Research on DC-DC power health management technology based on degradation test and deep learning

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Abstract. The health state of DC-DC power supply is the key factor to determine whether the electronic equipment can operate normally. The failure and deterioration of the power supply system will lead to the collapse of the entire electronic system. The research in this paper is based on the long-term high temperature degradation test data of a certain type of DC-DC power supply. The degradation law of power supply is studied by data preprocessing and noise reduction of sensitive parameters such as input current, output current, input voltage and output voltage. On this basis, we use the method of deep learning to model the efficiency of power supply in the process of degradation test. The experimental results show that the efficiency time series modeling of power supply degradation using LSTM method can effectively reflect the law of power supply efficiency degradation. Based on the DC-DC power health management technology combining degradation test and deep learning, the advanced fault prediction model is used to reflect the change law of power supply in the real degradation process. This method has certain theoretical and engineering value for power PHM modeling and application.

Keywords: degradation, DC-DC, Health Management, deep learning.

1. Introduction
With the progress and development of modern science and technology, switching power supply in power electronics, aerospace, ships, computers, electric vehicles, industrial control, communication equipment and other fields have been a big rule of application, in the development of the national economy where people's lives are indispensable. In recent years, with the significant increase of power consumption of system equipment, the improvement of load has put forward higher requirements for the performance and reliability of power supply system. As we know, switching power supply usually works in harsh environment, the environment including thermal stress, humidity, shock vibration, vacuum, salt spray and other stress environment, but also includes electromagnetic radiation, higher particles, strong electromagnetic interference and other harsh working conditions. Power supply as the core component of equipment, its importance is self-evident. Switching power supply often plays the role of the "heart" of the electronic system, and the failure and deterioration of the power supply
system can lead to the collapse of the entire electronic system. Whether the power supply works normally or not determines the stability, safety and reliability of the electronic system. Prognostic and Health Management (PHM) technology was first developed by the U.S. Military to improve equipment safety and mission success, and is an important means to improve support effectiveness and reduce support costs. The research contents include condition monitoring, fault diagnosis, fault prediction, health management and decision, data communication, transmission and expression, etc.

This technology has been promoted and applied by researchers at home and abroad, and is becoming an important part of the development and application stages of new-generation aircraft, ships, vehicles, electronic systems, mechanical systems and other equipment or systems [1]-[2]. With the rapid development of electronic products, it is necessary to introduce state-based maintenance method into the field of power supply reliability assurance. At present, the research on intelligent maintenance of power supply equipment at home and abroad mainly focuses on fault diagnosis and life prediction of key components of power supply. Zhou Shihong [3] based on the analysis of the main degradation mode of aluminum electrolytic capacitor and the influence of degradation on the output signal of DC-DC converter, and taking a specific DC-DC converter as the research object, preprearily constructed an experimental system for predicting the remaining service life of DC-DC power supply. Yu Shan et al. [4] analyzed and studied the influence of ambient temperature and ripple current on the service life of electrolytic capacitors from the internal structure and failure mechanism of electrolytic capacitors, and predicted and analyzed the capacitor life of switching power supply by measuring the internal temperature rise of the capacitor. Li Xiaohong et al. [5] used the accelerated degradation test method to evaluate the reliability and predict the life of a highly reliable DC-DC hybrid power supply. From the perspective of health management of power supply, Wang Fengru et al. [6] studied the method of fault feature extraction, condition monitoring and fault prediction related technologies of intelligent secondary power system level. The premise of realizing intelligent maintenance of module power based on health management is to accurately obtain the health status of power supply.

In this paper, the DC-DC power supply was subjected to high temperature degradation test for 9 months, and the health sensitive monitoring parameters during the degradation test were collected. Through feature analysis, data preprocessing, efficiency analysis and deep learning modeling of monitoring data, the variation rule of power degradation test data is analyzed, which provides experimental analysis and data demonstration for power failure prediction and health management engineering application.

