

Neural Network Based Adaptive PID Controller of Shell-and-tube 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 due to the factor of friction, temperature dependent properties, and unmeasured disturbance. As the heating process is nonlinear in nature and conventional PID is a linear controller, change in process dynamics cause instability of the controller parameters i.e proportional gain, integral time and derivative time. Thus, these controller parameters need to be repeatedly retuned. In this circumstance, auto tuning of the controller parameters is incredibly important. 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. The dynamic behavior of the process is accurately modeled using nonlinear ARX model with 96.17% of validation accuracy and 97.5% of fit to estimation accuracy. Dynamic time series neural network model was used together with Levenberg-Marquardt algorithm as the training method. Single hidden layer feed forward neural networks with 20 neurons in hidden layer was selected. The neural network model consists of 4 input variables and 4 output variables. Simulation and development of the controller was done in the Simulink environment meanwhile the effectiveness of the controller was evaluated based on the set point tracking and disturbance rejection. 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. However, there is no significant improvement in controller performance when disturbance is introduced to the controller.

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

I. INTRODUCTION

Heat exchanger is commonly used in industries for heating or cooling the fluid. Heat exchanger is equipment that controls the temperature of a fluid by applying heat transfer principles which the hot fluid will be cold down or vice versa without physical mixing [1]. There are several types of heat exchanger in industries and one of those is 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. 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. [2]. There are 3 controller parameters which are controller gain(K_p), integral(K_i) and derivative(K_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 K_p 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 [3]. Thus, it becomes a challenge to control and tune the heat exchanger.

The artificial neural network was introduced and was being combined with the PID controller to increase the effectiveness of the controller by recognized the dynamic input and output of shell and tube heat exchanger and by auto tuning the controller parameters of K_p , K_i , and K_D . The artificial neural network has the ability to recognize the process dynamic and independent of human expert experiences. Many studies were conducted using the artificial neural network to improve the performance of the controller for the heat exchanger. Diaz, Sen, Yang, and McClain [4] used the neural network to conduct the simulation of the time dependent behaviour of gas-liquid heat exchanger for controlling the temperature of air passing over it. They developed an internal model controller scheme for controlling the temperature with two artificial neural networks. Compared with the PID controller, they found out that internal model controller was better compare to PID in case of the step change and disturbance rejection. This research was supported by Varshney and Panigrahi [5] in investigating the control of a heat exchanger in closed flow using neural network. The objective was to study the behaviour of controller and to control the heat exchanger when disturbance appear and set point are changing. The neural network controller shows a better and faster response compared to PID controller with less steady state error.

Rivas-Echeverría [6] use neural network as controller to auto tune the PID parameter. Integrals error criteria were implemented instead of Zingler-Nichols method 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. Haiyang, Yu, Deyuan, and Hao,[7] 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.

Riverol and Napolitano [8] used neural network to auto tune the PID parameter for heat exchanger. They used internal model controller (IMC) to design the adaptive system. Error signal, process output and controller output are taking into account as input for the first layer of neural network. The neural network adaptive PID controller is directly train at heat exchanger in pilot plant. From the result, author concluded that the neural network adaptive PID controller is effective for disturbance rejection. Lee and Park [9] used neural network combined with multi-loop PID controller to control the concentration of bottom product and overhead product from the distillation column. 3 layer neural networks with back propagation method were chosen to train the neural network. In the proposed scheme, disturbances, manipulated variables, controlled variables, and set points are used as input variables for the neural network and the output from neural network is manipulated variable. The author compared the performance of the controller with conventional PID controller. They found that the proposed control scheme gives superior performance in tracking the set point and disturbance rejection.

Yeo and Kwon [10] proposed neural network to tune PID parameters by using the multilayer feed forward network. The set point, process outputs, and manipulated variable are the input parameters to neural network and the controller tuning parameter is the output from the neural network. Authors tested the controller scheme on simulation of pH neutralization process with back propagation as learning pattern. The neural network PID controller shows good control performance for both load changes and set point changes. Lincoln and Prakash [11] designed multiple Model Adaptive-PID controller and neural network adaptive PID controller 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.

Guo [12] 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. Rad, Bui, Li, and Wong [13] investigated the on-line PID tuning method for first order plus dead time system. 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.

