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RESEARCH ARTICLE AUTOMATIC CONTROL

PID Controller Tuning for Electro Hydraulic Actuator using Radial Basis Function Neural Network

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ABSTRACT

The purpose of this study is to improve the position control performance of an industrial electro hydraulic actuator (EHA) system. Therefor PID controller tuned via Radial bases Function (RBF) Metamodeling approach is proposed. Mathematical model of EHA is obtained using system identification technique by estimating model using System Identification Toolbox in MATLAB. The scheme is implemented in linear discrete model to obtain the transfer function for the system. To verify the capability of the controller, the parameters are applied in simulation and experimental.

معايرة المتحكم التناسبي التكاملي التفاضلي لمشغل كهر هيدروليكي باستخدام شبكة دالة التوزيع القطري

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الكلمات المفتاحية

مشغل كهروهيدروليكي
دالة التوزيع القطري
تحديد النظام.

الملخص

تهدف هذه الدراسة إلى تحسين أداء التحكم في موضع نظام مشغل كهروهيدروليكي صناعي (EHA). لذلك، تم اقتراح منهج النمذجة الفوقية لوحدة تحكم PID مضبوطة عبر دالة القاعدة الشعاعية (RBF). تم الحصول على نموذج رياضي لـ EHA باستخدام تقنية تحديد النظام من خلال تقدير النموذج باستخدام تطبيق MATLAB. تم تنفيذ المخطط في نموذج خطي منفصل للحصول على دالة النقل للنظام للتحقق من كفاءة وحدة التحكم. وتم إجراء محاكاة للتجارب العملية.

Introduction

Hydraulic actuators have been adopted and are widely used in industry not only because of their high-power capability but also their good positioning capability and fast smooth response characteristics in various modern applications [1-3]. The electro-hydrostatic actuator (EHA) utilizes a pump driven directly by an electric motor to drive the hydraulic piston or motor. It differs from the conventional hydraulic servo actuator by employing a motor controller that regulates both the speed and direction of the motor, in accordance with the actuator position sensor and rate command.

EHA have been adopted across a wide range of applications such as robotics, steel and aluminum mill equipment, flight simulation, paper machines, electromagnetic marine engineering, and injection molding machines, among others.

To achieve optimal performance of the EHA in terms of position, force, or pressure, it is essential to employ an appropriate controller to enhance their efficiency and effectiveness [4]. Numerous efforts have been made by researchers over the years to enhance the EHA controllers. In general, controllers can be designed if the mathematical model of the system exists and all the parameters are known. The process may prove to be challenging if the system model and parameters are not known. In this scenario, System Identification (SID) can be used to determine the system model. SID is the procedure that develops models of a dynamic system based on the input and output signals from the system. The input and output data must show some of the dynamics of the process. The parameters of the model will be adjusted until the output from the model is similar to the output of the real system.

One of the beigest challenging in using SID that the system needs to be stable. Additionally, the output data generated from an unstable system fails to provide sufficient information or dynamics regarding the system's behavior. Feedback controllers are developed to stabilize the system before SID can take place. There is several SID techniques that can be applied to estimate the EHA model in form of linear models, non-linear models and intelligent models. Linear model such as Auto-regressive Exogenous (ARX) model with PRBS signal as input signal [5]. Nonlinear model

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such as observer canonical form using a modified Recursive Instrument Variable [6], and Hammerstein model which makes the assumption that the nonlinearities of the systems can be separated from the system dynamics [7]. Intelligent models such as neural networks have been successfully used in various fields, such as back-propagation applied in identification of EHA model [8]. In the last few years, neural networks have been developed in form online identification using Recurrent High Order Neural Networks method [9]. Another online identification of the systems parameters is based on recursive least square algorithm, with constant trace [10].

The EHA controller can be developed using the PID controller strategy. PID controller has been one of the most sophisticated methods and frequently used in the industry due to its simple architecture, easy tuning, cheap and excellent performance [11,12].

However, the conventional PID is difficult to determine the appropriate PID gains in case of nonlinear and unknown controlled plants. Various modified forms of this control strategy have been developed to improve its performance such as: an adaptive/self-tuning PID controller [13,14], self-tuning PID control structures [15-16], self tuning PID controller [17-18], and self-tuning predictive PID controller [19]. Though satisfactory performance can be obtained and the proposed controllers above provide better response.

