Method for Building Health Index of Darlington Transistor Based on KPCA and Mahalanobis Distance

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Abstract. In order to obtain characteristic parameters which can describe the healthy status of Darlington transistor, a method for building Health Index (HI) based on KPCA and Mahalanobis distance was proposed. Through the failure mechanism analysis and Accelerated Degradation Testing (ADT) of Darlington transistor, the degradation data of collector current and saturation voltage were obtained. For the degradation data has obvious nonlinear features and some noise which are unfavorable for failure analysis, a data processing method was put forward by using wavelet packet decomposition and Kernel Component Analysis (KPCA). The interference signal was filtered and the main components were obtained. By using this method. Finally, the Mahalanobis distance was used to fuse these components into Health Index. And the Health Index could represent how the healthy status of Darlington transistor changes. Through multiple sets of data verification, the Health Index used Mahalanobis distance showed higher prediction accuracy than the Euclidean distance with the same fault predict algorithm.

1. Introduction

The Darlington transistor is a kind of high-power transistor which magnification is very high. As the core device of the whole drive circuit, Darlington transistor's health state plays a decisive role in the normal operation of the whole circuit.Whether it is fault diagnosis or prognostics, it is the precondition to obtain the characteristic parameters that can accurately represent the healthy state of the research object [1]. Because the original signals collected tend to show non-linear characteristics, and there are adverse factors such as doping noise, the real health status of the device cannot be understood through direct monitoring data. Therefore, prior to the study, the collected data should be processed. Document [2] features extraction of features of the photovoltaic system by Principal Component Analysis (PCA) to construct the health state of the system; Document [3]uses cascade neural network to fuse various data and complete the fault diagnosis of mechanical rotor imbalance; Document[4]uses instantaneous mixing function to fuse frequency and time data to estimate the crack of the gear wire. In the Document [5], a fault prediction indicator is obtained by using the feature fusion method based on fuzzy reasoning to predict the failure through trend analysis. The above documents only deal with the data from a single aspect, and the results have obvious defects. The PCA used in the Document [2] has great limitation, and the processing ability of nonlinear signal is poor. The Document [3-5] is the feature fusion of non-supervised learning classes, which is to predict the future state of the equipment

through trend analysis. However, the variation range of the characteristic quantity obtained by using the above method is too small, and the change trend of the system is not intuitive, and the prediction accuracy is low.

Therefore, this paper proposes a method to construct a Darlington transistor health index based on KPCA and Mahalanobis distance. Combining wavelet packet decomposition and KPCA, wavelet packet decomposition identified the signal component contained in the original data, then use the KPCA to identify the data feature extraction, filter out noise, the main component of signals are extracted; For multidimensional principal component signal is unable to establish a unified standard, put forward using Mahalanobis distance on the multidimensional signal feature fusion method, the resulting health index showed a good trend, conform to the changes of the Darlington transistor health. Finally, the superiority of this method is verified by compared with other characteristic processing methods.

2. The introduction and failure mechanism analysis of Darlington transistor

2.1. A brief introduction to Darlington Transistor

The Darlington transistor, also known as a compound tube, is a high-power transistor that is often used to drive the power circuit of a high-power device. It is a current amplifier device like the normal triode, and the three pins are base, collector and emitter. There is a typical driver circuit using the Darlington transistor TIP122 in Figure 1.
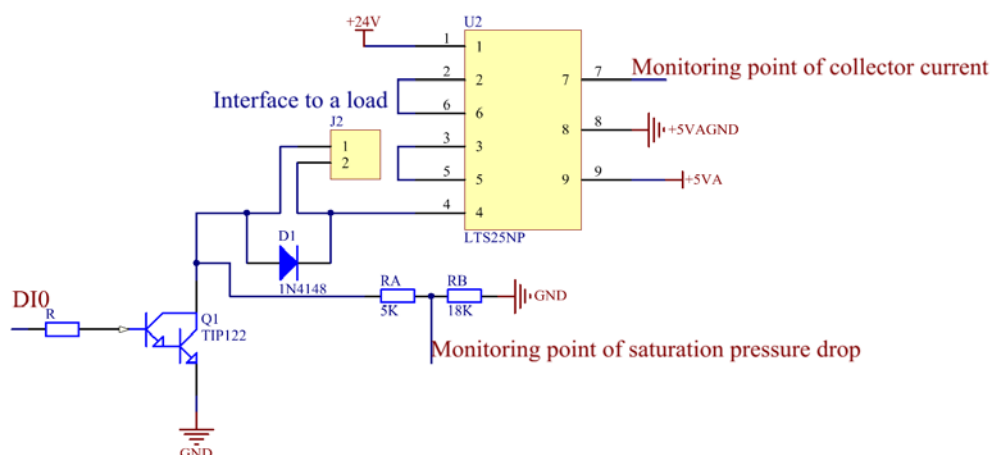
Figure 1. Circuit diagram of TIP122.