Chopra [3] proposed an intelligent tuning technique to tune the PID controller using fuzzy logic, artificial neural network, adaptive neuro fuzzy inference system (ANFIS) and genetic algorithms (GA). The controller is use to control concentration of mixture in continuous stirred tank reactor (CSTR). From the results, the author concluded intelligent tuning method provide better performance that Zeigler Nichols (ZN) method in terms of rise time, overshoot and settling time. Cheng, Zhang, Kong, and Meng [14] 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.

Nuella, Cheng, and Chiu,[15] proposed adaptive PID controller for nonlinear system. They simulate the proposed controller at the polymerization reactor where the main objective was to control the inlet flow rate of raw material to the 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. Alam, Gupta, Sindri, and Email [16] designed intelligent controller for controlling the temperature of heat exchanger. The authors had done a comparative analysis for various types of controller which included the conventional PID controller, internal model controller, fuzzy controller and ANFIS controller. In order to find the most effective controller , the capability of those controller in track the set point was the parameter that have been evaluate .They found that fuzzy logic controller and Feed-forward gives quick response without any oscillations. Mohana Sundaram, Sivanandam, and Renupriya [17] used neural networks to control the heat exchanger. Elman Recurrent Neural Networks, Time Delay Neural Networks, Cascade Feed Forward Neural Networks and Feed Forward Neural Networks had been used. From the result , its show that Elman Recurrent Neural Network have the best accuracy by having the lowest Mean Square Error (MSE) and best Regression.

Although there are many studies on neural network control systems, this paper investigate the system that can adapt to the nonlinearity of shell-and-tube heat exchanger by updating the PID controller parameter. These papers suggest an idea using neural network as an adaptive system to the conventional feedback PID controller. In this paper, the nonlinearity of the shell-and-tube heat exchanger were studied by recognize the dynamic input and output data and proposed the best configuration of neural network adaptive controller scheme for the shell-and-tube heat exchanger.

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 the pilot plant using shell-and-tube heat exchanger as heating equipment for desire stream. The type of heat exchanger was used is BDT921 and 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 from 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 varies from 27 to 30 °C and the flow rate varies from 176 to 178 $m^3 hr^{-1}$. The hot water temperature in the boiler tank varies from 56 to 60 °C.

In this research, an open loop method was perform using distributed control system (DCS). For the first step, start-up the plant and wait until the process reaches steady state at the valve opening equal to 0%. For the second step increase the valve opening by 1% and wait until it reaches steady state condition. For the last step repeat the second step until it reach 50% of valve opening.

B. Determine the mathematical model of the process

System identifications in MATLAB were used to determine the correlation within the process based on dynamic input and output data of shell-and-tube heat exchanger. In this system, the data were used in the estimate the process was 78407 with the valve position as the input and heated water temperature as the output with 0.03 second of step time. The data was filtered first and mathematical model was develop using transfer function estimation and nonlinear ARX 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)

C. Tuning parameter of the PID controller.

Conventional PID controller was developed in Simulink and used to find the controller parameters which are controller gain (K_p), integral (K_i), derivative (K_d) and filter (N) for several step respond. 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 architecture of the neural network consists of 3 layers, 1 input layer, 1 hidden layer and 1 output layer. 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 controller gain (K_p), integral (K_i), derivative (K_d) and filter (N). Dynamic times 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.

