SYSTEM IDENTIFICATION AND CONTROL OF PRESSURE PROCESS RIG® SYSTEM USING BACKPROPAGATION NEURAL NETWORKS

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ABSTRACT

A neural networks based direct inverse controller for Pressure Process Rig® system is presented, including with the performance analysis using an open-loop and a closed loop system. In order to enhance the performance characteristics of this direct inverse controller, a Fine-Tuning method is proposed. Experimental results show that the open-loop system shows lower MSE compare with that of the closed-loop system, and the Fine-Tuned NN-DIC method always performed better with lower MSE compare with that of the normal NN-DIC method.

Keywords: direct inverse controller, neural networks, back propagation learning, fine-tuned DIC method.

INTRODUCTION

The dynamic behavior of a time-dependent nonlinear system is in general could not be accurately modeled by static input-output mapping strategy. In order to deal with this problem, the control system of a time-dependent nonlinear system should design to be adaptive, robust and flexible. The conventional proportional-integral-derivative (PID) controllers are widely used in industry due to their simple control structure, ease of design and low cost (Shin *et al.* 2012), (Rodriques *et al.* 2012), (Guzinski *et al.* 2013), (Holmes *et al.* 2012), however, the PID controller could not provide a perfect control performance if the controlled system is highly nonlinear. As the consequence, PID controller could not guarantee that the system would work with the same level of accuracy in the entire operating range.

Considerable works has been reported, recently, concerning the use of artificial neural networks algorithm as a control system for a time-dependent nonlinear system. Artificial neural networks is a machine that is designed to model the performance of the brain on its ability to solve a particular task of interest based on a pattern recognition scheme. A neural networks is a massive parallel distributed processor made up of a simple processing neuron for memorizing the knowledge and making it available after training. The procedure used to perform the learning process is called the learning algorithm. The main objective of this mechanism is to modify the connection weights between neurons in the networks in an orderly fashion to attain the mapping capability of a set of input patterns onto a corresponding set of output patterns. A simple but powerful neural networks is a multi-layer perceptron (MLP) with one hidden layer, trained by using a back-propagation learning mechanism for updating the neural networks parameters.

In recent years, there has been a significant increase in the number of control system methods that are based on nonlinear concepts. The nonlinear inverse model based control is one of such methods, which is dependent on the availability of the inverse of the plant model. As the neural networks have the ability to model any nonlinear system, including their inverse, their use as a controller is promising.

In this paper, the design and evaluation of a neural network based inverse controller to a Pressure Process Rig® system, or PPR® in short, is presented. Pressure Process Rig® system is one of the nonlinear systems that the neural network shall be implemented and its control performance could be evaluated for future development of an adaptive and robust controller system based on Neural Networks. Especially, this performance analysis is very important for the development of the error-based direct inverse controller with disturbance rejection capability.

This paper is organized as follows. Section II presents description of the Pressure Process Rig® as a system plant. In addition, the data collection and its processing are also described. Section III discusses the design and the development of the neural networks based controller in detail, including with the system identification of the plant, as the strong system identification capabilities of a neural networks could be extended and utilized to design a better nonlinear controller. The validity of the design procedure and the robustness of the proposed controller are verified by means of a computation simulations and experimental analysis, which is presented in Section IV, follows by the conclusion that is presented in Section V.

The Pressure Process Rig® System

Pressure Process Rig® control that was used in this experiment is a laboratory model developed by Feedback Instrument Ltd. The schematic diagram of the Pressure Process Rig control is borrowed from the manual provided from the manufacture that illustrated in Figure 1. For more specific information regarding the system, please refer to the available manual book (Feedback, 2006). When the system is in the operation mode, a mini compressor supplied a gas through a pipeline into the orifice of the system, and a control valve is put in this line for controlling the P_{out} outlet pressure. A control signal is

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inputted into this control valve and can be adjusted in order to have a determined P_{out} outlet pressure.

The P_{out} outlet pressure measurement is calculated by a differential pressure transmitter that was embedded in the system. The PPR® system is connected to a PC computer through a Process Interface (Feedback 38-200) with a two signal conditioning subsystems, i.e., V/I converter and I/V converter, respectively, and a Data Acquisition Card NI-PCE-6024E. The supervisory adaptive controller is programmed in C-MEX language, compiled into the hexa-code, and can be implemented in SIMULINK environment. The measured data can be obtained through the Data Acquisition card for every *0.45* seconds.

