Jurnal
Teknologi

Full Paper

LINEAR AND NONLINEAR ARX MODEL FOR INTELLIGENT PNEUMATIC ACTUATOR SYSTEMS

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Article history
Received
7 September 2015
Received in revised form
14 October 2015
Accepted
15 May 2016

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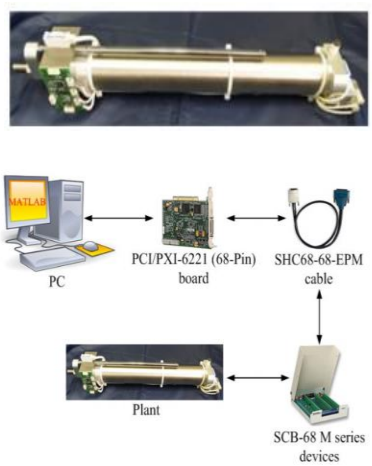
Graphical abstract



Abstract

System modeling in describing the dynamic behavior of the system is very important and can be considered as a challenging problem in control systems engineering. This article presents the linear and nonlinear approaches using AutoRegressive with Exogenous Input (ARX) model structure for the modeling of position control of an Intelligent Pneumatic Actuator (IPA) system. The input and output data of the system were obtained from real-time experiment conducted while the linear and nonlinear mathematical models of the system were obtained using system identification (SI) technique. Best fit and Akaike's criteria were used to validate the models. The results based on simulation reveals that nonlinear ARX (NARX) had the best performance for the modeling of position control of IPA system. The results show that nonlinear modeling is an effective way of analyzing and describing the dynamic behavior and characteristics of IPA system. This approach is also expected to be able to be applied to other systems. A future study exploring the execution of other model structures in demonstrating the position control of IPA system would be exceptionally intriguing.

Keywords: Intelligent pneumatic actuator, position control, system identification, ARX, NARX, best fit

Abstrak

Pemodelan sistem dalam menerangkan tingkah laku dinamik sesuatu sistem adalah sangat penting dan dianggap sebagai cabaran di dalam bidang kejuruteraan sistem kawalan. Artikel ini membentangkan pendekatan linear dan tak linear menggunakan struktur model AutoRegresi dengan Input secara luaran (ARX) untuk pemodelan kawalan kedudukan bagi sistem Penggerak Pneumatik Pintar (IPA). Data masukan dan keluaran bagi sistem diperoleh dari eksperimen masa sebenar yang telah dijalankan manakala model matematik linear dan tak linear telah diperoleh menggunakan teknik sistem pengenalpastian (SI). Penyuaian terbaik dan kriteria Akaike digunakan untuk mengesahkan kedua-dua model. Keputusan berdasarkan simulasi mendedahkan bahawa model tak linear ARX (NARX) mempunyai prestasi yang terbaik untuk pemodelan kawalan kedudukan bagi sistem IPA. Keputusan ini menunjukkan bahawa pemodelan tak linear merupakan cara yang paling berkesan untuk menganalisis dan menghuraikan tingkah laku dinamik dan ciri-ciri sistem IPA. Pendekatan ini juga dijangka boleh digunakan untuk sistem lain. Kajian masa depan dalam meneroka pelaksanaan struktur model lain dalam menunjukkan kawalan kedudukan sistem IPA akan menjadi lebih menarik.

Kata kunci: Penggerak pneumatik pintar, kawalan kedudukan, sistem pengenalpastian, ARX, NARX, penyuaian terbaik

1.0 INTRODUCTION

Pneumatic actuator is a type of actuator that converts energy (typically in the form of compressed air) into mechanical motion. This type of actuator is considered as one of the most popular actuators other than hydraulic and electrical. Pneumatic actuator has been widely used in industries where the field of automatic controllers are required [1], such as robotics, automotive and manufacturing, and recently, it is often used as the main subject in research and development (R&D) activities [2]. This is because pneumatic actuator offers numerous advantages compared to hydraulic and electrical actuators, such as high power-to-weight ratio, cost effectiveness, cleanliness, safe to be used in high temperature and explosive environment [3] and most importantly, this type of actuator has a fast and accurate response as has been offered by hydraulic [4]. Each system has its weaknesses and pneumatic actuator is no exception. The well-known weakness in a pneumatic actuator is its highly nonlinear properties such as compressibility of medium, friction effect, air leakage, and uncertainties in system parameters [5] making it one of the most researched' topics in control systems engineering. Moreover, the major drawbacks in pneumatic actuator system also makes the modeling of position control and designing the controller for the system more challenging.

