CEAI, Vol.21, No.4 pp. 34-42, 2019 Printed in Romania

Fast parameter identification of permanent magnet synchronous motor for electric vehicles

Qinmu Wu, Xiaoyan Li, Mei Zhang, Likun Pang, Jiahao Li

School of Electric Engineering, Guizhou University, GuiZhou, 550025, China
（email:to_qmwu@gzu.edu.cn）

Abstract: This paper proposes a new recurrent neural network method (RNN) that can be used for parameter identification and optimal current (OC) solution for interior permanent magnet synchronous motor (IPMSM) in electric vehicles (EVs). Firstly, the problem of parameter identification of IPMSM is modeled as a regression problem, and the least absolute deviation method (LAD) is used to estimate the parameters. Then the optimization theory and variational theory are adopted to convert it into a variational problem, and the projection dynamic equation (PDS) is utilized to find the solution. Finally, the RNN corresponding to the PDS is designed which can be multiplexed for the optimal solution, aiming at achieving the motor parameter identification in parallel. This paper proves the convergence of the proposed projection dynamic equation. The convergence value and the identity of the PMSM parameter are estimated. The IPMSM drive system is built and simulated. The simulation results show that the proposed method can identify the motor parameters quickly and accurately, and it verifies the rationality and effectiveness of the proposed method.

Keywords: electric vehicles; IPMSM; optimal current; parameter identification; recurrent neural network.

1. INTRODUCTION

Permanent magnet synchronous motors (IPMSM) are superior to other types of motors, such as induction motors, in that they have high efficiency and high power density. They are widely used in electric vehicles and as power supply components (JianHua Wu et al., 2018). In the EV power-driven system, the motor is the largest energy-consuming device. In order to improve its efficiency and increase the endurance mileage for one charge, it is very important to adopt efficiency optimization control strategy for the power-driven system (Qingbo Guo et al., 2017; A. M. Bazzi et al., 2010). Compared with other efficiency optimization control methods, model-based efficiency optimization control is most suitable for electric vehicle drive systems (Guangxu Zhou et al., 2007; Xianqing Cao et al., 2009; M. A. Khan et al., 2011). Since the operating state of the motor needs to be switched frequently, it is difficult to maintain a stable status for a long time. When optimizing the efficiency of the system, it is necessary to calculate the OC for performing the efficiency control as quickly as possible. However, for model-based efficiency optimization control methods, the performance of the efficiency optimization depends on the accuracy of the motor parameters. Due to the characteristics of IPMSM for electric vehicles, e.g. high power density, small volume, large power, the internal temperature range of the motor varies greatly. In a short time, the winding current varies greatly and changes rapidly. Therefore, the parameters of the motor are almost always changing during the operation duration (Chi D. Nguyen et al., 2015).

In order to improve the performance of IPMSM efficiency optimization for electric vehicles, it is necessary to accurately and quickly estimate the parameters of the motor. According to the real-time of parameter identification, it can be divided into online and offline identification. The offline methods can be divided into two categories: finite element analysis and experimental test. On-line methods include single parameter and multi-parameter identification where recursive least squares method, differential algebra method and artificial intelligence method, etc, are widely used. The finite element method was adopted to determine the parameters of the motor (T. Windisch et al., 2011; W. Peters et al., 2012), aiming at achieving the efficiency optimization control of PMSM. However, for methods based on finite element parameter identification, a priori knowledge of motor structure and materials is required. Most of the experimental test-based methods are to apply DC excitation or AC excitation in the stator loop of the motor when the motor is at standstill. The off-line identification of the motor parameters is realized by analyzing the relationship between excitation and response (Weisgerber. S, 1997; Khatounian. F et al., 2006). The offline identification method of the motor parameters can obtain accurate identification results without considering the computational complexity and time overhead. However, this method cannot accurately reflect the influence of different operating conditions and temperature changes on the motor parameters during actual operation of the motor.

The IPMSM parameter identification is performed online (Junggi Lee, 2009), considering only the variation of the q-axis inductance of the motor with the q-axis current, and the q-axis inductance and the q-axis current are expressed in an approximate linear relationship, while ignoring the changes of other parameters. The recursive least squares method with fading factor was applied to realize the parameter identification of the motor (Cui Naxin et al., 2007), but its parameter identification speed is slow, which is not suitable for the efficiency optimization control of EVs. Differential algebra method is adopted to realize the parameter identification of the motor (Li Hongmei et al., 2017). However, the matrix operation is involved in the identification process. If it is implemented by a digital controller such as DSP, it requires a large amount of calculation. A genetic algorithm-based IPMSM parameter identification method is proposed (Xiao Xi et al., 2017). This method inherits the advantages of strong robustness of intelligence control methods and achieves higher recognition accuracy and convergence speed. The above mentioned methods are all based on software code to implement parameter identification in a sequential execution manner; Parameter identification is sensitive to measurement noise, such as least squares method, parameter estimation is unbiased only when measurement noise has Gaussian distribution characteristics; The parameter identification and the OC calculation of the motor drive system are implemented by different algorithms and cannot be balanced with each other. Based on the motor voltage equation, this paper models the motor parameter identification as a parameter regression problem, and uses the least absolute deviation method (LAD) for identification estimation. This method is not sensitive to the measurement noise distribution characteristics and outliers (bad data points). The identification of motor parameters based on LAD is transformed into variational problem by optimization theory and variational theory. Finally, a RNN is used to solve the variational problem, and the network can be used for finding OC solution of IPMSM drive system as well. Through theoretical and simulation analysis, the proposed method can estimate IPMSM parameters quickly and accurately. Since the parameter identification is implemented by RNN, it is easy to implement in parallel in hardware.

