Research on Power Supply Performance Degradation Based on Neighborhood Rough Set and Multiple Linear Regression

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***Abstract*—Aiming at the health monitoring of radar transmitting power supply, a new method of equipment performance degradation based on neighborhood rough set and multiple linear regression was proposed. Firstly, circuit modeling and fault simulation injection are adopted to obtain characteristic parameters such as peak value, mean value and frequency of voltage at monitoring points related to power supply. Secondly, based on the multivariate linear regression analysis method under the simulation conditions, the relationship model between the "threshold voltage of MOSFET" and the reduced characteristic parameters of the key performance indicators of the power supply was established. The model could be used to quantify the degree of degradation of power supply performance, and time series analysis method was used for predictive analysis. Finally, the simulation and analysis of the radar transmitting power source were used to prove the effectiveness of the method.**

Keywords- The power supply; Health monitoring; Neighborhood Rough Set; Multivariate Linear Regression Analysis; The PSPICE software simulation.;Time Series Analysis.

I. INTRODUCTION

Based on the technology of Prognostics and Health Management (PHM)[1], various abnormal states of electronic devices can be predicted in advance, in order to reduce the failure loss and improve the safety and reliability of electronic devices. The technology of PHM for electronic equipment such as radar transmitting power supply has not been mature enough until now. Usually, characteristic parameters related to health state are selected for modeling and predicting.

How to select appropriate monitoring parameters is the key issue to drive the research on fault prediction. There are common methods to select monitoring parameters, including the method based on expert experience, the method based on circuit analysis and the method based on test case. Current academics contribute more attention on how to model linear or nonlinear methods, such as Auto Regressive Moving Average Model (ARMA) and Radial Basis Function Neural Network Model (RBF). However, if the parameter selection is not correct the modeling accuracy will be affected. In order to improve the prediction accuracy, it is necessary to select appropriate monitoring parameters.

At the same time, with the development of electronic system's complexity and intelligence, it is inevitable to cause the surge of monitoring data. Therefore, the idea of data mining should be introduced to accurately reduce the original data, extract effective information, remove redundant information and improve the efficiency of health monitoring and prediction. The method of rough set can extract valued information from a large amount of information, which is uncertain, fuzzy or even incomplete. However, classical Rough Set theory[2] can only deal with discrete data, while continuous data such as voltage and current should be discretized first. Different discrete methods have some deviations, and in the process of discretization, important information of the original data may be lost, resulting in inaccurate final results. Therefore, Lin et al. proposed the Neighborhood System[3], and Qinghua Hu further proposed the concept of Neighborhood Rough Set[4]. The Neighborhood Rough Set can not only process discrete data and continuous data, but also process and reduce the attributes of symbolic data and mixed data, and retain a large amount of information of the original data.

In this paper, radar transmitting power supply was taken as the research object, and the failure of power MOSFET (Metal-Oxide -Semiconductor Field Effect Transistor) with high failure rate was studied. On the basis of circuit analysis method, fault injection simulation method was adopted to simulate the changes of monitoring parameters with MOSFET performance degradation, and state information was obtained. And the Neighborhood Rough Set method was used to reduce the monitoring parameters. After selecting suitable monitoring points, the relational model between key performance indexes 'threshold voltage' and monitoring parameters was established by linear regression method. In engineering application, in order to achieve the performance prediction of MOSFET, monitoring parameter data could be collected at equal time intervals, and the change of threshold voltage could be quantitatively expressed based on the relational model, so as to obtain the time series of threshold voltage observation. Then, the statistical modeling method was used to predict and analyze the time series, and the linear autoregressive model (such as ARMA model) between the future value of threshold voltage and the current and historical

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view observation measurement was established for engineering application.

II. FAILURE ANALYSIS OF RADAR TRANSMITTING POWER SUPPLY

A. *Introduction to radar transmitting power supply*

Radar transmitting power supply is a switching power supply that converts 380V, 50Hz three-phase alternating current into 34V direct current. ZVS converter is the core of switching power supply.

