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Hybrid Intelligent Method of Identifying Stator Resistance of Motorized Spindle

Lixiu Zhang[a], Yuhou Wu [b], Ke Zhang [c]

School of Traffic and Mechanical Engineering, Shenyang Jianzhu University,

Shenyang Liaoning province, China, 110168

Emails: [a]sanyoe@sina.com, [b]wuyh@sjzu.edu.cn, [c]zk690902@126.com

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Abstract- Aiming at the problem that changes of nonlinear dynamic resistance of stator affect the performance of speed sensorless vector control system, a hybrid computing intelligence approach is used in the identification of stator resistance of motorized spindle. The partial least squares (PLS) regression is combined with neural network to solve the problem of few samples and multi-correlation of variables in complicated data modeling. The PLS method is used to extract variable components from sample data and then reduced the dimension of input variables. Moreover, neural network is used to fit the non-linearity between input and output variables. The model based on partial least squares regression and neural network can identify stator resistance under different conditions of the motorized spindle. The results show that the method has high identification precision and is helpful to improve the performance of vector control system.

Index terms: vector control, stator resistance, neural network, PLS, identification, Motorized Spindle

I. INTRODUCTION

The motorized spindle is the core components of high speed machine, and then its performance directly determines the quality of high-speed processing machine tool. The driver technology is the fundamental guarantee that of the motorized spindle obtains the high performance [1]. Commonly, the servo drive mode of the motorized spindle includes V/f control, vector control and direct torque control. Under the condition of high performance requirements, due to the complex characteristics of high-frequency motor, such as nonlinear, multivariable and strong coupling， the V/f control strategy is difficult to adapt, but direct torque control and the vector control has become the mainstream technology of high performance spindle control. Application of vector control technology of high performance spindle control system is the most widely, because it has a wide range of speed, high precision torque control, and fast dynamic response. However, vector control has fatal flaws which need detailed motor control parameters. In spite of the vector control with identification system of motor parameter, usually it only identifies the static parameters of motor. However, with the change of the operating condition of the motorized spindle, the stator resistance and other parameters of motor are dynamic. Therefore, it has important significance to identify the stator resistance according to the operation condition of the motorized spindle to improve control precision of system speed and torque, better the flux shape.

At present, the stator resistance identification methods are mostly based on adaptive observer, model reference adaptive control, artificial neural network, fuzzy logic and neural fuzzy artificial intelligence [2-16]. These identification methods reduce the influence of stator resistance variation on control performance on the different degree. But due to the single model is easily affected by noise or the number of samples, the identification accuracy is limited and reduce the universal adaptability, so a hybrid model identification of nonlinear dynamic parameters become the future development direction[17-18].

Now neural network is commonly method used in identification and estimation system[19-20]. It does not depend on the model, and has the ability of learning and good adaptability, and is very effective to solve nonlinear problem, but the accuracy of the identification is limited because of the high correlation between the input data of neural network. Partial least squares regression algorithm can effectively handle multiple correlations between variables data using information decomposition and screening technique [21-25]. From this point, A hybrid intelligence method is proposed about stator resistance identification based on partial least squares regression algorithm and RBF neural network, to enhance the identification accuracy and improve the performance of control system.

In this paper, section II describes the experiment which the stator resistance change with the working condition of the motorized spindle，and the influence of stator resistance on the speed sensorless vector control system has been discussed in this section. Section III discusses the principle of the identification and algorithms. Section IV discusses the simulation of the hybrid intelligence mode. The simulation experiments which the stator resistance identification applied in the control system and analysis have been discussed in section V. The lecture has been concluded in section VI.

II. INFLUENCE OF STATOR RESISTANCE ON THE SPEED SENSORLESS VECTOR CONTROL SYSTEM

a. The experimentation about the effect of conditions on the stator resistance of the motorized spindle

In order to analyze the effect of conditions on the stator resistance of the motorized spindle, the experiment has been done to detection the stator resistance by changing the time, frequency and other operating factors. The experimental instrument shown in figure1 is the LCR-821 tester which the precision is 0.1%. Rated power of the tested motorized spindle is 9Kw and used grease.

