Control Modelling of Coupled Shell and Tube Heat Exchangers using Combined Neural Network and Fuzzy Logic

Moses Omolayo Petinrin[1,*], Olusola Samuel Oke[1], Adedayo Samuel Adebayo[1], Olumide Adewole Towoju[2] and Olawale Saheed Ismail[1]

[1]*Department of Mechanical Engineering, University of Ibadan, Ibadan, Nigeria*
[2]*Department of Mechanical Engineering, Lead City University, Ibadan, Nigeria*

[*]*(layopet01@yahoo.com) Email of the corresponding author*

Abstract – Control of the temperature of the outlet fluid in heat exchanger network is very important to maintain safety of equipment and meet the optimal process requirement. Conventional PID controllers have the limitations of meeting up with wide range of precision temperature control requirements, and then the predictive controllers have recently emerged as promising alternatives for advanced process control in heat exchanger systems and other industrial applications. This paper focuses on the control of output temperature of coupled shell and tube heat exchanger by combining fuzzy logic and Neural Network control system. To achieve effective control, transfer functions from the energy balance equations of the heat exchanger unit and other components were obtained. Simulation of the control process was carried out using Simulink interface of MATLAB. The time response analysis in comparison with variants of conventional PID controllers shows that combination of Neural Network and fuzzy logic controllers can efficiently improve the performance of the shell and tube heat exchanger system while in with 0.505% overshoot and less settling time of 12.74 s, and in parallel with the same overshoot of 0.505% and settling time of 11.37 s. The demonstration of the lower error indices of the neuro-fuzzy controlled system also indicated its better performance.

Keywords – Neural network, fuzzy logic, PID controller, feedforward, heat exchanger

I. INTRODUCTION

Heat exchangers are extensively utilized in industrial processes, such as in the medical applications, manufacturing, power generation, chemical processes and HVAC systems, for transferring of heat energy between the fluids at varying temperatures [1]–[3]. The shell and tube heat exchangers are the most frequently used among the heat exchangers for their wide range of operating temperatures and pressures, effective functionality at high pressure, and easy disassembly for periodic cleaning and maintenance [4]. Modeling and controlling the heat exchanger's dynamics are challenging because of its high nonlinearity and poor dynamics [5]. However, to achieve the system's maximum efficiency, designing of heat exchangers with the application of appropriate control strategies are required [6].

The challenging task of designing a controller for any regulatory or servo problem rests on many factors. Such factors are not limited to the measurement noise, process uncertainty and robustness of system, and combine with an accurate mathematical model required to design a controller. Regardless of equipment saturation, nonlinearity, process and load disturbances, and other factors, the controller quickly adjusts the temperature of the outgoing fluid to the required set point [5],[7]. In the literature, several techniques have been used to design control systems for heat exchangers. These techniques have been used to devise controllers ranging from the conventional proportional-integral-derivative (PID) to the more sophisticated controllers utilizing artificial intelligence [6].

Over the years, there have been a few improvements in heat exchanger controller design. The proportional-integral (PI) and proportional-integral-derivative (PID) controllers enjoy great popularity and are most frequently used in industrial applications due to their simple design, inexpensive price, and ease of maintenance, as well as their reliable performance across a wide operating range [8],[9]. According to Kishore et al. [10], PID controllers combine the advantages of proportional, integral and derivative control action. These are mostly used controllers in industries such as in the power stations, chemical and petrochemical, robotics, and so on. However, the PID controllers are characterized with large inertia and lag appeared by using PID controller which could not regulate with variation of the object [5]. Undesired excessive overshoot is exhibited by PID controllers. A feed forward controller and a feedback controller are both used to decrease overshoot and improve control performance. In comparison to the feedback PID controller, the combined effect of feed forward and feedback control systems produces a comparatively better performance.

There are numerous soft computing-based intelligent tuning controllers available in addition to traditional controller tuning methods like PI and PID controllers. A class of control systems known as intelligent controllers makes use of artificial intelligence computing techniques such as fuzzy logic, neural networks, genetic algorithms, reinforcement learning and machine learning. According to Naik et al. [11], neural network (NN) controllers are employed primarily when control issues are non-linear in nature. Before a neural network can be used as a controller, it must first learn the model of the plant. Guaranteed closed-loop performance in terms of small tracking errors and constrained controls is provided by the NN controller design. The NN learns on-line in real-time using NN controller structures since they do not require any off-line learning prior to initializing the NN weights. In contrast to adaptive control, there is no requirement to find a regression matrix, and there is also no assumption of certainty equivalence [12]. Tamilselvan et al. [13] examined the response of various controllers to manage the output temperature of hot fluid to a desired set point within the heat. Their results showed that the MPC performed better than PI and PID because it rejects external disturbances with a moderate oscillation and shorter stabilization time. Charan et al. [14] developed an artificial neural network-based self-tuned PID controller for a heat exchanging unit, which functioned in the presence of disturbances.

