Design of Embedded Fault Detection Module for Metro Locomotive

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***Abstract* — In order to improve the scientific value and facilitate maintenance decisions for bolt components of high-speed rail and reduce the maintenance cost for such bolt components, a maintenance decision approach based on fuzzy weight adaptive Petri net is proposed. Firstly, Petri net is introduced to the maintenance decision problem; moreover, in order to enhance the adaptability of the application of Petri nets in maintenance decisions, it is improved with fuzzy weight adaptive approach. Secondly, a cost target decision model for maintenance of high-speed rail components is built, and decision optimization is made with fuzzy weight adaptive Petri net and then the maintenance time decision is made. Finally, the advantages of the proposed maintenance decision approach in terms of the maintenance cost are verified by experiments.**

Keywords - fuzzy weight; self-adaptation; fault detection; high-speed rail; metro locomotive; embedded

I. INTRODUCTION

The performance of bolt component of contact line equipment of traction power supply system of high speed rail degrades gradually under high speed bow net operation status, i.e. the bow net vibration can cause loosening of bolt. The final consequence of bolt status degradation will lead to the occurrence of function failure. And the fault of loosening will also trigger the contact line equipment to experience major fault like coming off, seizing, wearing and break. Therefore, it is very important to grasp the operation status of the bolt. However, since the skylight time of high speed rail is very limited, and the time bucket is usually at night, the insufficient light reduces extremely the equipment patrol effect. Besides, there are many bolts, so it is rather difficult to check the bolt loosening status. Given this, in order to realize the transformation of the maintenance of contact line from extensive inspection to economic and scientific inspection approach, it is quite necessary to conduce the study on the bolt loosening of contact line equipment of high speed rail.

With the wide application of Petri net, many scholars have further studied the fuzzy Petri net (FPN)which more suits the human idea and cognitive style, showcasing the synchronization and concurrence ability of the Petri net. One approach to diagnose the fault of electric system based on Petri net and probability information is proposed in literature [7]. While Petri net is used for modeling, the probability information is used to handle the uncertainty in diagnosis of fault of electric system and satisfactory results are achieved; in literature [8], fuzzy Petri net is used to establish sub-models separately for elements in the electric system, and protection, the influence of uncertainty of break action and and incomplete factors are also considered; in literature [9], one fuzzy inference Petri net is used to finish the fault diagnosis and inference process of power system through matrix iteration calculation. in literature [10], the fault diagnosis improvement approach for power transmission network based on fuzzy Petri net is studied and incidence matrix reduction technology is introduced which reduces the order of incidence matrix and greatly reduces the calculation amount, thus conducive to the improvement of subsequent inference.

Fuzzy weight adaptive Petri net mode is used in this paper to describe the degradation of status performance of bolt equipment. The equipment status data is extracted and analyzed through decision model with cost as the purpose, reflecting the health status of equipment. The predication of remaining life is realized with this model and the predication results are used to optimize the maintenance decision model so that the maintenance effect can reach the optimum.

II. FUZZY WEIGHT ADAPTIVE PETRI NET

A. Fuzzy Weight Adaptive Petri net

The fuzzy weight adaptive Petri net (WFPN) can be defined as one 9-tuple with the form as follows:

$$S_{WFPN} = \{P, T, I, O, \alpha, T_h, W, \theta^0, U\} \tag{1}$$

Among which: $P = \{p_1, p_2, \cdots, p_n\}$ is the limited set of place nodes; $T = \{t_1, t_2, \cdots, t_m\}$ is the limited set of transition nodes; $I: P \to T$ reflects the mapping from the place to the transition, $I = [\delta_{ij}]$, δ_{ij} is the logic amount, $\delta_{ij} \in [0,1]$, when p_i is the input of t_j (i.e. when there is directed arc from p_i to t_j), $\gamma_{ij} = 0$, among which $i = 1, 2, \cdots, n$, $j = 1, 2, \cdots, m$; $\alpha: P \to (0,1]$ is the confidenceof the proposition corresponding to the place; $T_h: T_h \to [0,1]$ is one mapping, define one threshold value $T_h(t_j) = \lambda_j$ for transition $t_j \left(t_j \in T\right)$, among which $j = 1, 2, \cdots, m$, $W = [w_1, w_2, \cdots, w_n]$, it is the regular weight matrix, reflecting the support degree of prerequisite in the rules for the conclusions; θ^0 is the initial status, $\theta^0 = \left[\theta^0_{p_1}, \theta^0_{p_2}, \cdots, \theta^0_{p_i}\right]^T$, $\theta^0_{p_i}$ is the initial logic status of proposition p_i, $\theta^{\sigma}_{p_i}, \in [0,1]$ is the confidence when the status p_i is true, $i = 1, 2, \cdots, n$; U is the rule confidence matrix, $U = diag(\mu_1, \mu_2, \cdots, \mu_m)$, μ_j is the confidence of rule t_j, $\mu_j \in [0,1]$, among which $j = 1, 2, \cdots, m$, when $\mu_j = 1$, it is normal inference Petri net not including fuzzy variables. The specific structure of fuzzy wight adaptive Petri net is as follows:

