Heath Assessment Method of EMU Trains in Level 3–5 Maintenance and Repair

SONG Wenbin[1], FU Shuangbo[2], WU Keming[3]

1. Rolling Stock Dept. of China Railway Shanghai Group Co., Ltd.;
2. Science and Technology and Information Dept. of China Railway Shanghai Group Co., Ltd.;
3. EMU Depot. of China Railway Shanghai Group Co., Ltd.

Abstract: An accurate and objective assessment of the health status of EMU trains is of great importance. In order to make sure the trains are functional, reliable, and endurable in their full life cycle (FLC), health assessment method for EMU trains after Level 3–5 maintenance and repair is studied. First, the element-selection principles and the assessment rules are defined; second, to present the complex topological relationship between the elements in assessment, a functional logical structure construction method is proposed; third, a health value calculation model is defined based on the element's characteristics and their logical structures. The health variables of each element is calculated and fitted following the steps in the corresponding weight calculation methods. The assessment method is proved to be applicable and effective.

Keywords: EMU; Level 3–5 maintenance and repair; health assessment; PHM; full life cycle

(This paper is selected from *China Railway*)

1 Introduction

With the rapid economic and social development, high-speed railway is becoming more and more important in the national transportation system. As the major passenger transportation vehicle, safety is always the top priority. The design and manufacturing capability of EMU trains in China has been greatly strengthened in recent years, and China not only has become more experienced in high-speed railway operation but also gleaned a huge amount of data from detection and inspection. Research institutions and operational bodies have conducted further studies on the full-life cycle performance of EMU trains. The China State Railway Group Co., Ltd. (herein after referred to as CHINA RAILWAY) has been actively advancing the reform of regulations and institutions of EMU maintenance and promoting cutting-edge technologies such as PHM[1-4]. The research on EMU operation and maintenance is focused on creating an assessment method which can comprehensively, objectively and accurately reflect the EMU's health status. Current researches are mostly centered on assessing the health status of a single core system or equipment, and thus, only a few objects are assessed with the data-driven method. The frequently used algorithms for parameter-fitting and weight calculation are hierarchy analysis, clustering analysis, gray correlation and neutral networks and so on[5]. Most of the researches are focused on real-time operation assessment, but the data and feature thresholds are different from those in real situations, and thus very few of the research results can be directly applied in practical operations. There are also some researchers who study the full-life cycle health assessment based on building a working mechanism model for the component.

As EMUs are massive complicated integrated equipment, working mechanism models for all the components have not been fully studied. Therefore, based on the huge amount of data collected in operation and maintenance as well as relying on the standard procedures and technical guide books, it is possible to analyze performance degradation trends and to construct a health assessment system for a certain period in the service life.

This paper is focused on the EMU health assessment in Level 3–5 maintenance and repair which provides data of a larger scale and of a wider coverage, and thus the health assessment is more accurate and objective. The health assessment for EMUs in Level 3–5 maintenance and repair is of great importance for routine maintenance & operation, repair system reform, FLC performance analysis, cost analysis and independent repair and maintenance system construction.

2 Element Selection Rules for Health Assessment

The object for assessment is called an element and the feature parameters of the element or the calculation results are called variables. The health status of an EMU is influenced by many factors such as equipment degradation, maintenance method, working load, working environment and so on. But the combined impacts of all the influencing factors on the equipment can be observed via feature variables or the vehicle status like failure. For complicated massive equipment, too many elements or variables do not necessarily make a more effective assessment. The key point is to select elements which are able to comprehensively, objectively and accurately reflect the health status of an EMU train which is highly systematic and integrated[6]. The selected elements should cover core equipment on major levels and the variables should be complete, objective, independent, sensitive and consistent. The principles of element selection are as follows:

(1) Consistent with regulations and applicable in practice. Based on the inspection and maintenance regulations and standards of EMU management and operation units while referring to the maintenance guidebooks provided by manufacturers, elements should be properly selected for assessment according to different levels of maintenance so that the assessment results are applicable.

(2) Consistent with operation reality. The chosen elements should reflect the real everyday operation, including the equipment's importance degree, performance degradation, failure correlation and applicability and so on.

(3) Available in maintenance and repair. The elements or the variables chosen should be available either quantitatively or qualitatively via calculation or observation and can provide enough data to reflect the equipment's status, including the recent and historic inspection records, testing records, failure records and equipment quality records of the same EMU models and so on.

(4) Analytical methods. Data correlation analysis tool is used and the most relevant elements for performance degradation are included to reflect EMU's health condition. The most widely used methods are covariance matrix, correlation coefficients and information entropy and so on[7].

3 Key Technology in Health Assessment

3.1 Principles in health assessment

The health score of an element is defined as *H*, $H \in [0,1]$, the closer H is to 1, the healthier the assessed object and vice versa. The assessment principles under multi-variable coupling effects are determined by combining health assessment methods with the EMU operational reality and the health scores are set in 4 categories[8].

(1) Healthy. $H \in (0.9, 1]$. Feature variables of the element are far from the threshold values or degradation values. The equipment is reliable, functional and ready for operation.

(2) Good. $H \in (0.8, 0.9]$. Feature

variables of the element begin to deviate from healthy scores and performance begins to decline. The overall performance is good and the equipment is still functional for operation.

(3) Usable. $H \in (0.6, 0.8]$. Feature variables of the element deviate from the healthy scores and performance decline is remarkable with high failure rate. Ordinary or easy operation is allowed but should be under close inspection. Intense maintenance and repair should be arranged on a preferential basis.

