

An Under Load Servo Actuator Identification and Comparison between the Results of Different Methods

M. Maboodi*, M. H. Ashtari Larki** and M. Aliyari Shoorehdeli***

Abstract: This paper addresses the experimental identification of a servo actuator which is used in many industrial applications. Because the system consisted of electrical and mechanical components, the behavior of the system was nonlinear. In addition, the under load behavior of this servo was different. The load torque was considered as the input and a two input-one output model was presented for this servo actuator. Special was given in order to present a simple and applicable model for this servo actuator. For identification of this servo actuator, classic and intelligent methods have been used. ARMAX model as a classic model and MLP and LOLIMOT networks as intelligent models were selected for this purpose and their results have been discussed. The comparisons between these methods show that the intelligent methods have a better accuracy than classical method, but they have more complexity in the implementation. These models can be applied as references for characterizing different designs and future control strategies.

Keywords: ARMAX, Identification, LOLIMOT, MLP, Modeling, Servo actuator.

1 Introduction

Models of real systems are of fundamental importance in all disciplines. They can be useful in system analysis, i.e., for gaining a better understanding of the system, and make it possible to predict or simulate a system's behavior. In engineering, models are required for designing new processes and for the analyzing an existing process. Advanced techniques for the design of controllers, optimization, supervision and fault detection are also based on the model of processes [1].

Actuators are one of the important parts in the control loop of a system [2, 3]. Servo actuators have many applications in industry, because of specifications like high accuracy and easy application [4, 5].

An exact plant model should produce output responses similar to those of the actual plant. The complexity of most physical plants, however, makes the development of an exact model infeasible. Therefore, in order to design controllers which are reliable and easy to understand, simplified plant models are obtained by

the linearization around operating points and/or reduction in model order [6, 7].

Mathematical models can be developed in two routes (or a combination of them). One route is to split up the system into subsystems whose properties are well understood from previous experience. These subsystems are then joined mathematically and a model of whole system is obtained. Another route to mathematical as well as graphical models is directly based on the open-loop experimentation. Input and output signals from the system are recorded and subjected to data analysis in order to infer a model. When an open-loop experiment is not viable, a close-loop experiment can be done to obtain the plant model [1, 8]. Numerous studies have been reported on model identification using modern tools such as MATLAB System Identification Toolbox and LabVIEW System Identification Toolkit [9, 10].

Because the under load behavior of this servo was different, the load torque was considered as the input and a two input-one output model was presented for this actuator. Thus, inputs of this actuator were input voltage and load torque and its output was a voltage proportional to the shaft position.

For identification of this servo actuator, classic and intelligent methods have been used. ARMAX model as a classic model and MLP and LOLIMOT networks as intelligent models were selected for this purpose and their results have been discussed. The comparison between simulation and experimental results showed the effectiveness of the propose models. These models can

Iranian Journal of Electrical & Electronic Engineering, 2012.

Paper first received 15 Oct. 2011 and in revised form 4 July 2012.

* The Author is with the Electrical Engineering Group, Islamic Azad University, Hashtgerd Branch, Karaj, Iran.

E-mail: maboodi@ee.kntu.ac.ir

** The Author is with the Department of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran.

E-mail: h_ashtari@iust.ac.ir

*** The Author is with the Department of Mechatronics, K.N. Toosi University of Technology, Tehran, Iran.

E-mail: m_aliyari@eetd.kntu.ac.ir

be applied as references for characterizing different designs and future control strategies.

ARMAX is an important linear dynamic model which was used as a classic model for this purpose. The multilayer perceptron (MLP) is the most widely known and used neural network architecture. In many publications the MLP is even used as a synonym for neural network. The local linear model tree (LOLIMOT) approach is based on a divide-and-conquers strategy. A complex modeling problem is divided into a number of smaller and thus simpler sub problems, which are solved (almost) independently by identifying simple, e.g., linear models. After the discrete model is identified, the continuous model can be obtained.

The paper is organized as follows. Section 2 presents an overview of the servo actuator under study. Section 3 is dedicated to an overview of the ARMAX identification method. The experimental setup is discussed in Section 4. Model parameter identification and the proposed method are discussed in Section 5. Some conclusive remarks are stated in Section 6.