Figure1. Experiment equipment for Electric spindle

From 10Hz to 250Hz, the experiments have been done every 5Hz and each frequency experiment spends 120 minutes. The 580 sets of data are obtained from whole experiment. Its rated speed is 18000r/min and stator resistance cold average value is 0.4295Ω . The partial testing data of stator resistance of the motorized spindle in different conditions is shown in Table 1. Tab.1 shows the stator resistance changes with the frequency of operation, operation time, the stator current and the surface temperature changes.

Table 1 Data of stator resistance

frequency f/Hz	operation time t/min	surface temperature T/℃	stator current i_s /A	stator resistance R_s/ Ω
10	10	25.1	5.79	0.430
	20	25.2	5.66	0.431
	…	…	…	…
	110	27.3	5.58	0.431
	120	27.5	5.61	0.438
…	…	…	…	…
120	10	28.8	5.53	0.4371
	20	30.0	5.37	0.4398
	…	…	…	…
	110	31.8	5.40	0.4401
	120	32.4	5.44	0.4430
125	10	28.6	5.58	0.4372
	20	29.7	5.40	0.4399
	…	…	…	…
	110	32.0	5.43	0.4406
	120	32.1	5.43	0.4424
250	10	35.1	5.79	0.4411
	20	36.3	5.74	0.4423
	…	…	…	…
	110	37.3	5.66	0.4442
	120	36.9	5.77	0.4438

b. The simulation analysis the influence of stator resistance on the vector control system of speed sensorless

The speed sensorless vector control system is rotor field oriented and easily influenced by the motor parameters. The motor model of the motorized spindle shows the spindle speed can be calculated actually. The rotor flux model of voltage equation and current equation of three-phase asynchronous motorized spindle in the α - β coordinate system are

$$\begin{cases} \psi_{r\alpha} = \dfrac{L_r}{L_m}[\int (u_{s\alpha} - R_s i_{s\alpha})dt - \sigma L_s i_{s\alpha}] \\ \psi_{r\beta} = \dfrac{L_r}{L_m}[\int (u_{s\beta} - R_s i_{s\beta})dt - \sigma L_s i_{s\beta}] \end{cases} \tag{1}$$

where $\psi_{r\alpha}$ is the α axis component of the rotor flux linkage and $\psi_{r\beta}$ is the β axis component of the rotor flux linkage, L_r is the rotor inductance and L_m is the mutual inductance between the stator and rotor, $u_{s\alpha}$ is the α axis component of the stator voltage and $u_{s\beta}$ is the β axis component of the stator voltage, $i_{s\alpha}$ is the α axis component of the stator current and $i_{s\beta}$ is the β axis component of the stator current, R_s is the stator resistance and L_s is the stator inductance, σ is magnetic flux leakage coefficient, $\sigma = 1 - M^2/(L_s L_r)$, $M = L_m/L_r$.

$$\begin{cases} \psi_{r\alpha} = \dfrac{1}{T_r p + 1}(L_m i_{s\alpha} - \omega T_r \psi_{r\beta}) \\ \psi_{r\beta} = \dfrac{1}{T_r p + 1}(L_m i_{s\beta} + \omega T_r \psi_{r\alpha}) \end{cases} \tag{2}$$

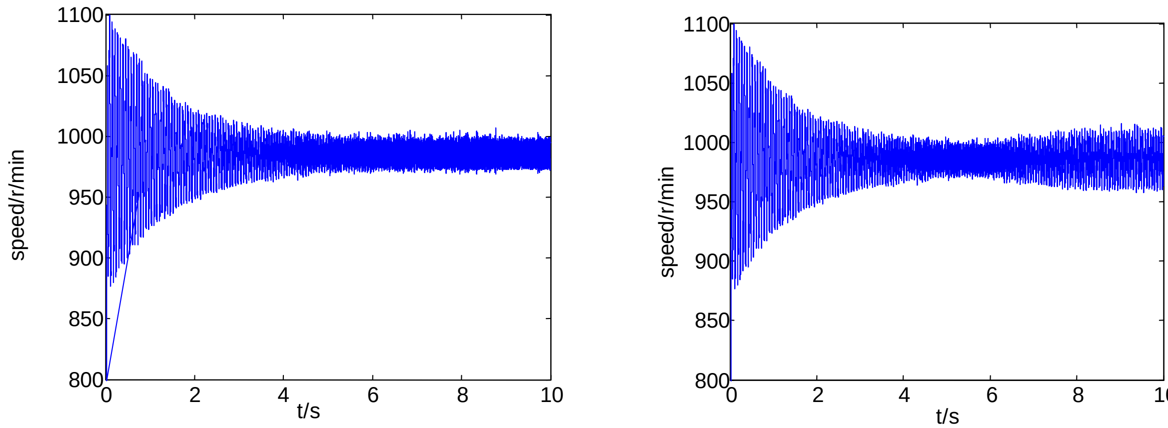
where ω is the angular velocity of rotor and ρ is the differential operator, T_r is the electromagnetic time constant of the rotor, $T_r = L_m/R_r$, the R_r is the rotor resistance.