For the purpose of system identification of the PPR®, the data input–output is collected through a multi sinusoidal signal with a range of *0%-85%* from its maximum range, following the defined equation as

$$v(k) = 0.3\sin\frac{0.2}{\pi}k + 0.35\sin\left(\frac{2}{\pi}k + 90^\circ\right) + 0.4\sin\left(\frac{0.6}{\pi}k + 90^\circ\right) + 0.8(k) + e(k) \quad (1)$$

where *e(k)* is a random signal within interval of [*0, 0.5*]. Figure 2 shows the system input-output data generated by the PPR® system in an open loop mode. It is clearly shown that the identification database covered the predefined operating points of the PPR® system, by including the low, the medium, and the top of the operating region of the system (Subiantoro et.al. 2013). As the sampling time is determined to be *0.45* second, a total of *5000* samples are collected and can be directly used for the experiments.

Neural Networks Based Controller Design

The nonlinear inverse model based control strategy is one of the promising methods within various nonlinear concepts that are being developed recently. As the neural networks have the ability to model any nonlinear system, direct inverse neural networks controller is one of the several types of neuro-controllers which have been used due to its simplicity. Neural networks has been studied as one of the most accurate system identification for nonlinear dynamical system (Narendra *et al.* 1990).

The application of a neural networks as a system identification and a controller of a nonlinear process have been used such as in greenhouse temperature (Frausto *et al. (*2004), thermal dynamic of pulsating heat pipe (Lee *et al.* (2009), and other industrial applications (Valamarthy *et al.* 2009), (Sastry *et al.* 1994).

The utilization of a direct inverse system model is done by cascading the inverse neural controller with the controlled plant. The cascaded system then provided an identity mapping between the signal reference or the desired response of the system and the output of the plant or the controlled plant response, where the neural networks acts directly as the neural controller.

Figure-1. Pressure Process Rig® control.

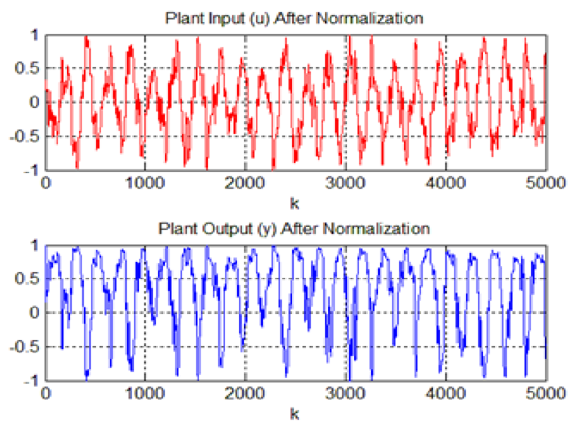

Figure-2. Input and output data provided from open-loop generated identification data of the plant.

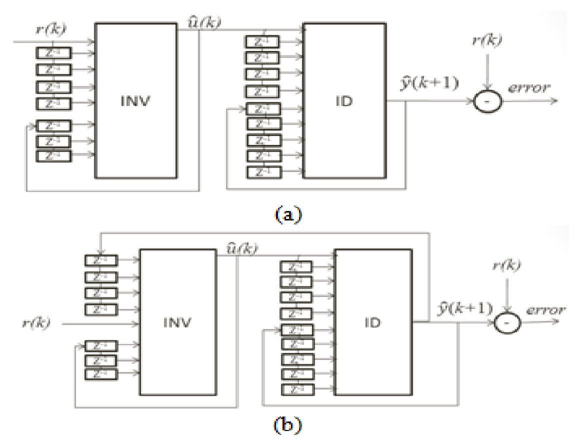

Figure-3. Direct Inverse Control system in cascading with the plant (a) open-loop system, (b) closed-loop system.

Block diagram of an open-loop direct inverse model is schematically depicted in Figure-3a. The advantage of the direct inverse neural controller lied on its capability of using the most powerful characteristics of neural networks learning mechanism. However, the plant may lose robustness at the beginning of the control process, since the initial output depends directly by the semi-randomly initial weight matrix determination of the neural networks. As can be seen clearly seen from Figure

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3a, the direct inverse neural controller relies on the fidelity of the inverse model used as the controller.