To overcome these deficiencies, intelligent control techniques have emerged as highly potentialmethods. One of these novel intelligent theories includes well-known artificial neural network. There are many successful commercial and industrial applications using neural network based controlling techniques [20]. In this project, the development of position control of electro hydraulic actuator by using a self tuning Radial Basis Function Neural Network (RBFNN) will be used to overcome appearance of nonlinearities and uncertainties in the system.

Mathematical Model of Electro-hydraulic Servo System

Electro-hydraulic servo system equipments involve servo valve, hydraulic cylinder and load attached at the end of the piston as shown in Figure 1. The hydraulic cylinder is double-acting hydraulic cylinder with single-rod piston. When difference between P1 and P2 exists, the hydraulic cylinder piston extends or compresses.

The complete mathematical model of the system as shown in Figure 1 consists of the hydraulic cylinder dynamics including the load environment, and the servo-valve dynamics. It also describes behaviors of the electro-hydraulic servo system [4].

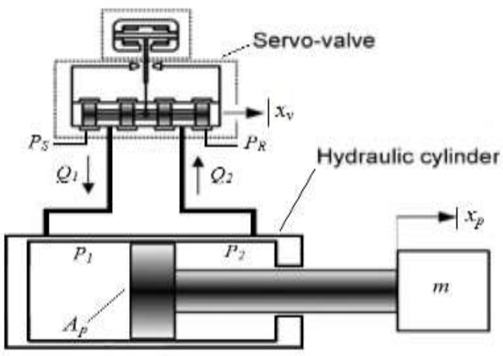

Fig.1: Electro-hydraulic servo system

The mechanical subsystem dynamics of the piston are depending on the load environment. The dynamic equations is written as

$$\dot{x}_p = v_p \tag{1}$$

$$m\dot{v}_p = F_a - F_f - d_u \tag{2}$$

$$\dot{x}_p = v_p m\dot{v}_p = F_a - F_f - d_u$$

The hydraulic actuating force, F_a and the hydraulic friction force, F_f are commonly derived in the dynamics of servo hydraulic system. The hydraulic actuating force F_a is a nonlinear function of the control input voltage, load environment, cylinder pressure, etc, and it can be represented as:

$$F_a = A_P P_L \tag{3}$$

Hence, equation (2) represents as

$$m\dot{v}_p = A_p P_L - F_f - d_u \tag{4}$$

In this model,

$$P_L = P_1 - P_2 \tag{5}$$

The differential equations governing the dynamics of the actuator are given. Defining the load pressure to be the pressure across the actuator piston, the derivative of the load pressure P_L, is given by the total load flow through the actuator divided by the fluid capacitance

$$\frac{V_t}{4\beta_e}\dot{P}_L = Q_L - C_T P_L - A_P v_p \tag{6}$$

Using the equation for hydraulic fluid flow through an orifice, the relationship between spool valve displacement x_v, and the load flow Q_L, is given

$$Q_L = C_d w x_v \sqrt{\frac{2(P_S - sgn(x_v)P_L)}{\rho}} + Q_S \tag{7}$$

Therefore, from (4) to (7), the hydraulic dynamics of the actuating force of the cylinder is given by

$$\dot{P}_L = -\alpha v_P - \beta P_L + \gamma\left(C_a\sqrt{\frac{2(P_S - sgn(x_v)P_L)}{\rho}}x_v + Q_S\right) \tag{8}$$

where , $C_a = C_d w \alpha = \frac{4A_P\beta_e}{V_t}$, $\beta = \frac{4C_T\beta_e}{V_t}$, $\gamma = \frac{4\beta_e}{V_t}$

Spool displacement dynamic equation for of the servo valve x_v, is controlled by an input servo valve u. The corresponding relation can be simplified as

$$\dot{x}_v = \frac{1}{\tau_v}(-x_v + k_v u) \tag{9}$$

From equation (1) to (9), if the state variables are selected as $x = [x_1, x_2, x_3, x_4]^T \equiv [x_p, v_p, P_L, x_v]^T$,the state equations of the servo hydraulic systems may be written as