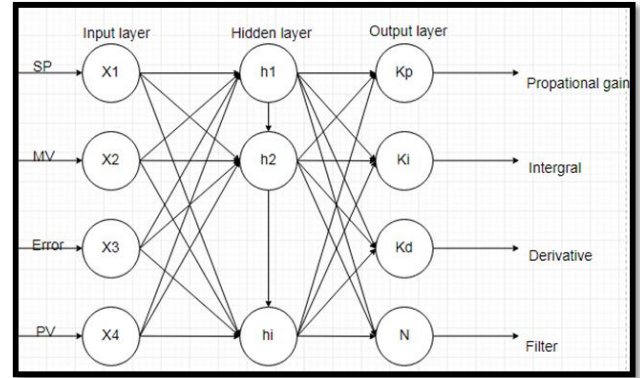


Figure 1: Neural Network Architecture

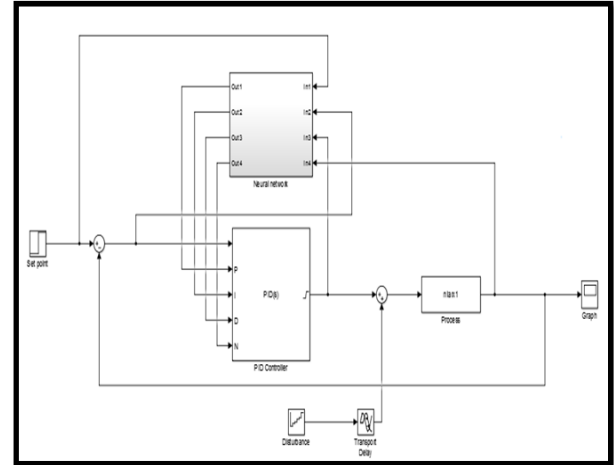


Figure 2: Neural Network Adaptive PID controller Scheme.

The neural network was combined with PID controller scheme. When the process value did not achieve the set point, the neural network will automatically update the optimum PID controller parameter.

E. Determine the effectiveness of the controller

Using Simulink environment, the effectiveness of the controller will be determined by comparing neural network adaptive PID controller with conventional PID controller. The parameter that will be measured is the effect of set point changing and disturbances rejection. The set point change will be selected randomly. The disturbance was manually set by increasing the manipulated variable by 10% until 50% from the last stable value of the manipulated variable. The effective controller was evaluated based on overshoot condition, rise time and settling time.

III. RESULTS AND DISCUSSION

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

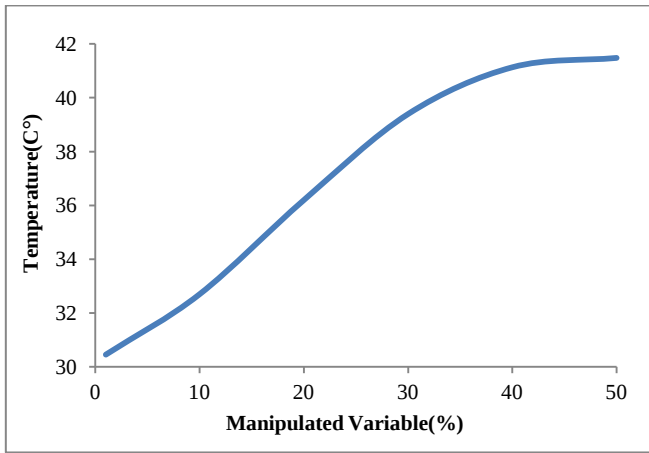


Figure 3: Nonlinearity of the process

From figure 3 indicates 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 % show a little bit of increment of temperature with the smallest gradient. 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.[1]

B. Estimation of mathematical model of the process

Table 1: Mathematical Model Estimation

Mathematical modeling of Shell-and tube Heat exchanger BDT 921 using Continuous Transfer Function					
No of Pole	No of Zero	Fit to Estimation %	MSE	FPE	Validation %
2	1	70.590	2.757	1.178	68.410
3	0	95.680	0.0254	0.025	90.790
3	3	95.680	2.507	5.290	54.220
Mathematical modeling of Shell-and tube Heat exchanger BDT 921 using Nonlinear ARX 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 Application in MATLAB R2015b toolbox. The factor that takes into account to get the most accurate result from the mathematical model is the Fit to estimation, MSE, FPE and Validation value. These values will determine the behavior of the process such as step respond of the process, settling time and amplitude response of the process. By referring to table, the best of 3 configuration transfer function estimation model and Nonlinear ARX model were chosen.

The number of poles represents the number of the denominator and the order of the transfer function. Meanwhile the number of zero represents the number of nominator of the transfer function. The estimation of transfer function started with 2 number of pole and 1 number of zero and the last configuration was 3 the number of pole and zero. The most accurate estimation from this method is in third order by using 3 number of pole and 0 number of zero with 95.680% fit to estimation 0.0254 MSE, 0.025 FPE and 90.790% validation value. However, this mathematical model represents oscillation respond which will result in high response amplitude and longer settling time. Since the first method did not predict the desire mathematical model of the process, Nonlinear ARX estimation was used.

