A Direct Torque Control of Permanent Magnet Synchronous Motor for Electric Vehicles Based on ADRC Optimized by CKMTOA-KELM

Lingzhi Yi, Chengdong Zhang, Yanfang Jia and Yangbo Ou

ABSTRACT

Electric vehicles are considered as a new generation of transport to solve the energy crisis. Permanent magnet synchronous motor (PMSM) has been widely used in electric vehicle drive system. A new direct torque control (DTC) for PMSM based on active-disturbance rejection control (ADRC) optimized by improved kernel extreme learning machine (KELM) method is proposed in this paper, which aims to overcome the defects of traditional PI controller. The CKMTOA-KELM optimal regression model is obtained by using chaotic kinetic molecular theory optimization algorithm (CKMTOA) to optimize the kernel parameters and penalty coefficients of KELM regression model. CKMTOA uses chaos search to prevent the algorithm from falling into local optimum and improves the convergence rate by employing adaptive inertia weighting factor. Finally, the ADRC controller embedded the CKMTOA-KELM optimal regression model is analyzed and optimized to improve the dynamic response speed and anti-jamming capability of the system and enhance the robustness of the system. The simulation and experiment results have verified the feasibility and effectiveness of this method.

Keywords: electric vehicles; permanent magnet synchronous motor (PMSM); direct torque control (DTC); ADRC; chaotic kinetic molecular theory optimization algorithm (CKMTOA); KELM.

INTRODUCTION

Along with the world environmental pollution and energy crisis, the development of electric vehicles is getting more and more attention [1]. Many automobile manufacturers continue to introduce new electric vehicles. The core part of the electric vehicle is the motor...
drive system, which determines the main performance index of the vehicle driving [2]. Permanent magnet synchronous motor has the advantages of small size, high precision, high torque density, high power factor, wide speed range, etc., has been widely used in electric and hybrid electric vehicles drive system [3]. In order to make full use of the excellent performance of the permanent magnet synchronous motor, the motor drive control technology is needed.

Due to the strong non-linearity of the rotor speed and the stator current of PMSM, the speed control system is difficult to achieve high precision control performance [4]. In the traditional DTC, the speed loop adopts the traditional PI controller. When the controlled system is in the strong interference environment, the traditional PI controller is difficult to reach high precision control effect [5]. Han [6] combines the advantages of PI control and overcomes its shortcomings to propose active-disturbance rejection control technology. The ADRC can estimate the disturbance value of the control system in real time, realize the automatic compensation, improve the response speed of the control system and enhance the anti-interference ability. Kinetic molecular theory optimization algorithm (KMTOA) is proposed in 2013 by Fan Chao dong [7]. The algorithm can better balance the convergence performance and strong global search ability. Kernel extreme learning machine (KELM) is proposed in 2012 Huang Guang bin [8]. Through a large number of comparative experiments show that, KELM has a better, more stable generalization performance than the traditional ELM algorithm and LSSVM [9]. KELM has been widely used in classification and regression, wind power range prediction, power system economic scheduling and video-based image processing.

In this paper, a direct torque control method of PMSM for electric vehicles based on CKMTOA-KELM optimized ADRC is proposed. The CKMTOA-KELM optimal regression model is obtained by using CKMTOA to optimize the kernel parameters and penalty coefficients of KELM regression model. The CKMTOA with improves the convergence rate and performance of jumping out of local optima by introducing chaos search and adaptive inertia weighting factor. Then, the realization of the CKMTOA-KELM optimal regression model embedded in ADRC controller was analyzed, which optimized the ADRC controller. To improve the dynamic response speed, the anti-jamming capability and enhance the robustness of the system. Compared with the traditional PI controller and ADRC controller, the simulation and experiment results have verified the feasibility and effectiveness of this method.

DTC OF PMSM BASED ON ADRC CONTROLLER

Mathematical Model of PMSM

To establish the PMSM healthy model, without loss of generality, the assumptions are as follows. Firstly, the magnetic circuit is not saturation. Secondly, the eddy currents and the hysteresis losses are negligible. Thirdly, the electrical conductivity of the permanent magnetic material is zero. Fourthly, the rotor magneto motive force is sinusoidal and the slot effect is neglected. Lastly, the stator winding current is sinusoidal, symmetrical and non-harmonic.

