

Research Article

Dynamic Model Identification for 6-DOF Industrial Robots

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A complete and systematic procedure for the dynamical parameters identification of industrial robot manipulator is presented. The system model of robot including joint friction model is linear with respect to the dynamical parameters. Identification experiments are carried out for a 6-degree-of-freedom (DOF) ER-16 robot. Relevant data is sampled while the robot is tracking optimal trajectories that excite the system. The artificial bee colony algorithm is introduced to estimate the unknown parameters. And we validate the dynamical model according to torque prediction accuracy. All the results are presented to demonstrate the efficiency of our proposed identification algorithm and the accuracy of the identified robot model.

1. Introduction

In recent years, industrial robots have been greatly used as orienting devices in industry, especially in the shipbuilding, automotive, and aerospace manufacturing industries [1, 2]. Advanced control techniques for robots have become more and more affordable thanks to increasing power of computing resources and their dramatic cost reduction. However, the dynamical model of robot contains uncertainties in some parameters and many control methods are sensitive to their values especially in high speed operations. Hence, dynamical parameters identification approach has importance for developing model based controllers.

In terms of academic research, a standard robot identification procedure consists of dynamic modeling, excitation trajectory design, data collection, signal preprocess, parameter identification, and model validation [3]. The parameter identification has attracted considerable attention from numerous researchers. Atkeson et al. [4] proposed the least square method to realize the estimation of dynamical parameters. Grotjahn et al. [5] used the two-step approach to perform the identification of robot dynamics. Gautier and Poignet [6] obtained a dynamical model of SCARA robot from experimental data with weighted least squares method. Behzad et al. [7] applied fractional subspace method

to identify a robot model in simulation field. Recently, some intelligence computation algorithms have been reported as a useful tool in robot model identification. A traditional genetic algorithm (GA) was proposed to identify the autonomous underwater robot in [8]. Liu et al. [9] introduced the improved genetic algorithm to obtain the space robot model. However, while dealing with complex and large-scale parameters identification problems, the GA algorithm would be stuck on local optimum.

Artificial bee colony algorithm (ABC) was first proposed by Karaboga in 2005 [10] and successfully applied to parameters identification of aerial robot [11]. The ABC algorithm has been proved to possess a better performance in function optimization problems, compared with differential evolution algorithm (DE), particle swarm optimization algorithm (PSO), and GA algorithm [12]. As we know, usual optimization algorithms conduct only one search operation in one iteration, but ABC algorithm can conduct both local search and global search in each iteration, and as a result the probability of finding the optimal parameters is significantly increased, which efficiently avoids local optimum to a large extent. In this paper, the ABC algorithm was introduced to conquer the parameters identification problem of the industrial robots. The identification experiment was implemented on 6-DOF ER-16 robot manipulator.

The outline of this paper is organized as follows. Firstly, the linear robot dynamical model is given in Section 2. Then, Section 3 presents the identification process of the linear model based on the ABC algorithm, where excitation design, data collection, and signal preprocess are described. Later on, the experimental platform, identified results, and model validation are presented in Section 4. Finally the main conclusions are given in Section 5.

2. Dynamic Modeling

Since the n -DOF industrial robot is represented by a kinematic chain of rigid bodies, the exhaustive description for its motion can be found in [13]. The dynamic model of industrial robot is derived by the Newton-Euler or Lagrangian method:

$$\boldsymbol{\tau}_{\text{dyn}} = \mathbf{M}(q)\ddot{q} + \mathbf{C}(q, \dot{q}) + \mathbf{G}(q), \quad (1)$$

where $\boldsymbol{\tau}_{\text{dyn}}$ is the n -vector of actuator torques as well as the joint positions q , velocities \dot{q} , and accelerations \ddot{q} . $\mathbf{M}(q)$ is the $n \times n$ inertia matrix, $\mathbf{C}(q, \dot{q})$ denotes the n -vector including Coriolis and centrifugal forces, and $\mathbf{G}(q)$ is the n -vector of gravity.

According to the modified Newton-Euler parameters [14] or the barycentric parameters [15], (1) can be rewritten as a linear form:

$$\boldsymbol{\tau}_{\text{dyn}} = \Phi_{\text{dyn}}(q, \dot{q}, \ddot{q})\boldsymbol{\theta}_{\text{dyn}}, \quad (2)$$

where Φ_{dyn} denotes the $n \times 10n$ observation or identification matrix, which depends only on the motion data. $\boldsymbol{\theta}_{\text{dyn}}$ is the barycentric parameter vector. This property considerably simplifies the parameters identification.

Dynamic model of robots also contains the torques caused by joint frictions and inertias of actuator rotors apart from the effects of dynamic parameters in (2). The inertias of actuator rotors are generally provided by producers, and corresponding torques should be compensated for the dynamic equations. In fact, joint friction is a complex nonlinear model, especially during motion reversal. In order to simplify the model, the friction model consisting of only Coulomb and viscous friction [16] is given by

$$\boldsymbol{\tau}_{\text{fric}} = f_c \text{sign}(\dot{q}) + f_v \dot{q}, \quad (3)$$

where $\boldsymbol{\tau}_{\text{fric}}$ is the friction torques and f_c , f_v , respectively, mean the Coulomb and viscous friction parameters.

