



# Monitoring Method of Permanent Magnet Synchronous Motor Temperature Variation Signal Based on Model Prediction

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**Abstract.** In order to improve the monitoring accuracy and quality of permanent magnet synchronous motor (PMSM) temperature variation signal, and achieve the ideal effect of high-precision monitoring of PMSM temperature variation signal, model prediction is introduced, and the monitoring method of PMSM temperature variation signal based on model prediction is studied. The wireless sensor technology is used to collect the temperature signals of various parts of the motor, integrate, clean, replace and protocol the original data, establish a deep learning network model to predict the characteristics of the motor temperature variation, identify the motor temperature variation signal, combine the variation pruning and variation interval, and use the delayed reporting strategy to monitor the early warning of the motor temperature variation signal, complete the monitoring of temperature variation signal of permanent magnet synchronous motor based on model prediction. The experimental analysis results show that the recall rate and accuracy rate of the design method are above 90%, and maintain detection efficiency above 97%, the monitoring accuracy of the temperature variation signal of the permanent magnet synchronous motor is high.

**Keywords:** Model prediction · Permanent magnet synchronous motor · Abnormal temperature signal · Monitor · Wireless sensor technology

## 1 Introduction

Permanent magnet synchronous motors (PMSM) are widely used as driving motors for electric vehicles, ships, etc. due to their excellent power density, efficiency and initial torque. But in actual use, its high power density will bring serious temperature rise problems, which will affect the working efficiency of the motor, and even damage the core components of the motor. For example, when the temperature exceeds a certain limit, it will cause aging or damage of the stator winding insulation layer, causing damage to the motor; It will lead to irreversible demagnetization of the permanent magnet,

which will affect the performance of the entire motor, resulting in high maintenance costs [1]. Therefore, the monitoring of temperature variation signal has always been the focus of the research of permanent magnet synchronous motor. Installing sensors inside the permanent magnet synchronous motor is the most direct method [2] to obtain the abnormal temperature signal of components. This method has high requirements for the installation position, quantity and accuracy of sensors. The internal wiring of the motor will be more complex, and the cost will also increase. Therefore, the monitoring method of indirect temperature variation signal of permanent magnet synchronous motor has always been a research hotspot in this field. Therefore, in order to ensure the safe, stable and efficient operation of the permanent magnet synchronous motor in the work, an effective and reliable method is needed to monitor the temperature variation signal of the permanent magnet synchronous motor. The temperature variation signal monitoring and thermal protection of the permanent magnet synchronous motor provide certain technical support.

Based on the above background, in recent years, more research has been done on the monitoring methods of temperature variation signal of permanent magnet synchronous motor. The existing traditional monitoring methods of temperature variation signal of permanent magnet synchronous motor can be summarized into the following two categories: first, finite element method. Finite element analysis [3] is a common method for electromagnetic design and calculation in 2D and 3D models. The temperature of permanent magnet synchronous motor [4] is obtained by discretizing the finite element of the motor model, setting the physical field boundary, conducting nonlinear transformation on the thermal boundary, establishing the heat balance equation of each element, and solving the domain total equation to simulate the heat dissipation calculation. The finite element analysis method can accurately calculate the uneven distribution of power loss inside the motor, and obtain the specific distribution of temperature field inside the motor. However, the modeling of the finite element analysis method is more complex and requires a lot of computing resources, which is difficult to meet the actual engineering needs.

Second, magnetic flux observation method. With the increase of temperature, the residual magnetic flux density of permanent magnetic materials will decrease significantly. The flux observation rule is to obtain the change of the flux through the flux observer, establish an accurate parameterized motor temperature model, and obtain the temperature of the permanent magnet synchronous motor rotor [5]. Takashi et al. proposed a magnetic temperature estimation method for variable flux leakage built-in permanent magnet synchronous motor based on flux linkage observer, which consists of Gopinath flux observer, flux linkage observer and magnet temperature estimator based on lookup table. Min et al. used stator current, permanent magnet flux and stator resistance as state variables to construct extended Kalman filter, estimate permanent magnet flux chain and stator resistance and indirectly obtain stator temperature rise [6]. The flux observation method is applicable to the whole torque range of the motor, and can track the aging effect of the permanent magnet. However, the magnetic flux observation method has high requirements for the accuracy of observation instruments in practical applications, and the magnetic flux deviation due to measurement errors has a greater

impact on the prediction results of temperature, so attention must be paid to reducing the magnetic flux deviation in use.