Generally, serious problem may arise, due to lack of the neural controller robustness that attributed primarily to the absence of a feedback signal. Optimizing the open-loop system of the direct inverse controller, a feedback signal from the system output is then inputted backward to the neural controller such in a closed-loop system as can be seen in Figure 3b. The neural networks that was used as the controller is also a multi-layer perceptron, the same architectural neural networks that was used as the system identification but with different data training for its learning. For both of the systems, a multi-layer perceptron with one hidden layer is usually used, and the learning mechanism is accomplished by using a back propagation method.

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During the iterative process, an input vector is presented to the network and propagated forward to determine the output vector from the output layer. The differences between the actual output vector and the desired output vector represents as the error that should be minimized, by adjusting the connections weight. The adjustment of the neural weights is calculated through the back propagated error as a function of the mathematical model of the neurons. The learning process continues until the network output vector provided a root-mean square error less than a determined value.

As the neural controller that be applied directly on the system may disturb the plant, a simulation calculation by using a model of the plant is recommended. The dynamic behavior of the plant system is already modeled using a neural network, as the system identification.

Neural Networks Based System Identification

The system identification is a science of how to construct a mathematical models of a dynamic system by using an observation through an input and output data. The first step in the identification process is by designing a suitable experiment which brings out the acquired input-output data that contain maximum information regarding the process (Ljung, 1999). The collected data is subjected to some preprocessing technique in order to remove the effect of undesired noise and imperfections that disturbs the system under investigation. In the next step, a set of candidate models is proposed, and a rigorously examination of the proposed models are conducted in order to verify the quality of the developed model. When the proposed model meets the chosen criteria which reflect the intended use of the model, the proposed model is accepted and can be applied, otherwise, it is rejected and another model is examined again. This procedure is repeated until the satisfactory model can be determined.

Various methods have been vigorously studied and developed for nonlinear system identification, mainly based on a parameterized model. The parameters are updated repeatedly to minimize the error of the system identification output. A nonlinear dynamical system with input ***x*** and output ***y*** can be modeled as:

$$y(k) = f(\varphi(k), \theta) \quad (2)$$

where $y(k)$ is the output of the model, $\varphi(k)$ is the regression vector and θ is the parameter vector. Depending on the choice of the regressors $\varphi(k)$, for Nonlinear Auto Regressive with eXogenous input (NARX) model structure, the regression vector is derived from a collection of a finite number of the past inputs and outputs, and can be written as

$$\varphi(k) = (y(k-1), \ldots, y(k-N_y), x(k-1), \ldots, x(k-N_x)) \quad (3)$$

where N_x denotes the maximum lag of input and N_y is the maximum lag of the output.

The use of back propagation neural networks (BPNN) to approximate the nonlinear mapping of NARX identification model is shown in Figure 4a. The neural architecture is determined by using input neuron that consists of the input and output signals with N_x = 5 and N_y= 5, respectively, followed by one hidden layer with twenty neurons and one output neuron. The inputs $x(k\text{-}1)$, $x(k\text{-}2),\ldots,$ $x(k\text{-}N_x)$ and $y(k\text{-}1)$, $y(k\text{-}2),\ldots,$ $y(k\text{-}N_y)$ are multiplied by weights v_{xnm} and v_{ynm}, respectively, and summed at each hidden neurons. Noted that $n=1,2,\ldots, N$ is the number of input neuron and $m=1,2,\ldots, M$ the number of the hidden neuron.

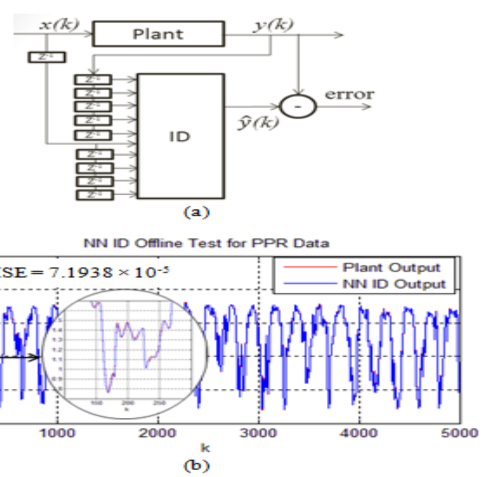

Figure-4. System identification of the PPR® (a) neural network architectural for system learning (b) comparison of the output signal of plant and the neural network based system identification.

