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Prediction of the Remaining Useful Life of a Switch Machine, Based on Multi-Source Data

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Abstract: Aimed at the shortcomings of a single feature to characterize the health status and accurately predict the remaining life span of the equipment, a prediction method for a switch machine, based on the weighted Mahalanobis distance (WDMD), is proposed. The method consists of two parts: the construction of a health indicator, based on the weighted Markov distance and the prediction of the remaining useful life, based on the hidden Markov model (HMM). Firstly, a kernel principal component analysis (KPCA) is used to extract the characteristics of the power curve data of the switch machine, and the characteristics with a high correlation with the degradation process are screened, according to the trend indicators. Secondly, the resulting features are combined with multi-source information, as the input, and a comprehensive health indicator (HI) is constructed by the weighted fusion of the WDMD algorithm, to characterize the degradation process of the switch machine. The degradation model of this HI is established and trained by the HMM, so as to predict the remaining life span of the equipment. Finally, the actual operation data of the railway field is selected to verify the prediction method proposed in the paper. The results show that the state recognition and the life prediction accuracy of the proposed method is higher, which can provide effective opinions for the predictive maintenance of the switch machine equipment.

Keywords: weighted Mahalanobis distance; kernel principal component analysis; hidden Markov model; remaining useful life prediction; switch machine

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1. Introduction

The switch machine is an electromechanical integration piece of equipment used to realize the conversion, locking and representation of a railway turnout. The number of switch machines is large, the action is frequent, the failure rate is high, and the failure prevention is difficult on the railway site [1,2]. Due to the influence of various factors, the whole piece of equipment and the components of the switch machine will be degraded or fail in varying degrees, during the service process [3–5]. Unless there is no sign of failure, it will cause huge casualties and property damage. At present, the maintenance of the switch machine is mainly carried out by manual inspection and parameter adjustments, according to the plan. This maintenance method will lead to the over maintenance and under maintenance of the railway turnout, and even to a repair fault [6]. Therefore, the effective health status identification and life prediction of the switch machine can ensure the safe and reliable operation of the equipment and reduce maintenance costs, which is of great significance in the predictive maintenance of the equipment.

At present, many scholars have analyzed and studied the fault diagnosis and prediction technology of switch machines [7–10]. For the establishment of the degradation model and the prediction of the remaining useful life of the switch machine, the existed methods mainly take the action power curve as the analysis object, and conduct research in a single operating environment. Liu Yingjun used the ensemble empirical mode decomposition algorithm to extract the features of the power curve and combined it with the long short-term memory neural network to predict the state of the switch machine [11]. Yilboga et al. used the voltage and current data collected by sensors to build a fault degradation experimental environment. The degradation state of the running process before the switch machine failure, is divided by the manual experience. However, the method of division, based on the artificial experience, will have the problem of a low accuracy [12]. Li Wanwan et al. divided the degraded state of the switch machine by calculating the cloud similarity between the real-time power curve data and the normal operation power curve data and used LSTM algorithm to complete the state recognition. However, there are problems such as a large amounts of calculation and a low accuracy [13]. He Zhuobing diagnosed the degraded state of the switch machine by calculating the cosine similarity between the real-time action curve and the standard curve. However, this method ignores the process information of the switch maneuver changing with time, and the pre-similarity itself, is not sensitive to the power data size [14]. However, the structure of the switch machine is complex, and the actual operating state is affected by various factors, such as the working environment, load, switching frequency, and the structure of the equipment itself [15]. Wang Guang found that the weather is an important factor affecting the action of the switch machine, by reading the maintenance records of the switch machine equipment on the railway site. Then, he used text mining technology to extract the weather-related features and used them as the input of the Bayesian neural network, to realize the fault prediction of the switch machine [16]. It is difficult to accurately establish the failure model of the equipment, according to a single working condition. However, the monitoring data cannot fully describe the deep operation information of the equipment, which may affect the accuracy of the remaining useful life prediction results. Wang An and others proposed a method to indirectly obtain the conversion force curve, by fitting and monitoring the voltage and current of the switch machine, but the conversion force curve obtained by this method is no more accurate than the conversion pressure reflected by the voltage and current of the switch machine. For other influencing factors, there are practical difficulties in the data collection [17]. The existing life prediction methods also have involved some research on the fusion technology of the multi-source sensors. Wang Fengfei et al. considered the stochastic use of the expectation—maximization algorithm and integrated the degradation and the failure data of the equipment to estimate the parameters of the stochastic model for its life prediction, which considered the linear and nonlinear degradation processes [18]. Zheng Jianfei et al. constructed a health index considering the multiple performance indicators through a conditional sampling algorithm [19]. Then, they used this index to train the long-term memory neural networks and predict the remaining life span of aero-engines. However, only the correlation between the binary variables is analyzed for the multi-performance indicators, and there is no direct description of the multivariate variables. Sun Shuguang et al. proposed a life prediction model for the energy storage operating mechanism of low-voltage universal circuit breakers, based on the univariate index model [20]. The comprehensive health index is obtained by fusing the features with a good correlation, in the current, vibration signals and other information, which reduce the prediction error. However, the data utilization rate is low, and more data information needs to be obtained. H. Zhang et al. obtained the comprehensive health indicators, based on multi-sensors, by optimizing the relevant characteristics of the HIs, and predicted the remaining life span of aircraft turbine engines, through the degradation model constructed by the HIs [21]. Aiming at the shortcomings of the existing linear fusion methods in complex systems, F. Wang et al. proposed a fusion method, based on machine learning, to construct health indicators and used a sampling algorithm of the root mean square propagation to estimate the model parameters [22]. The proposed method is validated with the aero-engine degradation data, showing that the proposed method is efficacious in the life prediction. The above life prediction methods use the same processing methods for each sensor data, for processing the fusion of the multi-source sensor data. However, in actual operation, the degree of correlation between the different sensors and the degradation process is different, and the impact on the life prediction is also different.