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = \frac{1}{m}(A_P x_3 - F_f - d_u) \tag{10}$$

$$\dot{x}_3 = -\alpha x_2 - \beta x_3 + \gamma\left(C_a\sqrt{\frac{2(P_S - sgn(x_{4v})P_L)}{\rho}}x_{4v} + Q_S\right)$$

$$\dot{x}_4 = -\frac{1}{\tau_v}x_4 - \frac{k_v}{\tau_v}u$$

where, x_p is the displacement of the piston,
v_p is the piston velocity and,
d_u is an external disturbance
A_L is the cross section area of a hydraulic cylinder,
P_L is the cylinder differential pressure,
V_t is the total actuator volume,
β_e is the bulk modulus of hydraulic oil,
C_T is the total leakage coefficient,
C_d is discharge coefficient,
w is the spool valve area gradient, and
ρ is the oil density

Metamodeling Review

Metamodeling or sometimes called as "Surrogate" have been successfully used in many fields to provide simpler model of the input and output function that approximates the relationship between system performances and controller parameters of a system. The set of data that required for each PID controller parameter that can fit the actual set of data will give the best results of approximation. Recently, as studied in [19], Metamodeling had been used to optimize various type of system, included the nonlinear system. The Metamodeling technique successfully used to optimize some of the systems such as the flexible robot manipulator; Cartesian coordinates control of hovercraft system, the fluid mixing system, and the cruise control system. Through these studying, they proved that the Metamodeling technique can optimize various types of controller parameters, for example, the PID controller and the fuzzy logic controller.

Radial Basis Function

In this study, a Radial Basis Function Neural Network (RBF NN) was used in this case as a metamodel to approximate the mapping of the controller gains. The architecture of the RBF NN is illustrated in Figure 2.

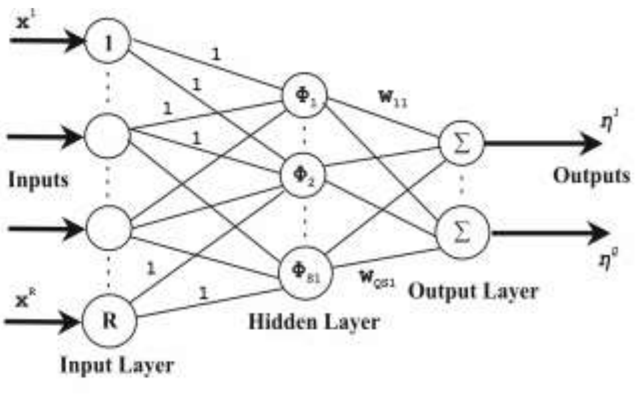

Fig.2: Radial Basis Function Neural Network

The network consists of three layers: an input layer, a hidden layer and an output layer. Here, R denotes the number of inputs while Q the number of outputs. Equation 11 is used to calculate the output of the RBF NN for $Q = 1$,

$$\eta(x,w) = \sum_{k-1}^{S1} w_{1k}\ \phi_k(\| x - c_k \|_2) \tag{11}$$

Where $x \in \mathcal{R}^{R\times 1}$ is an input vector, $\phi_k(.)$ is a basis function, $\|.\|_2$ denotes the Euclidean norm, w_{1k} are the weights in the output layer, $S1$ is the number of neurons (and centers) in the hidden layer and $c_k \in \mathcal{R}^{R\times 1}$ are the RBF centers in the input vector space. Equation 11 can also be written as:

$$\eta(x,w) = \phi^T(x)w \tag{12}$$

Where

$$\phi^T(x) = [\phi_{k1}(\| x - c_1 \|)\quad \phi_{k2}(\| x - c_1 \|)\ \ldots.\phi_{ks1}(\| x - c_{s1} \|)] \tag{13}$$

and

$$w^T = [\,w_{11}\ \ w_{12} \ldots\ldots w_{1s1}] \tag{14}$$

The output of the neuron in a hidden layer is a nonlinear function of the distance given by:

$$\phi(x) = e^{-x^2/\beta^2} \tag{15}$$

Where β *is* spread parameter of the RBF NN. For training, the least squares formula was used to find the second layer weights while the centers are set using the available data samples.

RBF NN offer several advantages compared to the Multilayer Perceptrons. RBF NN has also been successfully used, as reported by [20]. Two of these advantages are they can be trained using fast 2 stages training algorithm without the need for time consuming non-linear optimization techniques and an ANN RBF possesses the property of 'best approximation'. In Metamodeling, RBF NN has also been successfully used, as reported by [20].