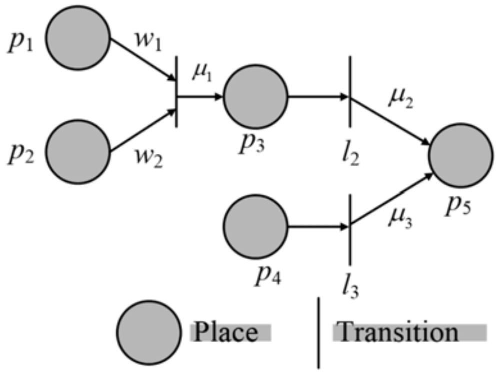

Figure 1. Fuzzy weight adaptive petri net

B. *Inference of Fuzzy Weight Adaptive Petri Net*

The inference of fuzzy weight adaptive Petri net adopts the matrix calculation. In order to represent the matrix calculation clearly and simply, five operators are adopted in this paper. The matrix multiplication: $C = A \cdot B$, then $c_{ij} = \sum_{k=1}^{l} a_{ik} b_{kj}$, addition operator $\oplus$: $C = A \oplus B$, then A, B, C are all the matrix of $m \times n$, $c_{ij} = \max(a_{ij}, b_{ij})$. The multiplication operator $\otimes$: $C = A \otimes B$. When $a_{ij} \geq b_{ij}$, $c_{ij} = 1$, otherwise $c_{ij} = 0$. Comparison operator Θ : $C = A \Theta B$, when $a_{ij} \geq b_{ij}$, $c_{ij} = 1$; otherwise $c_{ij} = 0$; direct multiplication operator $\Xi : C = A \Xi B$, then $c_{ij} = a_{ij} b_{ij}$.

Then it is also specified that: 1) when p_i is one start position, $\theta_{p_i}^0 = y_i$, $y_i \in [0,1]$, then define p_i is the start place, and its confidence can be given by the user; 2) when p_i is one end position, $p_i \in o(t_{lk})$ and $p_{jk} \in I(t_{lk})$, then $y_i = \max(y_{jk} u_{lk})$, among which $t_{lk} \in I(p_i)$.

To sump up, the derivation formula for No. k+1 inference is:

(1) calculate the confidence of synthetic input of each transition, i.e.:

$$E^{k+I} = I\theta^k \tag{2}$$

Then realization equation: $\sum_{j=1}^{n} a(P_i) w_j$

(2) compare the confidence of synthetic input with the transition threshold, i.e.:

$$G^{k+1} = E^{k+1} \Theta T_h \tag{3}$$

Among which: G^{k+1} is the m-dimension column vector. When the confidence of synthetic input is larger than the transition threshold, $g_i = 1$, otherwise $g_i = 0$, $i = 1, 2, \cdots, m$.

(3) use the direct multiplication operator to remove the input item whose confidence is smaller than the transition threshold value in the synthetic input confidence. After further calculation, there is only synthetic input confidence which can trigger the transition in *H*, i.e.

$$H^{k+1} = B^{k+1} \Theta G^{k+1} \tag{4}$$

(4) the next step status of the place can be calculated as:

$$\theta^{k+1} = I \otimes H^{k+1} \theta^k \tag{5}$$

The derivation process above can be summarized as one equation and we can get:

$$\theta^{k+1} = \theta^k \oplus I \otimes ((I^T \theta^k) \Theta ((I^T 0^k) \Xi T_h) \tag{6}$$

To sum up, the calculation steps for inference calculation are:

Step 1: read in input matrix I , initial status θ^0 , input data $i = 1, 2, \cdots, n$, $j = 1, 2, \cdots, m$;

Step 2: set the inference step k=0;

Step 3: use the formulas (1)~(3), finally to get the synthetic input confidence H^{k+1} which can trigger transition.

