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Research Article

Life Prediction of DC Motor using Time Series Analysis based on Accelerated Degradation Testing

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Abstract: This study presents a method of life prediction for DC motor using time series modeling procedure based on DC motor accelerated degradation testing data. DC motor accelerated degradation data are treated as time series and stochastic process are utilized to describe the degradation process for life prediction. An accelerated degradation test is processed for DC motor until they failed and the accelerated degradation data are collected for life prediction. A comparison between the predicted lifetime and the real lifetime of DC motors is processed and the results show that the life prediction of DC motors using time series analysis is effective.

Keywords: Accelerated degradation testing, DC motor, life prediction, time series

INTRODUCTION

For long lifetime and high reliability products, it is difficult to obtain failure data in a short time period. Hence, Accelerated Degradation Testing (ADT) is presented to deal with the cases where no failure data could be obtained but performance degradation data of parameters of the product are available.

Life prediction technology is used to predict the probable failure time of a product based on performance degradation data while operating to help people decide whether to fix or replace the product before its failure. It acquires the main performance indexes variations with time of a product, processes real-time data analysis and presents a lifetime prediction of the product.

For most kinds of mechanical and electrical products, such as DC motor, the main performance index of the products degrades with time and it will lead to the failure of the product if it passes a specified threshold. Hence, if the degradation path of the performance of the product is predicted, the lifetime of the product could be estimated.

In recent years, many scholars have made great success for reliability estimation of DC motor. However, most researchers have focused on the use of intelligent methods, which exist some shortage, such as that they only emphasis the fitting ability of model and take little consideration of the reasoning ability and prediction ability of model (Payganeh, 2012).

Time series analysis is a good method to establish a stochastic model for time series data based on its property and utilizes the stochastic model to predict the long term trend. As the performance degradation data of products are random variables arranged in temporal order which could be treated as time series, time series method is applicable to prediction the lifetime (Wang *et al*., 2011).

TIME SERIES ANALYSIS OF DEGRADATION DATA

The stochastic analysis of performance degradation data using time series analysis is based on the following hypotheses:

The performance of the product degrades monotonously

- The failure mechanism of product remains the same during the degradation process

In ADT, performance degradation data is usually equally spaced and its variance is homogeneous for a fixed sampling frequency. And the degradation data is nonstationary according to the first hypothesis.

Degradation data decomposition: Let Yt denote the performance degradation measurement at time t. Based on Cramer Decomposition Theorem, any time series {Yt} can be decomposed into two components: deterministic component and stationary random component. Hence, Yt could be expressed as:

$$Y_t = T_t + S_t + \xi_t, \quad t = 1, 2, \cdots \tag{1}$$

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where, *Tt* is the trend component and *St* is the seasonal component, both of which are deterministic components. *ξt* is residual component and it is the stationary random component.

Trend component modeling: The trend component Tt is extracted from performance degradation data using regression model:

$$T_t = c_1 f(t) + c_2, \quad t = 1, 2, \cdots \tag{2}$$

where, *f(t)* is a specified regression function which fits the degradation trend of the data well, *c*1 and *c*2 are regression parameters which could be estimated by performance degradation data.

Seasonal component modeling: Extract the season component St, which is modeled by Hidden Periodicity (HP) regression model:

$$S_t = \sum_{j=1}^{q} A_j \cos\left(\omega_j t + \phi_j\right), \quad t = 1, 2, \cdots \tag{3}$$

where, $0<\omega_1<\omega_2 \ldots <\omega_q \leq \pi$

Residual component modeling: The residual component *ξt* is modeled by autoregressive (AR) model:

$$\begin{aligned} &\xi_t = \sum_{j=1}^{p} \varphi_j \xi_{t-j} + \varepsilon_t, \quad t = 1, 2, \cdots, \\ &E(\varepsilon_t) = 0, \ \ Var(\varepsilon_t) = \sigma^2, \\ &Cov(\varepsilon_t, \varepsilon_{t-i}) = 0, \ \ \forall i \geq 1 \end{aligned} \tag{4}$$

As the stationary random series {*ξt*} and time series {*Yt*} are dependent, it is needed to separate the estimation of the parameters in *St* and *ξt* with the estimation of parameters in *Tt*. Hence, HP regression model of season component *St* and AR model of residual component *ξt* are combined into *Xt* using Auto Regression-Hidden Periodicity (ARHP) model to estimate the parameters. Set:

$$X_t = S_t + \xi_t, \quad t = 1, 2, \cdots \tag{5}$$

Substitute (3) and (4) to Eq. (5), it is expressed as:

$$X_t = \sum_{j=1}^{p} \varphi_j X_{t-j} + \sum_{j=1}^{q} A_j \cos\left(\omega_j t + \phi_j\right) + \varepsilon_t \tag{6}$$

Eq. (6) is an ARHP model.

