Deep Degradation Feature Extraction and RUL Estimation for Switching Power Unit

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***Abstract*—Switch power unit is the power supply module for the control system of vehicles, ships and aircraft, etc. So, the safety of switching power supply determines the safety of control system. Usually, the failure of electronic devices is consider as a random event. However, the failure is caused by the degradation of internal components to the failure threshold. Therefore, it is found that the performance degradation of the main components in the switching power supply will eventually be manifested in the output ripple voltage by analyzing the output characteristics of the switching power supply. According to the performance degradation, we can divide the ripple into several stages, and get the time-frequency spectrum characteristics by the wavelet transform. Then the performance degradation model of switching power supply is obtained by using a ResNet convolution neural network with time-frequency spectrum characteristics. Finally, get the degradation state of switching power unit by ResNet model and get the remaining useful life.**

Keywords-Switching Power Unit; Ripple Voltage; Wavelet Transform; ResNet.

I. INTRODUCTION

Switching power unit has the characteristics of small size, low power consumption, high efficiency and wide range of voltage stabilization, etc. So, it has been widely used in vehicles, ships, aircraft and other industries. In switch power unit, the capacitors and MOSFET have higher degradation rate and failure, because of the high voltage, high temperature and Strong vibration, etc[1]. For the control system, it is very dangerous if the switch power unit fails, because it can cause the error control or control failure. So, it is necessary to study the performance degradation and residual life prediction of switching power supply.

The performance degradation and residual life prediction method can be divided into two main categories: Model-based method and data-driven method[2]. The model-based method usually starts from the failure mechanism of the object, establishes the relationship between the performance degradation amount and the stress (high temperature, high pressure, strong vibration, etc.) and obtains the physical model of the performance degradation, so as to analyze the residual life of the object. But usually, it is difficult to establish an accurate physical model because of the diversity of the environment and working conditions. Data-driven method is a more general method in that it extract features directly from data to analyze the degradation and estimate the remaining useful life without any parameter simplification and model assumptions[3].

For the switching power unit, it is more difficult to use Model-based method to analyze the degradation because of the complex correlation between a large number of electronic components. So, it mainly use data-driven method to study the degradation of switching power unit. Zhou Yuege proposes a step-stress accelerated life test model and evaluates the remaining life by utilizing model for the secondary power supply of spacecraft[4]. But this method only consider the output current and voltage, which can't reflect early degradation. Considering the relationship between ripple voltage and internal components, the degradation of internal components such as capacitors and MOSFET will be reflected in ripple voltage[5].

Therefore, this paper selects ripple voltage as the performance index of switching power unit and uses data-driven method to analyze the degradation and RUL. Through the wavelet transform, get the time-frequency spectrum of ripple voltage which includes all the features in time domain and frequency domain[6]. Through analyzing the ripple amplitude, divide the ripple voltage into several stages. Then, we can establish a state discriminant model by training a neural network model. The ResNet convolution neural network is a deep learning neural network which can classify data sets from slightly changing features and easy to train the model[7]. Finally, establish the relationship between performance state and residual life and then we can determine the state of switching power unit by ResNet model to predict RUL.

II. THEORETICAL DESCRIPTION

In order to better describe the performance degradation of switching power unit and predict its residual life, the characteristics of output ripple are deeply excavated. The output waveform includes both time domain and frequency domain features, the two-dimensional characteristic matrix

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(time-frequency spectrum) of ripple can be obtained by wavelet transform. According to different performance degradation time points, the output ripple of switching power supply is divided into several states. Then ResNet neural network is used to train the data, and the performance degradation model of switching power supply is obtained. Using degradation model, the degradation stage of switching power supply can be determined. Because the degradation state corresponds to residual life, the remaining service life can be predicted. The flow chart of the method is shown in Fig. 1.