Results

Experimental setup

An Industrial EHA system that is used in this project is made up of a single-rod hydraulic cylinder driven by a direct servo valve Bosch Rexroth 4WREE6, 40 lpm flow rate at 70 bars. The dimension of the hydraulic cylinder is 63/30/300 mm. Piston position is measured by using 300mm draw wire sensor which is Linear Variable Differential Transformer (LVDT) transducer. 100 bar pressure transducer is use to gauge the pressure from and into the cylinder. International instrument Peripheral Component Interconnect (NI PCI 6221) card is use as interface between EHA with MATLAB'S programs in PC tested. Figure 3 represents the experimental workbench where the measurements of input-output were acquired for identification process.

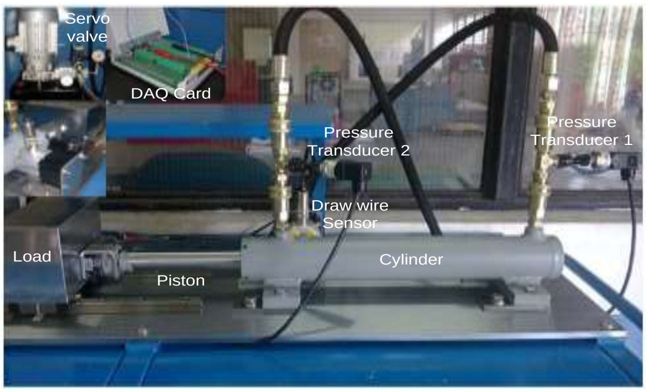

Fig.3: Experimental set-up

The model of the hydraulic actuator system will be present as the goals of this study are to represent a mathematical model of Electro-Hydraulic Actuator (EHA) system using system identification technique. It is followed by designing suitable PID controller for the system in simulation and real-time mode.

Model estimation

The set of data for model estimation and validation are taken from an experimental works on the hydraulic actuator with multi frequency sine wave input. The input and output signals as shown in Figure 4. The length of data is 2000 and time sampling 0.05 second. The data was divided into two parts for estimation and validation. The first part of data from 1 to 1001 used is for estimation to determine the model of the system and another part of data from 1001 to 2000 is applied to validate the model. All procedures to estimate and validate are done by using System Identification Toolbox in MATLAB.

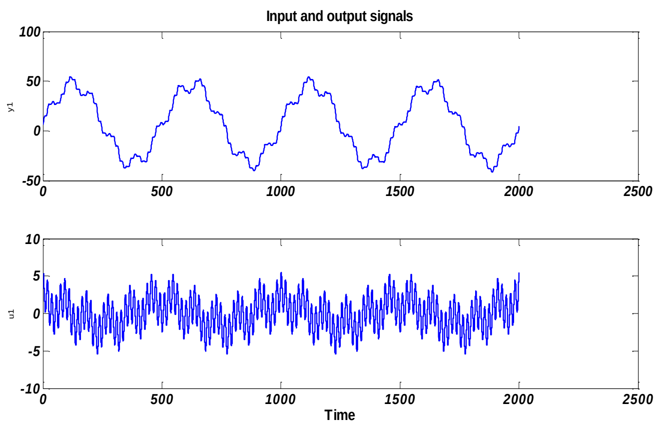

Fig.4: The input-output data of EHA system

The discrete polynomial transfer function for the model can be derived by starting with the general expression below

$$H(s) = \frac{L\{(x(t)\}}{L\{(y(t)\}} = \frac{b_m s^m + b_{m-1} s^{m-1} + \cdots + b_1 s + b_0}{s^n + a_{n-1} s^{n-1} + \cdots + a_1 s + a_0} \quad (16)$$

Similarly, the discrete LTI transfer function shows that

$$H(s) = \frac{Y(z)}{U(z)} = \frac{c_0 + c_1 q^{-1} + \cdots + c_{m-1} q^{-m-1} + c_m q^{-m}}{q^{-1} + d_1 q^{-2} + \cdots + d_{n-1} q^{-n-1} + d_n q^{-n}} \quad (17)$$

Since the general equation to describe ARX model is $A(q^{-1})\, y(k) = B(q^{-1})\, u(k-d) + C(q^{-1})\, e(k)$

Where d is the time delay, m is number of zeroes, n is number of poles and e(t) is a white noise with zero mean.