(4) Failure. $H \in [0, 0.6]$. The general status cannot meet the requirements and the equipment is no longer safe or reliable and should be repaired immediately.

The classification defines the boundary conditions allowed for the safe operation of equipment and systems. EMUs are integrated and complex massive equipment and given the operational reality, the score ranges of Failure and Usable are set four times bigger than those of the Healthy and Good categories, so as to ensure the reliability margin of the assessment results. The above categories are preliminarily set and could be further modified according to different technological platforms, different train models, and different stages of service life if the database is big enough.

3.2 Building the functional logic structure

In order to objectively and comprehensively present the main topological relations of the correlated and inter-dependent elements on all levels for EMU trains, and based on the *Functional Classification for EMU Systems* issued by CHINA RAILWAY, elements chosen are organized into a tree structure, which is also convenient for building the assessment model and the following calculation. There are 7 layers in the structure: variable, component, equipment, functional group, sub-system, system and completed train. The completed train layer is at the root node and the elements with no further branching are at leaf nodes. A non-leaf node is an element with a certain number of child nodes. Leaf nodes are the lowest assessment level and any level above leaf nodes could be defined as the lowest level for repair[9]. There are three typical types of EMU system structural trees: cascaded, parallel and mixed.

(1) Cascaded. For a parent element on a certain level, the functions of child elements are correlated and interdependent, and if one of the child elements is degrading or failing, the parent element cannot function either.

(2) Parallel. For an element on a certain level, if one or some of the component elements at lower levels fail, the function of the element in upper layer will not be affected or only partly affected.

(3) Mixed. For an element on a certain level, if some of the component elements at the lower levels are cascaded and some are parallel, the overall structure is a mixed one.

3.3 Health assessment for elements at leaf nodes

The health scores of leaf nodes or the elements on the lowest layer are fundamental for health assessment of elements on all layers. Based on whether the element is newly replaced or whether the quantitative data is enough, there are three assessment types: assessment of newly replaced elements, assessment of variables, and assessment of equipment elements.

3.3.1 Assessment of newly replaced elements

For the newly replaced elements, which are in the initial state, the health scores can be qualitatively set between 0.95~0.98, based on a brief classification and synthesis of the factors such as historic failure rate, importance degree and safety margin.

3.3.2 Assessment of variables based on testing data

For the objects with sufficient data, if there is any performance degradation or abnormality, the values of one or more variables will deviate from the proper range. Therefore, the health score of a feature variable is defined by the deviation of the measured value from the normal or ideal value, and ranges from [0, 1]. The closer the measured score to the ideal score or range, the closer the health score is to 1 and vice versa. Different variables have different ideal scores and there are four types of calculation of the health score of a variable. As all the measured values of a variable will be within a required range after a Level 3−5 maintenance and repair, the measured values beyond the required ranges are eliminated.

(1) For a variable whose measured value is the bigger the better, the health score is calculated as:

$$H_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Where: is the measured value of the variable, $x_{\max}$ is the maximum proper value and $x_{\min}$ is the minimum proper value.

(2) For a variable whose measured value is the smaller the better, the health score is calculated as:

$$H_i = \frac{x_{\max} - x_i}{x_{\max} - x_{\min}} \tag{2}$$

(3) For a variable whose ideal value falls at a certain point in a range, the health score is calculated as:

$$H_i = \begin{cases} \dfrac{x_i - x_{\min}}{x_s - x_{\min}}, & x_i \in [x_{\min}, x_s) \\ 1, & x_i = x_s \\ \dfrac{x_{\max} - x_i}{x_{\max} - x_s}, & x_i \in (x_s, x_{\max}] \end{cases} \tag{3}$$

Where: is the ideal intermediate value in the appropriate range.

(4) For a variable whose ideal value is within a certain range (x_i $[x_1, x_2]$), the health score is calculated as:

$$H_i = \begin{cases} \dfrac{x_i - x_{\min}}{x_1 - x_{\min}}, & x_i \in [x_{\min}, x_1) \\ 1, & x_i \in [x_1, x_2] \\ \dfrac{x_{\max} - x_i}{x_{\max} - x_2}, & x_i \in (x_2, x_{\max}] \end{cases} \tag{4}$$

Where: x_1 and x_2 are the upper and lower limits of the appropriate range respectively.

Moreover, as the thresholds of measured values of all inspected components defined by the Level 3−5 maintenance and repair regulations are different from the values for performance degradation and failure, all testing and inspected values acquired in Level 3−5 maintenance and repair should be within the range required by the regulations. As long as the measured feature variables meet the regulation, they are qualified. Hence, the health scores of all variables should be at least in the Usable category after Level 3−5 maintenance and repair. This is an important difference from the EMU health assessment in real time operation.

Based on different train models and different stages of service life, the health status within the quality guarantee period after Level 3−5 maintenance and repair is presented by the following steps: a base value from the Usable category is selected: $H_b \in [0.6, 0.8]$; after computation correction, the health scores of variables will be mapped in the range of $[H_b, 1]$. Take the CRH380B model as an example, the base value is 0.65 and the calculation formula is:

$$H_i' = 0.35H_b + 0.65 \quad (5)$$

3.3.3 Equipment assessment based on failure data

This method is suitable for critical equipment for EMU health assessment but with only limited amount of measured data, or not included in this round of maintenance or only inspected briefly.

