Abstract—In order to improve the reliability in torque calculation of SRM, an accurate nonlinear torque model regresses by recursive robust least squares support vector regression (RR-LSSVR) is proposed in this paper. The model is in terms of a segmented-rotor switched reluctance motor (SSRM). The characteristics of the SSRM is introduced to show its nonlinear characteristics both in magnetic and torque. Then, its mathematic model is established, and an accurate inductance measurement method and a torque calculation method are presented. After this, the principle of the RR-LSSVR and why it can adjust weights according to errors are described. The model used the RR-LSSVR algorithm shows an outstanding capability in accuracy and quickness compared with other algorithms. Finally, to further validate the accuracy of the proposed model in practical application, simulation and experiment are designed based on a 16/10 SSRM.

Index Terms—Switched reluctance motor, intelligent algorithm, nonlinear modeling, torque calculation, LSSVR

I. INTRODUCTION

S
witched reluctance motors (SRMs) have been utilized widely in numerous industrial devices thanks to its advantages in structure, cost, and fault-tolerance [1]-[4]. However, the nonlinear characteristics in magnetic and torque make its torque calculation lack of reliability and accuracy [5, 6]. Thus, to improve the reliability of the SRM drive system, there are two different perspectives to research. One is motor structure innovation, and another is establishing an accurate nonlinear model to calculate torque accurately, quickly, and reliably.

From the perspective of structure innovation, Segmented-rotor SRM (SSRM) is a good choice. SSRM was firstly proposed in [7]. In [8]-[10], a series of novel SSRMs were presented and a kind of auxiliary pole which is only functioned as providing magnetic circuit, was introduced. This structure appears to improve the electromagnetic utilization, and thereby increases output torque and efficiency. Besides, the fault tolerance of the motor drive system has also been improved obviously [11].

From the perspective of establishing an accurate nonlinear model, there are numerous researches have been done. They can be classed as four aspects. First, finite element method [12], it is a method that uses finite element analysis software to simulate the operation of the motor. This method is relatively accurate, but it is time consuming and need some hardware conditions. Second, experimental measurement techniques [13], it is a method that directly measures the value of inductance or flux linkage. Although it is the most accurate method, it usually needs specific experiment apparatus and complex experimental operations which increase the economic and time costs. Third, analytical method [14]-[16], it is a method based on theoretical analysis of the motor. Thus, what it needs are the motor parameters. However, the accuracy is modest as there is some assumption in analysis. Other analytical methods according to the magnetic equivalent circuit [17, 18] have become emerging research hotspots and its accuracy and reliability is uncertain. Fourth, intelligent method, it has been used widely since the development of intelligent algorithms and some specific researches are shown as follows.

In [19], a B-spline neural networks (BSNN) was used to establish the nonlinear model of the SRM. The scheme behaves well in estimation at low and medium speed. However, it is not suitable for high speed and the reliability is modest as it is based on theoretical analysis. In [20], an adaptive neural fuzzy inference system (ANAFS) was utilized to establish the nonlinear model of SRM. However, the neural fuzzy inference usually converges to its local solution. To obtain the global global solution, in [21], support vector machine (SVM) was used to establish a flux linkage model. The drawback of this method is time-consuming. To reduce the computation time, least squares support vector machine (LSSVM) was used in [22]. The computation time has been reduced effectively. Furthermore, for improving the accuracy of regression model, there were numerous researches aimed at hyperparameters optimization of LSSVM. In [23], different evolution (DE) was used for hyperparameters optimization of LSSVM. However, it is unstable if there are outliers in the samples.
To improve the robust of the algorithms and reduce the influence of the outliers, an improved LSSVR that can adjust the weights according to errors is needed. In [24], an improved LSSVR called recursive robust LSSVR (RR-LSSVR) was proposed. It is based on maximum correntropy criterion (MCC) instead of sum of squares error (SSE) as cost function, and it is efficient and has adaptive weight. Thus, this algorithm will be utilized in nonlinear modeling of the SSRM, to realize accurate, fast, and reliable torque calculation.

In this paper, nonlinear torque model will be established based on the advanced algorithm RR-LSSVR. To reveal the effectiveness and advantage of the established model, comparisons will be made with models based on other intelligent methods. Additionally, to validate the accuracy of the proposed model in the specific applications, simulation and experiment are carried out.

The arrangement of the paper is the following: In Section II, characteristics and data collection of SSRM, obtainment of inductance and torque are presented. The fundamental of RR-LSSVR will be introduced in Section III. In Section IV, the nonlinear model will be established based on RR-LSSVR. Validations from simulation and experiment are carried out in Section V, then conclusions follow it.

