Thermal Modeling of Tubular Permanent Magnet Linear Synchronous Motor Based on Random Forest

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***Abstract*—This paper proposed a novel thermal modeling analysis method of tubular permanent magnet linear synchro−nous motor(PMLSM) based on machine-leaning method.First−ly, the structure and main parameters and the finite element (FE) thermal modeling of motor are introduced.A small sample about the average temperature rise of permanent magnet, overall average temperature rise of PMLSM and coil temperature rise are obtained by FE method, corresponding to different heat source inputs. Based on the sample dataset, a powerful machine learning algorithm called Random Forest(RF) is employed to fit the function relationship between output design objectives and input sources parameters. The accuracy of thermal prediction model is verified by the remaining group of sample data. Comprehensive performance comparison shows that the motor thermal prediction model was established by RF is better than other methods such as KNN and SVM.**

Keywords—PMLSM, RF, thermal analyse

I. INTRODUCTION

The permanent magnet linear motor is widely used in daily life and factory production due to its simple structure and high system efficiency. The current research on the temperature field of permanent magnet linear motor is also in the stage of rapid development. With the increase of the power density of permanent magnet linear motors, especially cylindrical permanent magnet linear motors, due to the sealed structure, it is easy to cause excessive local temperature rise in many special occasions. Excessive temperature rise causes irreversible demagnetization of the permanent magnets of the motor, which has a certain impact on the performance and service life of the motor. Therefore, the study of the temperature field of the permanent magnet linear motor is of great significance for improving the performance of the motor. The calculation research of linear motor temperature rise started later, but it has gradually begun to receive attention, and it is currently in a stage of rapid development. There are two main methods for thermal analysis of motors: equivalent thermal circuit method and numerical solution method.

The equivalent thermal circuit method is a method to establish a thermal circuit model based on heat transfer and circuit theory [1-5]. The loss generated when the motor is working constitutes the heat source in the heat circuit. And the distributed heat source inside the motor is assumed to be a concentrated heat source at a certain point. The heat conduction of each structure and the heat dissipation effect of each surface are reflected by the equivalent thermal resistance. The method of solving the heat circuit is the same as that of the circuit. First, the heat balance equation is listed, and then the equation is solved to get the average temperature rise of each part of the motor. So far, the thermal circuit method is still widely used. Usually, it is used in conjunction with the motor temperature rise experiment. A simplified thermal circuit model is established on the basis of the motor temperature rise test and thermal parameter test, so that it can be more accurately estimated The temperature rise of the motor in different states [6-7].

Numerical solution methods include finite element analysis method and computational fluid dynamics method. Literature [8] uses the thermal analysis function of Ansys finite element software to simulate permanent magnet synchronous motors. The influence of permanent magnet eddy current loss on the temperature field is analyzed, and the importance of permanent magnet eddy current loss is proved. Literature [9] used the finite element method to calculate the steady-state temperature field distribution and transient temperature rise curve of the in-wheel motor under rated conditions. Literature [10] uses the finite element method to conduct a nonlinear simulation analysis that comprehensively considers the loss and transient temperature rise of electromagnetic, thermal, and control strategies. Literature [11] uses the method of coupling the fluid field and the temperature field to calculate the temperature field of the permanent magnet synchronous motor (PMSM) for vehicles under rated and peak operating conditions. Literature [12] uses computational fluid dynamics (CFD) methods to study the temperature field of automotive PMSM under rated conditions and continuously variable power conditions.

The above methods have been widely used in the calculation of the motor temperature field, and each has its own advantages and disadvantages. However, when the loss of the PMLSM changes, the simulation calculation needs to be performed again to obtain the temperature rise change of the motor, and the research efficiency is low. In order to improve the calculation efficiency of motor temperature rise, this paper proposes proposed a novel thermal modeling analysis method of PMLSM based on RF[13].