Hence, the transfer function is performed as

$$H_{arx} = \frac{B(z)}{A(z)} = \frac{0.3937q^{-1} - 0.5916q^{-2} + 0.3108q^{-3}}{1 - 2.237q^{-1} + 1.818q^{-2} - 0.581q^{-3}} \quad (18)$$

The model can be accepted based on the smallest values criteria of FPE and AIC, and good percentage best fit Loss function 0.0209026 and FPE 0.0211532.

From the output model shown in Figure 4, the polynomials of the model ARX331 can be reached. The measured output is compared with the simulated output in order to validate the developed model. From the polynomials, the transfer function is derived and the rest of the response curves are analyzed. Figure 6 shows the output model curve the best fit percentage is 96.75% which means the agreement is very good. The residuals graph in Figure.5 also revealed that the auto correlation and cross correlation of the input and output data are mostly within the range of confidence interval. Figure 7 shows that all poles lies inside the unit circle. The model is marginally stable because one pole is on the unit circle. Because of all roots are inside the unit circle, this is called a minimum phase model Causality and stability issue have been addressed by the model. Hence, more in-depth analysis will be conducted in order to derive a relation between the input and output.

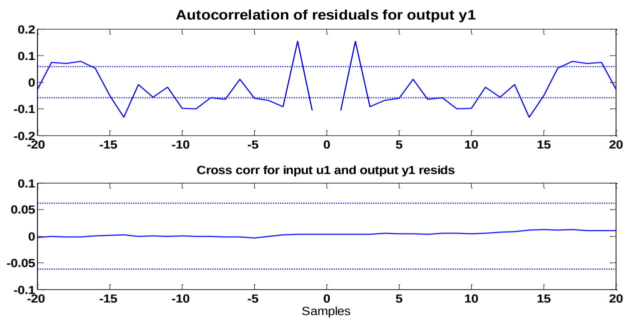

Fig.5: The residuals graph

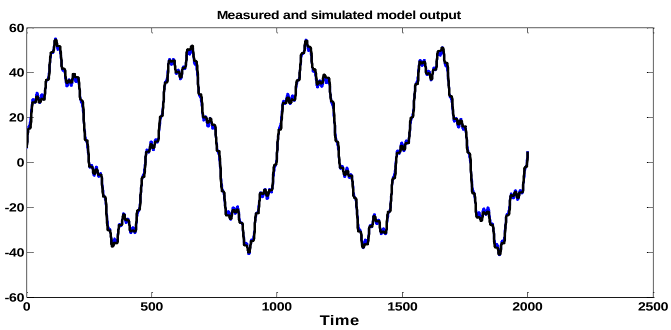

Fig.6: The best fit graph of the estimated mode

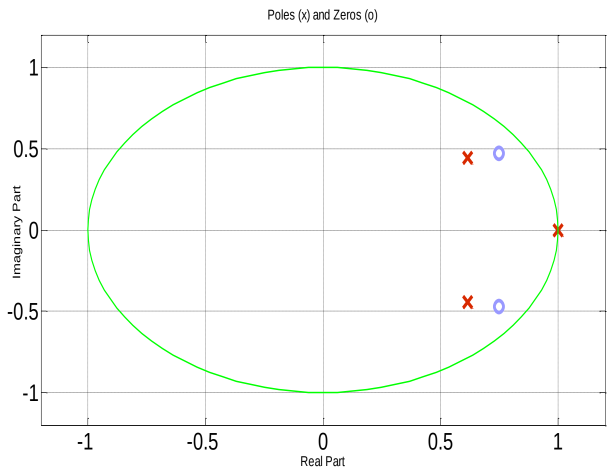

Fig.7: poles and zeroes plot for the model

Simulation and real-time results

The approach that has been applied to using used Radial Basis Function Neural Network in the metamodeling approach. RBF ANN was used as the metamodel to approximate the relationship between system performances and controller parameters of a system.

Before proceeding in finding the controller parameters, the stability of the system needs to be considered first. This has been done by testing the data using SID technique and shown by unite circle earlier during this chapter. It has been found out that the system is indeed stable and hence the control of the system should be possible. The approach to optimize the controller parameters is summarized as follows:

Step1 Define the input design space, D, which consists of a set of initial values of the controller parameters.

Step2 Obtain the ISE for the output position for all the design space defined in 1.

