parameter value of device.

Device n	τ	σ	θ_i	C_{fj}	C_{mj}	t_{mj}	A_{j0}	R_{j0}	C_{pr}
1	0.001	-0.1	1.1	1000	1000	20	0.8	0.8	1000
2	0.002	-0.2	1.2	2000	2000	30	0.7	0.75	2000
3	0.003	-0.3	1.3	3000	3000	40	0.6	0.85	3000
4	0.004	-0.4	1.4	1500	4000	50	0.85	0.76	4000
5	0.005	-0.5	1.5	2500	5000	60	0.9	0.83	5000

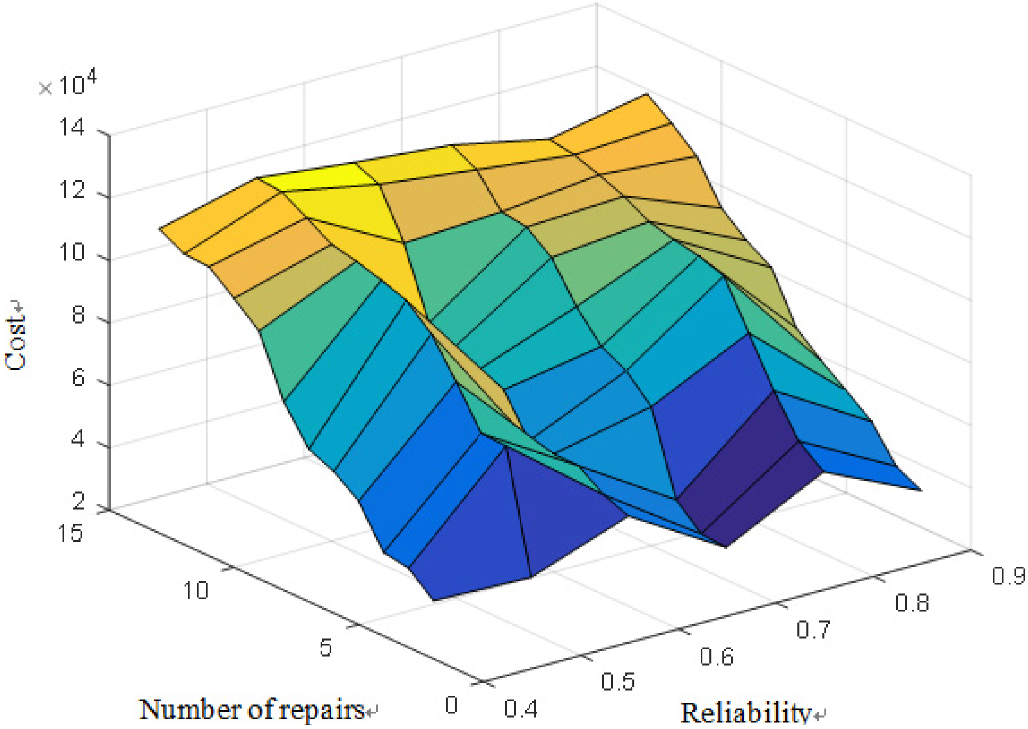

FIGURE 14. System maintenance cost based on system reliability constraints.

TABLE 4. Model solution results when system maintenance cost is minimal.

Number of preventive maintenance i	System preventive maintenance interval T_i
1	77.3419
2	72.0492
3	57.3181
4	49.7646
5	49.1073
6	49.0573
7	48.0005
8	40.1096
9	26.2159
10	23.9942

According to the above steps, by changing the reliability threshold of the multi-device traffic system of the control unit, the value of R_0 is increased from $R_0 = 0.4$ to $R_0 = 0.9$, and the value of R_0 is changed step by step, and is run in MATLAB and calculated by the total minimum maintenance cost of the system for the i-th preventive maintenance under the condition that the value of the system reliability R_0 is different. Figure 14 shows the number of preventive maintenance of the system, the reliability of the system $R_i(t)$ and the total maintenance cost C of the system for the control unit traffic system based on different system reliability thresholds R_0.

As can be seen from Figure 14, when the reliability threshold R_0 of the control unit traffic system is different, that is, the minimum requirements for the reliability of the system are different, the obtained preventive maintenance plan is also different, and the solution of the model can calculate the corresponding minimum maintenance costs. As the reliability threshold R_0 of the control unit traffic system is increased, the maintenance interval of the traffic control equipment is gradually shortened, and the maintenance cost is increasing. Joint maintenance of the control unit traffic equipment can greatly reduce the maintenance cost of the entire system while ensuring the reliability of the system and the effectiveness of the equipment. All of the above indicate that the model is consistent with the actual situation, which proves the validity of the model.

V. CONCLUSION

1) In this paper, PHM theory and technology are introduced into the maintenance management of manufacturing equipment. Taking traffic equipment in intelligent control unit as the research object, the influencing factors of equipment failure prediction and maintenance decision-making are analyzed and summarized. Several factors affecting the maintenance decision-making of traffic control equipment are introduced in detail.

2) Based on the PHM theory, the data source of intelligent control unit traffic equipment for fault prediction and maintenance decision is firstly explained, and the fault monitoring model for intelligent control unit traffic equipment is proposed. In this paper, according to the characteristics of control unit traffic equipment, Bayesian network method is selected to predict the faults of control unit traffic equipment. Finally, an example is given to prove that the method is suitable for fault prediction of traffic control equipment.

3) Considering the increase of the traffic control equipment's working time and the number of times it is repaired, the effective age of the equipment changes accordingly. This paper also considers the traffic control equipment failure rate increment factor and the age-return factor. And combining the two, and considering the variability of the preventive maintenance cost of the control unit traffic system, this paper establishes a preventive maintenance decision model for the joint equipment of the CBM-based control unit multi-equipment system, through the multi-equipment system in the control unit. The advancement and delay of the preventive maintenance time of the traffic control equipment reduces the total downtime of the system, thereby increasing the availability of the system and reducing the economic loss caused by the system, making the preventive maintenance activities of the joint equipment maintenance more realistic. The demand, therefore, this idea is of great significance for the extension of the preventive maintenance theory of joint equipment for control unit multi-equipment traffic systems.

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HUAN-YAN LI received the B.Sc. degree in engineering management from the Shenyang University of Technology, in 2019. Her current research interests include automation systems, manufacturing systems control, and numerical control.

ZHOU WANG received the B.Sc. degree in electronic commerce from Bohai University, in 2016, and the M.Sc. degree in management science and engineering from the Shenyang University of Technology, in 2019. Her current research interests include automation systems, manufacturing systems control, and numerical control.

WEI XU received the B.Sc. degree in engineering management, the M.Sc. degree in business management, and the Ph.D. degree in management science and engineering from the Shenyang University of Technology, in 2003, 2006, and 2018, respectively. His current research interests include automation systems, manufacturing systems control, and numerical control.

MENG XIAO received the B.Sc. degree in engineering management from Northeastern University, in 2002, the M.Sc. degree in business management from the Harbin Institute of Technology, in 2005, and the Ph.D. degree in business management from Northeastern University, in 2019. Her current research interests include automation systems, manufacturing systems control, and numerical control.

YANJUAN CUI received the B.Sc. degree in international economics and trade and the M.Sc. degree in international trade from Jilin University, in 2001 and 2004, respectively, and the Ph.D. degree in finance from the Dongbei University of Finance and Economics, in 2012. Her current research interests include financial development, international finance, and fin-tech.

ZHI-XIAO SUN received the degree in engineering management from the Shenyang University of Technology. Her current research interests include automation systems, manufacturing systems control, and numerical control.