2 The Servo Actuator

Today, servo actuators are used in manifold applications, including toys, home equipment, computers, automobiles, ships, aircrafts, missiles, etc. The servo actuator in this study is shown in Fig. 1. The schematic of actuator is depicted in Fig. 2.



Fig. 1 Photos of the servo actuator.

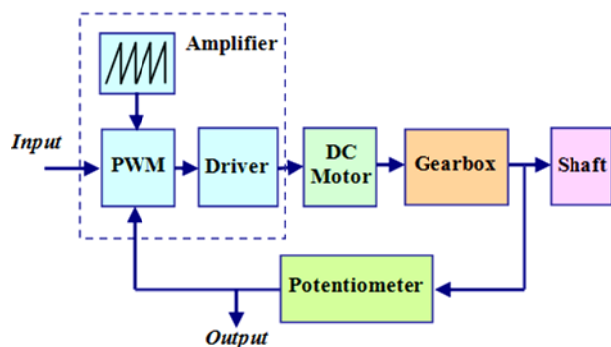


Fig. 2 Block diagram of the servo actuator.

This system consists of amplifier, DC motor, Gearbox, Potentiometer, etc. The Potentiometer type position sensor is used for detecting the deflection of the shaft, the scale factor of which is 0.357 volt/deg. The range of the input voltage of this actuator is between -10 volt and +10 volt.

3 System Identification Methods

System identification is a technique that allows find mathematical models of a dynamical system using input-output. The input-output data can be organized in a vector form, as follow.

$$Z^k = \{u(1), y(1), u(2), y(2), \dots, u(k), y(k)\} \quad (1)$$

where

$u(k)$ Is the input to dynamic system in instant k.

$y(k)$ Is the output to dynamic system in instant k.

The model of the dynamical system can be seen as mapping from a subset of the past data $\in Z^{k-1}$ into the next output $y(k)$.

The input signal of the process plays an important role in system identification. Clearly, the input signal is the only possibility for influencing the process in order to gather information about its behavior. For identifying this servo actuator, a pulse signal with different width and height were used.

3.1 ARMAX

The ARMAX model is a widely applied linear dynamic model. Some controller designs such as minimum variance control are based on the ARMAX model and exploit the information in the noise model. The ARMAX model is depicted in Fig. 3, and can be written in a compact way using the following notation

$$A(q)y(k) = B(q)u(k) + C(q)v(k) \quad (2)$$

where

$$A(q) = 1 + a_1q^{-1} + \dots + a_{n_a}q^{-n_a}$$

$$B(q) = b_1 + b_2q^{-1} + \dots + b_{n_b}q^{-n_b+1} \quad (3)$$

$$C(q) = 1 + c_1q^{-1} + \dots + c_{n_c}q^{-n_c}$$

In above equation a_i , b_i and c_i are the parameters to be estimated. n_a is the number of poles of the system. $n_b - 1$ is the number of zeros of the system. n_c is the number of c coefficients.

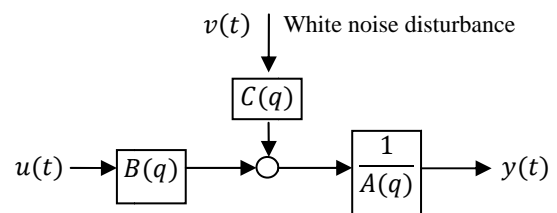


Fig. 3 ARMAX: standard structure.

There are some methods for estimation of parameters of ARMAX model, such as least square optimization [1, 8].

3.2 MLP

One of the most common neural network architecture is MLP. The main feature of the MLP is their propriety as universal approximation [11]. This propriety ensures that is possible to use a MLP to approximate any function from an input space of dimension N to an output space of dimension M. In Fig. 4 is showed the MLP structure.

The MLP can be written as Eq. (4)

$$\hat{y} = \sum_{i=0}^M \omega_i \Phi_i \left(\sum_{j=0}^p \omega_{ij} u_j \right) \quad (4)$$

with $\Phi_0(\cdot) = 1$ and $u_0 = 1$

where

- $\hat{y}(k)$ Estimate output produce by the MLP.
- ω_i Weights from the output layer.
- ω_{ij} Weights from hidden layer.
- M Number of neuron in the hidden layer.
- p Number of the input.