II. CHARACTERISTICS AND DATA COLLECTION

A. Characteristics of SSRM

Fig. 1 illustrates the machine topology of the proposed 4-phase 16/10 SSRM. It is combined with sixteen stator teeth and ten segmented-rotor teeth, where the stator teeth are divided into excited stator and auxiliary stator. The tooth width of the excited stator is twice that of the auxiliary stator. Besides, only the excited stators are wound by windings, the auxiliary stators are just functioned as magnetic circuit without any windings. The segmented-rotors are evenly embedded in the nonmagnetic isolator to form the magnetic circuit. Table I lists some main parameters of the SSRM according to work [25].

![Fig. 1. Machine topology of the 16/10 SSRM.](image)

Table I

| Parameter | SSRM |
|-----------|------|
| Number of phases | 4 |
| Rated speed (r/min) | 6000 |
| Stator outer diameter (mm) | 128 |
| Rotor outer diameter (mm) | 82 |
| Axial length (mm) | 80 |
| Stator yoke width (mm) | 8 |
| Rotor yoke width (mm) | 5.5 |
| Stator pole arc (°) | 21.375/10.69 |
| Rotor pole arc (°) | 26.64 |
| Air gap length (mm) | 0.25 |
| Turns number of each pole | 26 |
| Rated power (kW) | 1.8 |
| Rated speed (r/min) | 120 |

B. Analytical Model for Torque Calculation of SSRM

Based on the mechanical knowledge, the mechanical motion equation of SSRM can be obtained as follows.

\[
J \frac{d\omega}{dt} = \sum_{m=1}^{4} T_m(\theta, i_m) - T_L - c_j w
\]

where \( J \) is the moment of inertia, \( \omega \) is the mechanical angular velocity, \( \theta \) is rotor position angle, \( i_m \) is phase \( m \) winding current, \( T_m \) is the phase \( m \) electromagnetic torque, \( T_L \) is the load torque, \( c_j \) is damping coefficient, and \( n \) is the number of machine phases.

The electromagnetic torque can be derived under one phase excited using the co-energy at a given position \( i_0 \).

\[
T_m(\theta, i_0) = \frac{\partial W_m'(\theta, i_0)}{\partial \theta}|_{i_0} = \text{const}
\]

The co-energy \( W_m'(\theta, i_0) \) can be calculated by integrating the flux over the current at a given rotor position \( \theta \) as follows.

\[
W_m'(\theta, i_0) = \int_{0}^{i} \psi_m(\theta, i) di |_{\theta} = \text{const}
\]

where \( \psi_m \) is the flux linkage of phase \( m \) winding with given \( L_m \), \( i \) and \( \theta \), and it can be calculated as

\[
\psi_m(\theta, i_0) = L_m(\theta, i_0) \cdot i_0
\]

where \( L_m \) is phase \( m \) winding inductance.
When \( \theta \) is constant, the function of flux linkage and current can be fitted.

\[
\psi_m(\theta_i, i) = f_m(\theta_i, i) |_{\theta = \text{const}}
\]  

(5)

Substituting (5) into (3), the co-energy \( W_m' \) \((i_0, \theta)\) can be calculated with given position \( \theta \) and current.

Then, hold the current \( i_0 \) to calculate the co-energy \( W_m'(\theta_0+\Delta\theta, i_0) \), where the SSRM rotor position is \( \theta_0+\Delta\theta \).

Based on (2) and get the torque of SSRM at different positions by derivation as follows.

\[
T_m(\theta_0, i_0) = \frac{\partial W_m'(\theta, i_0)}{\partial \theta} |_{\theta = \theta_0}
\]  

(6)

Finally, repeat the above calculation method to obtain the torque at the other positions \((\theta, i)\).

C. Obtainment of Inductance and Torque

To improve the reliability of the data which will be used as training samples in the follow intelligent methods. In this paper, data are obtained by experiment instead of FEM. Thus, the data can reflect the practical situation of the motor.

The experimental setup is designed to obtain the inductance under different current excitations at different rotor positions as shown in Fig. 4. it consists of a prototype, an indexing head which is used to fasten the rotor and an LCR digital bridge which is used to provide excitation current and measure the inductance.

During the measurement, the first step is to find the aligned position of the motor, which the position \( \theta \) is set as 360° for a 16/10 4-phase SSRM. The method is exciting one of the phase windings of the SSRM by applying dc current, and then the rotor will rotate to reach at an equilibrium position, which is the position \( \theta \) is used to provide excitation current and measure the inductance.

