Data Driven Remaining Life Prediction of Electrolytic Capacitor in DC/DC Converter

Chenguang Zhang1*, Junkang Ni1, Xiaobin Zhang1 and Tao Lei1
1Department of Electrical Engineering, Northwestern Polytechnical University, Xi’an, Shaanxi, 710129, China
*Corresponding author’s e-mail: 2018100216@mail.nwpu.edu.cn

Abstract. A remaining useful life prediction model for electrolytic capacitor in DC-DC converter is presented in this paper based on Neural Network method. First, the degradation data of electrolytic capacitor is acquired from mathematical models. Next, the neural network prediction model is established by processing the degradation data of the electrolytic capacitor. Finally, the effectiveness of the developed life prediction model is verified using Matlab/Simulink. This paper provides the basis for the overall life prediction of dc/dc converter.

1. Introduction
The current aerospace vehicles are getting more and more complicated due to the definite improvement in functionality and comfortability. On the other hand, aerospace vehicles are facing the increasing demand on reliability and cost-effectiveness. Extremely high requirements of reliability are essential since a single unpredicted failure or fault may result in fateful consequences. It’s significant and meaningful that astronautics and aviation corporation could have the ability to grasp the health status of aerospace vehicles in time, thus maintenance work could be arranged deliberately.

The past few decades have experienced a rapidly developing of health management from component level to circuit board level, but few attempts have been made at system level. Nevertheless, most methods often require triggering mechanisms which can record data automatically when failure occurred. When facing much more severe scenarios, this kind of passive methods could not be effective. Advanced equipment needs an active maintenance and repair method which is capable of forecasting failure.

Prediction technology is to make timely and accurate early warning before the fault occurs. During system operation, health states of the system should be monitored from time to time. Prediction technology is an important part of the concept of prognosis and health management (PHM) methodologies.

Prediction technology can be divided into three categories:

Model based approach: Physical of failure (PoF) model, Kalman/Extended kalman filter, expert system based method or empirical system method can be included into model-based method[1]. With the deepening research on the mechanism of equipment failure, the accuracy of this method is gradually improved. Since the dynamic model of some complex systems is difficult to establish accurately, this method cannot be used in these systems. Grewal et al. employed three models a physical model, energy model and State of Charge (SoC) model to accurately predict EV range which
can be applied to both BEV and PHEV applications[2]. Li et al. developed a Wiener-process-model (WPM)-based method to describe the various degradation processes of different system units[4].

**Data driven approach**: This method is based on data acquired from system outputs and does not need the prior knowledge of the object system (mathematical model or expert system). This approach avoids many complicated basic work and becomes a practical prediction method. Tarek et al. [5] proposed a new Denoising Online Sequential Extreme Learning Machine (DOS-ELM) with double dynamic forgetting factors (DDFF) and Updated Selection Strategy (USS) to predict RUL of aircraft engines. However, the incomplete data will greatly increase the difficulty of this method. Si et al.[6], Sikorska et al.[8] and Tsui et al.[9] have discussed the application of data-driven method in feature extraction, fault diagnosis and life prediction, and their conclusions are quite comprehensive.

**Statistics based approach**: This approach is also known as probability based approach. The probability density function (PDF) of the system can be obtained through statistical data, and it can be used to predict system fault trend. The typical failure probability curve based on statistics based approach is "bathtub curve". The Bayesian method[10], Dempster Shafer theory, Fuzzy logic method and Weibull distribution[11] are all the methods based on statistical reliability. Farsi et al. made a comparison between statistical distributions and artificial neural network (NN) in RUL prediction of components[12].

In this paper, a neural network prediction algorithm is presented to predict remain life of electrolytic capacitor in DC-DC converter. First, the degradation data of electrolytic capacitor is acquired from mathematical models. Next, the neural network prediction model is established by processing the degradation data of the electrolytic capacitor. Finally, the effectiveness of the developed life prediction model is verified using Matlab/Simulink.

The rest of the paper is organized as follows. Section 2 outlines motivation and background for this work. In Section 3, the fundamental of neural network theory are elaborated. Section 4 establishes an electrolytic capacitors NN prediction model as an example. Conclusions and future work are discussed in Section 5.