II. MOTOR STRUCTURE AND TEMPERATURE FIELD MODELING

A. *Permanent Magnet Linear Motor Structure*

The actual structure of PMLSM studied in this paper is shown in Fig.1. In the figure, 1 refers to the impact anvil, 2 refers to the cushion and buffer spring, 3 refers to the stator,

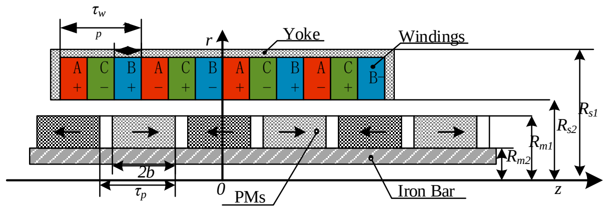


Fig.1. STRUCTURAL DIAGRAM of the PMLSM

TABLE I MAIN PARAMETERS OF THE PMLSM

Description	Symbol	Value	Unit
Outer radius of coil (Mover)	R_{s1}	33	mm
Inner radius of coil (Mover)	R_{s2}	18	mm
Outer radius of PM (Stator)	R_{m1}	17	mm
Inner radius of PM (Stator)	R_{m2}	9	mm
Current density	J	4	A/mm^2
Iron loss Range	P_{fe}	20-300	W
Copper loss Range	P_{cua}	100-1500	W
Eddy current loss Range	P_{el}	5-20	W

including ring-shaped permanent magnets and iron rods, and 4 refers to the It is a linear bearing, which is used to fix and reduce the friction between the various parts of the motor to ensure the smooth operation of the motor. 5 refers to the mover, including the coil and the iron yoke, 6 refers to the shell, and 7 refers to the buffer spring. The main parameters of the motor are shown in Table I.

B. *Finite Element Analysis of Motor Temperature Field*

The establishment process of the finite element (FE) thermal model of the motor is as follows. First, the geometric model of the motor is drawn in ANSYS software according to the size parameters of PMLSM. Secondly, according to the geometric structure characteristics of the motor model, the grid is divided automatically by the software. Then the losses of various parts of the motor are added to the motor model in the form of loads. After the relevant parameters are set and simulated. Finally, the simulation results are post-processed to obtain the overall temperature rise of the motor, the temperature rise of the coil and the temperature rise of the permanent magnet. The main materials and material coefficients of the motor are shown in Table II. the convective heat transfer coefficients of each contact surface are shown in Table III.

TABLE II MAIN MATERIALS COFFICIENTS OF THE PMLSM

Motor parts	Material	Thermal Conductivity（W/m•K）
coil	copper	400
PM	NdFeB	9
end cover	stainless steel	13.8

TABLE III CONVECTION COFFIENTS OF THE PMLSM

Contact surfaces	Convection heat transfer coefficient（W/m^2•K）
contact surface of moving stator and air gap	60
contact surface between the housing and the motor	25

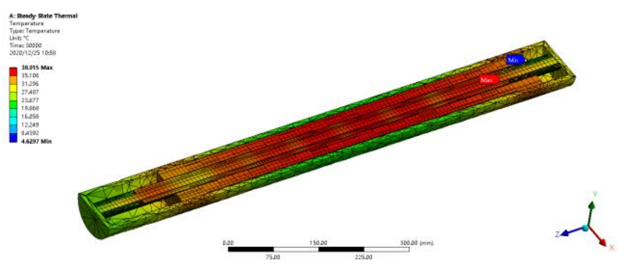


Fig.2. Temperature rise diagram of PMLSM

In this paper, the variation range of copper loss is 100-1500W, the variation range of iron loss is 20-300W, and the variation range of eddy current loss is 20-200W. Under other conditions unchanged, the values of copper loss, iron loss and eddy current loss were changed to simulate the temperature field of the motor and the simulation results were obtained.