Among the existing traditional methods, the accuracy of finite element analysis method is the highest compared with other methods, but due to the limitations of large amount of calculation, long time consumption and so on, it is not much in practical use. The flux observation method has high requirements for the accuracy of the signal observer. These classic traditional methods require researchers to have a lot of motor thermal knowledge and experience in parameter selection, and the traditional methods can no longer meet the actual needs. Therefore, a monitoring method based on model prediction for temperature variation signal of permanent magnet synchronous motor is proposed. The use of mathematical modeling to predict the temperature variation of a permanent magnet synchronous motor allows for temperature monitoring without the need for sensors. Model predictive algorithms can accurately forecast the motor's temperature based on historical data and environmental parameters. This enables appropriate control actions based on the predicted results. By continuously updating the model parameters and input variables, dynamic monitoring and adjustment of the motor's temperature variation can be achieved, ensuring its normal operation within a safe temperature range.

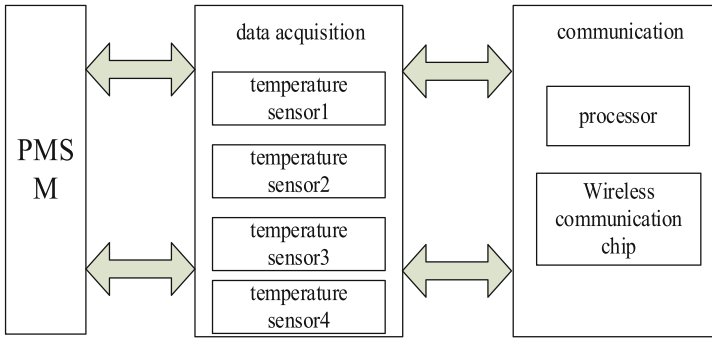
## 2 Design of Monitoring Method for Abnormal Temperature Signal of Permanent Magnet Synchronous Motor Based on Model Prediction

### 2.1 Temperature Data Acquisition of Permanent Magnet Synchronous Motor

In order to monitor the abnormal temperature signal of permanent magnet synchronous motor (PMSM), it is necessary to obtain the temperature monitoring data of PMSM during operation. This time, the wireless sensor technology is used to collect the temperature signal of the permanent magnet synchronous motor [7]. Suppose that the temperature wireless sensor sequence of a permanent magnet synchronous motor [8] is  $S$ , which is expressed by the formula:

$$S = \begin{bmatrix} S_1^1 & S_1^2 & \cdots & S_1^t \\ S_2^1 & S_2^2 & \cdots & S_2^t \\ \cdots & \cdots & \cdots & \cdots \\ S_n^1 & S_n^2 & \cdots & S_n^t \end{bmatrix} \quad (1)$$

where,  $S_n^t$  Represents the No  $n$  Temperature sensors at monitoring points  $t$  The status value of the time step. Given the multi-dimensional sensor sequence of the permanent magnet synchronous motor [9] in the whole day in combination with the actual scene, the permanent magnet synchronous motor [10] temperature variation signal is measured and recognized in real time using the data driven method, and the temperature variation signal record [11] is formed. In particular, the text is mainly based on model prediction for research, so the abnormal signal of motor temperature needs to be monitored online and in real time, rather than a global comparison check after obtaining all data. The following figure is the schematic diagram of motor temperature data acquisition.