Hence, the performance degradation measurement *Yt* is obtained as:

$$Y_t = T_t + X_t, \quad t = 1, 2, \cdots \tag{7}$$

Eq. (7) is a Regression-Auto Regression-Hidden Periodicity (RARHP) model (Wang *et al*., 2009).

LIFE PREDICTIONS AND RELIABILITY ESTIMATION

In ADT, to obtain the life prediction at use-stress level, it is necessary to convert the life prediction at each test-stress level to the equivalent life prediction at the use-stress level. A traditional method in ADT is modeling product performance accelerated degradation data based on stochastic process and assuming life-stress relationship to obtain product lifetime at use-stress level. However, it is difficult for time series model to assume the life-stress relationship. Therefore, accelerated degradation data is modeled using the time series method to predict life data at test stress levels and assuming the life distribution and life-stress relationship to obtain product lifetime at use-stress level.

Life predictions: In practice, failure occurs often as product performance level achieves a specified threshold which is denoted as D. Product lifetime is time scale from the beginning of operating to the first achieving. In this study, lifetime is obtained by prediction of degradation data:

$$t_{life} = \inf\left\{t : \frac{Y_t}{y_0} = D; t \geq 0\right\} \tag{8}$$

Life distribution: The life prediction is assumed to obey a certain location-scale distribution as determined by a Pearson chi-square Goodness of Fit Test. The estimate of the location and scale parameters of the life distribution are obtained by MLE. This study denotes life prediction of i^{th} product as $t_{life(i)}$, when total number of products is m and then the prediction of the maximum likelihood function for the life distribution is*:*

$$L(\beta) = \prod_{i=1}^{m} f\left(t_{life(i)}, \beta\right) \tag{9}$$

here, $\beta = (\mu, \sigma)^T$, *T* means transpose of matrix.

Accelerated modeling: Spread in life data depending on stress is most important in ADT. This study converts the life prediction of products from each test-stress level into a life prediction for the product at its' use-stress level based on the stress level-median life relationship and accelerated model, that is:

$$\mu = a + b\varphi(S) \tag{10}$$

here, μ is median life at each test-stress level; S is test-stress level; a, b are parameters estimated from degradation data. $\varphi(S)$ is a known function of S.

Reliability estimation: This study denotes life distribution as $F(t)$, reliability of product is estimated by:

$$R(t) = 1 - F(t) \tag{11}$$

here, μ, σ are mean value and variance of life distribution.

DC MOTOR ACCELERATED DEGRADATION TESTING

DC motor failure mechanism analyses: DC motor structure principle is shown as Fig. 1. From Fig. 1, the DC motor consists of electric brush, commutator, coil winding and ferrite magnet.

In practice, most DC motor failure mechanism is electric brush and commutator wear. It leads to DC motor degradation. High power voltage accelerates its degradation process. Figure 2 shows the failure mechanism.

Accelerated degradation testing system design: An ADT system for DC motors is built to predict lifetime of DC motors at use-stress level and compare them with the real lifetime recorded to verify the life prediction method based on time series analysis. Power voltage is served as the test stress of ADT.
The ADT site is shown in Fig. 3.

The construction of the ADT system is shown in Fig. 4.

The ADT system consists of PC, data acquisition board, I/O connector, DC motor, resistor and power. The power supplies voltage to motor and resistor which are series connected, the I/O connector acquires the voltage over the resistor and sends it to PC through data acquisition board. The PC records the voltage of the resistor in a specified frequency.

The output voltage is defined as the voltage over the motor and it is given as:

$$V_{output} = V_{power} - V_{power} \times \frac{R_{resistor}}{R_{resistor} + R_{motor}} \tag{12}$$

As the motor degrading, the resistance of the motor is increasing and it would result in the decreasing current in the circuit, hence, the voltage over the resistor is decreasing and the output voltage is increasing. Therefore, the output voltage could reflect the performance state of the motor.

