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Remaining useful life prediction for PMSM under radial load using particle filter

Younghun Lee, Inhwan Kim, Sikgyoung Choi, Jaewook Oh and Namsu Kim*

Department of Mechanical Engineering, Konkuk University, 120 Neungdong-ro, Gwangjin-gu, Seoul, Republic of Korea

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Abstract. Permanent magnet synchronous motors (PMSMs) are widely used in systems requiring high control precision, efficiency, and reliability. Predicting the remaining useful life (RUL) with health monitoring of PMSMs prevents catastrophic failure and ensures reliable operation of system. In this study, a model-based method for predicting the RUL of PMSMs using phase current and vibration signals is proposed. The proposed method includes feature selection and RUL prediction based on a particle filter with a degradation model. The Paris-Erdogan model describing micro fatigue crack propagation is used as the degradation model. An experimental set-up to conduct accelerated life test, capable of monitoring various signals was designed in this study. Phase current and vibration data obtained from an accelerated life test of the PMSMs were used to verify the proposed approach. Features extracted from the data were clustered based on monotonicity and correlation clustering, respectively. The results identify the effectiveness of using the current data in predicting the RUL of PMSMs.

Keywords: accelerated life testing; particle filter; PMSM; RUL prediction

1. Introduction

PMSMs are widely used in electric vehicles and other industrial applications for their high efficiency and torque to weight ratio. In applications where continuous operation is required, PMSM failure causes catastrophic safety issues and economic loss (Khlaief *et al.* 2013, Ebrahimi and Faiz 2012). Thus, considerable research has focused on improving the reliability and safety of PMSM.

Condition-based maintenance (CBM), which continuously monitors the state of the system and predicts failures in advance, is effective for efficient system operation. In contrast, traditional maintenance is performed after failure or periodically to prevent a failure without considering the condition of the system, which can be inefficient and incurs significant cost. The system health state is monitored based on its operating conditions to determine the appropriate maintenance schedule; this is the main concept of CBM. Forecasting failure in advance is the first step in CBM; the second step is prediction of the remaining useful life (RUL) to identify when maintenance is required.

There are two main approaches to predicting RUL; one is to create a new life model or use a known life model to predict life, and the other is to use only data with artificial intelligence or traditional statistical methods to learn degradation and predict life. The former is a model-based method, and the latter is a data-driven method (Gansar and Tiwari 2020, Lei *et al.* 2019, Yin *et al.* 2014). Data-driven methods for predicting RUL use previously observed data to predict the next state of system. A main advantage of data-driven approaches is that RUL can be predicted without considering the degradation mechanism of the system; thus, data-driven approaches are more appropriate for complex systems and non-linear varying sequential data. Recent advances in computing technology allow the use of artificial intelligence such as machine learning and deep learning to process large amounts of data quickly and efficiently. For example, Loutas et al. established an e-support vector regression technique for the RUL estimation of rolling-element bearing (Loutas *et al.* 2013) and Medjaher et al. used a mixture of Guassian hidden Markov model to represent the evolution of bearing health conditions (Medjaher *et al.* 2012). For the rotary machinery, Yang *et al.* presented the methodology for RUL estimation of electric machines based on proposed a data-driven health index(HI) construction method (Yang *et al.* 2016). The novelty of this method is to construct the HI with monotonicity, gradualness, and consistency and these are incorporated to smooth the current health index with the previously predicted ones. In addition, artificial intelligence(AI) such as artificial neural network(ANN) or recurrent neural network(RNN) based fault diagnostics and prognostics approach for brushless DC motor have been proposed to predict remaining useful life (Alam and Hur 2021, Alam and Hur 2020).