**Fig. 1.** Schematic diagram of motor temperature data acquisition

As shown in Fig. 1, during the operation of the motor, wireless sensors are introduced to collect the temperature data of the motor. The temperature monitoring area includes the generator winding, generator bearing, rectifier, tower base control cabinet of the permanent magnet synchronous motor [12] and the environment of the motor. The communication standard of temperature wireless sensor is based on IEEE802.15.4 standard, also known as Zigbee standard, which is promoted by international Zigbee alliance. Compared with common wireless communication standards, IEEE802.15.4 standard protocol stack is compact and simple, with low specific implementation requirements. As long as the 8-bit processor is equipped with 5 kb ROM and 64 kb RAM, it can meet its minimum needs, thus greatly reducing the cost of the chip [13]. In wireless sensor networks, the channel contention of nodes is realized by CS-MA/CA (Carrier Sense Multiple Access/Collision Avoidance) mechanism. CSMA/CA has two modes to choose from: slotted CSMA/CA and slotless CSMA/CA, which are respectively applied to beacon enabled communication and non enabled communication [14]. In this design method, the beacon enabled time slot CSMA/CA mode is used to compete for the channel access. CSMA/CA with timeslots involves the timeslot guarantee mechanism - GTS oGTS, which is similar to the time division multiple access (TDMA) mechanism, but it can dynamically allocate timeslots for devices with receiving and sending requests. The use of time slot guarantee mechanism requires time synchronization between devices. The time synchronization in IEEE 802.15.4 is achieved through the “super frame” mechanism.

The superframe divides the communication time into active and inactive parts. During inactivity, the devices in the PAN network will not communicate with each other, so they can enter the sleep state to save energy. The active period of the superframe is divided into three stages: beacon frame transmission period, competitive access period (CAP) and non competitive access period (CEP).

In the contention access period of superframe, IEEE 802.15.4 network equipment has a time slot CSMA/CA access mechanism, and any communication must be completed before the end of the contention access period. In the non competitive period, the coordinator divides the non competitive period into several CTS according to the CTS application of the device in the last superframe PAN network. Each CTS consists of several time slots, and the number of time slots is specified when the device applies

for CTS. If the application is successful, the application device will have the specified number of time slots. The timeslot in each CTS is assigned to the timeslot application device, so there is no need to compete for channels. The IEEE 802.15.4 standard requires that any communication must be completed within the CTS assigned by the user.

It is specified in the superframe that the non contention period must follow the contention period. The functions of the competition period include that network devices can send and receive data freely, devices in the domain apply to the coordinator for the CTS period, and new devices join the current PAN network. In the non competitive phase, the equipment designated by the coordinator sends or receives data packets, and sends the received motor temperature signal to the computer for subsequent prediction and analysis of temperature variation signals.

## 2.2 Motor Temperature Signal Conversion

After obtaining the required monitoring data, process the data. The data extracted from the PMSM temperature database is often missing or the value of the data is too low. Therefore, in order to ensure that there are sufficient data support conditions for subsequent temperature variation signal prediction and monitoring, the original data shall be integrated, cleaned, replaced and protocol processed. The first step is to summarize the heterogeneous data in the monitoring data and refine the original data at the bottom. The second step is to clean the data [15] by filling missing data and processing noise. Step 3, perform decimal scaling transformation on the data, and the expression is:

$$V(n) = v^S(n) / 10^k \quad (2)$$

where,  $V(n)$  Indicates the monitoring point after transformation  $n$  Temperature signal sample;  $v^S(n)$  Indicates the original temperature signal;  $k$  Indicates the minimum ratio [16] to ensure that the maximum value of the transformed temperature signal is less than 1. Use the above formula to complete the data transformation. Step 4: Since the data set obtained from the wireless sensor monitoring database is large, it will consume a lot of time in the later modeling, so the data needs to be processed by specification. Reduce the amount of data in the camphor form by extracting data at 10 min intervals.

## 2.3 Temperature Anomaly Signal Recognition Based on Model Prediction

The recurrent neural network in deep learning is a mainstream learning model used to serialize data modeling. This time, the deep learning technology is used to establish a prediction model, expand the input sequence data in the direction of time or event evolution, and establish the structure of the deep learning network model as shown in the following Fig. 2.

As shown in Fig. 2,  $x$  Represents the input matrix;  $e$  Represents hidden layer vector;  $a$  Represents the output matrix;  $V$  Represents the weight matrix of the output layer;  $U$  Represents the weight matrix of the input layer;  $W$  Represents the weight matrix [17] of the hidden layer. In the deep learning network model, the hidden layer of the current time of the cyclic network depends not only on the input of the current time, but also on

