Neural Network Based Adaptive PID Controller of Nonlinear Heat Exchanger

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***Abstract*—This research presents the design and simulation of nonlinear adaptive control system on the heating process of shell-and-tube heat exchanger model BDT921. Shell-and-tube heat exchanger is a nonlinear process and change in process dynamics cause instability of the PID controller parameters i.e proportional gain, integral time and derivative time. Thus, the PID controller parameters need to be repeatedly retuned. In this study, neural network approach was introduced to auto-tune the controller parameters. The dynamic data from the BDT921 plant was collected to formulate the mathematical model of the process using MATLAB System Identification Toolbox. NARX model was used to represent the heat exchanger. Neural network was used as adaptive system to the PID controller. The neural network model consists of 4 input variables and 4 output variables. Single hidden layer feed forward neural networks with 20 neurons in hidden layer is the optimum topology of the network. The effectiveness of the controller was evaluated based on the set point tracking only. Simulation result proved that the adaptive PID controller was more effective in tracking the set point with faster settling time and lower or no overshoot respond compared to conventional PID controller.**

Keywords—Nonlinear process, Neural Network, Shell-and-tube heat exchanger, Adaptive controller

I. INTRODUCTION

Shell and tube heat exchanger is equipment that applying heat transfer principles for heating or cooling the fluid. It is made up with double-pipe configuration that consists of bundle of pipes or tubes enclosed within a cylindrical shell.

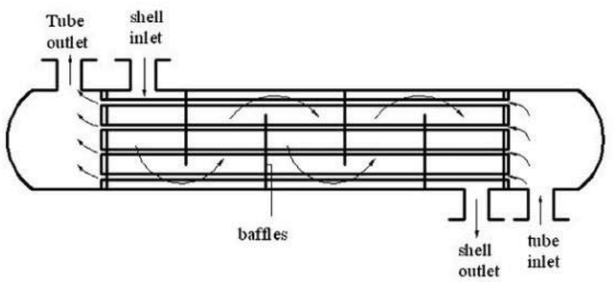

Figure 1: Schematic diagram of shell-and-tube heat exchanger [1]

One fluid flows through the tubes and another fluid flows within the space between the tubes and shell without physical mixing between the fluids. Figure 1 shows a schematic diagram of the shell-and-tube heat exchanger. Shell-and-tube heat exchanger is naturally nonlinear system and has a complex nature due to friction, temperature dependent properties, and unknown fluid properties. These condition leads to uncertainties to heat exchange process such as uncertainties in process gain, process dynamics, and unmeasured disturbance. The nonlinear model needs to be used to represent the nonlinear dynamic behaviour of shell and tube heat exchanger. Mulyana [2] found out that nonlinear autoregressive with exogenous input (NARX) model able to accurately predict the nonlinearity of shell-and-tube heat exchanger model BDT921.

Conventional PID has been widely used in order to control the process of shell-and-tube heat exchanger. Due to the nonlinear condition, conventional PID controller was not effective in tracking the set point and rejects the disturbance, so, an expertise required to manually tune the PID controller parameter. [3]. There are 3 controller parameters which are proportional gain (K_c), integral time (τ_I) and derivative time (τ_D).The parameters can be tuned with several tuning methods such as Ziegler–Nichols (ZN) method and Cohen–Coon technique. Ziegler–Nichols was developed for set point change and disturbance rejection by finding out the proportional gain at oscillatory output condition. While, Cohen- Coon method was designed to reject the disturbance but this method can only be applied to first order models and large process delays only [4]. Thus, it becomes a challenge to control and tune the heat exchanger.

The artificial neural network has been widely used in control system in order to improve controller performance especially by recognized the dynamic input and output of the process. The artificial neural network has the ability to recognize the process dynamic and independent of human expert experiences. In controlling heat exchanger process, several control strategies has been proposed such as internal model controller [5], neural network controller [6] and classic and modified IMC [7]. They found out that applying the neural network to the control system improves the performance of the controller.