The current equation contains angular velocity item but voltage equation without, so the output of voltage model is used as the expected value of the rotor flux and the output of current model as estimated. The spindle speed is expressed as:

$$\omega_r = (K_P + \frac{K_I}{s})(\hat{\psi}_{r\alpha}\psi^*_{r\beta} - \hat{\psi}_{r\beta}\psi^*_{r\alpha}) \tag{3}$$

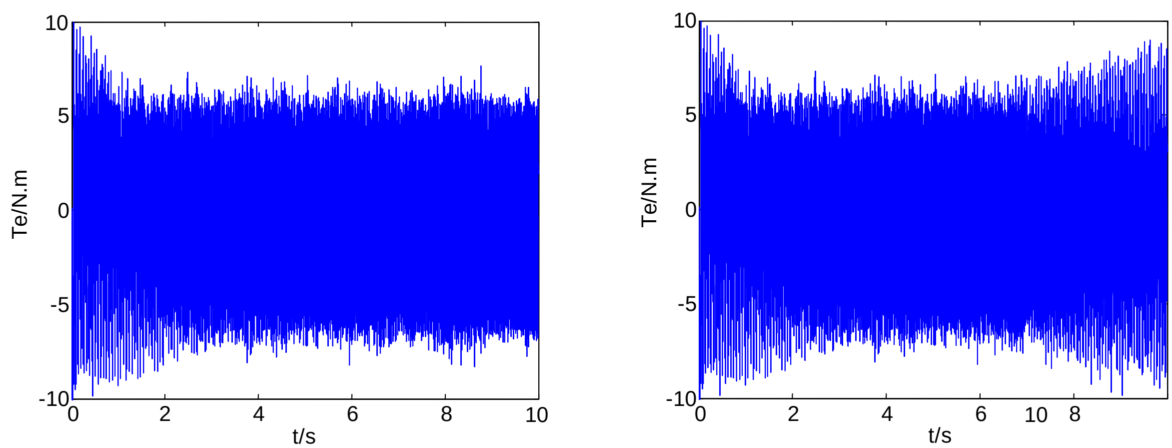
where $\psi^*_{r\alpha}$ and $\psi^*_{r\beta}$ are rotor flux linkage calculation value according to the voltage equations, $\hat{\psi}_{r\alpha}$ and $\hat{\psi}_{r\beta}$ are the calculation value of rotor flux linkage according to the current equations, s is the slip, K_P and K_I are the proportional coefficient.

The equations from (1) to (3) show the variation of the stator resistance will affect the estimation of motorized spindle flux and speed. It leads to flux shape change and torque control accuracy degradation.