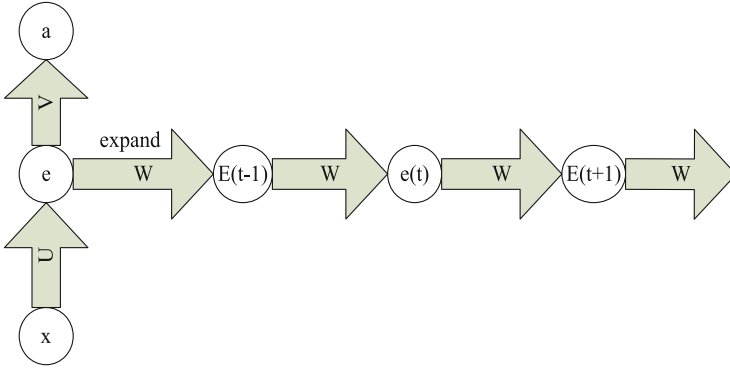


Fig. 2. Structure diagram of deep learning network model

the hidden layer of the previous time, and the weight matrix of the hidden layer determines how much information will be retained to the current time at the previous time. This structure has a natural advantage for processing serialized data. It can mine the relationship between the front and back sequences and give weight, form memory and participate in the following operations [18]. Input the transformed motor temperature signal into the deep learning network model, use the network model to predict the temperature variation of each motor component, and determine the memory and forgetting of information through the forgetting gate of the memory block, which is expressed by the formula:

$$C(t) = f \odot C(t - 1) + i^{V(n)} \odot \tilde{C} \tag{3}$$

where,  $C(t)$  Indicates the current cell state;  $f$  Indicates the forgotten door;  $C(t - 1)$  Indicates the cell state at the previous moment;  $i^{V(n)}$  Indicates the input door;  $\tilde{C}$  Indicates the internal cell status [19]. The forgetting door needs to be activated by the activation function, which is expressed by the formula:

$$f = \varepsilon(W_i[g_{t-1}, V(n)] + eab) \tag{4}$$

where,  $\varepsilon$  Represents the activation function;  $g_{t-1}$  Indicates the hidden state at the previous time;  $b$  Represents the corresponding offset matrix. The value of the forgetting gate is limited to (0,1), which can directly control how much information of the cell state at the previous time can participate in the operation at the current time, that is, 0 is discarded and 1 is retained, playing the role of selection and forgetting. According to the current cell state, the output gate is calculated to calculate the characteristics of the temperature signal variation of the permanent magnet synchronous motor. The calculation formula is:

$$y = a \odot \tanh[C(t)] \tag{5}$$

where,  $y$  Represents the output vector of the deep learning network model, that is, the characteristics of the motor temperature variation signal;  $\tanh$  Indicates the activation operation [20]. According to the characteristics of the temperature abnormal signal

calculated above, the mean square error of the motor temperature signal is predicted, which is expressed by the formula:

$$h = \frac{1}{N} \sum (y - y^*)^2 \quad (6)$$

where,  $h$  Mean square error of motor temperature signal;  $N$  Represents the number of training samples of deep learning network model;  $y^*$  Indicates the maximum allowable limit of motor temperature signal. If  $h$  If it is greater than zero, it means that the current temperature signal is abnormal. If  $h$  If it is less than zero, it means that the current temperature signal is a normal signal, so the model can be used to predict the characteristics of motor temperature variation, and identify the abnormal signal.

#### 2.4 Alarm Monitoring of Abnormal Motor Temperature Signal

Judging based on the prediction results of the deep learning network model alone will produce many false positives and false alarms. This is because the essence of the deep learning network model prediction is to judge abnormal changes based on the density between samples. In this way, the temperature value of a motor measurement point is too different from that of most other motors, and the motor temperature signal will be considered as abnormal changes. Although this is correct, the actual situation is that the temperature values of different motors will change slightly when the motor is running, but it is still fluctuating up and down in the normal range as a whole. In addition, it is only considered that the abnormal change is valid when the temperature of one measuring point is higher than that of other measuring points. The “abnormal change” caused by temperature lower than other measuring points is not considered in this paper. Therefore, we will eliminate these false positives through a series of rules, that is, pruning.