III. Random Forest Permanent Magnet Linear Motor Temperature Field Modeling

A. *Random Forest Algorithm*

Random forest is an algorithm based on decision trees. Similar to decision trees, random forest can be used for both classification and regression. It is a forest constructed randomly by many unrelated decision trees. In essence, random forest belongs to an important branch of machine learning called ensemble learning. When used for classification, it is mainly composed of a decision tree classifier, which is also called a classification forest at this time. When used as a regression, it is mainly composed of a large number of regression trees, at this time it is called a regression forest. This article is mainly used for motor temperature prediction. It is a continuous variable and belongs to a regression problem. Therefore, this article uses regression forest to model.

The random forest regression algorithm is similar to the bagging algorithm, and the details are as follows:

(1) The bootstrap sampling method is used to randomly sample with replacement from the training data set with a total number of N samples. Each time K samples are drawn, K decision trees are generated, and a total of N times are drawn with replacement. The probability that each sample will not be drawn in a round is $(1-1/N)^N$. When N is large enough, this value will converge to 1/e. In each round of sampling, 36.8% of the samples will not be drawn.

(2) Each decision tree is independently generated under each training sample. At non-leaf nodes, branches are constructed according to the principle of MSE addition and minimum. According to the random subspace theory, when generating non-leaf nodes, some feature attributes should be randomly selected from all feature attributes to form a subset of feature attributes. Then the feature attribute with the smallest MSE in the subset is selected as the split variable.

(3) Each decision tree grows independently and will get different branches. When making a decision, the input data passes through K decision trees to obtain K decision results, and the final decision result of the model is the arithmetic average of the K decision results. Suppose the decision result of the input data x through the i-th decision tree is $h_i(x)$, then the decision tree result of the random forest regression tree is $H(x)=\frac{1}{K}\sum_{k=1}^{K}h_i(x)$.

B. *Random Forest Permanent Magnet Linear Motor Temperature Field Modeling*

In this paper, on the permanent magnet linear motor temperature field data set, the random forest algorithm is used to model the motor temperature field. The modeling process is shown in Figure 3. First, the sample set containing three characteristic indicators copper loss, iron loss, eddy current loss, and three target values of the overall temperature rise of the motor, the temperature rise of the motor coil, and the temperature rise of the permanent magnet of the motor are divided into a training set and a test set. Then a subset of training samples is randomly selected from the training set by Bootsrap sampling, and regression decision tree modeling is performed on each subset. The decision result of the comprehensive regression decision tree, the average value of the decision result is used as the corresponding temperature prediction result of the motor. Because random forests are generally single-input single-output or multiple-input single-output modeling. In this paper, there are multiple feature indicators and target values, so this paper uses multiple input and single output modeling. To model each target value separately, a total of three motor temperature prediction models need to be established, collectively referred to as motor temperature rise prediction models.

The original sample set is composed of permanent magnet linear motor temperature rise data. There are three characteristic indexes, namely copper loss, iron loss and eddy current loss. There are also three target values, which are the overall temperature rise of the motor, the temperature rise of the motor coil, and the temperature rise of the permanent magnet of the motor. The original sample set is split into training set and test set according to 8:2. The Boostrap sampling method is used to randomly select n sample subsets from the training set to construct n regression trees.

In order to ensure the randomness of regression decision tree construction and avoid over-fitting, each decision tree construction needs to randomly select several random feature variables from three feature indicators to participate in the splitting process of decision tree nodes.

The basis of the random forest in this paper is regression decision tree. Therefore, the criterion of the motor temperature rise prediction effect is the mean square error (MSE). The MSE calculation formula is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i) \qquad (1)$$

In the formula, $\hat{y}_i$ is the predicted value, y_i is the actual value, and n is the total number of samples. From the MSE calculation formula, it can be seen that the larger the MSE value, the worse the model prediction effect, and vice versa, the better the model prediction effect.

When building a regression decision tree, the steps are as follows:

(1) The original motor temperature rise training sample set is assumed to be S, and the depth of the tree is 0 at this time;

(2) For the motor temperature rise training sample set S, each value of each feature (referred to in this article as copper loss, iron loss and eddy current loss) is traversed separately. And the sample set S is split into two sets by value: they are respectively recorded as the left set S_left (samples with a value less than or equal to value) and the right set S_right (samples with a value greater than value). Each set is also called a node. The MSEs of the left and right sets are calculated and added, so that the value with the smallest added value of the left and right MSEs is found. The feature name and value at this time are recorded. The feature and value at this time are the best split feature and the best split value.