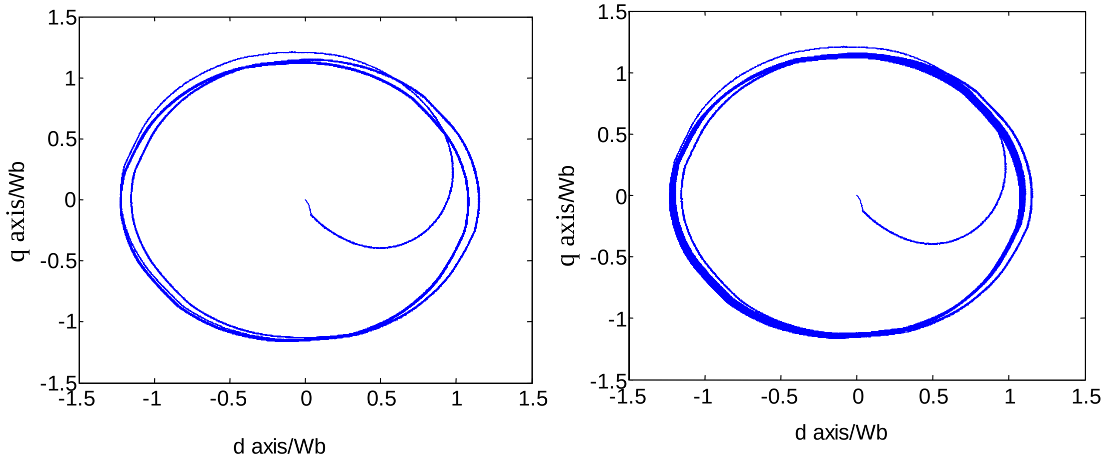
（a） R_s =0.4295Ω （b） R_s =0.4295Ω →0.4376Ω

Figure2 Simulation figure of speed



（a） R_s =0.4295Ω （b） R_s =0.4295Ω →0.4376Ω

Figure 3 Simulation figure of torque



(a)

R_s =0.4295Ω (b) R_s =0.4295Ω →0.4376Ω

Figure 4 Flux linkage locus

In this paper, we use the speed sensorless vector control system as an example, analysis the affect that the stator resistance variation when the motorized spindle is running. The speed sensorless vector control system is adopt and operating at a frequency of 10Hz, then stator resistance from 0.4295Ω change to 0.4376Ω at the moment of 6s, the simulation result about the influence of the stator resistance variation of flux and speed and torque is shown in figure 2 to figure 4.

Figure 2 shows the influence of the stator resistance on speed. Fig.2 shows the variation of stator resistance effects on the speed reliability to a great degree. When the stator resistance is no change, the speed of spindle reaches a steady state in the 4s, with smaller the speed fluctuation. The spindle speed reaches steady state after 4s but with distinct wave change when the variation of the stator resistance changes.

Figure 3 shows the influence of the stator resistance on torque control. Fig.3 (a) and Fig.3 (b) show the torque ripple is increased by 33.3% before and after the stator resistance mutations, and in a divergence shape.

Figure 4 shows the influence of stator resistance on the flux track. Fig.4 (a) and Fig.4 (b) show the stator resistance affect on the flux trajectory, the flux trajectory distortion.

The above analysis proved the influence of the stator resistance variation on speed, torque and flux linkage in speed sensorless vector control system, so it is necessary to identify the stator resistance in order to obtain the superior control performance.

III. METHOD OF HYBRID INTELLIGENT STATOR RESISTANCE INDENTIFICATION

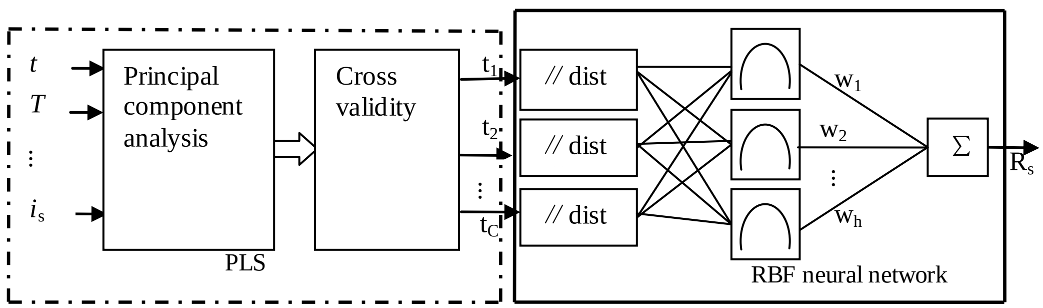


Figure5. Functional block diagram of based on hybrid intelligent stator resistance identification

The stator resistance with the change of temperature, operation time and stator current into a nonlinear change [26]，using RBF neural network to identify can handle good nonlinear problem of stator resistance. However, if between the inputs data of RBF neural network are multiple correlative highly, that will severely affect the identification accuracy of neural network. Partial least squares regression can remove the information which is overlapping and didn't to explain dependent variables through principal component analysis, and are also good at handle multiple correlations between variables. The components extracted by the partial least square regression algorithm as the input of RBF neural network, this can get better identification result. Based on the method of partial least squares regression algorithm and RBF neural network stator resistance identification principle diagram as shown in figure 5.