The initialization matrix is used to evaluate the abnormal degree of motor temperature signal from different feature dimensions. The calculation formula is as follows:

$$flag \begin{cases} 1 & h \geq \max(95\_percentile(h), y^*) \\ 0 & else \end{cases} \quad (7)$$

where,  $flag$  Indicates the abnormal index value of the motor based on different characteristic dimension variables; If the temperature of the first measuring point of the motor is greater than 95% of the quantile and the maximum temperature limit of all motor temperature measuring points at the same time point, then the abnormal temperature signal indicator of this measuring point of the motor is set to 1, indicating that the current temperature value of this measuring point of the motor is at a high level, that is, the temperature signal of this measuring point is a abnormal signal; otherwise, the signal indicator is set to 0, indicating that the temperature signal of this measuring point is a normal signal.

After the aforementioned pruning operation, the state of the motor monitoring results at each time may be discontinuous. Therefore, if the starting point of an abnormal change is determined directly based on the original results, a large number of records will be generated. How to determine the start of a mutation record and balance the detection

accuracy and false alarm rate requires a reasonable design of the monitoring process. In this paper, in order to accurately determine the starting point, duration and other key information of the temperature anomaly signal, the strategy of delayed reporting is designed for the real-time monitoring of the flow type. The specific way is as follows.

If there is no abnormal change reported in the front interval, when the front 1 bit is merged into the front interval to form a abnormal change record, the starting point of the abnormal change record is the first non-zero bit in the motor lead time window. If there is an exception in the leading interval, the leading 1 bit is merged into the abnormal change record in the leading interval. If an abnormal change is reported continuously, and then all the changes in the motor lead time window are set to normal, the record of the abnormal change ends. At this time, the starting point of the motor lead time window is the end point of the abnormal change record. Since then, the newly reported changes have been regarded as another record of changes. According to the above strategies, the warning and monitoring of the motor temperature change signal is carried out to realize the monitoring of the permanent magnet synchronous motor temperature change signal based on the model prediction.

### 3 Experimental Analysis

#### 3.1 Experiment Preparation

In order to verify the reliability and feasibility of the monitoring method for temperature variation signal of permanent magnet synchronous motor based on model prediction designed in this paper, a permanent magnet synchronous motor is taken as an experimental object, and the following table shows the parameters of permanent magnet synchronous motor (Table 1).

**Table 1.** Parameters of Permanent Magnet Synchronous Motor

S/N	Parameter	Numerical value
1	Rated current	4 A
2	Rated speed	400 rpm
3	DC Bus Voltage	36 V
4	Measured stator winding resistance	0.33 $\Omega$
5	External wiring resistance	0.04
6	Self perception	2.91 mH
7	Mutual inductance	-0.33 mH
8	Flux linkage	77.6 mWb
9	Polar logarithm	5
10	D-axis inductance	3.24 mH
11	Q axis inductance	3.24 mH

The experiment takes the temperature signal of permanent magnet synchronous motor in one day as the unit, and the sampling interval is 1 min. It contains the temperature sensor signal sequence of five permanent magnet synchronous motors in 43 days, including stator temperature, driving end temperature, non driving end temperature, and the temperature difference between driving end and non driving end. Therefore, the one-day sequence includes a total of  $32 * 4$  dimensional features. According to the specific manifestation of signal abnormal change, the temperature signal of permanent magnet synchronous motor presents abnormal mainly in two types, point abnormal and context abnormal. The value of one time step in the sequence is significantly higher than that of other points in the adjacent time step, which is considered as point anomaly, generally referred to as isolated point, and may be caused by sensor failure. Context exception means that within the length of a window, the sequence value obviously deviates from other sequence values of the same type. It is considered as a context exception and is usually related to the abnormal working state of the motor. According to the above rules, the real abnormal record labels that can be captured from the perspective of post inspection are shown in the table below (Table 2).