2. IPMSM PARAMETER IDENTIFICATION MODELLING

According to literature (Junggi Lee et al., 2009), in the synchronous frame, the voltage equation of IPMSM can be expressed as

$$\begin{cases} u_d = r_s i_d + L_d \dfrac{di_d}{dt} - \omega_e L_q i_q \\ u_q = r_s i_q + L_q \dfrac{di_q}{dt} + \omega_e L_d i_d + \omega_e \psi_f \end{cases} \tag{1}$$

The physical meanings of the variables in (1) are as shown in Table 1.

The q-axis voltage equation of equation (1) is discretized according to the sampling period *T* and subjected to a certain transformation, considering the measurement noise, it obtains

$$\chi = \varphi\theta + w \tag{2}$$

where $\varphi = [i_q(k), i_q(k-1), \omega_e(k-1) i_d(k-1), \omega_e(k-1)]$, $\chi = u_q(k-1)$, $\theta = [a,b,c,d]^T$, $a = L_q / T_S$, $b = (R_S - L_q / T_S)$, $c = L_d$, $d = \psi_f$, w is measurement noise.

When parameter identification is performed, multiple sets of data are adopted (let the number of sets as m), then the matrix form corresponding to equation (2) can be obtained. The parameter identification model of IPMSM is described as:

$$y = Y\theta + v \tag{3}$$

where $Y = (a_{ij})_{m\times n} = \left[\varphi(1)^T \quad \varphi(2)^T \quad \cdots \quad \varphi(m)^T\right]^T$,

$y = (b_i)_{m\times 1} = [\chi(1) \quad \chi(2) \quad \cdots \quad \chi(m)]^T$

$v = [w(1) \quad w(2) \quad \cdots \quad w(m)]^T$

Table 1. Physical meaning of the variables.

r_s	Stator resistance	ψ_f	Permanent magnet flux
i_d	d-axis current	i_q	q-axis current
u_d	d-axis voltage	u_q	q-axis voltage
L_d	d-axis inductance	L_q	q-axis inductance
ω_e	Electrical angular velocity		

3. IPMSM PARAMETER IDENTIFICATION DYNAMIC PROJECTION EQUATION

Lemma 1:

set $u = [\theta^T, e^T]^T$, $q = [0_{1\times4}, y^T_{m\times1}]^T$, $M = [0_{4\times4}, Y^T{}_{4\times m}; -Y_{m\times4}, 0_{m\times m}]$, $F(u) = Mu + q$, $e = [e_1, ..., e_m]^T$, $|e_i| \le 1$, thus the solution u_1^* of the following equation (4) is in fact the solution of (3) which is the parameter identification value based on LAD.

$$\left(F(u^*), u - u^*\right) \ge 0 \tag{4}$$

Proof: for (3), the LAD method is utilized for parameter identification, that is, the $\phi(\theta)$ of the formula (5) is minimized, thus, the objective function (Youshen. X et al., 2008) of the LAD is

$$\phi(\theta) = \|Y\theta - y\|_1 \tag{5}$$

Set $e = [e_1, ..., e_m]^T$, where $|e_i| \le 1$, it obtains

$$e^T(Y\theta - y) \le \|Y\theta - y\|_1 \tag{6}$$

Let $r_i = (Y\theta - y)_i$, $e^0 = [sign(r_1), ..., sign(r_m)]^T$, one can get

$$e^0(Y\theta - y) = \|Y\theta - y\|_1 \tag{7}$$

Then $\|Y\theta - y\|_1 = \max\limits_{e\in\Omega_1} e^T(Y\theta - y)$, where $\Omega_1 = \{e \in R^m \mid \max|e_i| \le 1, i = 1 \cdots m\}$, The parameters estimation can be transformed into an optimization problem as in equation (8), that is

$$\begin{aligned} &\min \quad \max_{e\in\Omega_1} e^T(Y\theta - y) \\ &\quad subject \quad to \quad \theta \in R^4 \end{aligned} \tag{8}$$

Thus, a variational inequality corresponding to (8) is obtained (Youshen. X et al., 2008)

$$\begin{cases} (\theta - \theta^*)^T (Y^T e^*) \ge 0 \\ (e - e^*)^T (-Y\theta^* + y) \ge 0 \end{cases} \tag{9}$$

rewritten as a matrix form, one can get the formula (4).

Theorem 1:

Set $\gamma > 0$, $\beta > 0$, $H = (I + \beta M^T)$, $\Omega = [\Omega_2, \Omega_1]$, $\Omega_2 = \{\theta \in R^n \mid \theta_j \in [l_j, h_j], j = 1, 2, \cdots n\}$,

$\Omega_1=\{e\in R^m \mid \max|e_i|\le 1, i=1\cdots m\}$, $\sigma_{\max}(H)$ is the maximum value of singular value of H, if $\sigma_{\max}(H)<\sqrt{2}$, then the projection dynamic equation

$$\frac{du}{dt}=-\gamma H[u-P_\Omega(u-\beta F(u))] \tag{10}$$

$$P_{\Omega_2}(y_j)=\begin{cases} l_j & y_j\le l_j \\ y_j & l_j<y_j<h_j \\ h_j & y_j\ge h_j \end{cases},\quad P_{\Omega 1}(e_j)=\begin{cases} -1 & e_j\le -1 \\ e_j & -1<e_j<1 \\ 1 & e_j\ge 1 \end{cases}$$

is stable, and the convergence value is the solution of formula (4) .

