Military Technical College
Kobry El-Kobbah,
Cairo, Egypt.

13th International Conference
on Applied Mechanics and
Mechanical Engineering.

MIXED-REALITY ENVIRONMENT FOR ONLINE SYSTEM IDENTIFICATION OF NONLINEAR SYSTEMS

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ABSTRACT

This paper presents a method to identify non-linear-systems in a real time environment. Acquiring the system's transfer function accurately could be extremely difficult once it has been assembled, which causes a great difficulty in the non-linear system modeling and control. Therefore in this research, Mixed Reality Environment (MRE) has been employed to identify the system's transfer function using Auto-Regressive Moving Average (ARMAX) model algorithm in order to avoid the complexity associated with nonlinear systems modeling. Online system identification can be conducted effectively and efficiently using the proposed method. The advantages of the proposed method are high accuracy in the identified system, simplicity, and low cost. The results obtained from on line experimental measured data are used to determine discrete transfer function of the system, 4th order model with one step prediction shows best performance.

KEY WORDS

On-line Identification; Auto-Regressive Moving-Average; Pneumatic servo drive; Mixed Reality Environment.

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INTRODUCTION

In practical fields of applications one often does not have available values for the model parameters and/or part of the model structure. Therefore, one tries to obtain these parameters and/or structural elements using experimental data from the real process. Researchers have developed various system identification methods and applied them to many engineering systems in order to estimate different parameter values. Carducci G. et al [1] presented identification of viscous friction coefficients for a pneumatic system model using optimization methods. They reported that pneumatic systems are not only nonlinear, but also involve several tuning parameters. Line-Chen Y. et al [2] developed a software tool for pneumatic actuator.

For system simulation, Kiaei K.and Sepehri N. [3] discussed some practical concerning the identification of electro-hydraulic actuators using discrete time linear models. Abdrabbo S. and Tutunji T. [4] presented identification model and sensitivity analysis of hydrostatic transmission system. Angerer B.T. et al. [5] used a structured recurrent neural network to identify physical relevant parameters and nonlinear characteristics of a nonlinear two-mass system with friction and backlash. Yan M. et al. [6] used a recursive prediction-error method based on an ARMA model to identify the transfer function of a CNC milling machine in order to apply a combined self-tuning adaptive control and cross-coupling control to retrofit the machine with DC motors instead of stepper motors. Tutunji T. et al. [7] used Recursive Least Squares (RLS) algorithm to identify gyroscopic system behavior. Ostring M. et al. [8] identified the behavior of an industrial robot in order to model its mechanical flexibilities while Johansson R. et al. [9] used a state-space model to identify the robot manipulator dynamics.

In this work a method or technique is adopted to identify the system's transfer function on line which is considered one of the crucial issues that influence the control design of non-linear systems. Matlab/Simulink, has been devised to facilitate the realization of the proposed method to identify the system model online. This developed platform would also provide an excellent environment to support design, simulation, and emulation of control system.

The rest of the paper is organized as following: section 2 provides the ARMAX models and recursive estimation algorithm. Section 3 introduces the concept of Mixed Reality Environment (MRE). A case study is provided in section 4, and finally the obtained results are discussed in section 5.

ARMA MODELS AND RECURSIVE ESTIMATION ALGORITHMS

System identification is the field of modeling dynamic systems from measured data using mathematical algorithms. Those algorithms use a black box model and assume no prior knowledge of the system physics.

In general, the output y(t) of a continuous-time system is a function of its inputs u_1 to u_q , time t , the system parameters β_1 to β_k , and noise $\varepsilon(t)$.

$$y(t) = f\left(u_1,...,u_q,t,\beta_1,...,\beta_k\right) + \varepsilon(t) \tag{1}$$

Discrete-time signals are resulted from A/D sampling and represented as $y(kT_s) = y(k)$. Here T_s is the sampling time and k is an integer value that represents the sample number. The model structure used to identify the system dynamics for a single-input-single-output is given by

$$\hat{y}(k) = g\big(u(k)...u(k-m), y(k-1)...y(k-n), a_1,...,a_n, b_1,...,b_m\big) \tag{2}$$

Equation 2 shows that the estimated output sample $\hat{y}(k)$ is a function of present input *u(k)*, past inputs *u(k-m)*, past outputs *y(k-n)*, and parameters vector $[a_1 \quad ... \quad a_n \quad b_1 \quad ... \quad b_m]$. Note that the noise is included in the model parameters.