The integrated dynamic model of robots can be written as

$$\boldsymbol{\tau}_s = \Phi_s(q, \dot{q}, \ddot{q})\boldsymbol{\theta}_s, \quad (4)$$

where $\boldsymbol{\tau}_s$ is actuator torques including $\boldsymbol{\tau}_{\text{dyn}}$ and $\boldsymbol{\tau}_{\text{fric}}$. Φ_s is the $n \times 12n$ observation matrix, and $\boldsymbol{\theta}_s$ is $12n$ -vector of unknown dynamic parameters. In addition, the dynamic parameters of link i are governed by the form:

$$\boldsymbol{\theta}_s^i = \begin{bmatrix} I_{xxi}, I_{xyi}, I_{xzi}, I_{yyi}, I_{yzi}, I_{zzi}, m_i r_{xi}, m_i r_{yi}, m_i r_{zi}, m_i, f_{ci}, \\ f_{vi} \end{bmatrix}^T, \quad (5)$$

where $I_{\zeta\zeta i}$ ($\zeta = x, y, z$) is the inertial tensor of link i . Similarly, $m_i r_{\zeta i}$ denotes the first-order mass moment and m_i is the mass of link i .

In general, the observation matrix Φ_s in (4) is not a full rank; that is, not all dynamic parameters have an influence on the dynamic model. In order to obtain a set of minimum parameters, a case-by-case analysis method is adopted [17]. Consequently, the dynamic model based on the basic dynamic parameters can be rewritten as

$$\boldsymbol{\tau} = \Phi(q, \dot{q}, \ddot{q})\boldsymbol{\theta}, \quad (6)$$

where Φ is the $n \times (p + 2n)$ observation matrix. $\boldsymbol{\theta}$ is $(p + 2n)$ -vector of dynamic parameters, including the basic parameters and the friction parameters. p denotes the number of the minimum dynamical parameters. $2n$ denotes the number of the friction parameters.

3. Parameters Identification Procedures

3.1. Basic Principles of Identification Algorithm. In order to introduce the search mechanism of ABC algorithm, we should define three essential components: employed bees, unemployed bees, and food source [11]. And the unemployed bees are divided into following bees and scout bees. The population of the colony bees is N_s , the number of employed bees is N_e , and the number of unemployed bees is N_u , which satisfies the relation $N_s = 2N_e = 2N_u$. We also define D as the dimension of solution vector, that is, the number of the unknown parameters. ABC algorithm treats each unknown parameter as a food source. The detailed procedure of executing the proposed algorithm is described as follows.

Step 1. Randomly initialize a set of possible solutions (x_1, \dots, x_{N_s}) , and the particular solution x_i can be governed by

$$x_i^j = x_{\min}^j + \text{rand}(0, 1)(x_{\max}^j - x_{\min}^j), \quad (7)$$

where $j \in \{1, \dots, D\}$ denotes the j th dimension of the solution vector. x_{\min}^j and x_{\max}^j mean the lower and upper bounds, respectively.

Step 2. Apply a specific function to calculate the fitness of the solution x_i according to the following equations and select the top N_e best solutions as the number of the employed bees:

$$\text{fit}_i = \frac{1}{(1 + F_i)}, \quad (8)$$

$$F_i = \frac{1}{N} \sum_{i=1}^N (\delta_1 \|\tau_{1i} - \tau_{p1i}\| + \delta_2 \|\tau_{2i} - \tau_{p2i}\| + \delta_3 \|\tau_{3i} - \tau_{p3i}\|), \quad (9)$$

where fit_i is the fitness function, F_i is the objective function, N is the data length, and $\tau_{\xi i}$ ($\xi = 1, 2, 3$) is the vector of the actual torques data from the first three joints. Similarly, $\tau_{p\xi i}$ ($\xi = 1, 2, 3$) is the vector of the predicted data from the identified model. δ_ξ ($\xi = 1, 2, 3$) is a weight coefficient between 0 and 1.

Step 3. Each employed bee searches new solution in the neighborhood of the current position vector in the n th iteration as follows:

$$v_i^j = x_i^j + \lambda_i^j (x_i^j - x_k^j), \quad (10)$$

where $k \in \{1, \dots, D\}$, $k \neq i$, both k and j are randomly generated, and λ_i^j is a random parameter in the range from -1 to 1 . Next, we apply the greedy selection equation (11) to choose the better solution between v_i^j and x_i^j into the next generation:

$$x_i^j = \begin{cases} v_i^j, & \text{fit}(v_i^j) > \text{fit}(x_i^j), \\ x_i^j, & \text{fit}(v_i^j) \leq \text{fit}(x_i^j). \end{cases} \quad (11)$$

Step 4. Each following bee selects an employed bee to trace according to the parameter of probability value. The formula of the probability method is described as

$$p_i = \frac{\text{fit}_i}{\sum_{i=1}^{N_e} \text{fit}_i}. \quad (12)$$

Step 5. The following bee searches in the neighborhood of the selected employed bee's position to find new solutions. Update the current solution according to their fitness.