In our work we used MLP structure with nonlinear activation functions in the hidden layer.

3.3 Local Linear Model Tree (LOLIMOT)

LOLIMOT is an incremental tree-construction algorithm that partitions the input space by axis-orthogonal splits. In each iteration a new rule or local linear model (LLM) is added to the model [1]. To do that, validity functions are calculated and the local linear models are adapted with the least squares method. The LOLIMOT algorithm consists of an external loop in which the structure of the model is determined and an inner loop in which the parameters of the model are estimated by local least squares.

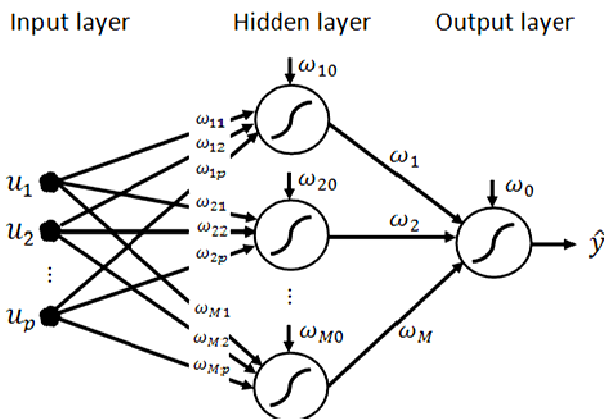


Fig. 4 A multilayer perceptron network.

Short description of the algorithm:

1. Start with an initial model.
Construct the validity functions for the beginning input space partitioning and estimate the LLM parameters by local least squares.
2. Find the worst LLM.
Calculate the loss function for each of the $I = 1, \dots, M$ local linear models. Find the worst LLM, where $Max_i(I_i)$. i defines the index of the worst LLM.
3. Check all possible divisions.
The worst LLM i will be considered for further optimizations. Each hyper rectangle of the local linear. Models will be divided orthogonally along the axes in two pieces. Divisions in every of p dimensions are carried out.
4. Find the best division.
The best among p alternatives of step 3 is chosen. The optimized local linear models, will be added to the model. The number of LLM are incremented to $M + 1$.
5. Check for convergence.
If the final criteria is met, then stop the algorithm, otherwise return to step 2.

Fig. 5 illustrates the operation of the LOLIMOT algorithm in the first four iterations for a two-dimensional input space.

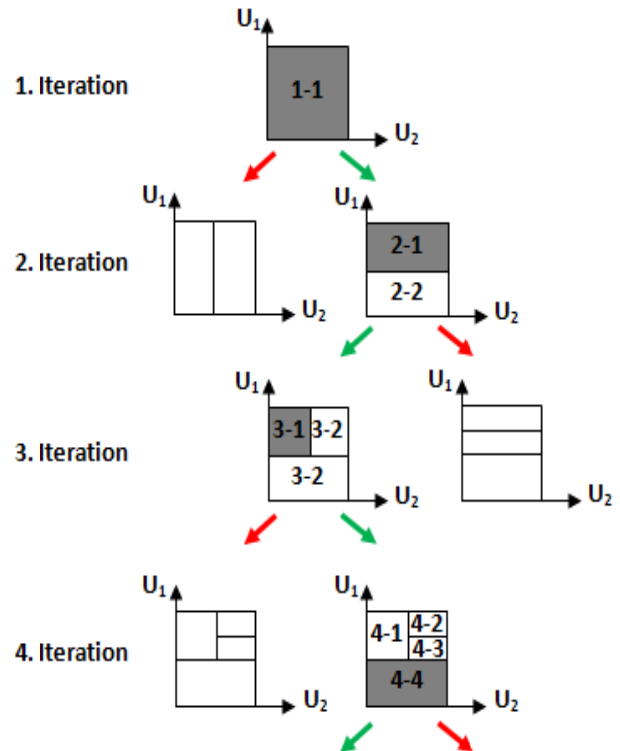


Fig. 5 Operation of the LOLIMOT structure search algorithm.

4. The Experimental Test Rig

4.1 Test Bed

Because the system consists of electrical and mechanical component, the behavior of the system is nonlinear. These nonlinearities arise from several sources; however, the important part of that is the external load applied to the shaft.