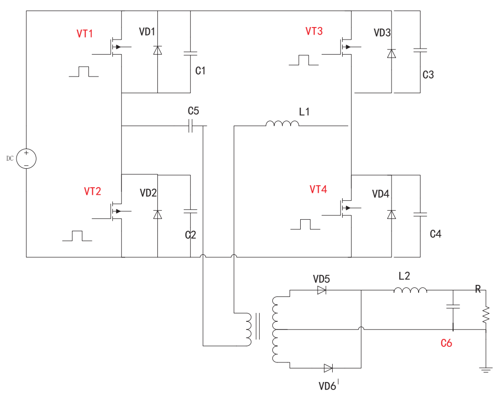


Figure 1. ZVS PWM DC/DC full bridge converter

As shown in figure 1, in ZVS PWM DC/DC full-bridge converter, aluminum electrolytic capacitor and power MOSFET are the two components with the largest failure rate in the device. This power circuit employs military capacitors, which adopts redundant design to increase its reliability. When a capacitor fails, the power supply can continue to run normally. However, MOSFET has no redundancy. It can be seen from Failure modes and Effect Analysis (FMEA) that MOSFET is the main factor influencing the Failure of transmitting power supply. Therefore, the MOSFET's failure monitoring is the focus of the research.

B. *The failure mechanism of MOSFET*

There are many failure mechanisms of MOSFET, and most of these failure mechanisms are determined by its material and device production process，among which Off-state Avalanche Breakdown Induced Degradation, Hot Carrier Injection (HCI), and Time-dependent Dielectric Breakdown (TDDB) are the most common ones[5]. Since the situation of sudden failure cannot be predicted, the following analysis only focuses on degenerate failure.

In the Figure 2, the structure diagram of MOSFET is shown. When conducting, only carriers of one polarity (multiple carriers) are involved in conducting electricity, which is a unipolar transistor. In the figure, the current channel under the inner gate of MOSFET is generated by the reverse p-base region, and the N+ source current flows through the gate and then vertically passes through the drain region.

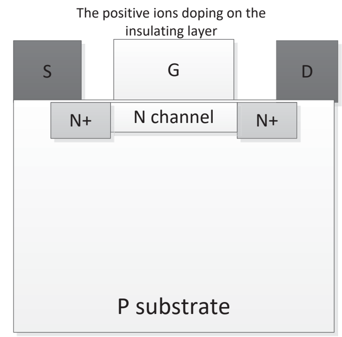


Figure 2. The structure diagram of MOSFET

The electric stress and temperature stress affect the inner structure, dielectric and material thickness and length of MOSFET from different aspects. These influenced factors together determine the degradation of the MOSFET, which can be embodied as changes in the static parameters of the MOSFET. Related research shows that the degradation failure of MOSFET will cause its on-resistance R_{ds}, threshold voltage V_{th} and transconductance g_m to decrease[6].

Therefore, threshold voltage V_{th} is selected as the characteristic parameter of MOSFET's degradation failure. According to the investigation and statistics, 20% of the threshold voltage change is used as the failure criterion of power MOSFET[7].

C. *The degradation of the simulation of MOSFET*

PSPICE is a general circuit simulation software with powerful circuit drawing, circuit simulation and processing functions. Compared with other simulation software, it is easy to modify the component parameters, and has the ability of hybrid simulation of digital circuit and analog circuit.

There are three main methods for fault simulation injection in PSPICE: modifying circuit schematics, modifying network topology files(The netlist file)and modifying model definitions. The essence of these three methods is to replace the original device model with the reconstructed fault model. For the fault injection of parameter drift and performance degradation, the model definition can be modified, that is, the device model can be modified in the model definition file of the circuit.

Due to the manufacturing process and operating conditions, there are random errors between the component parameters and their nominal values in the actual circuit. Monte Carlo Analysis in PSPICE was used to change the tolerance range of other components (such as inductance, capacitance, etc.) except key components. As shown in figure 3, these changes have no significant impact on the experimental results.

In engineering application, in order to make the simulation closer to the reality, for each threshold voltage, multiple sample points were generated randomly within the tolerance range of other original devices.