Step 6. If the search time trial is larger than the pre-determined threshold limit and the optimal value cannot be improved, then the location vector can be reinitialized randomly by scout bees according to the following equation:

$$x_i(n+1) = \begin{cases} x_{\min} + \text{rand}(0, 1)(x_{\max} - x_{\min}), & \text{trial} > \text{limit}, \\ x_i(n), & \text{trial} \leq \text{limit}. \end{cases} \quad (13)$$

Step 7. Output the best solution parameters achieved at the present time, and go back to Step 3 until termination criterion T_{\max} is met.

The detailed procedure of ABC algorithm for parameters identification can be also depicted in Figure 1.

3.2. Excitation Trajectory. When designing an identification experiment for the robot, it is necessary to design proper excitation trajectories to ensure the accuracy of estimation in presence of disturbances [18]. In this work, a finite Fourier series is adopted as excitation trajectories, that is, a finite sum of harmonic sine and cosine functions. The trajectories for joint i of a robot are designed as

$$q_i(t) = q_{i,o} + \sum_{k=1}^N a_{i,k} \sin(k\omega_f t) + \sum_{k=1}^N b_{i,k} \cos(k\omega_f t), \quad (14)$$

where $q_{i,o}$ is the offset term and ω_f is the fundamental pulsation of the Fourier series. This Fourier series specifies a periodic function with period $T_f = 2\pi/\omega_f$. Each Fourier

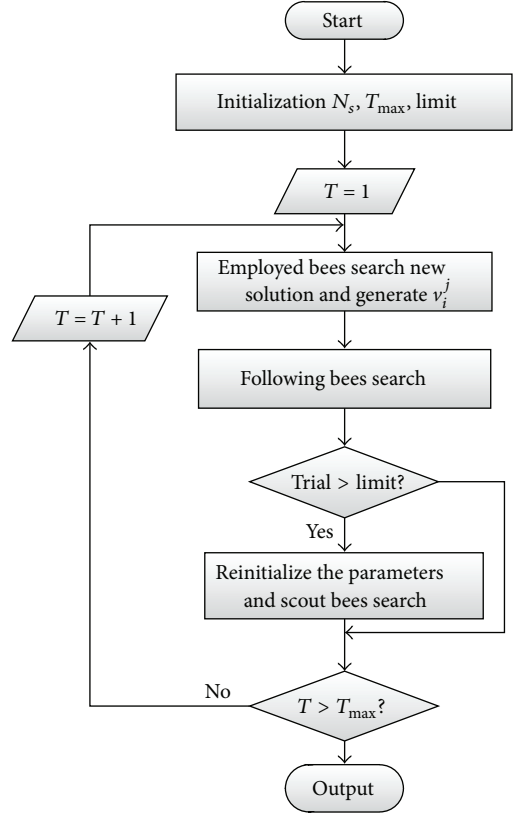


FIGURE 1: Sketch of the identification algorithm.

series contains $2N + 1$ parameters, and $a_{i,k}$, $b_{i,k}$ are the amplitudes of the sine and cosine functions.

The noise immunity and convergence rate of an identification experiment depend directly upon the constraints of the excitation trajectories. It is important to emphasize that the configurations for which measurements are taken must correspond to a well-conditioned reduced observation matrix since the constraints represent some limits for input/output. In the literature, the constraints of the excitation trajectories can be described as

$$\min \text{cond}(\Phi)$$

$$q_{\min} \leq q(\beta) \leq q_{\max},$$

$$|\dot{q}(\beta)| \leq \dot{q}_{\max}$$

$$|\ddot{q}(\beta)| \leq \ddot{q}_{\max}$$

$$w(q(\beta)) \subset W_o$$

$$\tau_{\min} \leq \Phi(q(\beta), \dot{q}(\beta), \ddot{q}(\beta)) \theta \leq \tau_{\max},$$

where q_{\min} and q_{\max} are the lower and upper of the joint positions, \dot{q}_{\max} and \ddot{q}_{\max} are the upper of velocities and accelerations, β is optimal trajectory parameters, W_o is the available workspace of robot, and τ_{\max} is the maximum joint torque.

3.3. *Preprocessing of Measured Data.* The measured torques are obtained through collecting the data of motor current, which is described as follows:

$$\tau = KI, \quad (16)$$

where I is motor current. K is just coefficient.