In the figure, TIP122 is the NPN type Darlington transistor. The work of the whole drive circuit is described as: "the microprocessor sends the high and low level signal through the pin DI0 to provide the base current for the Darlington transistor TIP122. The base current is used to control the size of the collector current through the Darlington transistor amplification function, thus driving the high-power load work. Therefore, it is necessary to ensure that the Darlington transistor is in good condition in order to realize the function of controlling high power load with microprocessor. In the practical engineering application, it is found that in the driving circuit, the high power transistor which produces the large current is the least reliable and the most prone to failure [6].So it is very important to study the failure mechanism of Darlington transistor. In this paper, the failure mechanism of Darlington transistor is analyzed.

2.2. Analysis of failure mechanism of Darlington transistor

Temperature, humidity stress and electrical stress are the main stresses for Darlington transistor that cause its failure. The failure modes caused by these three stresses mainly include transistor forward

current transmission ratio, leakage flow through large or open circuit and reduced saturation pressure drop. There are multiple failure mechanisms in each failure mode, as shown in table 1.

**Table 1.** Main failure mechanism of Darlington transistor.

Failure modes	The failure mechanism (chip)	The failure mechanism(encapsulation)
The forward current transmission ratio decreases	1.Oxide breakdown 2. Emission characteristics degenerate. 3. The emitter and the base layer multilayer metallization transfer. 4. Electrode contact resistance degradation.	1. Lead bonding degradation. 2. The degradation of the bonding interface between the chip and beryllium ceramics increases the thermal resistance. 3.Chip crack
Leakage flows through large or open channels.	1. Dielectric leakage or defect. 2.Metal transfer	1. The shell contains a lot of water vapor. 2. Lead bonding process defects, common solder accumulation or climbing to PN junction surface. 3. Chip bonding process defects.
The saturation pressure decreases.	1.Electrochemical erosion of the chip and bond 2.Contact resistance degradation	1. Chip bonding degenerates. 2. Lead bonding degenerates.

Through the analysis of the Darlington transistor failure mechanism, shows that the main degradation characteristic parameters for the forward current transfer ratio decreased and saturated pressure drop decreases with the Darlington transistor life falling. Therefore, after synthesizing the feasibility of the failure mechanism and the actual observation point, this paper selects the collector current I_C and the saturation voltage drop V_{CE} of Darlington transistor for data monitoring.

3. Construct the model principle of health index

3.1. Theoretical model
Combining wavelet packet decomposition, KPCA and Mahalanobis distance, the method of building a healthy factor of Darlington transistor is shown in figure 2.
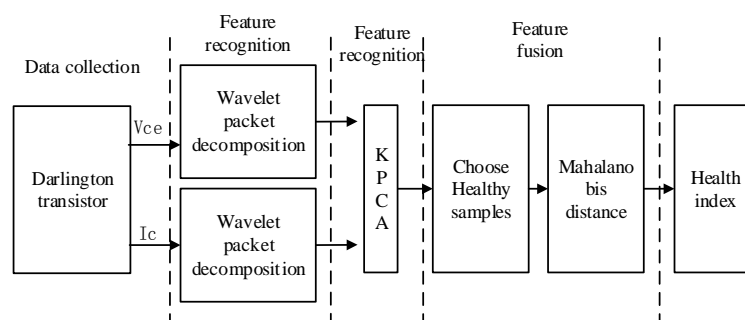
Figure 2. The theoretical model for building HI.

Firstly, wavelet packet decomposition is carried out for the acquired characteristic parameters, and realized the multidimensional data elements exist in the original data. Then, the main components of the data are extracted by using KPCA to reduce dimension data [7]. Finally, the Mahalanobis distance was used to fuse the principal component data to obtain the health index.