Partial Least Squares regression (PLS) is referred to as the second generation of the regression analysis method. The PLS combines with the basic properties of the multiple linear regression analysis, canonical correlation analysis and the principal component analysis, and combines modeling prediction type of data analysis methods and the data model type recognition analysis method. It not only has the general function of these analyzes, and has better reliability and precision. The process flow diagram of Partial Least Squares regression (PLS) is shown in figure 6.

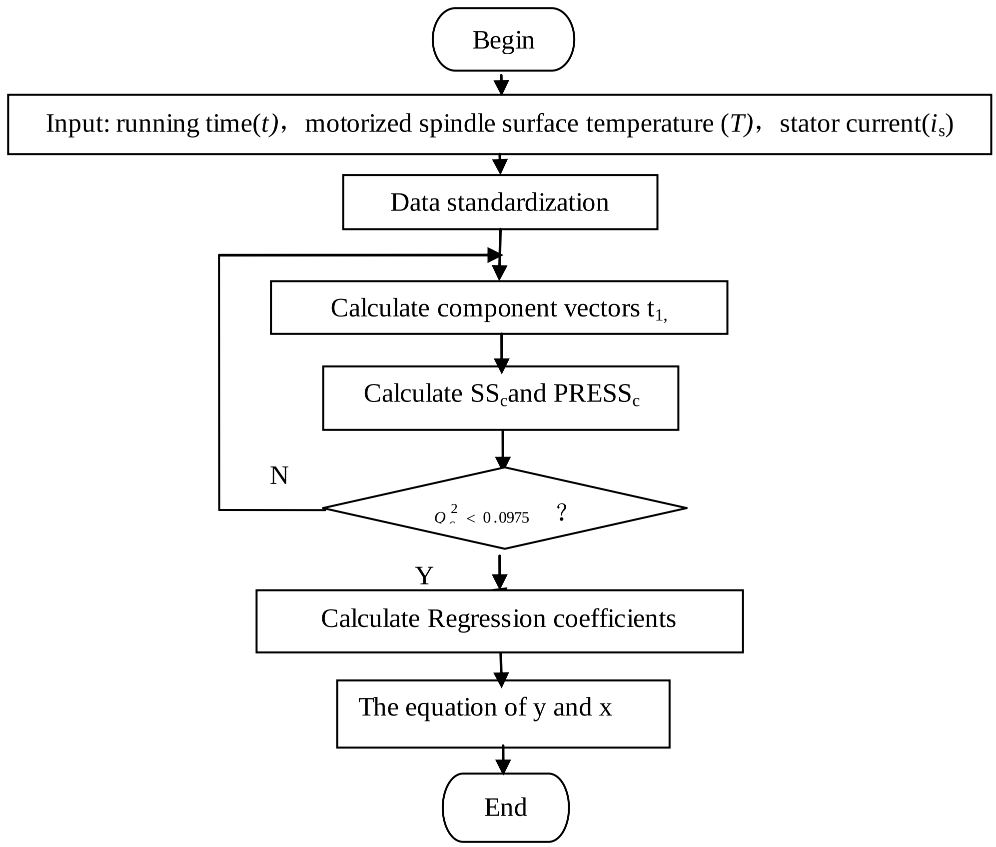


Figure 6 PLS modeling flowchart

According to the experimental data in table 1, the correlation coefficient matrix between independent variables such as the running time t, the surface temperature of the motorized spindle T and the stator current i_s, and the dependent variable stator resistance is calculated . The correlation coefficient matrix is shown in table 2. Tab.2 is shown that the correlation coefficient between the running time t and the surface temperature T of motorized spindle is nearly 90%, and that is the maximum correlation.