Proof: let $\tilde{u}=P_\Omega[u-\beta F(u)]$, set u^* as a solution of (10), then one can obtain (Francisco Facchine et al., 2003):

$$\begin{cases}(\tilde{u}-u^*)^T\beta F(u^*)\ge 0\\ (\tilde{u}-u^*)^T([u-\beta F(u^*)]-\tilde{u})\ge 0\end{cases}$$

Add the two equations, it gets

$$\{(u-u^*)-(u-\tilde{u})\}^T\{(u-\tilde{u})-\beta M(u-u^*)\}\ge 0$$
$$\Leftrightarrow (u-u^*)^T H(u-\tilde{u})$$
$$\ge \|u-\tilde{u}\|^2+\beta(u-u^*)^T M(u-u^*)$$

Since M is semi-positive, one gets

$$(u-u^*)^T H(u-\tilde{u})\ge \|u-\tilde{u}\|^2$$

Set $\tilde{u}^k=P_\Omega[u^k-\beta F(u^k)]$, according to a literature (Bing. S. H, 2015), select measure function as

$$\varphi(u^k,\tilde{u}^k)=\|u^k-\tilde{u}^k\|^2$$

and the favourable direction as

$$d(u^k,\tilde{u}^k)=H(u^k-\tilde{u}^k)$$

thus

$$(u^k-u^*)^T d(u^k,\tilde{u}^k)\ge\varphi(u^k,\tilde{u}^k)$$

take proper value of γ, discretization (10), one gets

$$u^{k+1}=u^k-H(u^k-\tilde{u}^k)$$

set

$$\vartheta(k)=\|u^k-u^*\|^2-\|u^{k+1}-u^*\|^2$$
$$=\|u^k-u^*\|^2-\|u^k-u^*-d(u^k,\tilde{u}^k)\|^2$$
$$=2\left(u^k-u^*\right)d(u^k,\tilde{u}^k)-\|d(u^k,\tilde{u}^k)\|^2$$

then

$$\vartheta_k(k)\ge 2\varphi(u^k,\tilde{u}^k)-\|d(u^k,\tilde{u}^k)\|^2$$
$$=2\|u^k-\tilde{u}^k\|^2-\|H(u^k-\tilde{u}^k)\|^2$$

If $\vartheta_k(k)\ge 2\|u^k-\tilde{u}^k\|^2-\|H(u^k-\tilde{u}^k)\|^2>0$

Thus (10) is convergent.

Since M is an anti-symmetric matrix, M and M^T have the same eigenvalue, and the eigenvalue is zero or pure imaginary number. H is a matrix polynomial of M^T, let eigenvalue of M as $\lambda'=0+a_j i$, then the eigenvalue of H is $\lambda=1+\ \beta a_j i$. H is a regular matrix, and the singular value of H is $\sigma=\sqrt{1+\left(\beta a_j\right)^2}$. Set $\sigma_{\max}(H)$ as the maximum value of singular value of H , then

$$\|H(u^k-\tilde{u}^k)\|\le\sigma_{\max}(H)\|(u^k-\tilde{u}^k)\|$$

Thus, if $\sigma_{\max}(H)<\sqrt{2}$, $\vartheta_k(k)>0$, then the equation (10) is stable and convergent, and the convergence value is the parameter identification value of the formula (3) based on LAD.

Comment 1: Due to that $M=[0,Y^T;-Y,0]$, and $\rho(M)\le\|M\|_\infty$, in (3), the left and right sides of the equation are divided by a constant ε at the same time, and the parameter value to be estimated is not changed. Therefore, proper selection of the constant ε can always satisfy $\sigma_{\max}(H)<\sqrt{2}$, which ensures that the equation (10) is stable and converges to the parameters to be estimated of the motor.

According to the literature (Qinmu Wu et al., 2016), rewrite the formula (5) in the literature, it obtains

$$\frac{du_2}{dt}=-\gamma_e[u_2-P_{S_0}(u_2-\beta_e F(u_2))] \tag{11}$$

That is, the OC of IPMSM can be solved by (11), where the constant γ_e is greater than zero, $\beta_e=1$ and the detailed convergence analysis of equation (11) can be found in (Qinmu Wu et al., 2016).

Comment 2: According to equations (10) and (11), the parameter identification and optimization current of IPMSM can be solved by a unified projection dynamic equation, as follows:

$$\frac{du}{dt}=-\gamma_u K[u-P_\Omega(u-\beta_u F(u))] \tag{12}$$

4. UNIFIED RECURRENT NEURAL NETWORKFOR IPMSM PARAMETER IDENTIFICATION AND OPTIMIZED CURRENT SOLUTION

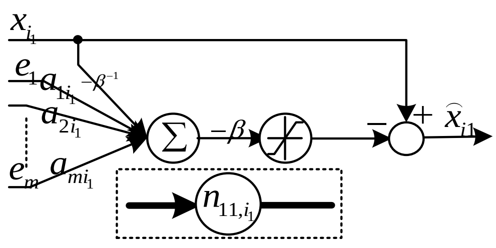
4.1 RNN for IPMSM parameter identification

Based on Theorem 1, a recursive neural network for IPMSM parameter identification is available, which consists of four types of neurons, namely: n_{11,i_1} , n_{21,k_1} , n_{12,i_2} and n_{22,k_2} , as shown in Fig.1, where n_{11,i_1} , n_{21,k_1} constitute the first layer of the network, its weight is related to matrix Y and coefficient β. n_{12,i_2} and n_{22,k_2} constitute the second layer of the network, its weight is related to matrix H. If the number of parameters to be identified is n and the number of sampled samples of the data is m, then there are n nodes of n_{11,i_1}, n_{12,i_2} types of nodes, m nodes as type of n_{21,k_1}, n_{22,k_2}, Then the IPMSM parameter identification recursive neural network diagram is shown in Fig. 2.