**Table 2.** Abnormal Change Record of Temperature Signal

Date	ID	Starting point	End point
0109	21	643	639
0110	22	1084	1167
0111	23	350	400
...	...	...	...
0116	27	1000	1100

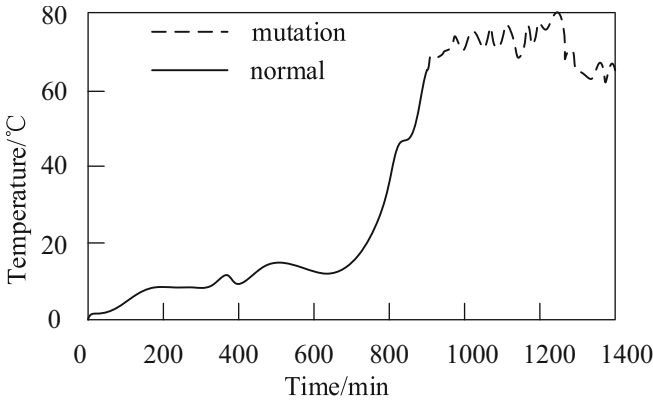
As shown in the above table, there are 9 records of temperature signal variation, and each record includes the date of occurrence and the start and end time points. If the sensor sequences under different dates are marked according to the true abnormal records, the data description is shown in the table below (Table 3).

**Table 3.** Abnormal sequence count (by date)

Category	Number	Average length	Characteristic dimension
Normal sequence	36	1010	128
Aberrant sequence	7	1213	128
Total	43	1043	128

As shown in the above table, the normal sequence has 36 days and the abnormal sequence has 7 days. The abnormal sequence here refers to the abnormal records that have occurred within the time range of that day. If there is no abnormal change in the

whole day, the sequence is considered normal. The monitoring results are shown in the following Fig. 3.



**Fig. 3.** Signal Diagram of Abnormal Temperature Change of Motor

The experimental data set contains a number of sensor data collected from the PMSM on the test bench, with a total of 13 temperature related characteristics. The specific characteristics are shown in the following Table 4.

**Table 4.** Characteristics of Experimental Data Set

S/N	Characteristic tag name	Describe
1	u <sub>q</sub>	Voltage q component in d-q coordinate
2	Coolant	Coolant temperature
3	Stator_winding	Stator winding temperature
4	u <sub>d</sub>	Voltage d component in d-q coordinate
5	Stator_tooth	Stator tooth temperature
6	Motor_speed	Motor speed
7	i <sub>d</sub>	Q component of current in d-q coordinate
8	i <sub>q</sub>	D component of current in d-q coordinate
9	Pm	Permanent magnet temperature
10	Ststor_yoke	Stator yoke temperature
11	Ambient	Ambient temperature
12	Troque	Motor torque
13	Profile_id	Measurement Session ID

The results of the entire data set are obtained with a measurement frequency of 2 Hz, including 69 mutually independent measurement sessions, with a total of more

than 1.3 million pieces of data. Due to the huge data set, there are inevitably some distorted data due to measurement errors. In order to avoid the impact of these data on the prediction accuracy of the deep learning model and reduce the calculation cost. The whole benchmark data set is de sampled, and the training set and test set are divided. About 32000 pieces were selected as the training set and 544 pieces were selected as the test set. All deep learning models use five fold cross validation in training to avoid model over fitting as far as possible.

According to the actual situation of the permanent magnet synchronous motor in the experiment, the parameters of the deep learning network model are set. The time step of the deep learning model is 5. The specific super parameter settings are shown in the table below (Table 5).

**Table 5.** Parameters of deep learning network model

S/N	Parameter	Numerical value
1	Hide Layer	3
2	Neurons in each layer	(64, 16)
3	Weight	Random-normal
4	Optimizer	Nadam
5	Learning rate	0.01
6	Number of training rounds	100
7	Noise	$1 \times 10^{-3}$

In addition, the number of neurons in the hidden layer of the deep learning network model is set to 32, and the deep learning network model has a layer of 1D-CNN convolution before entering the gated cycle unit, and the number of convolution cores is 16. The input features of the deep learning network model are filtered, and the filtered features are put back, and the weight initialization adopts rand\_Normal mode. In the experiment, the random variance of all Gaussian noises is uniformly set to  $1 \times 10^{-3}$ . In the actual motor operating environment, there is a lot of noise. Although part of the hardware circuit settings have been partially filtered, the noise will still have a certain impact on the signal acquisition. In traditional methods, basically a series of filtering operations are carried out on the collected signals to filter out the noise. In this experiment, the noise is filtered by the nonlinear transformation of deep learning, which is also a test of the robustness of the deep learning network model. The deep learning network model predicts the temperature of the four core components of the permanent magnet synchronous motor, namely, the stator teeth, the stator yoke, the stator winding and the permanent magnet. Due to certain differences in the electrical structure and temperature rise properties of the four core components, the temperature prediction models of each target component are trained separately, that is, each component corresponds to a model, but the super parameters remain the same.