(1) Health score degradation model. For complex massive equipment, the failure distribution is usually exponential. Therefore, it is assumed that the health failure distribution is also exponential for highly integrated equipment on EMU. In this paper, an empirical health assessment formula for aging equipment is introduced, which is widely adopted in Europe and America [10]. This formula was invented by a British company—EA Technology, and is based on the equipment aging theory which presents the exponential trend of equipment degradation through time. This formula has been widely applied to electrical equipment like voltage transformers or current transformers. A revised version of this formula is as follows:

$$\mathrm{HV}_t(t) = 1 - (1 - \mathrm{HV}_0)\mathrm{e}^{B(t - t_0)}, \quad (6)$$

$$B = \frac{\ln(1 - \mathrm{HV}_s) - \ln(1 - \mathrm{HV}_0)}{T_d}, \quad (7)$$

$$T_d = \frac{T_D}{f_1 \cdot f_2}, \quad (8)$$

HV_t is the health value at the time of t; t is the corresponded time for assessment; HV_0 is the health score at t_0; t_0 is the time when the equipment is put into operation; B is the aging coefficient; HV_s is the health score at retiring time, which could be the average value of EMUs of the same model or could be set at an appropriate value according to the Healthy category; T_d is the expected service life; T_D is the designed service life; f_1 is the safety coefficient ($f_1 > 1$) , ranging from 1.1~1.3, based on the importance degree and the historic records of equipment of the same model; is the load coefficient ($f_2 > 1$), ranging from 1.05~1.50, based on the everyday work intensity and working environment, such as the average daily operational mileage of this EMU, the average mileage of the EMUs of the same model, and the maximum mileage allowed in the regulation as so on.

(2) Calculate failure rate of an element. This calculation involves all the operational EMUs of the same model under the management of an operational unit. As the health score is a combined result of different failures, failure severity degree will be taken into consideration in the element's failure rate calculation. After failure severity degree is quantified and corrected, it is then put into calculation. The failure rate P_i between the last two high-level maintenance and repair of an element i is calculated as follows:

$$P_i = 1 - \mathrm{e}^{-\lambda_i L_i} \quad (9)$$

$$\lambda_i = \sum_{j=1}^{n} \frac{10^6 m_j E_j}{M_i \cdot \sum L} \quad (10)$$

Where: λ_i is the failure rate per one million km; L_i is the running mileage between two latest Level 3−5 maintenance and repair; m_j is the occurrence of failure type j; E_j is the conversion coefficient of failure type j for element i, based on failure severity degree calculation; M_i is the element number in criteria group; $\sum L$ is the cumulated running mileage of all the EMUs of the same model in statistics.

(3) Failure rate function based on health scores. Theoretically, the higher the failure rate of an element, the lower the health score, and vice versa. In order to properly depict the inner correlation, it is assumed that the correlation of equipment failure rate and the health score is exponential[11] as follows:

$$P_i = K\mathrm{e}^{CH} \quad (11)$$

Where: P_i is the failure rate of element i; K is the scaling coefficient; C is the curvature coefficient; H is the health score.

The function of failure rate and health score is shown in Fig.1. Calculating the element's health score via formula (11) needs to determine the values of K and C first. P_{it} is the failure rate of element i in a certain time period by calculating all the samples (all EMUs of the same model under management of the operational unit) and the average health score HV_{it} is calculated by the aging formula. With the failure rate for the first 3 months in operation of this element in the sampling EMUs and the corresponded average health score HV_3 via aging formula, the values of K and C can be obtained. Then, put the failure rate between the last two high-level maintenance and repair P_i into formula (11), the health score at the assessment time can be obtained.

3.4 Element weight calculation

Weight calculation for elements on all levels is very important. The assessment after a Level 3−5 maintenance and repair usually covers a large number of elements with a large scale of sampling variables, and the health scores of feature variables are generally satisfying, and therefore, the static weight calculation methods, namely the Entropy Weight Method (EWM) and Fuzzy Analytic Hierarchy Process (FAHP), are applied here.

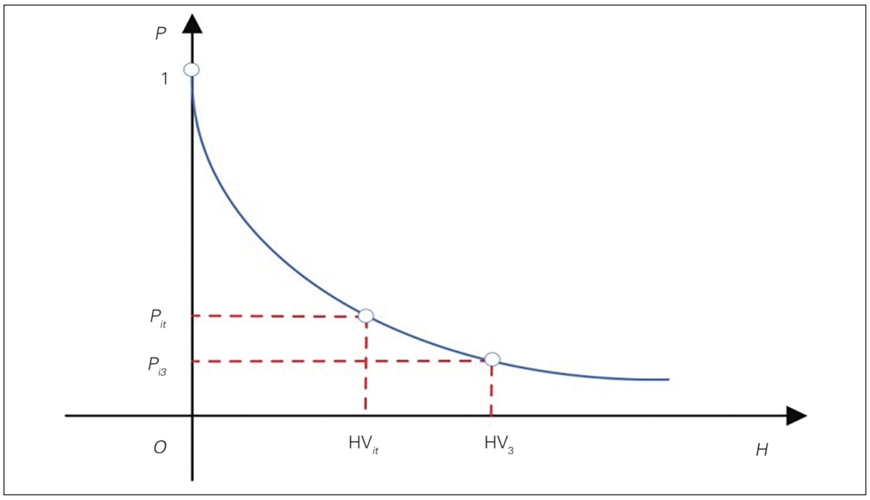

Fig.1 Function of failure rate and health score

The two weight calculation methods are widely adopted and their application in health assessment of EMU trains is introduced in the paper.

