Internal Model Controller Using Neural Network for Shell and Tube Heat Exchangers

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Abstract— **In this research paper, a nonlinear internal model using neural network (NNIMC) is proposed to the shell and tube heat exchanger system. In past studies, PID controller is implemented in shell and tube heat exchanger, however it is exhibited high overshoot and long settling time. Therefore, NNIMC is introduced to improve the performances of PID controller. The manipulated variable of the controller is the flowrate of the hot fluid in the shell and the controlled variable is the outlet temperature of the cold fluid in the tubes. The addition of the neural network is to compensate time delay and ensures the offset performances. The control structure uses both a forward and an inverse neural network process model. The forward model is placed in parallel to the process model. The inverse neural model (INN) has two input which are previous flowrate and present temperature and one output which is present flowrate. After training for multiple times, one hidden layer INN model with 5 neurons is considered. The forward neural network (FNN) has two inputs which are previous flowrate and previous temperature and one output which is present temperature. After training for multiple times, one hidden layer with 7 neurons is considered. From simulation result, NNIMC outperforms PID controller as it exhibits no overshoot and less settling.**

Keywords— Internal model controller, neural network control, Shell and tube heat exchanger.

I. INTRODUCTION

There are many types of heat exchanger and the most common ones is shell and tube heat exchanger. Shell and tube heat exchanger builds up with nonlinear system that consists of uncertainty and robustness that leads to the uncertainty and disturbance(1). Therefore, designing controller that suitable for this nonlinearity to produce a good performance by minimizing overshoot and settling time is a challenging task until internal model controller is proposed into the system. Internal model controller can overcome the uncertainty and disturbance in the system because it has the good robustness as designed according to model of actual process(2). The main feature of this controller is designed of inverse model whereas the forward model is placed in parallel with the actual process as can limit the effect of error and disturbance that caused by model mismatch(3). Figure 1 shows the block diagram of internal model controller.

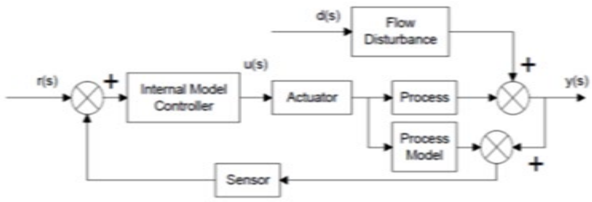

Fig. 1: Black diagram of internal model controller.

There are many controllers have been implemented into the shell and tube heat exchangers and Table 1 shows the performances of each controllers based on overshoot and settling time. Classical PID was first controller introduced into nonlinear system using Zieglar-Nichols tuning parameter to control the robustness(4). This past study resulted of high overshoot and slow settling time due to unsuitable Zieglar-Nichols to control dynamic process(2)(3)(5). Then, feedback plus feedforward controller is introduced to improve the performance of classical PID controller and found out it can reduce overshoot and took faster settling time than PID controller, however these results are undesired results(3) because the percentage of the overshoot is still considered as high. Therefore, to reduce the overshoot of the feedforward controller, fuzzy logic controller introduced to the system and resulted very little overshoot, however steady state value was slightly higher(6). Therefore, to improve the steady state value, internal model controller is introduced and found out it exhibit least overshoot, minimum settling time and lowest steady state value(2)(3)(7).

Table 1: Performance of controllers

Controller	Performances	
	Overshoot	Settling time
Classical PID	High overshoot	Slow settling time
Feedback plus feedfoward	Reduce overshoot in PID	Reduce settling time in PID
Fuzzy Logic	Very little overshoot	Shorter settling time but higher steady state
Internal Model	Least overshoot	Minimum settling time and lowest steady state.

Neural Network (NN) is added as adaptive system identification of the plant to be utilized in internal model control since it able to approximate nonlinear system(8) to improve the performance of internal model. Table 2 shows the past studies about neural network and its ability to estimate complicated process control system. In past, neural network is used to estimate polymer quality and found out neural network can improve model's robustness and accuracy(9). Neural network also implemented into a heat exchanger in closed flow air circuit using Back Propagation training algorithm and found out neural network can minimize set point and total energy consumption errors, also improve the intense abrupt oscillation caused in PID controller by decreasing oscillation period as it has higher speed of response and steady state error(10). Neural network also implemented into internal model controller as control strategy and proposed in SISO process in continuous stirred tank (CSTR) and pH neutralization process(11). It yielded fast response with very little overshoot, exhibited fast setpoint tracking by decreasing set point filter, able to reject the disturbance effectively by tuning down filter parameter. In pH neutralization process, it showed good tracking and produced fast response with least overshoot.