On the other hand, several studies have revealed that neural network based adaptive PID controller is superior compared to conventional PID controller in controlling various controlled variables. Haiyang, Yu, Deyuan, and Hao [8] , use an adaptive PID controller based on the radial basis function (RBF) neural network to address the temperature control problem in the thermal vacuum tests. In order to verify the effectiveness and the superiority of the designed neural network adaptive PID algorithm, two comparison simulations between neural network adaptive PID control and the conventional PID control approach were carried out with the result show that the neural network adaptive PID controller reduces the overshoot. They also concluded that the neural network adaptive PID controller have good adaptive ability for nonlinear temperature-controlled model.

Guo [9] developed adaptive PID controller based on back propagation neural network to control electro-hydraulic position servo. The author stressed that back propagation neural network is simple algorithm. The purpose of the neural network is to adjust the controller parameter when the controller respond is unstable. Using simulation method, the result show that adaptive PID controller in electro-hydraulic position servo have a better control characteristics, adaptability, strong and robustness in the nonlinear and time vary system.

Nuella, Cheng and Chiu [10] proposed adaptive PID controller to control the inlet flowrate of raw material to the polymerization reactor. They compare the adaptive controller with PID controller and found that the proposed controller give superior performance in disturbance rejection and set point tracking.

Application of adaptive PID controller for first order plus dead time system has been studied by Rad, Bui, Li, and Wong [11] investigated the on-line PID tuning method. Neural network was used to tune the controller parameter. The tuning method that was used to determine the controller parameter is Ziegler-Nichols method. From the simulation result, it indicates the feasibility and adaptive property of the proposed scheme.

Cheng, Zhang, Kong, and Meng [12] study the method to control the light gasoline etherification process by proposing back propagation neural network adaptive PID controller to control the process. In order to evaluate the performance of the propose controller, the comparison with conventional PID control was done. From the result, the neural network based adaptive PID controller give advantages in term off overshoot condition, rise time and settling time.

Comparison of multiple model with NN model in adaptive control has been carried out by Lincoln and Prakash [13] to control product concentration and temperature in CSTR reactor. In neural network adaptive PID controller, they used feed forward back propagation as training algorithm with concentration of product as input parameter to the neural network. Meanwhile the controller tuning parameter is used as the output from the neural network. Author compared the performance of both proposed controller and found that neural network adaptive controller was effective in set point tracking compared to multiple model adaptive controllers.

Rivas-Echeverría [14] used neural network as controller to auto tune the PID parameter. Integrals error criteria were implemented to determine the PID controller parameter. The result showed that the neural network auto tune controller is able to stabilize the controller output with less oscillation compared to conventional PID controller but have same settling time.

Although there are many studies on inferential control, but handful of research has been conducted by identifying the degree of nonlinearity of the process prior proposing the control strategy. Low order of transfer functions are widely used to represent the nonlinear process. This paper investigates the system that can adapt to the nonlinearity of shell-and-tube heat exchanger by updating the PID controller parameter. The degree of nonlinearity of the process is identified and the nonlinear process is modelled. The nonlinearity of the shell-and-tube heat exchanger were studied by recognize the dynamic real time input and output data. The neural network model is used as an adaptive system of the inferential control. The best configuration of neural network adaptive controller for the shell-and-tube heat exchanger is proposed and the performance of the controller is compared to the conventional feedback PID controller.

II. METHODOLOGY

A. Dynamic input and output data of shell-and-tube heat exchanger model BDT921

The dynamic behaviour of heat exchanger is determined based on experimental data from a pilot scale shell-and-tube heat exchanger model BDT921. The parameter that has been considered was the flow rate of heating fluid/percentages of valve opening and the outlet temperature of the cool stream. The cool stream will enter the heat exchanger at shell side while the hot stream will enter the heat exchanger at tubes side with one shell passes and two tube passes design. Hot fluid form heating tank is pump to the heat exchanger and the flow rate is controlled by valve with valve opening from 0 to 100% .The heated stream from the heat exchanger is measured by resistance temperature detector transmitter within the range of 0-100°C. The temperature of cool water was 28± 2°C and the flow rate was varies from 177± 2 m^3/hr. The hot water temperature in the boiler tank varies from 58 ± 2˚C.

Open loop test is conducted after the process reaches steady state at the valve opening equal to 0%. Next, the valve opening is increased by 1% and repeated until 50% of valve opening. The steady state value of the outlet temperature at each increment of valve opening was recorded.