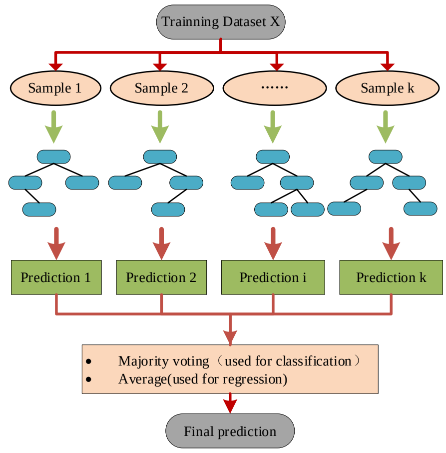


Fig.3. Flowchart of the RF algorithm

(3) After the best split feature and the best split value are found, the best split value is used to split the motor temperature rise training sample set S into two sets, the left set S_left and the right set S_right. Each set is a node. At this time the depth of the tree is increased by one;

(4) The left set and the right set are repeated steps 2 and 3 respectively until the termination condition is reached.

(5) The set that is finally generated and no longer split is called a leaf node. The predicted value of the sample falling in the leaf node is the value of the leaf node.

For each subset of random training samples, trees are generated according to the principle of minimum sum of MSE of the left and right sets to form a "forest". This paper selects 1,000 regression decision trees to form a random forest.

C. Evaluation of Temperature Field Model of Random Forest Permanent Magnet Linear Motor

In order to verify the accuracy of the random forest algorithm for predicting the temperature rise of the motor, this paper respectively predicts the overall temperature rise of the motor, the temperature rise of the motor coil, and the temperature rise of the permanent magnet of the motor in the sample set of motor temperature rise. And compare the obtained prediction results with the results obtained by other prediction models, such as K-nearest neighbor algorithm (KNN), SVM, ridge regression model (RR), etc. In this paper, MSE, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are selected as the measurement standards of model training accuracy and generalization performance.

The difference between the predicted value of the motor temperature rise model and the actual value of the motor temperature rise is measured by MSE and RMSE. The MSE calculation formula is as (1), and the RMSE calculation formula is as (3):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y} - y)^2} \qquad (2)$$

Where $\hat{y}$ represents the predicted value of the temperature rise of the motor by the random forest algorithm, y represents the actual value of the temperature rise of the motor, and n represents the number of samples of the motor temperature rise. The smaller the root mean square error value, the better the prediction effect of the regression model.

MAE is used to measure the unbiasedness of the prediction model, and the calculation formula is as (3):

$$MAE = \frac{\sum_{i=1}^{n} |(F_i - E_i)|}{n}, i = 1, 2, \cdots, n \qquad (3)$$

Where F_i represents the predicted value of the random forest for the temperature rise of the motor, and E_i represents the actual value of the temperature rise of the motor. and n represents the number of samples of the temperature rise of the motor. Since MAE can avoid the mutual cancellation of errors, it can accurately reflect the actual prediction error.

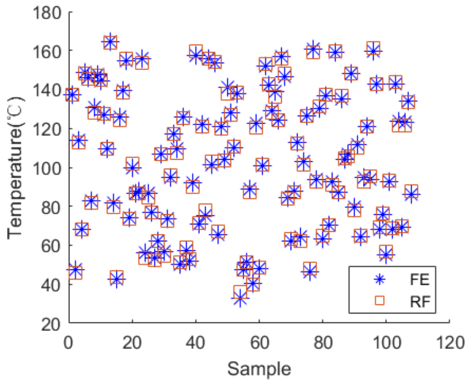
IV. RESULT ANG ANALYSIS

In this paper, a prediction model of permanent magnet linear motor temperature rise is established based on random forest. The models established in this paper can be divided into three categories: the overall temperature rise prediction model of the motor, the prediction model of the motor coil and the prediction model of the permanent magnet temperature rise of the motor. This section will conduct a detailed analysis of the model simulation results. At the same time, in order to verify the validity and accuracy of the prediction model, it will be compared with other model simulation results.