Therefore, this paper takes the action power curve of the switch machine as the analysis object and uses the kernel principal component algorithm to extract the characteristic information of the power curve. The health index HI is obtained by the weighted fusion of the switch machine operation data, according to the WDMD, which is used to characterize the degradation process of the switch machine. The obtained HI is used as the input of the HMM model to train the prediction model, and the remaining useful life of the equipment is calculated with the trained model.

2. Construction of the Health Indicators

2.1. Feature Extraction, Based on the KPCA

In order to improve the accuracy of the prediction results, it is necessary to extract the effective features of the original data. The kernel principal component analysis algorithm has distinctive advantages in removing the redundant information and retaining the global nonlinear information [23]. Therefore, the KPCA algorithm is used in this paper to extract the features of the power curve data of the switch machine. It is a dimensionality reduction method that uses a kernel function to map the original nonlinear data to a high-dimensional feature space for the linear PCA calculation. That is to map the original data vector $\boldsymbol{X} = [x_1, x_2, \ldots, x_m]^T \in \mathrm{R}^{m\times l}$ to the high-dimensional feature space $\Omega \in R^n$ as $\Theta(x_i)$. Then perform a linear PCA calculation on $\Theta(x_i)$ to achieve the nonlinear dimensionality reduction [24]. The covariance matrix that defines the high-dimensional space is:

$$C = \frac{\sum_{i=1}^{m}\Theta(x_i)\Theta^T(x_i)}{m-1} \tag{1}$$

The eigenvalues and eigenvectors of solving the covariance matrix $\boldsymbol{C}$ in high-dimensional space are $\lambda\boldsymbol{V} = \boldsymbol{CV}$, and $\boldsymbol{V}$ can be linearly expanded by coefficient $\zeta_i (i = 1, 2, \ldots, m)$:

$$V = \sum_{i=1}^{m}\zeta_i\Theta(x_i) \tag{2}$$

To get further

$$\begin{aligned} &\lambda\sum_{i=1}^{m}\zeta_i\left\langle\Theta(x_i),\Theta(x_l)\right\rangle \\ &= \frac{\sum_{i=1}^{m}\zeta_i\left\langle\Theta(x_i),\sum_{j=1}^{m}\Theta(x_j)\right\rangle}{m}\cdot\left\langle\Theta(x_j),\Theta(x_i)\right\rangle \end{aligned} \tag{3}$$

Define a kernel matrix $\boldsymbol{K} \in \mathrm{R}^m$ as:

$$K = k(x_i, x_j) = \left\langle\Theta(x_i),\Theta(x_j)\right\rangle \tag{4}$$

Substituting Equation (4) into Equation (3) can obtain the characteristic equation:

$$m\lambda\zeta = K\zeta \tag{5}$$

Center $\boldsymbol{K}$ in the feature space means to $\boldsymbol{K}_1$:

$$K_1 = K - EK - KE + EKE \tag{6}$$

where $\boldsymbol{E}$ is a square matrix of order m.

