Model Error Analysis of Load Simulator System

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Abstract—The load simulator is the main semi-physical simulation equipment to detect the performance of the steering gear. Linear models or black box models are often used in load simulator modeling, but the modeling error needs to be further analyzed due to its prominent nonlinear and strong coupling characteristics. In this paper, the semi-physical simulation platform of the electric load simulator was built, and a linear model and a system identification model based on Artificial Neural Network (ANN) were established respectively. The error characteristics of the above models were further analyzed by statistical distribution and power spectral density. The research results can provide support for the controller design and the selection of state estimation method.

1. INTRODUCTION

After decades of development, the performance of the load simulator is getting higher and higher. The loading torque has increased from 6Nm ultra-small torque to 7000Nm super-large torque, the excess torque compensation has increased from 80% to more than 95%, and the frequency response has also changed from low frequency 0.02 Hz to high frequency 60 Hz [1]. The nonlinear and strong coupling characteristics of the load simulation system are prominent because of the redundant torque [2], inertia torque [3] and connection stiffness [4]. Those problems pose a challenge to system modeling. In the mechanism modeling of load simulator, the linear model is usually used to express the nonlinear system. In the process of test modeling, the system identification method is used to establish the relationship between system input and output data. Due to the nonlinearity and uncertainty of the system, both mechanism modeling and system identification methods have certain modeling errors.

In order to analyze the modeling error characteristics, this paper built a semi-physical simulation test platform to collect system response data under Chirp signals. A linear model is established by mechanism analysis and parameter identification. And an ANN is used for system identification. The probability density and power spectrum density are used to analyze the modeling errors of the two models. The results provide support for the design of the controller design and state estimator selection.
2. LOAD SIMULATION SYSTEM AND EXPERIMENTAL DATA

The structure of the electric load simulator is shown in Figure 1, including the motor under test, loading motor, measurement control system and mechanical equipment. The loading system consists of ac power, loading motor and the servo driver. The measurement control system includes torque sensor, conditioning circuit and controller. The torque sensor measures the loading torque on the transmission mechanism in real time. The mechanical equipment are composed of test bench and coupler.

The main parts of the system are shown in Figure 2. The controller adopts the CompactRIO series controller of National Instruments. CompactRIO adopts the real-time system based on VxWorks and is equipped with FPGA (Field Programmable Gate Array). The real-time performance of the control system can be guaranteed.

Prior to identification, input and output data need to be collected for the normal operation of the system, and the signal should cover as many aspects of the system modeling as possible. For nonlinear systems, it is desirable to include all desired amplitudes and frequencies in the input excitation signal. Chirp signal is a commonly used random excitation signal, which is superimposed by a series of sinusoidal signals with gradually increasing frequency. The expressions are formula (1) and (2), and the parameters used in this article are $\omega_{end} = 100\pi$, $T_0 = 0.001$, $u_0 = 0$ and $\alpha = 10c$.

$$u(k) = u_0 + \alpha \sin(\omega_k T_0) 1 \leq k \leq N$$  

$$\omega_k = \omega_{start} + \frac{k}{N}(\omega_{end} - \omega_{start})$$

With the above experimental equipment, the Chirp signal is used as the loading motor voltage signal and dynamic torque sensor is used to collect data when the motor under test is stationary. Because the load simulation system is affected by environmental factors such as temperature, the test is carried out for 10 consecutive cycles. The motor moves for 5s and stops for 55s in each cycle.
3. PARAMETER IDENTIFICATION OF LINEAR MECHANISM MODELS

$K_f$ is the stiffness coefficient of the sensor, $\theta_m$ is the output angles of the loading motor, $\theta_r$ is the steering gear, and the actual torque value loaded into the snake machine is $T_L$. The model expression of the torque sensor is

$$T_L = K_f (\theta_m - \theta_r)$$  
(3)

Keep $\theta_r = 0$ for the duration of the experiment, formula (3) is simplified as

$$T_L = K_f \theta_m$$  
(4)

The voltage balance equation of the PMSM is:

$$U_m = L_m \frac{di_m}{dt} + R_m i_m + K_e \omega_m$$  
(5)

The torque balance equation of the loading motor is:

$$T_m = J_m \frac{d^2 \theta_m}{dt^2} + B_m \frac{d\theta_m}{dt} + T_L$$  
(6)

Figure 3. Block diagram of the load motor model.

The electromagnetic torque equation is

$$T_m = K_T i_m$$  
(7)

According to the formula (4) ~ (7), the mathematical model of the loading motor can be obtained, as shown in Figure 3.

When the permanent magnet synchronous servo motor of the loading system works in the torque control mode, it contains the current loop and the negative feedback controller $G_{iqm}(s)$ adjust the current setting, as shown in formula (8).

$$u_m = K_T i_m G_{iqm}(s)$$  
(8)

Current loop controller $G_{iqm}(s)$ is usually a PI controller, whose transfer function is shown as follows:

$$G_{iqm}(s) = \frac{K_P + K_I}{s}$$  
(9)

The torque loading system model with the current loop is shown in Figure 4. The transfer function of the load system's open-loop torque control is formula (10).

$$\frac{T_L(s)}{T_m(s)} = \frac{K_T K_P + K_T K_I s + K_I K_P}{k_4 s^4 + k_3 s^3 + k_2 s^2 + k_1 s + k_0}$$  
(10)

Where $k_0 = K_T K_I$, $k_1 = K_T K_P + K_I K_R + B_m K_H$, $k_2 = R_m B_m + K_J K_T + K_J L_m + B_m K_P + J_m K_H$, $k_3 = L_m B_m + J_m R_m + J_m K_R$, $k_4 = L_m J_m$. Parameters of EDLS is shown in Table 1.