3.2. Wavelet packet decomposition

Given the orthogonal scaling function $u_n(t)$ and wavelet function $u_{2n}(t)$, the following relation is satisfied[8]:

$$u_{2n}(t) = \sqrt{2}\sum_{k\in Z}h(k)u_n(2t-k) \tag{1}$$

$$u_{2n+1}(t) = \sqrt{2}\sum_{k\in Z}g(k)u_n(2t-k) \tag{2}$$

Among them are low pass and high pass filter coefficients respectively.The set defined above is the orthogonal wavelet packet.

3.3. Kernel principal component analysis (kpca)

$X = [x_1, x_2, \cdots, x_m]$ There are N variables in each sample. Define it as a data set for input space R^N.Define nonlinear mappings: $\Phi : x_i \to \Phi(x_i)$, $i = 1, 2, \cdots, m$.The original data is mapped from the low-dimensional input space R^N through the nonlinear transformation Φ to the high-dimensional space F.

The covariance matrix after mapping:

$$C = \frac{1}{m}\sum_{i=1}^{m}\Phi(x_i)^T\Phi(x_i) \tag{3}$$

Assuming that the sample has been centralized, then define the verification matrix $K_{m\times m}$

$$K(x_i,x_i) = \Phi(x_i)^T \bullet \Phi(x_j) = \left\langle \Phi(x_i), \Phi(x_j) \right\rangle \tag{4}$$

A projection main component $V_j(j = 1, 2, \cdots, p)$ on the feature space can be obtained, and the main component t_k obtained by projection of the original sample x_i on V_j is:

$$t_k = \left\langle v^k, \Phi(x) \right\rangle = \sum_{i=1}^{m}\alpha_{ik}\left\langle \Phi(x_i), \Phi(x) \right\rangle \tag{5}$$

Mahalanobis distance

Mahalanobis Distance (MD) is a statistical measure proposed by Mahalanobi, an Indian statistician, to calculate the covariance Distance between data samples [9].The similarity of two sample sets can be represented by Mahalanobis distance calculation. The larger the Mahalanobis distance, the more obvious the difference between the samples. Compared with Euclidean distance, Mahalanobis distance is not affected by dimensions, can reflect the connection between the various characteristic parameters, the relationship between the characteristic parameters and eliminate interference [10].

The calculation formula of Mahalanobis distance between sample Y and sample set $X_{m\times n}$ is as follows:

$$d_{MD} = \sqrt{(y-\overline{x})\Sigma^{-1}(y-\overline{x})^T} \tag{6}$$

$\bar{x} = \dfrac{1}{n}\sum\limits_{i=1}^{n}x_i$ is the center of mass of the sample set X, and $\Sigma = \dfrac{1}{n-1}\sum\limits_{i=1}^{n}(x_i - \bar{x})(x_i - \bar{x})^T$ is the covariance matrix of X.

4. Experiment and result analysis

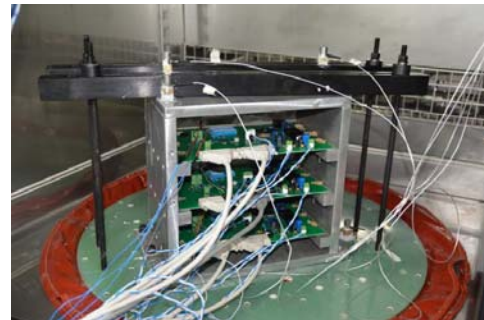### 4.1. Accelerated degradation experiment of Darlington transistor

In this paper, the accelerated degradation experiment is carried out on the driver circuit board shown in FIG. 1. The core experimental device selected in this experiment was TIP122 Darlington transistor made by STM.The package model is TO-220.

This experiment by GWS comprehensive stress test chamber for circuit board environment temperature of 60℃, relative humidity is 90%, the whole experiment process conditions remain the same. The ADLINK-PCI9114 data acquisition card was used to collect data and the sampling frequency was 1000Hz.

Since electrical stress is also an important factor affecting the health status of Darlington transistor, in addition to setting environmental stress, the microprocessor in this experiment has always maintained a high level output for Darlington transistor, which makes the Darlington transistor moment in the lead state. At the same time, the power resistor with the same resistance as the driving load is selected as the load to ensure the stability of the driving circuit. The specific test bed situation is shown in figure 3. The flow chart of the experimental system is shown in figure 5.