A. *Random forest motor's overall temperature rise prediction model*

In this paper, a random forest prediction model for the overall temperature rise of the motor is established and simulated. Figure.4 shows the overall average temperature rise of the motor.

It can be seen from Fig.4 that the overall average temperature rise of the motor predicted by RF is very similar to the result calculated by FE.. At this time, the MAE, RMSE, and MAE are 0.00009, 0.00952, and 0.00789, respectively, and the model prediction is more accurate.



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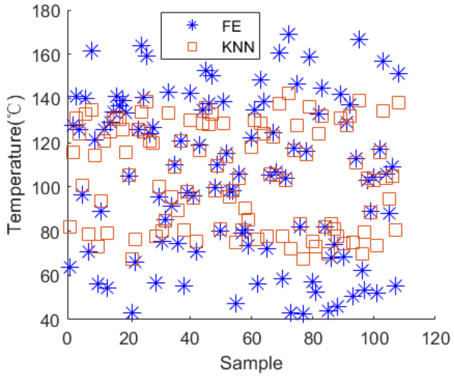

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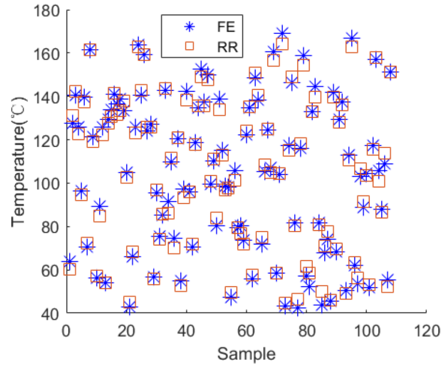

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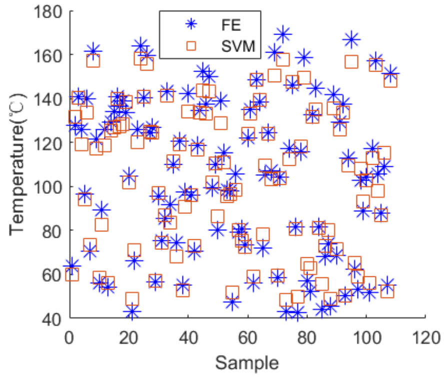

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Fig.4. The overall average temperature rise of the motor

TABLE IV INDEX PARAMETERS OF THE OVERALL TEMPERATURE RISE MODEL OF THE MOTOR

Methods \ Metrics	MSE	RMSE	MAE
KNN	0.00980	0.09899	0.07432
RR	0.00039	0.01966	0.01635
SVM	0.00131	0.03620	0.02960
RF	0.00009	0.00952	0.00789

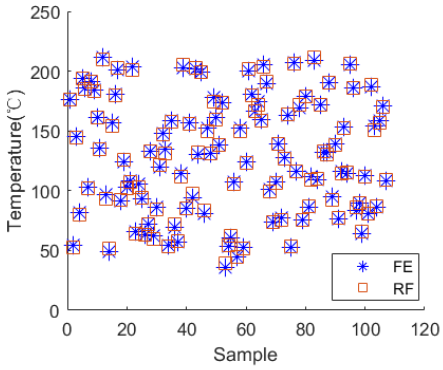
In order to further verify the effect of the model, the paper conducts a comparative experiment of random forest prediction model and ridge regression model, SVM and KNN. In order to reduce the deviation caused by random sampling, a 3-fold cross-validation method is used in the simulation, and the average value is obtained and used as the model prediction index. Under the premise of ensuring that the error is within a certain range, MSE, RMSE, and MAE are used as model measurement indicators.