The stator voltage equation of PMSM in the d-q synchronously rotating reference frame are as follows:

\[
\begin{align*}
\frac{du_d}{dt} &= R_{ld}i_d + L_{ld}\frac{di_d}{dt} - n_p\omega_L i_q \\
\frac{du_q}{dt} &= R_{iq}i_q + L_{iq}\frac{di_q}{dt} + n_p\omega_L i_d + n_p\omega_L\psi_f
\end{align*}
\]

The electromagnetic torque equation is written as:
The moment balance equation is written as:

\[ T_e - T_L = J \frac{d}{dt} \left( \frac{\omega}{n_p} \right) + B \frac{\omega}{n_p} \]  

(3)

Where \( i_d \) and \( i_q \) are the \( d-q \) axis' currents, \( u_d \) and \( u_q \) are the \( d-q \) axis' stator voltages, \( R_s \) is the stator resistance, \( \omega_r \) is Rotor mechanical angular speed, \( L_d \) and \( L_q \) are the \( d-q \) axis' inductances, \( R_d \) is the damping coefficient, \( n_p \) is number of pole pairs by motor, \( \psi_f \) is rotor flux linkage, \( J \) is moment of inertia, \( T_L \) is load torque, \( B \) is viscous friction coefficient.

**DTC of PMSM Based on ADRC Controller**

ADRC controller mainly consists of tracking differential (TD), nonlinear state error feedback control rate (NLSEF) and expansion state observer (ESO) [10]. TD gives a reasonable control signal to solve the contradiction between response speed and overshoot in traditional PI control. ESO is the core control part of auto-disturbance rejection controller, which can real-time estimates of the system’s disturbed values by the input and output of the controlled object. NLSEF can reduce the error of the controlled object in exponential form.

By the PMSM moment balance equation (3) available:

\[ \frac{d\omega}{dt} = \frac{n_p T_r}{J} - \frac{n_p T_i}{J} - \frac{B\omega}{J} \]  

(4)

From the formula (4) can be drawn, \( T_L, J, B \) changes can have a greater impact on the system control accuracy. Based on the principle of ADRC controller, the state equation of the speed control system of PMSM is written as:

\[
\begin{align*}
\dot{\omega}_f &= \omega(t) + bT_e^* \\
y &= \omega_f 
\end{align*}
\]

(5)

Where \( \omega(t) = \frac{(n_p T_r + B\omega)}{J} \) is the disturbance of the system, \( bT_e^* \) is the amount of system control, \( b = \frac{n_p}{J} \), \( \omega(t) \) is a factor that is difficult to determine in the system. ADRC doesn't need to know the specific expression of \( \omega(t) \), the value of \( \omega(t) \) can be estimated by \( a(t) \), and compensate \( \omega(t) \) real-time compensation to the control system.

The reference speed of the motor is given the reference value \( \omega_r^* \) and the actual speed value \( \omega_f \) as the input signal, and the reference value \( T_e^* \) is given as the output signal by the electromagnetic torque, and the system based on the ADRC speed adjustment controller is designed.

The TD mathematical model of DTC system for PMSM based on ADRC is written as:

\[
\dot{v}_1 = -f_1 (v_1 - \omega_f^*, r, T) 
\]

(6)

Where \( v_1 \) is the tracking value, \( r \) is the tracking velocity factor, and \( T \) is the sampling period, and \( f_1 \) is defined as follows:

\[
\begin{align*}
d &= rT \\
d_0 &= dT \\
y &= v_1 \\
a_1 &= \sqrt{d^2 + 8r^2} \\
\bar{a} &= \left\{ \begin{array}{ll}
(\omega_1 - d) / 2, & |\omega_1| > d, \\
y / T, & |\omega_1| \leq d, 
\end{array} \right. \\
f_1 &= \left\{ \begin{array}{ll}
ra / d, & |\omega_1| \leq d, \\
rs\operatorname{sgn}(a), & |\omega_1| > d 
\end{array} \right.
\end{align*}
\]

(7)

The ESO mathematical model of DTC system for PMSM based on ADRC is written as:
Where $z_1$ is the tracking value, $z_2$ is the system disturbance estimate, $\alpha_1$ is the non-linear factor, $\delta_1$ is the filter factor, $\beta_1$, $\beta_2$ is the coefficient, and $f_2$ is defined as follows:

$$f_2(e, \alpha_1, \delta_1) = \begin{cases} e^{\text{sgn}(e)}, & |e| > \delta \\ \frac{e}{\delta}, & |e| \leq \delta \end{cases}$$