**Figure 3.** Accelerated degradation testing platform of Darlington transistor.

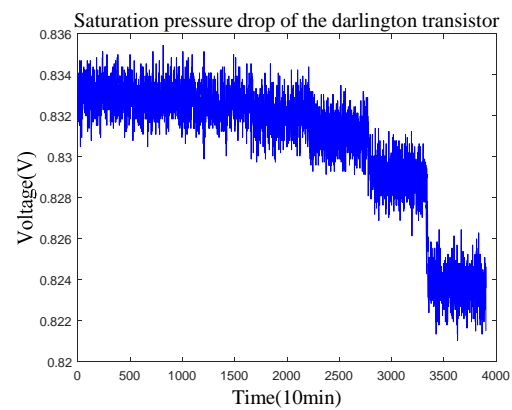**Figure 4.** The photo of the experimental Scene.
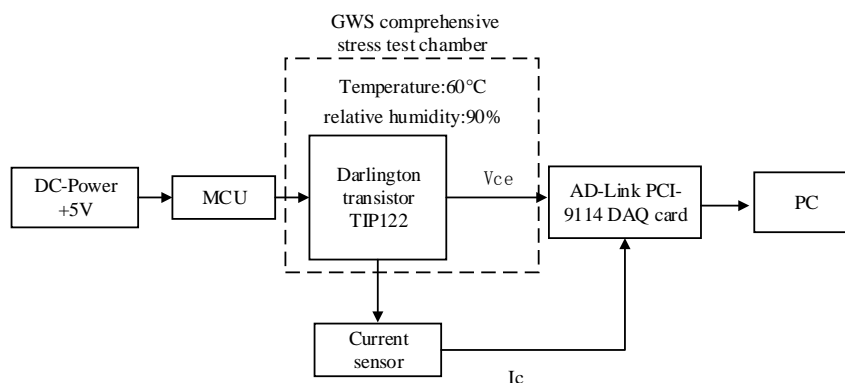
Figure 5. The flow diagram of ADT.

The Darlington transistor accelerated degradation experiment was conducted in 4 groups, with 3 samples in each group for 39,000 minutes, and the experimental scene was shown in figure 4.

Experimentally obtained 12 samples of the collector current and saturation pressure drop data, the contrast found that all the sample data are presented similar trends, namely the collector current saturated flow and pressure drop are reduced. The experimental results are the same as that of the Darlington transistor failure mechanism. Taking the data of the conduction current I_C and saturation pressure drop V_{CE} of sample 1 as an example, the method presented in this paper is described and verified. The data of sample 1 is shown in figure 6 and figure 7.
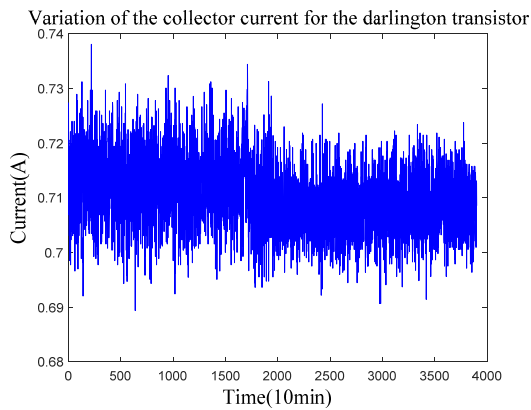
**Figure 6.** The data image of collector current   **Figure 7.** The data image of saturation voltage drop

It can be seen from the original data graph that, there is a certain trend of change in the conduction flow and saturation pressure drop of the Darlington transistor collector in the time range of monitoring, and the saturation pressure drop of the collector conduction current is reduced. If the direct and practical raw data is used as the characteristic parameter to evaluate the health status of the device, it will increase the complexity of the processing algorithm, reduce the performance of all kinds of algorithms, and introduce a huge error, which cannot reflect the true health status of the device. Therefore, the raw data is selected for pre-processing to construct health index.