The characteristic square matrix in formula (5) can be further expressed as:

$$m\lambda\zeta = K_1\zeta \tag{7}$$

According to the above formula, the orthogonal eigenvector $\boldsymbol{\zeta}$ and eigenvalue λ can be obtained. The principal component characteristic number d is determined, according to the cumulative percentage error as follows [25]:

$$\frac{\sum_{i=1}^{d}\lambda_i}{\sum_{i=1}^{m}\lambda_i} \geq 95\% \tag{8}$$

2.2. Construction of the Health Index, Based on the WDMD Weighted Fusion

The power information extracted by the KPCA can better reflect the degradation mechanism of the equipment, but the sensitivity of the different feature information to the degradation process of the equipment is different. So this paper selects the trendability index reflecting the correlation degree between the features and time to evaluate the extracted features and selects the feature with the best trend as the power feature information. The trendability indicator is expressed as:

$$p^i = \frac{\left|\sum_{l=1}^{L}(T_l - \overline{T}_l)(X_l^i - \overline{X}_l^i)\right|}{\sqrt{\sum_{l=1}^{L}(T_l - \overline{T}_l)^2 \sum_{l=1}^{L}(X_l^i - \overline{X}_l^i)^2}} \tag{9}$$

where $\{T_l\}_{l=1:L}$ and $\{X_l^i\}_{l=1:L}$ represent the data collection time point and the corresponding eigenvalue, respectively, L represents the total time length, $\overline{T}_l$ represents the average value of $\{T_l\}_{l=1:L}$, X_l^i, represents the average value of $\{X_l^i\}_{l=1:L}$.

The degradation state of the switch machine in actual operation is affected by various factors, such as the environment, operating years, and maintenance level, and various failures of the different components may occur at the same time. Therefore, the evaluation of the health state of the equipment cannot only be represented, based on a single power curve feature. In order to obtain a health index that can cover more information about the degradation process, various characteristic information from the different perspectives should be comprehensively considered. The Mahalanobis distance is commonly used to fuse multiple features into a one-dimensional health indicator (HI). That is, the health indicator is constructed by calculating the Mahalanobis distance between the normal state and the monitoring state. This reflects the difference between the state of a certain test time and the health state, so the MD can reflect the health state of the switch machine equipment. In the process of the HI construction, each type of feature is given the same weight coefficient in the same way, which means that they have the same effect on the integration results of the health indicators. However, some features may have a weak or no correlation with the degradation process, which will not affect the fusion results or even have a negative impact. However, in practice, those features that are sensitive to the degradation process have a greater impact on the prediction results and should be given higher weight coefficients. Therefore, this paper evaluates the different raw data information collected and weighted the representative features. The WDMD is introduced to fuse the multi-source features of the switch machine to obtain a comprehensive HI [26]:

$$WDMD = \frac{(Z_r - \mu)W\eta^{-1}W(Z_r - \mu)^T}{R} \tag{10}$$

where R represents the number of feature categories, $\boldsymbol{Z}_r = [Z_1, Z_2, \ldots, Z_R]$ represents the feature vector, composed of each feature at time t, μ represents the mean of the data series, $\boldsymbol{\eta}$ represents the covariance matrix of the data set. $\boldsymbol{W} = \mathrm{diag}(w_1, w_2, \ldots, w_R)$ represents the weight matrix of the feature sequence, and the weight coefficient of the feature Z_r is:

$$w_r = \frac{p^r}{\sum_{r=1}^{R} p^r} \tag{11}$$

3. Prediction of the Remaining Life of the Switch Machine

3.1. Establishment of the HMM Degradation Model

The HMM is a statistical data model for constructing a time-varying vector sequence and is an effective tool for pattern recognition and life prediction processes [27]. Since the switch machine fails to repair itself, the left and right HMM are selected as the prediction model structure. The HMM usually consists of five basic elements, such as N, M, π, $\boldsymbol{A}$, $\boldsymbol{B}$. Where N and M represent the number of hidden states and state observations, respectively, $\boldsymbol{A} = \{a_{ij}\}_{N\times N}$ and $\boldsymbol{B} = \{b_{ij}\}_{N\times M}$ represent the state transition matrix from state a_i to state a_j, and the observation probability matrix under state b_i, $\boldsymbol{\pi} = [\pi_i]$ is the probability distribution of the initial state. Specifically expressed as:

$$\pi_i = P(x_1 = k_i) \tag{12}$$

$$a_{ij} = P(x_{i+1} = k_j \mid x_i = k_i) \tag{13}$$

$$b_{ij} = P(o_t = \rho_j \mid x_t = k_i) \tag{14}$$

The HMM can be defined as $\lambda = (\boldsymbol{A}, \boldsymbol{B}, \pi)$. It is necessary to solve the learning and identification problems of the HMM in the process of the health state identification and life prediction. That is, determine a model λ to maximize the probability $P(\mathrm{O}|\lambda)$ and calculate the probability of the occurrence of the observation sequence under the condition of the known model. During the state identification, the Baum–Welch algorithm is used to estimate the model parameters. Once the model is determined, the maximum likelihood probability $P(\mathrm{O}|\lambda)$ of the observation sequence under the various HMMs is obtained, according to the Viterbi algorithm, and the one with the highest probability is determined as the current health status of the observation sequence [28]. The RUL of the switch machine can be expressed as:

$$RUL = \sum_{i=1}^{L} \frac{P_i}{1 - a_{ii}} \tag{15}$$

3.2. Remaining Life Prediction, Based on the WDMD-HMM

In this paper, a remaining life prediction method, based on the WDMD-HMM is proposed for the health status identification and the remaining life prediction of the switch machines. The process architecture is shown in Figure 1. The specific ideas are as follows:

(1) Collecting the initial data of the switch machine through multiple sensors. The notch sensor, oil level sensor, power acquisition device, and switching value acquisition device is used to collect the notch value, oil level value, power curve, and operation duration of the switch machine, respectively, and then standardize all of the initial information.
(2) The KPCA is used to extract the feature information from the collected switch machine action power curve data, and the feature with the highest degree of correlation with the degradation process is selected, according to the trendability index.
(3) The collected gap, oil level, operation duration, vibration, humidity, and extracted power feature information of the switch machine are weighted and fused to obtain a one-dimensional health indicator (HI), based on the WDMD.
(4) The HMM is trained with the comprehensive health index as the input, and the HMMs under different operating conditions are obtained. The trained model is used to identify the health state of the switch machine, and the model with the maximum likelihood probability is identified as the current running state of the switch machine. The remaining life is then calculated by Equation (14). A predictive maintenance strategy is proposed for the switch machine, according to the prediction results.