Internal model using neural network also applied to a level control of laboratory process and used Back Propagation to train neural network as at the end of research, found out it can reduce the tracking error into reasonable time and has smooth control action because neural network is suitable to estimate the filter gain in internal model control strategy(12). Besides that, internal model suing neural network also implemented on reduced scare prototype kiln at University Aveiro as at the end of research, found out it has a good control and can reduce disturbance's influences(13).

Table 2: Past Studies of Neural Network

Model / estimators	Aim	Performances
Neural network	To estimate quality polymers products(9).	• Improve model's robustness and accuracy. • Increase quality of polymers products.
Neural network control.	To control flow air circuit(10).	• Minimizing errors. • Decrease oscillation period. • High speed response.
Internal model control using neural network.	To determine its performance in CSTR. and pH neutralization(11).	• Fast response with very little overshoot. • Fast setpoint tracking. • Reject disturbance effectively.
Internal model control using neural network.	To control level in laboratory process(12).	• Reduce tracking error into reasonable time and smooth action control.
Internal model control using neural network.	To compare its performance with PID controller on reduced scale prototype at University of Aveiro(13).	• Good control and reduce disturbances. • Perform better than PID controller.

From all these past studies(8)(9)(10)(11)(12), neural network is best choice to be added as adaptive system identification as it can improve internal model performance. Even though neural network gives an excellent result when applied in many devices, however it is not yet applied on shell and tube heat exchanger. Therefore, we will work to find out the performance of this advanced internal model controller using neural network on the shell and tube heat exchanger system to control temperature.

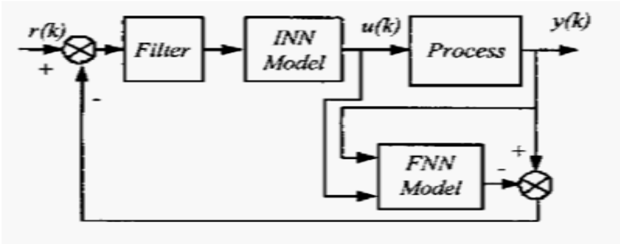

Fig. 2: Internal model Control with detail of the implementation of inverse and forward neural network model.

II. METHODOLOGY

In this research, the process dynamics are modelled from a step response by changing the hot fluid flow rate at different cold fluid inlet temperature. The controlled variable is the outlet temperature of cold fluid. The performance of IMC using neural network is based on rise time and settling time. The estimators used in the IMC is neural network. The design of NNIMC requires two steps where the first step is training a network to present the plant response to be used as the plant model in the control structure. The second step is training an inverse and forward neural network of plant to be used as the controller block in the control structure.

A. Determination of Variables

The variables associated with a shell and tube heat exchanger are flowrates and temperatures(7). The performance of IMC using neural network is based on overshoot percentage and settling time. Parameters are determined at Pilot Plant of UiTM Shah Alam.

Table 3: List of Variables

Variable	Properties
Manipulated variable	Flowrate of hot fluid
Controlled variable	Outlet Cold fluid temperature
Dependent Variable 1	Percentage of overshoot
Dependent Variable 2	Settling time

B. Modeling of Shell and Tube Heat Exchanger

Modeling shell and tube heat exchanger is conducted in MATLAB where the system identification application applied where time domain data used. The input is flowrate of hot fluid while the output is outlet cold fluid temperature. The starting time is 0s while the sample time is 0.03s. There are several estimation models used to model the plant which are transfer function model, process model and nonlinear model. The best estimation model between those three is determined.

C. Developing a Nonlinear Neural Network into Internal Model Controller.

Adapting neural network required training process. The neural network model development is conducted in Neural Network Toolbox (NNTOOL) that available in MATLAB where the dynamic time series is chosen. An Input-Output model is chosen and the Levenberg-Marquardt algorithm was used for training the both neural network because it can obtain lower mean squared errors than any other algorithms(14).