The NLSEF mathematical model of DTC system for PMSM based on ADRC is written as:

$$\begin{cases} e = z_1 - \omega_r \\ \dot{z}_1 = z_2 - \beta_1 f_2(e, \alpha_1, \delta_1) + bu \\ \dot{z}_2 = -\beta_2 f_2(e, \alpha_1/2, \delta_1) \end{cases}$$

DESIGN OF ADRC CONTROLLER OPTIMIZED BY CKMTOA – KELM

Review of KELM

KELM is a new kind of single hidden layer forward learning algorithm derived from ELM theory [11]. The Compared with the traditional ELM, KELM obtains better regression prediction accuracy by introducing kernel functions.

The output of KELM regression model is shown in formula (12):

$$f(x) = h(x) H^T (I/C + HH^T)^{-1} T$$

$$f(x) = \begin{bmatrix} K(x, x_1) \\ \vdots \\ K(x, x_N) \end{bmatrix} (I/C + \Omega_{i,j})^{-1} T$$

(12)

Where $I$ is the diagonal matrix, $C$ is the penalty coefficient, the random matrix HHT in the ELM is replaced by the kernel matrix $\Omega_{i,j} = h(x_i)\cdot h(x_j) = K(x_i, x_j)$.

The kernel function $K(u, v)$ selects the RBF kernel function.

$$K(u, v) = \exp \left( -\frac{(u-v)^2}{\delta} \right)$$

(13)

The weight of the KELM regression model is derived from Eq. (13) as follows:

$$\beta = (I/C + \Omega_{i,j})^{-1} T$$

(14)

KELM enhances the stability and generalization ability by kernel function and penalty coefficient, but the parameter $\delta$ and the penalty coefficient $C$ in the kernel function affect the performance of the regression prediction. Therefore, this paper chooses the chaotic molecular motion theory optimization algorithm to optimize the parameter $\delta$ and the penalty coefficient $C$. 

\[208\]
Improved CKMTOA

Each individual in KMTOA is considered as a molecule, and each individual in the population will be subject to the gravity or repulsion or free fluctuations [12]. The forces of the molecule will produce an acceleration, which is to speed up the speed of the molecules, and to further modify the position of molecules in space. The relationship is presented in (15)-(17).

\[
F_i = \begin{cases} 
GM_iM_{best} (X_{best} - X_i) \\
- GM_iM_{best} (X_{best} - X_i) \\
AM_i (X_{max} - X_{min}) N(0,1)
\end{cases}
\]

\[
V_i(t+1) = \omega V_i(t) + \frac{F_i}{M_i} 
\]

\[
X_i(t+1) = X_i(t) + V_i(t+1)
\]

However, if all the molecules in the population satisfy \(|x_{max}(x_j) - x_{min}(x_j)| \leq \varepsilon\), the algorithm is easy to fall into local precocity, lack of local optimization mechanism, and affect the global search ability and convergence speed. In order to improve the overall search capability and avoid the local optimization of the algorithm, this article improves KMTOA as follows.

1) We use adaptive inertia weight factors in the speed updating and the equation can be express as follows.

\[
\omega = \begin{cases} 
\omega_{min} - \frac{(\omega_{max} - \omega_{min})(f - f_{min})}{f_{avg} - f_{min}}, & f \leq f_{avg} \\
\omega_{max}, & f \geq f_{avg}
\end{cases}
\]

Where \(\omega_{min}\) and \(\omega_{max}\) is maximum and minimum inertia weight respectively, \(f\) is the current fitness function value, \(f_{avg}\) is the current fitness function value of the average of all particles, \(f_{min}\) is the minimum fitness function value.