Obtainment of Inductance and Torque

During the measurement, the first step is to find the aligned position of the motor, which the position \( \theta \) is set as 360° for a 16/10 4-phase SSRM. The method is exciting one of the phase windings of the SSRM by applying dc current, and then the rotor will rotate to reach at an equilibrium position, which is the aligned position of the motor. The second step is to fasten the motor rotor at a recorded position. Third, apply a current excitation to the motor and measure the inductance with bridge. At last, record the \( L-i-\theta \) data and repeat the test procedure under different current excitations at different rotor positions. Finally, the 3D map of inductance is obtained and shown in Fig. 5 (a).

The \( T-i-\theta \) characteristic is calculated according to the \( L-i-\theta \) data utilizing the co-energy method described in Section C and the results are shown in Fig. 5 (b).

III. FUNDAMENTAL OF RR-LSSVR

A. Fundamental of LSSVR

The fundamental of LSSVR is to transform a set of training sample input vectors in a low-dimensional input space into feature vectors in a high-dimensional Hilbert space. Construct a regression hyperplane in the Hilbert space to fit the nonlinear relationship between the feature vector and the output value. By minimizing structural risk, a decision function is obtained which represents the optimal regression hyperplane. Assume \( (x_i, y_i) \) \( i=1,2,...,m \), are training samples where \( x_i \) is input variable, and \( y_i \) is output variable.

The goal of the SVM model is to construct a discriminant function as follows.

\[
f(x) = \omega^T \phi(x) + b
\]

(7)

where \( \phi \) is a function that can map the input space into a higher dimensional feature space, \( \omega \) is weight vector, and \( b \) is bias term.

LSSVR solves the following optimization problems

\[
\begin{align*}
\min_{\omega, b, \xi} & \frac{1}{2} \| \omega \|^2 + \frac{\gamma}{2} \sum_{i=1}^{m} \xi_i^2 \\
\text{s.t.} & \quad y_i = \omega^T \phi(x_i) + b + \xi_i, \quad i = 1,2,...,m
\end{align*}
\]

(8)

where \( \xi_i \) is a fitting error, and \( \gamma \) is a regularization parameter.

Since the optimization problem of LSSVM is a quadratic programming problem with equality constraints as shown in (8), it is complicated to calculate and optimize (8) directly, and it is usually converted into its dual problem according to Lagrange function as follows.

\[
L(\omega, b, \xi, \alpha) = \sum_{i=1}^{m} \alpha_i \left( \omega^T \phi(x_i) + b + \xi_i - y_i \right)
\]

(9)

where \( \alpha \) is Lagrange multiplier and the conditions for the optimal solution are as follow.

\[
\begin{align*}
\partial L \partial \omega &= 0 \Rightarrow \omega = \sum_{i=1}^{m} \alpha_i \phi(x_i), \\
\partial L \partial b &= 0 \Rightarrow \sum_{i=1}^{m} \alpha_i = 0, \\
\partial L \partial \xi_i &= 0 \Rightarrow \alpha_i = \gamma \xi_i, \\
\partial L \partial \alpha_i &= 0 \Rightarrow \omega^T \phi(x_i) + b + \xi_i - y_i = 0
\end{align*}
\]

(10)

So, further eliminate \( \omega \) and \( \xi \) by variable substitution and it can obtain:

\[
\begin{bmatrix}
0 \\
e^T \\
eK + \gamma^1I
\end{bmatrix}
\begin{bmatrix}
b \\
\alpha \\
Y
\end{bmatrix}
=\begin{bmatrix}
0 \\
0 \\
Y
\end{bmatrix}
\]

(11)

where \( K \) is a kernel matrix which satisfies \( K_{ij} = \phi(x_i)^T \phi(x_j) = K(x_i, x_j) \), \( Y = [y_1, y_2, ..., y_m]^T \), \( e \) is a one-dimensional column vector consisting of 1, and \( I \) is an identity matrix. Then, the parameters \( \alpha \) and \( b \) can be obtained and a new regression function is established as follows

\[
f(x) = \sum_{i=1}^{m} \alpha_i K(x, x_i) + b
\]

(12)

and the kernel function \( K(x, x_i) \) is selected as follows.
\[ K(x_i, x_j) = e^{-\frac{\|x_i - x_j\|^2}{\delta^2}} \]  
(13)

where \( \delta \) is a bandwidth parameter.

**B. Recursive Robust LSSVR**

Although the LSSVR behaves well in terms of soft computing, it is modest in tackling the problem brought by outliers of the samples. Thus, to improve the robust of estimation when there are outliers in the samples, weight must be adjusted according to the errors to realize adaptive weight.

Usually, sum of squares error (SSE) is used in the cost function in LSSVR, while the proposed recursive robust LSSVR adopts maximum correntropy criterion (MCC) in its cost function.