2. High temperature degradation test of power supply
In order to study the degradation law of DC-DC power supply at high temperature, we carried out high temperature degradation test of switching power supply. The hardware and software of the whole test included high temperature box, power supply, DC-DC module power supply, load, current sensor, data acquisition card, temperature acquisition card, acquisition software, etc., as shown in Figure 1. The power supply test lasted from April 7, 2020 to December 4, 2020, and the temperature box was set at a constant temperature of 80 degrees Celsius. Six DC-DC power supplies were used in the high temperature degradation test of power supply. The power supply is supplied to a power system manufacturer with specifications of 18-75VDC input and 5VDC output. In the test, the input voltage is 28V and the output voltage is 5V. Through self-developed data acquisition software, input current, input voltage, output current, output voltage four parameters are collected for each power supply. In fact, the acquisition software can support 56 channels of data acquisition at the same time, here the power data only used 24 channels. All the test data were covered from April 21, 2020 to December 4, 2020. Adopt the method of random or fixed selection, select one of the 20 folders in a certain time as the data representative of one day.1 folder contains about 3 minutes of sampling data, 24 parameters of 6 power supplies are collected and stored in DAT format. Through continuous power supply test and data collection analysis, the health status of power supply in power supply test can be evaluated and analyzed in real time, and the method and model of power supply health evaluation can be established.
3. Power failure prediction based on Deep-learning

Deep neural network (DNN) has attracted more and more attention from researchers in various fields in recent years [7]-[9]. It employs a multi-neural layer hierarchy that extracts information from input data by processing it layer by layer, a "deep" layer structure that allows it to learn the representation of complex raw data with multiple levels of abstraction. Starting with raw input, DNN automatically discovers complex structures in large data sets and learns useful features layer by layer.

LSTM (Long Short-Term Memory) [10]-[12] is a deep learning method, which is a kind of neural network used to process sample time series data. It has obvious advantages in solving the gradient disappearance and gradient explosion problems in the process of long sequence training.

3.1. Power degradation modeling method based on LSTM

Recurring Neural Network (RNN) can realize long-term dependence in learning. Different from BP neural network, every time RNN network is trained, the hidden layer will be affected by the previous state. The RNN network can be expanded according to the time series, as shown in Figure 2. Long Short Temp Memory Network (LSTM) is a special structure of RNN, which was proposed by Hochreiter & Schimidhuber (1997) and has been continuously improved since then. Figure 3 shows the network structure of LSTM. The key position of LSTM lies in the unit, which runs from the beginning to the end along the transfer line. There is a linear interaction in the middle, and information can be transferred directly along it without changing.

Fig. 1 High temperature test of DC-DC power supply: There are 6 power supplies in the high temperature box.

Fig. 2 RNN expansion diagram of cyclic neural network
LSTM uses the structure of gates to add or drop information to each cell. The units of the LSTM network have three types of gates: 1. Forgetting gate 2. Input gate 3. State the door. One of the most critical LSTM gates is the forgetting gate, which controls the flow of information in and out (or through and out) through the following three functions:

\[ f_t = \sigma(W_f x_t + b_f) \]
\[ i_t = \sigma(W_i x_t + b_i) \]
\[ o_t = \sigma(W_o x_t + b_o) \]

Where \( \sigma(\cdot) \) is the network output SIGMOID activation function. \( \sigma(\cdot) \) The activation function selects Sigmoid to make it impossible to pass the gate when approaching 0, but it can pass the gate when approaching 1. Therefore, the output of the network depends on the current information itself.

Set the current time as \( t \), and after the state expression of LSTM network is expanded, we can get:

\[ S_t = \sigma(W_f x_t + b_f)S_{t-1} + \sigma(W_o x_t + b_o)X_t \]

After the activation function, there are:

\[ S_t = \tanh[\sigma(W_f x_t + b_f)S_{t-1} + \sigma(W_o x_t + b_o)X_t] \]

By calculating the partial derivative, we can know that the LSTM network has a term similar to the above RNN, but in LSTM, it is:

\[ \prod_{j=k+1}^{t} \frac{\partial S_j}{\partial S_{j-1}} = \prod_{j=k+1}^{t} \tanh(\sigma(W_f x_t + b_f)) \]

In the process of long-term use, the conversion efficiency of power supply will degrade, so the degradation data of long-term power supply forms the time series of conversion efficiency. When the efficiency of the power supply degenerates to a certain threshold, it indicates that the fault occurs. Therefore, the memory characteristics of LSTM network can be used to better predict the trend of power degradation, and the accurate prediction of power conversion efficiency plays an important role in the health management of power supply.