B. *Determine the mathematical model of the process*

System Identifications ToolBox in MATLAB was used to determine the correlation within the process based on dynamic input and output data of shell-and-tube heat exchanger. 78407 of time series data sets with 0.03 second of step time obtained from experimental work has been used for process identification and modelling. The mathematical model of the process was developed using transfer function estimation and NARX estimation. The best estimation of mathematical model is chosen based on highest percentage of Fit to estimation, highest validation value, lowest value of Mean Square Error (MSE), and lowest Fit Percentage Error (FPE).

The NARX model equation is as follow:

$$y(t)=f(y(t-1),\ y(t-2)\ldots y(t-n_y),\ u(t-1),\ u(t-2)\ldots u(t-n_x)) \qquad (1)$$

where the output y(t) is regressed from the past value of output, y and past value of input, x. The function f is determined using polynomial form.

C. *Tuning parameter of the PID controller.*

Conventional PID controller was developed in Simulink and used to find the controller parameters which are proportional gain (K_c), integral time (τ_I) and derivative time (τ_D) and filter (N) for several step respond. The PID controller algorithm is as follow:

$$e(t)= K_c\,[e(t) +1/\tau_I \textstyle\int edt + \tau_D\,(de(t)/dt)] \qquad (2)$$

Ziegler- Nichols based tuning method was used to tune the parameter at the optimum condition with several fine tuning.

D. *Neural Network Development and training.*

The feedforward neural network architecture with one hidden layer is selected as the adaptive system. The input layer consists of 4 parameters which are process variable, set point, manipulated variable and process error, while the output layer consists of 4 controller parameters which are proportional gain (K_c), integral time (τ_I) and derivative time (τ_D) and filter (N) as shown in Figure 2. Dynamic time series neural network model was used with Levenberg-Marquardt algorithm as a training method. The activation function for hidden layer is tan sigmoid (Tansig) meanwhile for output layer was purelin. The number of neuron in hidden layer was determined by evaluating the lowest value of Mean Square Error (MSE) and highest value of regression R.

The neural network was combined with PID controller scheme. Figure 3 shows the block diagram of the adaptive NN-PID controller. Simulink MATLAB is used to conduct the simulation study of the NN-PID controller.

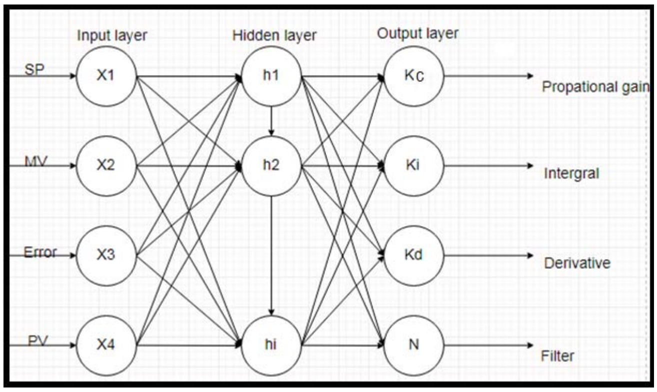

Figure 2: Neural Network Architecture

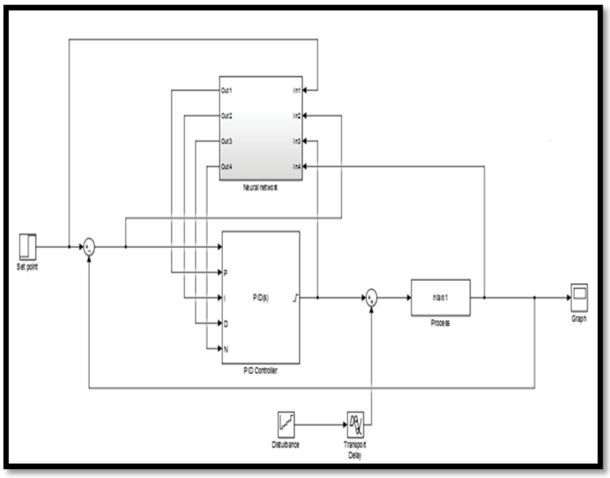

Figure 3: Neural Network Adaptive PID controller Scheme.