For linear models, the function "*g*" becomes a linear multiplier and therefore the output can be represented as an ARMA model

$$\hat{y}(k) = \sum_{j=1}^{n} a_j y(k-j) + \sum_{i=0}^{m} b_i u(k-i) \tag{3}$$

The transfer function H(z) can be obtained by transforming the ARMA model to the Z-domain

$$AY(z) = BU(z) \Rightarrow H(z) = B/A \tag{4}$$

where $\quad A = 1 + a_1 Z^{-1} + a_2 Z^{-2} + ... + a_n Z^{-n}$

and $\quad B = b_1 Z^{-1} + b_2 Z^{-2} + ... + b_m Z^{-m}$

The vector format for equation 3 is given by

$$\hat{Y} = \Psi^T \theta \tag{5}$$

where $\hat{Y}$ is the output vector with dimension Kx1 composed of the elements y(1)… y(K), ε is the error vector, θ is the parameter vector $[a_1 \quad ... \quad a_n \quad b_1 \quad ... \quad b_m]$, and ψ^T is a matrix whose elements are the delayed input and output components

$$\Psi^T = \begin{bmatrix} \psi^T(1) & ... & 0 \\ ... & ... & ... \\ 0 & ... & \psi^T(K) \end{bmatrix} \tag{6}$$

$$\psi^T(k) = [-y(k-1) \quad ... \quad -y(k-n) \quad u(k-1) \quad ... \quad u(k-m)]$$

Input-output patterns *(u,y)* are available. They are used in the equation 5 calculate $\hat{Y}$. The parameters a_j and b_i are updated to minimize a cost function

$$V_K = \sum_{k=1}^{K} \big(\hat{y}(k) - y(k)\big)^2 \tag{7}$$

Figure 1 shows the block diagram of the described model.

Recursive estimation algorithms can be used to find the optimal system parameters *θ*. The general recursive estimation algorithm is given by

$$\begin{aligned} &\theta = \theta + Q\left(Y - \hat{Y}\right) \\ &\hat{Y} = \Psi^T \theta \\ &Q = P\Psi \\ &P = \{P - P\Psi\Psi^T P / (\lambda + \Psi^T P\Psi\} / \lambda \end{aligned} \tag{8}$$

where *P* is a positive definite matrix initialized to be *cI* (*I*: identity matrix, 100< c <10,000) and *λ* is the forgetting factor (0.95< *λ* < 0.99).

The choice of matrix *Q* depends on the algorithm used. One method is to use an initial value for the matrix *P* is the identity matrix multiplied by a large scalar (in the range of 1000)

The disadvantage of off-line system identification is the need to acquire a sufficient set of experimental test data of the system which may require long time and high efforts. Furthermore, this approach can not be adopted as a general analysis or configuration for modular servo-pneumatic system since the model is created for particular actuator with certain dimensions. Therefore, a new data collection and training procedure should be conducted if any modification on the system is applied. This was the main motivation to develop a new method in order to identify the system on-line. MRE was employed in order to facilitate system identification and control on-line control. On-line identification saves time in data collection and improve the model accuracy and reliability. Moreover, any change in the system structure and/or components will be reflected on the system model without the need to data recollection.

A METHOD FOR ON-LINE IDENTIFCATION

Generally, classical Mechatronic systems comprise of a controller, actuators, and sensors. The controller generates an output according to the feedback signal from the sensors and sends it to the actuator that performs a certain task. According to the above situation, some of the hardware components such as controller can be substituted by its model and simulated in real time. The simulated component(s) can be run in conjunction with real components under the same environment. This environment can be regarded as MRE. Fig. 2 shows the concept of the proposed environment.

The MRE is an environment whereby virtual components can be applied on real system's components. From the control perspective, working with MRE should include control system synthesis off-line (or under simulation environment) and then apply the simulated model on the real system under the MRE. Off-line simulation, on the one hand, will normally take place before moving onto MRE, where the system should be tested and the controller should be tuned or optimized. On the other hand, the MRE will be used to apply the optimized controller on the real system.

This environment should allow the system to be controlled with different control schemes by simply replacing the “Controller” component according to the application requirements. Furthermore, the MRE gives the capability to monitor the system's behavior by observing the output signals such as speed and position signals. These signals can be utilized to identify the real system using one of the system identification methods. In the context of this research work, ARMA model was employed for on-line system identification using the MRE. The following sections give an overview of the experimental setup of the system.