Model-based or physics-based RUL prediction methods establish a mathematical or physical model to describe the degradation process of system and use the measured data to update the model parameters. These mathematical or physical model should describe the physics of the system and failure mode. Setting the health indicator and selecting an appropriate life model are significant in accurately predicting RUL. In addition, for accurate prediction, a health indicator reflecting the degradation mechanism of the system should exhibit a monotonic trend. The crack propagation or spall growth is one of a common physics-

*Corresponding author, Professor
E-mail: nkim7@konkuk.ac.kr

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based approach to estimate remaining useful life. As an example, Li et al. related the defect growth rate of rolling element bearing to the instantaneous defect area size and material constant based on Paris's formula to predict RUL. For fatigue spall growth, Orsagh et al. used spall progression model to calculate the time to spall initiation and the time from spall initiation to failure (Orsagh *et al.* 2003, Orsagh *et al.* 2004). Even though this model can provide accurate RUL under determined operating condition, various physics parameters need to be determined by experiment. With respect to model-based RUL prediction, a lot of research have been conducted focusing on degradation of materials and simple mechanical or electrical parts, but it can be found that a lot of research have not been focused on complicated system composed of various types of part such as motor. It is due to that there is no life model that can reflect all the corresponding failure modes for complicated system. Therefore, if a life model for is not developed based on defined failure mode, which frequently occurs under specified operation environment, physics-based models might not be the most practical approach (Heng *et al.* 2009).

For efficient maintenance and reliable motor operation using CBM, two main technologies must be applied. Signs of failure are detected in advance, prior to catastrophic failure of the system, and the period from the detection of signs of failure to the time when parts must be replaced is predicted (RUL). However, most studies have been conducted to identify the signs of failures in advance than studies on predicting remaining useful life due to previously explained reasons (Gansar and Tiwari 2020, Benbouzid 2000). In this study, a method of predicting the RUL with model-based approach is proposed, and the effectiveness and accuracy of the proposed method are experimentally validated. Among the different failure modes of the motors such as eccentricity, demagnetization, mechanical failure of shaft or bearing, and inter-turn short fault of coil, our study is focused on the mechanical failure induced by cyclic load on the shaft in the radial direction. To address these issues, accelerated life test of PMSM with the load in the radial direction was carried out and the data of current, vibration, temperature were monitored during accelerated life test. An experimental apparatus capable of controlling a load in the radial direction of the motor axis was devised. The RUL of the motor was predicted using current and vibration data from the experiment.

2. Proposed model-based prognostics

To predict the next state of a system, features from the sensing data and degradation models regarding the degradation mechanisms of the system are identified. The proposed method consists of three steps: feature selection, degradation modeling, and RUL prediction.

2.1 Feature selection

A methodology for selection of features sensitive to the degradation process in different time domains, and extraction of frequency domain features from the time-series data set are suggested. With the assumption of irreversible system degradation, features with a monotonically increasing or decreasing trend during the degradation process are selected. To evaluate the monotonicity of the features, the Spearman correlation between features and the time sequence are calculated. The Spearman correlation coefficient is defined as (Spearman 1904, Kim *et al.* 2012, Yaguo *et al.* 2016)

$$\rho_{X,T}\frac{\left|\sum_{i=1}^{n}(X_i-\bar{X})(T_i-\bar{T})\right|}{\sqrt{\sum_{i=1}^{n}(X_i-\bar{X})^2(T_i-\bar{T})^2}} \tag{1}$$

where $X_{1:n}$ and $T_{1:n}$ are the ranks of feature $x_{1:n}$ and time $t_{1:n}$, respectively; $\bar{X}$ and $\bar{T}$ are the mean values of $x_{1:n}$ and $t_{1:n}$, respectively. The Spearman correlation coefficient is calculated in the range of [0,1]. A value closer to 1 indicates a more monotonic trend of the feature. In this study, features with Spearman coefficient values greater than 0.5 are selected as guided in reference (Yaguo 2016).

To identify the similarity of features selected based on monotonicity, the features are classified by correlation clustering. The PBM index is used to define and validate the optimal number of clusters. The PBM index is defined as

$$PBM(K)=\frac{1}{K}\times\frac{1}{E_K}\times D_K \tag{2}$$

where K is the number of clusters; E_K and D_K are the summations of cluster dispersion and maximum distance between cluster separations, respectively. In the correlation clustering process, selected features are classified into K clusters. The clustering process can eliminate redundancy and identify similarities between different measured physical quantities.