For arbitrarily distributed \( P \) and \( Q \), when giving samples \( (p_i, q_i) \) \( i=1,2,...,n \), the sample estimator of correntropy can be obtained as follows:

\[ \hat{J}_\eta(P, Q) = \frac{1}{n} \sum_{i=1}^{n} h(p_i, q_i, \eta) \]  
(14)

where \( h \) is a Gaussian kernel with bandwidth \( \eta \) as follows:

\[ h(a-b, \eta) = e^{-\frac{\|a-b\|^2}{\eta^2}} \]  
(15)

In terms of (8), replace its SSE-based cost function with MCC-based cost function and it can be obtained:

\[ \max_{\alpha, b} J(\alpha, b) = \frac{k}{2} \sum_{i=1}^{k} h(\alpha^T \cdot \varphi(x_i) + b - y_i, \eta) - \frac{1}{2} \|\alpha\|^2 \]  
(16)

Introduce a convex function \( \phi \) to simplify (14) and the problem, which satisfies

\[ h(x, \sigma) = \max_{k>0} (k \|\frac{x-\phi(k)}{\sigma}\|)^2 \]  
(17)

and the maximum is obtained at \( k=\frac{\|x-\phi(k)\|}{\sigma} \) when \( x \) is fixed.

By eliminating the other unrelated variables, the equivalent problem can be obtained as follows:

\[ \min_{\alpha, b, \xi} \frac{k}{2} \sum_{i=1}^{k} \xi_i^2 + \frac{1}{\eta^2} \|\phi(k)\|^2 \]  
(18)

s.t. \( y_i = \alpha^T \cdot \varphi(x_i) + b + \xi_i, \quad i=1,2,...,n \)

Compared with (8), the regularization parameter \( \gamma \) has converted into \(-\gamma k/\eta^2\).

By solving and simplifying the problem, it can obtain the parameters \( \alpha \) and \( b \) as follow:

\[ b = e^T (K + D)^{-1} Y \]  
\[ e^T (K + D)^{-1} e \]  
\[ \alpha = (K + D)^{-1} (Y - eb) \]  
(19)

where \( D \) is a diagonal matrix whose diagonal \( D_{ii}=(-\eta^2/\gamma k_i) \) \( >> 0 \) since \( k_i << 0 \). Thus, \( K + D \) is symmetric, positive-definite, and invertible.

According to (17), the optimal \( k \) can be given as follows.

\[ k_i = -h(\xi_i, \eta) = - e^{-\frac{\xi_i^2}{\eta^2}} \]  
(20)

Considering that \( a = -\frac{\gamma}{\eta^2} \xi_i \) in (10) and \( \gamma \) has converted to \(-\gamma \eta^2 k_i/\eta^2\), the calculation formula of \( \xi_i \) is obtained as follows:

\[ \xi_i^2 = -\frac{\eta^2 a_i}{\gamma k_i} \]  
(21)

To illustrate the RR-LSSVR clearly, its implementation steps are given as follow.

Step 1: Initialization. Set \( k_i \) as \(-1 \) for all samples, tolerance \( \epsilon \) as \( 1 \times 10^{-3} \), correntropy parameter \( \eta \), kernel parameter \( \delta \), regularization parameter \( \gamma' \), and building kernel matrix \( K \).

Step 2: Calculate diagonal matrix \( D \) and then solve (19) to obtain coefficient \( \{a, b\} \).

Step 3: When the change of \( \{a, b\} \) is less than \( \epsilon \), execute Step 5 else execute Step 4.

Step 4: Calculate error variable \( \xi_i \) by (21) and update \( k \) by (20) and then return to Step 2.

Step 5: Determine the final regression estimation by (12).

So far, the RR-LSSVR based on MCC has been introduced completely. According to (21), it is found that the error variable \( \xi_i^2 \) is weighted by a factor \( k_i \) and according to (20), it is found that the larger the error, the smaller the weight.

**C. PSO-based Hyperparameter Optimization for RR-LSSVR**

By the above analysis, it is found that there are three hyperparameters need to be optimized, including kernel parameter \( \delta \) and \( \eta \), and regularization parameter \( \gamma' \). In addition, according to principle of recursive robust LSSVR, it needs to solve Eq. (19) for several times to obtain the final solution of RR-LSSVR. Thus, the computation of RR-LSSVR on every hyperparameter combination is time-consuming which restricts the application of classic grid-based model selection technique. In order to resolve this problem, particle swarm optimization (PSO) is used to select hyperparameters of RR-LSSVR.