Table 2 Correlation coefficient of each variable

variable name	t	T	i_s	R_s
t	1	0.8973	-0.5595	0.3749
T	0.8973	1	-0.5806	0.3567
i_s	-0.5595	-0.5806	1	-0.3928
R_s	0.3749	0.3567	-0.3928	1

In the algorithm of least squares, by calculating the cross validity to determine whether to need to continue to extract ingredients,

$$Q_c^2 = 1 - \frac{PRESS_c}{SS_{(c-1)}} \qquad (4)$$

Where PRESSC is the prediction error sum of squares of Rs, SS(c-1) is the error sum of squares of R_s.

If the Q_c^2 is greater than or equal to 0.0975, then it is necessary to continue to extract. But if the Q_c^2 is less than 0.0975, and then stop the extract. Through MATLAB write partial least-squares regression, extract the t1 can be obtained. When extracting, the correlation about the component t1 and run time t and the surface of the motorized spindle temperature T is more than 90%, at this point the component t1 can represents the independent variable to interpret well on the dependent variable. The component t1 after extract is shown in table 3.

Table 3 Composition t_1

i	1	2	3	4	5	6	7	8	9	10	11	12
t_1	-3.2736	-1.9380	-1.0873	-0.3460	-0.8200	0.5288	1.0153	1.0055	0.8977	0.5936	1.6876	1.7363

IV. THE SIMULATION OF STATOR RESISTANCE IDENTIFICATION

Put the component t1 as the input of RBF networks, then training. After a two-step training RBF network, the first step is no mentor training to learn the weights of input layer to hidden layer, and then the second step is to get weights of hidden layer to output layer using a mentor type of training. After the training, if the input of the network for any given to be able to produce the desired output, then argues that networks training completed. Desired output is refers to the network output and the error of the sample data can be achieved within a prescribed scope. In this paper, the error value of the goal is 0.005Ω , means the error between the network output and the sample data is achieved between -0.0025 and 0.0025Ω .

（1）Network training: using the data in table1 that the frequency is 15Hz as the training data of the network. Figure 7 is the error between the sample data and the network output value. Figure 8 is the comparison curve between sample data and network output data. Fig.7 shows the training results have reached the target error range. Fig.8 shows the network has learned to solve the relationship between the input and output, and can be used to work.

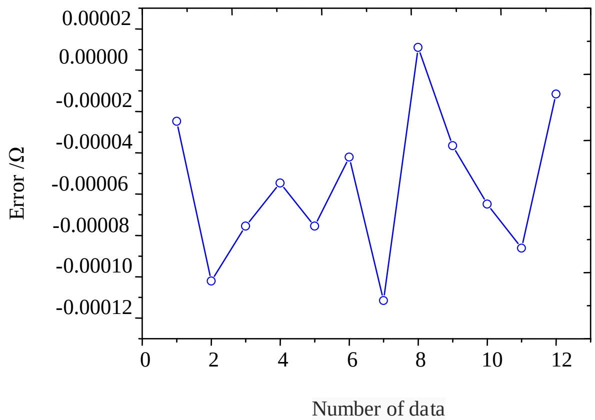


Figure 7. Error of sample data and network output

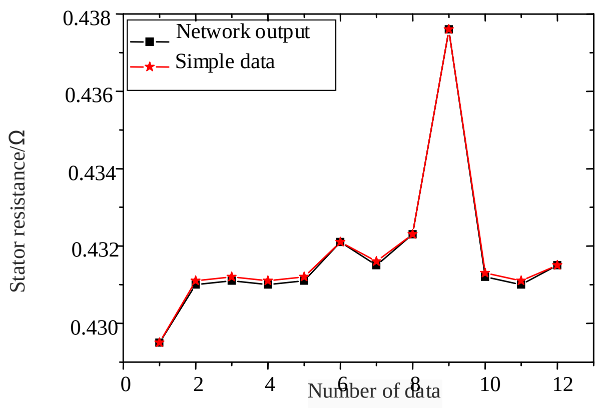


Figure 8 Simple data and network output

(2) Network detection: using the data in table1 that the frequency is 120Hz to test the network. Network test results as shown in figure 9 and figure 10. Fig.9 is the relationship between output prediction model of the network and experimental testing when the frequency is 120 Hz. Fig.10 is the error curve from prediction model of the stator resistance. Fig.10 shows the error is 0.0007Ω , and the relative error is 0.16%. The training precision of the network is high, so that the hybrid intelligent method is effective.

