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Tension Identification of Two-Motor System Based on Neural Network Left-Inverse

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***Abstract*—Tension detection is a key to improve performance of two-motor system under sensorless operation. This paper presents a new identification method for two-motor system based on artificial neural network and the left-inverse theory. Considering that the system parameters are time-variant and the mathematic model of left-inverse identification is complex, BP neural network is used to build the left-inverse model in this method, which is easy to implement. A simulation model of a two-motor system is developed. The simulated results verify the proposed method. By using this control strategy, the tension can be identified quickly and accurately, in which satisfactory robustness is offered.**

I. INTRODUCTION

Multi-motor synchronous system is a multi-input multi-output (MIMO), strong coupling control and nonlinear system. It has been widely used in many applications such as electric vehicles, printing and urban rail transit [1-3]. The two-motor variable frequency speed-regulating system is a typical application, which is used to keep speed and tension invariable to transmit or enlace wire products. In order to improve quality and productivity, high precise control performance is required.

In multi-motor system, tension control is an important factor to guarantee material rolling-up without accumulation or snap. To meet this requirement, the accurate measure of tension is very important. The tension is measured by mounting tension sensor in many conventional applications. However, it suffers from expensive cost, rigorous installation requirements and weak anti-interference performance. The sensorless operation theory has become a hot issue in recent years. The strategy of tension identification is introduced into the multi-motor system. Many research works focused on the tension identification strategy and obtained some effective methods. In [4], a nonlinear reduced-order tension observer was designed based on the dynamic mathematical model and the time-variant deviation equation of a two wound DC motor drive system. The friction torque, magnetic torque and inertia torque are used to identify the tension of unwinding machine and winder in the double drum winder machine tension control process [5]. In [6], according to the speed regulator output such as roll diameter, velocity, acceleration and dynamic torque, a full-order observer is designed to predict the tension of a paper reminders machine. In [7], the parameter of three winding motor drive control distribution system such as winding cross-sectional area, membrane elasticity are selected to built the tension observation model system. Then, The Lyapunov function is used to analysis the convergence rate of observation errors. The above-mentioned studies are based on the accurate system model. However, it is hard to be obtained. In addition, there is a certain degree disturbance in multi-motor operation and parameter adjustment. These factors are not conducive to accurate identification of tension.

Two-motor system is a MIMO, strong coupling control and nonlinear system. Therefore, it is necessary to identify tension no requiring model and parameters. Left inverse soft measurement method is recently proposed based on function approximation. It can directly identify unmeasured variables. The artificial neural network (ANN) can accurately approximate any nonlinear function and does not depend on the accurate identification model [8-13].

This paper presents the tension identification strategy based on ANN left-inverse (ANNLI), which is combined left inverse system method. The proposed controller can liberalize and decouple the original nonlinear system. The ANNLI tension identification not only totally depends on motor mathematical model, but also can reduce the system error, which is caused by dynamics modeling and the internal and external disturbances. Moreover, it has an excellent robustness and clear physical meaning. This paper will be organized as follows. The mathematical model of two-motor system is derived and its inverse system will be proved in Section II. In Section III, the ANNLI will be verified. Then, the ANN left-inverse system will be constructed. Finally, the simulated results will be given to verify the proposed control method.

II. MATHEMATICAL MODEL OF AND PROOF OF INVERSION SYSTEM

A. Mathematical model

The physical model of two-motor system two-motor system is shown in Fig. 1, in which motor roller1 is the master motor and motor roller 2 is the slave one [14]. Each motor and its inverter can be regarded as a modular cell. The belt-pulley is installed on the motor shaft, and two motors are combined by transmission belt on the pulley. When the two-motor system operates in vector control mode, both of the rotors pulls belt coordinately.

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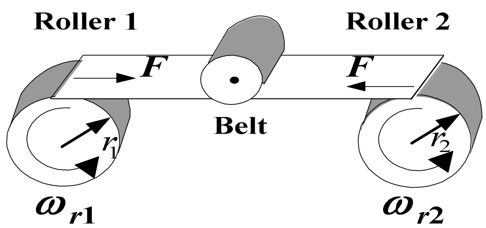

Fig. 1. Physical model of two-motor system.