For objects with a large number of variables or elements, EWM is preferred in weight calculation; if the technicians have a good knowledge of the functions of the other elements on the same level, FAHP can be used to calculate the weights of the second group. Finally, Moment Estimation is adopted in weight combination [12] as follows:

$$\omega_j = \frac{a_j\omega_{pj} + b_j\omega_{qj}}{\sum_{j=1}^{n}(a_j\omega_{pj} + b_j\omega_{qj})}, \quad (12)$$

Where: ω_p、ω_q are the weight coefficients obtained via the two weight calculation methods respectively; a_j and b_j are the relative importance values of ω_p and ω_q respectively, and $a_j = \omega_{pj}/(\omega_{pj} + \omega_{qj})$ and $b_j = \omega_{qj}/(\omega_{pj} + \omega_{qj})$.

3.5 Assessment model and algorithm

The health scores of leaf node elements are calculated first and then the health scores of elements on higher layers are calculated following the three logic structure models and ultimately, the health scores of the train can be obtained.

(1) Health scores of parallel elements. Assume the logic structure of three elements A, B and C is parallel (see Fig.2), the health score of the element on higher layer is obtained through weighted sum method:

$$H = \omega_A H_A + \omega_B H_B + \omega_C H_C, \quad (13)$$

Where: H_A, H_B and H_C are the health scores of the three elements respectively; ω_A, ω_B, ω_C are the weight coefficients of the three elements respectively.

(2) Health scores of cascaded elements. Assume the logic structure of three elements A, B and C is cascaded (see Fig.3), the health score of the higher layer element can be obtained through the exponential weighting product as in reliability calculation:

$$H = H_A^{\omega_A} H_B^{\omega_B} H_C^{\omega_C} \quad (14)$$

(3) Health scores of elements in mixed structure. In reality, the functional logic structure is not exclusively parallel or cascaded. Elements can be either parallel or cascaded or both on some level. Referring to the method proposed in the Reference [13] to calculate the health scores of a mixed structure.

Take the traction sub-system in Car 1 of model CRH380B as an example. This sub-system is consisted of two lower-layer elements: one is the traction converter and cooling fan module, and the other is the traction motor and cooling fan module. In functional logic structure, the traction converter and cooling fan module (MMU A) is a cascaded element and the traction motor and cooling fan module (MMU B) is a parallel element. In order to calculate the health score of the element on higher level, a weighted failure-free branch (MMU X) has been introduced to realize the mathematical expression of the mixed structure. The mixed structure of 1 parallel module and 1 cascaded module is shown in Fig.4.