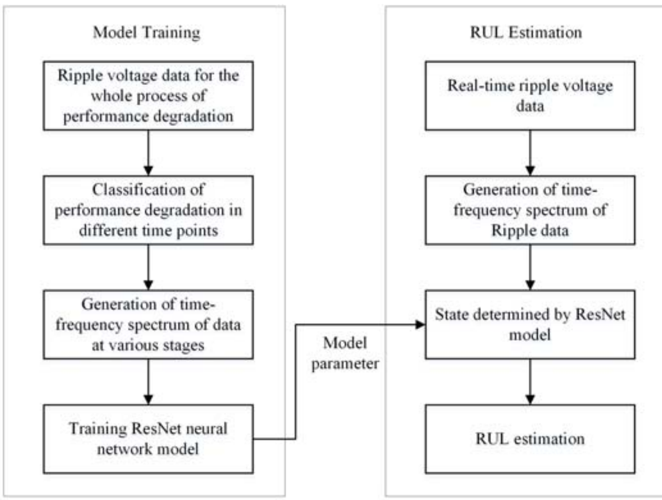


Figure 1. The flow chart of the method

A. Classification of Performance Degradation

Usually, the performance degradation of switching power supply is caused by the degradation of internal components. According to the formula for calculating output ripple shown in (1), it can be concluded that the ripple amplitude changes with the variation of capacitance, inductance and MOSFET voltage drop. When the performance of switching power supply deteriorates, the output ripple will change accordingly. Therefore, The performance state can be classified according to the variation of ripple voltage.

$$V_\omega = \frac{V_0(1-\frac{V_0}{V_i})}{f_s L}(ESR + \frac{1}{8 f_s C}) \tag{1}$$

where V_ω is the ripple amplitude, V_i is the input voltage, V_0 is the output voltage, f_s is the switching frequency, L is the inductance value, C is the capacitance value, ESR is the equivalent resistance of a capacitor.

Usually, the electrolytic capacitor is the component with the highest failure rate in switching power supply. As shown in Fig.2, the electrolytic capacitor can be regarded as consisting of an ideal capacitor (C) and an equivalent resistance (ESR). Therefore, the degradation of electrolytic capacitance is actually the degradation of C and ESR, whose degradation models are shown in (2) and (3). k_1 and k_2 are the degenerate parameters.

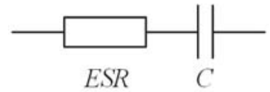


Figure 2. Equivalent Circuit Model of Electrolytic Capacitor

$$C(t) = \frac{C(0)}{1 + k_2 \cdot t} \tag{2}$$

$$ESR(t) = \frac{ESR(0)}{1 - k_1 \cdot t} \tag{3}$$

B. Time-Frequency spectrum

When the switching power unit begins to degrade, the non-stationary features of measured ripple signal will change. Usually, there are both time-domain and frequency-domain characteristics. Considering the characteristic of the switching power unit, In addition to the main switching frequency components, the ripple signal also includes Harmonic components. Compare to wavelet transform, Fourier transform can not express the time-frequency characteristics of non-stationary signals, and Short-time Fourier Transform (STFT) can not approximate the measured signal with arbitrary accuracy in both time and frequency space at the same time. Therefore, wavelet frequency Wavelet transform can well preserve the time-frequency domain characteristics of the original signal, and also meet the requirements of performance degradation model input. Grossmann and Morlet proposed the continuous wavelet transform.

$$\begin{aligned} W(\alpha,\beta) &= \langle x(t), \psi_{\alpha,\beta} \rangle \\ &= \int x(t)\overline{\psi_{\alpha,\beta}(t)} \\ &= \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\overline{\psi(\frac{t-\beta}{\alpha})}dt \end{aligned} \tag{4}$$

where α is the scale factor, β is the translation factor, $x(t)$ is the actual measurement signal. $\psi(t)$ is the wavelet mother function. Through the wavelet transform, the measured signal $x(t)$ is mapped to time-frequency spectrum $W(\alpha,\beta)$.