Then, the mathematic model of two-motor system can be described as:

$$f(x,u)=\begin{cases}\dot{\omega}_{r1}=\dfrac{n_{p1}}{J_1}[(\omega_1-\omega_{r1})\dfrac{n_{p1}T_{r1}}{L_{r1}}\psi_{r1}^2-(T_{L1}+r_1F)]\\ \dot{\psi}_{r1}=\dfrac{-1}{T_{ri}}\psi_{ri}+\dfrac{L_{m1}}{T_{ri}}i_{sdi}\\ \dot{\omega}_{r2}=\dfrac{n_{p2}}{J_2}[(\omega_2-\omega_{r2})\dfrac{n_{p2}T_{r2}}{L_{r2}}\psi_{r2}^2-(T_{L2}-r_2F)]\\ \dot{\psi}_{r2}=\dfrac{-1}{T_{r2}}\psi_{ri}+\dfrac{L_{m2}}{T_{r2}}i_{sd2}\\ \dot{F}=\dfrac{K}{T}(\dfrac{1}{n_{p1}}r_1k_1\omega_{r1}-\dfrac{1}{n_{p2}}r_2k_2\omega_{r2})-\dfrac{F}{T}\end{cases} \tag{1}$$

Where ω_i is the synchronous angular speed of stator frequency and ω_{ri} is the electric angular speed of no. i motor. F is the tension of the belt, n_{pi} is the pole-pairs number of the number i motor, i_{sdi} is d-axis stator current. J_i, ψ_{ri}, L_{ri} respectively are rotor inertia, rotor flux and rotor self-inductance. T_{ri} is electromagnetic time constant, T_{Li} is load torque, $K=E/v$ is the transfer coefficient. $T=L_0/Av$ is the time constant of tension variation; E is young's modulus of elasticity. v is the expected line speed. L_0 is distance between racks; A is section area; r_i is respectively the radius of belt pulley, k_i is the speed ratio (i=1, 2).

B. Construction of left-inverse

When both inverters work in vector control mode, the mathematic model of two-motor system can be described as:

$$\dot{\boldsymbol{x}}=f(\boldsymbol{x},\boldsymbol{u})=\begin{Bmatrix}\dfrac{n_{p1}}{J_1}[(u_1-x_1)\dfrac{n_{p1}T_{r1}}{L_{r1}}\psi_{r1}^2-(T_{L1}+r_1x_3)]\\ \dfrac{n_{p2}}{J_2}[(u_2-x_2)\dfrac{n_{p2}T_{r2}}{L_{r2}}\psi_{r2}^2-(T_{L2}-r_2x_3)]\\ \dfrac{K}{T}(\dfrac{1}{n_{p1}}r_1k_1x_1-\dfrac{1}{n_{p2}}r_2k_2x_2)-\dfrac{x_3}{T}\end{Bmatrix} \tag{2}$$

The following variables are chosen.
State variable are:
$x=[x_1,x_2,x_3]^T=[\omega_{r1},\omega_{r2},F]^T$
Input variable are:
$u=[u_1,u_2]^T=[\omega_1,\omega_2]^T$
Output variable are:
$\mathbf{y}=[y_1,y_2]^T=[\omega_{r1},F]^T$

State variable x_1, x_2 can be measured directly, and x_3 is to be estimated. For the inherent sensor subsystem, the input variable is x_3 and output variable are x_1, x_2. Which is assumed in induction motor system to estimate the rotor tension x_3? The subsystem can be regarded as an inherent sensor that contains variables u_1 and u_2. When the left-inversion condition is satisfied, the left-inversion system consists of "inherent sensor" [15]. The left inverse identification based on inherent sensor is shown in Fig. 2.

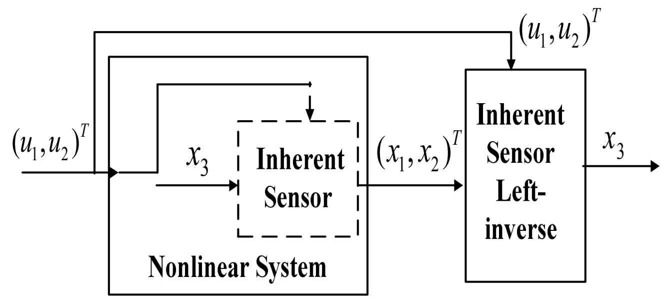

Fig. 2. Left-inverse identification based on inherent sensor.

According to the left inverse soft measurement theory, this work selects $x_1=\omega_{r1}$ as the directly measurable variable z and $x_3=F$ as the estimate variable $\hat{x}$. So, the directly measurable variable ω_{r1} can be expressed as:

$$\dot{y}_1=\frac{n_{p1}}{J_1}[(\omega_1-\omega_{r1})\frac{n_{p1}T_{r1}}{L_{r1}}\psi_{r1}^2-(T_{L1}+r_1F)] \tag{3}$$

The corresponding Jacobi matrix can be calculated and expressed as

$$rank\left(\frac{\partial\left(z^T,\dot{z}^T\right)}{\partial\hat{x}}\right)=rank\begin{pmatrix}0\\ -\dfrac{n_{p1}r_1}{J_1}\end{pmatrix}=1 \tag{4}$$

$$\frac{\partial\dot{\boldsymbol{y}}_1}{\partial u}=-\frac{n_{p1}r_1}{J_1}\neq 0 \tag{5}$$