E. *Determine the effectiveness of the controller*

The effectiveness of the controller is determined by comparing the output response from the neural network adaptive PID controller with conventional PID controller. The parameter that will be measured is the effect of set point changing. The set point change will be selected randomly. The effective controller was evaluated based on overshoot condition, rise time and settling time.

III RESULT AND DISCUSSION

Figure 4 show the nonlinearity behavior of the process. The trend shows that the shell-and-tube heat exchanger model BDT921 is a nonlinear process because the output temperature is not directly proportional to manipulated variable. It can be seen at the valve positioning from 1% to 40 % shows an increase of temperature rapidly with larger gradient. Meanwhile, at the valve positioning from 40% to

50 % there is a slight increment of temperature. These phenomena happen because of different in temperature between cold and hot stream. The greater the different in temperature the faster the heat transfer take place [15].

III. RESULTS AND DISCUSSION

A. Non Linearity of Shell-and-tube Heat Exchanger Model BDT921

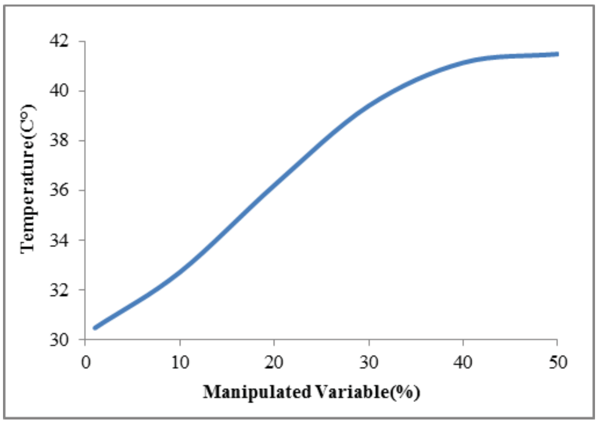

Figure 4: Nonlinearity of the process

B. Estimation of mathematical model of the process

Table 1: Mathematical Model Estimation

Mathematical modeling of Shell-and tube Heat exchanger BDT 921 using NARX model					
No of input Term	No of Output Term	Fit to Estimation %	MSE	FPE	Validation %
2	0	97.030	0.009922	0.009922	93.440
2	1	97.050	3.282	0.01185	95.630
2	2	97.500	3.284	0.01186	96.170

Estimation of mathematical process model was done using System Identification toolbox MATLAB R2015b. The factors that have being considered to determine the accuracy of the model are the fit to estimation, MSE, FPE and validation value. NARX model outperforms transfer function model in representing the nonlinear process (result not shown). From Table 1, the best of 3 configuration of NARX model were chosen. It can be seen that most of sequence of input and output term predicts the process model very well. The sequence of 2, 2 predict accurately the step respond with 300s to reach steady state and this model predict accurate with the real situation in shell-and-tube heat exchanger model BDT921 plant. The mathematical model with NARX method with sequence 2, 2 is selected to represent the process in Simulink.

The comparison of outlet temperature was made between NARX and experimental data to validate the process model. Based on figure 5, the output temperature from the simulation is almost same as the output temperature from the plant.

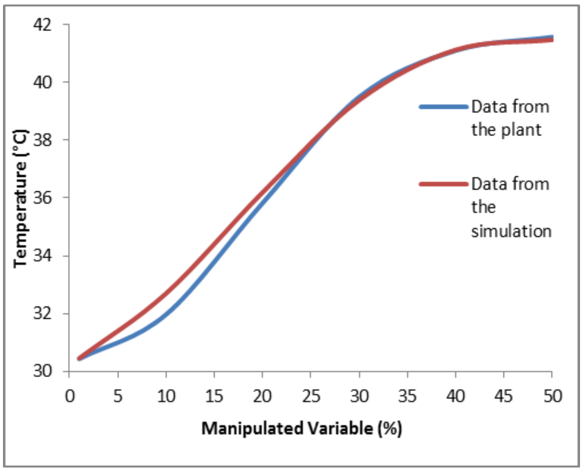

Figure 5: Comparison result between data from the plant and simulation data

C. Tuning parameter for the PID controller

Table 2: PID tuning parameter for various step change.