4.2. Feature recognition based on wavelet packet decomposition.
The wavelet packet decomposes by filtering the signal through a series of low pass filters and a high pass filter to break the signal into a binary tree. In this paper, three layers of decomposing are used to respectively extract the 8 signature signals from the low frequency to high frequency of the third layer. The specific decomposition is shown in figure 8:
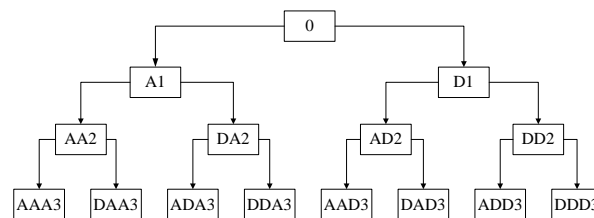

**Figure 8.** Three layers structure of wavelet packet

In figure 8, *A* denotes the low frequency and *D* represents the high frequency. The number at the end represents the number of layers of the current wavelet packet decomposition, and the specific decomposition relationship is:

$$S = AAA3 + DAA3 + ADA3 + DDA3$$
$$+ AAD3 + DAD3 + ADD3 + DDD3 \tag{7}$$

At present, the selection of wavelet basis function has no clear standard, and the research shows that in the field of health status evaluation, the researchers pay more attention to the overall change trend of the signal in the life cycle, and the selection of different wavelet basis functions does not have a significant impact on the wavelet packet energy value.In this paper, the *db*10 wavelet basis function is selected for three-layer wavelet packet decomposition, and each 100 minutes is set as one cycle, and the wavelet packet decomposition is carried out for the data in the period. The data graph of Darlington transistor collector and saturated pressure drop obtained by wavelet packet decomposition is shown in figure 9 and figure 10.
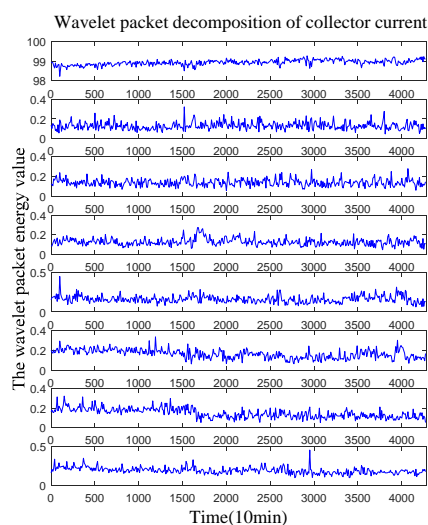
Figure 9. Wavelet packet decomposition of collector
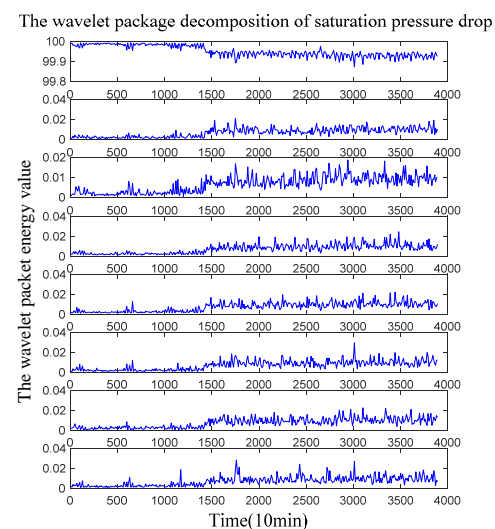
Figure 10. Wavelet packet decomposition of saturation voltage drop

The images from top to bottom are: signal energy in ($AAA3, DAA3, \cdots, DDD3$) frequency band. Through the analysis of the image, it can be learned that the energy value of the signal of $AAA3$ frequency band is far greater than the energy value of the signal in other frequency bands, indicating that the main component of the target signal to be obtained is in that frequency band. Point of view, from the trend of the energy in each band of the signal energy are changed with the increase of time, and illustrates the monitoring parameters from the side of performance degradation.
The data dimension through wavelet packet decomposition is 16.

4.3. Feature extraction based on kernel component analysis.
The key part of the kernel component analysis method is the selection of kernel functions. The commonly used kernel functions are polynomial kernel function, sigmoid kernel function and RBF kernel function [12].Selecting different kernel parameters for the same kernel functions can also have different effects. At present, no unified theory is put forward for the selection of kernel function [13].In this paper, PCA method, KPCA (p-kpca) based on polynomial kernel function and KPCA (rbf-kpca) based on radial basis (RBF) kernel function are used to extract data.
The specific results are shown in table 2.