PSO is an intelligent algorithm, it is not limited by the mathematical nature of the optimization model, the optimization mechanism is simple, and it has a good optimization effect for optimization problems with complex solution space and constraints. Besides, compared with other intelligent algorithms, PSO has the advantages of simple optimization principle, few adjustable parameters, parallel search and global convergence.

Each solution of an optimization problem is imagined as a bird, also termed as a particle. All particles are searched in a \( D \)-dimensional space. They are determined by a fitness function to judge the current position. Besides that, each particle must have a memory function to remember the best position it has found, and have a velocity to determine the distance and direction of flight. The velocity is dynamically adjusted based on its own flight experience and the flight experience of its companions.

Assuming that there are \( N \) particles in the \( D \)-dimensional space, and the location of the \( i \)th particle at iteration \( t \) is represented by \( X_i(t)=\{x_{i1}(t), x_{i2}(t),..., x_{id}(t)\}^T \) and the current velocity is denoted by \( V_i(t)=\{v_{i1}(t), v_{i2}(t),..., v_{id}(t)\}^T \). Then the velocity of \( i \)th particle is updated according to the particle personal best position (pbest), pbest=\( \{p_{i1}, p_{i2},..., p_{id}\}^T \) and the global best position (gbest), gbest=\( \{g_1, g_2,.., g_d\}^T \), where the Pbest is the position that particle has visited so far which gives the best fitness value. PSO includes updating the velocity and position of each particle at iteration \( t \) in the \( d \)-dimensional space.
as follows
\[
V_{id}(t) = wV_{id}(t-1) + c_1r_1(pbest_{id} - X_{id}(t-1)) + c_2r_2(gbest_{id} - X_{id}(t-1)) \\
X_{id}(t) = X_{id}(t-1) + \Delta V_{id}(t)
\] (22)

where \(c_1, c_2\) are acceleration constants used to adjust the maximum step size of learning, \(r_1, r_2\) are two random numbers between 0 to 1, and \(w\) is non-negative inertia weight used to adjust the search scope of the solution space.

In order to describe the optimized process of PSO clearly, a schematic diagram is developed and shown in Fig. 6.

**Fig. 6.** Specific process of PSO-based hyper-parameter optimization for RR-LSSVR.

In the initialization of Fig. 6, the number of particles is set as 20, maximum velocity of particle is set as 4, the number of evolutionary generations is set as 100, and initial inertia weight \(\omega\) is set as 0.9. The population of particles including \(\delta, \eta, \gamma^*\) are generated randomly in the initialization.

**IV. ESTABLISHMENT OF RR-LSSVR MODEL**

In this section, the RR-LSSVR will be used to calculate the phase inductance and torque of SSRM. To train the model, in this paper, the data is obtained by experimental measurement as shown in Figs. 5(a) and (b). The RR-LSSVR model based on PSO is utilized for regression the phase inductance and torque, where the inputs are current \(i\) and rotor position \(\theta\), and the outputs are phase inductance \(L\) and torque \(T\).

**A. Specific Implementation**

Step1: Randomly generate a population of particles composed of hyperparameters \(\delta, \eta, \gamma^*\).

Step 2: Utilizing the PSO algorithm to optimize and select the hyperparameters, and output optimized hyperparameters \(\delta^*, \eta^*, \gamma^{**}\).

Step 3: Input the samples obtained from Section II, Chapter D to the RR-LSSVR model. Then, use the optimized hyperparameters \(\delta^*, \eta^*, \gamma^{**}\) outputted from Step 2. By computation, it can output parameters \(a\) and \(b\). Thus, the regression function of RR-LSSVR model is obtained.

Step 4: According to the established regression function, when inputting the unknown vector into the function, the corresponding output value is obtained. In other words, when the 2-D vectors current-angle \((i, \theta)\) are given, their corresponding torques will be obtained.

By regression, the 3D map of phase inductance and torque are obtained as shown in Fig. 7. In order to reflect the computational load burden on the processors, the computational time \(t_c\) are also recorded.

**B. Performance evaluation for the RR-LSSVR Model**

To evaluate the performance of the RR-LSSVR model on accuracy and quickness, evaluation indexes mean absolute error (MAE) and root mean square error (RMSE) are chosen to evaluate the Quickness model. Their definitions are as follow

\[
\text{MAE} = \max_{j=1}^{n} \left| y_j - y_{j0} \right| \\
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{j=1}^{n} (y_j - y_{j0})^2}
\] (24)

where \(y_j\) is the regressed results and \(y_{j0}\) is the sample data.