Tuning	proportional gain (K_c)	integral time (τ_I)	derivative time (τ_D)	filter (N)
Step up less than 5%	28.260	0.509	120.080	0.094
Step up less than 50%	6.480	0.053	62.250	0.020
Step up above 50%	4.800	0.035	34.920	0.014
Step down less than 20%	5.800	0.060	23.360	0.065
Step down above 20%	6.480	0.053	62.250	0.020

Using conventional PID controller, step respond test was done to determine the controller parameters K_c, τ_I, τ_D and N. The controller parameter was determined using Ziegler-Nichols method as the foundation. From table 2 variation of optimum PID at different set point shows that this process is a nonlinear process. This tuning parameter was the best for the process to achieve the set point faster with over damped response and less overshoot response. The filter value was used to filter noise from the derivative parameter since pure derivative will give disturbance to the controller and oscillation respond.

D. Development of Neural network for adaptive PID controller

The development of the neural network begins with the selection of the input and output layer of the network. The neural network input layer consists of the set point (SP), manipulated variable (MV), error (e) and process variable (PV). Meanwhile the output layer of neural network is consists of proportional gain, integral time .derivative time and filter. After all the necessary data was collected, the training of the neural network begins with the input and output matrix of 4x16516 in dynamic times series neural network model. The number of neuron in hidden layer was chosen started from 12 to 20.The number of neuron in hidden layer was stop at 20. This is because larger value than 20 of neuron produced over fit condition. Each of these configurations was evaluated using the Mean square error, MSE and Regression Value, R (%) and Levenberg-Marquardt algorithms is used as the training method.

The MSE and R value will affect the fit of the configuration of the neural network. From table 3, the odd value number of neuron in hidden layer tend to produce higher value of MSE and lower value of R compared to the even value number. The best configuration of the neural network was 20 number of neuron in hidden layer with the lowest MSE and highest R value i.e 0.003028 and 0.9999, respectively. This finding can be supported by Sharma and Venugopalan [16] who found out that Levenberg-Marquardt algorithms have the ability to converge faster with the less mean square error value. Besides, the author also highlighted that Levenberg-Marquardt algorithms can be used from small to medium data set with less number of iteration.

The neural network was trained in order to combine with the conventional feedback PID controller. Once the set point was change in the system, the neural network will update the optimum PID controller parameter.

Table 3: Number of neuron in hidden layer chosen.

Number of neuron in hidden layer	Mean Square Error (MSE %)	Regression (R %)
12	0.1701	0.9998
13	0.3969	0.9995
14	0.1128	0.9998
15	0.4027	0.9995
16	0.1308	0.9998
17	0.1878	0.9998
18	0.1538	0.9998
19	0.1345	0.9999
20	0.003028	0.9999

E. The comparison of the effectiveness of conventional PID controller and Neural Network adaptive PID controller based on step change

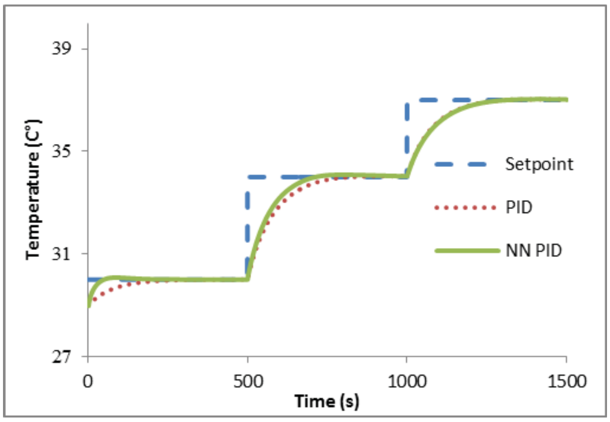

Figure 6: Comparison between PID controller and NN-PID for step increase in set point change