For nonlinear ARX, most of sequence of input and output term predicts the process model very well. Since all the sequence predicts the process model very well with the fit to estimation value and validation value is higher than 93%, the step responds of each prediction will be taken into account. The prediction with 2 number of input and 0 number of output term produced slowest settling time and take 800s to reach the steady state. The sequence of 2, 2 predict accurately the step respond with 300s to reach steady state and this value is same with the real situation in shell-and-tube heat exchanger model BDT921 plant. The mathematical model with nonlinear ARX method with sequence 2, 2 is selected to simulate the process in Simulink. Mulyana [18] also used nonlinear ARX estimation model to estimate the mathematical model of shell-and-tube heat exchanger.

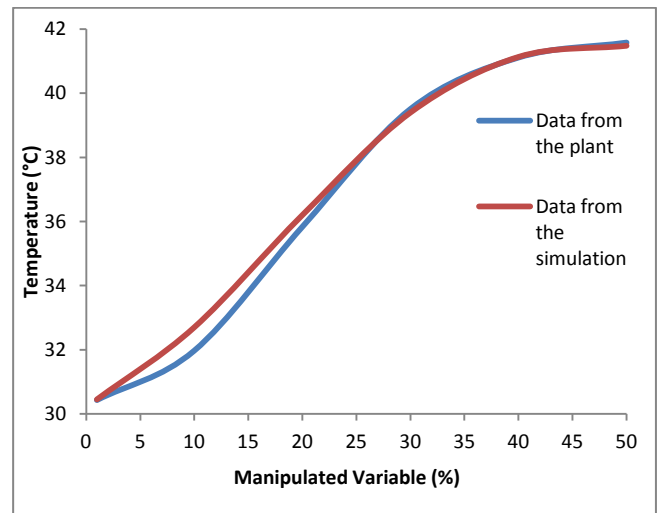


Figure 4: Comparison result between data from the plant and simulation data

To further validate the mathematical process model that was developed in the previous step using nonlinear ARX estimation, an open loop test was done in Simulink environment. The comparison

of outlet temperature was made between NARX and experimental data. Based on figure 4, the output temperature from the simulation is almost same as the output temperature from the plant.

C. Tuning parameter for the PID controller

Table 2: PID tuning parameter for various step change.

Tuning	K_p proportion al	K_i Integral	K_D Derivative	N Filter
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_p , K_i , K_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. For step up respond less than 5% from the previous set point, the value for K_p , K_i , and K_D was 28.260, 0.509 and 120.080. For step up respond less than 50% the value of K_p , K_i , and K_D was 6.480, 0.053 and 62.25 respectively. Meanwhile, for step up respond above 50% from the previous set point, the value for K_p , K_i , and K_D was 4.8, 0.035 and 34.92 respectively. Apart from that, for the step down respond less than 20% from the previous set point the value for K_p , K_i , and K_D was 5.8, 0.06 and 23.36 and lastly for the step down respond above 20% from the previous set point the value of K_p , K_i , and K_D was 6.480, 0.053 and 62.25. 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

Table 3: Number of neuron in hidden layer chosen.

Number of neuron in hidden layer	Mean Square Error (MSE %)	Regression (R %)
5	4.9320	0.9944
6	6.9370	0.9928
7	8.0910	0.9916
8	0.2124	0.9997
9	0.1008	0.9998
10	0.8854	0.9944
11	0.62780	0.9995
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

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 controller gain(K_p), integral(K_i), derivative(K_D) and filter (N). 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 5 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 this configuration 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 R is close to 1. This finding can be supported by Sharma and Venugopalan [19]. The author said 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 were change or disturbance appear in the system, the neural network will update the optimum PID controller parameter.

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

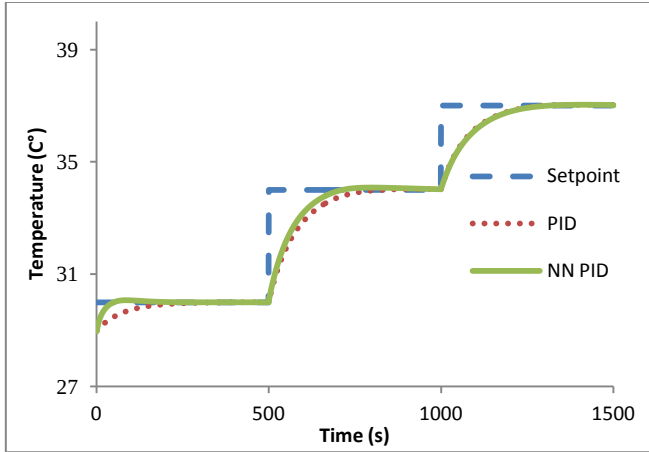


Figure 5: Comparison of Step Response between Conventional PID controller and Neural Network Based Adaptive PID controller (NN PID) on Shell- and-tube Heat Exchanger