The creation of an intelligent actuator system is a benchmark of research progress in control systems engineering and it can be considered as the next-generation of actuator development as described in [6]. An intelligent actuator system with construction of a servo mechanism was first introduced in 2005 by Suzumori *et al.* [7], whose research focused on controlling position and speed of the actuator. Five years later, Ahmad 'Athif *et al.* [8] developed a new system called Intelligent Pneumatic Actuator (IPA) to overcome the limitations of control devices, which are low in accuracy and force. This system was applied to Pneumatic Actuated Seating System (PASS); a new human-machine interaction tool to aid in chair design and three attributes have been proposed for chair design; shape, stiffness and damping characteristics. The results based on the experiment done showed that the IPA system helps in sensing, actuating and interacting with humans to give mechanical outputs of the proposed attributes. In 2015, Khairuddin *et al.* [6] stated that the IPA system is suitable to be applied to an application of Ankle-Foot Rehabilitation Exerciser (AFRE) device. Khairuddin *et al.* demonstrated that AFRE system was successfully tested with two experiments: measurement tool and real selected subjects. Apart from concern about the application of the IPA system, system modeling and controller design of the system is another branch of study that should be emphasized. In control systems engineering design, every system has to be modeled in order to get the mathematical representation of the system that describes the behavior of the system. It can be modeled using theoretical mathematical analysis or system identification techniques [9]. The first mathematical model of IPA system was derived by Ahmad 'Athif *et al.* [10] where the system dynamic equations are divided into three categories: 1) piston-load dynamics, 2) model of the cylinder chambers and 3) valve model. The results show that the mathematical model and simulation results in open-loop and closed loop were validated by real-time experiment. In 2012, the same authors estimate the plant using first-order Reaction Curve Method (RCM) approach and designed the Generalized Predictive Controller (GPC) based on the model obtained [11]. The results demonstrated that the GPC has the capability to control the plant with unstable open-loop and constraint. A year later, Nu'man *et al.* [12] proposed two methods to obtain the plant models: RCM and Bat Algorithm (BA). Both methods are used to calculate the parameter a and b for GPC. The results show that BA can eliminate the overshoot and at the same time reduce the steady-state error more effectively compared to RCM.

IPA system is very complex, making the system modeling of this system more challenging. The mathematical representation of the IPA system has a limitation to derive too because the system has several unknown parameters that have to be considered. As an alternative, system identification (SI) was chosen to model the IPA system. The system modeling using SI technique begins with modeling the IPA system using linear parameter estimation technique. In SI, there are a few structures of parametric model that can be utilized to represent the system, such as AutoRegressive with Exogenous Input (ARX), AutoRegressive Moving Average with Exogenous Input (ARMAX), Output Error (OE), and Box-Jenkins (BJ) model [13]. Recently, researchers have shown an increased interest of using ARX model in modeling the IPA system. System modeling of IPA system using ARX model structure were previously carried out by Khairuddin *et al.* [2], [6], [14], [15], [16], Muhammad Asyraf *et al.* [3], [17], and Ahmad 'Athif *et al.* [18]. All these work used third-order ARX model structure. According to an investigation by Khairuddin *et al.* [14], the third-order model is chosen because it represents the nearest model of the true plant. To validate the performance of the estimated model, the best fitting was utilized to demonstrate the preciseness of the approximated model as compared to the actual plant. According to Ljung [13], the model is accepted if the percentage of the best fit is 90 % and above. The system modeling using ARX model structure in [14] and [15] produced 89.54 % and 88.06 % of best fits respectively, while the best fits in [2], [3], [6], [16], [17], [18] have been reported >90 %. Thus, the findings are said to be consistent with the literature in [13]. There are also studies that show the usage of the third-order ARMAX model structure in modeling the IPA system [1], [17], [18]. However, the specific values of best fit are not mentioned in the work.

As shown above, most studies examined the linear parametric technique in modeling the IPA system but no study has examined the nonlinear technique. In SI, the nonlinear parameter estimation technique can also be used to estimate and model the system. For example, Tolgay and Ilyas [19] use linear and nonlinear ARX approach to model the speed of bidirectional DC motor. The result reveals that modeling the DC motor using nonlinear ARX approach gives the best result as far as the identification error is concerned. This is supported by Marumo and Tokhi [20], who revealed that the performance of the linear ARX has not been as good as nonlinear ARX in modeling the speed control of air motor with pneumatic H-bridge. In 2013, Carlos *et al.* [21] modeled the gait events using linear and nonlinear ARX. The performances of both models have been compared and the result shows that nonlinear ARX had better performance than linear ARX. In a different study, Fazlina *et al.* [22] proved that nonlinear ARX model successfully predicted the flood water level 10.833 hours in advance. Thus, it can be concluded that many studies have shown that nonlinear approach is better than linear. Hence, the goal of this study is to model the IPA system using nonlinear parametric approach using ARX model structure and compare the result with the linear ARX.