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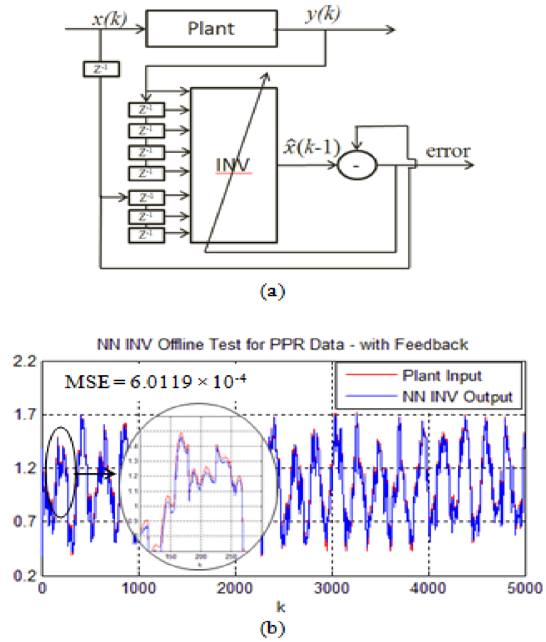

Figure-5. (a) Block diagram of the neural networks based inverse controller, (b) comparison of the control signals the $\hat{u}(k)$ and $u(k)$.

The Sigmoid activation function is then applied to this summed value yields the output of the hidden neuron, $z_m(k)$. Following the same procedure as for hidden neuron, multiplying the hidden neuron output $z_m(k)$ by weights w_m, and by applying the same Sigmoid activation function, the output $y(k)$ can be calculated as

$$y(k) = \sum_{m=1}^{M} w_m \left(\frac{1}{1 + e^{-\left(\sum_1^{Ny} y(k-n_y) v_{ymm} + \sum_1^{Nx} x(k-n_x) v_{xmm}\right)}} \right) \quad (4)$$

Figure-4b shows the output of the neural networks as the system identification. As clearly seen in this figure, the MSE between the actual and the output of the system identification is 7.1938×10^{-5}, which means that the neural system is successfully mimicking the plant behavior with a very high approximation.

Neural Networks Based Controller System

The inverse neural controller, as can be seen in Figure-3, is basically a neural networks structure representing the inverse of the system dynamic after the completion of a training process. The neural networks represents the inverse of the system dynamics is given by

$$x(k) = f(x(k-1), \ldots, x(k-N_x), y(k+1), \ldots, y(k-N_y)) \quad (5)$$

Schematic diagram of the learning the inverse neural controller is shown in Figure-5a, with $N_x = 4$ denotes the maximum lag of the input plant and $N_y = 4$ is the maximum lag of the output system. The three-layer networks consists of one input layer with 8 neurons, a hidden layer with 16 neurons and one output layer with one neuron. The 8-16-1 network is then trained to follow the desired output signal of the plant by using a back propagation algorithm.

Figure-5b shows the simulation result of the inverse neural controller, where the MSE between the controls signal, the output from the inverse controller, and the desired signal is 6.0119×10^{-4}. These numerical results indicate that back propagation neural networks show a good fidelity to be used as the direct inverse controller.

NUMERICAL SIMULATION AND DISCUSSION

The neural networks controller design and its experimental performance analysis for both the open-loop and the closed-loop systems are carried out on the MATLAB platform. The performance of the direct inverse neural networks controller for PPR® plant is firstly evaluated using an open-loop system, and the experiment results are depicted in Figure-6a, with the MSE between the outputs of the systems is 2.2060×10^{-4}. As can be seen from this figure, the numerical results of the NN-DIC are in good agreement with that of the reference signal.

Figure-6b shows the experimental output response of the PPR® when evaluated using a closed-loop system. The MSE between the outputs of the systems in the closed-loop system is 9.4241×10^{-4}. From the comparison of these experimental results, we can conclude that MSE of the open-loop system is lower than that of the closed-loop system.

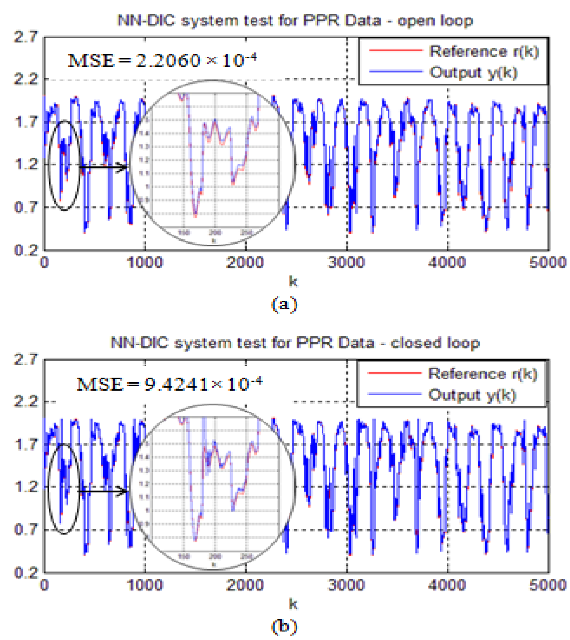

Figure-6. Results comparison of NN-DIC for (a) open-loop system and (b) closed loop system.