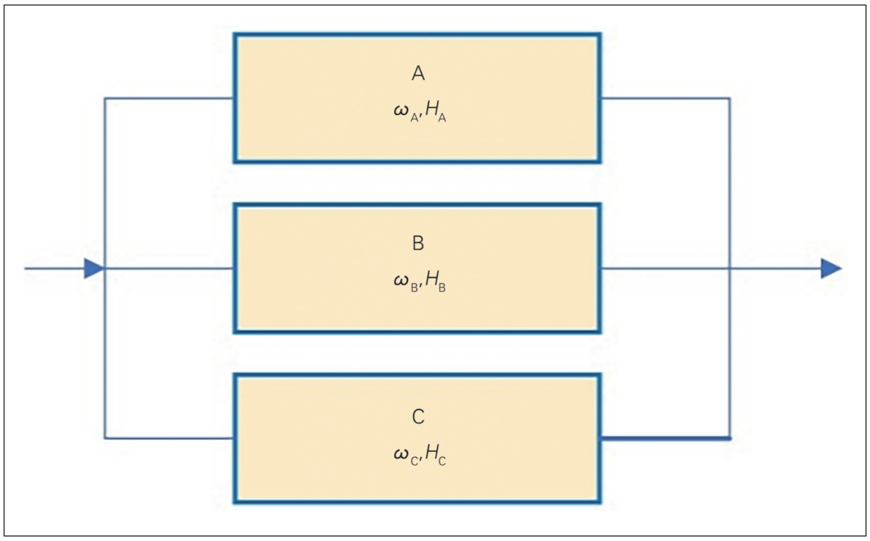

Fig.2 Function logic structure of 3 parallel elements

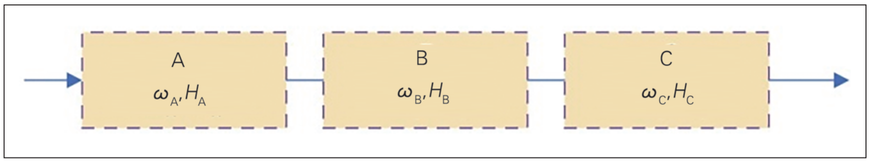

Fig.3 Function logic structure of 3 cascaded elements

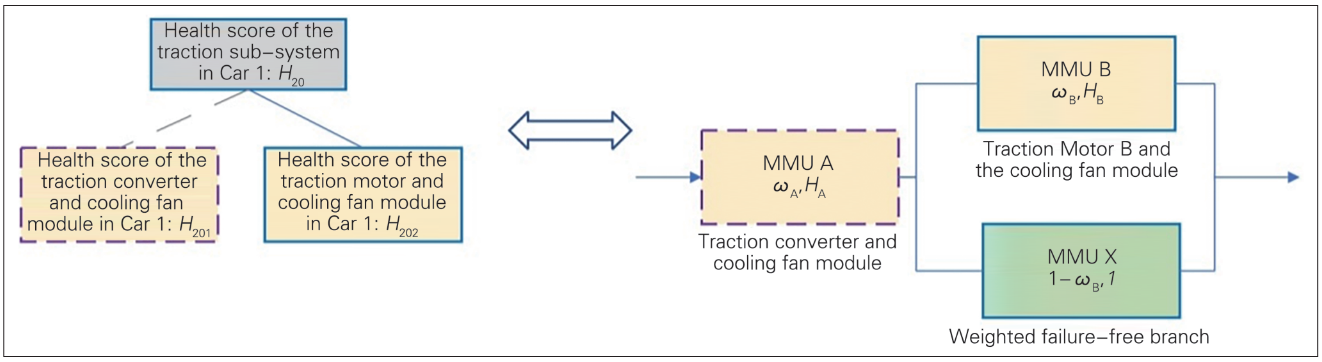

Fig.4 Mixed structure block diagram of 1 parallel and 1 cascaded

The overall structure of 1 parallel and 1 cascaded mixed structure is still a cascaded structure. Therefore, by calculating the health scores of the parallel and the cascaded structure respectively, the health score of this mixed structure is calculated as follows:

$$H = H_A^{\omega_A}\left[\left(1 - \omega_B\right) \times 1 + \omega_B H_B\right] \quad (15)$$

In order to conclude a general formula, it is assumed that $m + n$ are the number of the subordinate elements of a particular object, and the former m elements are parallel and the latter n elements are cascaded. A general formula for health score calculation in a mixed structure is as follows:

$$H = \left[\left(1 - \sum_{i=1}^{m}\omega_i\right) + \sum_{i=1}^{m}\omega_i H_i\right]\prod_{j=1}^{n}H_j^{\omega_j} = \left[1 - \sum_{i=1}^{m}\omega_i\left(1 - H_i\right)\right]\prod_{j=1}^{n}H_j^{\omega_j} \quad (16)$$

4 Case Study of Health Assessment

4.1 Element selection for assessment

The following is a case study of an EMU model CRH 380B based on the above assessment algorithm. According to the selection rules, there are 10 systems, 45 sub-systems/function modules, 180 equipment and around 300 feature variables in total selected for the assessment.

In this paper, only the assessment of traction motor and the cooling fan module after the third-level maintenance is taken as an example to show the assessment procedures and results. This function module is consisted of two pieces of equipment: the cooling fan and the traction motor. Due to limited data, the lowest assessment level for cooling fan is the level it is on. The traction motor is divided into five components based on the minimum maintenance unit: stator, rotor, power cable, bearing, and temperature detection. As the old bearing has been replaced, there is no variable for the bearing while the other four components have 12 variables in total: the maximum of cable single phase shielding, the maximum of cable inter-phase shielding, post-washing dielectric loss of stator, inter-UV winding resistance, inter-VW winding resistance, inter-UW winding resistance, maximum imbalance of winding resistance, imbalance value at the driving end, imbalance value at the non-driving end, resistance of the bearing temperature sensor at the driving end, resistance of the bearing temperature sensor at the non-driving end, and resistance of the stator temperature sensor.

4.2 Building the functional logic structure

Analyze the logic between the elements at different levels and build the logic tree based on the three types of functional logic structures mentioned above (Fig.5).

4.3.2 Health scores for leaf-node components

As the old motor bearing has been replaced with a new one, based on the historic bearing operation records of model CRH380B, the initial value of this new replacement is set at 0.97.

4.3.3 Health values for leaf-node equipment

In a third level advance overhaul, only a brief examination is conducted for the cooling fan of the traction motor, and therefore, data volume is limited. For a third level advanced overhaul, health assessment of cooling fan is based on failure data. According to the health assessment model for aging equipment and the health value function, the calculated health value of the cooling fan is at 0.913.

4.4 Element weight calculation

4.4.1 Weight calculation for variable

Traction motor has enough variables and components, and element weight calculation is based on the EWM method[12], and the results are shown in Table 2.

4.4.2 Weight calculation for components

Weight calculation for components follows the FAHP method[13].

(1) Set up a fuzzy complementary matrix of correlated importance values. Compare the importance values of the components of the same traction motor in pair and set up the fuzzy complementary matrix R_I:

$$R_1 = \begin{bmatrix} 0.5 & 0.5 & 0.6 & 0.6 & 0.8 \\ 0.5 & 0.5 & 0.6 & 0.6 & 0.8 \\ 0.4 & 0.4 & 0.5 & 0.5 & 0.7 \\ 0.4 & 0.4 & 0.5 & 0.5 & 0.7 \\ 0.2 & 0.2 & 0.3 & 0.3 & 0.5 \end{bmatrix}$$

