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Research on Residual Life Prediction for Electrical Connectors Based on Intermittent Failure and Hidden Semi-Markov Model

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Abstract: Based on the dynamic properties of electrical connector intermittent failure, the model and methods for residual life prediction for electrical connectors are studied in this paper. Firstly, the mechanism of electrical connector intermittent failure is analyzed, and the area enclosed by the contact resistance curve and the fault threshold is defined as the generalized severity of intermittent failure to describe how severe the electrical connector's intermittent failure is. Then, the Hidden Semi-Markov Model (HSMM) is introduced to build the residual life prediction model of the electrical connector. Further, the evaluation method of using the state and prediction method for residual life are studied. Finally, by carrying out the residual life prediction test, the effectiveness of the residual life prediction method for electrical connectors based on intermittent failure and HSMM is verified.

Keywords: intermittent failures; intermittent failure dynamics; residual life prediction; electrical connector

1. Introduction

Electrical connectors are widely used in equipment systems and are of great importance. The contact condition of connectors significantly affect the reliability and the success rate of the equipment [1,2]. However, with the increasing service time and the influence of environmental stress, the using states of electrical connectors will be continuously deteriorated, and eventually the connectors failed. To avoid a catastrophic accident, it is necessary to assess the using state of the electrical connectors in good time, and predict the residual life of electrical connectors.

Residual life prediction is an important part of Prognostics and Health Management (PHM) technology. At present, experts and scholars have carried out a lot of research on residual life prediction for various connectors, including relays, circuit breakers, contactors, electrical connectors, and so on. Because of the different structures and functions of connectors, the residual life prediction methods for connectors are different, as well as the accuracy of these prediction methods. Generally, the accuracy of the prediction methods heavily depends upon extracted life features. With the rapid development of electronic technology, many new features of life prediction have emerged [3–6]. For example, in the study of the prediction of relay and circuit breakers, the overrange time, the effective contact distance, the surface roughness, the arc time, the contact quality loss and the arc voltage spectrum are often extracted for residual life prediction. Unlike relays and circuit breakers, the plug and socket of electrical connectors are pressed together; this mechanical structure made the life prediction features difficult to extract. The new features can, however, directly reflect the damage and degradation of the electrical connectors but the new prediction features are not suitable for on-line monitoring, and are also difficult to extract. Therefore, more suitable features need to be studied for the residual life prediction of electrical connectors.

Considering practicality and generalization, most of the research on the life prediction of electrical connectors is still based on contact resistance data. Recently, many new prediction methods for contact resistance have been proposed [7,8]. Jordi-Roger Riba et al. proposed a FEM-based method to estimate the contact resistance of two mating metallic rough surfaces. Francesca Capelli et al. developed a genetic algorithm (GA) approach to predict the constriction resistance. Besides, much engineering and experimental data show that contact resistance is nonlinear through the whole life cycle of the electrical connector [1,9,10] and only when the contact resistance is approaching permanent failure does the contact resistance quickly rise, showing the obvious failure feature. The contact resistance remains low in the early and middle stages of degradation. Therefore, it is difficult to ensure the accuracy of life prediction in the early and middle stages of the degradation. With the aging of electrical connectors, intermittent failure often occurs during the operation period. An intermittent failure is defined as a failure of an item for a limited period of time, following which, the item recovers its ability to perform its tasks without being subjected to any external corrective action. Once the first intermittent failure occurs, the intermittent failure will continue to occur during the residual life of electrical connectors and the "severity" of the intermittent failures will grow with increasing service time. By obtaining the "severity" characteristics of intermittent failures, guidance can be provided for research, such as using states estimation, residual life prediction, maintenance plan, false alarm suppression and so on. Therefore, much research is focused on the characterization of intermittent failure "severity." By defining the pseudo cycle of intermittent failure, Steadman et al. investigated the dynamics of intermittent failures [11]. By constructing the density of intermittent failure, Correcher et al. proposed methods to establish maintenance policy [12]. Cui et al. introduced the failure test profile method to construct an intermittent failure mechanism model and the number of intermittent failures is used to optimize the sensor threshold to reduce the false alarm rate [13]. Similarly, Li et al. proposed a method to estimate the using state of electrical connectors through the frequency of intermittent failure. Based on the previous literature, it is obvious that the most common feature for intermittent failure characterization includes the frequency, duration and amplitude of failures. However, a single feature is not sufficient for intermittent failure characterization. These features need to be integrated, forming a comprehensive feature that is suitable for the residual life prediction of electrical connectors.

Except for intermittent failure features, the residual life prediction model for electrical connectors needs to be conducted. Currently, the life prediction model mainly includes a physical model and a data driven model. Considering the randomness of intermittent failures, the data driven model is more suitable for the residual life prediction of electrical connectors [14–19]. Combined with the degradation processes of electrical connectors, it is helpful to improve the prediction accuracy of the residual life of electrical connectors by selecting a suitable model.

In this paper, the dynamic properties of electrical connector intermittent failure are analyzed and a residual life prediction method for electrical connectors is studied. The residual contents are structured as follows: Section 2 builds a residual life prediction model of the electrical connector using the Hidden Semi-Markov Model (HSMM); Section 3 studies an extraction method for intermittent failure features and provides a definition of intermittent failure generalized "severity"; Section 4 investigates using state estimation and residual life prediction for electrical connectors; Section 5 conducts a test for residual life prediction; and Section 6 summarizes the work in this paper.