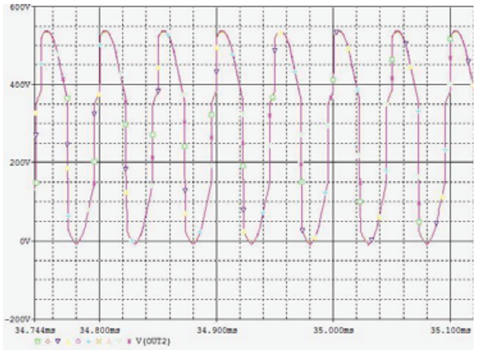


Figure 3. Monte carlo analysis of a monitoring point

III. THE REDUCTION ALGORITHM OF NEIGHBORHOOD ROUGH SET

A. Introduction to the Neighborhood Rough Set

The neighborhood decision system is defined as $\mathrm{NDT} = < \mathrm{U}, \mathrm{A}, \mathrm{D} >$,among them, A is a set of real-type attributes describing the domain $\mathrm{U} = \{x_1^*, x_2^*, \cdots, x_n^*\}$. Decision attribute D divides the theory domain U into N equivalent class $\mathrm{X}_j^* (j = 1,2,\ldots,N)$. For any attribute$\mathrm{B} \subseteq \mathrm{A}$, the lower approximation of the decision system (that is, the positive decision domain) $\underline{N_B}D$ is defined as

$$P_B(D) = \underline{N_B}D = \cup_{j=1}^{N}\{x_i | \delta_B(x_i^*) \subseteq \mathrm{X}_j^*,\ \ x_i \in U\} \quad (1)$$

Where, $\delta_B(x_i^*)$ is the neighborhood particle generated according to property B. The larger the positive field $\underline{N_B}D$ of decision D is, the stronger the effect of attribute classification will be. It can be concluded that the dependence of decision attribute D on conditional attribute B is

$$\gamma_B(D) = \frac{Card(\underline{N_B}D)}{Card(U)} \quad (2)$$

Dependency is closely related to attribute importance and will affect the final attribute reduction result. When you have a dependency function for an attribute, you can give a neighborhood system NDT, $\mathrm{B} \subseteq \mathrm{A}$,for any $\mathrm{a} \in \mathrm{A} - \mathrm{B}$,the relative importance of A to B is defined as

$$\mathrm{S}_{IG}(\mathrm{a}, \mathrm{B}, \mathrm{D}) = \gamma_{B\cup\{a\}}(D) - \gamma_B(D) \quad (3)$$

B. Attribute Reduction Algorithm

For the decision-making system, not every conditional attribute is necessary for the decision table. Attribute reduction is to delete the unimportant or redundant information in the original decision table on the premise of keeping the original information unchanged.

In the paper, the forward greedy numerical attribute reduction based on attribute importance is adopted. This kind of method takes the attribute importance as the inspiration information and gradually selects the attribute with the highest importance until the attribute reduction is obtained. Specifically, the forward greedy reduction algorithm based on dependent function is adopted[8]. Since the dependency function defines the contribution of conditional attributes to classification, it can be used as an evaluation index of the importance of attribute sets.

The algorithm starts from the empty set and calculates the importance of all the remaining attributes every time. The attribute with the largest value of the importance of the attribute is selected and added to the reduction set until the importance of all the remaining attributes is 0, that is, any new attribute is added and the value of the dependency function of the system no longer changes. The resulting reduction set is the desired result.

The specific implementation steps are as follows:

1) Initializes a subset of attribute reduction $B = \emptyset$;

2) For any $a \in A$, compute the neighborhood relation N_a;

3) For any residual attribute $a_i \in A - B$, the importance of the attribute relative to the reduced subset B is calculated;

$$\mathrm{S}_{IG}(\mathrm{a}, \mathrm{B}, \mathrm{D}) = \gamma_{B\cup\{a\}}(D) - \gamma_B(D) \quad (3)$$

4) Select the most important attribute to satisfy the following equation:

$$\mathrm{S}_{IG}(\mathrm{a}_k, \mathrm{B}, \mathrm{D}) = \max_i\left(\mathrm{S}_{IG}(\mathrm{a}_i, \mathrm{B}, \mathrm{D})\right) \quad (4)$$

When $\mathrm{S}_{IG}(\mathrm{a}_k, \mathrm{B}, \mathrm{D}) > 0$,add attribute a_k to attribute reduction subset B, that is, $\mathrm{B} = \mathrm{B} \cup \{\mathrm{a}_k\}$, and skip back to step 3 to continue calculation until program termination;

5) Output the reduction result B of final calculation.