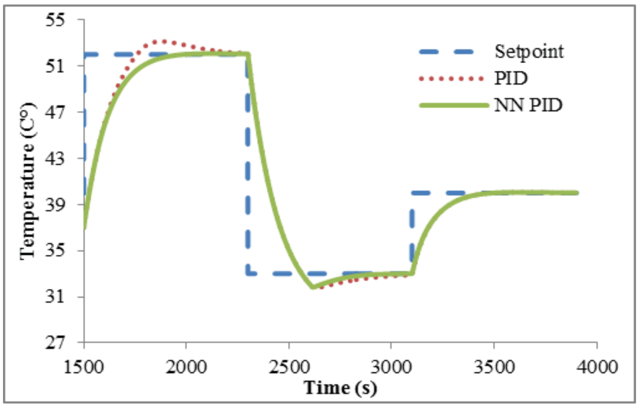

Figure 7: Comparison between PID controller and NN-PID for random in set point change

In order to evaluate the performance of these controllers, set point test was conducted and 3 different pattern of set point change has been made as shown in Figure 6, 7 and 8. The controller parameters values use in conventional PID were K_c =6.48, τ_I =0.053, τ_D=23.36 and N=0.0654. Based on figure 6, the set point were changes in every 500s for the range of temperature of 28 to 30 °C, 30 to 34 ºC and 34 to 37 ºC. Based on the observation from the figure 6, the neural network gives superior performance in first 2 set point by showing faster settling and rise time meanwhile both controllers give the same performance at the third set point change.

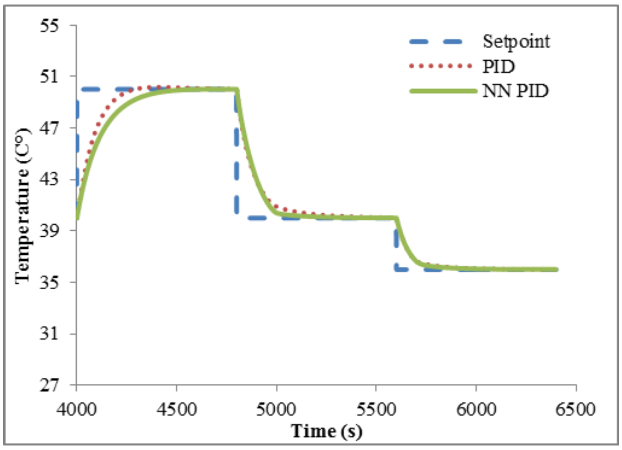

Figure 8: Comparison between PID controller and NN-PID for step decrease in set point change

From figure 7, the step respond was made for every 1000s and the set points were change from 37 to 52°C , 52 to 33°C and 33 to 40°C. In this case, the changing of set point was more aggressive with larger interval gap. It can be seen that in first set point change, the respond of NN-PID controller was more efficient to achieve the set point with fast settling time and no overshoot condition. Meanwhile the respond of a NN-PID controller for second step respond produced overshoot condition but these controller has faster settling time. For the third step respond from the figure 6 both controllers give same respond characteristic.

From figure 8 it can be seen that for the first step respond which is from 40 to 50 °C, the conventional PID controller is faster to achieve the desire set point and has faster rise time. For the second step respond which is from 50 to 40 °C, the NN-PID controller have faster settling time and less under damp condition. Lastly, for the third step respond, both controllers give the same behavior to achieve the desire set point. From figure 6 to 8, it can be concluded that the behavior of this controller did not haves significant difference in lower percentage of set point change which is normally below than 50%. This condition happens because the process itself is slightly nonlinear condition and one optimum PID parameter was effectives enough to control the process. However, when the aggressive set point change was made larger than 50%, it needs several optimum PID parameters to give superior performance. From figure 6 to 8 for the third step respond, both controller give the same respond because at this point NN-PID controller produce same optimum PID parameter as PID controller.

IV. CONCLUSION

In this paper, NARX method was used to represent the nonlinear process i.e shell-and-tube heat exchanger with 2, 2 configurations due to highest percentage of fit to estimation and validation value. 20 number of neuron in hidden layer of neural network architecture was the best fit for estimating the controller parameter and neural network adaptive PID controller was proposed to control the process of shell-and-tube heat exchanger. The NN-PID controller is effective in handling the set point change. The process output has faster settling time, thus give better result in controlling the process. In conclusion, the NN-PID controller is more effective to control the process in term of set point change compare to PID controller.

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