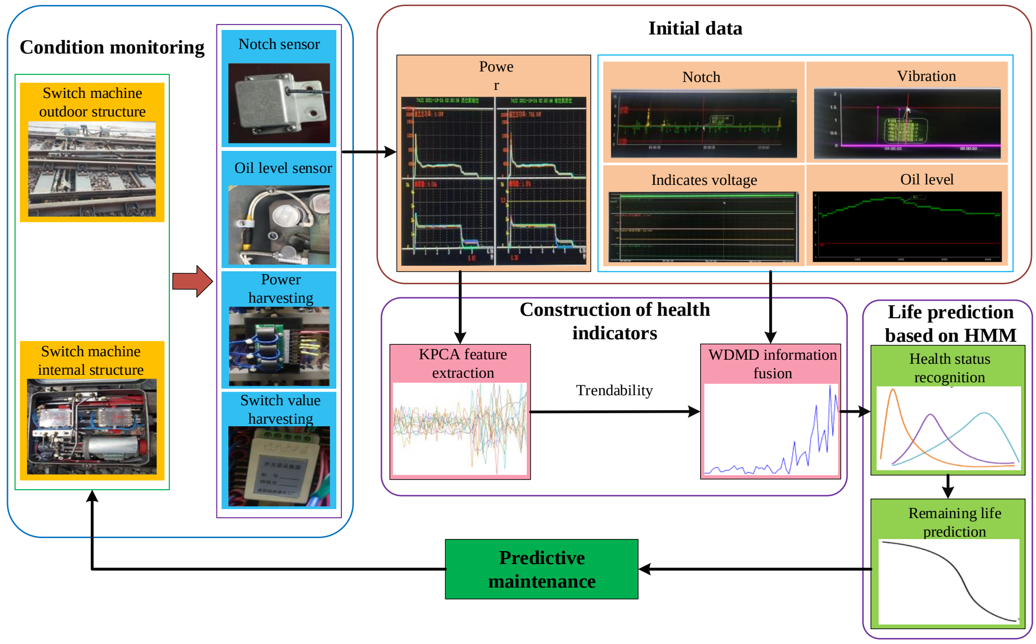

Figure 1. The structure of the remaining life prediction model of the switch machine.

In order to illustrate the effectiveness of the proposed method, based on the weighted Mahalanobis distance fusion data for life prediction, the commonly used algorithm indicators, such as the prediction score, accuracy and root mean square error, is selected to evaluate the performance of the prediction method. It is expressed as:

$$score = \sum_{i=1}^{N} S_i \\ S_i = \begin{cases} \exp(-\dfrac{R_0 - R}{10}) - 1, R_0 < R \\ \exp(\dfrac{R_0 - R}{13}) - 1, R_0 \geq R \end{cases} \tag{16}$$

where R_0 is the actual life of the equipment, and R is the predicted lifetime value of the equipment.

$$accuracy = \frac{\sum_{i=1}^{N} H_i}{N} \times 100\% \tag{17}$$

where

$$H_i = \begin{cases} 1, -10 \leq R_0 - R \leq 13 \\ 0, others \end{cases} \tag{18}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (R_0 - R)^2}{N}} \tag{19}$$

4. Example Verification

In this paper, the actual operation data and historical operation record data of the railway switch machine are used to verify the proposed method. The data set contains seven types of data, such as the active power curve, action duration, indicated voltage, oil level, vibration, gap, and humidity (sequentially numbered f_1–f_7) of the different switch machines in different operating environments. According to the statistics of the maintenance records of the railway signal equipment, the failure modes of the switch machine system can be mainly divided into circuit failure and mechanical failure, among which the circuit failure accounts for 20% of the total number of failures, and the mechanical failure accounts for 80% [29]. Therefore, this paper selects five groups of switch machines (represented by S_1–S_5 in turn) that run 50 times before a failure, as the data set to verify the prediction method. Four groups of mechanical faults were selected for four types of faults: oil leakage from the oil cylinder, locking frame grinding card, guide iron grinding card, and oil pipe rust and rupture; one group of circuit faults is the rust fault of the moving contact. All of these are shown in Figure 2a–e.

(a) (b) (c) (d) (e)

Figure 2. 5 groups of switch machine fault types. (**a**) oil leakage from the oil cylinder; (**b**) locking frame grinding card; (**c**) guide iron grinding card; (**d**) oil pipe rust and rupture; (**e**) rust fault of the moving contact.

The power curve of the switch machine contains rich action information, but the redundant information is not conducive to the effective analysis of the equipment. Therefore, it is first necessary to extract the features of the power curve of the switch machine, in order to filter out the effective information. The data of the power curve running for 5.92 s is selected, the switch machine transmits data every 40 ms, and each running will output 149 sample points [30]. The KPCA algorithm is used to perform the dimension reduction analysis on the power curve data. According to formula (8), the number of principal component features after the dimension reduction, is determined to be 10. According to formula (9), the trend indicators of the 10 features are calculated, respectively. Taking S_1 as an example, the results are shown in Table 1. The larger trend index value is the stronger correlation between the eigenvalues and the equipment degradation process, which can better represent the degradation mechanism of the equipment. Feature 1 is selected as the characteristic data of the power curve.

Table 1. Results of the KPCA feature extraction.