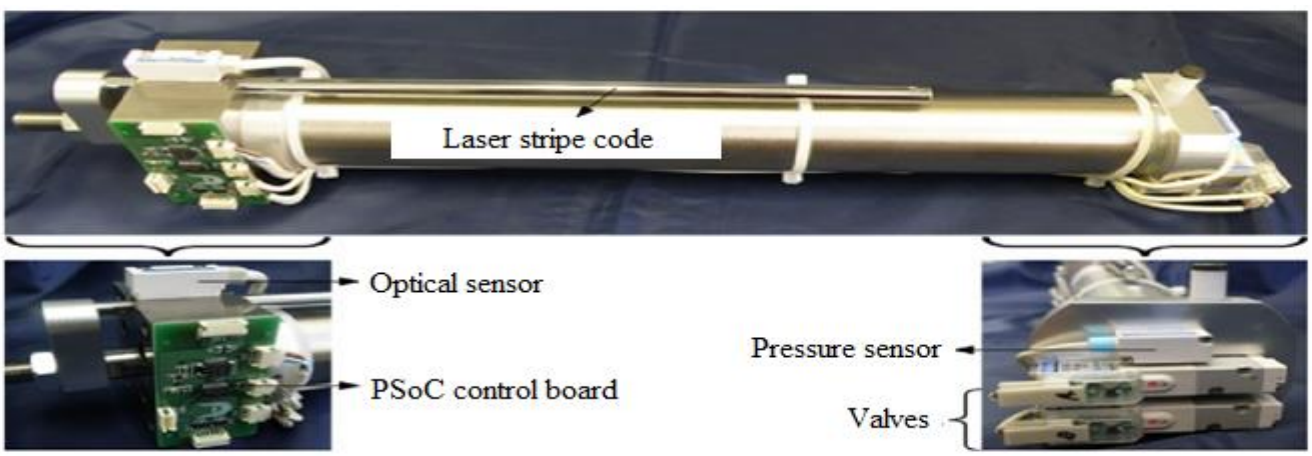


Figure 1 The IPA system and its parts [6]

2.0 EXPERIMENTAL DESIGN

The Intelligent Pneumatic Actuator (IPA) system used in this study was referred from work done by Ahmad 'Athif *et al.* [23], [24], [25], [26]. IPA system can be classified into two types of actuator specifically with position accuracy of 0.169 mm and 0.01 mm. The system's operation for both actuators are the same, the contrast between these two actuators is only in terms of their design. The design of IPA system with position accuracy of 0.01 mm was enhanced from the design of pneumatic actuator with accuracy of 0.169 mm. The IPA system with accuracy 0.01 mm has higher accuracy position sensor, durable tape type stripe code and enhanced circuit design. It has also never been used for any application and for this reason, only IPA system with accuracy of 0.01 mm was considered in this work. The IPA system with accuracy of 0.01 mm used in this work is shown in Figure 1. The IPA system consists of 200 mm cylinder stroke and capable to deliver a force up to 120 N (maximum). The system is also equipped with two sensors: optical sensor and pressure sensor. KOGANEI-ZMAIR optical sensor is used to detect the smaller pitch of 0.01 mm while the pressure sensor is used to check the pressure in the chamber to perform control action of the cylinder. Two valves are attached toward the end of the cylinder to control the inlet and outlet air. The right and left movements of the cylinder rely on the calculation to drive the valve of the second chamber and this can be done by manipulating the duty cycle of a Pulse-Width Modulation (PWM) signal. The cylinder movement based on valves ON/OFF is summarized in Table 1.

Table 1 The cylinder movement based on valves ON/OFF

Valve 1 status	Valve 2 status	Cylinder Movement
OFF	OFF	Stop
OFF	ON	Retract
ON	OFF	Extract
ON	ON	No operation

The IPA framework displays the up and coming era of actuator improvement with new elements that give better control, higher position and speed, force accuracy, communication ability, and all-in-one mechanism for compact system design [6]. The IPA system is also furnished with Programmable System on Chip (PSoC) microcontroller, which goes about as the brain for the framework and performs the neighborhood control to suit the necessities of any related applications.