2. Modeling of Residual Life Prediction for Electrical Connector

2.1. Degradation Process of Electrical Connector

The failure modes of electrical connectors mainly include contact failure, insulation failure and mechanical failure, where the contact failure accounts for more than 45.1% of all failures. The contact surface of the connector is the key component of delivery current and signal. With the degradation of the metal surface, the contact resistance will increase. When the contact resistance reaches the failure threshold, the electrical connector fails [20].

Together with the equipment, the electrical connectors installed in the equipment are always subjected to various environmental stresses. Under environmental stress, the metal surface suffers fretting wear, which results in the oxidation and corrosion of the contact surface. The oxidized layer is composed of insulating materials. It grows thicker around the contact interface and gradually covers most of the area of the interface. The growth of the oxidized layer on the surface leads to increased contact resistance and easily causes contact failure. The growth process is shown in Figure 1. Initially, the film is formed around the contact surface. With the contact surface being continuously oxidized, the oxidized layer accumulated gradually. Finally, the oxidized layer, which is an insulating material, will cover the original contact surface. When the whole contact surface is covered by oxidized film, the electrical connector fails.

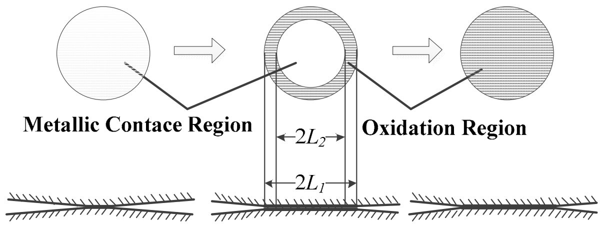


Figure 1. The degradation process of the contact surface.

With the degradation of the contact surface, the contact surface is gradually covered by the insulating layer and some of the conductive spots disappear and some of the conductive spots become smaller. The number and size of conductive spots can reflect the using state of electrical connector. Since the conductive spots are difficult to observe, the contact resistance related to the conductive spot is usually used to analyze the using state of the electrical connector. However, the contact resistance has some limitations in the degradation analysis of electrical connectors.

For the sake of analysis, it is assumed that the shape of the conductive spots is circular with a radius of a. The contact resistance of a conductive spot is $R_a = \rho/4a$, where ρ is the resistivity of the metal material [21]. Considering the parallel structure between the conductive spots, the contact resistance R_c can be expressed as:

$$R_c = \frac{R_a}{N_c} \tag{1}$$

where N_c denotes the number of conductive spots.

The common degradation curve of contact resistance is as shown in Figure 2. In the early and middle stages of electrical connectors, the contact resistance remains low. Only in the later stage does the contact resistance increase rapidly, showing significant failure features. Therefore, simply extracting contact resistance as the feature is difficult for accurately predicting the residual life during the whole life cycle of the electrical connector.

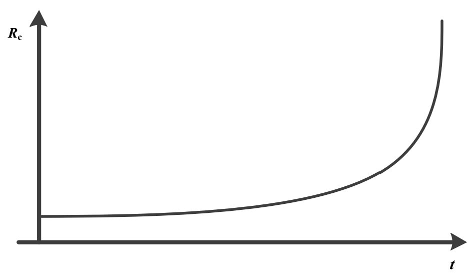


Figure 2. Degradation curve of contact resistance.

2.2. Intermittent Failure Dynamics of Electrical Connectors

In practical engineering applications, the "severity" of intermittent failure will grow with the degradation of connectors. For example, the frequency, duration and magnitude of intermittent failure increase. The typical evolution of intermittent failure dynamics is shown in Figure 3.

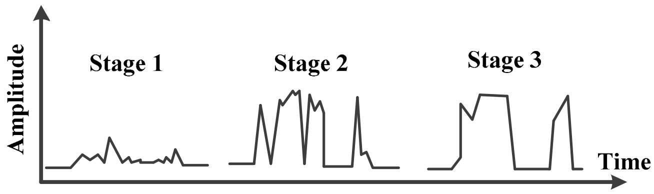
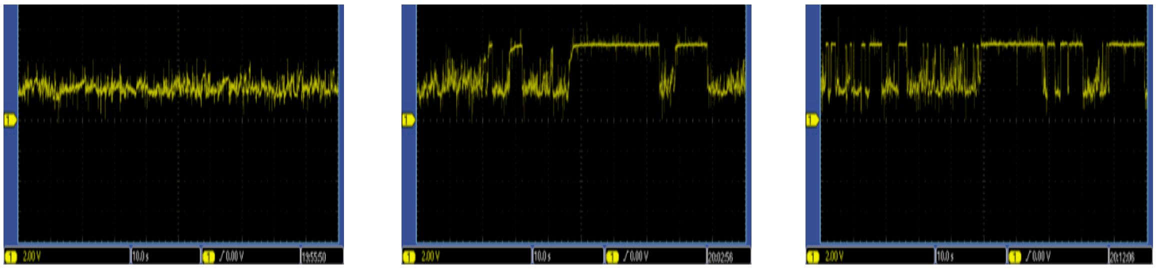


Figure 3. Evolution of intermittent failure dynamics [11].

The whole life of electrical connectors is simply divided into three stages. The four-wire method is introduced to test the contact resistance under three stages, respectively. The curves of resistance are shown in Figure 4.



(**a**) Stage 1 (**b**) Stage 2 (**c**) Stage 3

Figure 4. The curve of contact resistance under different states of the electrical connector.

Traditionally, only one feature is selected to characterize the "severity" of intermittent failure. However, a single feature is not sufficient for intermittent failure characterization. Therefore, we are committed to extract a more effective feature from contact resistance data for intermittent failure characterization.