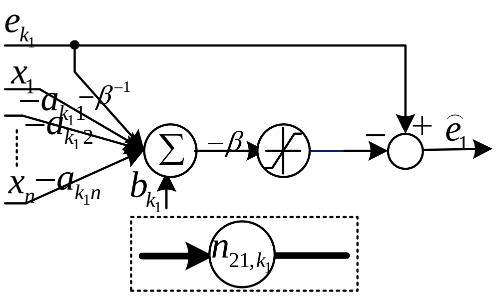
4.2 PMSM Optimized Current Calculation Module

According to the formula (5) in the literature (Qinmu Wu et al., 2016).), also the formula (12) in this paper, the RNN shown in Fig. 3 can be obtained. The network consists of three neurons. When the neural network calculates its output, some of the weights are adjusted in real time. The adjustment functions are $f_1(\bullet) = 1.5p_n(L_d - L_q)x_2$, $f_2(\bullet) = 1.5p_n(L_d - L_q)x_1$, $f_3(\cdot) = \max(0, y + g(x))$

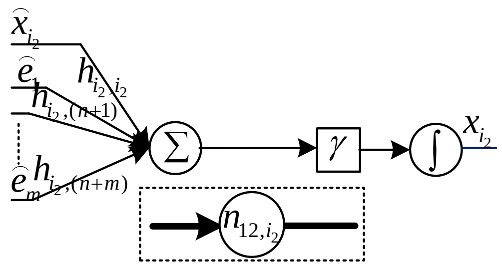
From Fig. 2 and Fig. 3, the neural network shown in Fig. 3 can be implemented by multiplexing three neurons of the neural network input layer and three neurons of the output layer shown in Fig. 2, as the neurons in the dotted box section in Fig.4. The second layer of non-multiplexed neurons has the ownership value set to 0, and the multiplexed 3 neurons only need to be adjusted to set part weights to 0, recalculate or set some weights and offsets. During the operation of the motor controlled by efficiency optimization control method, the OC calculation is required for each control cycle. The parameter identification of the motor can be performed once per control cycle, or once during multiple control cycles. Whatever, the parameter identification and optimized current calculation of the motor are performed at different time periods of a control cycle, it provides a condition for a neural network to take into account the parameter identification and the OC calculation of the motor.



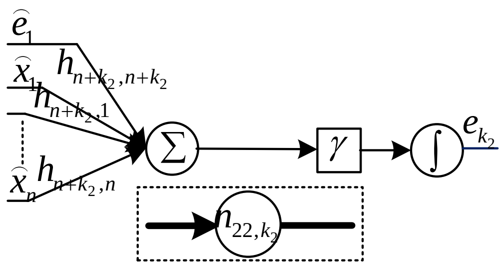
a. n_{11,i_1}



b. n_{21,k_1}



c. n_{12,i_2}



d. n_{22,k_2}

Fig. 1. Four types of neurons for IPMSM parameter identification.

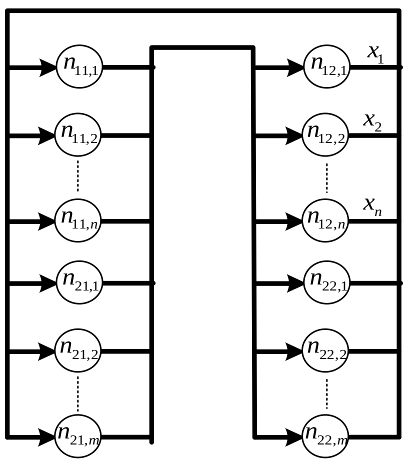


Fig. 2. RNN for IPMSM Parameters Identification.

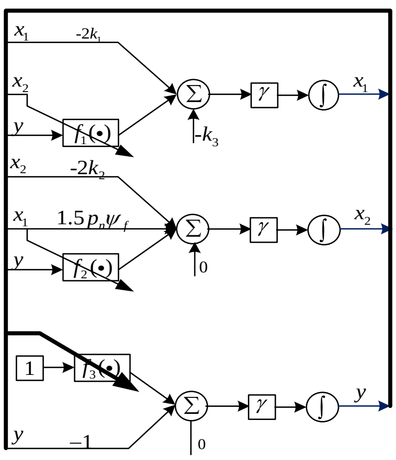


Fig. 3. PMSM OC Calculation Module based on Recurrent Neural Network.

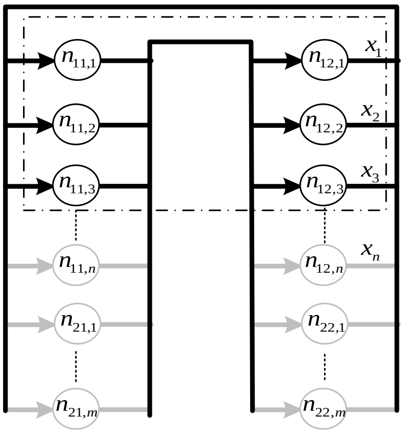
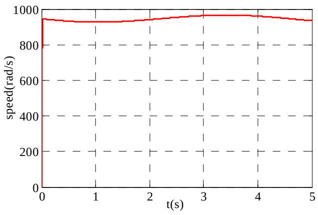


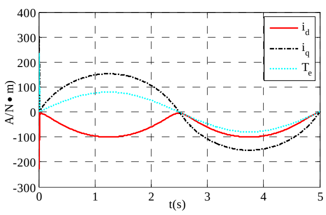
Fig. 4. Network Diagram of OC Calculation Implemented by RNN shown in Fig. 2.

5. SIMULATION EXPERIMEAT AND ANALYSIS

The vector control-based IPMSM drive control system is established by MATLAB Simulink. The motor parameters used can be found in the literature (Junggi Lee et al., 2009). The system is simulated to obtain the motor d/q -axis current, q- axis voltage and rotor speed, as shown in fig. 5. In order to ensure that the input and output of each neuron in the neural network system identifying motor parameters will not be too large, each entry of φ in equation (3) is multiplied by 0.01, 0.01, 0.001, 0.01 separately. By extracting 200 data sample among 4000 data values sampled from the speed, d/q-axis currents, torque and q-axis voltage signal of the motor starting from t=0s, which a datum point is record every interval 20 data points, the matrix Y and y of the formula (3) whose column length are 200 are obtained. A suitable ε is selected such that H satisfies the requirement of the theorem 1. Based on Fig. 2, the RNN simulation model is built in the MATLAB Simulink.



a. The speed curve



b. The d/q-axis currents and torque curves

Fig. 5. The speed, d/q-axis currents and torque curves of the motor.