System identification (SI) technique was applied in this work to acquire the real-time model for the IPA system. This technique can be as simple as a 'blind' approach using black-box model concept to obtain a linear and nonlinear model of the framework in view of measured exploratory information. For the most part, SI procedure will go through these accompanying steps:

i. Observation and data gathering (obtain input and output data from real-time experiment)
ii. Model structure selection and estimation
iii. Model validation

2.1 Observation and Data Gathering

The technique utilized as a part of this work is the same as in [14] and [18]. A sampling time, t_s of 0.01 s, new continuous step input signal design and a new push-pull PWM signal generator was applied to improve the performance of position control of IPA system. Many studies have suggested using the smaller value of t_s. This is because more samples can be taken for SI process while for IPA system, smaller value of t_s will make the system approaches real conditions of the microcontroller architecture [26]. Other than that, studies in [6], [15], [27] also found that smaller value of t_s can improve the controller performance especially the continuous type of controller.

1500 measurements of input and output data were collected from a real-time experiment. The input data contains 1500 data points, consisting of continuous step input signal applied to the IPA system, while the output contains 1500 measurements of position signal. The plot of 1500 input and output data at sampling interval of 0.01 s are shown in Figure 2. $u1$ is the continuous step input signal applied to the IPA (specially designed for the ON/OFF valves) and $y1$ is the output/position signal.

To capture the dynamics of the system, different types of inputs could be applied to the system such as pulse, step, Random Binary Sequence (RBS), Pseudo-Random Binary Sequence (PRBS), multi-sine inputs, etc. [28], [29], [30], [31]. Figure 2 (bottom) also shows the design of continuous step input signal as an excitation signal for SI purposes. This step signal is specially designed for the ON/OFF valves of the pneumatic system. The amplitude of the signal is situated to ±255, also zero to constrain the valve to be completely opened in their periods. The new PWM generator is additionally intended to impersonate the 8-bit PWM modules found on a PSoC microcontroller to straightforwardness execution of this stage later on. MATLAB Simulink was used to generate the comparator algorithm between the continuous step input signal and the carrier wave (sawtooth) signal.

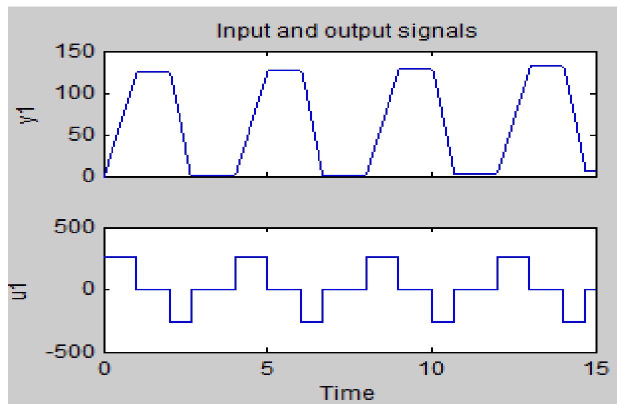


Figure 2 The plot of input and output data

Before proceeding with the accompanying steps, which are analyzing the measured data and applying some preprocessing, the input and output data should be divided into two sets; one set for training and the other for testing/validating the identified model. In this study, the first 750 samples are selected for training while the last 750 for validation purposes.

2.2 Model Structure Selection and Estimation

As mentioned before, there are a few structures of parametric model that can be utilized to represent the system such as AutoRegressive with Exogenous Input (ARX), Auto-Regressive Moving Average with Exogenous Input (ARMAX), Output Error (OE), and Box-Jenkins (BJ) model [13]. The ARX parametric model was chosen in this study since it provides a great choice which satisfies the criteria for SI and it is a basis model forming a few other model structures. Two approaches are used in this study, which are linear and nonlinear using ARX model structure.

2.2.1 Linear ARX Model

The linear ARX model can be expressed with single input and single output (SISO) signals. Generally, the linear ARX model can be written as:

$$y(k) + a_1 y(k-1) + \cdots + a_{n_a} y(k-n_a) = b_1 u(k-n_k) + \cdots + b_{n_b} u(k-n_k-n_b+1) + e(k) \quad (1)$$

where $y(k)$ is the output at time k, $u(k)$ is the input at time k and $e(k)$ is the error signal at time k. n_a is the number of poles, n_b is the number of zeros, and n_k is the number of pure time-delay (the dead-time) in the system.