Hence, in order to simulate a real situation, a test bed, which can apply external load to the shaft, is needed. To produce a suitable torque in a fix level, an electrical motor was used and to control the amplitude of the torque, during the test, the S type load cell (STC-A-30kg) was used. One end of the load cell was jointed to the base plate and another end, was linked to the shaft of the motor with a fixed arm. A good alignment is necessary between the ends of the shaft; hence, flexible coupling was used for connecting the shaft of the electrical motor to the shaft of the servo actuator.

4.2 Data Acquisition Software

The servo link monitoring and diagnosis software was developed for the online monitoring of servo actuator and it was used here to acquire experimental data from the real-time HIL (Hardware in the Loop) test. The software is based on simulink® and Real-time work shop with the sampling rate of 100 Hz. The software communicates with the servo actuator thorough an analog input card (Advantech 818 HG) and analog output card (Advantech PCL 726). The performance of the servo actuator is illustrated by nature of Volt-Time curve, resulting from a PE input command.

In addition to plotting the system response curve, the software specified the amplitude of external load which must be applied to the shaft of the actuator. This actuator can support the external load up to 15 N.m.

5. Model Parameter Identification

The identification of this system, was considered with two inputs (v_{in} , $Torque$) and one output (v_{out}), as shown in Fig. 6.

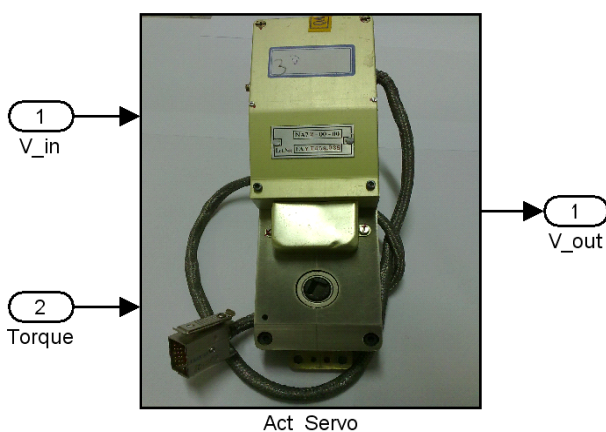


Fig. 6 Input/output model of the servo actuator.

A special case is a single-input single-output (SISO) system where $u_2 = 0$ or $u_2 = cte$. The SISO model is well-established model structures having an input/output behavior like:

$$y(s) = G(s)U(s) \quad (5)$$

where

$$G(s) = \frac{b_m s^m + b_{m-1} s^{m-1} + \dots + b_0}{a_n s^n + a_{n-1} s^{n-1} + \dots + a_0} \quad (6)$$

$n > m > 0$

which is transfer function of the system, i.e. mathematical representation of servo actuator. Because of the researchers' knowledge about the servo actuator, the second order ARMAX model was selected to estimate the actuator dynamic. Moreover, order of the system can be found using system identification methods with the test data, which is shown in Fig. 7.

Using MATLAB System Identification Toolbox, three different models were obtained with the second and third orders (ARMAX3221, ARMAX2221 and ARMAX2121). Table 1 shows the result of three different models. Based on the Best Fit criteria, we see that the performance don't change very much. So, it seems that second order is enough for our purpose.

Table 1 Comparison between models.

Model	Best Fit
ARMAX3221	96.01%
ARMAX2221	95.93%
ARMAX2121	95.91%

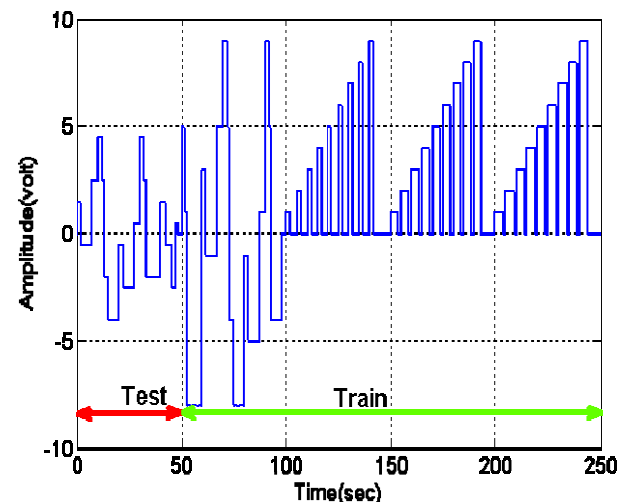


Fig. 7 Input data for exciting the system in different operating condition.