(2) Transform and verify the con-

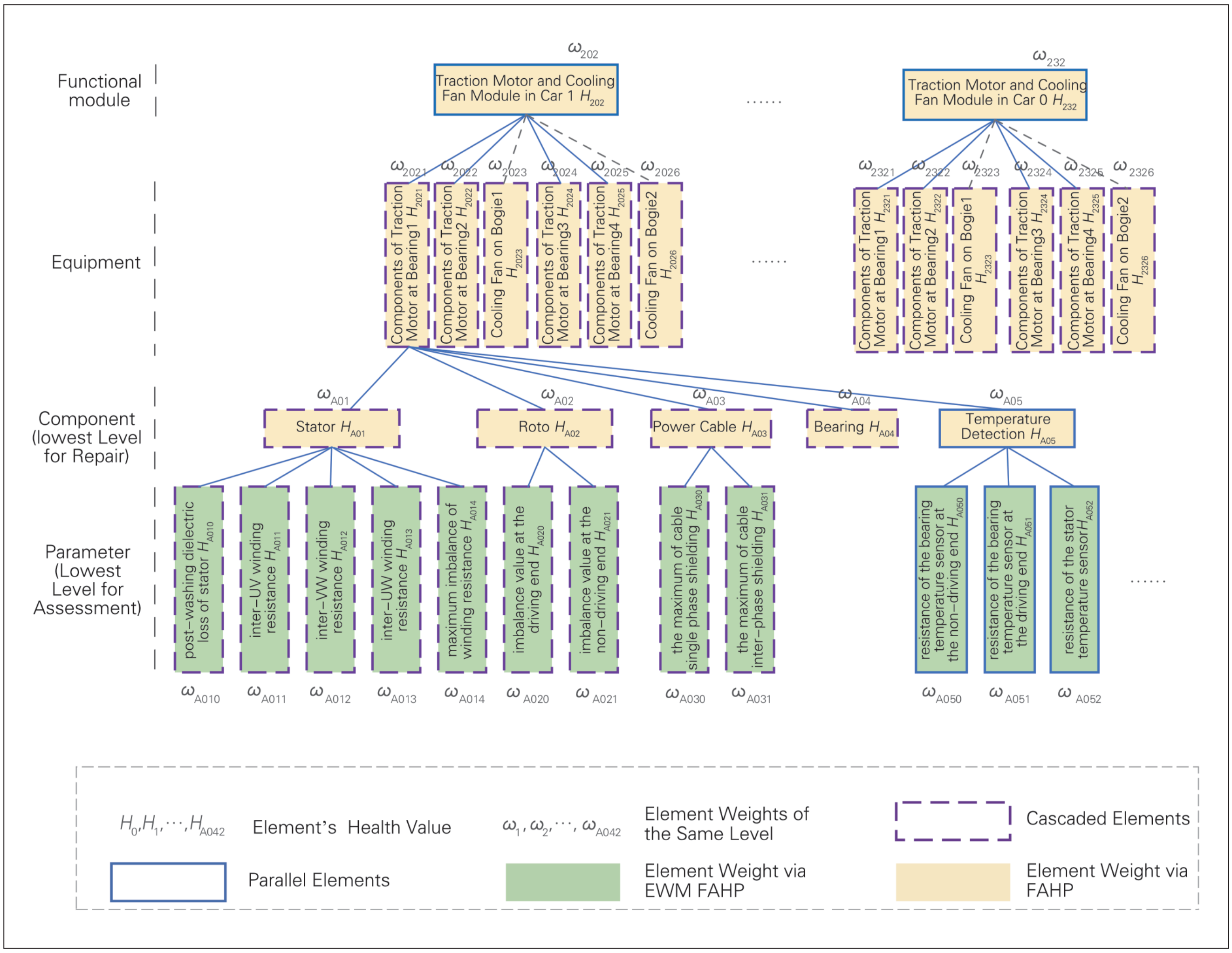

Fig.5 Logic structure of the traction motor and cooling fan of the EMU model CRH380

Table 1 Health values of the traction motors in Car1 of CRH380B

Variables	Health Values of Traction Motors			
	Bearing 1	Bearing 2	Bearing 3	Bearing 4
post-washing dielectric loss of stator	0.916 9	0.916 9	0.899 0	0.915 7
inter-UV winding resistance	0.820 7	0.792 8	0.745 2	0.848 5
inter-VW winding resistance	0.838 0	0.808 9	0.727 3	0.857 2
inter-UW winding resistance	0.847 3	0.796 6	0.736 0	0.984 5
maximum imbalance of winding resistance	0.945 8	0.966 8	0.963 3	0.973 8
imbalance value at the driving end	0.985 9	0.878 5	0.928 8	0.838 6
imbalance value at the non-driving end	0.904 9	0.865 4	0.858 2	0.898 6
resistance of the bearing temperature sensor at the driving end	0.708 1	0.708 1	0.766 2	0.679 0
resistance of the bearing temperature sensor at the non-driving end	0.780 7	0.766 2	0.766 2	0.751 7
resistance of the stator temperature sensor	0.853 3	0.911 4	0.882 4	0.896 9
the maximum of cable single phase shielding	0.811 0	0.860 0	0.798 8	0.807 5
the maximum of cable inter-phase shielding	0.965 0	0.991 3	0.825 0	0.873 1

Table 2 Variable weight coefficients of traction motor

Upper level Components	Variables	Weight Coefficients
Stator	post-washing dielectric loss of stator	0.071 1
	inter-UV winding resistance	0.313 8
	inter-VW winding resistance	0.297 7
	inter-UW winding resistance	0.311 2
	maximum imbalance of winding resistance	0.006 3
Rotor	imbalance value at the driving end	0.493 0
	imbalance value at the non-driving end	0.507 0
Temperature Detection	resistance of the bearing temperature sensor at the driving end	0.509 9
	resistance of the bearing temperature sensor at the non-driving end	0.380 4
	resistance of the stator temperature sensor	0.109 7
Power Cable	the maximum of cable single phase shielding	0.259 6
	the maximum of cable inter-phase shielding	0.740 4

sistence of the fuzzy complementary matrix in the following steps:

$$r_{ij} = r_{ik} - r_{jk} + 0.5,\quad i, j, k = 1, 2, 3, \cdots, n, \tag{17}$$

Where: r_{ij} is the quantified compared importance value of element i to element j, and ranges from 0.1 ~ 0.9.