When the motor parameter is the rated parameter, this is, $L_q = 835e-6(H)$, $L_d = 375e-6(H)$, $R_s = 29.5(m\Omega)$, $\psi_f =$ $0.07(Wb)$, and the noise signal overlap on the q-axis voltage is as shown in Fig.6, the identification results of L_q, L_d, R_s, ψ_f of the motor are obtained by the recursive neural network based least absolute deviation method (RLADM) in this paper and the recursive least-squares method (RLSM) based on the above-mentioned Y and y , respectively, as shown in Fig.7 and Fig.8. According to the two figures, the RLADM can ensure that the parameter identification value is almost total equal to the real value. While the identification results obtained by the RLSM are $L_q = 837e-6(H)$, $R_s = 30.6(m\Omega)$ $L_d = 360e-6(H)$, $\psi_f = 0.0698(Wb)$, obviously, there exists a small deviation between the identification value and the real parameter value.

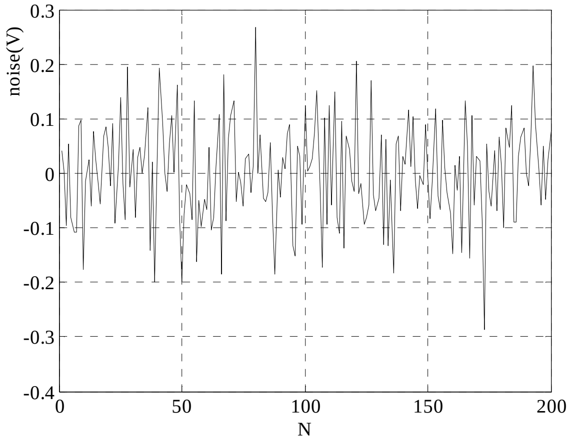
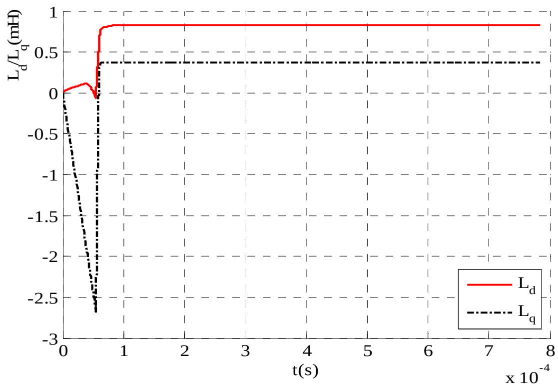
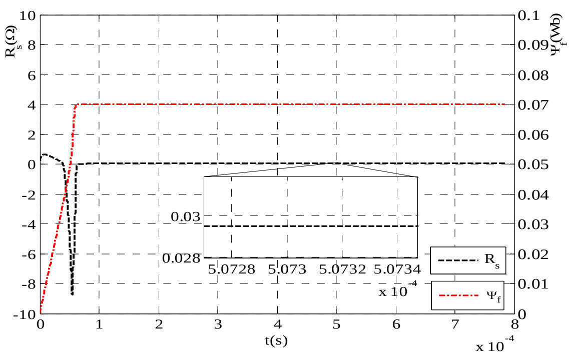


Fig. 6. The noise signal overlapped in the q-axis voltage.

If a certain set of measured values is abnormal caused by some reasons during the measurement process, e.g. the normal value of the above-mentioned $Y(100,:)$ should be

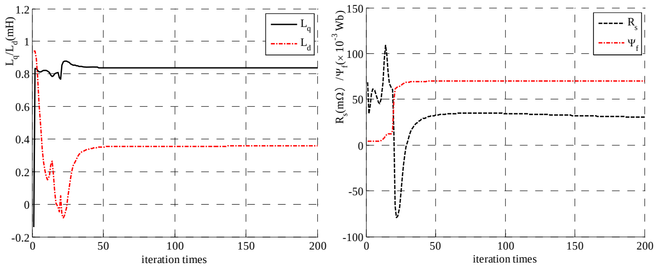


a. L_q and L_d identification curves



b. R_s and ψ_f identification curves

Fig. 7. The identification curves when the motor parameters are rated by using the RLADM.

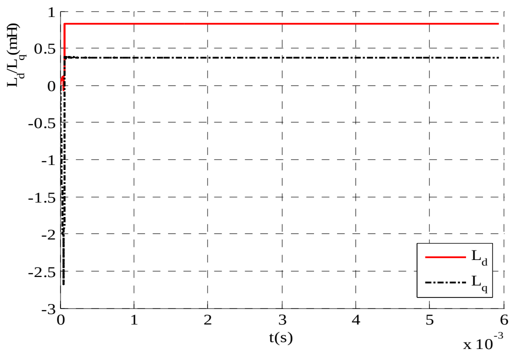


a. L $_q$ and L $_d$ identification curves

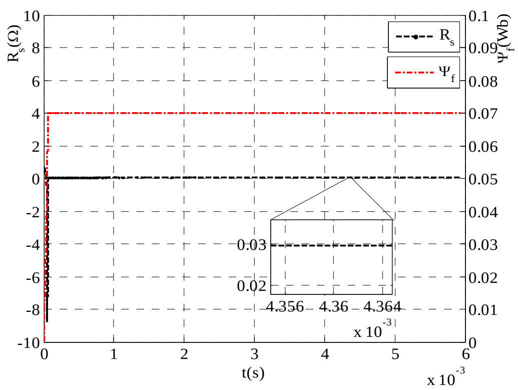
b. R $_s$ and ψ_f identification curves

Fig. 8. The identification values when the motor parameters are rated by using the RLSM.