Table 2. Accumulative contribution rate of the top ten main components

Method	σ	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
PCA	—	61.08	68.88	75.73	81.24	86.29	90.99	94.96	98.52	98.93	99.24
P-KPCA	2	78.12	90.14	93.45	97.58	98.76	99.21	99.58	99.79	99.90	99.97
	3	78.64	90.35	93.80	98.01	99.14	99.35	99.62	99.81	99.94	100
	4	77.27	90.44	94.57	98.55	99.21	99.47	99.70	99.84	99.97	100
	5	76.86	90.45	94.77	95.68	99.30	99.52	99.74	99.88	99.95	100
RBF-KPCA	2	83.34	91.47	95.83	99.75	99.80	99.87	99.92	99.98	100	100
	3	81.14	91.52	95.36	98.79	99.45	99.63	99.81	99.01	99.99	100

It can be seen from the analysis results that KPCA method is significantly better than PCA method for data reduction. The cumulative contribution rate of the first nine principal components of PCA is less than 99%；When $\sigma = 2$, the cumulative contribution rate of the first 5 principal components of Polynomial KPCA is less than 99%;When $\sigma = 3, 4, 5$, the cumulative contribution rate of the first 4 principal components of Polynomial KPCA is less than 99%;When $\sigma = 2$, the cumulative contribution rate of the first 3 principal components of KPCA (rbf-kpca) is less than 99%;When $\sigma = 3$, the cumulative contribution rate of the first 3 principal components of KPCA (rbf-kpca) is less than 99%.By contrastive analysis, the radial basis KPCA $(\sigma = 2)$ extracts the most concentrated feature information, and the reduction effect is most obvious. Therefore, the radial basis KPCA is selected as the kernel function of feature extraction. The first four main ingredients (rbf-kpca) which make the cumulative contribution rate over 99% is used to be the feature extractions.

4.4. Features fusion based on Mahalanobis distance.
The data dimension through the extraction of KPCA is 4.Since each data contains some information to monitor the target signal, if a single feature is selected as the characteristic parameter to characterize the health status of the Darlington transistor, it will not be able to meet the requirements of precise system health assessment and life prognostics and diagnosis [13]. According to the raw data, it can be seen that the forward current and the saturation pressure drop of the Darlington transistor remain essentially unchanged within 0-15000 minutes. It can be considered that the device is in good condition during this period of time, and no degradation of performance occurs. So, the first 150 samples are used as a healthy sample. The Mahalanobis distance of the current sample from a healthy sample is calculated as a health index in the chronological order.

Figure 11. is the data information after the normalized Mahalanobis distance after the feature processing.

In order to evaluate the advantages and disadvantages of the methods presented herein, the results of the characteristic fusion of the feature extraction data using the Euclidean distance method and the characteristic fusion of the original data using the martensite data are listed. The specific data is shown in figure 12 and figure 13.

Through the comparison, it can be seen that the three sets of data show a certain tendency, and the overall value of the data increases with time. The difference of the current state sample and the healthy state sample becomes larger over time, and the Darlington transistor presents a state of continuous deterioration, which conforms to the real life change of the device. It is due to that difference in the magnitude of the data present by KPCA, which is due to the difference of the order of magnitude of the data extract from KPCA, the corresponding weight is automatically generated when calculating Euclidean distance for different order of data, the error due to the introduction of scale is obtained. The Mahalanobis distance is not affected by dimensionality, and can reflect small changes in data. Therefore, the trend of Mahalanobis distance data is more obvious and the difference between samples is more real. In order to quantitatively evaluate the performance of the above three sets of distance data, this paper adopts the Autoregressive Moving Average model (ARMA) model to predict the

failure of the above three types of data, and evaluates the data performance through the relative error between the predicted data and the real data. The first 180 sample points were selected as the training samples of the model, and the latter 60 sample points were predicted. The predicted results are shown in figure 14, figure 15 and figure 16.
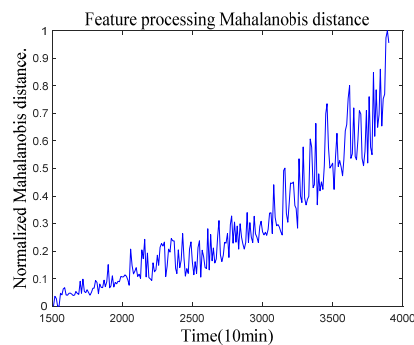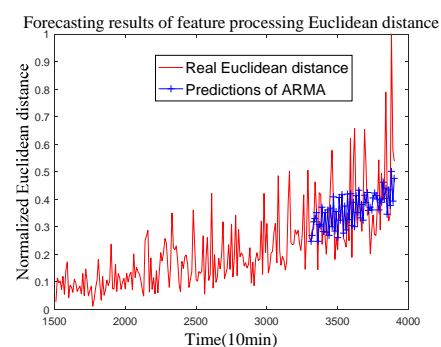