3.2. Power data preprocessing and power conversion efficiency calculation

All types of switching power supply involve conversion efficiency, which is defined as the ratio of output power to input power, for DC/DC switching power supply. The power supply with 100% efficiency is the ideal power supply, and the conversion efficiency of the actual switching power supply is less than 1. This is because the power loss will be generated inside the switching power supply. The greater the power loss, the lower the conversion efficiency of the switching power supply. The loss of switching power supply is mainly caused by on-off loss, switching loss and hysteresis...
eddy current. For the non-isolated DC/DC switching power supply such as Buck, Boost and Buck-Boost, there is no transformer inside, so it is mainly the conduction loss and switching loss. For forward, flyback, half bridge, full bridge and other isolated DC/DC switching power supply, its internal transformer, so the three kinds of losses have. For the sake of generality, only the influence of on-off loss and switching loss on the switching power supply conversion efficiency is considered here. Switching power supply in the process of long-term use of the on-off loss will increase, the change of switching loss is temporarily unknown. Considering that most of the loss of the switching power supply is the on-loss, the power loss of the switching power supply will gradually increase and the conversion efficiency will gradually decrease in the process of use. Therefore, the health assessment of DC/DC switching power supply can be realized by monitoring and calculating the conversion efficiency of the switching power supply.

In view of the degradation situation of the 6 power supply, we choose the test data of the 3# power supply for analysis. The experiment lasted from 2020.04.21 to 2020.12.04. Figure 4 shows the changes of input current, input voltage, output current and output voltage of 3# power supply. Obviously, the data we collected contains outliers and noise. In order to analyze the hidden rules in the data, we carried out a cleaning operation on the data. Fig. 5 shows the characteristic parameter curve of power supply after cleaning operation. It can be seen that the output voltage changes very little during the degradation test, while the other three parameters have certain amplitude changes. In order to further analyze the performance variation of the power supply in the degradation test, we calculated the conversion efficiency of the power supply 3#. Fig. 6 and Fig. 7 respectively show the change curve of power supply efficiency of No. 3 in the high temperature degradation test of power supply after the abnormal data were not cleaned and the abnormal data were cleaned. Data unwashed, that power the degradation law of hidden in the noise and outliers, and after cleaning the rule of data is more noticeable after data processing and analysis of the 3 # power supply, can find the following test: phase 1 test (2020.05.22-2020.07.02) the efficiency of the power supply change first appeared certain amplitude periodic increase, this is caused by faults test load in the early set, then the efficiency of power supply 3 changes tend to be stable, but not obvious degradation trend. By adding the data of 2020.07.02-2020.12.04 in the second stage, after cleaning the data, it can be found that the power performance degradation in this stage is obvious, which is manifested as a significant decline in the power conversion efficiency.

![Fig. 4 Variation of the four monitoring parameters of power No. 3 in the high-temperature degradation test of power supply without cleaning abnormal data.](image-url)
Fig. 5 Variation of the four monitoring parameters of No. 3 power supply in the high-temperature degradation test under the condition of cleaning abnormal data.

Fig. 6 Change curve of power efficiency of No. 3 in high temperature power supply degradation test without cleaning abnormal data.

Fig. 7 Variation curve of power efficiency of No. 3 in high temperature power supply degradation test under the condition of cleaning abnormal data.
3.3. Power failure prediction model and analysis based on LSTM

In order to establish a fault prediction model for power degradation, a machine learning model can be established to predict the time prediction of efficiency in the process of power degradation based on the time series of power efficiency, to judge the trend of efficiency change and to predict the degree of efficiency decrease in the future.