D. Development of Inverse Neural Network (INN) and Forward Neural Network (FNN).

The training of both neural networks are important components of the control methodology using feedforward model. The FNN model is trained first as its output consist of the present process variable and previous process variables as the input. The model used two inputs which are previous flowrate, F_{i-1} and previous temperature, T_{i-1}. The output is the present temperature, T_i. Figure 3 shows the feedforward model of FNN.

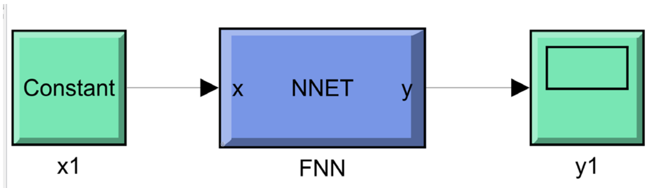

Fig. 3: Feedforward FNN model.

Then, INN model is trained as its output consists of present and previous variables and present variable as output. The model used two inputs which are previous flowrate, F_{i-1} and present temperature, T_i. The output is present flowrate, F_i. Figure 4 shows the feedforward model of INN.

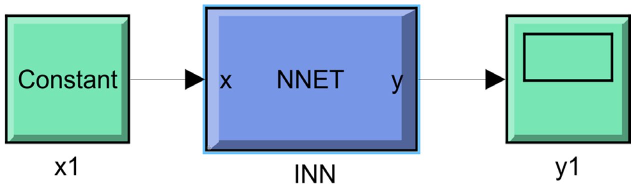

Fig. 4: Feedforward INN model

E. Internal Model Control Strategy for Neural Network Model.

After training for both neural network, the general structure of neural network structure for internal model control is conducted in Simulink. Figure 5 represents the Simulink modelling of internal control using neural network model of shell and tube heat exchanger.

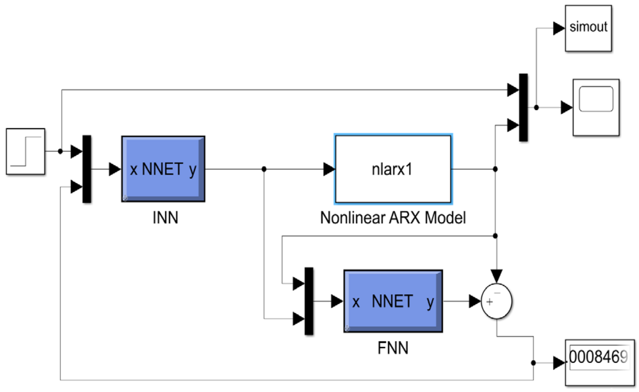

Fig. 5: Simulink Model of Shell and Tube Heat Exchanger with Internal Model Using Neural Network.

F. Set point Test.

Internal model controller is then, tested its performance with set point test to capture the dynamic behavior of the controller. The internal model controller using neural network is developed and the control loop performance is tested.

G. PID Tuning

Tuning of PID control is done mathematically and tuning the controller to give the best match of controller/model. Table 4 shows the tuning of PID parameter as the performance of internal model using neural network is determined and value of Kp, τ, and θ. The method used is IMC-based PID tuning.

Table 4: Tuning of PID parameter

Variable	Properties
G(s)	$\frac{Ke^{-\theta s}}{\tau_s+1}$
Kp	$\frac{\Delta PV}{\Delta MV}$
τ	$(63.2\%\ of\ \Delta MV)-\theta$
θ	Time delay
τ_c	$\frac{\tau}{3}$
Kc	$\frac{1}{Kp}\frac{\tau+\frac{\theta}{2}}{\tau_c+\frac{\theta}{2}}$
τ_I	$\tau+\frac{\theta}{2}$
τ_D	$\frac{\tau\theta}{2\tau+\theta}$

III. RESULTS AND DISCUSSION

A. ARX Nonlinear Model of Plant

Transfer function model, process model and nonlinear model are considered to model the process. Table 5 shows the estimation summary of these three models output and found out nonlinear ARX model gives the highest percent of best fit to the process. This result is obtained because shell and tube heat exchanger has nonlinear process. Therefore, nonlinear model gives the best result and used as estimation model the process.

Table 5: Estimation summary of Nonlinear ARX, Transfer function and Process model

Parameter	Nonlinear ARX model	Transfer function model	Process model
Fit (%)	94.89	68.41	-312
Loss Function	$3.274e^{-5}$	1.360	231.3

B. Inverse Neural Network in Internal Model Control

The internal model control based on INN was applied and after training for multiple times, one hidden layer INN model with 5 neurons is considered because it gives best result when being tested with the data experiment. The activation function is Levenberg-Marquardt algorithm. Result of the training is tabled in Table 6 where the MSE of training, validation and testing recorded.