Step 3 Create the target data set, T'; which consists of the ISE for the output position.

Step 4 Fit the RBF-NN using D and T'.

Step 5 Evaluate the RBF-NN on a larger input space, D'.

Step 6 Find the minimum of the RBF-NN output (estimated). The corresponding controller gains that minimized the RBF output will be the gains to be verified in actual model simulation.

Step 7 Repeat step 1 to 6 until the result of parameter gains is satisfactory.

In this study, D and D' are the sets of initial and large data of discrete values given in Table.1. The parameters for the RBF-NN used to fit the data D is summarized as:

• 30 RBF centers are used. Centers are added one by one until the RBF NN reaches an error goal of 0.1.

• β=200.

Figure 8 shows the simulation of the system with PID controller. The performance measure that has utilized in this study is the Integral Square Error (ISE), which is defined by:

$$ISE = \int \left(y_d(t) - y(t)\right)^2 dt \tag{19}$$

Where y_d is the desired output displacement (set point), where y is the actual output displacement. This criterion, although not very selective, has been used because of the ease of computing the integral both analytically and experimentally.

Table 1 shows the input design space defined as D, and large input data space defined as D', The D contains the initial set of data gives the error for the position parameters and also utilizes to train the RBF Neural Network. The large input space, D' dependent on the chosen of the initial input data, so each set of the initial input data should be defined properly in accordance to the suitability of the large input space, D' for each model of the system. On other hand the input design space, D is defined with minimal number of input data, but with as much as possible data that matched the large input data space, D'. or at least double input design space, D. That is, the proper initial data will extract quickly the exact patent of the error of the large input data space, D'. Table1 shows the initial and large data sets for EHA system.

Table 1: Initial and large data sets

	Initial Data Sets (D)
K_p	{0.5, 0.015, …, 0.9}
K_i	{0.05, 0.015, …, 0.07}
K_d	{0.0001, 0.001, …, 0.01}
Total number of data configurations	540
	Large Data Sets (D')
K_p	{0.55, 0.011, …, 0.97}
K_i	{0.04, 0.011, …, 0.08}
K_d	{0.0001, 0.001, …, 0.01}
Total number of data configurations	1560