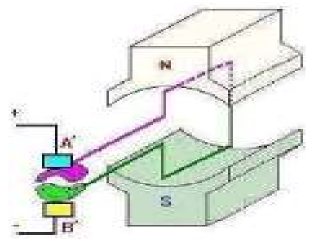

Fig. 1: DC motor structure principle

Fig. 2: DC motor failure mechanism

Fig. 3: Accelerated degradation testing site

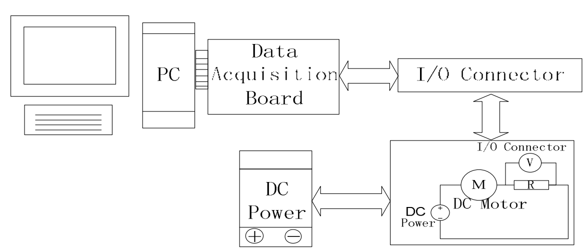

Fig. 4: Degradation testing system construction

ACCELERATED DEGRADATION TESTING DATA ANALYSIS

An ADT is processed for DC motors and the accelerated degradation data of 14 motors are utilized to

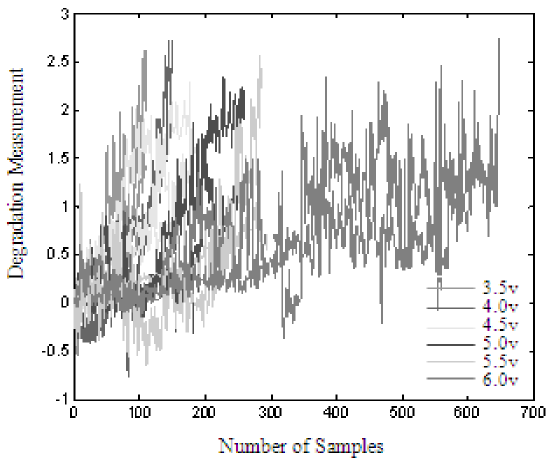

Fig. 5: Preprocessed degradation path of DC motors

Table 1: ADT parameters

Power Voltage	3.5v	4v	4.5v	5v	5.5v	6v
Number of products	2	2	2	3	2	3

verify the time series analysis method. The PC records the voltage over the resistor every 100 min. The accelerated degradation path of motors at each test-stress level are preprocessed by initial value processing for eliminating influence of their initial value difference and normalizing the failure criterion, which are shown in Fig. 5. Table 1 shows test parameters.

Life prediction for DC motors using time series analysis is processed as follows.

The trend component Tt is set as a power form as it fits the degradation path well,

$$T_t = c_1 t^{c_2} + c_3, \qquad t = 1, 2, \cdots \tag{13}$$

The estimations of parameter $c1$, $c2$ and $c3$ are obtained by regression analysis using degradation data. The estimation of trend component Tt is shown in Fig. 6.

HP regression model of season component St and AR model of residual component ξt are combined into Xt using ARHP model and the performance degradation measurement Yt is obtained by RAR model. Then, the prediction of degradation measurement Yt is shown in Fig. 7.

The life prediction for test-stress levels is converted into the use-stress level by accelerated model, which is assuming an Inverse power accelerated model. That is:

$$\ln t_{life} = a + b \ln V$$

Figure 8 shows median life inverse and voltage stress level relationship.