Considering the characteristics of intermittent failure, such as frequency, amplitude and duration, we use the area enclosed by the contact resistance curve and the fault threshold for intermittent failure characterization—called the area of intermittent failure in this paper. From the previous literature and measured results, it is found that intermittent failure is closely related to the degradation of the electrical connector. With the deterioration of the electrical connector, the area of intermittent failure will increase in general; the process is shown in Figure 5.

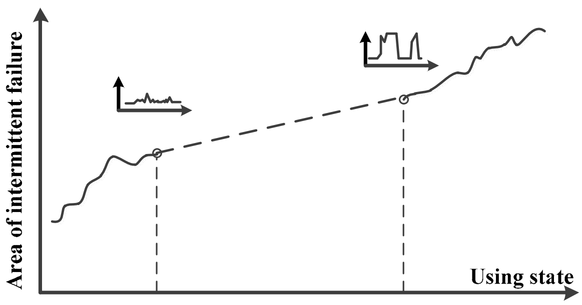


Figure 5. The "severity" of intermittent failure increases with the degradation of the using state.

Simply extracting the area of intermittent failure at any time to predict the residual life of the electrical connector, the prediction result may have a great deviation from the real residual life, so a statistical model needs to be used for modeling the using state of the electrical connector. The Hidden Markov Model (HMM) is an important statistical method, which is especially suitable for describing stochastic processes with state transitions. Similar to HMM, with the degradation of the using state, the area of intermittent failure shows a specific distribution characteristic. To facilitate the prediction of the residual life of electrical connectors, the Hidden Semi-Markov Model (HSMM) is introduced for modeling the using state of electrical connectors.

2.3. Model of Using States Based on HSMM

According to the degradation process of electrical connectors, these using states are degraded gradually. However, the degraded using states are difficult to observe. Combined with the intermittent failure "severity" proposed previously, the using state of a connector can be estimated using the area of intermittent failure extracted from contact resistance curve. The HSMM is introduced to modeling the using state.

An HSMM is a Hidden Markov Model (HMM) with temporal structures. An HMM is a dual stochastic process, and a Markov chain that has some states and generates random characters. A complete HMM can be described using the following parameters:

1. The states number in the model are N. Let N states are $s_1, s_2, \ldots, s_N$. Assuming that the state at time t is q_t, $q_t \in (s_1, s_2, \ldots, s_N)$.
2. The number of distinct observations which is correspond to intermittent failure "severity" is M. the M observation symbol are denoted by $V_1, V_2, \ldots, V_M$. Assuming that the observation at time t is O_t, $O_t \in (V_1, V_2, \ldots, V_M)$.
3. The initial state distribution π, $\pi = (\pi_1, \pi_2, \ldots, \pi_N)$, where $\pi_i = P(q_1 = s_i)$, $1 \leq i \leq N$.
4. The state transition probability distribution A. $A = (a_{ij})_{N\times N}$, $1 \leq i, j \leq N$, where $a_{ij} = P(q_{t+1} = s_j \mid q_t = s_i)$, $1 \leq i, j \leq N$.
5. The observation probability distribution in state j, $B = (b_{jk})_{N\times M}$, where $b_{jk} = P(O_t = V_k \mid q_t = s_j)$, $1 \leq j \leq N$, $1 \leq k \leq M$.

To predict the residual life of an electrical connector, it is necessary to analyze the time duration of each state first. Since the hypothesis of the Markov chain, the time duration obeys the geometric distribution implicitly. It is obvious that the time duration of each state obeys exponential distribution which is not suitable for many practical applications. To overcome this limitation, the HSMM is introduced to modeling the transition process of states [22].

Unlike HMM, an HSMM allows modeling of the time duration of the hidden states and is therefore capable of prognosis. The HSMM-based modelling framework for the residual life prediction of electrical connectors is described in Figure 6.

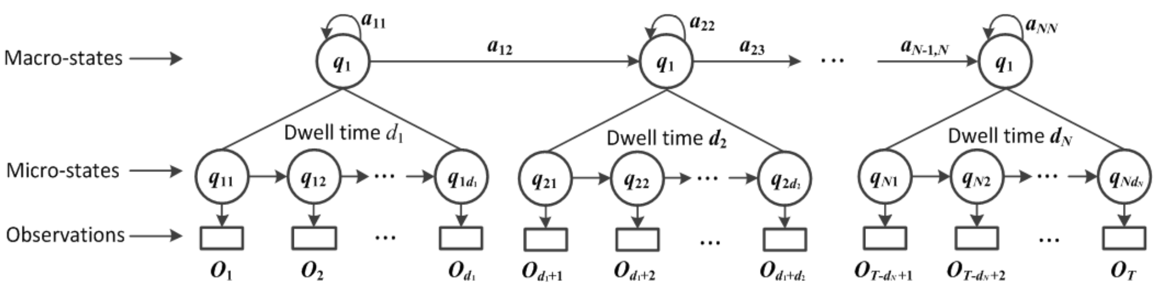


Figure 6. Schematic of HSMM modeling framework.

A state generates a segment of observations in HSMM, and the states are called macro-states. Each macro-state has N segments, let q_n be the time index of the end-point of the nth segment ($1 \leq n \leq N$).

Compared with HMM, an HSMM allows modeling of the time duration of the hidden states, and the time duration distribution function of each state is defined.

$$P_i(d) = P(d|q_t = i), \quad 1 \le i \le N \ , \quad 1 \le d \le D \tag{2}$$

where the $P_i(d)$ represents the probability of staying in state i with d time steps, D denotes the maximum duration within any state.