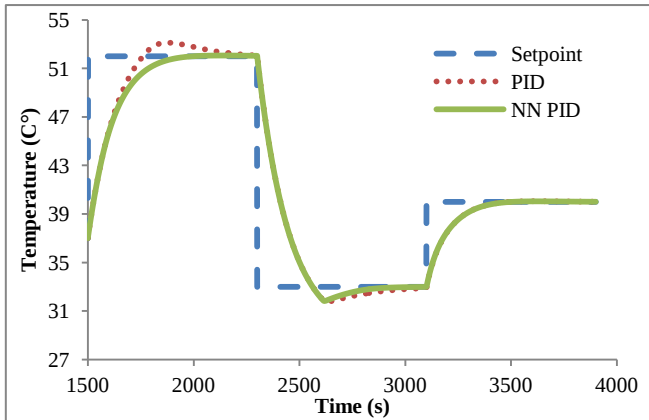


Figure 6: Comparison of Step Response between Conventional PID controller and Neural Network Based Adaptive PID controller (NN PID) on Shell- and-tube Heat Exchanger

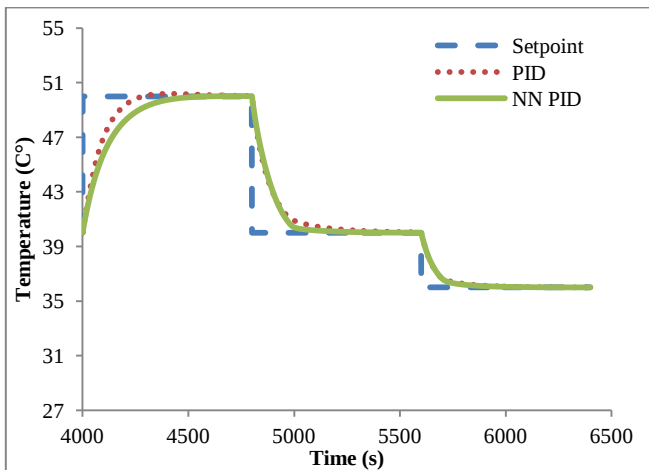


Figure 7: Comparison of Step Response between Conventional PID controller and Neural Network Based Adaptive PID controller (NN PID) on Shell- and-tube Heat Exchanger

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 5, 6 and 7. The controller parameter values use in conventional PID were 6.48,

0.053, 23.36 and 0.0654 for K_p (proportional), K_i (Integral), K_D (Derivative) and N (Filter) respectively. Based on figure 5, the set point were changes in every 500s for the range of temperature of 28 to 30°C, 30 to 34°C and 34 to 37°C. Based on the observation from the figure 5, 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.

From figure 6, 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 7, the step respond were done for every 800s. From the observation, 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 5 to 7, it can be concluded that the behavior of this controller did not have significant difference in lower percentage of set point change which is normally below than 50%. This condition happens because the process itself is slightly non linear condition and one optimum PID parameter was effective enough to control the process. However, when the aggressive set point change were made normally larger than 50% its, need several optimum PID parameter to give superior performance. From figure 5 to 7 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.

Varshney and Panigrahi [5] stated that neural network adaptive PID controller show faster response compared to PID controller with less steady state error.

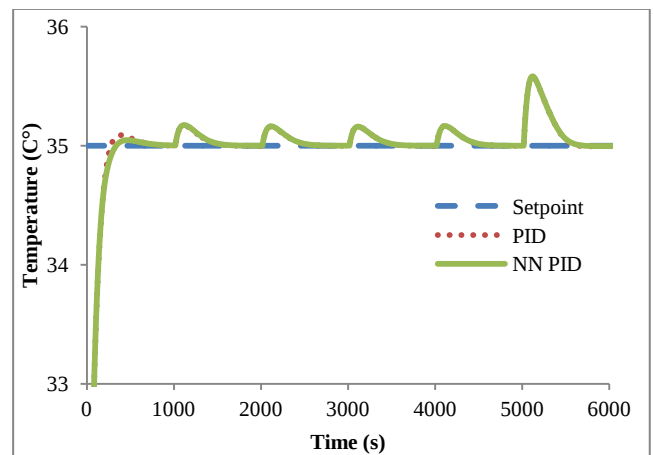


Figure 8: Comparison of disturbance rejection Between Conventional PID controller and Neural Network Based Adaptive PID controller (NN PID) on Shell- and-tube Heat Exchanger