### 2. Motivation and Background

The data-based method can omit tedious work of physics of failure and greatly reduce the complexity of prediction. Therefore, more energy and time can be invested in algorithm designing and verification. In general, data-based prognosis methods can be divided into two technical routes. One is to take the external characteristics of the system as the data source. By taking a large number of experiments, operational data of different periods can be obtained. A model will then be built based on the data. Intelligent algorithms like machine learning may be used to extract features, and future working states can be forecasted. The other route takes advantages of the associations between characteristic parameters of sensitive components and external characteristics of the system. The aging state of sensitive components can be judged by the acquisition of external characteristics.

In many cases, researchers prefer to use external characteristics directly for prediction. This method is more intuitive and easier to operate. However, this method is only applicable to the system with single degradation mechanism and obvious degradation characteristics. It is why this method is widely used in the prediction of lithium batteries or mechanical bearings. For dc/dc converters, its external characteristics are the result of the interaction of many internal components. Thus the degradation state of the whole system can be related to the degradation state of the components. The degradation process of the individual component needs to be identified and deliberated by means of on line parameter identification, principal component analysis (PCA) or other relational analysis methods. The method of component degradation state prediction will be described in this paper. The correlation analysis of system characteristics to component parameters and the prediction of the overall future state of the system will be presented in the future work.

Dc/dc converters are widely used in electrical equipment to realize direct power conversion between different electric energies. After years of unremitting reform, the topology of the dc/dc converter have basically settled down, and only small changes or improvements could be made in
some particular occasions. Direct dc/dc converter circuit is also called chopper circuit, which convert the input dc power directly into another fixed or adjustable voltage power output. There are no isolation between input and output in this case. Indirect dc/dc converter circuit, which add AC link in the middle, is also called dc/dc converter with isolation. Transformer is usually used to realize the isolation between input and output. In recent years, with the leaping development of related technologies in the field of electric vehicles, the topology of bi-directional converter (BDC) has also been widely studied. It is studied that the failure of dc/dc converters can directly result in the electronic systems working unconventionally, significant downtime or loss of lives[14].

The steady state or dynamic characteristics of a dc/dc converter, such as power efficiency, ripple of voltage or current, impedance characteristics, will degrade with time and working stress. These degradations are the result of coupling caused by the joint degradation of its internal components. The main components that cause this coupling result, or components that have a close influence on external characteristics, are so called degradation sensitive components. The degradation process of dc/dc converters can be detailed drafted by means of studying the degradation mechanisms of sensitive components.

The main components of a dc/dc converter include MOSFETs, power rectifiers, voltage regulators, isolating transformers, pulse width modulation controller circuit and filter electrolytic capacitors. These components have their own failure modes or aging characteristics (see Table 1). Referring to MIL-HDBK 217F standard[15], the electrolytic capacitors have the highest probability of failure (About 60% of the total failures)[16]. Therefore, the failure of electrolytic capacitor will be emphasized in this article.

Table 1. Failure/aging precursor for typical components.

| Electronic Components       | Failure/Aging Indicated Parameter     |
|----------------------------|---------------------------------------|
| Electrolytic capacitors    | - Equivalent series resistance        |
|                            | - Capacitance value /Dissipation factor|
|                            | - RF noise                            |
| General purpose diodes     | - Reverse leakage current             |
|                            | - Forward voltage drop                |
|                            | - Thermal resistance                  |
|                            | - Power dissipation                   |
| Power MOSFETs              | - Threshold voltage drift             |
|                            | - Channel resistance                  |
|                            | - Leakage current                     |
| Inductors & Transformers   | - Inductance value                    |
|                            | - DC Resistance                       |
|                            | - Working frequency                   |
| CMOS IC                    | - Supply leakage current              |
|                            | - Operating signature                 |
|                            | - Signal noise                        |
| Cables and connectors      | - Impedance change                    |
|                            | - Physical damage                     |

3. Artificial neural network method
In most cases, the data we get from experiments are discrete. But the prediction of future trends requires us to establish a continuous mathematical model, therefore, it is necessary to abstract the discrete data sets as a mathematical description.