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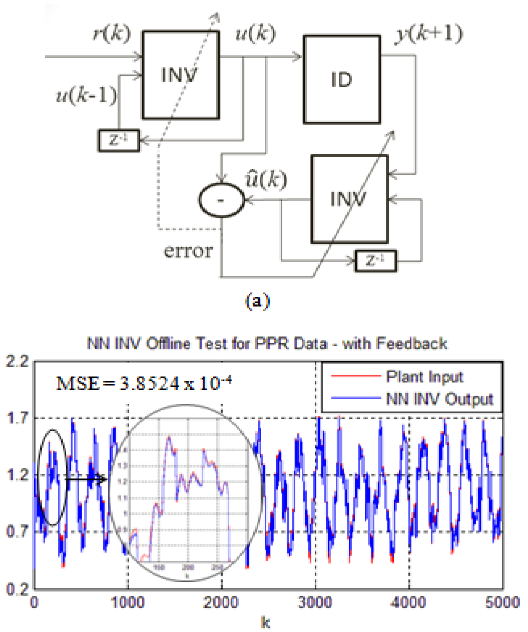

Figure-7. (a) Schematic diagram of the fine-tuning method for the NN-DIC (b) comparison of the control signal u(k) and the output of fine-tuned NN-DIC system $\hat{u}(k)$.

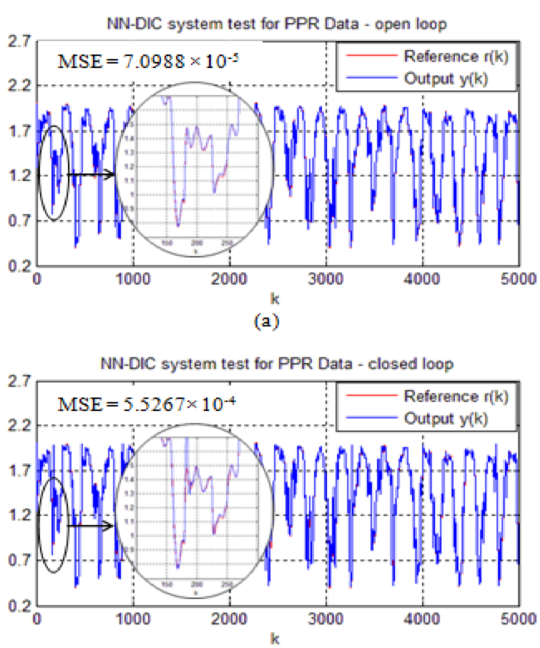

Figure-8. Comparison of the Output and reference signals using NN-DIC fine tuning method (a) open-loop system configuration (b) closed loop system configuration**.**

In order to have a better performance of the NN-DIC on producing a lower MSE of the output plant and the reference input, a fine tuning of the DIC is implemented. Block diagram of the fine tuning system is depicted in Figure-8, where the output of the plant is inputted back to the NN-DIC, in order to produce the control signal $\hat{u}$, which may differ from the control signal produced by NN-DIC. Using the error difference between the $\hat{u}(k)$ and $u(k)$, the NN-DIC is trained again until reaches it's confidence. The Fine-tuned NN-DIC is now ready to be used as a new NN-DIC for both the open-loop and the closed loop systems.

Table-1. Performance comparison of the normal NN-DIC and the Fine-tuned NN-DIC.

NN-DIC	Open-loop system		Closed-loop system	
	Control signal	Output signal	Control signal	Output signal
Normal NN-DIC	5.4×10^{-4}	2.2×10^{-4}	6.0×10^{-4}	9.4×10^{-4}
Fine-tuned NN-DIC	3.9×10^{-4}	7.0×10^{-5}	5.4×10^{-4}	5.5×10^{-4}

Using the same experimental procedure such as in Figure-4, numerical result of using the Fine-tuned NN-DIC on the open-loop system is shown in Figure 9a. The MSE between the output signal *y(k)* and the reference signal *r(k)* is 7.0988×10^{-5}. Figure 9b shows the comparison between the output signal *y(k)* and the reference signal *r(k)* for the closed-loop system, with the MSE is 5.5267×10^{-4}. As can be clearly see from this figure, the open-loop system shows a lower MSE compared with that of the closed-loop system.