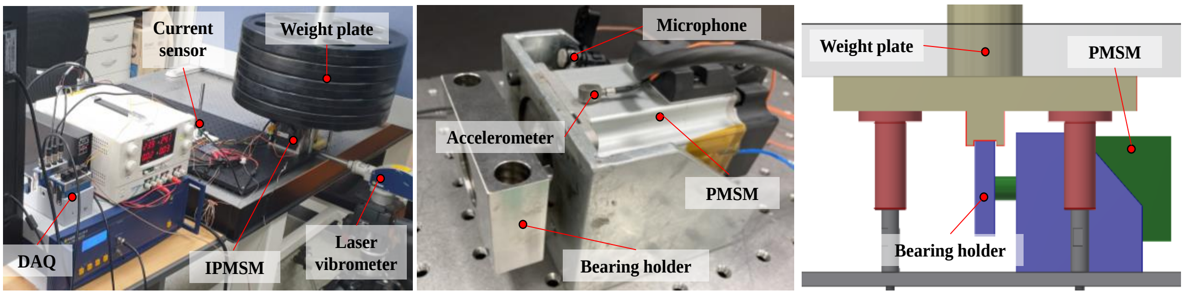
2.2 Degradation model: Paris-Erdogan law

The Paris-Erdogan law explains the propagation rate of micro fatigue crack growth from cycling loading in a metallic materials and details about this model can be found in references The growth of fatigue cracks caused by mechanical loading can result in catastrophic failure of shaft and for this reason, this model was used as model-based approach for the shaft of the motor with radial load (Han *et al.* 2019, Ojaghi *et al.* 2017). Hence, the Paris-Erdogan model effectively describes the mechanical failure of the motor. Eq. (3) is the original form of the Paris-Erdogan model (An *et al.* 2013, Paris *et al.* 1963).

$$\frac{dx}{dn}=c(\Delta K)^{\gamma},\ \Delta K=\ \varepsilon\sqrt{x} \tag{3}$$

where x is the crack length; n is the number of stress cycles; c, γ, and ε are the material and environmental parameters; ΔK is the stress intensity factor, roughly proportional to the square root of x. Eq. (3) can be transformed with $\alpha=c\varepsilon^{\gamma}$ and $\beta=\gamma/2$.

$$\frac{dx}{dn}=\alpha x^{\beta} \tag{4}$$



(a) (b) (c)

Fig. 1 Experimental set-up for accelerated life test of PMSM with radial loading: (a) actual experimental set-up including different sensors and DAQ; (b) detailed experimental setup including bearing holder for loading in radial direction; (c) Schematic of experimental set-up including weight plate and bearing holder

Eq. (4) can be rewritten in the form of a state space equation

$$\begin{cases} x_k = x_{k-1} + \alpha_{k-1} x_{k-1}^{\beta} \Delta t_k \\ \alpha_k = \alpha_{k-1} \\ s_k = x_k + v_k \end{cases} \tag{5}$$

where $\alpha_k \sim N(\mu_\alpha, \sigma_\alpha)$; β is a constant parameter; x_k is the health state at t_k, and s_k measures the value with $v_k \sim N(0, \sigma_v^2)$.

2.3 RUL prediction: Particle filter

The particle filter method is based on the transition function and measurement function

$$x_k = f(x_{k-1}, \omega_k) \tag{6}$$

$$z_k = h(x_k, v_k) \tag{7}$$

where x_k, z_k are the state and measured data, respectively; ω_k, v_k are the process noise and measurement noise, respectively, which are independent and identically distributed. In prognostics, x_k is the health state, and transition function *f* represents the degradation model.

In the particle filter method, the system state is assumed to be a probability density function (PDF) approximated by a set of particles that refer to sampled values from a state space with unknown transition function parameters. Particles contain probability information of unknown parameters and are updated when a new measurement is available. The updating process is based on the Bayesian update and the likelihood function of the transition function.