Then, according to the negative function existing principle, the left-inversion of "inherent sensor" is existed. The assumed inherent sensor can be expressed as

$$\dot{y}_1=\frac{dw_{r1}}{dt}=\frac{n_{p1}}{J_1}[(\omega_1-\omega_{r1})\frac{n_{p1}T_{r1}}{L_{r1}}\psi_{r1}^2-(T_{L1}+r_1F)] \tag{6}$$

So, the left-inversion used to estimate F exists and can be described by:

$$F=\varphi\left(\omega_{r1},\dot{\omega}_{r1},\omega_1,\omega_2\right) \tag{7}$$

The left-inversion system is shown in Fig. 3. It is very difficult to obtain the left inverse mathematic model of complex nonlinear system, even if the system model is precise enough. In fact, this drawback limits the practical applications of left inverse soft measurement method. Neural network has strong approximation ability for the nonlinear function. In addition, the neural network has superior generalization ability and adaptive skills. This can greatly enhance the self-adaptive ANNLI soft measurement model and the robustness in theory [16]. The left inverse soft measurement model is combined with static neural networks. It can break through the bottleneck of the above-mentioned problem of ANNLI. It consists of several differentiators and a static neural network structure. The differentiator characterizes the dynamic process of the soft sensor model, and the neural network describes the nonlinear characteristics of soft measurement model. The model of ANNLI is shown in Fig 4.

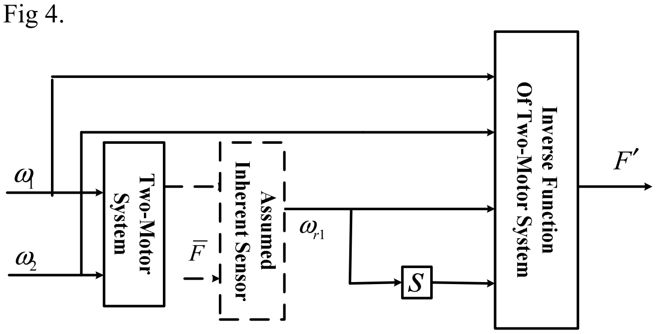

Fig. 3. Left-inversion soft measurement model of two-motor system two-motor system.

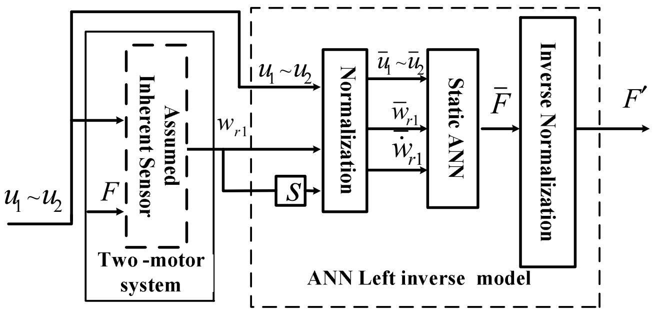

Fig. 4. ANNLI soft measurement model.

III. VERIFICATION

A. Training of ANN

In this paper, two motor speed control system model are built in Matlab [17-18]. In order to improve performance, the two-motor system operates in the vector control mode. The random square-shape tension reference signal e (0-50kg) is selected. Then, the corresponding input and output signals will be collected. Different random square-shape amplitude tension is used as the supply signal to motivate the system characteristics of each band. The input and output should cover all possible operating ranges of the motor in order to verify the tension identification capability under the varying circumstances. Tension supply and tension response is compared in Fig. 5.

Three feed forward neural network are chosen as the primary network, namely hidden layer using “tansig” nonlinear function, the output layer using “purelin” linear function. Offline trained neural network adopts Levenberg-Marquardt algorithm. The number of neural network input and output nodes are determined by the expression of left inverse soft measurement model. The number of node in the hidden layer is generally double times the input node number. The number node of the input layer is 4, the number nodes of hidden layer is10 and the number node of the output layer is 1.

The original sample is normalized as the training data. The times of off-line training are 800-2000 . Generally the error for the training of precision-mean square is less than 0.0005.

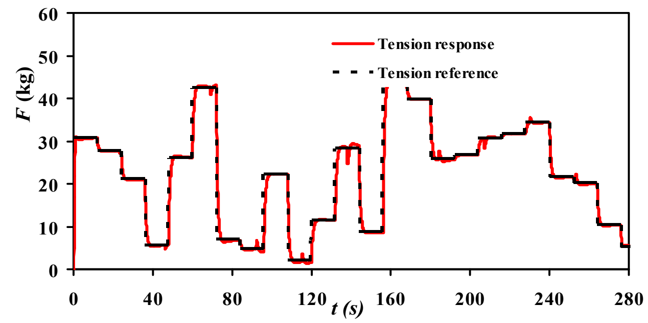

Fig. 5. Tension supply and tension response.