Comparative approach is used to evaluate the effectiveness of the proposed model. That means the motor and its magnetic characteristics, and training samples are all same. The main different is the modeling methods, since other modeling methods are based on the algorithms used in the references [19]-[22]. References [19]-[22] have been mentioned in the Introduction, the corresponding intelligent algorithms they used are popular and widely used. Thus, it is not difficult to reproduce these algorithms and use them to establish torque model in this paper, then compared with the proposed RR-LSSVR model. MAE and RMSE are selected as evaluation indexes, and their compared results are recorded in Table II. It can be found that the RR-LSSVR model behaves more effective than the others in terms of accuracy and time-consumption.

**Table II**

| Modeling methods | Inductance/mH | Time(s) | Torque/Nm | Time(s) |
|------------------|--------------|---------|-----------|---------|
| BSNN [19]        | 0.1231       | 0.1324  | 8.6       | 0.2342  | 0.2532  | 9.1 |
| ANAFA [20]       | 0.1125       | 0.1243  | 7.5       | 0.2234  | 0.2109  | 8.3 |
| SVM [21]         | 0.1056       | 0.1143  | 10.3      | 0.1987  | 0.1854  | 13.1 |
| LSSVR [22]       | 0.0862       | 0.0783  | 8.3       | 0.0945  | 0.0881  | 10.2 |
| RR-LSSVR         | 0.0235       | 0.0189  | 3.3       | 0.0312  | 0.0217  | 4.1 |

**V. SIMULATION AND EXPERIMENTAL VALIDATION**

To validate the effectiveness of the proposed RR-LSSVR model, it is essential to apply this model to the SSRM drive system both in simulation and experiment. In order to validate...
the applicable speed range of the proposed model, two control modes which cover the full speed range of the SSRM are applied in the simulation and experiment respectively. These are chopper current control (CCC) mode angle position control (APC) mode. To make fair comparisons, in specific simulation and experiment, whether using a measured model or a RR-LSSVR model, the only difference is the data, as one is raw data obtained from experiment measurement and analytical calculation, and the other is generated from the proposed model.

![Fig. 8. Simulation block diagram for performance validation: (a) Holistic block diagram, and (b) Phase A block diagram in SSRM block.](image)

A. Simulation Validation

To make simulation validation, the first thing is to build a simulation block diagram. As shown in Fig. 8 (a), from a holistic perspective, the simulation schematic diagram is consisting of a current reference block, given speed block, SSRM block, and mechanical motion equation. For SSRM block, it includes four phase and take phase A as example, it includes four main blocks, they are the Switch, RR-LSSVR \( i(\psi, \theta) \), RR-LSSVR \( T(i, \theta) \) and Modulo \( \pi/5 \). The block diagram is shown in Fig. 8 (b).

Switch block outputs pulse signal to control the power converter commutation via utilizing the input current demand signal \( \Delta i \), given speed signal \( \omega^* \) and position \( \theta \).

RR-LSSVR \( i(\psi, \theta) \) block estimates the current \( i \) according to the flux linkage \( \psi \) and rotor position \( \theta \). As shown in Fig. 7 (a), the 3D map of inductance based on RR-LSSVR model has been obtained. To estimate current \( i \) according to the flux linkage \( \psi \) and rotor position \( \theta \), the RR-LSSVR \( L(i, \theta) \) model is transformed to \( i(\psi, \theta) \) according to (4) and then converted to \( i(\psi, \theta) \) by inverting the relationship between \( i \) and \( \psi \) by angle \( \theta \) one by one.

RR-LSSVR \( T(i, \theta) \) block estimates the torque \( T \) according to the current \( i \) and rotor position \( \theta \). The relationship between torque, current, and rotor position is shown in Fig. 7 (b).

Modulo \( \pi/5 \) block is utilized to compensate the position angle difference between phases. \( \pi/5 \) represents the periodicity of the phase flux linkage and torque, and \( \pi/20 \) represents the phase difference.

In the simulation of CCC mode, set the reference current as 75 A, the hysteresis current bandwidth as 5 A, the DC voltage as 120 V, the given rotor speed as 600 r/min, and the turn on and turn off angles as 20° and 35° respectively. The simulation results are shown in Fig. 9. By comparison, it can be found that the results operated by the RR-LSSVR model are almost consistent with the results operated by the measured model. Furthermore, it is obvious for the current, flux linkage, phase torque, and total torque waveforms to be chopped at low speed. In order to show the accuracy of the proposed model more intuitively, according to Fig. 9, the errors between the two models are numerically analyzed. The evaluation indexes use MAE, RMSE and error percentage, where error percentage is the ratio between the MAE and the maximum true value. The results obtained are listed in Table III. It can be found that the errors are acceptable.