5.1 Linear SISO Model

In this part, a linear model is identified using measurement v_{out} and v_{in} . The method used for identification was described in Section III. To identify a second order SISO linear model, a different torque was applied to the shaft of actuator.

The actuator response in different operating conditions is depicted in Fig. 8. By increasing the external load to the shaft, overshoot decreased; however the DC gain of the system was almost fixed.

While Real-Time Workshop was used for experiments and data acquisition, the identification and modeling procedures were performed on MATLAB. The models obtained in the transfer function form, are represented in Table 2.

5.2 Linear MISO Model

Here we use a result of previous section to extract a second order MISO model, that is depend on amplitude of the Torque. All transfer function demonstrated in Table 2, can be represented with three parameters:

DC gain (K)

Damping ratio (ξ)

Undamped natural frequency (ω_n)

This parameters for each transfer function of Table 2, is tabulated in Table 3. It can be seen, by increasing the amplitude of external load to the shaft of actuator, DC gain is nearly fixed, ξ was increased and ω_n was decreased. Using classical curve fitting, the relationships between the K , ξ , ω_n and external load τ was found to correspond to the following functions.

$$\begin{aligned} K &= 0.7036 \\ \xi &= 0.006585 \times \tau + 0.7668 \\ \omega_n &= -0.06738 \times \tau + 13.69 \end{aligned} \quad (7)$$

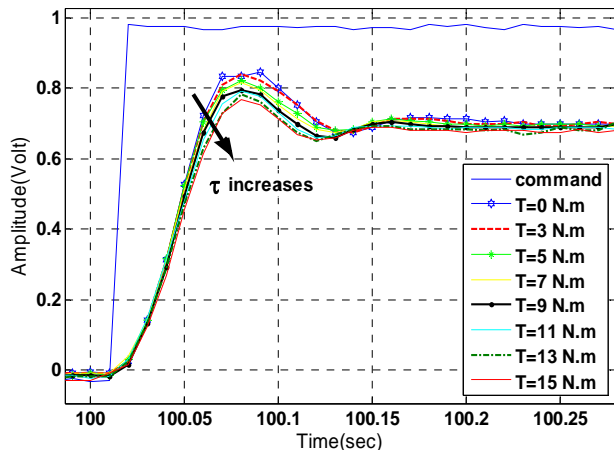


Fig. 8 Actuator response in different torques.

Table 2 Model of the system in different Torque.

Torque (N.m)	Transfer function
0	$G(s) = \frac{0.8288(s + 162.7)}{s^2 + 21.70s + 191.5}$
3	$G(s) = \frac{0.6966(s + 181.4)}{s^2 + 20.77s + 179.6}$
5	$G(s) = \frac{0.6954(s + 179.6)}{s^2 + 21.05s + 177.4}$
9	$G(s) = \frac{0.7596(s + 157.3)}{s^2 + 21.38s + 169.8}$
11	$G(s) = \frac{0.7516(s + 154.7)}{s^2 + 21.68s + 165.3}$
15	$G(s) = \frac{0.7414(s + 155.8)}{s^2 + 22.35s + 164.4}$

The transfer function V_{out}/V_{in} derived with standard transfer function model of second order system and the data is shown in Table 3.

$$\frac{V_{out}}{V_{in}} = K \cdot \frac{\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} \quad (8)$$

This is new representation and new transfer function model of the servo actuator. The coefficient in this model is depending on the external load.

The model was simulated and the results were compared with the data obtained from experiments. The correspondence between the measured and calculated output voltage was considered for verification.

In Fig. 9, the graphs show the experimentally obtained curves (in Torque = 7 N.m) with simulated ones. It can be seen that the results corroborate well with the experimental data.

Table 3 Models of the system in different Torque.