C. ResNet Convolutional Nerural Network.

A CNN is consisted of three parties which are the input layer, the hidden layer and the output layer, as shown in Fig. 3. Usually, the hidden layer includes the convolutional layer, the activation layer, the pooling layer and the fully connected layer. Convolutional layer is the core of CNN, which is used to convolute input layer and extract higher level features. Its parameters are composed of a set of learning kernels. The role of the activation layer is to add non-linear factors and increase the expressive ability of the model. The role of the pooling layer is to reduce the amount of data while retaining useful information. The function of the fully connection layer is to connect the advanced features of the last convolution pool and get the predicted values.

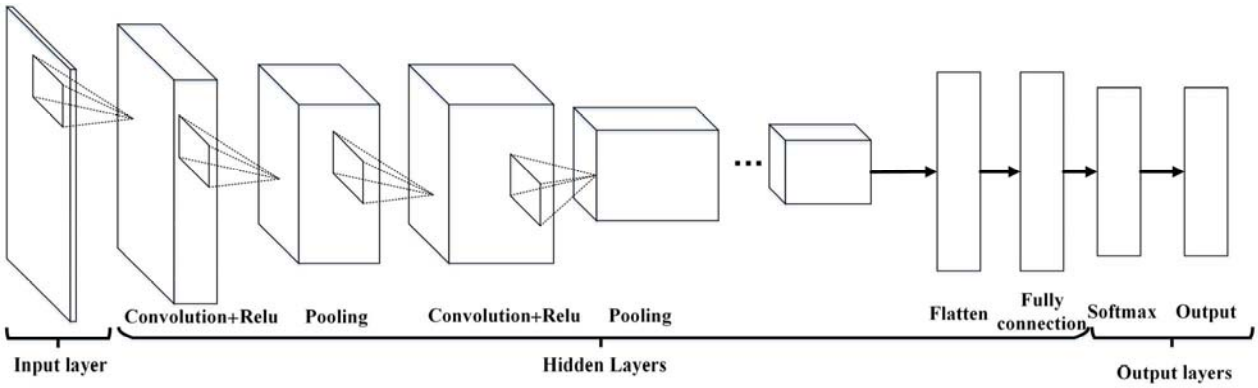


Figure 3. The Structure of Convolutional Neural Network

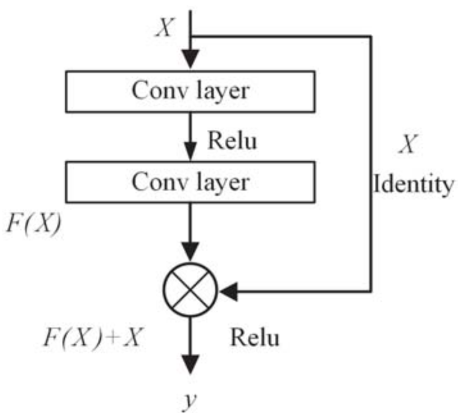


Figure 4. ResNet Residual Learning Module

The output of the convolutional layer is written as

$$a^l = \sigma(z^l) = \sigma(b^l + a_p^{l-1} * \omega^l) \tag{5}$$

The Max-pooling function can be written as

$$a_p^l(i,j) = \max_{0<p,q\le m}\left\{a^l(i\cdot m+p, j\cdot m+q)\right\}, 0<i,j\le n \tag{6}$$

Usually choose ReLU as activation function,

$$ReLU(x) = \begin{cases} x & if\ x>0 \\ 0 & if\ x\le 0 \end{cases} \tag{7}$$

where a^l is the result of l^{th} convolution layer, a_p^l is the result of l^{th} pooling layer, ω is the convolution kernel, b^l is the bias of l^{th} convolution layer, $\sigma(\cdot)$ is the activation function, m is the size of the pooling, n is the size of the result of pooling.