The unknown model parameters in Eq. (5) are denoted as $\Theta = (\mu_\alpha, \sigma_\alpha^2, \beta, \sigma_v^2)'$. According to Eq. (5), s_k can be rewritten as

$$s_k = x_{k-1} + \alpha_k x_{k-1}^{\beta} \Delta t_k + v_k \tag{8}$$

As the measurement noise v_k is negligibly small, the health state x_k is assumed to be identical to s_k. To initialize unknown model parameters, a likelihood function based on the measurements is established. After parameter initialization, the model parameter Θ is updated, and the RUL is predicted based on the resampled particles.

Table 1 Selected features extracted from current and vibration signals

Signal		Feature
Current	F1: Standard deviation	F4: 1st-9th harmonic
	F2: Root mean square	F5: Left sideband of F4
	F3: Entropy	F6: Right sideband of F4
Vibration	F7: Standard deviation	F10: Kurtosis
	F8: Root mean square	F11: Entropy
	F9: Shape factor	F12-F19: 1st-9th harmonics

3. Experimental verification

3.1 Experimental setup

The experimental setup for the accelerated life test of the PMSM is shown in Fig. 1. To apply a radial load on the shaft, a load capable of varying the weight according to the type of motor and level of acceleration was placed on top of the bearing holder, which was assembled on a motor shaft rotating at a speed of 6000 rpm. The phase current, vibration, acoustic emission, temperature, and shaft deflection signals were monitored during the test using a Hall sensor, an accelerometer, a microphone, thermocouples, and a laser vibrometer, respectively. The vibration signals were provided using a z-axis accelerometer. Current and vibration signals used in RUL prediction were obtained every 30 s at a sampling rate of 100 kHz for 1 s. The test was conducted until the motor failed and stopped, and the data used in this study were experimental data obtained for 5330 min from this setup.

3.2 Feature selection from experimental data

The Spearman correlation coefficients of the original features, generally used to assess how well the relationship between variables can be expressed using a monotonic function evaluate the trendability of a feature using the rank of the feature instead of the feature itself. The Spearman coefficient was introduced firstly by Spearman and details about it can be in reference (Spearman 1904, Yaguo *et al.* 2016). The trendability determined based on Eq. (1) by the Spearman coefficients and these were extracted from the current and vibration data in this study. Features with a