![Fig. 9. Compared results under CCC mode at 600 r/min: (a) Current, (b) Flux linkage, (c) Phase torque, and (d) Total torque.](image)

| TABLE III | NUMERICAL ANALYSIS OF ERRORS OF CCC MODE |
|-----------|------------------------------------------|
| Items     | Evaluation indexes | MAE  | RMSE | Percentage (%) |
| Current(A)| 0.0466 | 0.0182 | 0.62 |
| Flux linkage (Wb) | 5.12e-04 | 7.46e-04 | 0.64 |
| Phase torque (Nm) | 0.112 | 0.0081 | 0.74 |
| Total torque (Nm) | 0.1862 | 0.0783 | 0.78 |
In the simulation of APC mode, set the given rotor speed as rated speed 6000 r/min, other parameters like reference current, hysteresis current bandwidth, DC voltage, are same as CCC mode. The simulation results are shown in Fig. 10. By comparison, it can be found that the results operated by the RR-LSSVR model are also consistent with the results operated by the measured model. Furthermore, different from the waveforms of CCC mode, the value of current, flux linkage, phase torque, and total torque are all declined and the chopping traces are nonexistent. The numerical analysis of errors is also given as shown in Table IV. It can be found that the error percentages become large obviously, but it is still acceptable.

### B. Experimental Results Validation

The effectiveness of the proposed RR-LSSVR model has been validated by simulation. Thus, to make a further validation of the proposed model in practical application, a dynamic experiment platform is built as shown in Fig. 11. It can be found that the 16/10 SSRM prototype (1), torque and speed sensor (2), and magnetic power brake (3) are connected by two couplings. Power converter and drive circuit (4) outputs pulse voltage to excite the phase windings to realize driving the motor. DC power supply (5) provide power for power converter and drive circuit (4). DSPACE (6) is a software / hardware working platform for control system development and hardware-in-the-loop simulation based on MATLAB / Simulink. It uses the position signal detected by Hall sensor ATS675LSE and current signal detected by the current sensor to output PWM wave to realize controlling the power converter and drive circuit (4). PC (7) is matching with dCPACE (6) and it saves the Simulink model and can be adjusted online through control desk. Oscilloscope (8) is used to observe and save the experiment waveforms.

In the experiment, to reveal whether the proposed model is suitable for a wide speed range in practical operation of the motor, four speeds are selected as 600 r/min under CCC mode and 1500 r/min, 3000 r/min, and 6000 r/min under APC mode. During the experiment, to make a fair and intuitive comparison between the measured model and RR-LSSVR model, the sampling method and speed are the same. Meanwhile, each cell of the oscilloscope represents the same value.

Finally, the experimental results at the four speeds are shown in Figs. 12-15 respectively. For the sake of indicating the value of the experimental waveforms obtained by oscilloscope, the values represented by each division of the oscilloscope are given according to the voltage level chosen in oscilloscope and real value shown in control desk. As shown in Figs. 12-15, it can be found that the waveforms of current and total torque have similar amplitude and frequency between measured and RR-LSSVR model. Besides, as the speed increases, the results of the measured model become more unstable because of the RR-LSSVR model. Moreover, different from the waveforms of CCC mode, the value of current, flux linkage, phase torque, and total torque are all declined and the chopping traces are nonexistent. The numerical analysis of errors is also given as shown in Table IV. It can be found that the error percentages become large obviously, but it is still acceptable.
anti-interference, especially at high speeds. Therefore, it can be concluded that the proposed model can effectively regress the torque model of the SSRM, realize accurate and rapid calculation of torque, and then effectively improve the smoothness and reliability of motor operation in practical applications.

In the experiments, to save time and improve the accuracy and robustness of the proposed model. On the one hand, the initial torque model is obtained through off-line training to save time. On the other hand, to improve the accuracy and robustness, real time torque-flux linkage-current information obtained by sensors is used to update the original torque model. This may cause delays, especially at medium and high speeds. Thus, it needs to resolve this problem in the follow-up work.

VI. Conclusion

In this paper, to improve the reliability of the SRM, both the structure innovation and establishment of an accurate nonlinear model are introduced. The machine topology and characteristics of the SSRM are presented succinctly to show its nonlinear characteristics in magnetic and torque. Then, attainment of inductance and torque is presented as samples in the RR-LSSVR model. The RR-LSSVR is based on MCC and can reduce the interference of outlier due to its adaptive weight. The hyperparameters were optimized by PSO to improve the computation efficiency. For the inductance and torque models based on RR-LSSVR, they show an excellent learning performance and the regression errors are smaller than other models. Besides, simulation and experimental results at different speeds also validate that the proposed model has a good accuracy in torque calculation and can effectively improve the smoothness and reliability of motor operation in practical applications.