2) In order to avoid the algorithm into the local optimal value and improve the accuracy of the solution, this paper introduces the chaotic local search to enhance the local search capability of KMTOA. The best molecules individual of the population to retain the operation, as the elite population \(JS\) of each iteration. In this paper, Logistic map is chosen as chaotic map to the chaotic local search of the elite population in each iteration of algorithm. Sequences generated by the logistic mapping are formulated as below:

\[
z_{j,k+1} = \mu z_{j,k} (1-z_{j,k}), \quad k = 0,1,2,..., \quad 0 \leq z_{j,k} \leq 1
\]

The resulting chaotic sequence is returned to the new elite population according to equation (20).

\[
x_{j,k+1} = x_{j,k} + z_{j,k}, \quad k = 0,1,2,...
\]

Where \(z_{j,k}\) is the extended chaotic variable sequence, \(\mu\) is the control parameter (here, \(\mu=4\), \(z_{0} \in (0.025, 0.5, 0.75)\)), \(x_{j}\) is the individual of the current elite population, and the value of \(k\) based on the number of elite populations (here \(k=1/B\), \(B\) is the percentage of the elite population), Thus ensuring that the total number of populations does not change and is not reduced by each iteration.

3) Considering the better the prediction effect obtained by the smaller objective function value, the root mean square error (RMSE) is chosen as the objective function value. The \(J_{RMSE}\) equation as follows:
\[ J_{RMSE(i,j)} = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (y(j) - y_d(j))^2} \]  

(21)

Where \( y(j) \) is the output value of the regression model and \( y_d(j) \) is the desired output value.

**Design of ADRC Controller Optimized by CKMTOA – KELM**

As can be seen from the second section, DTC of PMSM based on ADRC controller shows that the system’s disturbance \( w(t) \) is obtained by real-time estimation of ESO in the ADRC controller. The total disturbance of the system is \( w(t) = w_1 + w_2 \). If the partial perturbation value \( w_1 \) of the system perturbation can be known, the estimated disturbance part of the system of ESO will be reduced, which will reduce the burden and improve the observation accuracy of ESO.

The trained CKMTOA-KELM regression model can estimate the partial disturbance value \( f_{CKMTOA-KELM} \) of the system in real time according to the input signal \( z_1 \). The sum of \( f_{CKMTOA-KELM} \) and the remaining disturbance \( z_2 \) estimated by ESO is taken as the total system disturbance, and the real-time feedforward compensation is performed by the subsequent operation. DTC system for PMSM based on ADRC optimized by CKMTOA-KELM can improve the system response speed, improve ADRC observation accuracy, and further improve the system anti-jamming capability.

The DTC system for PMSM based on ADRC optimized by CKMTOA-KELM mathematical model is as follows:

\[
\begin{align*}
\dot{v} &= f_1 \left( v_i - \omega_i^*, r, T \right) \\
e &= z_i - \omega_i \\
z_1 &= z_2 - \beta_{12} f_2 \left( e, \alpha, \delta \right) + bu + f_{CKMTOA-KELM} \\
z_2 &= -\beta_{12} f_2 \left( e, \alpha_1, \delta \right) \\
e_1 &= v_i - z_1 \\
u_0 &= \beta_{10} f_2 \left( e, \alpha_1, \delta_1 \right) \\
T_r &= u_0 - \frac{z_2}{b} + f_{CKMTOA-KELM}
\end{align*}
\]

(22)

Direct torque control system for PMSM based on ADRC optimized by CKMTOA-KELM is shown in Figure 1.

The detailed steps of ADRC optimized by CKMTOA-KELM are as followed.

Step 1: The data samples of \( z_1 \) and \( z_2 \) are sampled and preprocessed. The data samples of \( z_1 \) and \( z_2 \) respectively, \( z_1 \) and \( z_2 \) data sets are divided into training data sets and test data sets, where the odd set as training data, even set as test data.
Step 2: Using the CKMTOA to optimize kernel parameter $\delta$ and penalty coefficient $C$ of the KELM regression model. Initialize the parameters of CKMTOA and KELM, and randomly initialize each individual position $x_i(t)=[c_i(t), \delta_i(t)]^T$ according to the range of the kernel parameter $\delta$ and the penalty coefficient $C$, and randomly initialize velocity, and the kernel function of the KELM model selects the RBF kernel.

Step 3: The optimization of the CKMTOA algorithm is carried out, calculate the objective function value of each individual according to (21) and retain the best-performing partial individual in the population. The optimal kernel parameter $\delta$ and penalty coefficient $C$ are obtained by continuous iteration optimization.

Step 4: The CKMTOA-KELM optimal regression model is embedded in the ADRC controller. As shown in Fig. 1, the trained CKMTOA-KELM realizes the partial disturbance value $f_{CKMTOA-KELM}$ of the system by the input signal $z_1$. Output the partial disturbance value $f_{CKMTOA-KELM}$ of the system.