TABLE 1. PARAMETERS OF PMSM

| Symbol | Value |
|--------|-------|
| $J_m$  | $11.37 \cdot 10^{-4}$ kgm |
| $K_e$  | $31.69$ Nm·(rpm)$^{-1}$ |
| $K_I$  | $0.88$ N·m·s$^{-1}$ |
| $B_m$  | $0.26$ Ω |
| $L_m$  | $2.81$ mH |
| $B_m$  | $1.8 \cdot 10^{-4}$ Nms·(rad)$^{-1}$ |
In the model, $K_T$, $K_E$, $B_m$ and other coefficients are nominal values, which may be inconsistent with the actual motor parameters. At the same time, the parameters will change with the change of magnetic saturation degree and temperature [5]. Therefore, it is necessary to identify the system parameters to obtain more accurate parameters and improve the accuracy of the system model.

Since the system model structure and order have been determined, data storage space is not limited, and real-time data processing and identification methods are not required, but system parameters with higher accuracy are needed. Therefore, offline parameter identification method is chosen. The least square method is the most widely used and basic method in system identification. After using the least square method for parameter identification, the system transfer function is:

$$T_L(s) = \frac{4.43 \times 10^9 s + 1.77 \times 10^{10}}{s^3 + 962.87 s^2 + 6.25 \times 10^6 s^2 + 5.88 \times 10^9 s + 2.09 \times 10^{10}}$$ (11)

4. SYSTEM IDENTIFICATION BASED ON ANN

ANNs are commonly used in system identification [6]. BP neural network is the most commonly used multi-layer forward neural networks, which plays an important role in nonlinear system modeling and control. The research of Robert Hecht-Nielsen [7] shows that the BP neural network of single hidden layer can be used to approximate the continuous function on any closed interval, and the estimation formula of the number of hidden layer neurons is given.

Therefore, BP neural network with three layers (1 input layer, 1 hidden layer with 10 neurons and 1 output layer) was used to identify the load simulation system. In the neural network training process, LM (Levenberg-Marquardt) algorithm is used to adjust the network weights and thresholds.

The collected data are normalized to convert all data into [0,1] and divided into 3 groups, 60% of the data were randomly selected as training data, 20% for training effect evaluation, and the remaining 20% for identification test.

According to the engineering practice experience, the initial weights and thresholds are taken as random Numbers between [-1,1]. Based on the least square principle, the artificial neural network is trained based on the training data. As shown in Fig.5a, a total of 12 iterations were conducted in the training process. After 6 iterations, the error of the evaluation data remained stable. After the training (shown in Fig.5b), the linear correlation coefficient is 0.96435, and the intercept was 0.024, indicating a good training effect.
5. ANALYSIS OF SYSTEM MODEL ERROR

In order to evaluate the errors of the mechanism model and system identification results, SSE (the Sum of Squares due to Error), RMSE (Root Mean Square Error) and R-square are used for evaluation. The results are shown in the following table:

All the indicators of the linear mechanism model are better than the ANN system identification results, among which SSE is improved by 26.83% and RMSE by 14.46%. However, the R-square of the linear mechanism model is only 0.9488.

The modeling errors are analysed as the noise of the system model. As shown in Figure 7, the error of the linear mechanism model is normally distributed. The p-value within KS test is $1.6319 \times 10^{-5}$, which can be accepted within 99% confidence interval. After fitting to the Gaussian distribution, mean of the error is -0.0048 and standard deviation is 1.2511. It can be seen from the power spectral density (Fig.7b) that the error is concentrated in the region of 2Hz and below, and an anomaly occurs at 2.5hz.

|                          | SSE      | RMSE    | R-square |
|--------------------------|----------|---------|----------|
| Linear mechanism model   | $7.83 \times 10^3$ | 1.2510  | 0.9488   |
| ANN system identification| $1.07 \times 10^4$ | 1.4625  | 0.9300   |

(b) Figure 5. ANN training process and results.
Figure 6. Probability density and power spectrum density of linear mechanism model errors.

The error analysis results of ANN system identification model are shown in Figure 7. The KS test is used to verify the Gaussian distribution characteristics. The p-value is 2.87×10^{-10}, and the hypothesis can be accepted within 99% confidence interval. Mean of the errors is 0.0070 and the standard deviation is 1.4626. From the power spectral density (Fig. 8b), it can be seen that the errors are concentrated in the middle and low frequency region, and its frequency is mainly 1.5 Hz and below.

6. CONCLUSION
The above results show that both of the two model errors are close to the Gaussian colored noise, and the errors are mainly concentrated in the low frequency region. The linear mechanism model can reflect the characteristics of the system, but system nonlinear characteristics should be fully considered in the design of the controller. Non-linear controllers such as sliding mode control and robust control are more suitable for this system. When choosing the method of state estimation, the methods based on Gaussian white noise should be used carefully.
Figure 7. Probability density and power spectrum density of ANN system identification errors.

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