It can be seen from Table IV that the MSE, RMSE, and MAE values of the overall temperature rise prediction model for PMLSM based on random forest are all smaller than KNN,RR, and SVM. It shows that the performance of the prediction model for the overall temperature rise of PMLSM based on random forest is better.

B. Random Forest Motor Coil Temperature Rise Prediction Model

In this paper, a random forest prediction model for the temperature rise of the motor coil is established and simulated. Figure 5 shows the average temperature rise of the coil of the motor.

It can be seen from Fig.5 that the average temperature rise of the coil of the motor predicted by RF is very close to the result calculated by FE. At this time, the MAE, RMSE, and MAE are 0.00031, 0.01761, and 0.00812 respectively, and the model prediction is more accurate.



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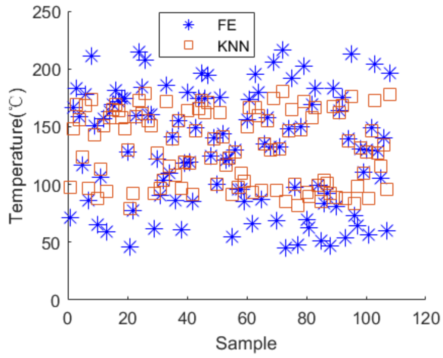

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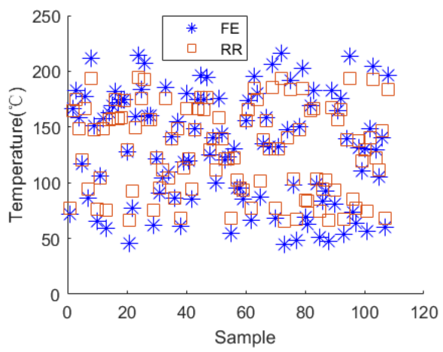

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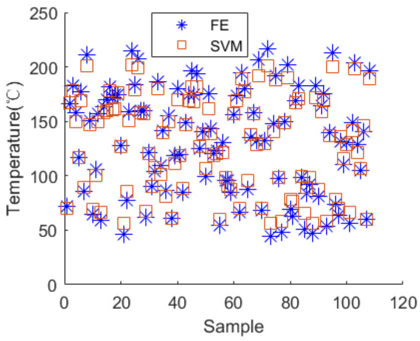

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Fig.5. The average temperature rise of the coil of the motor

In order to further verify the effect of the model, the paper conducts a comparative experiment of random forest prediction model and ridge regression model, SVM and KNN. In order to reduce the deviation caused by random sampling, a 3-fold cross-validation method is used in the simulation, and the average value is obtained and used as the model prediction index. Under the premise of ensuring that the error is within a certain range, MSE, RMSE, and MAE are used as model measurement indicators.

TABLE V INDEX PARAMETERS OF THE COIL TEMPERATURE RISE MODEL OF THE MOTOR

Metrics / Methods	MSE	RMSE	MAE
KNN	0.01071	0.10351	0.07763
RR	0.00354	0.05949	0.04963
SVM	0.00144	0.03789	0.03135
RF	0.00031	0.01761	0.00812

It can be seen from TableV that the MSE, RMSE, and MAE values of the PMLSM's coil temperature rise prediction model based on random forest are all smaller than KNN, RR, and SVM. It shows that the performance of the prediction model of PMLSM's coil temperature rise based on random forest is better..

C. Random Forest Motor Permanent Magnet Temperature Rise Prediction Model

In this paper, a random forest prediction model for the temperature rise of the permanent magnet of the motor is established and simulated. The average temperature rise of the permanent magnet of the motor is shown in Fig.6.