Combined with HMM and state duration distribution, an HSMM can be described as

$$\lambda = (\pi, A, B, P_i(d)) \tag{3}$$

where π, A, B denote the initial state distribution, the transition model and the observation model respectively.

Corresponding to the nth macro-state, the observations are $O_{d_{n-1}+1}, \cdots, O_{d_n}$ and these observations have the same micro-state label. It is worth noting that the transition of macro-states $s_{q_{l-1}} \to s_{q_l}$ is Markov process, but the transition of micro-states $s_{t-1} \to s_t$ is not Markov process.

2.4. Residual Life Prediction Model of Electrical Connector

According to the HSMM-based using state model, a new HSMM-based residual life prediction model for electrical connectors is proposed here as shown in Figure 7.

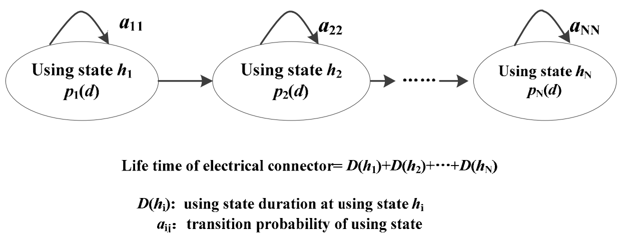


Figure 7. Residual life prediction model based on HSMM.

In our prediction model, each using state duration density $P(d_n/h_i)$ is modeled by single Gaussian distribution. Under the constraint $T = \sum_{i=1}^{N} D(h_i)$, each using state $D(h_i)$ can be calculated through maximize $\log P(S|\lambda, T) = \sum_{i=1}^{N} \log P(d_n/h_i)$.

$$D(h_i) = \mu(h_i) + \rho\sigma^2(h_i) \tag{4}$$

where $\rho = (T - \sum_{i=0}^{N} \mu(h_i))/\sum_{i=0}^{N} \sigma^2(h_i)$.

2.5. Evaluation and Parameter Estimation Algorithm of HSMM

Before applying the HSMM model for residual life prediction, it is necessary to solve the evaluation and learning problems of HSMM. Thus, given the observations $O = [o_1, o_2 \cdots o_T]$ and HSMM's parameters $\lambda = (\pi, A, B.P_i(d))$ how do we adjust the model parameters to maximize $P(O \mid \lambda)$. The basic algorithm for solving problems of HSMM evaluation and learning is as follows.

2.5.1. Forward-Backward Algorithm

The forward-backward algorithm mainly solves the evaluation problem of HSMM. Firstly, a forward variable $\alpha_t(i)$ represents the probability of generating $O = \{o_1, o_2, \ldots, o_t\}$ and ending at state s_i is defined as follows:

$$\begin{aligned} \alpha_t(j) &= P(o_1, o_2, \cdots o_t, q_t = j | q_{t+1} \neq i, \lambda) \\ &= \sum_{\substack{j=1 \\ ji}}^{N} \sum_{d=1}^{t} a_{t-d}(i) a_{ij} p_j(d) \prod_{s=t-d+1}^{t} b_j(O_s) \end{aligned} \tag{5}$$

A backward variable $\beta_t(i)$ represents the probability of generating $O = \{o_{t+1}, o_{t+2}, \ldots, o_T\}$ and ending at state s_i is given by

$$\begin{aligned} \beta_t(i) &= P(o_{t+1}, o_{t+2}, \cdots o_T, q_t = i | q_{t+1} \neq i, \lambda) \\ &= \sum_{\substack{j=1 \\ j \neq i}}^{N} \sum_{d=1}^{T-t} a_{ij} p_j(d) \prod_{s=t+1}^{t+d} b_j(O_s) \beta_{t+d}(j) \end{aligned} \tag{6}$$

Further, to evaluate all parameters in HSMM, three Forward-Backward variables are defined as follows:

- $a_{t,t'}(i,j)$ $a_{t,t'}(i,j)$ denotes the probability of the partial observation sequence $o_1 \ldots o_t$, and state i at time t and state j at time t'
- $\phi_{t,t'}(i,j)$ $\phi_{t,t'}(i,j)$ denotes the probability of the system being in state i for d time units and then moving to the next state j.
- $\xi_{t,t'}(i,j)$ $\xi_{t,t'}(i,j)$ denotes the probability of the system being in state i for d ($t' = t + d$) time units and then moving to the next state j, given the observation sequence $o_1 \ldots o_T$.

The forward-backward algorithm is shown as follows:

1. Forward algorithm

   - initialization($t = 0$)

$$\alpha_{t=0}(i) = \begin{cases} 1 & if \quad i = START \\ 0 & \quad otherwise \end{cases} \tag{7}$$

   - Forward recursion ($t > 0$). For $t = 1,2, \ldots, T$; $1 \leq i, j \leq N$, $1 \leq d \leq D$.

$$\alpha_t(j) = \sum_{i=1}^{N} \sum_{d=1}^{D} P(d = t' - t | j) a_{t,t'}(i,j) \tag{8}$$

   - End

$$P(O|\lambda) = \sum_{j=1}^{N} \alpha_T(j) \tag{9}$$

2. Backward algorithm

   - Initialization

$$\beta_T(i) = 1, \quad (t = T, 1 \leq i, j \leq N) \tag{10}$$

   - Backward recursion($t < T$). For $t = 1,2, \ldots, T$; $1 \leq i, j \leq N$, $1 \leq d \leq D$.

$$\beta_t(i) = \sum_{j=1}^{N} a_{ij} \phi_{t,t'}(i,j) \beta_{t'}(j) \tag{11}$$

$$\xi_{t,t'}(i,j) = \frac{\sum_{d=1}^{D} a_t(i)a_{ij}\phi_{t,t'}(i,j)\beta_{t'}(j)}{\beta_0(i = START)} \tag{12}$$

- End

$$P(O|\lambda) = \sum_{i=1}^{N} \beta_1(i) \tag{13}$$

2.5.2. Parameter Re-estimation Algorithm

According to the observation sequence $O = \{o_1, \ldots, o_T\}$, we can modify the parameters of HSMM $\lambda = (\pi, A, B, P_i(d))$ to maximize $P(O|\lambda)$ using a parameter re-estimation algorithm. Considering the randomness of intermittent failure data, it is necessary to use data from multiple electrical connectors to train an HSMM. The derivation of the parameters' re-estimation algorithm for multiple observation sequences is as follows.