IV. MULTIVARIATE LINEAR REGRESSION ANALYSIS

A. The mathematical model of multivariate linear regression

Multivariate linear regression is an important method in multivariate statistical analysis[9]. The general multiple linear regression model can be written as:

$$\mathrm{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \quad (5)$$

Where, y is the dependent variable; x_1, x_2, $\cdots$, x_k are the set of independent variables; β_0 is a constant; β_1, $\cdots$, β_k are the regression coefficient; ε is a random variable.

Regression analysis mainly gives the estimated value $\widehat{\beta_i}$ of each regression analysis coefficient β_i based on N groups of $x_1, x_2, \cdots, x_k, y$ observation data（x_{i1}, x_{i2}, $\cdots x_{ik}$, y_i $(\mathrm{i} = 1,2,\cdots,\mathrm{N})$）.Meanwhile, various statistical tests of $\widehat{\beta_i}$（$\mathrm{i} = 0,1,2,\cdots,\mathrm{k}$） are conducted to illustrate the reliability of the estimated value.

B. The ordinary least squares estimate of regression coefficients

Parameter estimation of multiple linear regression requires minimum sum of squares of error. Ordinary Least Square (OLS) is generally used to estimate model parameters.

Let $\widehat{\beta_0}$, $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\cdots$, $\widehat{\beta_k}$ be the least squares estimation of β_0, β_1, β_2, $\cdots$, β_k respectively, then the observed value of y can be expressed as:

$$y_i = \widehat{\beta_0} + \widehat{\beta_1}x_{i1} + \widehat{\beta_2}x_{i2} + \cdots + \widehat{\beta_k}x_{ik} + e_i \tag{6}$$

Where, $i = 1,2,\cdots,N$. Let $\widehat{y_i}$ be the estimate of y_i.

$$\widehat{y_i} = \widehat{\beta_0} + \widehat{\beta_1}x_{i1} + \widehat{\beta_2}x_{i2} + \cdots + \widehat{\beta_k}x_{ik} \tag{7}$$

$\widehat{\beta_0}$, $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\cdots$, $\widehat{\beta_k}$ should minimize the sum of squared errors between all the observed values y_i and the regression value $\widehat{y_i}$.

Let $X = \begin{bmatrix} 1 & \cdots & 1 \\ \vdots & \ddots & \vdots \\ x_{1k} & \cdots & x_{Nk} \end{bmatrix}$, $Y = \begin{bmatrix} y_1 \\ \cdots \\ y_k \end{bmatrix}$, $\hat{\beta} = \begin{bmatrix} \hat{\beta}_0 \\ \cdots \\ \hat{\beta}_k \end{bmatrix}$, and use the least square method to obtain the estimated value $\hat{\beta}$ of β:

$$\hat{\beta} = (X^T X)^{-1} X^T Y \tag{8}$$

C. Inspection and evaluation

After obtaining the estimated value of the least square method of parameters, necessary tests and evaluations are needed to determine whether the model can be applied. Among them, the four parameter values below can be used for statistical test of the model and model parameters.

1) coefficient of determination r^2

When r^2 is larger (i.e., close to 1), the fitting degree of sample data points is stronger, and the relationship between all independent variables and dependent variables is closer.

2) standard error of estimate $\hat{\theta}$

The estimated standard error is the standard error between the actual value of the dependent variable y and the estimated value obtained by the regression equation. The smaller the estimated standard error is, the higher the fitting degree of the regression equation will be.

3) The significance test of regression equation

The significance test of the regression equation is to test the significance of the entire regression equation, or to evaluate whether the linear relationship between all independent variables and dependent variables is close. Generally, the higher the F value is, the more significant the regression effect is.

4) the P value of the F test

ALPHA is the level of significance/confidence, and the default is 0.05 if missing. When P< ALPHA, the regression model is established.