CASE STUDY: PNEUMATIC SERVO DRIVE ON-LINE IDENTIFICATION

In order to show the feasibility, efficiency, and accuracy of the proposed method for online identification, a case study has been conducted. Pneumatic system has been chosen as a test rig. The experimental test station on which all tests were carried out is Fig. 2. The main feature of the test set up is to perform an integrated components of mechanical, electronics and computer interface structure, with high computational capacity and good software programmability. It is also designed to resemble the basic pneumatic circuit of various applications. The pneumatic unit consists of pneumatic power supply which includes compressor with air conditioning unit, lubricating unit, and manifold. Servo-pneumatic valve has 1/8 inch port and operating voltage from zero to 10 volts and pneumatic actuator has piston diameter of 27 mm, rod diameter of 8 mm and stroke length of 100 mm. A rotary potentiometer has resistance range from 2 to 12 KΩ with voltage source of 10 Volts, fixed on the cylinder is used for measuring the position of the piston and providing the position feedback. All signals are sent to a computer via National Instrumentation NI DAQ card 1036E through an A/D converter terminal. The DAQ card has 16 analog inputs, 2 analog outputs, sampling rate of 200 KS/s, and input voltage range of ± 10 V. The final signals are used to activate analog input block of MATLAB Real-time Windows Target (rtwt).

The input signal of the valve is the control voltage from the analog output block of MATLAB "rtwt" to D/A converter of NI DAQ card 1036E and finally to the servo valve. The change of input voltage from zero to 5 Volt produces the change of air flow through the valve to control the motion of piston of pneumatic actuator.

In order to examine the plant characteristics and obtain its model, a group of experiments were performed on the test rig explained in section 5. First, on-line identification using ARMA model was obtained using the impulse response of the real system. Fig. 4 shows the simulink block diagram of on-line system identification that was interfaced to the real system through the DAQ card. The input signal was applied to the servo drive via analog output block (DAQ output). The response of pneumatic actuator (piston displacement) was measured and sent back the computer through the analog input block (DAQ input).

To find the proper model structure, different prediction strategies were performed with 6 bars supply pressure, 2 bars back pressure, and 1 ms sampling time.

Effect of Prediction Orders

A set of experiments were conducted to show the effect of identification orders at one step prediction strategy. Fig. 5. shows on-line actual output and 3rd order predicted model with one step prediction. The square error was 7.09e-5 cm with standard deviation of 0.008468 cm. Referring to the ARMA model explained in section 3, the identified system's parameters vector (θ) was [0.0082979 -0.015416 0.020473 0 -1.3857 0.073178 0.32096], and therefore the resulted transfer function is

$$G_p = \frac{0.0082979z^3 - 0.015416z^2 + 0.020473z}{z^3 - 1.3857z^2 + 0.073178z + 0.32096} \tag{9}$$

Fig. 6 represents on-line actual output and 4th order predicted model with one step prediction. The square error was 3.22e-5 cm with standard deviation of 0.00571 cm and θ=[0.0070699 -0.017738 0.019649 0.00027783 0 1 -1.9827 1.2989 -0.43504 0.12436]. The corresponding transfer function is depicted as

$$G_P = \frac{0.0070699\,z^4 - 0.017738\,z^3 + 0.019649\,z^2 + 0.00027783\,z}{z^4 - 1.9827\,z^3 + 1.2989\,z^2 - 0.43504\,z + 0.12436} \tag{10}$$

Fig. 7 is the results of, on-line actual output and 5th order model at the same conditions. The square error was 3.397e-5 cm with standard deviation of 0.005861 cm. The identified following transfer function was

$$G_P = \frac{0.0075351\,z^5 - 0.017093\,z^4 + 0.013851\,z^3 + 0.012393\,z^2 - 0.0075649\,z}{z^5 - 1.9622\,z^4 + 1.2423\,z^3 - 0.2243\,z^2 - 0.22505\,z + 0.17458} \tag{11}$$

Table 1. shows a comparison of statistical analysis of the ARMA predicted output with different orders and one step prediction. Therefore, several transfer functions can give almost similar results with very small RMS errors. Fourth order model shows the best match between the actual output and the predicted model output. This is due to the nature of the separate components of the plant (servo valve, pneumatic actuator, pipes, load, and DAQ card). It is worth noting that since the ARMA model converges to a local minimum, the identified transfer functions in Eqs (18-20) are not unique consequently.