### 3.2 Result Analysis

After completing the above experimental preparation, the experimental evaluation indicators are selected. In order to make the experimental results and experimental data have a certain explanation and reliability, two traditional methods are selected for comparison. The two traditional methods are the monitoring method based on the finite element method and the monitoring method based on the magnetic flux observation method. The following are represented by the traditional method 1 and the traditional method 2 respectively. In the monitoring carried out on a daily basis, the sequence that actually contains abnormal changes is defined as a negative case under the positive case period. Then the accuracy of abnormal signal monitoring can be measured by classification related indicators. This selection is marked with confusion matrix, whose definition is shown in the following Table 6.

**Table 6.** Confusion matrix

Project	Negative example of monitoring value	Positive example of monitoring value
Negative example of actual value	TN	FP
Positive example of actual value	FN	TP

As shown in Table 6, TN (True Negative) refers to the correct negative case monitored, that is, the normal sequence correctly monitored; FPC (False Positive) refers to the positive example of monitoring error, that is, the error monitoring is a normal sequence of abnormal sequence; FN (False Negative) refers to the negative case of monitoring error, that is, the abnormal sequence with error detection as normal sequence; TPC (True Positive) means to monitor the correct positive example, that is, the correctly monitored abnormal sequence. Based on the above description, the monitoring accuracy is defined as follows:

$$Precision = TP / (TP + FP) \quad (8)$$

where, *Precision* It indicates the monitoring accuracy of motor temperature abnormal signal. The recall rate monitored is defined as follows:

$$Recall = TP / (TP + FN) \quad (9)$$

where, *Recall* Indicates the recall rate of motor temperature abnormal signal monitoring. In this experiment, the accuracy rate and recall rate are used as the evaluation indicators of the monitoring accuracy of the three methods of temperature variation signal. According to the way of identifying the abnormal records in the experimental scheme setting, the number of correctly hit anomalies and the number of falsely reported anomalies under different methods are respectively counted, and the accuracy rate of the three methods of temperature variation signal monitoring is calculated using formula (8), with time as the variable, according to the statistical data, the accuracy comparison chart of the three methods is shown below.

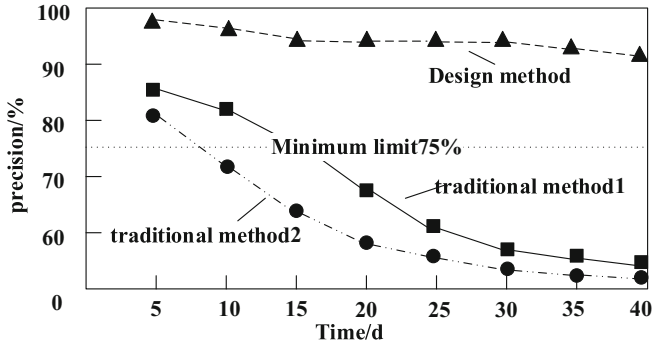


Fig. 4. Comparison Diagram of Accuracy of Three Methods

It can be seen from the above figure that the design method has relatively high accuracy in monitoring the temperature variation signal of permanent magnet synchronous motor, with an average accuracy rate of 96.48%. The average accuracy rates of traditional method 1 and traditional method 2 are 75.46% and 64.18% respectively. Moreover, the accuracy rate of the design method is less affected by the monitoring time, and does not decrease significantly with the increase of the monitoring time. When the monitoring time is 40, the accuracy rate is 94.46%, which is far higher than the two traditional methods, and is greater than the minimum limit value, indicating that the design accuracy monitoring accuracy is relatively high. In order to further verify the monitoring accuracy of the design method, take the number of permanent magnet synchronous motor temperature signal samples as the variable, compare the recall rate of the three methods of motor abnormal signal monitoring, use formula (9) to calculate the accuracy rate of the three methods of temperature variation signal monitoring, and draw the comparison chart of the recall rate of the three methods according to the statistical data as shown below.