Because CNN can extract low or mid or high-level features, the more layers of the network, the richer the features of different levels can be extracted. However, simply increasing the depth will result in gradient dispersion, gradient explosion or degradation problem. For ripple, its feature change is relatively weak, so deeper network is needed to extract features. ResNet adds direct connected Channels to the Convolutional Network to solve the degradation problem and increases the speed and accuracy of model training. As shown in Fig. 4, it is a ResNet Residual Learning Unit, which is composed of convolution layer and directly connected channel.

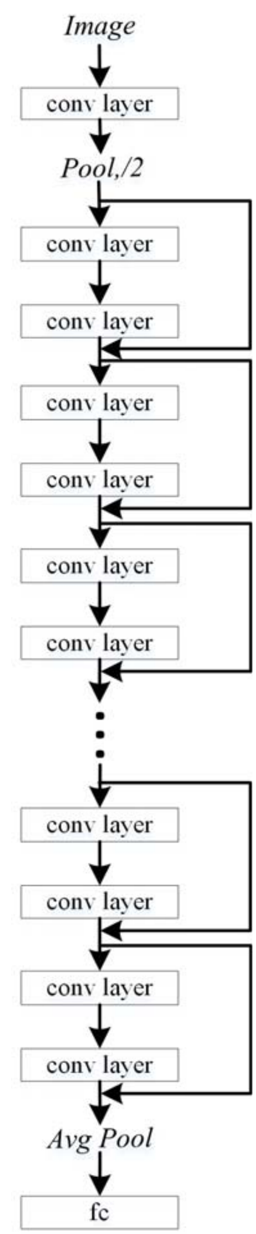


Figure 5. ResNet network architecture

The output of the residual learning unit,

$$y = F(X) + X \quad or \quad y = F(X) + W_s * X \tag{8}$$

when the dimensions of $F(X)$ and X are different, a conversion factor W_s needs to be multiplied. Then, the learning goal of the network becomes

$$F(X) = y - X \quad or \quad F(X) = y - W_s * X \tag{9}$$

it is easier to be optimized than the original $F(X) = y$.

According to the residual learning unit, the whole structure of ResNet can be established, which is composed of input pooling layer, output pooling layer, multiple residual learning units and fully connected layer(fc), as shown in Fig. 5. Then the output value of the fully connected layer will be sent into the output layer to perform the state estimation and predict the RUL. The loss function is defined as

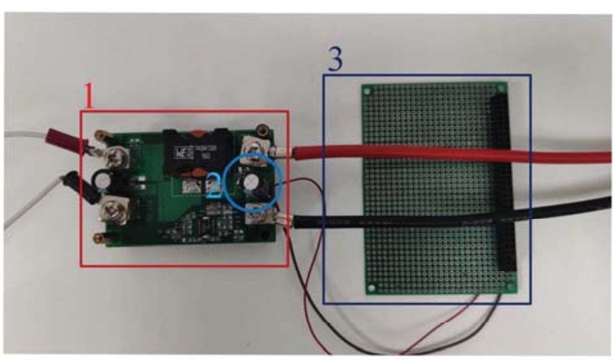
$$\begin{aligned} Loss = Z \bullet (-\log(sigmoid(V_{pre})) + \\ (1-Z) \bullet (-\log(1-sigmoid(V_{pre})) \end{aligned} \tag{10}$$

where Z is the target value and V_{pre} is the output value.

III. CASE STUDY

A. Experimental Description

The experimental device is shown in the following Fig. 6, where the input voltage is 28v, the output voltage is 5v. Because the degradation rate of switching power supply is slow, the degradation process is simulated according to the degradation mode of capacitance. Then a set of performance degradation data caused by capacitance is obtained.



1. the switching power unit
2. the output capacitance
3. the capacitance value regulating board

Figure 6. Experimental circuit diagram

B. Data analysis

According to the experiment, we got twenty-one sets of ripple data under different capacitance values, as shown in Fig. 8.