Effect of Step Predictions

To explain the effect of step size prediction, a number of experiments were performed using 4th order model and different step size predictions. Figs. (6, 8-9) show on-line actual output and predicted model outputs with different prediction step sizes (one step, 5 steps and 10 steps). It can be observed that the best result was the one step prediction. This is because in pneumatic systems, which are high nonlinear systems, one step prediction would succeed to track the changes in the system behavior while acquiring the system's parameters.

CONCLUSIONS

Nonlinear systems are characterized by high order time variant dynamics and nonlinearities due to inherent characteristics. Such systems usually have poor damping, low stiffness, significant friction, and limit bandwidth. An appropriate model of such systems is not easy. One good technique to obtain the system model is to use the identification algorithms based on experimental sampled data.

In the present work, different online discrete recursive identification in closed loop from experimental measured data has been made via mixed reality environment. 4th order discrete model shows the best model results. Good performance of 4th order one step prediction was observed, it shows square errors of 3.22e-5 cm. The performance of 5 step prediction and 10 step predictions was inadequate, as the system behaves high nonlinearities.

The results have shown a reasonably good match between the simulated and real system behaviors which implies that the accuracy of the system model that obtained through online identification is high, and the developed MRE is appropriate to apply different identification algorithms.

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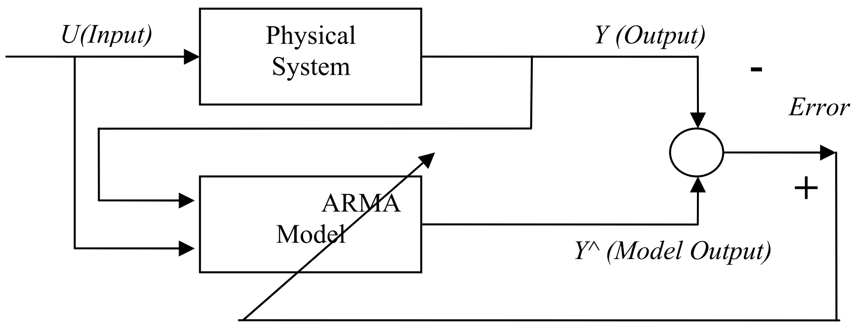