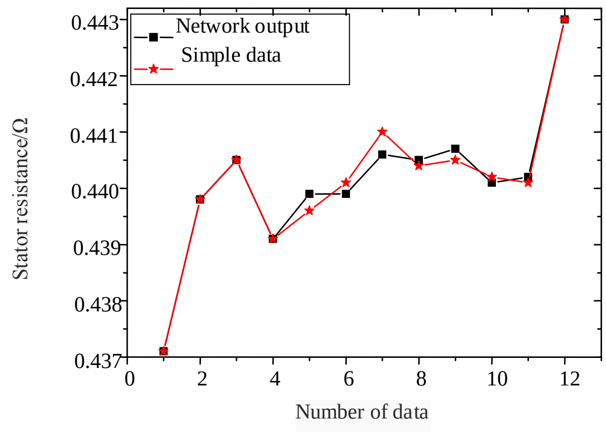


Figure 9. Test and network output

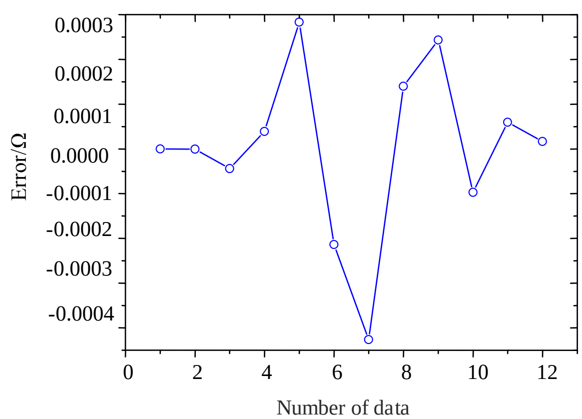
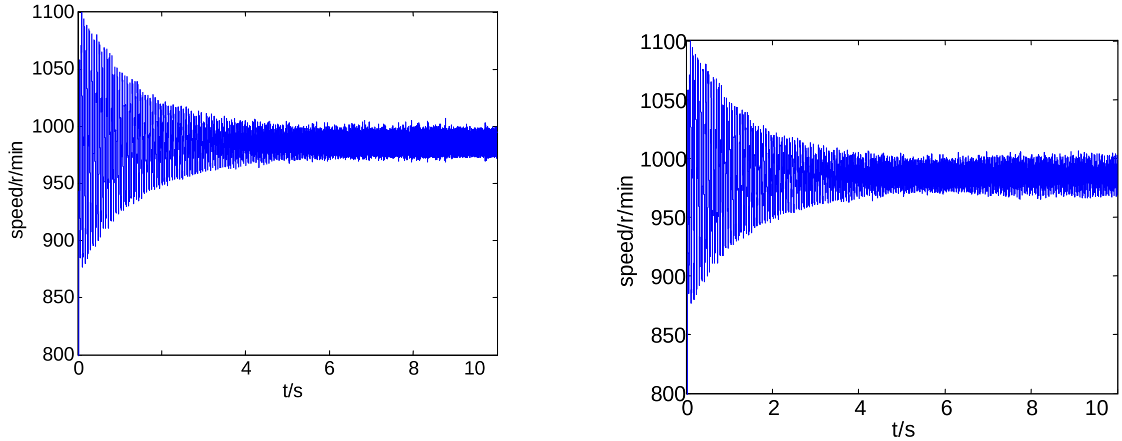