Such abstract methods are varied, and can be generally divided into regression, fitting and interpolation. The most widely used methods may be linear regression, polynomial(curve) fitting and
machine learning algorithms. The traditional fitting or regression methods focus on the data structure, and the model lacks flexibility. In many practical scenarios, the data to be regressed or fitted are not linear, and even some data present a very complex nonlinear relationship. Machine learning method can solve the problem of large amount of data, unclear data structure and complex nonlinear relationship.

Artificial neural network algorithm is one of the most widely used intelligent algorithms in engineering, and BP network is most attractive because of its simple structure, adjustable parameters and good operability. BP neural network is a kind of multilayer feedforward neural network, and its connection weight is adjustable and determined by a learning algorithm of error back propagation. The BP network can learn and store a large number of input/output mapping relations, without describing the mathematical equations of this mapping relationship in advance.

![Figure 1. Simulation data of capacitor degradation process.](image)

Artificial neural network is constituted by the large number of neurons (see Figure.1), which is composed of three basic elements:

- **Connections**: The strength of connection can be represented by the weight on the connection. Positive weights indicate activation while negative weights indicate inhibition.
- **Summator**: It is used to solve the weighted sum of input signals.
- **Activation function**: It is used to limit the amplitude of the neurons’ output, and make sure the output signal is suppressed within a certain range.

Sometimes an external bias is added to the neuron model, which is $b_k$. Therefore, the output of a neural network can be expressed as follows:

$$u_k = \sum_{i=1}^{m} w_{ik} x_i$$  \hspace{1cm} (1)

$$y_k = f(u_k + b_k)$$  \hspace{1cm} (2)

where $x_i$ represents the input signals, $w_{ik}$ represents the input weight of the neuron ‘$k’$, $m$ means the number of input signals, $u_k$ represents the output after linear summation, $b_k$ represents the bias of the neuron, $f(\cdot)$ means activation function, and $y_k$ represents the output of a neuron.

4. Main Results

4.1 Life-time data acquisition

The aging or degradation data of sensitive components can be obtained by experiments, which have been fully explained in the previous literatures or the results of research institutions[16][17][18]. Mathematical models have been abstracted from these aging or degradation data to reflect its operation state appropriately. This paper lays emphasis on the application of neural network algorithm in component aging process prediction, and its comparison with traditional polynomial fitting. Therefore, data acquisition is not the focus of our work. Aging models in references combine with reasonable jitter will be used as simulative data source of the real condition.
Take electrolytic capacitors as an example. Electrolytic capacitor is one of the most critical components in dc/dc converter, which contribute to output filtering. Electrolytic capacitor is also one of the most vulnerable components in power transmission part of the dc/dc converter and has the most obvious aging characteristics. In general, its equivalent circuit can be simplified as a series connection of ideal capacitor and resistor (see Figure.2). The capacitance value and ESR resistance value can be used as its degradation characteristic parameters.

\[
\Delta C(t) = e^{\alpha t} - \beta
\]

where \(\alpha\) and \(\beta\) are model constants that will be assessed from data of accelerated aging experiments. Based on the above formula, the capacitance value degrades with time can be described as the following form,

\[
C(t) = C(0) \times [1 - \Delta C(t)]
\]

It is noteworthy that \(\Delta C(t)\) in formula (4) should be written as a percentage value. \(C(0)\) represents the initial value of the capacitance.

Typically, degradation affects both the capacitance and ESR values. A linear inverse model has been derived as an extension of Arrhenius Law to define the change of the ESR value over time by Venet and Grellet[18]. The ESR value at a certain moment during its life time is given by[20]:

\[
\frac{1}{ESR(t)} = \frac{1}{ESR(0)} \left[1 - k \cdot t \cdot exp \left(\frac{4700}{T+273}\right)\right]
\]

where \(ESR(t)\) represents the ESR value at time ‘\(t\)’, while \(ESR(0)\) means the initial ESR value, \(t\) is the operating time, \(T\) is the temperature at which the capacitor operates, \(k\) is a constant value determined by geometry of the capacitor.