Let L observations be $O^{(l)} = O_1^{(l)}, \cdots, O_{T_l}^{(l)}$, $l = 1, \ldots, L$. assuming that each observation sequence is independent of each other, the probability of O given the model λ can be expressed as follows:

$$P(O|\lambda) = \prod_{l}^{L} P(O^{(l)}|\lambda) \tag{14}$$

Since the re-estimation algorithm is based on the frequency at different times, the re-evaluation algorithm for the L training observation sequences can be modified as follows:

$$\begin{aligned} \bar{a}_{ij} &\triangleq \frac{\sum\limits_{l=1}^{L} trans-counts(i,j,l)}{\sum\limits_{l=1}^{L} state-counts(i,l)} \\ &= \frac{trans-counts^{(A)} + trans-count^{(B)}}{state-counts^{(A)} + state-counts^{(B)}} \end{aligned} \tag{15}$$

$$\begin{aligned} \bar{b}_{jk} &\triangleq \frac{\sum\limits_{l=1}^{L} vect-counts(k,j,l)}{\sum\limits_{l=1}^{L} state-counts(j,l)} \\ &= \frac{vect-counts^{(A)} + vect-counts^{(B)}}{state-counts^{(A)} + state-counts^{(B)}} \end{aligned} \tag{16}$$

$$\begin{aligned} \bar{p}_i(d) &\triangleq \frac{\sum_{l=1}^{L} durationvect-counts(d,i,l)}{\sum\limits_{l=1}^{L} state-counts(i,l)} \\ &= \frac{durationvect-counts^{(A)} + durationvect-counts^{(B)}}{state-counts^{(A)} + state-counts^{(B)}} \end{aligned} \tag{17}$$

In Equations (15)–(17), *trans-counts* (B), *vect-counts* (B), *state-counts* (B) and *duration vect-counts* (B) denotes the transition number, vector number, state number and resident vector number.

2.6. Overall Scheme of Residual Life Prediction for Electrical Connectors

The overall scheme of the prediction method for the residual life of electrical connectors is shown in Figure 8. Firstly, the HSMM of the electrical connector's using state is constructed. Then, the feature of intermittent failure is extracted, which is the input for the HSMM. Further, the using state estimate model and the residual life prediction model can be constructed by training the HSMM. After collecting the intermittent failure data, the using state can be estimated according to the trained using state estimation model. Combined with the estimated state and the trained residual life prediction model, the residual life of electrical connectors can be predicted.

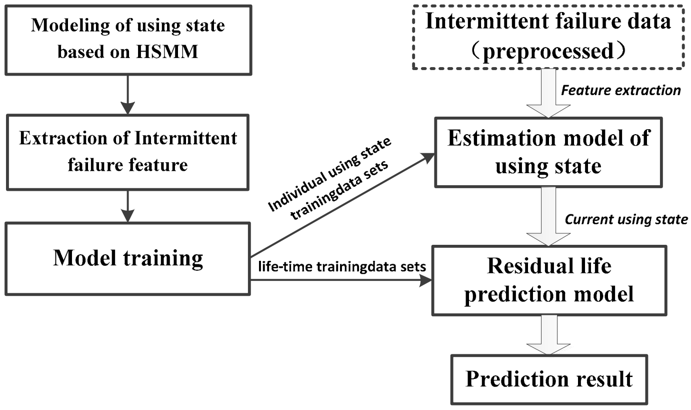


Figure 8. Overall scheme of residual life prediction for electrical connectors.

3. Extraction of Intermittent Failure Feature

According to the dynamics of intermittent failures under different using states, it is found that the area enclosed by the contact resistance curve and the fault threshold increases with the degradation of the electrical connector. In this paper, the area enclosed by the contact resistance curve and the fault threshold is defined as intermittent failure severity, which is a characterization of electrical connector intermittent failure.

3.1. Experiments for Intermittent Failure Severity Extraction

The severity of intermittent failure is extracted from the contact resistance data. Therefore, the four-wire method is introduced to measure contact resistance as shown in Figure 9.

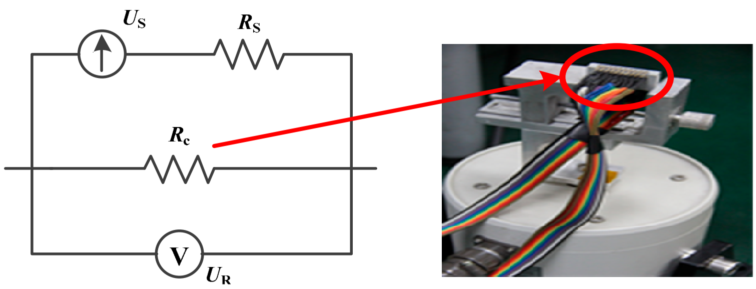


Figure 9. Test principle of contact resistance of four line method.