Fig. 1. Block diagram of ARMA identification mod

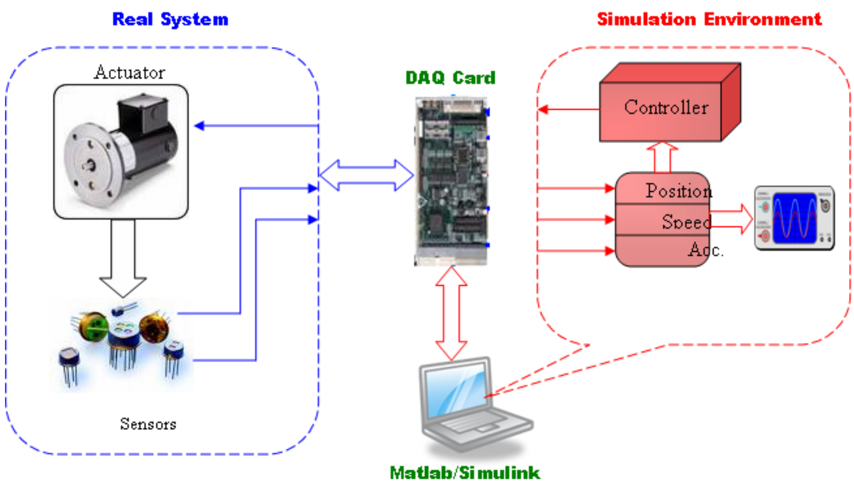

Fig. 2. MRE structure for control scheme implementation

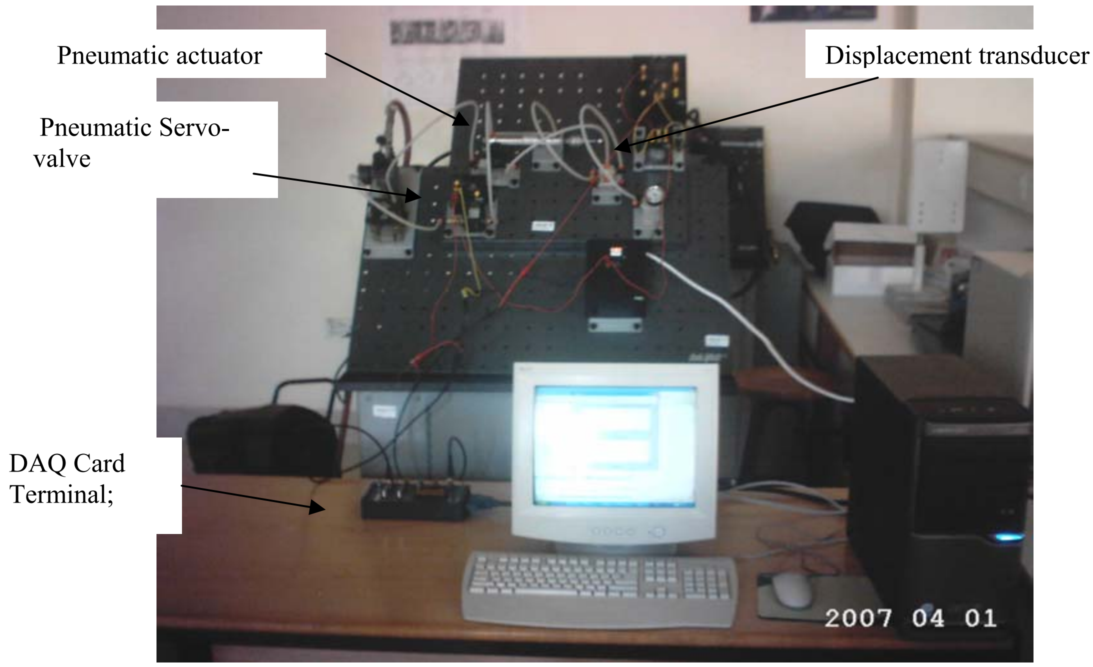

Fig. 3. Photograph of pneumatic test set up

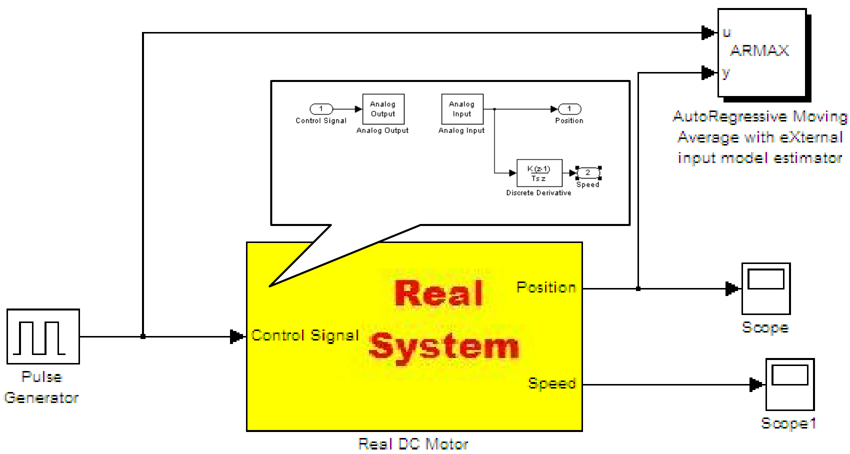

Fig. 4. Mixed reality environment (MRE) simulink block

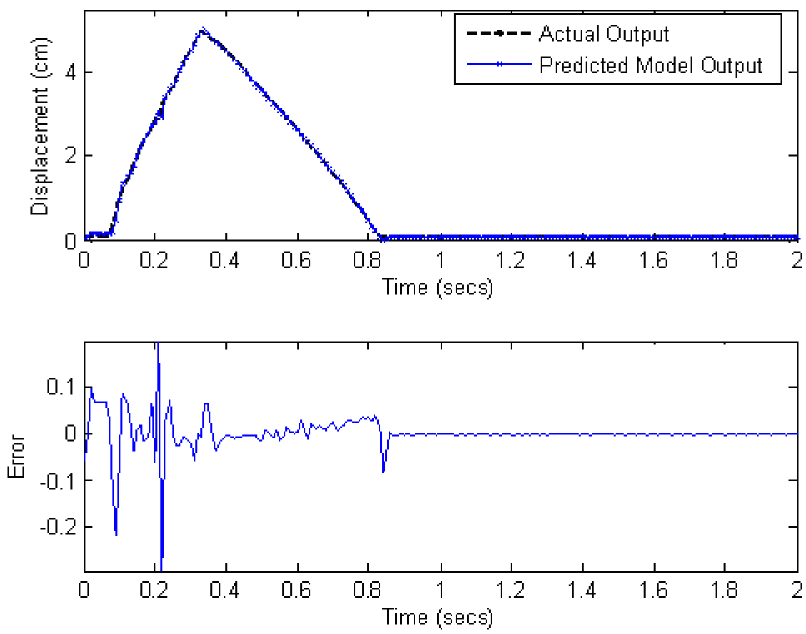

Fig.5. Variation of On-line actual output, 3rd order predicted model at one step prediction and the error verses time