Table-1 shows the comparison of the overall experiments results in terms of MSE for both normal NN-DIC and Fine-Tune NN-DIC under Open-loop and Closed-loop systems. As clearly shown in this table, for every signal parameters, i.e., the control signal and the output signal, the Fine-tuned NN-DIC shows lower MSE compare with that of normal NN-DIC, for both open-loop and closed-loop systems. While in the normal NN-DIC, the MSE difference between the output signal using Open-loop and Closed-loop systems are very small, Fine-tuned NN-DIC shows a big difference between the output signal of the Open-loop system in respect to the output signal of the closed-loop systems.

This phenomena is may due to the error of the neural networks as the system identification in a closed-loop system is also feeding back to the NN-DIC, which in turn making the control signal may deviate further from the actual requirement.

CONCLUSIONS

We have presented here, an in-depth performance analysis of a neural networks based direct inverse controller for a Pressure Process Rig® system. Improvement of the NN-DIC is performed by using a fine-tuning method, which significantly decreased the MSE of the controller. The experimental procedure was also investigated the performance of an open-loop system and the closed-loop system. It is clearly seen that the open-loop system shows lower MSE compare with that of the closed-loop system, indicating that the closed-loop system in this definition may differ from an error based controller system. Further research on developing the error based neural controller is now under investigation.

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REFERENCES

[1] Feedback Instrument Ltd (2006), Pressure Process Rig® 38-714 Manual Book.

[2] Frausto H.U. and Pieters J.G. 2004. Modelling greenhouse temperature using system identification by means of neural networks. Elsevier: Neurocomputing, Vol. 56, pp. 423-428.

[3] Guzinski J. and Abu-Rub H. 2013. Speed sensorless induction motor drive with predictive current controller. IEEE Trans. Ind. Electron, Vol. 60, No. 2.

[4] Holmes D.G., McGrath., B.P. and Parker S.G. 2012. Current regulation strategies for vector-controlled induction motor drives. IEEE Trans Ind. Electron, Vol. 59, No. 10, pp. 3680-3689.

[5] Lee Y.W. and Chang T.L. 2009. Applicaton of NARX neural networks in thermal dynamic identification of a pulsating heat pipe. Elsevier: Energy Conversiton and Management, Vol. 50, pp. 1069-1078.

[6] Ljung L. 1999. System Identification: Theory for the user. Prentice Hall, New Jersey.

[7] Narendra K. and Parthasarathy K. 1990. Identification and control of dynamical systems using neural networks. IEEE Trans, Neural Netw. Vol. 1, No. 1, pp. 4-27.

[8] Rodriques J., Kennel R.M., Espinoza J.R., Trincado M., Silva C.A. and Rojas C.A. 2012. High-performance control strategies for electrical drives: An experimental assessment. IEEE Trans. Ind. Electron, Vol. 59, No. 2, pp. 812-820.

[9] Rankovic V.M. and Nikolic I.Z. 2008. Identification of nonlinear models with feedforward neural networks and digital recurrent network. FME Transactions, Vol. 36, pp. 87-92.

[10] Sastry P.S., Santharam G. and Unnikhrisnan K.P. 1994. Memory neural networks for identification and control of dynamic systems. IEEE Trans. Neural Netw., Vol. 5, No. 2, pp. 306-319.

[11] Shin H.B. and Park J.G. 2012. Anti-windup PID controller with integral state predictor for variable speed motor drives. IEEE Trans. Ind. Electron, Vol. 59, No. 3, pp. 1509-1516.

[12] Subiantoro A., Yusifar F., Budiardjo B., Al-Hamid M.I. 2013. Identification and control design of fuzzy Takagi-Sugeno model for pressure process rig. Adv. Mat. Res., 605-607, pp. 1810-1818.

[13] Valarmathi K., Devaraj D. and Radhakrisnan T.K. 2009, Intelligent techniques for system identification and controller tuning in PH process. Brazilian J. of Chem. Engi., Vol. 26, No. 1, pp. 99-111.