(3) Calculate weight victor via fuzzy complementary matrix in following steps:

$$\omega_i = \frac{1}{n} - \frac{1}{2\alpha} + \frac{1}{n\alpha}\sum\nolimits_{k=1}^{n} r_{ik},\quad i = 1, 2, \cdots, n, \tag{18}$$

Where: α is the weight transformation coefficient, and $\alpha \geqslant (n-1)/2$; n is the number of elements. When α is set at the minimum, the weight victor .

4.4.3 Weight calculation for equipment

In the function module of traction motor, each element consists of 6 sub-elements and by comparing those sub-elements in pair via FAHP, a fuzzy consistent matrix R_2 is established.

$$R_2 = \begin{bmatrix} 0.5 & 0.5 & 0.7 & 0.5 & 0.5 & 0.7 \\ 0.5 & 0.5 & 0.7 & 0.5 & 0.5 & 0.7 \\ 0.3 & 0.3 & 0.5 & 0.3 & 0.3 & 0.5 \\ 0.5 & 0.5 & 0.7 & 0.5 & 0.5 & 0.7 \\ 0.5 & 0.5 & 0.7 & 0.5 & 0.5 & 0.7 \\ 0.3 & 0.3 & 0.5 & 0.3 & 0.3 & 0.5 \end{bmatrix}$$

Likewise, by further calculation, the weight victors of the 6 sub-elements:

$$\Omega_2 = [0.193,\ 0.193,\ 0.113,\ 0.193,\ 0.193,\ 0.113]$$

4.5 Health assessment for non-leaf-node elements

4.5.1 Health value for component elements

According to the health value algorithm and functional logic structure (Fig. 5), health value of all elements could be calculated in an upward manner—from the bottom layer to the upper layer. The health values of the four non-leaf-node components are shown in Table 4.

4.5.2 Health values for equipment

Similarly, the health values of all 16 traction motors can be calculated and what needs to be addressed is that the bearings' health values at leaf nodes should be introduced in calculation. Take the traction motor 1 in car 1 as an example, the calculation is as follows:

$$H_{2021} = H_{A01}^{\omega_{A01}} H_{A02}^{\omega_{A02}} H_{A03}^{\omega_{A03}} H_{A04}^{\omega_{A04}} [(1 - \omega_{A05})\cdot 1 + \omega_{A05}\cdot H_{A05}] \tag{19}$$

The health values of all the traction motors are seen in Table 5.

4.5.3 Health values for functional modules

In every functional module, the 6 elements are cascaded. When the health values of the cooling fans are introduced, the calculation results of the traction-motor-plus-cooling-fan functional modules in the four cars are: for Car 1, the score is 0.8675; for Car 3, the score is 0.9083; for Car 6, the score is 0.9121; for Car 8, the score is 0.8990.

Similarly, the health values of sub-systems and systems can also be calculated in an upward direction.

4.6 Conclusion of health assessment

The cumulated used mileage of traction-motor-plus-cooling-fan in this particular EMU is over 3 200 thousand km. For the 4 traction-motor-plus-cooling-fan modules, two are at the lowest level of healthy state and the other two are at the highest level of good health. Referring to the pre-maintenance operational records, the overall health status of the traction motor plus cooling fan module are deteriorating. According to further correlation analysis, health scores of lower-level elements follow 4 rules:

(1) The health scores of the traction motors at the head and rear ends of the train are lower than those in the middle, which is caused by comparatively lower health scores of the stators, rotors and temperature detective components. At variable level, this

Table 4 Health values of component variable

Position	Health Values for Component Elements			
	Stator	Rotor	Power cable	Temperature
Bearing 1 Car1	0.841 4	0.943 9	0.922 4	0.750 1
Bearing 2 Car1	0.808 1	0.871 8	0.955 4	0.750 1
Bearing 3 Car1	0.748 1	0.892 3	0.818 1	0.778 1
Bearing 4 Car1	0.897 0	0.868 5	0.855 6	0.727 7
Bearing 1 Car 3	0.814 8	0.912 2	0.770 0	0.969 5
Bearing 2 Car 3	0.871 5	0.960 4	0.953 9	0.879 6
Bearing 3 Car 3	0.980 1	0.951 2	0.953 4	0.725 7
Bearing 4 Car3	0.922 8	0.907 0	0.953 4	0.887 9
Bearing 1 Car 6	0.971 3	0.884 5	0.887 6	0.911 4
Bearing 2 Car 6	0.968 4	0.944 9	0.952 2	0.898 0
Bearing 3 Car 6	0.891 2	0.870 7	0.885 2	0.707 0
Bearing 4 Car 6	0.911 5	0.962 2	0.953 9	0.868 3
Bearing 1 Car 8	0.740 6	0.860 6	0.875 8	0.928 6
Bearing 2 Car 8	0.968 1	0.916 1	0.955 5	0.893 3
Bearing 3 Car 8	0.767 2	0.885 4	0.926 3	0.909 8
Bearing 4 Car 8	0.967 3	0.862 4	0.956 5	0.871 0

Table 5 Health values of all the traction motors

Position	Health Value of Traction Motor	Position	Health Value of Traction Motor
Bearing 1 Car 1	0.879 8	Bearing 1 Car 6	0.920 6
Bearing 2 Car 1	0.859 8	Bearing 2 Car 6	0.945 9
Bearing 3 Car 1	0.827 3	Bearing 3 Car 6	0.859 7
Bearing 4 Car 1	0.858 4	Bearing 4 Car 6	0.930 6
Bearing 1 Car 3	0.873 2	Bearing 1 Car 8	0.855 1
Bearing 2 Car 3	0.921 9	Bearing 2 Car 8	0.938 2
Bearing 3Car 3	0.917 1	Bearing 3 Car 8	0.875 2
Bearing 4 Car 3	0.923 3	Bearing 4 Car 8	0.920 0

can be implied from the low health scores of the 3 inter-phase winding resistances. This conclusion is consistent with historic failure distribution.