Since there are measurement noises in experiments, it is necessary to preprocess the collection data before identification. In order to remove outliers and attenuate the effect of interference signal, a five-spot triple smoothing method is adopted to smooth the raw data according to the following equations:

$$\begin{aligned} \bar{y}_1 &= \frac{1}{70} [69y_1 + 4(y_2 + y_4) - 6y_3 - y_5], \\ \bar{y}_2 &= \frac{1}{35} [2(y_1 + y_5) + 27y_2 + 12y_3 - 8y_4], \\ \bar{y}_i &= \frac{1}{35} [-3(y_{i-2} + y_{i+2}) + 12(y_{i-1} + y_{i+1}) + 17y_i], \\ \bar{y}_{m-1} & \\ &= \frac{1}{35} [2(y_{m-4} + y_m) - 8y_{m-3} + 12y_{m-2} + 27y_{m-1}], \\ \bar{y}_m & \\ &= \frac{1}{70} [-y_{m-4} + 4(y_{m-3} + y_{m-1}) - 6y_{m-2} + 69y_m], \end{aligned} \quad (17)$$

where $i = 3, \dots, m-2$, $\mathbf{Y} = [y_1, y_2, \dots, y_m]$ is the measured raw data, and $\bar{\mathbf{Y}} = [\bar{y}_1, \dots, \bar{y}_m]^T$ is the data for identification after preprocessing. The more the number of using (17) is, the smoother the curves will be. It should be noted that excessively using (17) to smooth the raw data can lead to the error of the parameters identification increasing.

In addition, the velocities and accelerations of joints cannot be measured directly. However, these pieces of information are usually obtained by joint positions, and numerical differentiation for joint positions can amplify the measurement noise and decrease accuracy of the velocities and accelerations. An analytical approach is adopted to overcome the aforementioned difficulty, which was proposed in [19] and used successfully in [20]. The average joint positions are approximated as finite Fourier series through the linear least square technique and the joint velocities and accelerations can be estimated by the derivatives of the obtained finite Fourier series.

4. Experiment Results

4.1. *Parameters Identification.* An experiment is conducted to test the proposed identification algorithm. The ER-16, shown in Figure 2, is a 6-DOF industrial robot manipulator without payload. And the link frame of the robot is depicted in Figure 3. The geometric parameters of the ER-16 robot are given in Table 1. Only the first joints are considered here. A fundamental pulsation of 0.05 Hz is selected for the excitation trajectories, resulting in a period of 25 s. As shown in Figure 4, the commanded trajectories are five-term



FIGURE 2: ER-16 6-DOF robot.

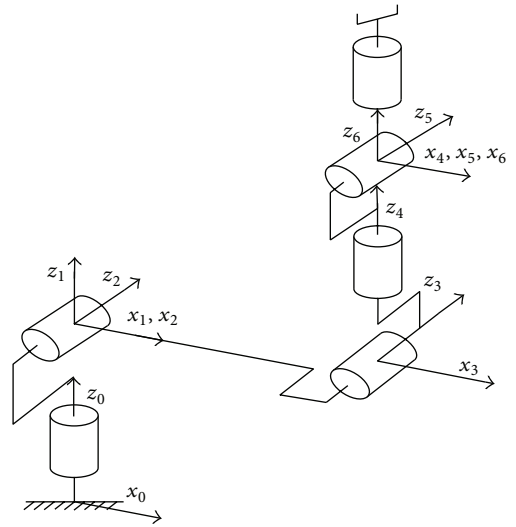


FIGURE 3: The link frame of ER-16 robot.

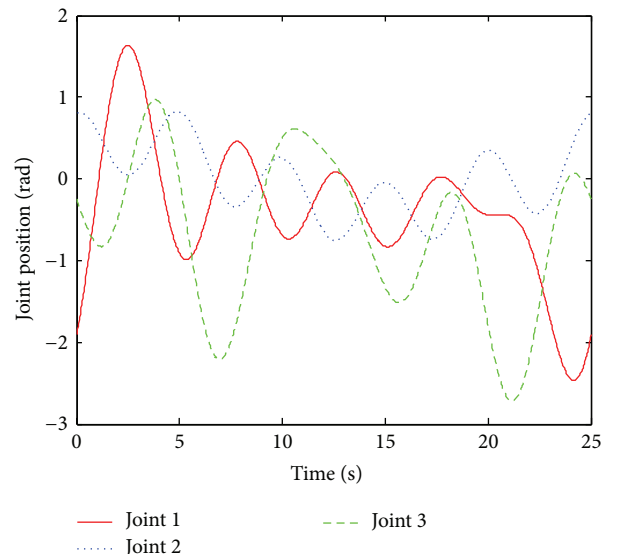


FIGURE 4: Optimized robot excitation trajectories.

TABLE 1: DH parameters of ER-16 robot.