Step 4: get θ^{k+1} depending on formula (4);

Step 5: if $\theta^{k+1} \neq \theta^k$, set the inference step $k = k + 1$, return to step 3 and re-calculate θ^{k+1} ; when $\theta^{k+1} = \theta^k$, then the inference process is over.

III. MAINTENANCE DECISION FOR BOLT COMPONENTS OF HIGH SPEED RAIL BASED ON DIRECTED FUZZY WEIGHT ADAPTIVE PETRI NET

A. *Decision Target*

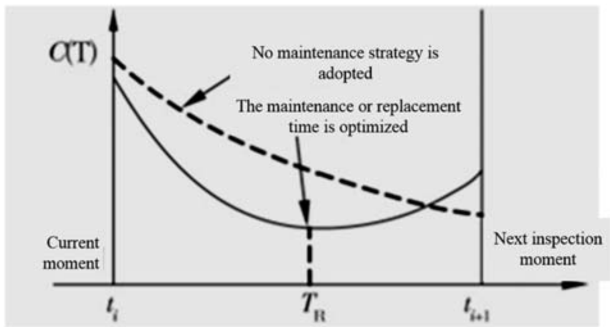

Figure 2. Decision process with minimum cost

In the maintenance strategy, there are two kinds of maintenance methods: (1) corrective maintenance, i.e. the maintenance or replacement for fault before the product reaches the expected maintenance time. It is also called fault maintenance or fault replacement; (2) preventative maintenance, i.e. the maintenance or replacement when the product reaches the scheduled maintenance time. Therefore, according to the target of the maintenance decision and depending on the probability density function for remaining life, the maintenance decision model with the minimum cost as the target is established. Its decision process is shown in Fig. 3.

Assumption and parameters:

(1) perform the status inspection once each other Δt and get the status data of current moment.

(2) when there is fault in the inspection interval, then perform the corrective maintenance immediately.

(3) the preventive maintenance cost of the equipment is smaller than the corrective maintenance cost after repair, i.e. *Tp*<*Tc*.

(4) the preventive maintenance and the corrective maintenance can make the equipment resume the initial status, i.e. it is renewed.

(5) parameters: $E(C)$ is the expected total cost of within the update cycle; $E(T)$ is the length of expected update cycle; Δt is the status inspection interval, $\Delta t = t_i - t_{i-1}$; $f\left(T_i \mid y_{0:i}\right)$ is the probability density distribution function for the remaining life of product when the status information is $y_{0:i}$ at the moment of t_i; P_p is the probability for the part to have preventative maintenance; P_f is the probability for the part to have corrective maintenance; c_p is the preventative maintenance cost; c_f is the corrective maintenance cost; T_R is the optimal maintenance replacement time; $C(T_R)$ is unit time cost during long term of use when the part maintenance and replacement time is T_R; t_i is the status monitoring point at the current moment, $t_0 = 0$; T_p is the average time required for the preventative maintenance; T_c is the average time required for the corrective maintenance; C_i is the cost to implement status inspection each time.

B. *Decision Model with Cost as the Target*

The unit time cost during long term use of equipment part can be represented as:

$$\begin{cases} C\left(T_B\right) = \dfrac{E(C)}{E(T)} \\ E(C) = c_f P_f + c_p P_p + nc_i \end{cases} \tag{7}$$

$$\begin{cases} E(T) = t_i + \left(T_R - t_i + T_p\right)\cdot\left[1 - f\left(\tau_i < T_R - t_i \middle| y_{0:i}\right)\right] \\ \qquad + \int_0^{T_R - t_i} \left(T_c + t_i\right) f\left(\tau_i \middle| y_{0:i}\right) d\tau_i \\ f\left(\tau_i < T_R - t_i \middle| y_{0:i}\right) = \int_0^{T_R - t_i} f\left(\tau_i \middle| Y_i\right) d\tau_i \end{cases} \tag{8}$$

Substitute formula (8) into formula (7) and then the cost mode is

$$C\left(T_R\right) = \frac{\left[c_p + \left(c_p + c_f\right) f\left(\tau_i < T_R - t_i \middle| y_{0:i}\right) + nc_i\right]}{t_i + \left(T_R - t_i + T_p\right)\cdot\left[1 - f\left(\tau_i < T_R - t_i \middle| y_{0:i}\right)\right] + \int_0^{T_R - t_i}\left(T_c + t_i\right) f\left(\tau_i \middle| y_{0:i}\right) d\tau_i} \tag{9}$$

Among which, nc_i is the cost generated to update the monitoring within the period. Since the inspection cost in the status inspection is mostly the equipment input cost, nc_i can often be neglected. Therefore, in actual decision making, take nc_i =0 approximately. When T_p and T_c are very small compared with T_R, they can also be neglected in the cost model.