$[-0.0295 \quad -0.0292 \quad -0.4250 \quad 0.9042]$ while the measured value is $[-3.000 \quad -3.0001 \quad -0.08 \quad 0.7038]$. The normal value of $y(100,1)$ should be 6.1700, however the measured one is 0.8. In this case, the identified parameter results of RLADM are shown in Fig. 9. It can accurately identify motor parameters, the results are $L_q = 835.34e-6(H)$, $R_s = 29.524 \ (m\Omega)$, $L_d = 375.02e-6(H)$, $\psi_f = 0.07001(Wb)$. However, the identifyed parameters results using RLSM change seriously when the abnormal measured values are introduced during identification process, as shown in Fig. 10; and they were significantly deviate from their real values within a period of time, therefore the results can not be used for the efficiency optimization of the motor.

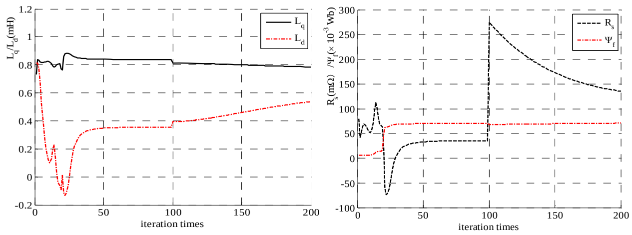


a. L $_q$ and L $_d$ identification curves



b. R $_s$ and ψ_f identification curves

Fig. 9. Identification curves when abnormal measured values existed with the RLADM.

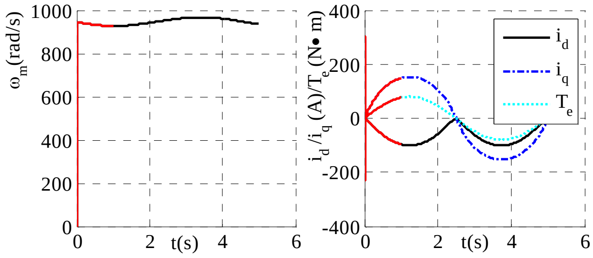


a. L $_q$ and L $_d$ identification curves

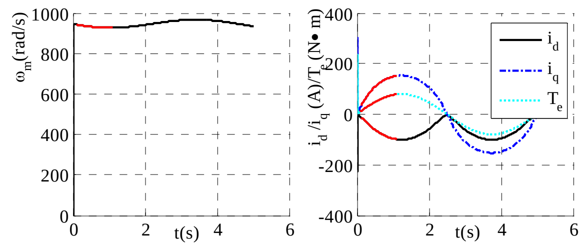
b. R $_s$ and ψ_f identification curves

Fig. 10. The identification curves when abnormal measured values existed with the RLSM.

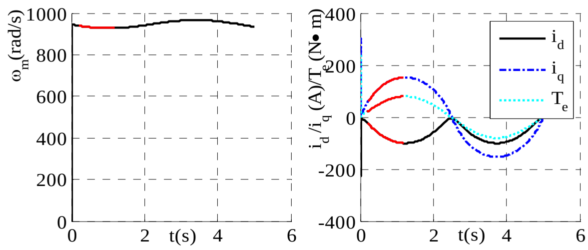
For verifying the effectiveness of the RLADM, five data sets are extracted from the data corresponding to the curves of Fig.5. As shown in Fig.11(a)-Fig.11(e), the data set are obtained from the red curve, and a datum point is recorded every interval 20 data points, every data set contains 100 data points, and 90 datum points is same in two neighbourhood data sets. The simulated measure noise overlapped on the q-axis voltage signal, as shown in Fig.11(f).



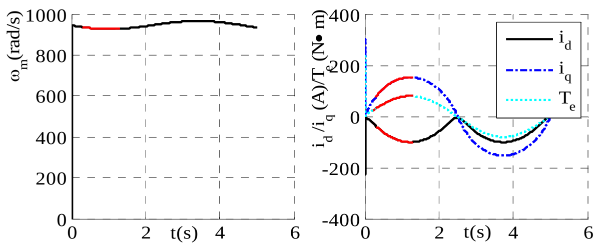
a. the curves forming the first data set with the red parts



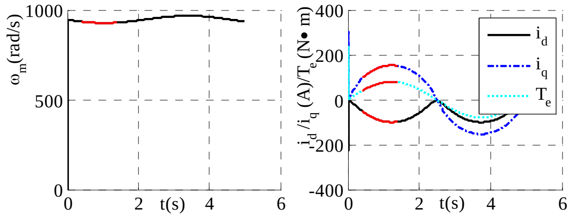
b. the curves forming the second data set with the red parts



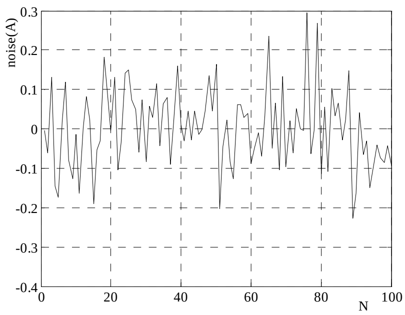
c. the curves forming the third data set with the red parts



d. the curves forming the fourth data set with the red parts



e. the curves forming the fifth data set with the red parts



f. The noise signal overlapped in the q-axis voltage

Fig. 11. Five data sets and noise signal.