Feature	1	2	3	4	…	50	Trend
1	0.065344	0.07612	0.050249	0.065737	…	−0.53335	0.613926
2	0.068771	−0.29766	−0.00865	−0.03281	…	−0.21019	0.162081
3	0.035478	−0.18273	0.004342	0.011665	…	0.350159	0.04045
4	−0.06498	−0.10732	−0.09541	−0.00298	…	−0.27299	0.197211
5	−0.1433	−0.01724	−0.25121	−0.19086	…	0.02871	0.019023
6	−0.04344	−0.00195	0.047139	0.036087	…	−0.13032	0.130231
7	0.386203	0.293974	0.132074	0.162881	…	−0.0372	0.346972
8	0.132166	−0.00948	0.121827	0.051875	…	0.255827	0.170949
9	0.134932	−0.2565	0.040945	0.16945	…	−0.00071	0.189856
10	0.010799	0.032331	−0.0995	0.154403	…	0.328442	0.043164

The final failure of the switch machine is not only caused by the failure of a certain component, but the interaction between the various subsystems is an important reason for the failure of the equipment. A single power data cannot completely contain the information on the equipment degradation process. Therefore, it is necessary to comprehensively consider the monitoring data of each sensor to evaluate the overall health status of the equipment and then formulate the corresponding maintenance strategies. Feature 1 is screened out by the trendability index, and the data of conversion time, vibration, expressed voltage, gap, humidity, oil level, etc., are combined to form a 7 × 50 feature matrix. Calculating the weight coefficients of the seven features to form a weight matrix as $\boldsymbol{W}$ = diag(0.193729707, 0.145776941, 0.145239333, 0.077631878, 0.17225416, 0.006536689, 0.258831292), and then obtain the weighted Mahalanobis distance by Equation (10). Taking S_1 as an example, is as follows in Figure 3. In order to verify the effectiveness of the WDMD, the Mahalanobis distances of seven kinds of features are calculated at the same time for comparison, which is shown in Figure 4. It can be seen from the figure that the WDMD shows a more obvious degradation trend during the operation, especially during the first ten times of the operation. In order to quantitatively compare the constructed HIs of the two methods, the trend index values of the WDMD and MD were calculated to be 0.6135 and 0.5228, respectively. So the WDMD is more sensitive to the degradation process of the switch machine and is more suitable for the prediction of remaining life.

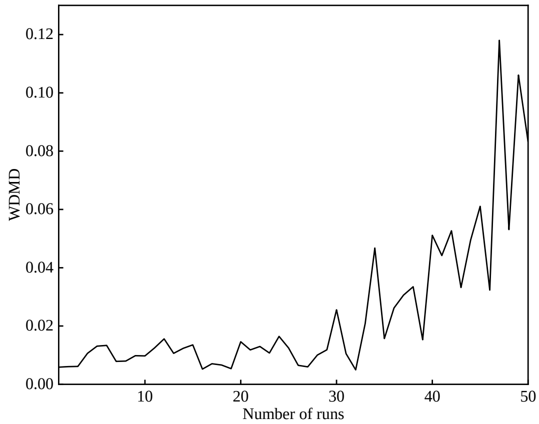

Figure 3. WDMD feature fusion.

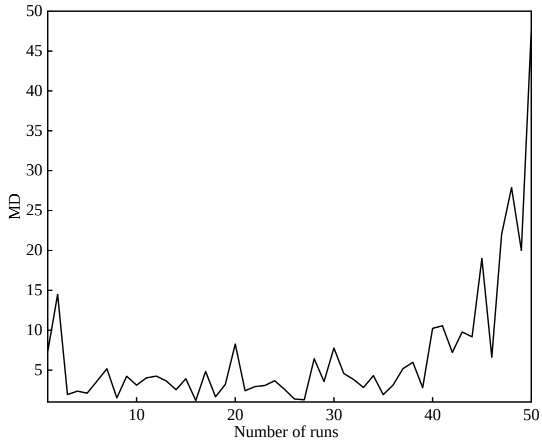

Figure 4. MD feature fusion.

According to the above method, the feature information of the other four groups of switch machines is weighted and fused, as shown in Figure 5. It can be seen from the figure that the five groups of switch machines have stable health indicators (HI) at the initial stage of the operation, and the HIs are all within the parameter range of a healthy operation. The degradation feature information is obvious, and the HI overall, shows an upward trend with the continuous operation of the switch machine. The HI values of the five groups of switch machines have entered the fault range by the 50th operation. Among them, the HI of the S_4 switch machine increased significantly when it ran for the 47th time and then dropped back to the original trend range. Following the reading, it was found that the fault was caused by the lack of oil on the slide bed, during the operation of the switch machine. On the whole, the five groups of health indicators have a good degradation trend, which is more obvious in the five operations before the failure, so it can characterize the degradation process of the switch machine equipment.