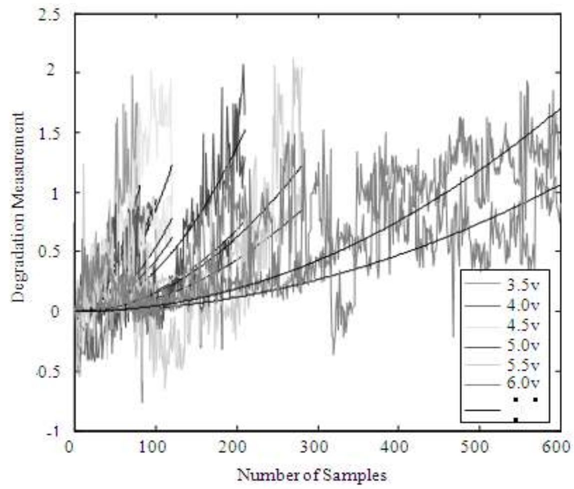

Fig. 6: The estimation of trend component

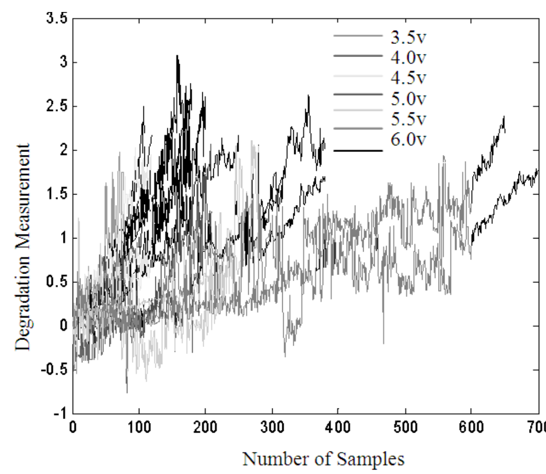

Fig. 7: The estimation of season component

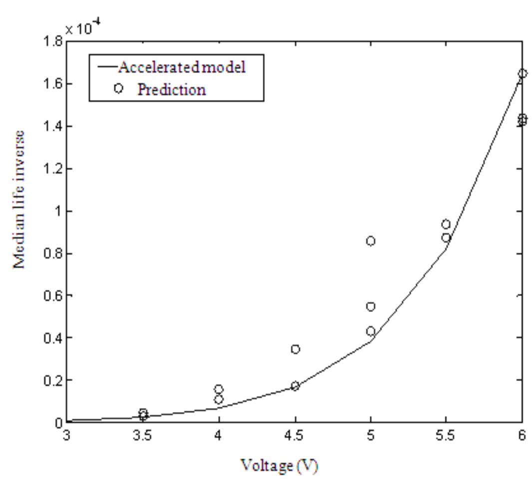

Fig. 8: The accelerated model

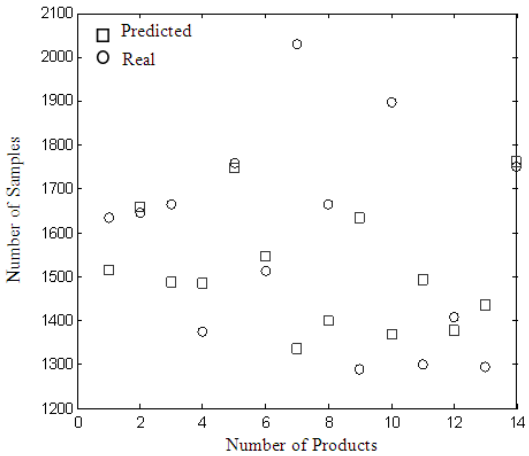

Fig. 9: The life prediction and real life time

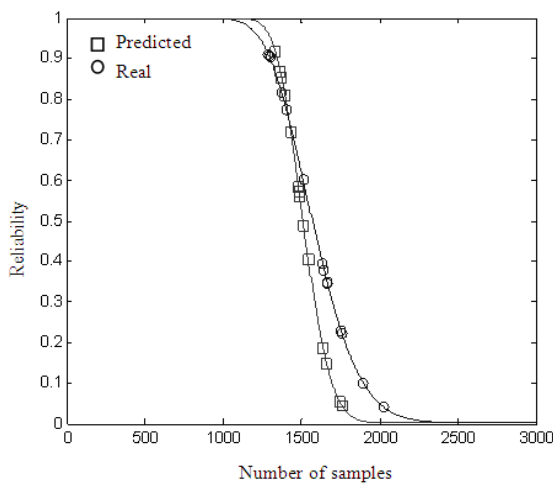

Fig. 10: The predicted reliability and the real reliability

Table 2: Reliability statistic data

Statistic Data	Log mean	Log variance	Median life
Real reliability	7.3601	0.1464	393 h
Predicted reliability	7.3215	0.0888	378 h

The prediction of life time and the real life time of each motor is shown in Fig. 9.
Reliability of DC motor is estimated by:

$$R(t) = 1 - \Phi\{[\ln t - \mu]/\sigma\} \tag{14}$$

Here, μ, σ are mean value and variance of lognormal distribution.
The predicted reliability and real reliability of DC motor are all showed in Fig. 10 for compare.

The statistic data of real reliability and predicted reliability is shown in Table 2.

From Table 2, it is obvious that the prediction of reliability curve is very near and just before the real reliability curve of DC motor.

CONCLUSION

This study presents a method to of life prediction for DC motor using time series modeling procedure based on DC motor ADT data. It describes the performance degradation measure of DC motor by Regression-Auto Regression-Hidden Periodicity (RARHP) model. An ADT of DC motors is processed and the degradation data are utilized to predict the life time and reliability of DC motors. The results show that life and reliability prediction by the proposed method is very near the real life and reliability of DC motor.

- This study proposes a product performance degradation model based on RARHP model using time series method. Spread in life data depends on stress levels and put forward a ADT data analysis method based on time series.
- A reasonable lifetime prediction for DC motor is presented by applying the proposed method to analyze ADT data.
- This study analyses ADT life prediction of DC motor based on RARHP model and real life, respectively. According to analysis results, the RARHP model combines parameters of Regression and ARHP model which improve the model precision accuracy greatly.
- According to this study, the proposed method is suitable to ADT of DC motor. Its applicability for other products deserves further research.

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