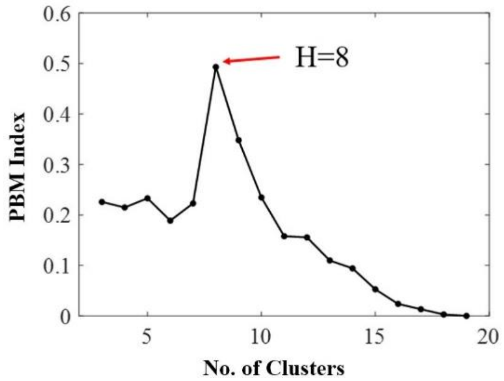


Fig. 2 Variation in PBM index with number of clusters for PMSM

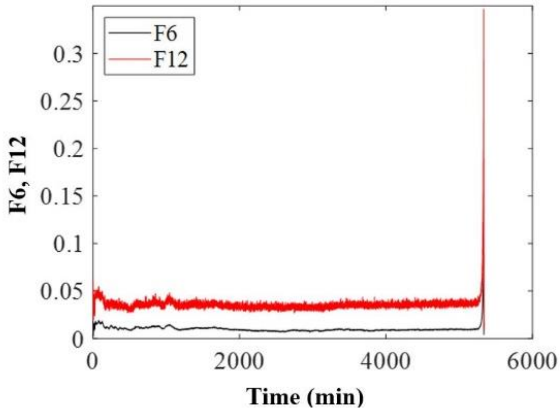


Fig. 3 Selected features of phase current and vibration

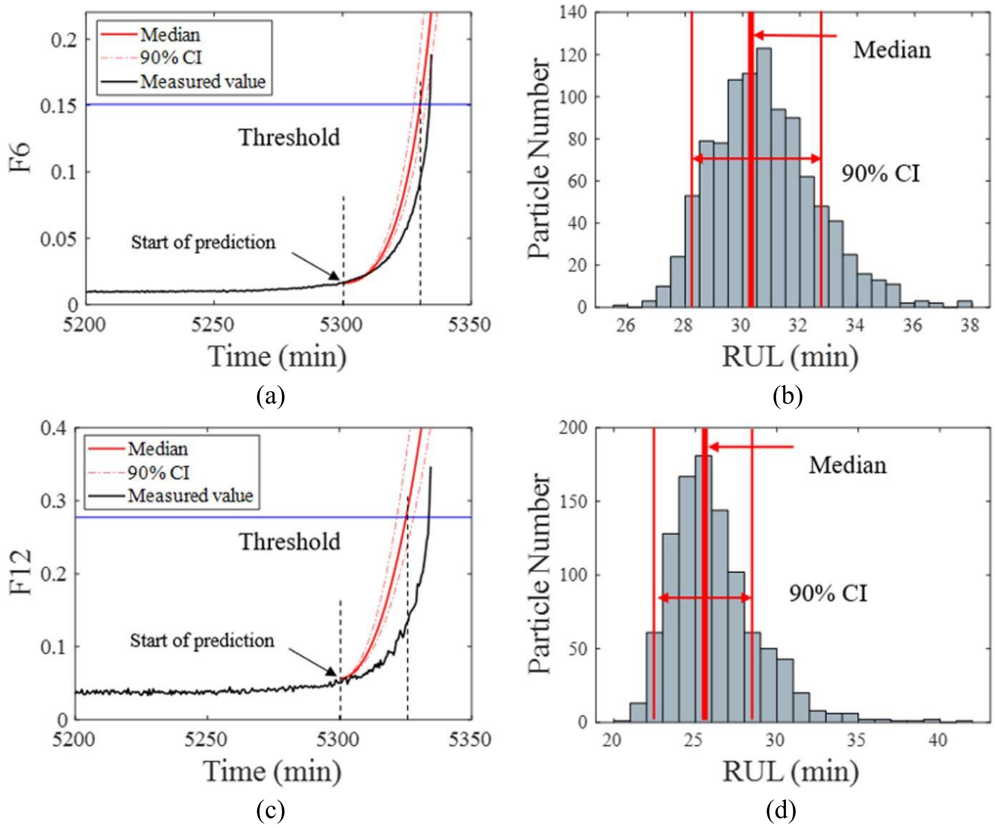


Fig. 4 RUL prediction result for PMSM: (a) prediction of F6; (b) distribution of predicted RUL from F6; (c) prediction of F12; (d) distribution of predicted RUL from F12

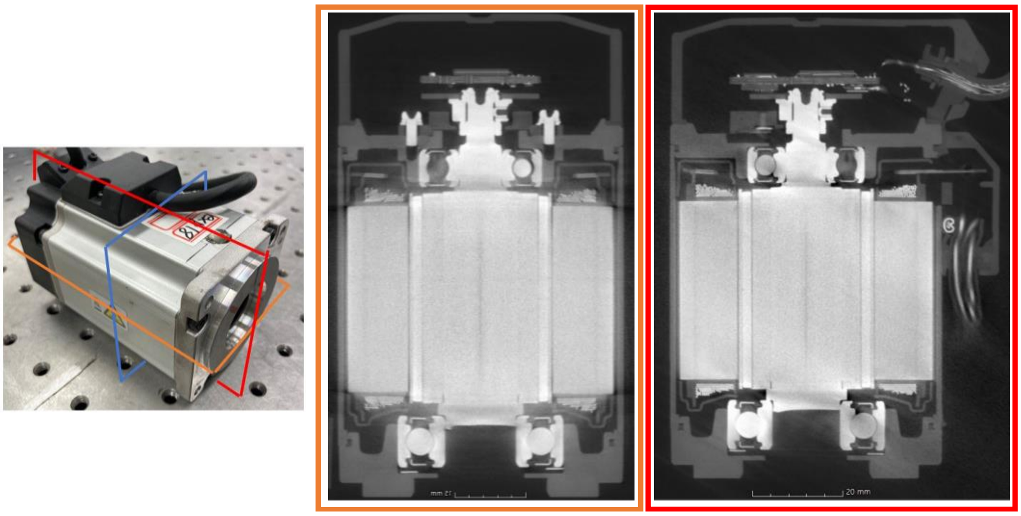
calculated coefficient of 0.5 or higher are presented in Table 1. The n^{th} harmonics of the current and vibration signals represent multiples of the fundamental frequency. The fundamental frequencies of the current and vibration signals are expressed as follows:

$N/60 * P(Hz)$ and $N/60(Hz)$, respectively, where N is the rotating speed (rpm), and P is the number of pole pairs in the PMSM.

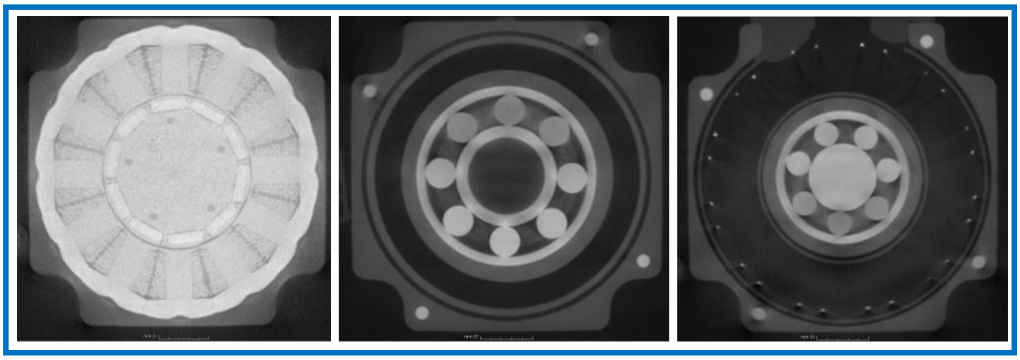
To determine the optimal number of clusters, the PBM index is calculated for the selected features, as shown in Fig. 2; 19 selected features were classified into eight clusters. From cluster analysis, it is observed that the similarity between F6 and F12 is the greatest; these features may provide degradation information, as shown in Fig. 3, indicating that both the current signal and the vibration signal can represent the state of the motor. In the next step, the RUL of the PMSM is estimated using F6 and F12.

3.3 RUL prediction

The threshold for estimating the RUL was set as 80% of the measured value at the moment of failure. The 20% margin was set simply to secure enough time for maintenance in actual applications. The moment at which the F12 value is 25% greater than the value in the stable region without a significant degradation sign was set as the starting point of the RUL prediction. It is due to predicting the RUL is not useful with no degradation and it only



(a) (b) (c)



(d) (e) (f)

Fig. 5 3-D CT images of PMSM used in this study: (a) PMSM indicating virtual cross section; (b) and (c) longitudinal cross-sectional views of PMSM; (d) transverse cross-sectional view for rotor and stator of PMSM; (e) and (f) transverse cross-sectional views for front and rear bearings of PMSM

increases the amount of computational time.

For both features, the model parameters were initialized using maximum likelihood estimation. The parameters were updated using the model-based particle filter algorithm. The particle number was set to 1000. The degradation trends of F6 and F12 are shown in Fig. 4(a) and (c), respectively. The distribution of 1000 particles is shown in Fig. 5(b) and (d). The median and 90% confidence level (CI) of the predicted RUL were calculated. The results indicate that the side band of the current data and the harmonics in the frequency domain of the vibration data are good health indicators for PMSM degradation. In addition, it was found that prediction of RUL based on F6 was more accurate than prediction based on F12 because the error between the experimental and predicted results is less for F6 than for F12, as shown in Fig. 4.