Figure10. Test error

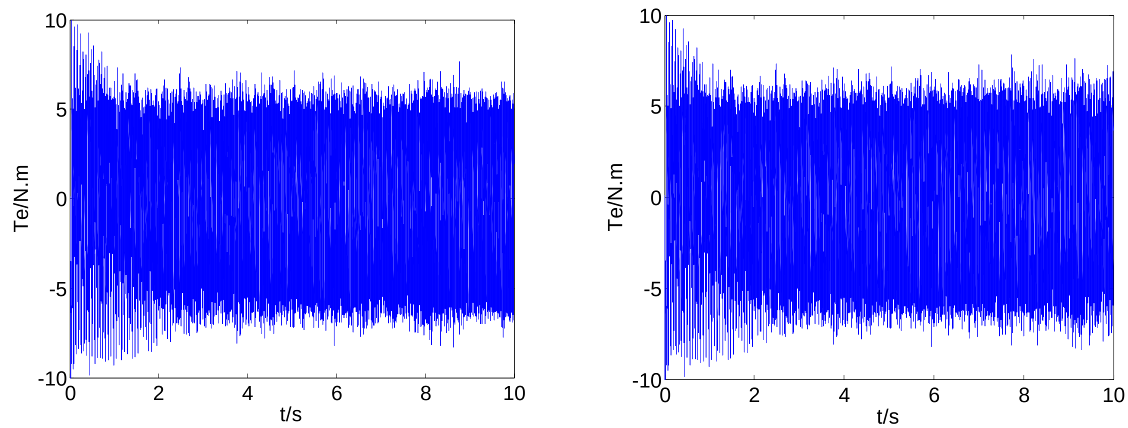
V. THE APPLICATION OF HYBRID INTELLIGENT STATOR RESISTANCE IDENTIFICATION METHOD

The application of the stator resistance after identification of hybrid intelligent method in the speed sensor less vector control simulation model based on MRAS, observed the influence on the model and the performance of system after identification of stator resistance. From figure 11 to figure 13, figure（a）is the simulation results when the motorized spindle stator resistance is no change; figure（b）is the simulation results after identification of stator resistance when the stator resistance jump in 6s after operation. These figures show the change of the stator resistance is very small influence on speed, torque and flux linkage of control system after the stator resistance identification.



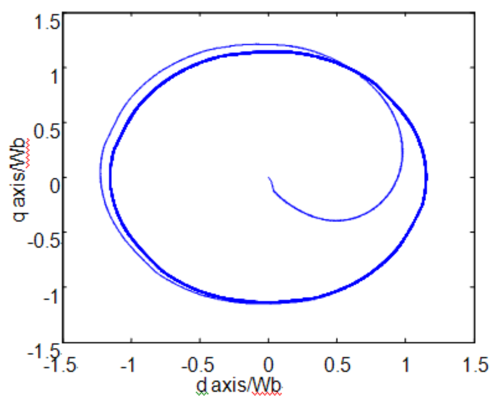
（a）Stator resistance no change （b）Stator resistance change (at 6s)

Figure11 The figure of speed contrast

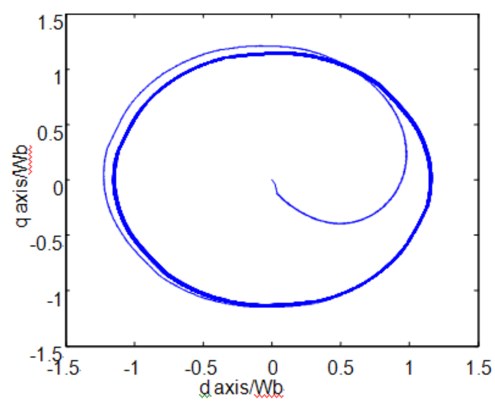


（a）Stator resistance no change （b）Stator resistance change (at 6s)

Figure12 The figure of torque contrast



（a）Stator resistance no change



（b）Stator resistance change (at 6s)

Figure13 The figure of flux linkage contrast

Ⅵ. CONCLUSIONS

During operation of motorized spindle, the stator resistance change affected significantly on speed sensorless vector control system based on MRAS. After the stator resistance changes, the speed and torque ripple is bigger, and the flux linkage locus distortion. With the combination of hybrid intelligent method based on partial least squares regression algorithm and RBF neural network to identify the stator resistance, it can obtain high recognition accuracy. Hybrid intelligent identification model is applied to vector control system, after stator resistance change, the rotating speed of system and the torque and the flux linkage have the small ripple, the system performance is improved.

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