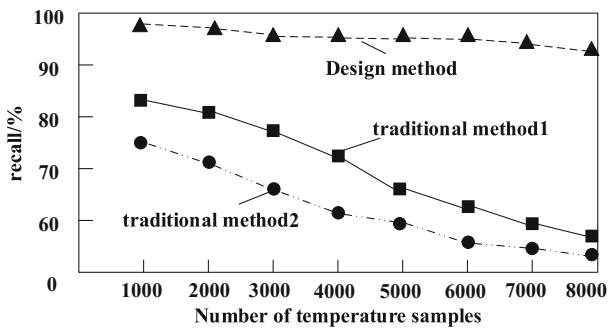


Fig. 5. Comparison of recall rate of three methods

It can be seen from the above figure that the recall rate of the design method is relatively high in this experiment. Although the recall rates of the three methods are constantly decreasing with the increase of the number of samples of permanent magnet

synchronous motor temperature signals, the reduction of the recall rate of the design method is relatively small. When the number of samples of motor temperature signals reaches 8000, the recall rate of the design method is 92.45%, nearly 31% higher than that of the traditional method 1, it is nearly 35% higher than traditional method 2. Therefore, this experiment proves that the design method in this paper has a high monitoring accuracy of temperature variation signal of permanent magnet synchronous motor, and can monitor the temperature variation signal of permanent magnet synchronous motor with high accuracy. The design method in this paper has good feasibility and reliability, and is more suitable for monitoring the temperature variation signal of permanent magnet synchronous motor than the traditional method.

Compare the detection efficiency of the three methods based on the accuracy and recall results obtained in Figs. 4 and 5. The comparison diagram is shown below (Fig. 6).

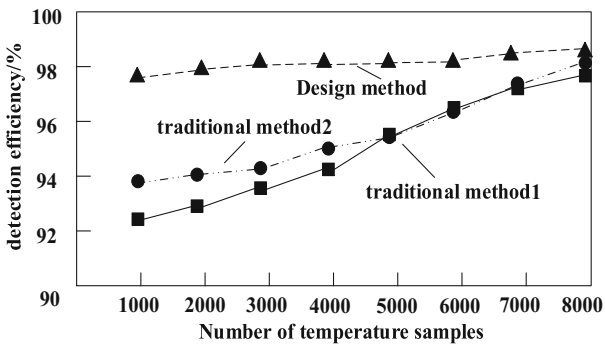


Fig. 6. Comparison of detection efficiency among three methods

From the above figure, it can be seen that the detection efficiency of the design method in this experiment remains above 97% as the number of temperature signal samples of the permanent magnet synchronous motor increases; The detection efficiency of traditional method 1 in this experiment remained above 92%; The detection efficiency of traditional method 2 in this experiment remained above 94%. Therefore, the design method in this article can efficiently detect the temperature variation signal of permanent magnet synchronous motors, and has high reliability.

## 4 Conclusion

As the power source, the safe and reliable operation of permanent magnet synchronous motor is very important. Motor temperature is the key parameter to reflect the running state of the motor. It is of great and positive significance to realize the monitoring of temperature variation signal to ensure the operation safety of permanent magnet synchronous motor. In this paper, a monitoring method of temperature variation signal of permanent magnet synchronous motor based on model prediction is proposed, aiming to address the key issue of ensuring the safe and reliable operation of these motors. The speed, current, torque and other state parameters of the permanent magnet synchronous

motor are taken as the input of the prediction model, and the motor temperature is taken as the output of the prediction model. The high-precision training of the prediction model is carried out to achieve the accurate prediction of the temperature variation signal of the motor, on this basis, the residual error of temperature prediction is used to alarm the abnormal change of motor temperature. The experimental data show the correctness and effectiveness of the proposed method. Compared with the traditional method, it can accurately monitor the abnormal temperature signal of the permanent magnet synchronous motor, ensure its healthy and safe operation, and has positive significance for improving the ability of the permanent magnet synchronous motor to operate safely. Future research can further explore the following directions:

Firstly, it can consider introducing more state parameters and environmental information to improve the accuracy and stability of model predictions.

Secondly, it can combine methods such as machine learning and deep learning to further optimize the training and predictive capabilities of the model.

Additionally, research can be conducted on how to achieve joint monitoring and control of multiple motors to address temperature variation issues in complex operating conditions.

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