To investigate the inside of PMSM, an X-ray computed tomography(CT) scanner was employed (vltomelx m300, Baker Hughes) was employed. Three-dimensional CT images of the PMSM used in this study were investigated as non-destructive failure analysis and these are shown in Fig. 5. Based on the CT images, it was confirmed that failures such as bearings, eccentricities, and axial sliding, which have been widely reported as mechanical failures of the motor, did not occur. Instead, it was clearly observed that the shaft of the motor supported by the front bearing was destroyed. Therefore, the mechanical failure of the shaft due to the mechanical cycling load was confirmed through the accelerated life test, which confirmed that the Paris-Erdogan law could be applied to the corresponding failure mode.

Additionally, the vibration occurred in the shaft before it was broken; this vibration before failure was monitored by the laser vibrometer. The data in Fig. 6 show the root mean square (RMS) of the deflection of the motor shaft, and the temperature of the front bearing of the motor and block bearing for loading before the shaft breaks. From these data, it can be also confirmed that the deflection of the motor shaft began to increase before it broke; as a result, the temperature also increased due to an increase in the friction between the bearing and shaft. It can be expected that the vibration of the shaft caused torque ripple on the axis, resulting in a small change in the phase current of the motor.

4. Conclusions

We proposed a model-based method based on the Paris-Erdogan model for predicting RUL to support the predictive

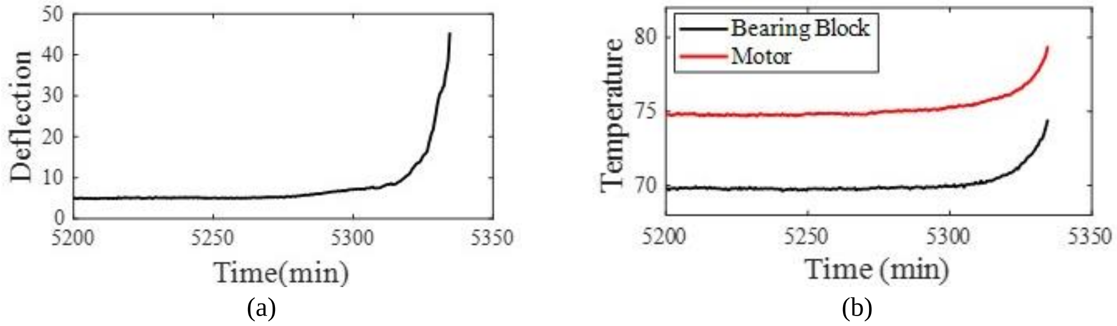


Fig. 6 Deflection and temperature as a function of time before the end of the experiment: (a) RMS of deflection (μm); (b) temperature of bearing block and motor (℃)

maintenance of PMSM with radial load used in electric vehicles. In the procedure of predicting the RUL, features extracted from the phase current and vibration signals were monitored during the accelerated life test of the PMSM. The sideband of the current data and the harmonics of the vibration data in the frequency domain were selected as robust health indicator. Although both current and vibration features were selected as good health indicators, the current signals demonstrated better accuracy than the vibration signals. RUL prediction results using the features from current signals were more accurate; it was confirmed that the current signals can be used as a health indicator. The Paris-Erdogan law was used as the degradation model. The model parameters were initialized and determined using maximum likelihood estimation. The PF was used to predict the state of health, including the RUL of the PMSM. Based on the deflection of the shaft and the temperature of the motor front bearing and block bearing, it was confirmed that the deflection increased before the motor shaft was broken; the resulting frictional force and temperature also increased, exhibiting significant changes before the motor shaft was broken. Additionally, non-destructive failure analysis was carried out to investigate the failure component as well as failure mode. It was confirmed that no other failure modes such as eccentricity or bearing failure other than mechanical failure of shaft occurred.

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