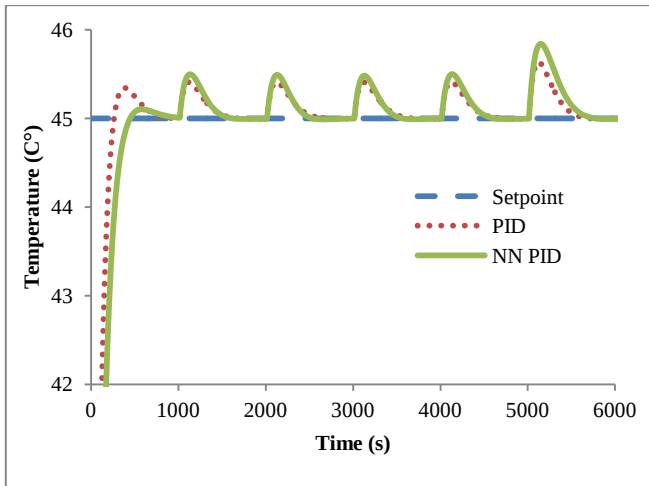


Figure 9: Comparison of disturbance rejection Between Conventional PID controller and Neural Network Based Adaptive PID controller (NN PID) on Shell- and-tube Heat Exchanger

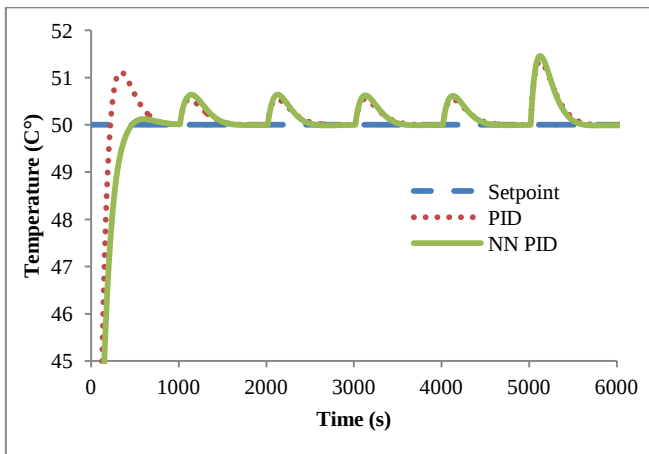


Figure 10: Comparison of disturbance rejection Between Conventional PID controller and Neural Network Based Adaptive PID controller (NN PID) on Shell- and-tube Heat Exchanger

Set point at 35, 45 and 50°C was selected in order to simulate the disturbance rejection behaviour of the controller. The controller parameter values use in conventional PID were 6.48, 0.053, 23.36 and 0.0654 for K_p (proportional), K_i (Integral), K_d (Derivative) and N (Filter). From figure 8 to figure 10, the disturbance was manually set by increasing the manipulated variable by 10% until 50% from the last stable value of the manipulated variable. The first peaks of the each graph represent the set point change condition. The disturbance rejection test started at peak number 2 for each graph. Based on the observation, both neural network adaptive PID controller and conventional PID controller were able to reject the disturbance and stabilize the process to the desire set point. Both controllers produces same settling time, however the neural network adaptive controller produce a higher overshoot condition at set point equal to 50 and 45°C. For the overall condition both controller produce same behaviour in disturbance rejection. This happen because of the temperature different between process output and set point are not larger, hence does not affect significantly the control system. This finding was contradicted from Riverol and Napolitano [8] which they stated that the neural network adaptive PID controller is effective for disturbance rejection.

IV. CONCLUSION

In this paper, nonlinear ARX method was used to estimate the mathematical model of nonlinear process with 2, 2 configurations have the 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 ability of neural network adaptive PID controller respond to set point changing was more effective with faster settling time and give a superior performance in tracking the set point change, thus give better result in controlling the process. However, both of the controllers scheme give same performance in disturbance rejection. In conclusion, the neural network PID controller is more effective to control the process in term of set point change compare to PID controller.

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