B. Simulation

In order to evaluate the predicting performances of ANNLI system, three quarters of the whole 500s samples are used to train a neural network and the other quarter of 500s samples to test the performance of the trained neural network. A suitable set of PID parameters are finally set after repeated training and simulation, namely (KP1, KI1 KD1) = (30, 2.75, 0), and (KP2, KI2 KD2) = (10, 5, 32).The tension F is set to be random square change, as shown in Fig. 6. Fig. 7. A good agreement can be obtained.

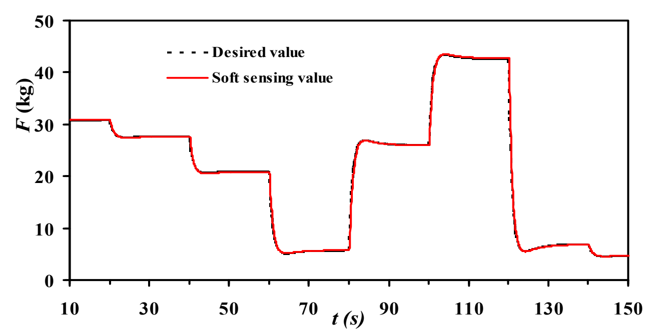

Fig. 6. Comparison between desired value and ANNLI soft-sensingvalue

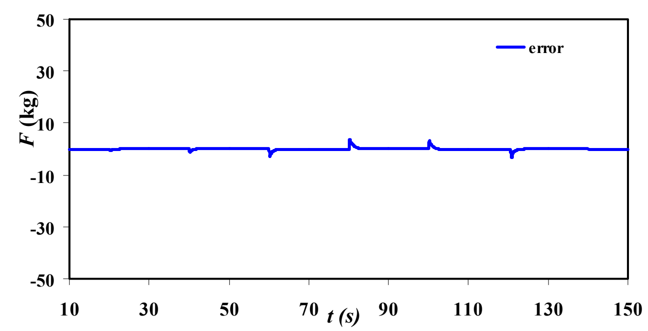

Fig. 7. The error between desired value and ANNLI soft-sensing value

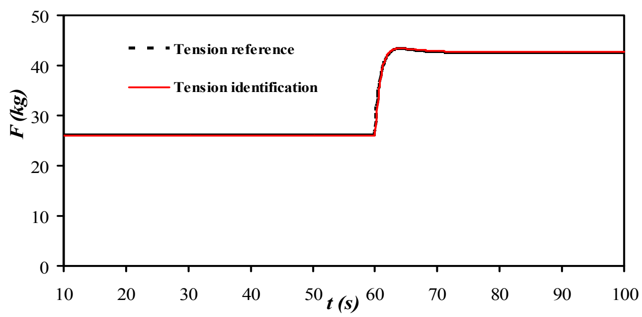

Fig. 8. Simulated dynamic responses based on ANNLI.

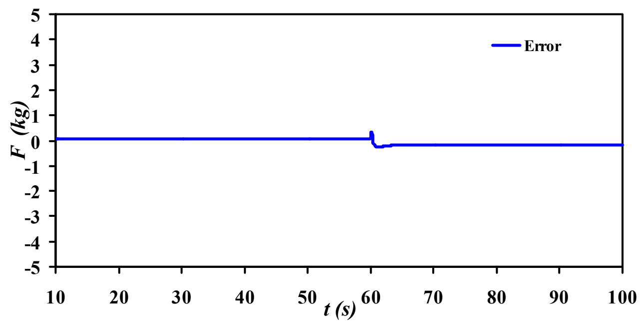

Fig. 9. The error of ANNLI soft-sensing value when F suddenly changes.

When PID is adopted as the closed-loop controller, the starting characteristics and dynamic tracking performance can be further improved. F is set to make square-shape changes and ω_{r1} is kept a constant of 100 rad/s. The tension reference F suddenly increases from 26 kg to 42.5 kg at 60s. The tension reference and the identification tension are compared in Fig. 8. It can be seen that the identification tension can track the reference tension very well and its dynamic response is fast. The steady-state waveform is not only smooth but also highly identification accuracy.

It can be received that the error between desired value and ANNLI soft-sensing value is small and the fluctuations of error occur only at such places where tension suddenly increase or decrease, as shown in Fig. 9. The soft-sensing value tracks the reference value accurately and the error of steady state is almost negligible.

IV. Conclusions

A new strategy of the tension identification based on ANNLI for two-motor system has been proposed. It can be known that the proposed controller can successfully identify the tension value. The identification tension can follow the reference tension value accurately, in which the error between desired value and soft-sensing value is almost negligible. In addition, the proposed tension identification has excellent dynamic and static performances. Especially, the proposed tension identification strategy only requires the original motor control and speed signal, thus reducing the cost of hardware.

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