Therefore, on the basis of the research in Section 3.2, we build a LSTM prediction model for the degradation test data of 3# power supply. The test time range covered by the data we intercepted is from May 22 to June 25. Based on the conversion efficiency calculation method of power supply, the efficiency change curve of 3# power supply during May 22 solstice and June 25 can be calculated, as shown in Figure 8 below.

![Figure 8 #3 Power Supply May 22 solstice June 25 Device conversion efficiency change.](image)

Table 1 Power efficiency LSTM prediction network training parameter Settings.

| Parameter name               | Parameter Setting | Parameter interpretation           |
|------------------------------|-------------------|-----------------------------------|
| The objective function optimizer | Adam              | Adaptive moment estimation        |
| Max Epochs                   | 120               | Maximum number of iterations      |
| Gradient Threshold           | 1                 | The gradient threshold            |
| Initial Learn Rate           | 0.005             | Initial learning rate             |
| Learn Rate Schedule          | piecewise         | Learning rate format              |
| Learn Rate Drop Period       | 125               | Learning rate decline cycle       |
| Learn Rate Drop Factor       | 0.2               | Learning rate attenuation factor  |

The time series length of the conversion efficiency of the power supply is 10000, and the power efficiency value of 500 time-steps in the future is predicted. In order to predict the future trend of power conversion efficiency, the deep learning LSTM model, namely the long and short memory network, is used here. The model training data is 95% of the power efficiency sequence length, that is, it contains 9500 data samples. The length of the model test set or prediction set is 500, that is, to predict the change of the power conversion efficiency at 500 steps in the future. In order to obtain better fitting and prevent training divergence, the training data are normalized to have zero mean value and unit variance. In the prediction, we used the same parameters as the training data to standardize the test data. The established LSTM network architecture contains one input feature dimension and one output feature dimension. The network structure of this deep learning model is composed of four layers of network, namely, the input layer, the LSTM layer, the full connection layer and the
regression layer. The LSTM hidden layer contains 200 neural network units. LSTM training parameters are set as follows: the maximum number of parameter iterations is 120, and the gradient threshold is 1 to prevent gradient explosion. The initial learning rate is set as 0.005, the learning rate framework is set as a segmented form, the fading cycle of the learning rate is 125, and the fading factor is 0.2. The parameter settings are shown in Table 1.

On the basis of setting relevant network parameters, the LSTM network training process is started. The error convergence and loss curves of the training process are shown in Fig. 9. The whole training session lasted seven minutes and 25 seconds. After obtaining the trained LSTM model, we predict the power efficiency data of 500 time-steps in the future based on the model. Fig. 10 and Fig. 11 respectively show the future 500-step conversion efficiency of power supply 3# predicted by LSTM model and the comparison curves between the predicted and observed values of power supply 3# based on power efficiency LSTM model. It can be found that LSTM has a relatively high accuracy in predicting the conversion efficiency of power supply degradation, which can reach the accuracy of 1e-2. Therefore, the Long-Short Term Memory network is adopted to predict the power supply degradation, which has a relatively good prediction effect and accuracy.

![Fig. 9 Training error convergence and loss curves of power efficiency LSTM model.](image1)

![Fig. 10 Predicts the future 500-step conversion efficiency of power supply # 3 based on the power efficiency LSTM model.](image2)
4. Conclusions
This paper carried out high temperature degradation test for DC-DC power supply, and monitored and collected the parameters related to the health state of the power supply during the degradation test. The paper analyzes the data of power supply with certain degradation characteristics in the test process, and excavates the degradation law of power supply through the pretreatment and cleaning of data characteristics. It is found that the conversion efficiency of the power supply degrades to a certain extent in the process of long-term high temperature test, which reflects the performance of the power supply is decreasing. We selected the time series of conversion efficiency in the degradation test process, and predicted the variation trend of power efficiency through the LSTM model, and achieved a good prediction effect. The modeling technology based on the combination of test and data mining model proposed in this paper has certain guiding significance and practical value for the excitation of power failure law and the establishment of power health management model.

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