The simulation results of the parameter identification of the motor based on the five data sets are shown in Table.2. According to Table.2, the RLADM can obtain the identification results which are almost equal to the real parameter values. The identified results with the RLSM are closed to the real parameter values when using the first data set, it is because a white noise signal with zero even value is overlapped on the q-axis voltage, the identification results do not equal to the real parameter values. However, the identified results are increasingly deviated from their real parameter values from the second data set to the fifth data set. Especially, the identified results based on the fifth data set are seriously deviate from their real values, because the variation of the d/q-axis currents, the torque, the speed and the q-axis voltage of the motor are the slowest in the five data sets, in another word, the motor simulation systems is in severe under-excitation state. However, the RLADM does not have this problem.

Table 2. the identified parameter results with the RLADM and the RLSM based on five data sets.

	Data set 1		Data set 2	
	RLADM	**RLSM**	**RLADM**	**RLSM**
L_q(H)	0.000835	0.000844	0.000834	0.000963
L_d(H)	0.000375	0.000396	0.000376	0.000602
R_s(Ω)	0.029530	0.033039	0.029615	0.191338
Ψ_f(Wb)	0.070002	0.068950	0.069997	0.065604
	Data set 3		Data set 4	
	RLADM	**RLSM**	**RLADM**	**RLSM**
L_q(H)	0.000832	0.000242	0.000832	0.001498
L_d(H)	0.000375	0.001686	0.000377	0.002316
R_s(Ω)	0.029461	1.023055	0.029423	1.541884
Ψ_f(Wb)	0.070018	0.036560	0.069967	0.013800
	Data set 5			
	RLADM	**RLSM**		
L_q(H)	0.000831	-0.0000046		
L_d(H)	0.000378	0.002300		
R_s(Ω)	0.029408	1.565558		
Ψ_f(Wb)	0.070130	0.009084		

For yielding a data set, some data are extracted from the red curve of Fig.12, which is the local zoom figure of the Fig.5. It forms Y and y in formula (3) with 50 column length. In order to analyse the immune ability of the RLADM against the noise, a noise signal whose length is 50 is yield, as shown in Fig.13. Four simulation experiments are finished which overlapped different intensity noise signal on the q-axis voltage signal, these noise signals come from the noise signal shown in Fig.13 multiplied a coefficient k_e, k_e =0.001, 0.01, 0.1, and 1. Some experimental results with the RLADM and the RLSM are obtained, as shown in Table.3. The Table.3 can achieve a conclusion that the identified parameter values are hardly affected by noise intensity when applying the RLADM, the deviation between these identification results are very small. Regardless of the value of the coefficient k_e, the identification results are all almost equal to the real parameter value. By contrast, when using the RLSM, with the increase of the value k_e, the identification results increasingly deviate from the real parameter value. When $k_e = 1$, the deviation between the identified parameter values and the real parameter value of the L_q, L_d, R_s, ψ_f are the biggest, and they are equal to 5.3%, 33.9%, 97% and 1.6% of the real parameter value of the motor, respectively. Especially, the identified parameter values of the L_d, R_s are seriously deviated from the real parameter values.

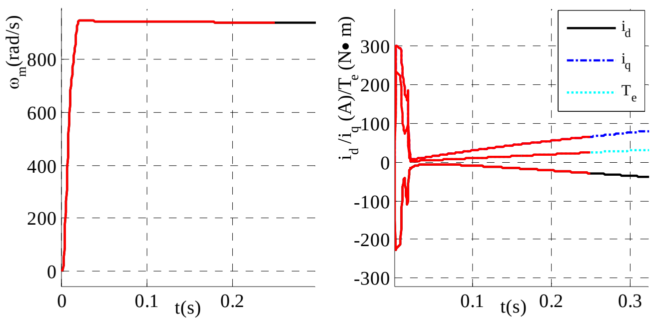


Fig. 12. The curves forming the data set with the red parts.

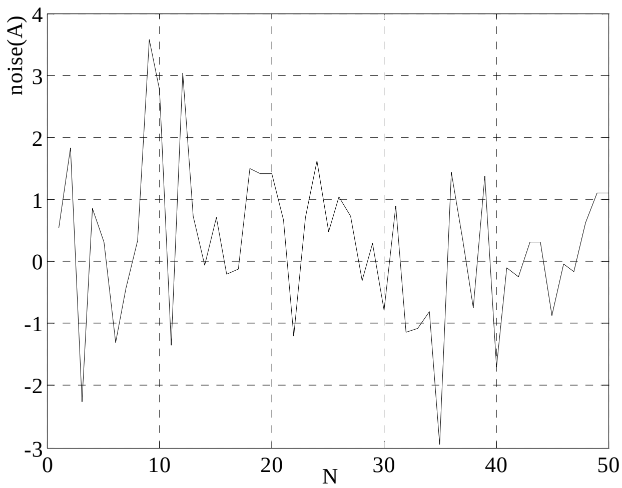


Fig. 13. The noise signal overlapped on the q-axis voltage.

Table 3. the identified parameter results with the RLADM and the RLSM under four different intensity noise signals.

	ke = 0.001		ke = 0.01	
	RLADM	**RLSM**	**RLADM**	**RLSM**
L_q(H)	0.000835	0.000835	0.000835	0.000835
L_d(H)	0.000375	0.000374	0.000375	0.000375
R_s(Ω)	0.029524	0.029845	0.029593	0.030091
Ψ_f(Wb)	0.069999	0.069973	0.069996	0.069970
	ke = 0.1		ke = 1	
	RLADM	**RLSM**	**RLADM**	**RLSM**
L_q(H)	0.000835	0.000834	0.000832	0.000790
L_d(H)	0.000376	0.000380	0.000377	0.000502
R_s(Ω)	0.029672	0.033551	0.029900	0.058103
Ψ_f(Wb)	0.069987	0.069928	0.070238	0.071093