C. *Decision Algorithm Frame*

The fuzzy weight adaptive Petri net is used as the basic tool in this paper to present the diagnosis idea for power grid failure based on direction: as for the bolt components of high speed rail, two ends of the bolt component (defined as end S and end R) are taken as the objectives to establish separately the model of fuzzy weight adaptive Petri net; model of fuzzy weight adaptive Petri net is established separately aiming at each fault spreading direction. The diagnosis frame is shown in Fig.3.

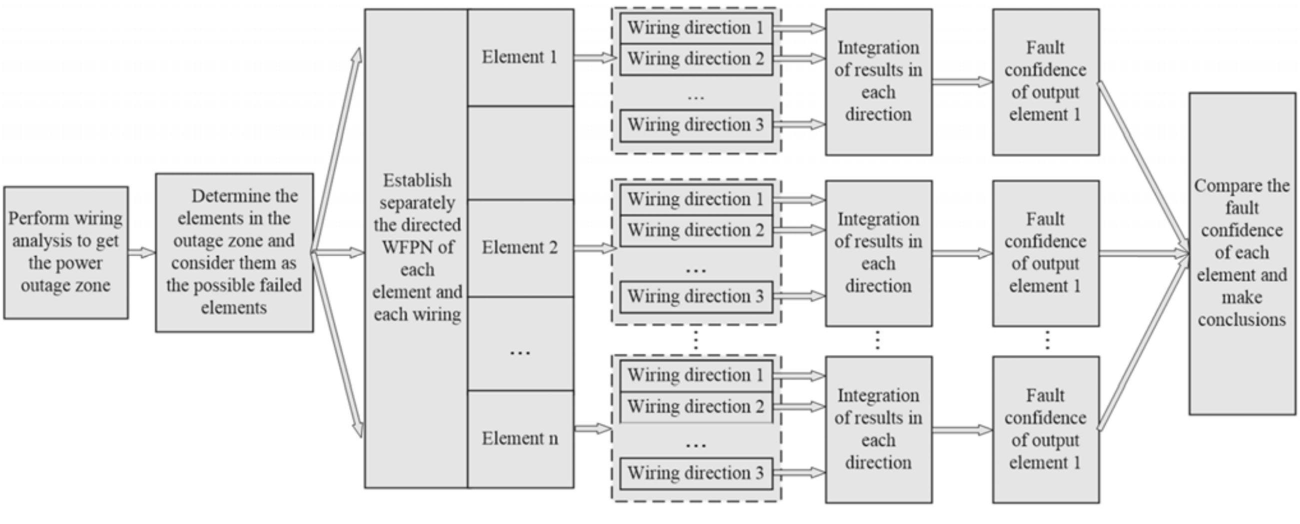

Figure 3. Maintenance decision for Petri net of high speed rail bolt component

The minimization of Petri net model (9) formula is used to get the reachable minimum unit cost and the corresponding maintenance time T_R for the equipment based on the status maintenance. When the new status information value $y_{0:i+1}$ is obtained, the data has to be substituted into formula (9) to re-calculate the update results.

The maintenance time TR for each inspection time can be obtained through the cost model so that the unit time maintenance cost is the minimum. When $T_R - t_i > \Delta t$, no part is maintained until next normal inspection time; when $T_R - t_i < \Delta t$ occurs for the first time, the part shall be maintained or replaced when reaching the T_R, and the T_R at this time is the optimal maintenance time based on status maintenance.

IV. EXPERIMENT ANALYSIS

The digital torque tester is used to measure the torque value of each wire clamp after flat pushing (reference value of bolt torque) and the original account is established. Aiming at the 250Km/h speed zone, the accounts are established individually for each type of wire clamp and they are divided into four types of account tables like positioning device, support device, contact suspension and other bolt torque test comparison tables. One account can reflect the change of torque value of one kind of wire clamp under the same speed zone and same geological conditions so as to analyze the attenuation law of torque value.