Consider a certain type of capacitor, its initial capacitance value is 1000\(\mu\)F with an ESR value of 0.07\(\Omega\). After 1200h of typical working conditions, the capacitance value changes to 800\(\mu\)F with an ESR value of 0.21\(\Omega\). Two normal distributed noise signals with mean value 0, variance 0.00002 and
0.005 are injected into \( C(t) \) and \( ESR(t) \) respectively. 200 sets of data are randomly selected from the continuous data with noise to simulate the real experimental data (see Figure.3).

### 4.2 Training and verification of prediction model

Neural Network Toolbox of MATLAB R2017A has integrated several useful tools to facilitate the network building, training, optimizing and verifying, which greatly simplifies the algorithm design work. Classification, regression, clustering, dimensionality reduction, time-series forecasting, and dynamic system model and control can all be performed based on this toolbox.

A neural network with five hidden nodes is established to predict the life of electrolytic capacitors. The 200 sets of data described above are divided into three groups: 140 sets of data (70%) were used to train the algorithm, 30 sets of data (15%) were used for validation and the remaining 30 sets (15%) for testing. Levenberg-Marquardt method, a method of least squares estimation of regression parameters, is used as training algorithm. The trained neural network is evaluated by the residual value \( R \) and mean squared error value MSE (see Figure.4).

![Figure 4. Training results of neural network.](image)

![Figure 5. Test model in Simulink platform.](image)

It is worthy of note that the least mean squared error value appeared at epoch 7, and parameters at that time would be used as the optimum parameters. The regression R Values indicate the correlation between outputs and targets, \( R=1 \) means an extremely close relationship. The trained neural network is encapsulated into Simulink platform to build a test model (see Figure.5).

As we can see in Figure.5, with input values of \( C = 800\mu F \) and \( SR = 0.21\Omega \), the trained neural network outputs a prediction result of 9.49h (Under the assumption that the total life is 1200 hours).
By this means, the predicted values of the neural network model can be compared with the values in the data set (see Table 2).

| Capacitance (\(\mu F\)) | ESR (\(\Omega\)) | Model prediction (\(h\)) | Data set value (\(h\)) | Absolute Error (\(h\)) | Percentage Error |
|--------------------------|------------------|--------------------------|------------------------|------------------------|------------------|
| 981                      | 0.0728           | 1137                     | 1150                   | 13                     | 1.13%            |
| 945                      | 0.0923           | 889.2                    | 906.1                  | 16.9                   | 1.87%            |
| 921                      | 0.1123           | 640.8                    | 649.5                  | 8.7                    | 1.34%            |
| 884                      | 0.1524           | 411.1                    | 415.2                  | 4.1                    | 0.987%           |
| 845                      | 0.1732           | 236.5                    | 230.1                  | 6.4                    | 2.78%            |
| 819                      | 0.1966           | 55.65                    | 53.72                  | 1.93                   | 3.59%            |

From the structure and basic principle of neural network, it is obvious that the number of hidden layer nodes will affect the training quality (see Figure 6), and further affect the prediction accuracy.

![Figure 6. Global regression R value changes with the number of hidden layer nodes.](image)

However, too many hidden layer nodes will make the structure of neural network complex, increase the computational cost, and prolong the training time. Therefore, a trade off should be made between data size, data structure, computing capability and required model accuracy when selecting an appropriate number of hidden layer nodes.

5. Conclusions
Prediction is a novel and challenging work, which is of great significance for the maintenance of equipment. In this paper, the remaining life prediction of electrolytic capacitor in dc/dc converter is realized by establishing neural network model based on simulated degradation data. First, the degradation data of electrolytic capacitor is acquired from mathematical models. Next, the neural network prediction model is established by processing the degradation data of the electrolytic capacitor. Finally, the effectiveness of the developed life prediction model is verified using Matlab/Simulink. Our future work will identify the characteristic parameters of sensitive components by the method of on-line parameter identification. The method described in this paper can also be used in lithium battery, bridge circuit and other scenarios.