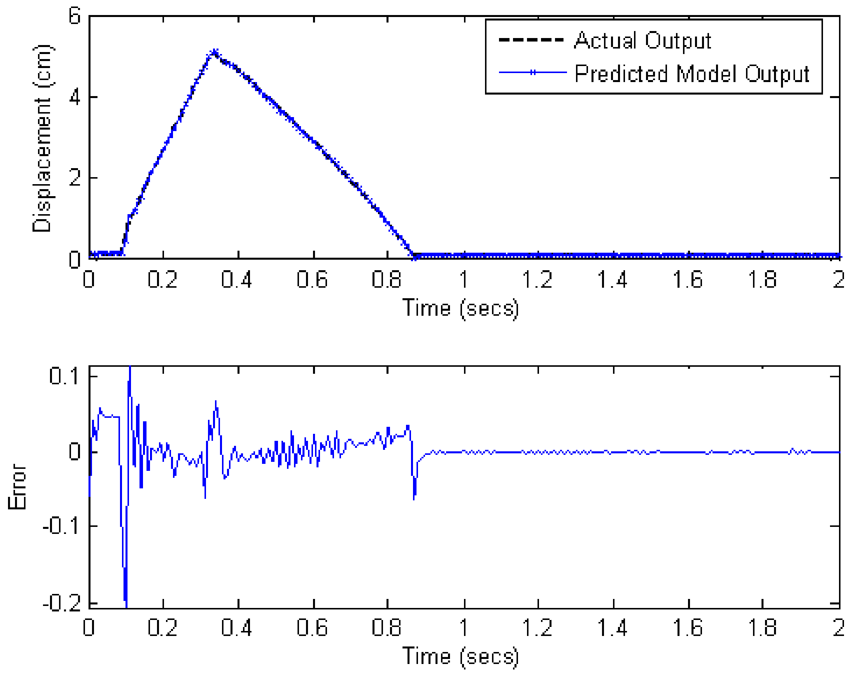

Fig. 6. Variation of On-line actual output, 4th order predicted model at one step prediction and the error verses time

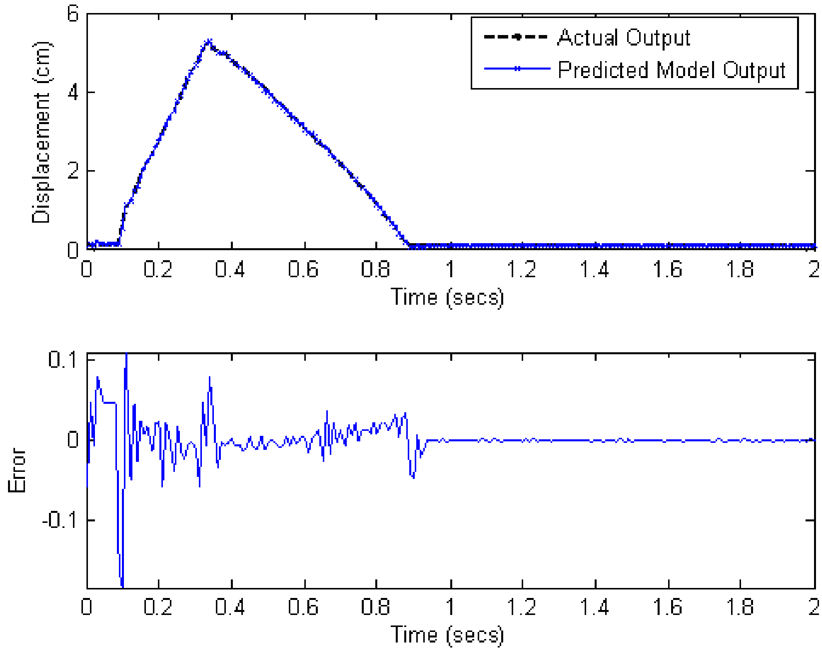

Fig.7. Variation of On-line actual output, 5th order predicted model at one step prediction and the error verses time