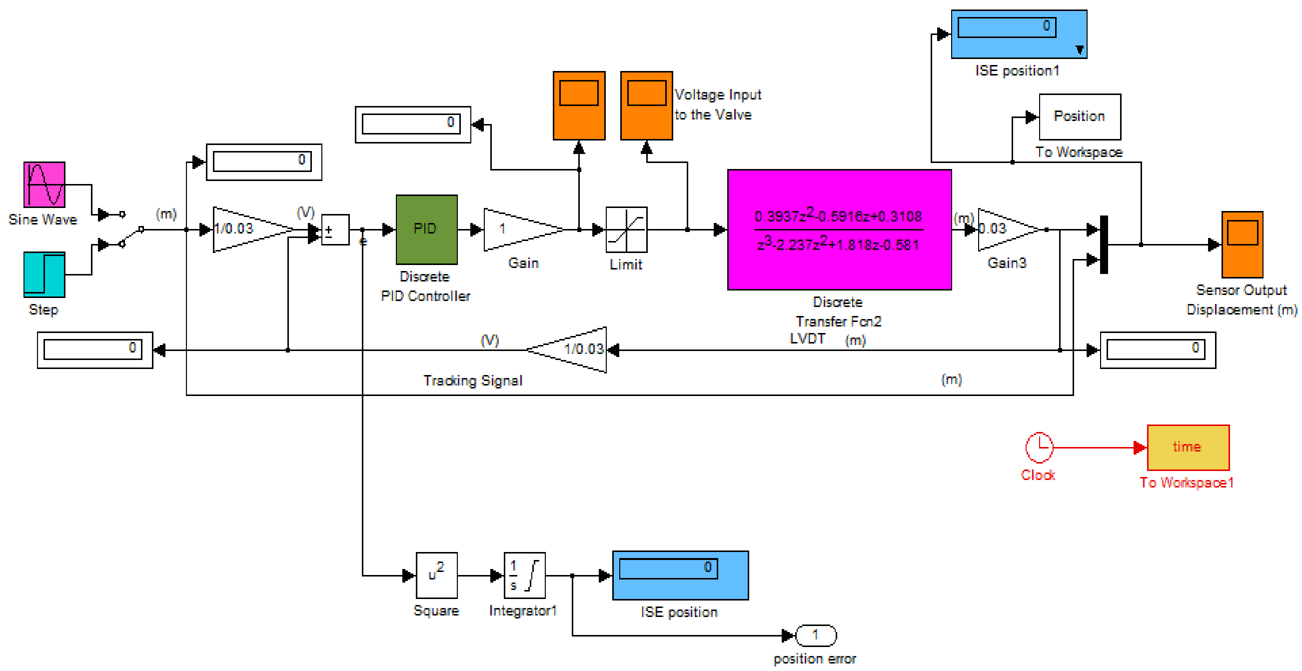

Fig.8: The simulation of the system

Once the training stage is done, the RBF-NN will automatically generate the error (ISE) simulation for large data space controller parameters sets, D’, which comprises of1560 discrete data.

Table 2: represents the best gains of PID controller

STEP INPUE	
K_p	0.709
K_i	0.07
K_d	0.0091
SINUSOIDAL INPUT	
K_p	0.968
K_i	0.04
K_d	0.0091

The block diagram of the system with PID controller has been presented in Figure. 8 and the output response is illustrated by Figure 9 and 10. These responses are obtained through simulation mode. Figure 11 presents the similar PID is inserted in the forward path of the system in real-time mode. Based on that, the response of the system with step input is revealed by Figure 12.

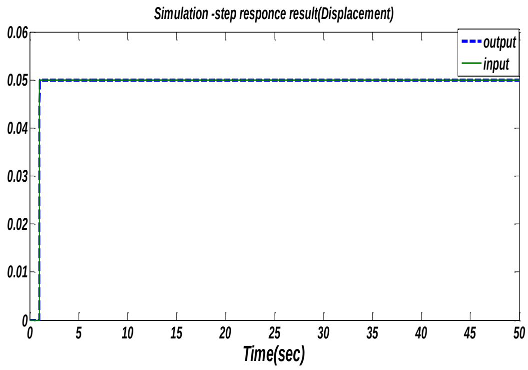

Fig.9: Response of the system with PID controller with step input (simulation)

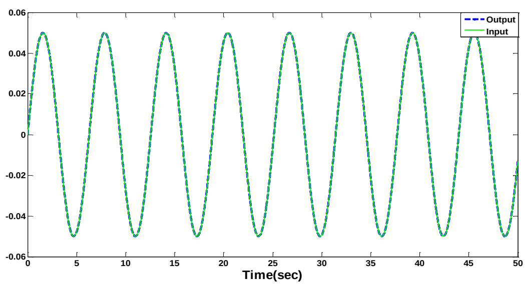

Fig.10: Response of the system with PID controller with sine input (simulation)

It can be noted that the response obtains the steady state conditions without overshot and with very fast rise time and settling time.
From Table 4.2, it can be seen that the best PID gains are selected by using RBF neural network. Figure 4.6shows that PID controller was applied to simulation/SIMULINK with step input and sinusoidal input response respectively. According to Figure 9 and 10 the output response of the system with step and sinusoidal input are produced zero steady-state error with the input. The output of the system tracked the input injected. The similar PID with same parameters was inserted in forward path of real-time system. Figure 11 reveals the PID controller with real-time system. As depicted in Figure 12, the response obtains the steady state conditions without overshot with very fast rise time and settling time.

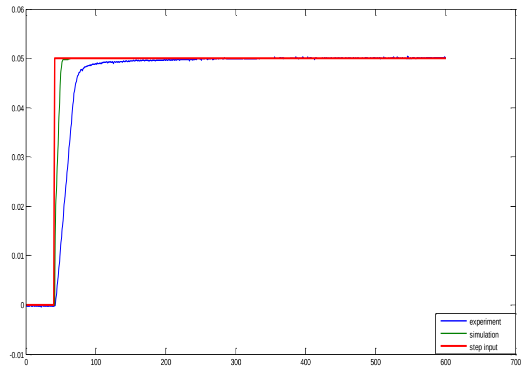

Fig.12: Response of real-time PID controller with step input (experiment)