6. CONCLUSION

The motor model-based efficiency optimization control method requires online estimation of the electromagnetic parameters of the IPMSM for EVs in real time. The accuracy of the estimation determines the performance of the efficiency optimization control. Based on IPMSM's voltage equation and flux equation, the motor parameters identification problem is modelled as regression problems. In addition, based on optimization theory, variational theory and projection dynamic theory, the regression problem is transformed into optimization problem, variational problem and finding projection-dynamic-equation solution. Finally, a RNN is used to deal with motor parameters identification, as well as analyzing the convergence conditions of the projection dynamic equation theoretically. The simulation results confirm the effectiveness and correctness of the proposed method. The weight of the designed recurrent neural network is directly taken from the state of the motor and some deter-mined coefficients of the projection dynamic equation, without pre-learning training. The RNN can be implemented in an FPGA or a dedicated neural network chip. Therefore, the proposed method provides effective technical support for implementing the IPMSM driven system in a fully hardware manner for efficient and accurate efficiency control.

ACKNOWLEDGEMENTS

This research is supported by National Natural Science Foundation of China (NSFC 51367006, 51867006) and Natural Science and Technology Foundation of Guizhou province, China (Ref. [2018]5781,[2018]1029).

REFERENCES

A. M. Bazzi, P. T. Krein, Review of Methods for Real-Time (2010) Loss Minimization in Induction Machine, *IEEE Trans. Ind. Appl., vol.46, no.6*, pp. 2319 -2328.

Bing. S. H(2015) PPA-like Contraction Methods for Conves Optimization: A Framework Using Variational Inequality Approach. *J. per. Res. Soc. China 3*, pp.391-420.

Chi D. Nguyen, Wilfried Hofmann(2015) Model-Based Loss Minimization Control of Interior Permanent MagnetSyn-chronous Motors. *IEEE International Conference on Industrial Technology*, pp.2104-2111.

Cui Naxin, Zhang Chenghui, Li Ke, Zhang Chengin(2007) Efficiency Optimization Control of Induction Motor Drives Based on Online Parameter Estimation. *Transac-tions of China Electrotechnical Society*, Vol.22, No.9, p.80-85.

Francisco Facchinei, Jong-Shi Pang(2003) Finite-Dimens-ional Variational Inequalities and Complementarity Problems, *Volume I, Springer*.

Guangxu Zhou, Huijun Wang, Dong-Hee Lee, Jin-Woo Ahn, (2007) Study on efficiency optimizing of PMSM for pump applications, *the 7th Internatonal Conference on Power Electronics*, pp. 912 - 915.

JianHua Wu, Jing Wang, Chun Gan, QingGuo Sun and Wubin Kong(2018) Efficiency Optimization of PMSM DrivesUsing Field-Circuit Coupled FEM for EV/HEV Applications, *IEEE Access*, April 4. Digital ObjectIden-tifier 10.1109/ ACCESS.2018.2813987 page:15192-15201.

Junggi Lee, Kwanghee Nam, Seoho Choi, Soonwoo Kwon(2009) Loss-Minimizing Control of PMSM with the Use of Polynomial Approximations. *IEEE Transactions on Power Electronics*, vol. 24, Feb , pp. 1071–1082.

Khatounian.F, Moreau.S, Monmasson. E, et al(2006) Parameters estimation of the actuator used in haptic interfaces: Comparison of two identification methods. *International Symposium on Industrial Electronics*, 2006, pp.211-216.

Li Hongmei, Chen Tao(2017) Demagnetization Fault Diagnosis and Fault Mode Recognition of PMSM for EV. *Transactions of China Electrotechnical Society*, Vol.32, No.5,p.1-8.

M. A. Khan, M. N. Uddin, M. Aziz Rahman(2011) A new loss minimization control of interior permanent magnet motor drives operating with a wavelet based speed controller. *IEEE Industry Applications Society Annual Meeting*, pp. 1-8.

T. Windisch, W. Hofmann(2011) Loss minimization of an IPMSM drive using pre-calculated optimized current references. *IEEE Industrial Electronics Conference IECON*, Melbourne, Australia, pp. 4704 -4709.

Qinmu Wu, Xiangping Chen, Min Cao,Wenli Zhang(2016) A study on a method solving optimal currents of IPMSM based on the PDS for electric vehicles. *the IEEE International Conference on Mechatronics and Automa-tion*, pp. 2366- 2370.

Qingbo Guo, Chengming Zhang, Liyi Li, Mingyi Wang and Tiecheng Wang(2017) Efficiency Optimization Control of Permanent Magnet Synchronous Motor System with SiC MOSFETs for Electric Vehicles, *the 20th Internat-ional Conference on Electrical Machines and Systems*, pp.1-5.

W. Peters, O. Wallscheid, J. Böcker(2012) A precise open-loop torque control for an interior permanent magnet synchronous motor (IPMSM) considering iron losses. *The 38th Annual Conference on IEEE Industrial Electronics Society*, pp. 2877-2882.

Weisgerber. S(1997) Estimation of permanent magnet motor parameter. *IEEE Industry Applications Society Annual Meeting*, pp. 29-34.

Xiao Xi, Xu Qingsong, Wang Yating, Shi Yuchao(2017) Parameter Identification of Interior Permanent Magnet Synchronous Motors Based on Genetic Algorithm. *Transactions of China Electrotechnical Society*, Vol.29, No.3,p.21-26.

Xianqing Cao, Liping Fan(2009) Efficiency-optimized vector control of PMSM drives for hybrid electric vehicle, *International Conference on Mechatronics and Automation.*

Youshen. X, Mohamed. S. K(2008) A Generalized Least Absolute Deviation Method for Parameter Estimation of Autoregressive Signals. *IEEE Transactions on neural networks,* Vol.19, No.1, pp.107-117.