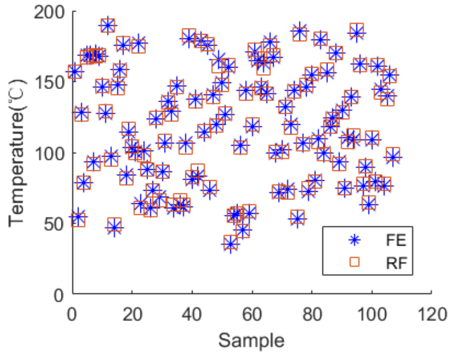
It can be seen from Fig.6 that the average temperature rise of the permanent magnet of the motor predicted by RF is very close to the result calculated by FE. At this time, the MAE, RMSE, and MAE are 0.00023, 0.01532, and 0.00969, respectively, and the model prediction is more accurate.

In order to further verify the effect of the model, the paper conducts a comparative experiment of random forest prediction model and ridge regression model, SVM and KNN. In order to reduce the deviation caused by random sampling, a 3-fold cross-validation method is used in the simulation, and the average value is obtained and used as the model prediction index. Under the premise of ensuring that the error is within a certain range, MSE, RMSE, and MAE are used as model measurement indicators.

It can be seen from Table VI that the MSE, RMSE, and MAE values of the permanent magnet temperature rise prediction model for permanent magnet linear motors based

TABLE VI INDEX PARAMETERS OF THE TEMPERATURE RISE MODEL OF THE PERMANET MAGNET OF THE MOTOR

Methods \ Metrics	MSE	RMSE	MAE
KNN	0.00884	0.09405	0.07074
RR	0.00068	0.02604	0.02200
SVM	0.00186	0.04311	0.03572
RF	0.00023	0.01532	0.00969



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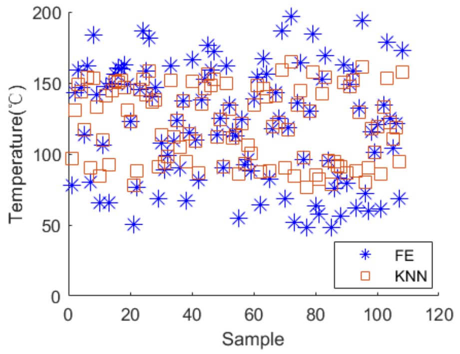

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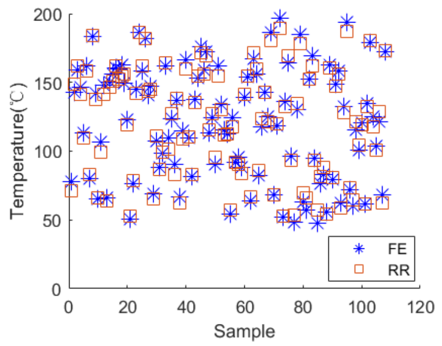

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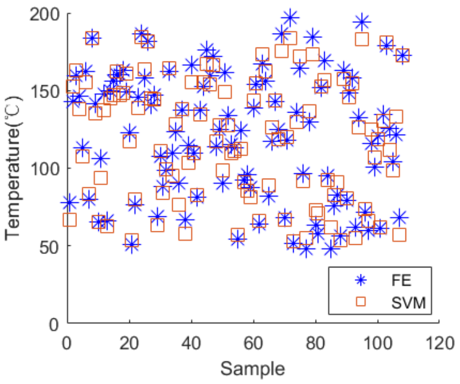

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Fig.6. The average temperature rise of the permanent magnet of the motor

on random forest are all smaller than KNN, RR, and SVM. It shows that the prediction model of permanent magnet temperature rise of permanent magnet linear motor based on random forest has better performance.

V. CONCLUSION

This paper mainly establishes a permanent magnet linear motor temperature rise prediction model based on random forest, takes the motor temperature field data obtained by ANSYS simulation as a sample set, and then models the permanent magnet linear motor temperature field based on the random forest algorithm to obtain the permanent magnet temperature rise of the motor The prediction model, the motor coil temperature rise prediction model, the overall motor temperature rise prediction model and the result graph. At the same time, the prediction model is compared with the KNN, RR, SVM temperature rise prediction model, and the conclusion is that the random forest permanent magnet linear motor temperature rise The prediction model works best.

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