Link i	α_{i-1} (rad)	a_{i-1} (m)	d_i (m)	θ_i (rad)
1	π	0	0	θ_1
2	$\pi/2$	0.16	0	$\theta_2 - \pi/2$
3	0	0.68	0	θ_3
4	$\pi/2$	0.13	-0.75	θ_4
5	$-\pi/2$	0	0	θ_5
6	$\pi/2$	0	0	θ_6

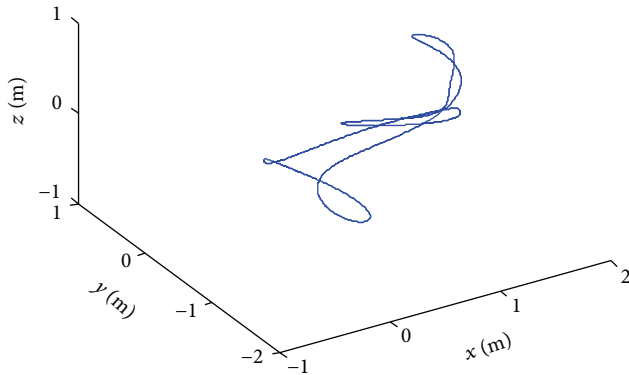


FIGURE 5: 3D visualization of the optimized trajectory.

Fourier series, involving 11 optimal trajectory parameters for each joint which are listed in the Appendices, and a 0.25 Hz bandwidth. The 3D visualization of this optimized trajectory in the workspace of the robot is shown in Figure 5. The total measured time is 25 s, corresponding to 1 period of the excitation trajectory. The data is sampled with 1 kHz.

Identification procedures are carried out with ABC algorithm in Matlab 2013b programming environment on an Intel Core i7-3770 PC running Windows 7. No commercial tools are used. According to [12], the performance of ABC algorithm is relative to the population size of colony bees. As the population size increases, the algorithm produces better results. However, after a sufficient value for colony size, any increment in the value does not improve the performance of ABC algorithm. And the control parameter limit is based on location vector reinitialized frequency. As the value of limit approaches infinity, the total number of location vectors reinitialized goes to zero. After many trials, in this paper, we set the parameters of ABC algorithm as follows: $N_s = 30$, $\text{limit} = 15$, and $T_{\max} = 50$. It should be noted that when the predetermined iterations exceed 50, the ABC algorithm converged and the objective value could not be obviously improved. And the search scope of the unknown parameters is also listed in the Appendices. The objective value of optimization process for the parameters is shown in Figure 6. The result shows that the convergence speed of our algorithm is fast and the final objective value which is calculated by (9) is 0.3182.

The robot dynamic model for the first joints contains 21 parameters, 15 base parameters, and 6 friction parameters.

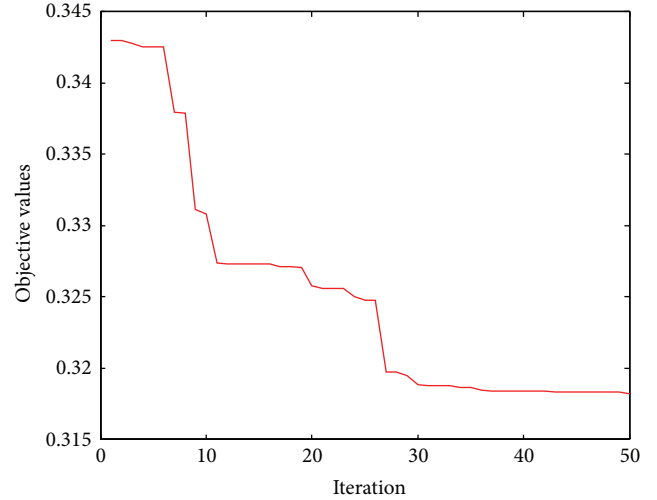


FIGURE 6: Evolutionary curves of identification algorithm.

TABLE 2: Identification dynamic parameters.

Parameter	Value
I_{zz1} (kg·m ²)	50.4438
I_{xx2} (kg·m ²)	37.7503
I_{xy2} (kg·m ²)	16.1693
I_{xz2} (kg·m ²)	-23.0075
I_{yz2} (kg·m ²)	3.2047
I_{zz2} (kg·m ²)	1.5512
$m_2 r_{x2}$ (kg·m)	5.9390
$m_2 r_{y2}$ (kg·m)	46.8898
I_{xx3} (kg·m ²)	30.9319
I_{xy3} (kg·m ²)	-0.7515
I_{yz3} (kg·m ²)	63.2997
I_{zz3} (kg·m ²)	-0.4069
$m_3 r_{x3}$ (kg·m)	2.3608
$m_3 r_{y3}$ (kg·m)	1.4471
f_{c1} (N·m)	-0.0448
f_{v1} (Nm·s/rad)	0.1144
f_{c2} (N·m)	11.0195
f_{v2} (Nm·s/rad)	5.3853
f_{c3} (N·m)	10.9173
f_{v3} (Nm·s/rad)	27.3475
I_{xz3} (kg·m ²)	2.3092