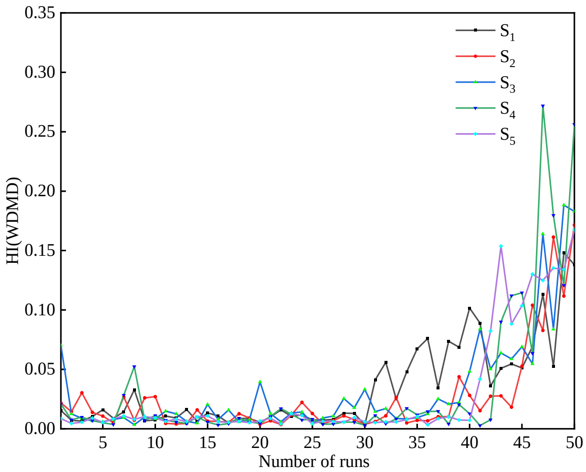

Figure 5. Results of health indicator construction.

The HMM is trained with the health index constructed, based on the weighted Mahalanobis distance. The selected data set has a total of 250 sample points, of which 190 sample points are selected as the training set, and 60 sample points are used as the test set. The equipment degradation process is divided into four states: normal, early warning, alarm, and fault, which are respectively expressed as states A, B, C, and D, according to the actual failure process record of the switch machine and the HI index. The HI values of the four states are $0 \le HI_A < 0.05$, $0.05 \le HI_B < 0.08$, $0.08 \le HI_C < 0.15$, $HI_D \ge 0.15$. The switch machine works stably and normally when HI < 0.05 and cannot realize the corresponding conversion function when HI ≥ 0.15. The switch machine operates less frequently from the fault characteristic to the fault, so it must be arranged for maintenance immediately, when the HI is between 0.08 and 0.15. It is necessary to train the corresponding HMM for each state. The number of the HMM states is set to four, which corresponds to the four operating states of the switch machine. First, we initialize the parameters of the state transition probability matrix, the observation probability matrix, and the initial state probability distribution in the model. Then, the EM algorithm is used to train the model, and the parameter matrix is re-evaluated to form a new HMM. The maximum likelihood probability of the input data is calculated using the model. The larger the probability, the greater the match to the model. Zero is the maximum. Finally, the Viterbi is used to calculate the maximum probability state transition path. The corresponding HMM is trained for each state, and the current state of the equipment is determined, according to the monitoring data with the highest likelihood probability among the four types of models. Fifteen samples are randomly selected from each state of the five groups of switch machines, to identify the state, among which the sample numbers 1–15 are in state A, the sample numbers 16–30 are in state B, the sample numbers 31–45 are in state C, and the sample number 46–60 are in state D. The recognition result is shown in Table 2. In the process of identifying the four degradation states of the switch machine, all samples in the normal state and the fault state can be correctly identified, one sample in the early warning state is incorrectly identified as the normal state, and one sample in the alarm state is incorrectly identified as the fault state. In the test of 60 samples in four states, the overall recognition result has a correct rate of 96.7%. The data of a certain running time of the S_1 switch machine is selected as the input for the HMM training, and the maximum likelihood probabilities of the corresponding four state models are calculated as inf, inf, −0.671244, and inf, respectively. The calculation of the state transition probabilities of each state is shown in Table 3. The one with the maximum likelihood probability is diagnosed as the current operating state, and the health state level of the switch machine is judged as state C. The maintenance shall be arranged as soon as possible.

Table 2. The result of the state recognition.

State Type	A	B	C	D	Recognition Accuracy
A	15	0	0	0	100%
B	1	14	0	0	93.3%
C	0	0	14	1	93.3%
D	0	0	0	15	100%

Table 3. The state transition probabilities.