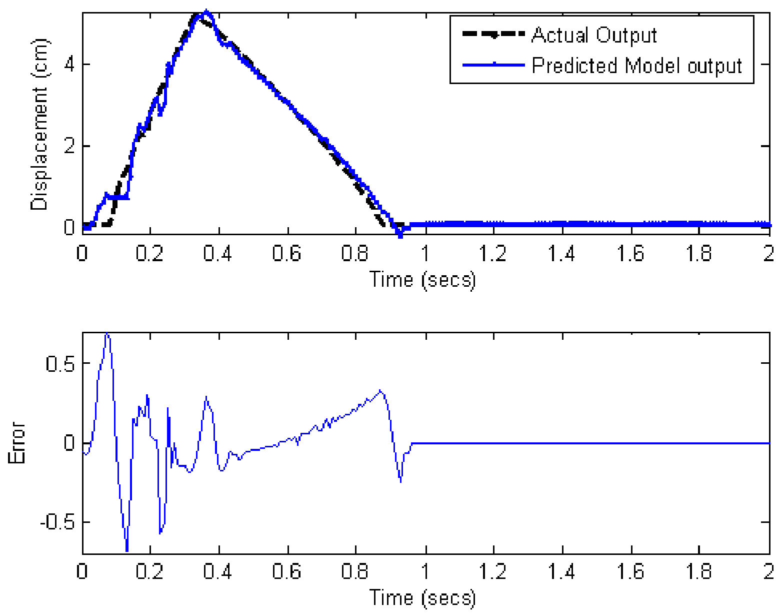

Fig.8. Variation of On-line actual output, 4th order predicted model at 5 step prediction and the error verses time

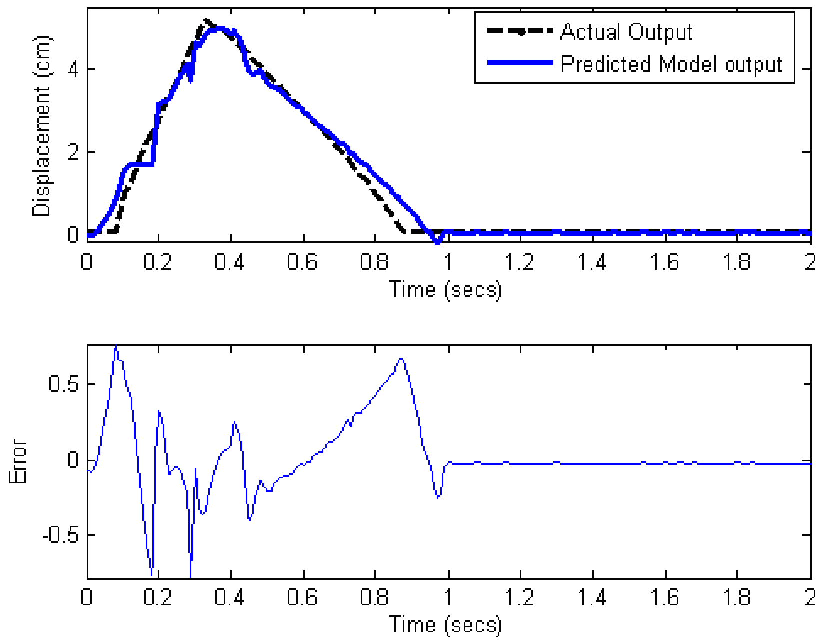

Fig.9. Variation of On-line actual output, 4th order predicted model at 10 step prediction and the error verses time

Table (1) Comparison of Statistical error analysis of different orders at one step prediction

T.F Order	**Statistical Criteria** / **Signal**	**Min**	**Max**	**Square error**	**Std Deviation**
Third Order	Actual Output	0	4.958	7.09e-5	0.4231
	Predicted Model Output	0	5.007		0.423
	Error	-0.2923	0.1987		0.008468
Fourth Order	Actual Output	0	5.036	3.22e-5	0.4351
	Predicted Model Output	0	5.08		0.435
	Error	-0.2052	0.1147		0.00571
Fifth Order	Actual Output	0	5.2	3.397e-5	0.456
	Predicted Model Output	0	5.251		0.456
	Error	-0.1818	0.1089		0.005861