The parameters identified by our proposed algorithm are listed in Table 2. It should be noted that the values of the dynamic parameters of the first three joints are much bigger than those of the other three joints. It is reasonable to ignore the effect of the torques caused by the 4, 5, and 6 joints. Figure 7 compares the measured torques for the excitation trajectories with the predicted torques based on the identified dynamical model. Although the results show that the predicted error is slightly big during velocity reversal, the predicted torques have the same trend as the measured

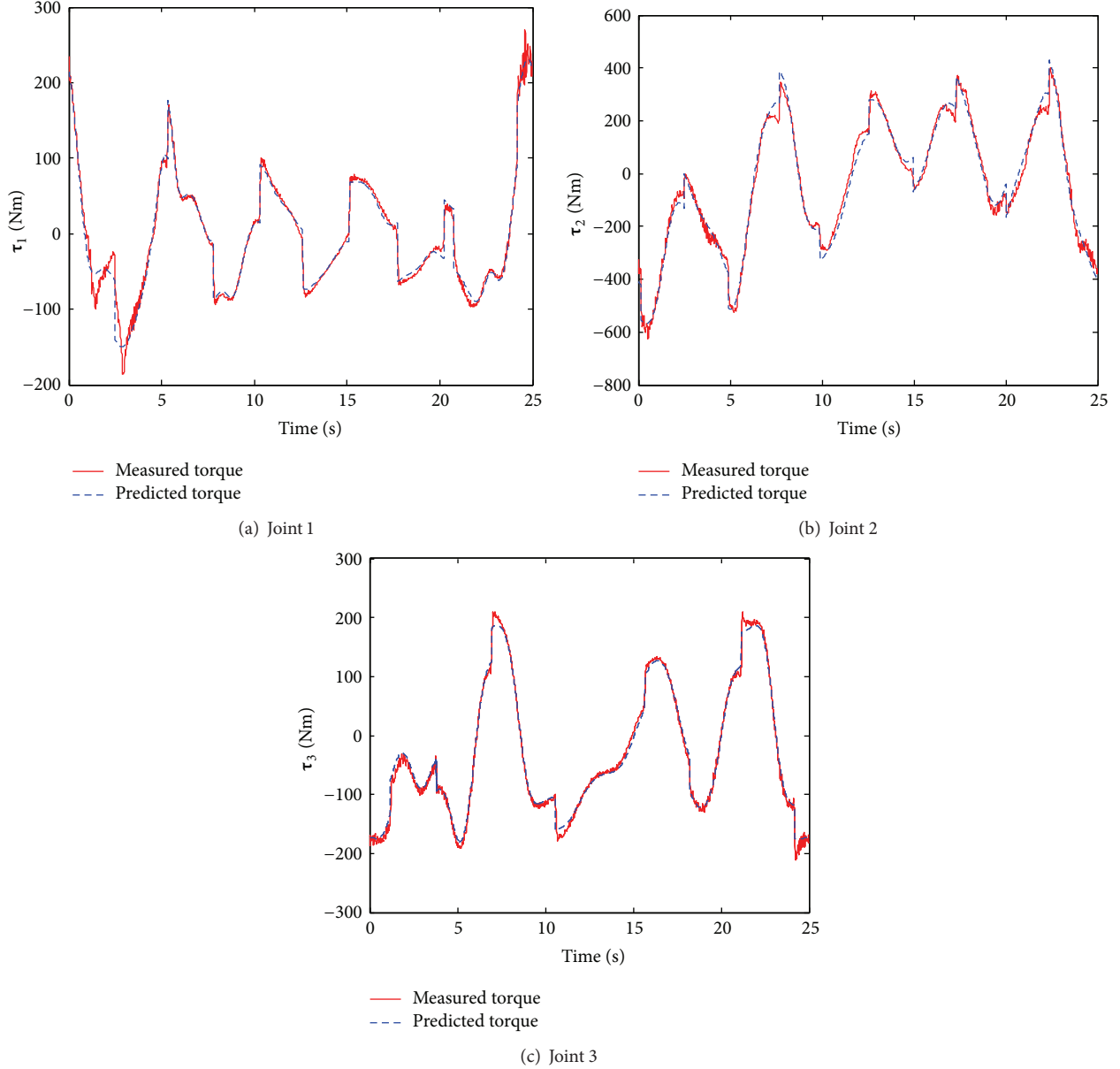


FIGURE 7: Comparison of the measured torques and predicted torques.

torques. It indicates that ABC algorithm has a strong ability to find the optimal parameters.