Table 6: MSE Result of Training INN

Training	$1.4720e^{-8}$
Validation	$1.89020e^{-11}$
Testing	$7.35585e^{-11}$

C. Forward Neural Network in Internal Model Control

The internal model control based on FNN was applied and after training for multiple times, one hidden layer FNN model with 7 neurons is considered because it gives best result when being tested with the data experiment. The activation function is Levenberg-Marquardt algorithm. Result of the training is tabled in Table 7 where the MSE of training, validation and testing recorded.

Table 7: MSE Result of Training FNN

Training	$4.88102e^{-8}$
Validation	$4.80474e^{-8}$
Testing	$4.2927e^{-8}$

D. Internal Model Control Strategy for Neural Network Model.

Figure 6 shows the step response of internal model using neural network. From the figure, the internal model reached the set point without exhibit overshoot. This is very impressive performance because it can control the robustness and nonlinearity of shell and tube heat exchanger system as stated by past study found that implementation of internal model controller in process control can limit the effect of error and disturbance that caused by model mismatch(3).

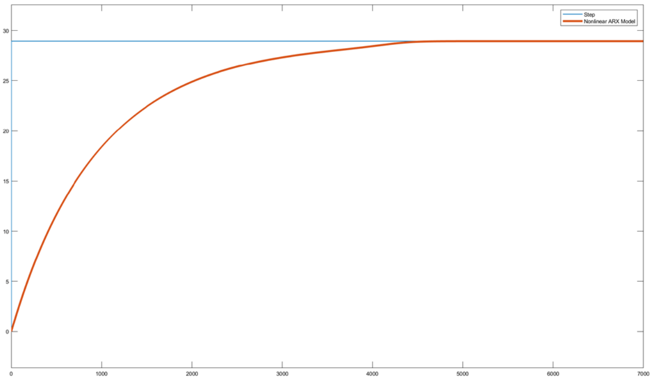

Fig. 6: Step Response of Shell and Tube Heat Exchanger with Internal Model Using Neural Network.

As internal model control using neural network can reduce the overshoot in shell and heat exchanger, then this controller is also tested its performance of reducing the settling time by compared with the performance of PID controller. Figure 7 shows the performance of both controllers. From the figure below, both of the controllers are reached their setpoint with difference of percentage of overshoot and settling time. Internal model controller using neural network performs better than PID controller as it committed zero percentage of overshoot (%) and lower settling time.

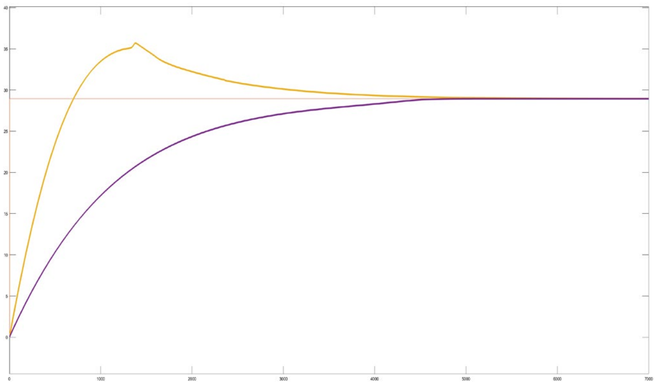

Fig. 7: Step Response of Shell and Tube Heat Exchanger with PID Controller and Internal Model Using Neural Network.

Table 8 shows the result of comparative step response of PID controller and internal model control using neural network. From simulation result, PID controller gives high overshoot of 23.87%. and NNIMC gives very excellent result as it reduces the overshoot to 0%. Besides that, it also improves the settling time in PID controller by reducing it from 5636s to 4868s. Therefore, the NNIMC outperforms PID controller as it exhibits no overshoot and less settling where this result is also proven by (15),(16),(17).

Table 8: Comparative Study of parameter of PIC controller and Internal Model Control using Neural Network

Controller	Overshoot (%)	Settling time (s)
PID controller	23.87	5636
IMC with NN	0	4868

E. Set point test

Tuning of PID controller had done mathematically to match with the model. Figure 8 shows the Simulink model for set point test after tuning and Table 9 shows the tuning of PID controller values.