V. MODELING OF POWER DEGRADATION BASED ON TIME SERIES

A. Time series of power supply performance observations

Time series is a series of monitoring samples collected in time sequence[10]. The time series of observation values at monitoring points of the power supply obtained by sampling at equal time intervals are marked as $\{X_{t,1}\}$, $\{X_{t,2}\}$, $\cdots$, $\{X_{t,k}\}$. Where, t represents a certain time of the sequence, $t = 1,2,\cdots,L$ (L represents the total length of the time series); k represents the number of monitoring points after reduction. Y_t represents the threshold voltage monitoring sequence of power MOSFET obtained by multiple linear regression.

Whether the relationship between threshold voltage and key monitoring points changes with time is unknown, the coefficient $\widehat{\beta_i}$ in chapter 3 can be written as the coefficient function $\widehat{\beta_i}(t)$, （$i = 1,2,\cdots,k$）, and when the relation between the two does not change with time, $\widehat{\beta_i}(t)$ is a constant. Substituting $\widehat{\beta_i}(t)$ into formula (5), we can get:

$$Y_t = \widehat{\beta_0}(t) + \widehat{\beta_1}(t)X_{t,1} + \cdots + \widehat{\beta_k}(t)X_{t,k} \tag{9}$$

As shown in figure 4, in practical engineering, the coefficient function $\widehat{\beta_i}(t)$ can be processed as piecewise approximate constant for the convenience of operation.

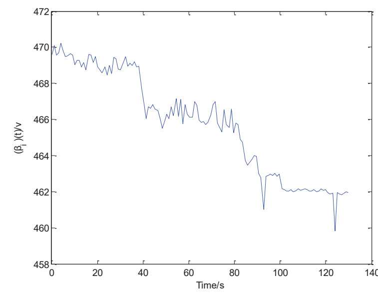
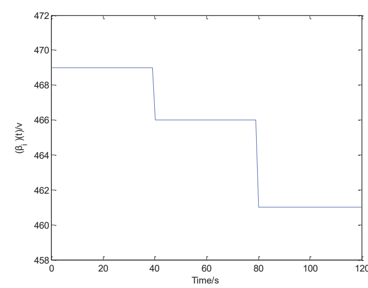


Figure 4. (a) The original graph of $\widehat{\beta_i}(t)$



(b) Approximate processing diagram of $\widehat{\beta_i}(t)$

If the time series of length L is divided into W segments, the size of each segment N=L/W. Among them,$r = 1,2,\cdots,W$.For the r stage, N sets of simulation sample values that can be used for linear regression are shown as follows.

$$\begin{cases} \{x_{(r-1)N,1}, & x_{(r-1)N+1,1}, & \cdots, & x_{rN,1}\} \\ & \cdots & & \\ \{x_{(r-1)N,k}, & x_{(r-1)N+1,k}, & \cdots, & x_{rN,k}\} \\ \{y_{(r-1)N}, & y_{(r-1)N+1}, & \cdots, & y_{rN}\} \end{cases} \tag{10}$$

In the engineering application, at time t, the coefficient function stage of each monitoring parameter data $x_{t,1}$, $x_{t,2}$, $\cdots$, $x_{t,k}$ is judged first. If the monitoring data is in the stage r, the threshold voltage performance evaluation quantity y_t^r of this stage can be obtained through formula (9)

$$y_t^r = \hat{\beta}_0^r + \hat{\beta}_1^r x_{t,1} + \hat{\beta}_2^r x_{t,2} + \cdots + \hat{\beta}_k^r x_{t,k} \tag{11}$$

Where, the coefficient approximation function $\hat{\beta}_i^r$ (i = 0,1,⋯,k) can be estimated from the sample in formula (10) according to formula (8).

The above formula iterates successively to obtain the time series $\{y_t\}$ of threshold voltage observations.