2.2.2 Nonlinear ARX (NARX) Model

The nonlinear ARX (NARX) is based on linear ARX model and it constitutes nonlinear expansions of the ordinary direct ARX model. This type of nonlinear model is commonly used in time-series modeling and it offers various preferences including exactness and compactness of representation, physical significance, and direct correspondence between the model and the physical system parameters [32]. The general equation of NARX model is as follows:

$$y(k) = f(y(k-1), y(k-2), \dots, y(k-n_a), u(k-1), u(k-2), \dots, u(k-n_b)) + e(k) \quad (2)$$

where the next value of the dependent output signal, $y(k)$ is regressed on the previous value of the output signal and input signal, $u(k)$. Same as linear ARX model, n_a is the number of poles, n_b is the number of zeros, and n_k is the number of pure time-delay (the dead-time) in the system.

Essentially, the models are restricted to second and third-order only. ARX model with two numbers of orders have different structures with three numbers of orders. More recent studies have confirmed that higher order models may produce unstable output [33][34][35]. Research done by Akaike in [36] suggested using third-order model since this model order represents the nearest model of the actual plant. Due to this reason, ARX with three numbers of order is selected in this study for linear and nonlinear modeling of position control of an IPA system.

2.3 Model Validation

After a suitable model estimation and structure has been chosen, the following step is validation process. In this step, the validity between the measured and desired data under a validation requirement was checked. Best fitting criteria was utilized to demonstrate the preciseness of the approximated model as compared to the actual plant. According to Ljung [13], the model is accepted if the percentage of the best fit is 90 % and above.

$$fit = 100\left[1 - \frac{norm(\hat{y} - y)}{norm(y - \bar{y})}\right]\% \quad (3)$$

where y is true value, $\hat{y}$ is approximate value and $\bar{y}$ is mean value.

The acceptance or rejection of certain obtained model can also likewise be possible using Akaike's Final Prediction Error (FPE).

$$FPE = V\frac{(1 + n_a/N)}{(1 - n_a/N)} \quad (4)$$

where

$$V = \frac{e^2(k)}{N} = \frac{e^T(k).e(k)}{N}$$

$e(k) = [e_k \quad e_{k-1} \quad \dots \quad e_{k-N}]^T$ is error vector, V is loss function, n_a is number of approximated parameter, and N is number of sample.

Selection of model from various orders can be done based on the smallest value of FPE or Akaike's Information Criteria (AIC).

$$AIC = \log\left[V\left(1 + \frac{2n_a}{N}\right)\right] \quad (5)$$

3.0 RESULTS AND DISCUSSION

This study highlights the comparative study between the performance of linear plant model of position control for Intelligent Pneumatic Actuator (IPA) system using the experimental results in [2], [3], [6] and nonlinear plant model based on the current research. The performance of each model was evaluated based on the percentage of the best fit and Akaike's criteria using system identification (SI) technique. The estimated plant model with the highest percentage of best fit and smallest value of errors was said to be similar to the actual plant.

In this study, linear and nonlinear ARX model structure with model order of $n_a = 3, n_b = 3$ and $n_k = 1$ was compared and analyzed. It is means that the model with 3 poles, 3 zeros and 1 delay has been introduced into the system.

3.1 Linear ARX

All the information about the models (i.e. discrete-transfer function, fit to estimation data, FPE, MSE, etc.) are available in MATLAB System Identification Toolbox. The discrete-transfer function for third-order linear ARX model is shown in Equation (6).

$$\frac{B(z^{-1})}{A(z^{-1})} = \frac{0.00127z^{-1} + 0.0004518z^{-2} - 0.0003494z^{-3}}{1 - 1.932z^{-1} + 1.09z^{-2} - 0.1578z^{-3}} \quad (6)$$

Apart from the information about the model, MATLAB System Identification Toolbox is also able to view the output, residual, transient response, frequency response, zero and poles, and noise spectrum of the model. As mentioned previously, the performance of the plant model will be evaluated based on the percentage of the best fit for the model output and smallest value of errors. Measurement and simulated model output for third-order linear ARX model shows that the simulated model fits the actual plant model about 90.71 % and this is shown in Figure 3.