The current passing through our electrical connector is driven by a voltage source and the voltage drop between the two terminals of the pins of the connector is recorded with a multimeter. Then, the electrical connector is mounted on the vibration stage to simulate the practical operating environment of the connector. By monitoring the contact resistance on-line, the curve of contact resistance can be obtained.

The next step is to post-process the obtained contact resistance. If the resistance exceeds the failure threshold, the difference between the resistance and the threshold is recorded. If the resistance does not exceed the threshold, the intermittent failure value is set to 0. After that, the intermittent failure curve can be obtained. Next, to satisfy the input requirements of the HSMM model, the generalized severity of intermittent failure is proposed in the following part.

3.2. Generalized Severity of Intermittent Failure

According to the four wire method, the measured voltage is U_H (intermittent failure upper boundary, $U_H = U_S$) when the connector is completely disconnected (permanent fault) and the measured voltage is less than U_L (intermittent fault lower boundary, $U_L = R_{th}U_S/(R_{th} + R_S)$) when the connector is in good contact. In the measurement interval of (0, t), the intermittent failure curve of electrical connector U_{IF}(t) can be obtained as shown in Figure 10.

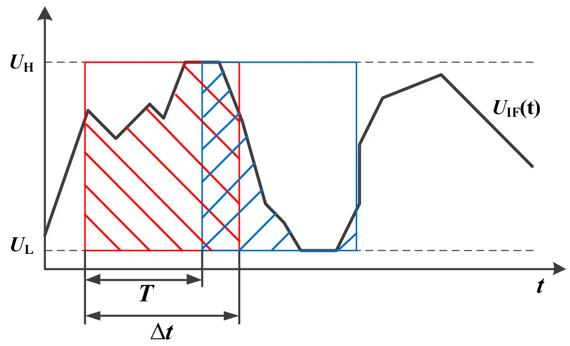


Figure 10. The curve of intermittent failure.

For convenience, we defined severity of intermittent failure, which is given by

$$I = \int_t^{t+\Delta t} [U_R(t) - U_L]dt \tag{18}$$

where Δt denotes the test window, and I denotes the severity of intermittent failure.

In fact, I is the area of the shadow part enclosed by the contact voltage curve and the Intermittent failure lower boundary U_L. Further, data is processed for the normalization of intermittent fault severity I.

$$\widetilde{I} = \frac{1}{\Delta t} \cdot \frac{\int_t^{t+\Delta t} [U_R(t) - U_L]dt}{U_H - U_L} \tag{19}$$

where $\widetilde{I}$ is defined as the generalized severity of intermittent failure, and $\widetilde{I} \in (0, 1)$. It means contact in normal state if $\widetilde{I}$ = 0, it means the permanent fault if $\widetilde{I}$ = 1, otherwise the connector suffered intermittent failure.

According to MIL-PRF 32516 "electronic Test Equipment, Intermittent Fault Detection & Isolation", the intermittent failure duration should not exceed 5 ms, otherwise a permanent fault is considered. Therefore, the length of the test window is set to 5 ms, thus, $\triangle t$ = 5 ms. Further, the sequences of generalized intermittent failure severity can be obtained through slipping the test window with a certain step length. Let the step length of slipping be T. it worth mentioned that the step length T should be less than $\triangle t$ to prevent the information leakage of intermittent failures.

4. Research on Using State Estimation and Residual Life Prediction of Electrical Connectors

4.1. Method of Using State Estimation

The HSMM-based estimation method for using state mainly includes five steps as follows:

1. Preprocessing of sampled data

Collecting the sample data of intermittent failure at each using state, then extracting the curve of intermittent failure. After that, the generalized severity of intermittent failure can be obtained using Equation (19).

2. Determination of the using states number

In this paper, the method of minimum description length (MDL) is introduced to optimize the number of using states in HSMM. First, the description length (DL) of all systems is defined as.

$$DL(K,\lambda) = -\log p(O|\theta,K) + \frac{1}{2}LK\log(M) \tag{20}$$

where K denotes the number of using states. λ denotes the parameters of HSMM, L denotes the number of parameter in an HSMM, M is the number of whole life data. For A group of G dimensional data with length of T, there exist M = GT.

The MDL-based estimation method for model parameters can be expressed as follows:

$$\begin{aligned}(\hat{K},\hat{\lambda}) &= \underset{k,\lambda}{\operatorname{argmin}} DL(K,\lambda) \\ &= \underset{k,\lambda}{\operatorname{argmin}}[-\log p(O|K,\lambda) + \tfrac{1}{2}LK\log(M)]\end{aligned} \tag{21}$$

First, a larger using state number K can be preliminarily determined by the evolution of the intermittent fault generalized severity within the whole life cycle. Then the KL distance criterion is introduced to describe the similarity of distance between the HSMM models, and combining the closest HSMMa and HSMMb, getting the incremental of the combined model $\ddot{A}DL$. According to the MDL method, if $\ddot{A}DL < 0$, it allows the combination of models, and let K turns to $K-1$. Otherwise, it is not allowed and the optimum number of using state is determined as K.

3. Determination of structure of model and classifier

Combined with the optimized using state number K and estimation model for using states, the classifier of electrical connector's using states can be constructed.

4. Training, estimation of model parameters and classifier parameters

Based on samples of generalized intermittent failure severity, then training the HSMM under each using state by forward-backward algorithm. And the model's library HSMMs can be constructed.

5. Estimation of using state

By inputting the sample data to classifier, the likelihood probability under each using state can be calculated, then the maximum likelihood probability corresponds to the current using state.