Figure 11. Feature processing Mahalanobis distance
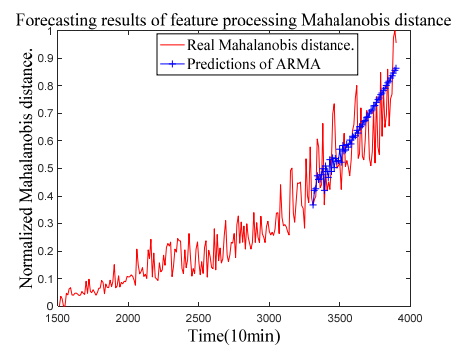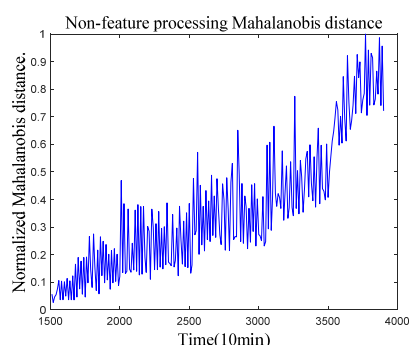

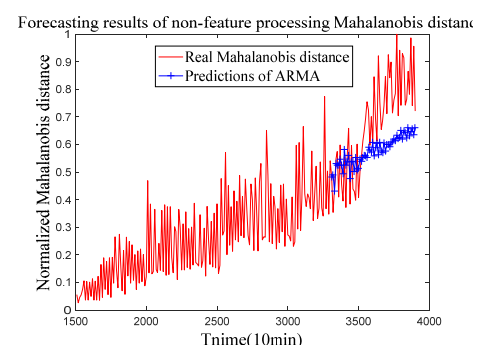**Figure 14.** Forecasting results of feature processing Mahalanobis distance
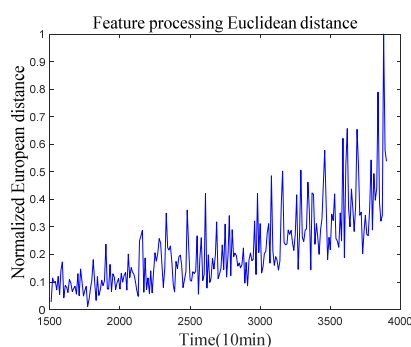
Figure 12. Feature processing Euclidean distance

Figure 15. Forecasting results of feature processing Euclidean distance

Figure 13. Non-feature processing Mahalanobisdistance

Figure 16. Forecasting results of non-feature processing Mahalanobis distance

In the case of using wavelet packet decomposition and KPCA for feature processing, the method of using Mahalanobis distance feature fusion is better than that of Euclidean distance; In the case of characteristic fusion using Mahalanobis distance, the method of using wavelet packet decomposition and KPCA feature processing is better than that of the uncharacteristic treatment, and the Mean

Relative Error of Mahalanobis distance with characteristic processing is the least, which is better than the other two methods.

5. Conclusion

(1)The deterioration of the health state of the Darlington transistor can be manifested as the performance degradation of the collector conductance current and the saturation pressure drop by analyzing the failure mechanism of the Darlington transistor and accelerating the degradation experiment.

(2)Using the KPCA signature extraction method to extract the main ingredient in the original signal, the results show that KPCA has a superior performance in the lower dimension than the PCA method; Using wavelet packet decomposition and KPCA to process raw data can effectively extract the degradation information of original characteristic parameters from raw data and improve the performance of data feature fusion effectively.

(3)Using the martentin distance to characterize the signature fusion, the resulting data contains more effective information that accurately reflects the health status of the Darlington transistor; The ARMA fault prediction model was used to predict the Darlington transistor's health index based on martenard distance characteristics, with a prediction error of 6.22%.

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