It can be seen from the Fig. 7 and Fig. 8 that the amplitude of ripple increases with the increase of ESR. In fact, as the performance of switching power supply deteriorates, the frequency characteristics of output ripple also change. therefore, use the wavelet transform to get the time-frequency spectrum of the data, as shown in Fig. 9, which represents three different stages, It can be seen from the figure that the time-frequency spectrum characteristics of different stages are different. The longitudinal direction shows the change of frequency, the depth of the color represents the magnitude of the corresponding frequency. With the degradation, the magnitude of different frequencies change, as show in Fig. 9.

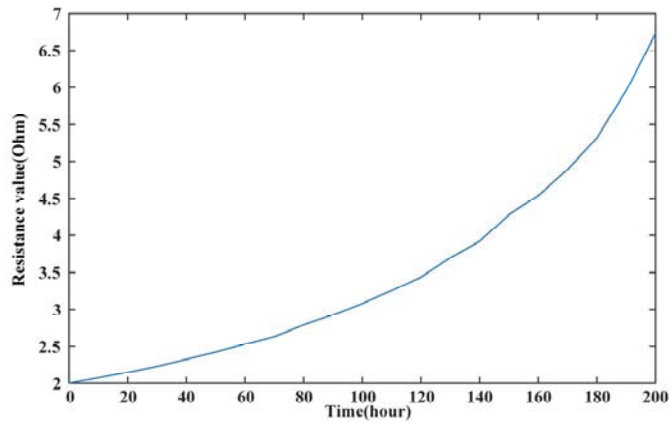


Figure 7. The degradation of ESR

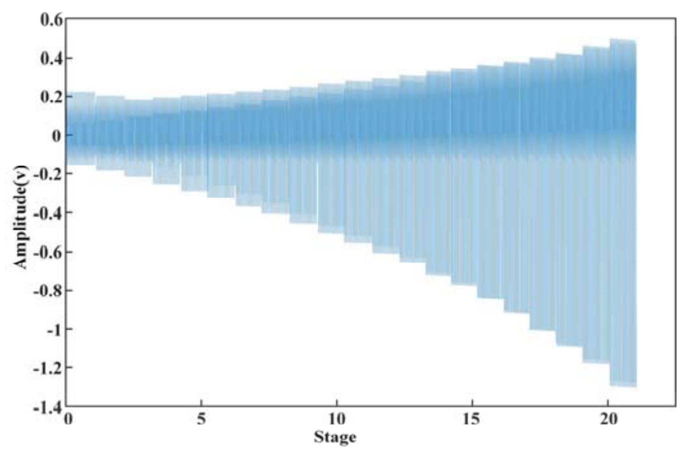


Figure 8. Output ripple voltage of switching power supply

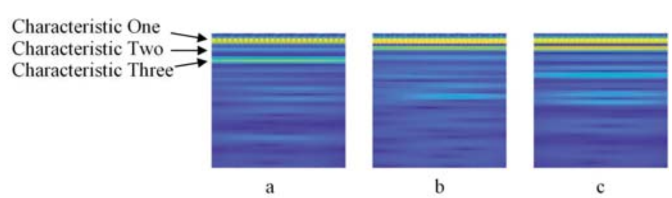


Figure 9. Time-frequency spectrogram of ripple in different performance stages (a is in the early degradation state, b is in the medium degradation state, c is in severe degradation state.)

Then, The time-frequency spectrum is corresponded to the state label and the data set is set up to train the ResNet network. When the model is trained, the test set is input into the trained model and the test results are obtained.

Test the model with training set. Fig. 10 shows that, in addition to individual data which are caused by inaccurate measurement, ResNet can accurately classify the slightly changed ripple data.

Test the model with the test data. Fig. 11 shows that the trained ResNet can determine the state of the new ripple data to determine the performance and state of the switching power supply. However, there are some fluctuations in the results, which may be caused by the insufficient training set or the change of working conditions.