Torque (N.m)	K	ξ	ω_n
0	0.7040	0.7839	13.84
3	0.7034	0.7747	13.40
5	0.7040	0.7903	13.32
9	0.7038	0.8204	13.03
11	0.7035	0.8432	12.85
15	0.7035	0.8717	12.82

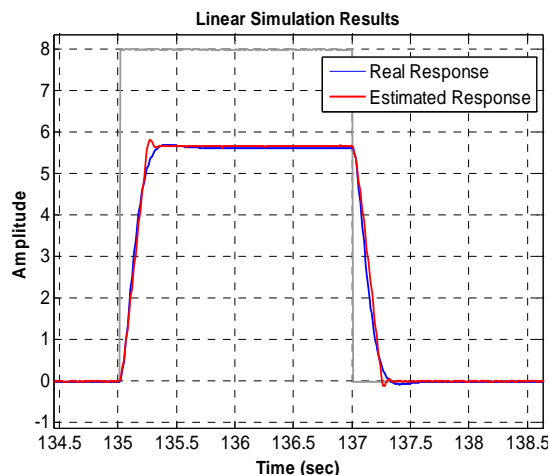


Fig. 9 Experimental Values vs. Model Estimated Values

5.3 Intelligent Modeling

The multilayer perceptron (MLP) and Local Linear Model Tree (LOLIMOT) are the most widely known and used neural network architecture. Now, we will obtain the model of the system using MLP and LOLIMOT method. We used two neurons in hidden layer of network. We used Levenberg Marquardt and gradient descend method for the training the MLP and LOLIMOT network, respectively.

In this modeling, to estimate the output voltage of actuator $v_{out}(t)$, we use four signal as a input of the network. These signal are input voltage $v_{in}(t)$, amplitude of the torque τ , output voltage in two previous sample $v_{out}(t-1)$ and $v_{out}(t-2)$.

With applying this method to the input data, the network output, is represented in Fig. 10.

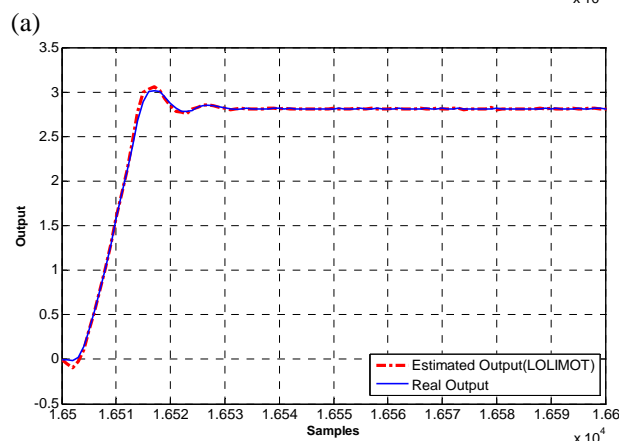
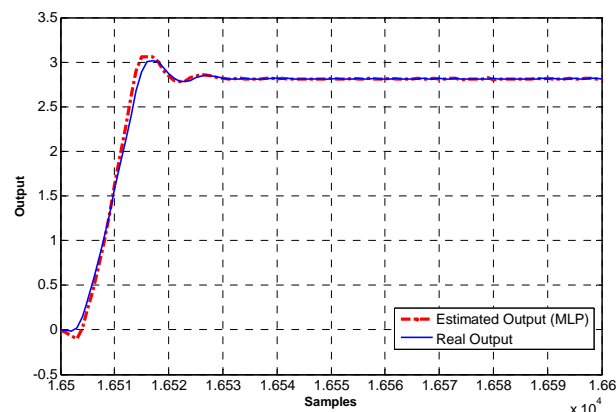
Note, the model obtained using MLP method is the same obtained using LOLIMOT method and both methods predict system behaviour, as well.

6. Conclusions

A two input-one output model was developed for an under-load servo actuator. The load torque was considered as the input. The unknown parameters (ARMAX parameters) were identified from experimental data. The system was excited using pulses with different height and width. The proposed method provided a linear MISO model for the actuator servo. The transfer function V_{out}/V_{in} was derived with standard transfer function model of the second order system. In this model the DC gain was nearly fixed. Damping ratio (ξ) and undamped natural frequency (ω_n) were linear functions of the external load to the shaft.