B. Degradation modeling based on ARMA model

For the time series $\{y_t\}$ of the power supply performance evaluation quantity obtained by regression, Autoregressive Moving Average (ARMA) model can be adopted for regression modeling[11]. ARMA model is a combination of autoregressive model (AR) and sliding average model (MA). The model has the following forms:

$$Y_t = \emptyset_1 Y_{t-1} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}, \quad t \in \mathrm{N} \quad (12)$$

Where p and q are the order of the model; $\emptyset_1, \emptyset_2, \cdots, \emptyset_p; \theta_1, \theta_2, \cdots, \theta_q$ are model parameters. $\varepsilon_t, \cdots, \varepsilon_{t-q}$ are independent identically distributed random sequences. The algorithm flow of ARMA model building is shown in figure 5:

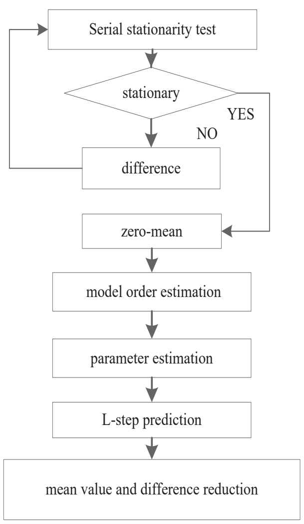


Figure 5. The modeling and prediction process of ARMA model

Among them, the stationary test of the sequence can adopt the methods of reverse sequence test, run test, etc., and the maximum likelihood, least square method and other methods to estimate the model parameters.

After obtaining the degradation model of power supply performance parameters, it can also predict its future value. The one-step predicted value can be given by the following equation:

$$Y_{t+1} = \emptyset_1 Y_t + \cdots + \emptyset_p Y_{t-p+1} - \theta_1 \varepsilon_t - \cdots - \theta_q \varepsilon_{t-q+1}, \quad t \in \mathrm{N} \quad (13)$$

The multi-step prediction of the model can be obtained iteratively from the one-step prediction results.

VI. SIMULATED ANALYSIS

A. The acquisition of characteristic parameters

The PSPICE simulation of the main circuit of radar transmitting power supply is shown in FIG. 6.

The type of MOS tube used in the transmitting power supply is IXFN50N80Q2. According to the chip manual, the threshold voltage V_{th} of this MOS tube is 3V-5.5V. Starting from the initial value of 4.4266v, the threshold voltage was gradually increased to 7.0826v with a step length of 5%, and the influence of simulation degradation on each monitoring point was simulated.

Because PSPICE did not have the function of reading parameters, the simulation data was exported in the form of EXCEL and then analyzed in time domain by MATLAB to obtain the characteristic parameters of waveform (such as mean value, peak value, mean square value and period). Finally, the neighborhood rough set was used to reduce these characteristic parameters. Through analysis and verification, the output voltage was independent of the mean value, mean square value and period of each monitoring point. Therefore, in the paper, the relationship between the threshold voltage and the peak voltage of each monitoring point was only analyzed.

B. Attribute reduction of Neighborhood Rough Set

1040 original data with different degradation states were selected as research samples. These samples included the peak voltage of 8 monitoring points as a conditional attribute parameter, which had covered all monitoring points of the power supply. In addition, the threshold voltage was set as the decision attribute parameter.

The first set $W = 3$ .The threshold voltage was roughly divided into three segments: 4.4266v to 5.3119v, 5.5333v to 6.1972V, and 6.4186v to 7.0826v. Part of the original data (threshold voltage 4.4266v, sample number 10) is shown in the table I.

TABLE I. MONITORING DATA OF SOME CHARACTERISTIC PARAMETERS OF SIMULATION

Sample points	**Waveform peak value of monitoring points（V）**			
	X_1^*	X_2^*	X_3^*	X_4^*
1	470.59198	535.8853149	658.253479	455.0954285
2	470.5107422	536.3687134	660.2072754	454.7179871
3	470.5547791	533.7441406	655.2172241	455.3572998
4	470.6781006	534.2294922	657.5973511	455.0343018
5	470.2027283	527.4317017	648.6554565	455.7512817
6	469.8072205	531.1170044	650.6151733	455.7391968
7	470.4784546	535.8312378	660.7312622	454.4075928
8	470.5107422	536.3687134	660.2072754	454.7179871
9	469.6346741	529.4949341	647.2844849	455.9950256
10	470.574646	530.7171631	653.5281982	455.3027954
Sample points	**Waveform peak value of monitoring points (V)**			
	X_5^*	X_6^*	X_7^*	X_8^*
1	64.51109314	64.67037201	43.70149231	34.30360213
2	64.77389526	64.85243225	43.63402557	34.34662869
3	64.27245331	64.49617767	43.69940948	34.18674589
4	64.56469727	64.7056427	43.65367889	34.41935749
5	63.97063446	64.26181793	43.79498672	34.09890515
6	63.96752548	64.2352829	43.76313019	34.10911186
7	64.93702698	65.00794983	43.70779419	34.42636778
8	64.77389526	64.85243225	43.63402557	34.34662869
9	63.68409348	63.99612808	43.77355957	33.89881672
10	64.29373932	64.50392151	43.66391373	34.27873297