4.2. Residual Life Prediction Method

HSMM-based residual life prediction method is shown as following:

1. Data training list

Collecting the intermittent failure data from the whole life cycle of electrical connector and the generalized severity of intermittent failure can be extracted for data training for the residual life prediction model.

2. Determination of the prediction model structure

Combined with the transition characteristics of using states, the structure of the prediction model can be determined.

3. Estimation of prediction model parameters

Based on the observation sequences from the whole life cycle, an HSMM-based prediction model with all using states can be trained using the Parameter re-estimation algorithm. Further, the probability of using state transition a_{ij}, mean of duration probability of using state i, $\mu(h_{\mathrm{i}})$ and variance of duration probability of using state i, $\sigma^2(h_i)$ can be calculated separately. Then calculating the time duration of each using state, which are denoted by $D\ (h_0)$, $D\ (h_1)$, … $D\ (h_{N-1})$.

4. Prediction of residual life

Assuming that the current using state is i. let RUL_i be the residual useful life (RUL) starting from state i. With the following recursive algorithm, the RUL of the electrical connector can be determined.

At using state $N-1$:

$$RUL_{N-1} = a_{N-1,N-1}[D(h_{N-1}) + D(h_y)] + a_{N-1,N-1}[D(h_y)]$$

At using state $N-2$:

$$RUL_{N-2} = a_{N-2,N-2}[D(h_{N-2}) + RUL_{N-1}] + a_{N-2,N-2}[RUL_{N-1}]$$

At using state i:

$$RUL_I = a_{Ni,i}[D(h_i) + RUL_{i+1}] + a_{i,i+1}[RUL_{i+1}]$$

5. Case Study

5.1. Test Setting

The using state estimation and residual life prediction of electrical connectors studied in this paper are based on the intermittent failure re-appearance test. The random vibration stress is selected for intermittent failure re-presentation [20]. For improving efficiency, the accelerated vibration stress is applied, which helps to predict the residual life of connectors in a short time. The random vibration stress is generated by the DC1000 electrical vibration table made by the SuShi company (Suzhou, China). The connector is installed on the vibration table. While the table drives the connector vibration, the value of contact resistance is measured using the four-wire method. The linear DC power supply of Motech LPS-305 (MOTECH, Taiwan) is used for inputting constant current to exciting circuit. The output voltage is collected by the NI PXI4472 data acquisition card (NI, Austin, TX, USA). The contact resistance is the ratio of output voltage to constant current. The test window is set as 0.5 ms and the step length of the test window is set as 0.4 ms and the contact resistance curve is obtained in the intermittent failure re-appearance test. Combined with the fault threshold (R_{th} = 50 Ω), the intermittent failure curve can be plotted, then the generalized severity of intermittent failure can be extracted using Equation (19).

5.2. Case Study for Estimation of Using State

Firstly, the groping test should be carried out to collect the sample data of intermittent failure. According to the obtained intermittent failure data, the optimum number of using states can be determined as 6 using MDL method. The using state 1 is the normal state, and the using state 6 is the permanent failure state. The initialization of model and training process is carried out as stated in Section 4.1. Through training, classifiers with 6 using states for electrical connectors were obtained. Eight samples are selected from each classifier for testing, the testing results are shown in Figure 11.