Acknowledgment

The authors would like to acknowledge the funding support of the Islamic Azad University, Hashtgerd Branch. This paper is a partial result of the project "An Underload Servo Actuator Identification and Comparison between the Result of Different Methods".



(a) (b) Fig. 10 Model estimated based on (a) MLP and (b) LOLIMOT networks.

References

- [1] Nelles O, "Nonlinear System Identification: From Classical Approaches to Neural Network and Fuzzy Models", Springer, Berlin, 2001.
- [2] Maboodi M., Ashtari Larki M. H., Aliyari Shoorehdeli M. and Bolandi H., "An Underload Servo Actuator Identification", 18th IFAC world Congress, Milano, Italy, 2011.
- [3] Lacy L. L., Bernstein D. S., "Identification of an Electromagnetic Actuator", 41th Int. IEEE Conf. On Decision and Control, Las Vegas, Nevada USA, 2002.
- [4] Schaab J., Muenchhof M., Vogt M. and Isermann R., "Identification of a Hydraulic Servo-Axis Using Support Vector Machines", 16th IFAC World Congress, Prague, Czech Republic, 2005.
- [5] Modabberifar M., Hojjat Y., Abdullah A. and Dadkhan M., "Identification of Three Phase Panel Type Electrostatic Actuator", 15th International Conference on Mechatronics and Machine Vision in Practice, pp. 447-454, 2008.
- [6] Laghrouche S., Ahmed F. S., El Baghdouri M., Wack M., Gaber J. and Becherif M., "Modelling and Identification of a Mechatronics Exhaust Gas Recirculation Actuator of an Internal Combustion

- Engine”, *American Control Conference*, pp. 2242-2247, 2010.
- [7] Koveos Y. and Tzes A, “Modelling and Identification of Resonance Fluid Actuator”, *Control Applications, (CCA) & Intelligent Control, (ISIC)*, pp. 560-565, 2009.
- [8] Ljung L, “*System Identification: Theory for the user*”, (2nd Edition), Prentice-Hall, Inc., Englewood Cliffs, NJ, 1999.
- [9] Jelavic M., Peric N. and Petrovic I., “Identification of Wind Turbine Model for Controller Design”, *12th Int. Conf. On Power Electronics and Motion Control*, pp. 1608-1613, 2006.
- [10] Shao J., Wang Z., Lin J. and Han G., “Model Identification and Control Electro-Hydraulic Position Servo System”, *Int. Conf. on Intelligent Human-Machine System and Cybernetics*, pp. 210-213, 2009.
- [11] Mühlenbein h., “Limitations of multi-layer perceptron networks-steps towards genetic neural networks”, *Parallel Computing*, Vol. 14, Issue 3, August 1990, pp. 249–260, 2003.



Mohsen Maboodi was born in Karaj, Iran, in 1984. He received his B.Sc. from K.N. Toosi University of Technology, Tehran, Iran in 2007 and M.Sc in Electrical Engineering from Sharif University of Technology, Tehran, Iran in 2009. He is currently a Ph.D. candidate in K.N. Toosi University of Technology. His research interests include Control Performance

Assessment (CPA), Predictive Control, System Identification and Optimization.



M. H. Ashtari Larki was born in Khuzestan, Iran, in 1984. He received the B.Sc. and M.Sc. degrees in Electrical Engineering from Khajeh Nasir Toosi University of Technology, Tehran, Iran, in 2006 and 2008, respectively. He is currently a Ph.D candidate in Electrical Engineering Department, Iran University of Science and Technology, Tehran, Iran. His doctoral dissertation concerned Satellite orbit determination Based on Optimization Technique. Ashtari's main research interests include flight control, optimal control and satellite orbit determination and orbit control.



Mahdi Aliyari Shoorehdeli received his B.Sc., M.Sc. and Ph.D. degrees in electrical engineering from Khajeh Nasir Toosi University of Technology, Tehran, Iran, in 2001, 2003 and 2008 respectively. He is currently an assistant professor at Department of Mechatronics Control, Faculty of Electrical Engineering K.N.T.U University. His research interest includes Mechatronics Systems, Fault Diagnosis, Neural Networks, Fuzzy systems, Nero-Fuzzy control, Identification and Predication, Pattern Recognition and Swarm Intelligence.