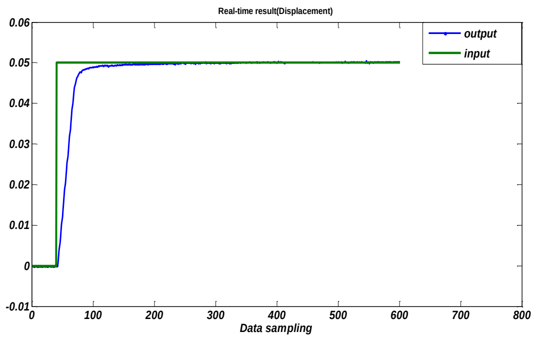

Fig.13: Compare the output response between simulation and experiment

Discussion

From Table 1 it can be observed that the best PID gains are selected by using RBF neural network. Figure 8 shows that PID controller is applied to simulation/SIMULINK with step input and sinusoidal input response respectively. Based on Figure9, 10 the output response of the system with step and sinusoidal input are produced zero steady-state error with the input. The output of the system is tracked the input that given to it. The similar PID with same parameters is inserted in forward path of real-time system. Figure 11 illustrates the PID controller with real-time system. As shown in Figure 12 the response obtains the steady state condition without overshot with fast rise time and settling time. From the Figure 13, it can be observed that the output from real-time experiment is almost similar with the output achieved from simulation which produces zero steady-state error and very fast response time. It indicates that the RBF-NN has capability to give the best values of K_p, K_i and K_d of the PID controller. Regarding to results it can involve acceptable and improve the performance of EHA system. A slight different between input and output happened because the EHA system which is nonlinear model is modeled in linear model and some nonlinearity and uncertainties characteristic are ignored.

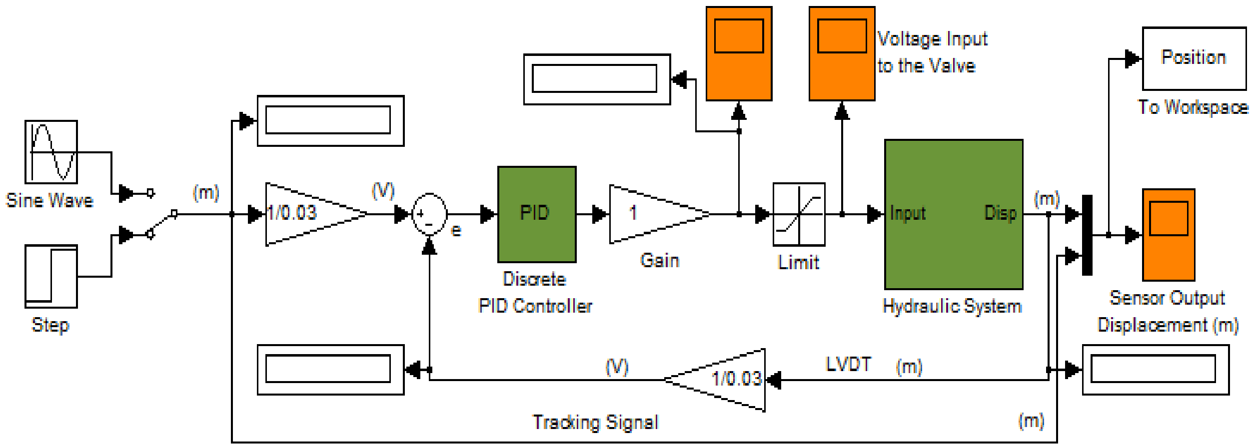

Fig.11: Real-time PID controller

Conclusion

System identification was employed to estimate unknown parameters from Electro Hydraulic plant and was tested to obtain a linear discrete model of the hydraulic system. The ARX Model structure in Matlab toolbox was used to obtain the transfer function of the system. The proposed of auto tuning conventional PID controller using neural network is applied to control the piston position of a hydraulic cylinder in the system. The Radial basic Function neural network Metamodeling was chosen to optimize the value of *Kp*, *Ki* and *Kd* of the PID controller, because this method offers several advantages as compared to the Multilayer Perceptrons. Two of these advantages are; they can be trained using fast 2 stages training algorithm without the need for time consuming non-linear optimization techniques and, an ANN RBF possesses the property of ‘best approximation. From the results it can be seen the outputs from real-time experiment is almost similar with the output attained from simulation which produce zero steady-state error and fast response time.

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Conflicts of Interest: “The authors declare no conflict of interest.”

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