Since the neighborhood rough set was to set the neighborhood diameter for the property parameters uniformly,

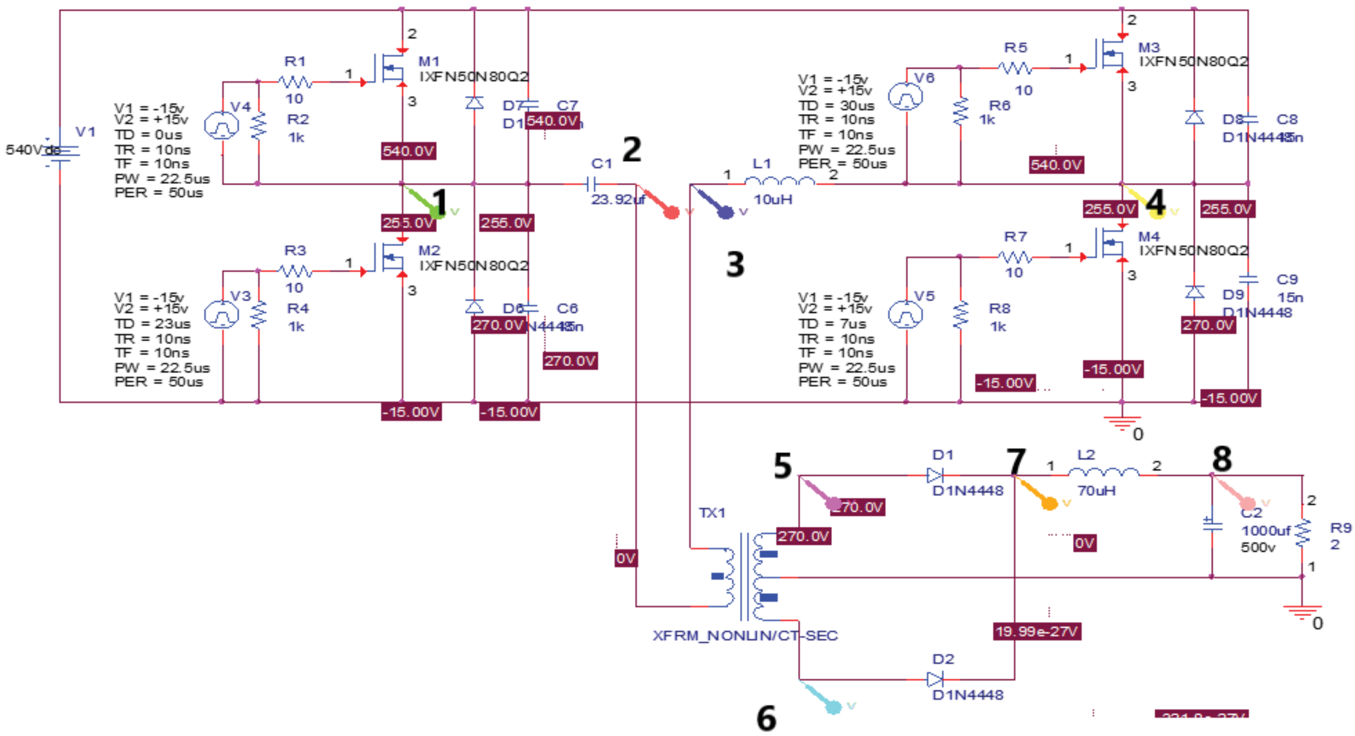


Figure 6. Simulation diagram with monitoring points

the normalization of each property parameter was carried out first. The maximum and minimum method was adopted, as shown in the following formula.