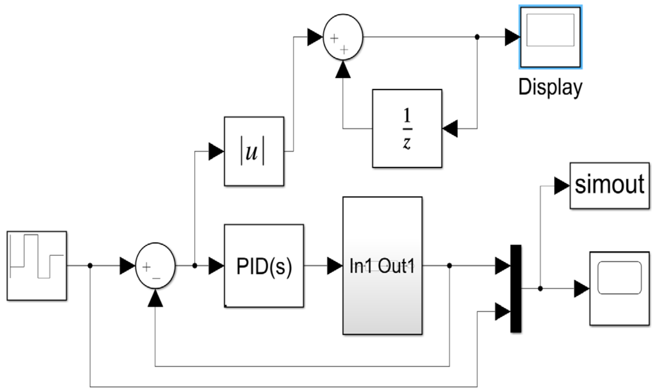

Fig. 8: Simulink Model PID controller with Internal Model Using Neural Network as subsystem.

Table 9: Tuning PID values

P	0.23556258
I	0.00023103
D	0

There are two type of set point test are done which are increasing of set points in Figure 9 and increasing and decreasing set points in Figure 10. Figure 9 shows the step response of PID controller in internal model using neural network (subsystem) with the set point sequences of 10, 15, 20 and 30. From the figure, the controller gives good performance as it reached each of the set points in 4868s of settling time with no overshoot. Figure 10 shows the step response of PID controller in internal model using neural network (subsystem) with set points sequences of 10, 25, 5 and 15. From the figure, the controller gives a good dynamic behavior as it reached each set.

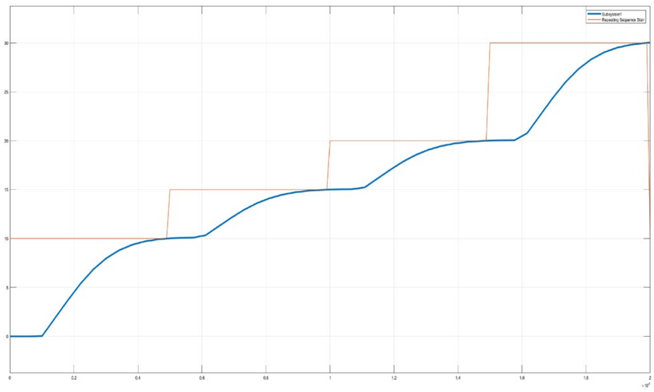

Fig. 9: Simulink Model of PID controller with Internal Model Using Neural Network with set point sequences of 10, 15, 20 and 30.

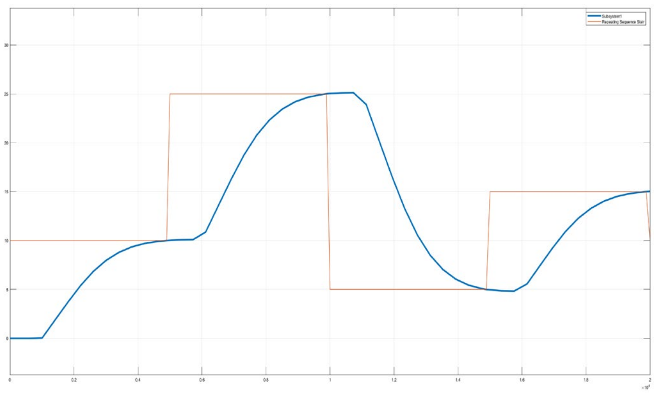

Fig. 10: Simulink Model of PID controller with Internal Model Using Neural Network with set point sequences of 10, 25, 5 and 15.

IV. CONCLUSION

This research is proposed internal model control using neural network in shell and tube heat exchanger. The proposed strategy was applied to determine the process dynamics that are modelled from a step response by changing the cold flow rate at different hot fluid inlet temperature. There are two neural network model are used which are inverse neural network and forward neural network. Neural network model with 5 neurons is considered while forward neural network with 7 neurons. The process is modelled with ARX Nonlinear model. In the way to know the performance of this controller, a comparison study with PID controller has been presented. From the simulation result, the internal model control with neural network leads to better result to control the outlet fluid temperature as it exhibits no overshoot and less settling compared to PID controller. Therefore, this proposed controller is works in shell and tube heat exchanger.

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