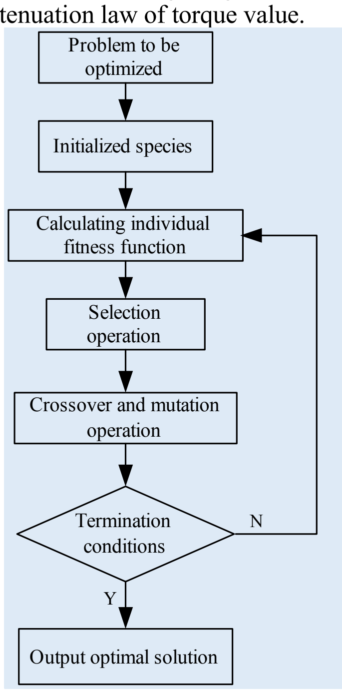

Figure 4. Workflow Diagram for Basic Genetic Algorithm

The data acquisition shall follow strictly the inspection cycle of three months. Digital torque wrench is used and the digital processing technology is applied. The tightening torque is applied quantitatively to the bolt tightening part and the tightening torque size is displayed in the form of numbers. During the whole life test, the rotation and the load of the bolt keep 18 bow frame times each day. Besides, the digital torque wrench is used to acquire the tightening torque of the bolt and the signal is collected once each three months.

As for the observation data of bolt, Matlab7.0 is used to realize the predication method for the remaining life. The probability density function at different status inspection time (500~980h) is shown in Fig.5, among which * represents the estimated value of the remaining life, * represents the real value of remaining life. The predicated value and the actual value of the remaining life is shown in Tab.1.

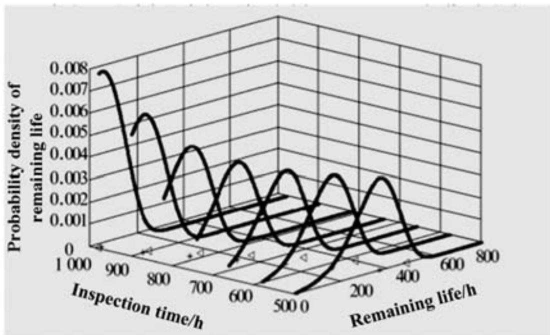

Figure 5. Probability density of remaining life at different detection time

TABLE 1. COMPARISON BETWEEN THE PREDICATED VALUE AND THE ACTUAL VALUE OF THE REMAINING LIFE

Monitoring point	1	2	3	4	5	6	7
Actual value	482	402	322	242	162	82	2
Predicated value	364	301	248	176	114	55	13

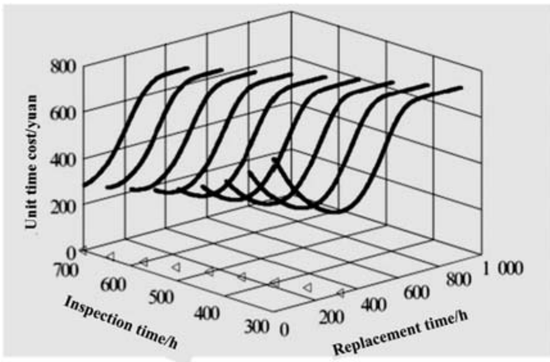

Figure 6. Maintenance and replacement time determined at different inspection time

As shown by the results above, this mode is practical to certain degree for predicating the remaining bearing life under this kind of test background. This model is used to make maintenance decision for bolt 3 below and determine the optimal maintenance time which makes the unit time cost minimal. Assume c_p =600 yuan, c_f =1200 yuan, after the probability density function for the remaining life of the bearing is obtained, substitute $f(T_i \mid y_{0:i})$ into formula (2), calculate the unit time cost at each maintenance time and get the replacement time T_R for minimum cost during each inspection time, as shown in Fig.6. As indicated in the figure, with the increase of replacement time, the unit time cost decreases and then increases at certain inspection time and the optimal maintenance time of the inspection at this time can be obtained at the extreme point. * in the figure represents the maintenance time for the minimal unit time cost at each inspection moment.

In combination with the method to determine the optimal maintenance time and with Matlab calculation, we can get that when the condition $T_R - t_i < t$ is met for the first time, T_R =701h. Therefore, the bolt is replaced at 701h so that the unit time cost $C(T_R)$ is at the minimum, which is about 289.6 yuan.

V. CONCLUSIONS

One maintenance decision approach for high speed rail bolt components based on fuzzy weight adaptive Petri net is proposed in this paper. Petri net is introduced to the maintenance decision for such components; meanwhile, in order to improve the adaptability of application of Petri net in the maintenance decision, it is improved with fuzzy weight adaptive approach; then cost target decision model for maintenance of high-speed rail components is built, decision optimization is made with fuzzy weight adaptive Petri net and the advantages of the proposed maintenance decision approach in terms of the maintenance cost are verified by the experiment.

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