References
[1] Nikhil, M., Vichare, Michael, G., & Pecht. (2006). Prognostics and health management of electronics. IEEE Transactions on Components & Packaging Technologies.
[2] Grewal, K. S., & Darnell, P. M.. (2013). Model-based EV range prediction for Electric Hybrid Vehicles. Hybrid and Electric Vehicles Conference 2013 (HEVC 2013). IET.
[3] Khandebharad, A. R., Dhumale, R. B., Lokhande, S. S., & Lokhande, S. D.. (2015). Real time remaining useful life prediction of the electrolytic capacitor. International Conference on Information Processing.
[4] Li, N., Lei, Y., Yan, T., Li, N., & Han, T.. (2018). A wiener process model-based method for remaining useful life prediction considering unit-to-unit variability. IEEE Transactions on Industrial Electronics, PP(3), 1-1.

[5] Tarek, B., Mouss, H., Kadri, O., Saidi, L., & Benbouzid, M.. (2020). Aircraft engines remaining useful life prediction with an adaptive denoising online sequential extreme learning machine. Engineering Applications of Artificial Intelligence, 96(103396), 1-10.

[6] Si, X. S., Wang, W., Hu, C. H., & Zhou, D. H.. (2011). Remaining useful life estimation – a review on the statistical data driven approaches. European Journal of Operational Research, 213(1), 1-14.

[7] Poon, J., Jain, P., Spanos, C., Panda, S. K., & Sanders, S. R.. (2017). Fault prognosis for power electronics systems using adaptive parameter identification. IEEE Transactions on Industry Applications, 2862-2870.

[8] Sikorska, J. Z., Hodkiewicz, M., & Ma, L.. (2011). Prognostic modelling options for remaining useful life estimation by industry. Mechanical Systems & Signal Processing, 25(5), 1803-1836.

[9] Tsui, K. L., Chen, N., Zhou, Q., Hai, Y., & Wang, W.. (2015). Prognostics and health management: a review on data driven approaches. Mathematical Problems in Engineering, 2015, (2015-5-19), 2015(PT.8), 1-17.

[10] Hess, A., Calvello, G., & Frith, P.. (2005). Challenges, issues, and lessons learned chasing the Big P. Real predictive prognostics. Part I. Aerospace Conference, 2005 IEEE. IEEE.

[11] Skormin, V. A., Popyack, L. J., Gorodetski, V. I., Araiza, M. L., & Michel, J. D.. (2002). Applications of cluster analysis in diagnostics-related problems. 1999 IEEE Aerospace Conference. Proceedings (Cat. No.99TH8403). IEEE.

[12] Farsi, M. A., & Hosseini, S. M.. (2019). Statistical distributions comparison for remaining useful life prediction of components via ann. International journal of systems assurance engineering and management, 10(3), 429-436.

[13] Kulkarni, C. S., Celaya, J. R., Biswas, G., & Goebel, K.. (2012). Prognostics of Power Electronics, methods and validation experiments. AUTOTESTCON, 2012 IEEE. IEEE.

[14] Qingchuan, H., Wenhua, C., Jun, P., & Ping, Q.. (2017). A prognostic method for predicting failure of dc/dc converter. Microelectronics Reliability, 74, 27-33.

[15] Military Handbook 217 F, (1995) “Reliability prediction of electronic equipment.”

[16] Lahyani, A., Venet, P., Grellet, G., & Viverge, P. J.. (2007). Failure prediction of electrolytic capacitors during operation of a switchmode power supply. Power Electronics IEEE Transactions on, 13(6), 1199-1207.

[17] Celaya, J., Kulkarni, C., Biswas, G., Saha, S., & Goebel, K.. (2011). A Model-based Prognostics Methodology for Electrolytic Capacitors Based on Electrical Overstress Accelerated Aging. Conference of the Prognostics & Health Management Society.

[18] Venet, P., Darnand, H., & Grellet, G.. (1993). Detection of faults of filter capacitors in a converter. Application to predictive maintenance. Proceedings of Intelec 93: 15th International Telecommunications Energy Conference. IEEE.

[19] Penna, J. A. M., Nascimento, C. L., & Rodrigues, L. R.. (2012). Health monitoring and remaining useful life estimation of lithium-ion aeronautical batteries. Aerospace Conference, 2012 IEEE. IEEE.

[20] Kulkarni, C., Biswas, G., Koutsoukos, X., Goebel, K., & Celaya, J.. (2010). Physics of Failure Models for Capacitor Degradation in DC-DC Converters. The Maintenance and Reliability Conference.