SYSTEM SIMULATION EXPERIMENT AND RESULT ANALYSIS

Simulation Parameter Setting

In order to verify the control performance of the direct torque control system of permanent magnet synchronous motor based on CKMTOA-KELM optimized ADRC controller, this paper uses Matlab/Simulink to construct the simulation model to carry on the experimental analysis, in which CKMTOA-KELM regression model training is realized with m file program. PMSM parameters are as follows: stator resistance $R_s=1.3\Omega$, equivalent inductance $L_d=L_q=0.00215\text{H}$, permanent magnet flux $\psi_f=0.175\text{Wb}$, moment of inertia $J=0.0013\text{kg} \cdot \text{m}^2$, motor pole pairs $n_p=4$.

The CKMTOA-KELM regression model parameter settings are as follows. The kernel function of KELM regression algorithm selects the RBF kernel function. The parameters of improved CKMTOA settings are as follows: the maximum number of iterations $T=200$, the population size $S=100$, the probability of attraction $P_{\text{attraction}}=0.3$, the rejection probability $P_{\text{repulsion}}=0.64$, the probability of thermal motion $P_{\text{wave}}=0.06$, the gravitational constant $G$ is a threshold in the interval $[0,1]$, the individual mass of $M_{\text{Best}}$ is 2, and the number of elite populations accounts for 20% of the total population.

Experimental Study on Anti-jamming Capability of System

In order to verify the effectiveness of the proposed method, firstly, compare the improved CKMTOA-KELM of this paper with the original KELM regression model to prove the superiority of CKMTOA-KELM regression model. At the same time, the optimization ADRC controller based on CKMTOA-KELM is established. Compared with the traditional PI controller and ADRC controller, the simulation and experiment results have verified the feasibility and effectiveness of this method. The initial condition of simulation is given as follows: the simulation time is 0.6s, the reference speed response is 200r/min, the initially load is 1N-m and rise to 4N-m in 0.3s.
From Figure 2 to Figure 3 it can be concluded that the improved CKMTOA-KELM regression model is superior to the KELM regression model, and the regression error is very small, which can meet the system requirements.

The speed response curves of traditional PI, ADRC and ADRC controller optimized by CKMTOA-KELM for PMSM drives are shown in Fig. 4. It can be seen from Figure 4 that, the speed response of CKMTOA PID controller has small overshoot and it needs a short time to achieve steady state. While the load is added at 0.3s, the speed of DTC system for PMSM based on the traditional PI controller instantly drops from 200r/min to 186r/min and return to the original steady state after 0.22s. The speed of DTC system for PMSM based on the ADRC controller instantly drops to 192r/min and return to the original steady state after 0.15s. However, using the DTC system for PMSM based on ADRC controller optimized by CKMTOA-KELM of this paper, the speed instantly dropped to 194r/min, and return to the
original steady state after 0.018s. From Figure 5 it can concluded that the ADRC controller optimized by CKMTOA-KELM can effectively reduce the torque ripple. While the command load and speed changes, the ADRC controller optimized by CKMTOA-KELM has small overshoot and take shorter time to reach steady-state compared with the Conventional PI and ADRC controller.

From Figure 6 to Figure 7 it can concluded that when the torque inertia of the PMSM changes. The speed rise time of the motor is almost unaffected in DTC system for PMSM based on ADRC controller optimized by CKMTOA-KELM.

Through the analysis of the simulation results shows that the DTC system for PMSM based on ADRC controller optimized by CKMTOA-KELM can accelerate the dynamic response speed of the system, and enhance the anti-interference ability of the system, and improve the observation accuracy, and reducing the steady-state error.

CONCLUSION

In order to improve the dynamic response speed and anti-interference ability of the DTC system of PMSM for electric vehicles, a DTC for PMSM based on ADRC optimized by CKMTOA - KELM method is proposed in this paper. The proposed method uses CKMTOA-KELM discrete training to get the optimal regression model. The trained optimal regression model is embedded in the ADRC controller to get the ADRC optimized by CKMTOA-KELM. The main conclusions of simulation and experiment are as follows:

1) The KELM model optimized by CKMTOA has a higher regression accuracy than the traditional KELM model, and it meets requirements of the control system.

2) This method can reduce the steady-state error of the system, and accelerate the dynamic response speed of the system, and improve the estimation accuracy of ADRC.

3) The anti-interference ability and robustness of the system are improved.

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