$$\mathrm{f}(x_i) = \frac{x_i - x_{min}}{x_{max} - x_i} \qquad (i = 1,2,\cdots,n) \tag{14}$$

Where, x_{max} and x_{min} were the maximum and minimum values of the sample array respectively. After normalization, the data all felled into the interval of [0,1], so as to reduce the impact of dimensionality inconsistency of various attributes on the results. In order to avoid that the neighborhood radius of the original neighborhood rough set could not be determined, it was calculated according to formula (15).

$$\delta(a_i) = \mathrm{Std}a_i/\lambda \tag{15}$$

Where $\mathrm{Std}a_i$ was the standard deviation of attribute data of a_i, and λ was a set parameter, which was used to adjust the size of the neighborhood according to the data classification accuracy, usually between 2 and 4. The diameter step of the neighborhood was set at 0.01. When the value was 1.5, the test effect was the best. In general, the reduction result of rough set attribute is not unique, and there can be more than one set of reduction. The related reduction results are shown in the table II.

TABLE II. REDUCTION RESULT OF NEIGHBORHOOD ROUGH SET

Period	**Reduction result of Neighborhood Rough Set**	
	The threshold voltage(V)	***Reduction results***
1	4.4266V---5.3119V	X_1^*、X_2^*、X_4^*、X_7^*
2	5.5333V---6.1972V	X_1^*、X_2^*、X_4^*、X_7^*
3	6.4186V---7.0826V	X_2^*、X_4^*、X_7^*

According to the principle that attribute reduction of rough set did not reduce the classification ability of the system, it could be speculated that the number of attribute reduction K=4. Only four monitoring points X_1^*、X_2^*、X_4^*、X_7^* were needed to monitor the degradation of threshold voltage in the transmitting power supply.

C. Multiple linear regression with MATLAB

According to the above reduction results, the monitoring parameters X_1^*、X_2^*、X_4^*、X_7^* were taken as the set of input independent variables, and threshold voltage as the dependent variable y of the output.

The estimated coefficient of linear equation b is obtained by the algorithm, and the first value of the matrix b was the constant β_0, while the remaining values were the regression coefficient β_1, $\cdots$, β_k in turn; At the same time, the statistics used to test the regression model were obtained: the determination coefficient r^2, the observation value of F statistic, the P value of F test, and the estimation of error variance.

By analyzing the data, the system estimates in table III and the test statistics in table IV could be obtained. It was verified that the test statistics all met the standard, and the relation between threshold voltage and key monitoring point was time-varying line.

TABLE III. SYSTEMATIC ESTIMATE OF LINEAR EQUATION

Period	Systematic estimate b					
	Threshold voltage	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_3}$	$\boldsymbol{\beta_4}$
1	4.4266V---5.3119V	148.9369	-0.095	-0.027	-0.178	-0.111
2	5.5333V---6.1972V	86.4769	-0.096	-0.013	-0.079	0.149
3	6.4186V---7.0826V	-5.4277	0.011	0.004	-0.036	0.479

TABLE IV. TEST STATISTIC FOR REGRESSION MODELS

Period	Test statistic for regression models				
	Threshold voltage	r^2	F	P	$\hat{\theta}$
1	0.9783	508.2485	8.1706×10^{-37}	0.0022	0.9783
2	0.9727	324.4918	3.9183×10^{-27}	0.0018	0.9727
3	0.8758	61.7123	2.2845×10^{-15}	0.0087	0.8758

It is now known that the threshold voltage has a linear relationship with the key monitoring parameters, and the autoregressive sliding average model ARMA mentioned above can be used for modeling and prediction. It will be discussed in detail in another paper.

VII. CONCLUSION

In order to realize the study of equipment performance degradation represented by power supply, a new idea combining neighborhood rough set and multiple linear regression was proposed in the paper. Because the actual sample data was difficult to obtain, the method of circuit modeling and fault simulation injection was adopted to obtain the characteristic parameters of the degradation of key components "power MOSFET", and the attribute reduction of the characteristic parameters was carried out through the neighborhood rough set. After selecting the appropriate monitoring points, the relationship model between the threshold voltage and monitoring parameters was established by using the linear regression method. In engineering application, how to use statistical modeling method to realize MOSFET performance prediction will be the follow-up work.

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