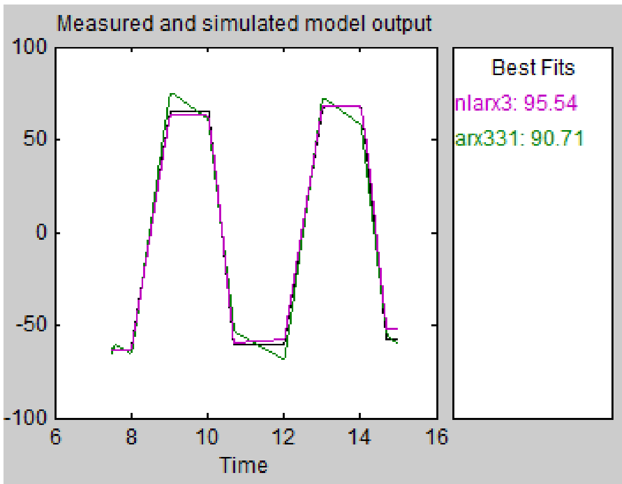


Figure 3 Model output for linear and nonlinear ARX model

From the model output shown in Figure 3, it is apparent that the third-order of linear ARX is similar to the actual plant. The losses of 9.29 % are most likely caused by dead zone, friction, air leakage, etc. in IPA system.

3.2 Nonlinear ARX

The nonlinear models can also be estimated using MATLAB System Identification Toolbox. Since the model is a nonlinear with model order of $n_a = 3, n_b = 3$ and $n_k = 1$, thus the number of terms for input $(u1)$ and output $(y1)$ channels was set to 3 respectively, while the number of delay was set to 1. The regressors for NARX model can be either linear and/or nonlinear. In this research, all the regressors were assumed to be used in nonlinear block and the number of units in nonlinear block was set to 8 (randomly selected value). The wavelet network was chosen as a nonlinearity estimator. The discrete nonlinear equation for the third-order nonlinear ARX model is shown in Equation (7).

$$y(t) = f(y(t-1), y(t-2), y(t-3)u(t-1), u(t-2), u(t-3)) \quad (7)$$

Measurement and simulated model output for third-order nonlinear ARX model using wavelet network nonlinear estimator with 8 number of units shows that the simulated model fits the actual plant model about 95.54 % and this is shown in Figure 3. Like linear ARX model, the losses of 4.46 % are most likely caused by dead zone, friction, air leakage, etc. in the actuator system.

The performances of both models in terms of the percentage of best fit, Final Prediction Error (FPE) and Information Criteria (AIC) are summarized and recorded as in Table 2.

Table 2 The performances of linear and nonlinear ARX

	Linear ARX	Nonlinear ARX
Best Fit	90.71 %	95.54 %
FPE	0.0128	0.0107
AIC	-4.3604	-4.5185

As shown in Table 2, there is a significant difference between the two models. What is interesting is that: 1) the percentage of best fit for nonlinear ARX model is much higher than linear ARX model. This indicates that the finding in this study is consistent with the findings of past studies by Tolgay and Ilyas [19] and Marumo and Tokhi [20], which proved that NARX model is more accurate and compact compared to linear model. 2) The nonlinear model successfully gives the smallest value of FPE and AIC compared to linear model. Thus, it is proven that the results support the literature in [19], [20], [21], [22]. The value of percentage of best fit, FPE and AIC for both models are sufficient to view that NARX model successfully estimates the position control of IPA system.

4.0 CONCLUSION AND RECOMMENDATION

This research was undertaken to present the linear and nonlinear approaches using Autoregressive with Exogenous Input (ARX) model structure for the modeling of an intelligent pneumatic actuator (IPA) system. The results will then be evaluated based on the performances of best fit and Akaike's criteria. The most obvious finding to emerge from this research is that nonlinear approach using ARX model structure had the best performance compared to linear approach in modeling the position control of IPA system. It was shown that NARX model successfully tracks the position control of IPA system and the analysis of the simulation result based on SI technique shows that the percentage of best fit for NARX model structure is 95.54 %, which is higher than linear ARX approach (90.71 %). Besides, NARX model also gives smallest value of Final Prediction Error (FPE) and Information Criteria (AIC) compared to linear ARX. It is recommended to apply this nonlinear approach to other actuator systems such as hydraulic and electrical system. A future study investigating the performance of other model structures such as AutoRegressive Moving Average with Exogenous Input (ARMAX), Output Error (OE) and Box-Jenkins (BJ) in modeling the position control of IPA system would be very interesting.

Acknowledgement

The authors would like to acknowledge Universiti Teknologi Malaysia (UTM), Universiti Teknikal Malaysia Melaka (UTeM) and Ministry of Higher Education (MOHE) of Malaysia for their support.

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