To verify the precision of the identified model by ABC algorithm, the correlation coefficient between the measured torques τ_i and predicted torques τ_{pi} , defined as the normalized cross-covariance function, is applied to estimate how well the identified model can reproduce the measured torques, and the function is defined as

$$\rho = \frac{\sum_{i=1}^N (\tau_i - \bar{\tau})(\tau_{mi} - \bar{\tau}_m)}{\sqrt{\sum_{i=1}^N (\tau_i - \bar{\tau})^2 \sum_{i=1}^N (\tau_{mi} - \bar{\tau}_m)^2}}, \quad (18)$$

where $\bar{\tau} = (1/N) \sum_{i=1}^N \tau_i$ and $\bar{\tau}_m = (1/N) \sum_{i=1}^N \tau_{mi}$. The closer the correlation coefficient is to unity, the better the identified model is. While the coefficient is close to zero,

the identified model is poor. As a result, the correlation coefficients of the predicted first joints are 0.9533, 0.9856, and 0.9801, respectively. It indicates that the identified parameters have satisfactory precision.

4.2. Model Validation. Since our aim for current stage is to investigate the validity of the model calculated by our proposed method, we focus on the validation test. Obviously, the appropriate validation test is to use the identified model in application and evaluate its success. As shown in Figure 8, three-term Fourier series are chosen as the excitation trajectories the same as the aforementioned excitation trajectories. Corresponding optimal trajectory parameters for each joint are listed in the Appendices. And the comparison of the measured and predicted torques is shown in Figure 9. It

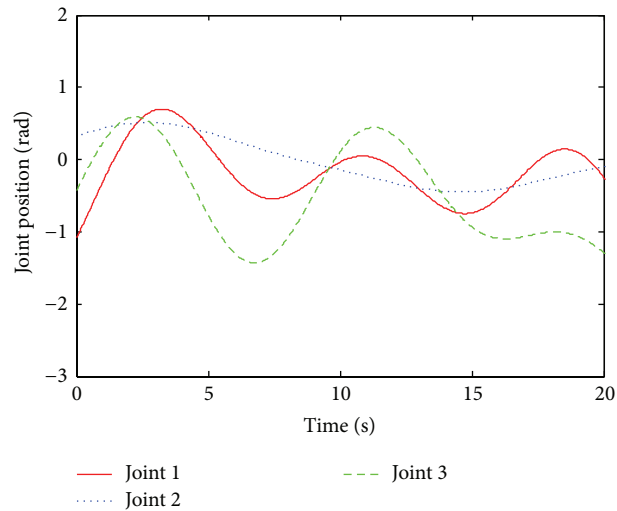


FIGURE 8: Robot model validation trajectory.