REFERENCES

[1] M. Zhang, I. Bahri, X. Mininger, C. Vlad, and E. Berthelot, "Vibration reduction control of switched reluctance machine," IEEE Trans. Energy Convers., pp. 1-1, 2019.

[2] X. Sun, K. Diao, and Z. Yang, "Performance improvement of a switched reluctance machine with segmental rotors for hybrid electric vehicles,", Comput. Electr. Eng., vol.77, pp. 244-259, Jul. 2019.

[3] F. Qi, A. Stippich, I. Ralev, A. Klein-Hessling, and R. W. D. Doncker, "Model predictive control of a switched reluctance machine for guaranteed overload torque," IEEE Trans. Ind. Appl., vol. 55, no. 2, pp. 1321-1331, 2019.

[4] K. Diao, X. Sun, G. Lei, Y. Guo, and J. Zhu, "Multiobjective system level optimization method for switched reluctance motor drive systems using finite element model," IEEE Trans. Ind. Electron., 2020, DOI: 10.1109/TIE.2019.2962483.

[5] S. Li, S. Zhang, T. Hubert, and R. Harley, "Modeling, design optimization and applications of switched reluctance machines -- a review," IEEE Trans. Ind. Appl., pp. 1-1, 2019.

[6] G. Davarpanah, S. Mohammadi, and J. L. Kirtley, "A novel 8/10 two-phase switched reluctance motor with enhanced performance: analysis and experimental study," IEEE Trans. Ind. Appl., pp. 1-1, 2019.

[7] H. Eskandari and M. Mirsalim, "An improved 9/12 two-phase E-core switched reluctance machine," IEEE Trans. Energy Convers., vol. 28, no. 4, pp. 951-958, Dec. 2013.

[8] X. Sun, K. Diao, G. Lei, Y. Guo, and J. Zhu, "Real-time HIL emulation for a segmented-rotor switched reluctance motor using a new magnetic equivalent circuit," IEEE Trans. Power Electron., vol. 35, no. 4, pp. 3841-3849, Apr. 2020.

[9] R. Vandana and B. G. Fernandes, "Design methodology for high-performance segment rotor switched reluctance motors," IEEE Trans. Energy Convers., vol. 30, no. 1, pp. 11-21, Mar. 2015.

[10] R. Madhavan and B. G. Fernandes, "Axial flux segmented SRM with a higher number of rotor segments for electric vehicles,", IEEE Trans. Energy Convers., vol. 28, no. 1, pp. 203-213, Mar. 2013.

[11] X. Sun, Z. Xue, S. Han, L. Chen, X. Xu, and Z. Yang, "Comparative study of fault-tolerant performance of a segmented rotor SRM and a conventional SRM," Bulletin of the Polish Academy of Sciences-Technical Sciences, vol. 65, no. 3, pp. 375-381, Jun. 2017.

[12] A. Afjei, A. Siadatan, and H. Torkaman, "Magnetic modeling, prototyping, and comparative study of a quintuple-set switched reluctance motor," IEEE Trans. Magn., vol. 51, no. 8, pp. 1-7, 2015.

[13] O. Ustun, "Measurement and Real-Time modeling of inductance and flux linkage in switched reluctance motors," IEEE Trans. Magn., vol. 45, no. 12, pp. 5376-5382, 2009.

[14] X. Sun, K. Diao, G. Lei, Y. Guo, and J. Zhu, "Direct torque control based on a fast modeling method for a segmented-rotor switched reluctance motor in HEV application," IEEE J. Emerg. Sel. Topics Power Electron.,
Jiangling Wu received the B.Eng. degree in Vehicle engineering from Jiangsu University, Zhenjiang, China, in 2018, and is currently working toward the M. Eng. degree at Jiangsu University, Zhenjiang, China.

His current research interests include modeling, structure designing and controlling of switched reluctance motors for electric vehicle propulsion.

Xiaodong Sun (M’12–SM’18) received the B.Sc. degree in electrical engineering, and the M.Sc. and Ph.D. degrees in control engineering from Jiangsu University, Zhenjiang, China, in 2004, 2008, and 2011, respectively.

Since 2004, he has been with Jiangsu University, where he is currently a Professor with the Automotive Engineering Research Institute. From 2014 to 2015, he was a Visiting Professor with the School of Electrical, Mechanical, and Mechatronic Systems, University of Technology Sydney, Sydney, Australia. His current teaching and research interests include electrical machines and drives, drives and control for electric vehicles, and intelligent control. He is the author or coauthor of more than 80 refereed technical papers and one book, and he is the holder of 36 patents in his areas of interest.