(2) For the traction motors which are in poor health condition, the inter-phase winding resistances of stators differ significantly. However, the health scores of the imbalance degree of resistance is good in spite of the remarkable differences in the stators' inter-phase winding resistances of different traction motors and therefore, further research should be carried out on the working mechanism of the traction motors, whereas in everyday operation, inspections and detections should be strengthened.

(3) Health scores are usually low for motor temperature sensor modules, indicating remarkable performance degradation. Reviewing the historic data and failure records shows that failure rate of temperature sensors has always been high, also consistent with the conclusion.

(4) The reason for low health scores of motors at the head and rear end of the train, especially the motor at bearing 4, is that the health score of the imbalance between driving-end and non-driving end is comparatively low. According to the motor's work-

ing mechanism, increase in imbalance will lead to the increase of excitation force and centrifugal inertia force of the bearing, worsening abrasion and degradation of the bearing. The data shows that this conclusion is consistent with the temperature trend and the failure reality of motor bearings. Further studies can be conducted on degradation of this specific component.

Relying on health assessment, the technical challenges and needs of Level 3–5 maintenance and repair should be addressed. In Level 3–5 maintenance and repair, for the components and EMUs in poor health condition, specific inspection items should be strengthened and the assembly relations of rotable spare parts should be improved so as to raise the overall health scores and to make sure the equipment is in a balanced and optimal condition. In operational practices, intensified inspection should be carried out of the components with lower health scores.

5 Conclusion

A health assessment system for EMU after Level 3–5 maintenance and repair has been established which is based on on-field practices and regulations. In this paper, a functional logic structure has also been built which is able to provide a tailored health assessment algorithm for different components with different detection scope and depth, and this structure also applies well when assessing component with limited data or not included in the maintenance. The algorithm is tested and verified in real practices and has proved effective and consistent with historic records and operation reality. This algorithm provides good reference for EMU health assessment in Level 3–5 maintenance and repair and full-life cycle health assessment in the future.

(Translated by ZHANG Yiran)

References

[1] ZHOU Bin, XIE Mingyuan, WU Keming. Analysis and prediction on the current situation of the repair class and repair system of electric multiple units (EMU) [J]. *Electric Drive for Locomotives*, 2017 (1): 1, 17-21.
[2] WANG Huangsheng, QIAN Xiaolei, WANG Jing, etc. Study of decision-making approach for EMU maintenance based on failure analysis [J]. *China Railway*, 2020 (10): 56-61.
[3] CHI Yugan. Research and application for prognostics and health management of EMUs [J]. *Electric Drive for Locomotives*, 2018 (5): 118-122.
[4] TIAN Guangrong, FU Zhengbo, YU Weidong, etc. Research on the optimization of repair cycle and repair system of key EMU system based on multi-dimensional fault evolution rule [J]. *China Railway*, 2020 (9): 34-39.
[5] HU Wentao, JianjuMEN. Assessment and prediction on the bearing health status of the traction motor for EMU [J]. *Journal of Lanzhou Jiaotong University*, 2021, 40 (2): 95-100.
[6] LI Jin, ZHU Qiangqiang, FAN Xufeng, etc. Research of health status evaluation method for large electromechanical equipment [J]. *Journal of Mine Automation*, 2015, 41 (1): 6-7.
[7] CAO Huiling, LIANG Jiawang, CUI Kelu. Residual life prediction of aeroengine based on health index similarity [J]. *Science Technology and Engineering*, 2020, 20 (1): 361-362.
[8] ZENG Delin, LU Junyong, ZHENG Yufeng. Improved FAHP-neural network health evaluation method for electromagnetic launch system [J]. *Journal of National University of Defense Technology*, 2020, 42 (6): 68-75.
[9] LU, Zheng, JIN Guang, YANG Tianshe, etc. Multi-level health evaluation for on-orbit satellites based on reconfigurable degree [J]. *Systems Engineering and Electronics*, 2018, 40 (8): 1770-1773.
[10] YANG Chunbo, TAO Qing, ZHANG Jian. Equipment status evaluation based on comprehensive health index [J]. *Power System Protection and Control*, 2019, 47 (10): 104-107.
[11] SHI Changkai, NING Xin, SUN Zhitao. Quantitative risk assessment of distribution network based on real-time health index of equipment [J]. *High Voltage Engineering*, 2018, 44 (2): 534-540.
[12] CHENG Zhiyou, TAO Qing, ZHU Weiwei. State evaluation of air compressor based on improved fuzzy comprehensive evaluation method [J]. *Electrical Measurement & Instrumentation*, 2020, 57 (3): 12-15.
[13] TENG Teng, ZHAO Zhihua, CUI Xiaopeng. Study on health assessment method of electromagnetic launching inverter [J]. *Journal of Naval University of Engineering*, 2019, 31 (4): 28-34.