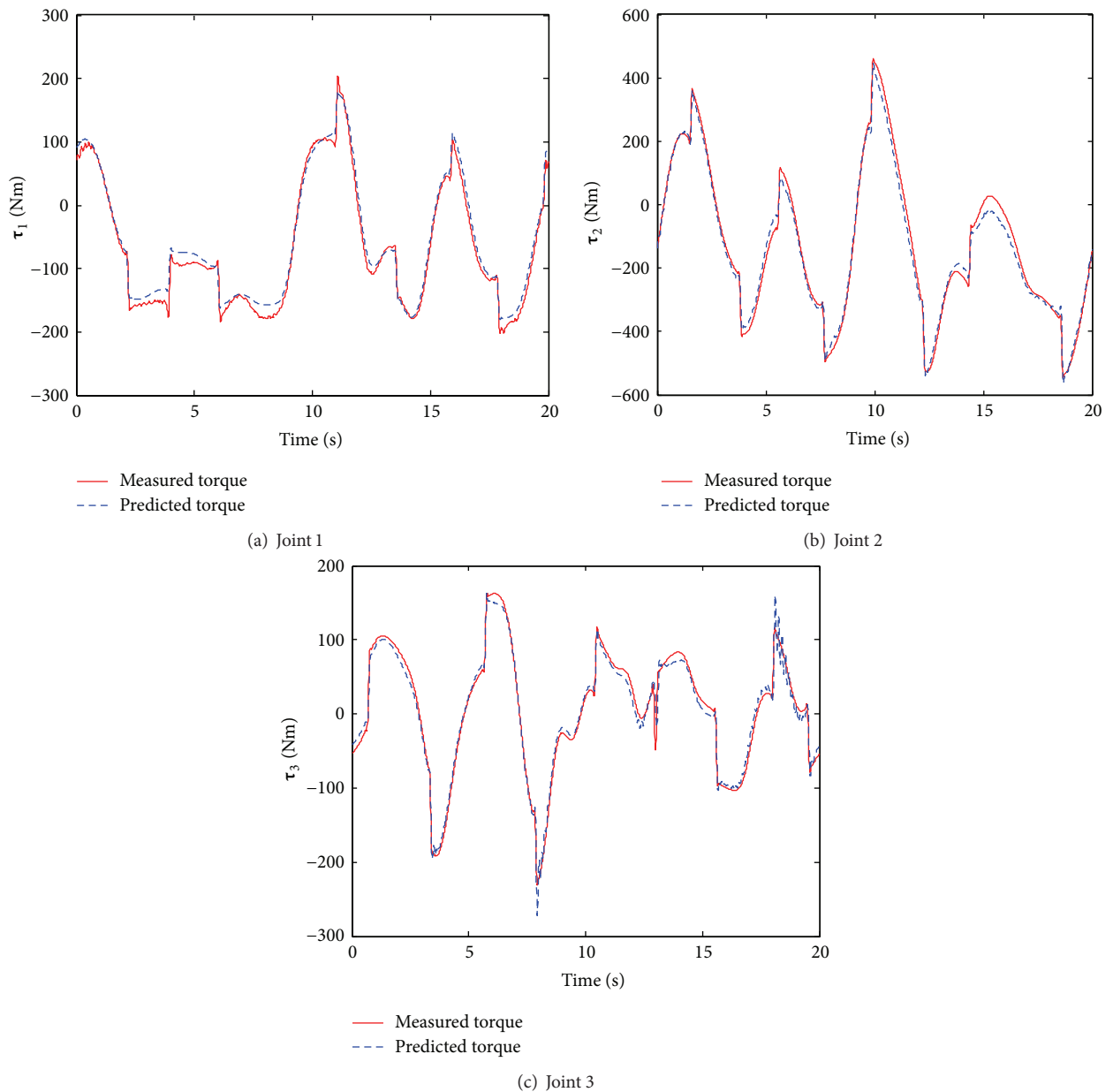


FIGURE 9: Comparison of the measured torques and predicted torques.

TABLE 3: Search scope of dynamical parameters.

Parameter	Scope
I_{zz1} (kg·m ²)	[-60, 60]
I_{xx2} (kg·m ²)	[-60, 60]
I_{xy2} (kg·m ²)	[-30, 30]
I_{xz2} (kg·m ²)	[-40, 40]
I_{yz2} (kg·m ²)	[-10, 10]
I_{zz2} (kg·m ²)	[-10, 10]
$m_2 r_{x2}$ (kg·m)	[-10, 10]
$m_2 r_{y2}$ (kg·m)	[-80, 80]
I_{xx3} (kg·m ²)	[-60, 60]
I_{xy3} (kg·m ²)	[-10, 10]
I_{yz3} (kg·m ²)	[-80, 80]
I_{zz3} (kg·m ²)	[-10, 10]
$m_3 r_{x3}$ (kg·m)	[-10, 10]
$m_3 r_{y3}$ (kg·m)	[-10, 10]
f_{c1} (N·m)	[-10, 10]
f_{v1} (Nm·s/rad)	[-10, 10]
f_{c2} (N·m)	[-10, 10]
f_{v2} (Nm·s/rad)	[-30, 30]
f_{c3} (N·m)	[-30, 30]
f_{v3} (Nm·s/rad)	[-30, 30]
I_{xz3} (kg·m ²)	[-10, 10]

indicates that the model we obtain is capable of accurately predicting the actuator torque data. In addition, the

$$\beta_1 = \begin{bmatrix} -0.3857 & -0.1911 & -0.2842 & -0.2289 & -0.2455 & -0.5705 & 0.3359 & 0.4129 & 0.5744 & 0.4842 & 0.0730 \\ 0.0011 & 0.3597 & -0.0179 & -0.0117 & 0.0443 & 0.4355 & 0.2551 & 0.0386 & 0.0411 & 0.0057 & -0.0065 \\ -0.6641 & -0.1638 & 0.5347 & -0.1448 & 0.1029 & 0.0826 & 0.4426 & 0.3359 & 0.6126 & -0.6714 & -0.5792 \end{bmatrix}. \quad (\text{A.1})$$

The optimal trajectory parameters for the three-term Fourier series are listed as follows:

$$\beta_2 = \begin{bmatrix} 0.3016 & 0.4006 & 0.6921 & -0.4210 & -0.0423 & 0.6066 & -0.9719 \\ -0.5026 & -0.0051 & 0.0492 & 0.8074 & 0.4578 & -0.2521 & 0.6288 \\ -0.1276 & -0.0624 & 0.3805 & 0.4006 & 0.3016 & 0.3531 & 0.1524 \end{bmatrix}. \quad (\text{A.2})$$

B. Search Scope of Dynamical Parameters

After many trials, the probable suboptimal or optimal search scope of the unknown parameters is listed in Table 3.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

correlation coefficients of the predicted first joints are 0.9272, 0.9534, and 0.9606 according to (18). The validation test not only shows very good results but also demonstrates that our proposed identification method is reliable enough.

5. Conclusion

In this paper a systematic procedure for the dynamical parameters identification of a 6-DOF industrial robot has been presented. We design optimal periodic excitation trajectories to integrate the identification experiment, data collection, and signal preprocess. All the unknown parameters are well identified by ABC algorithm. When comparing the measured torques and the predicting torques, we conclude that our proposed method can accurately estimate the robot dynamical parameters. Further, a model validation has been carried out to verify the validity of the identified model. The results of this paper are useful for researchers and manufactures of industrial robots.

Appendices

A. Optimal Parameters of Excitation Trajectories

The optimal trajectory parameters for the five-term Fourier series are listed as follows:

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