Therefore, according to the analysis of training results and test results, the neural network can be used to classify the states accurately, so as to realize the prediction of residual life. As shown in Fig. 12, use the training model to distinguish the current state of switching power supply, and each state has a residual life value, so we can get the prediction of the residual life.

IV. CONCLUSION

This paper presents a method of performance state classification and remaining life prediction of switching power unit based on ResNet neural network. The validity of this method to accurately distinguish small state changes is verified by experimental data. However, there are still some areas for further improvement.

- The data set is relatively small and the accuracy of the results is slightly low. Further experiments are needed to obtain life cycle data and analyze the characteristics of the data.
- This paper verifies that the method can accurately distinguish performance states under fixed operating conditions. However, the versatility under off-design conditions needs to be improved.
- The performance degradation characteristics of different switching power supply are different, and the residual life prediction results need to be updated with new data.

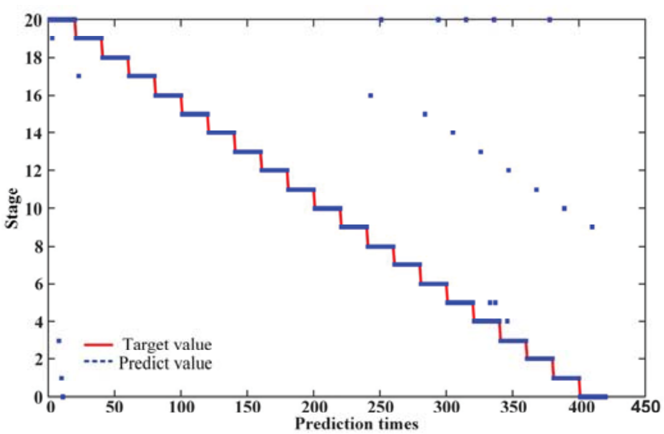


Figure 10. Training Set Test Classification Model

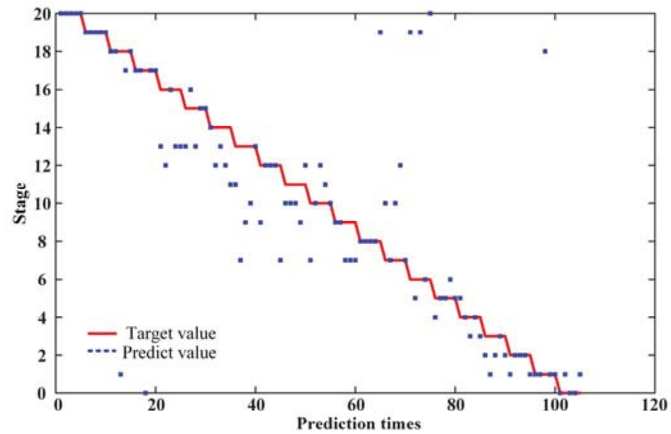


Figure 11. Test Set Test Classification Model

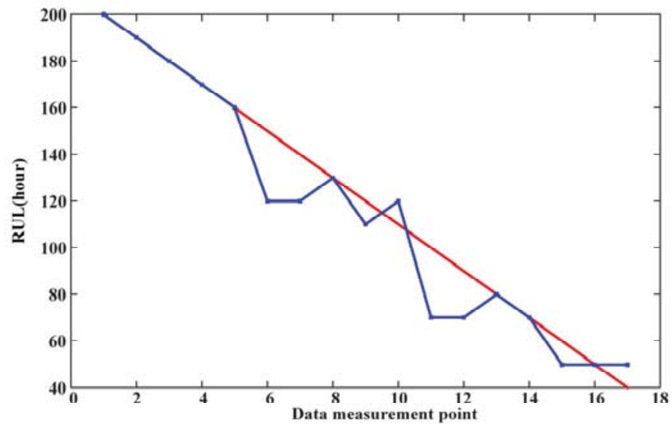


Figure 12. The prediction of the residual life

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