State Type	A	B	C	D
A	0.7980	0.1423	0.0598	0
B	0.1888	0.8407	0.9585	0
C	0	0	0.8800	01200
D	0	0	0	1

Calculating the remaining life, according to Equation (15), based on the operating data of the S_1 switch machine, the calculation result and the actual operating life are shown in Figure 6. It can be seen from the figure that the initial difference between the predicted value and the actual value is large. The difference between the calculation result of the prediction model and the actual life gradually becomes smaller with the continuous degradation of the switch machine. This is because the early degradation characteristics of the equipment are not obvious. In addition, some features will disappear or change in the continuous operation of the equipment, which makes the initial prediction result inaccurate and has a large deviation. The prediction results become more accurate and stable with the continuous degradation of the equipment, and the degradation characteristics are gradually obvious. In several operations before the equipment failure, the predicted life value is slightly less than the actual operating life, which is conducive to the staff finding fault information in advance and formulating maintenance strategies in time. The predicted value is 4.66376 when the switch machine runs for the 45th time. There is a fault alarm when it is called at 17:00 on October 4th, and it runs five times safely during this period. The prediction result is effective because it is more conducive to formulating a corresponding maintenance plan and ensuring the safe operation of the switch machine system, if the life prediction result fails in advance.

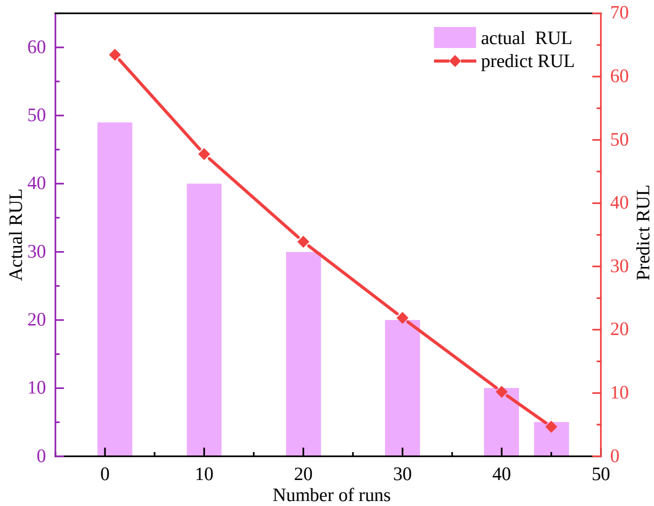

Figure 6. Prediction results of the remaining life of the switch machine.

In this paper, the residual life prediction method of the weighted Markov distance fusion proposed, is compared with the HMM [31], MD-HMM, WDMD-HMM, and the prediction methods are based on the dynamic weights [32]. The score, accuracy, and RMSE indexes of the four methods are calculated as shown in Table 4. It can be found from the evaluation results that the proposed method is lower than the HMM and the other prediction methods, based on the dynamic weights in the score indicators, but it has obvious advantages over the other three methods, in terms of accuracy and the RMSE indicators. The prediction accuracy is the highest.

Table 4. Evaluation of the prediction results.

Methods of Prediction	Score	Accuracy	RMSE
HMM	5.07396	71.2%	7.57841
MD-HMM	7.29157	66.7%	8.21984
WDMD-HMM	5.13758	83.3%	6.92353
Dynamic weight	6.31592	75.4%	9.06411

The domestic invention patent of "the method and device for predicting the residual life of the switch machine", has studied the residual life prediction of the switch machine [33]. The relevant parameters of the prediction model are initialized by the adaptive global particle swarm optimization algorithm, which effectively improves the prediction accuracy of the residual life of the switch machine. However, this method requires a large number of current curves with residual life labels, in order to train the model. In comparison, the method proposed in this paper requires less data and considers other factors that affect the running state of the switch machine, so it has more advantages.

5. Conclusions

(1) A method for predicting the remaining life of a switch machine that integrates multi-source information is proposed. It realized the weighted fusion of the multi-features through the WDMD algorithm, which makes up for the shortcomings of the single data representation degradation process and the multi-data blind fusion.
(2) The degradation state of the switch machine is reflected in the health index, which realized the transformation from the qualitative to the quantitative evaluation of the state.
(3) The example verification shows that the proposed method can predict the equipment failure earlier to make the equipment operation to be safe. The prediction accuracy of the proposed method is higher, compared with other methods. It is beneficial to the formulation of the switch machine maintenance plan.
(4) This paper only considers the correlation between multiple features and time that affect the remaining useful life of the switch machine. In future work, the influence of the coherence between the multiple features on the degradation process will be considered.

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