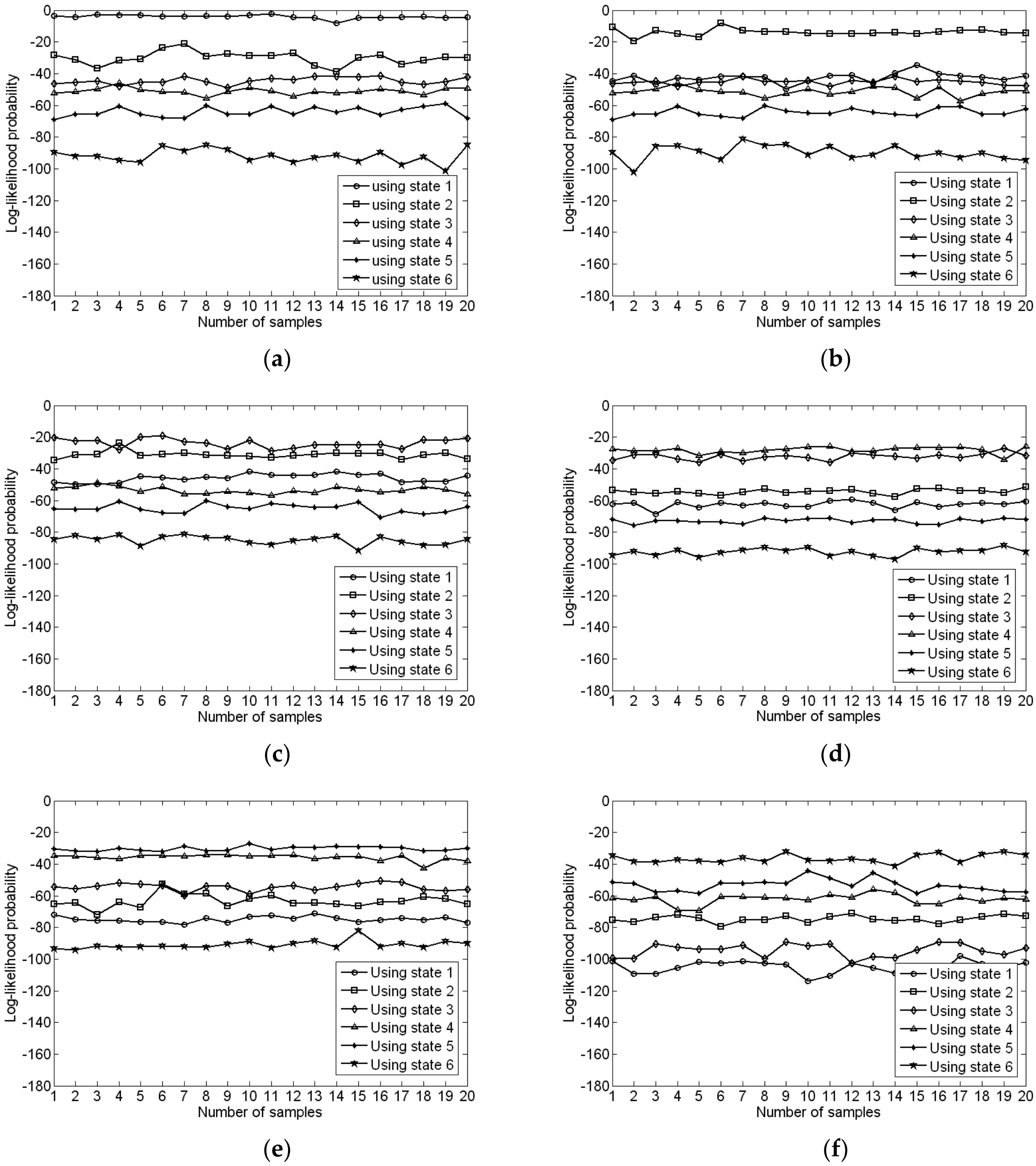


Figure 11. Evaluation results. (**a**) Evaluation results of the using state 1; (**b**) Evaluation results of the using state 2; (**c**) Evaluation results of the using state 3; (**d**) Evaluation results of the using state 4; (**e**) Evaluation results of the using state 5; (**f**) Evaluation results of the using state 6.

From Figure 11, except for a sample of the using state 3 and a sample of the using state 4, the other samples are evaluated correctly. In general, the proposed evaluation method for the using state is effective.

5.3. Case Study for Residual Life Prediction

The whole life process of the electrical connector is divided into 6 using states. Therefore, the 6 macro-state HSMM is introduced to build the model of residual life prediction (time unit: 10 min).

A group of whole life intermittent failure data is collected firstly, the HSMM-based prediction model HSMM_d (λ_d) is obtained using the parameter re-estimation algorithm. Then, by training the model, the probability matrix of using state transition A, mean and variance of duration probability of each using state is shown in Tables 1–3 separately.

Table 1. The matrix of state transition probability.

Using State	h_1	h_2	h_3	h_4	h_5	h_6
h_1	0.933	0.067	0	0	0	0
h_2	0	0.545	0.412	0.033	0	0
h_3	0	0	0.591	0.372	0.037	0
h_4	0	0	0	0.774	0.214	0.012
h_5	0	0	0	0	0.864	0.136
h_6	0	0	0	0	0	1

Table 2. The mean and variance of duration probability of each macro state.

Using State	h_1	h_2	h_3	h_4	h_5	h_6
$\mu(h_i)$	15.65	6.76	4.21	1.14	0.69	0.31
$\sigma^2(h_i)$	4.51	2.28	2.64	1.04	0.23	0.13

Table 3. The duration of each using state.

Using State	h_1	h_2	h_3	h_4	h_5	h_6
$D(h_i)$	16.19	7.03	4.53	1.26	0.72	0.33

According to the training results, the duration of each using state can be obtained by Equation (5) as shown in Table 3

Next, 20 samples were chosen from a life cycle test to verify the effectiveness of residual life prediction method proposed in this paper. The results of the prediction are shown in Table 4.

Table 4. The result of residual life prediction.

Test Groups	h_i	$[RUL_{mean} - RUL_{varance}, RUL_{mean} + RUL_{varance}]$	RUL	Results
1	1	[11.14, 20.16]	19.63	✓
2	1	[11.14, 20.16]	14.34	✓
3	1	[11.14, 20.16]	12.58	✓
4	2	[4.48, 9.04]	10.22	✓
5	2	[4.48, 9.04]	8.54	✓
6	2	[4.48, 9.04]	7.17	✓
7	3	[1.57, 6.85]	6.31	✓
8	3	[1.57, 6.85]	6.02	✓
9	3	[1.57, 6.85]	5.84	✓
10	3	[1.57, 6.85]	5.19	✓
11	4	[0.1, 2.18]	4.32	x
12	4	[0.1, 2.18]	2.12	✓
13	4	[0.1, 2.18]	1.50	✓
14	4	[0.1, 2.18]	0.91	✓
15	5	[0.46, 0.92]	0.77	✓
16	5	[0.46, 0.92]	0.51	✓
17	6	[0.18, 0.44]	0.39	✓
18	6	[0.18, 0.44]	0.21	✓

According to Table 4, except for one of samples of using state 4, the other samples are predicted correctly within the interval of residual life. The proposed method can be used for the residual life prediction of electrical connectors.

6. Conclusions

By investigating the relationship between the varying of the intermittent failure feature and the degradation of electrical connector, research on the residual life prediction of electrical connector is carried out in this paper. The main contributions are as follows:

1. The evolution of intermittent failure features with the degradation of electrical connectors is systematically analyzed. The generalized severity of intermittent failure is proposed innovatively for residual life prediction.
2. The HSMM-based residual life prediction model of electrical connectors is constructed and the residual life prediction method is studied.
3. A test for residual life prediction is carried out. The test results verify the effectiveness of the proposed method.

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