Also, fuzzy logic has been widely adopted in the control domain owing to its improved performance in minimizing overshoot and its ability to generate precise solution [15]. Using linguistic data from human experts, fuzzy systems have been shown to offer a framework for handling imprecision uncertainty [16]. Fuzzy systems' universal approximation property is frequently utilized in many fields, especially nonlinear modeling and robust control systems. The flexibility and ability of fuzzy logic systems to accept adjustments, along with their ease of construction, make them advantageous for solving complicated problems. Jamal and Syahputra [17] investigated a heat exchanger thermal control system that makes use of artificial intelligence. The heat exchanger was subjected to fuzzy logic control to maintain a constant temperature in the combined fluid. The results indicated that the fuzzy logic control effectively maintain the heat exchangers' temperature. Neethu et al. [2] employed a fuzzy controller and a neural network controller with an auxiliary controlled variable in their study to control a tubular heat exchanger. In comparison to traditional PID control, neural network and fuzzy control, their findings demonstrated the effectiveness and superiority of integrating the neural network predictive controller with the auxiliary fuzzy controller.

This paper is focused on a model that combines the application of artificial neural network and fuzzy logic controller for simultaneous temperature control of couple of two shell and tube heat exchangers in series and parallel using the Simulink toolbox of MATLAB. The series combination of heat exchangers have the advantage of preventing temperature cross while the parallel arrangement helps in keeping the pressure drop within tolerable limit [18]. The time response analysis of the control system will be explored and error indices parameters such as the integrated absolute error (IAE), integrated square error (ISE), integrated time absolute error (ITAE) and integrated time square error (ITSE) will be used to evaluate the performance of the system in comparison with the variants of PID controllers.

II. METHODOLOGY

The neural network controller and fuzzy logic controlled heat exchanger system was designed, simulated using the Simulink interface of MATLAB, and its performance is compared with various PID controller plant models.

A. Heat Exchanger Design

The energy balance equation for the tube-side and shell-side of a counter-current shell and tube heat exchanger are respectively given by Ogunnaike and Ray (1994)

$$m_t c_t \frac{dT_t(x,t)}{dt} = \dot{m}_t c_t \left[T_t(0,t) - T_t(x,t)\right] - UA\left[T_s(t) - T_t(x,t)\right] \quad (1)$$

$$m_s c_s \frac{dT_s(x,t)}{dt} = \dot{m}_s c_s \left[T_s(0,t) - T_s(x,t)\right] - UA\left[T_s(t) - T_t(x,t)\right] \quad (2)$$

The first order plus time delay process (FOPTD) was used to approximate the nonlinear dynamic system with the properties of the working fluids as indicated in Table 1 to obtain the transfer functions of the heat exchanger. Thus, the transfer functions of each unit of the control system as obtained from the governing equation of each component are as presented in Table 2.

Table 1: The heat exchanger parameters [19]

	T_{in} (K)	T_{out} (K)	$\dot{m}$ (kg)	ρ (kg/m^3)	c_p (J/kgK)	v (m/s)	h (W/m^{2}K)	Δp (Pa)
Tube-side	288	298	31.6	998	4180	1.11	4087	7706
Shell-side	371	338	14.9	777	2684	1.16	1308	7000

Table 2: The transfer functions of the heat exchanger control model

Unit / Element	Transfer Function
Thermocouple	$G_{tc}(s) = \frac{0.13}{10s+1}$
Temperature disturbance	$G_d(s) = 0.91e^{-4.4s}$
Control Valve	$G_{cv}(s) = \frac{0.13}{3s+1}$
Single Heat Exchanger	$G(s) = \frac{1-0.91e^{-4.4s}}{44.42s+1}$

B. The Heat Exchanger Control Model

The desired temperature output at the set point is connected directly to the fuzzy logic controller. Fuzzy logic controller takes both error and derivative of error between the set point and the process output as its inputs and based on predefined rules gives out the appropriate valve control action. Output of fuzzy logic goes directly to the valve (actuator) block, the valve block links directly to the process (heat exchanger). For feedback loop, the output of heat exchanger is measured by the thermometer and feed to the sum block, as a form of iteration this process is iterated for a defined time (200 s). The neural network (feedforward) controller receives the measured temperature output and disturbance as input and its predicted output goes to the sum block to determine the necessary valve control action to take to regulate the effect of the disturbance as illustrated in Fig. 1.

C. Designing of the Fuzzy Logic Controller

The processing structure of fuzzy logic control scheme is framed in terms of fuzzification, inference and defuzzification modules [5]. The fuzzy controller was designed with the mamdani based fuzzy inference system having two input variables; that is, the error and rate of error variables, and one output variable. The triangular membership functions were selected for both the input variables output variable.

Fuzzification converts a numerical error, rate of change of error, and valve control value into a linguistic value viz. Negative (N), Zero (Z), or Positive (P), together with a membership grade. Fuzzy "if-then" logic and fuzzy reasoning are primarily used throughout the entire decision-making process to illustrate the connection between inputs and outputs. The "if-then" statements are used in the inference system, together with "or" and "and" connectors [20]. Defuzzification produces a "crisp" numeric number from the fuzzy output of the rules that is utilized as the control input to the plant. Fig. 2 illustrates a fuzzy logic controller with the rule viewer.

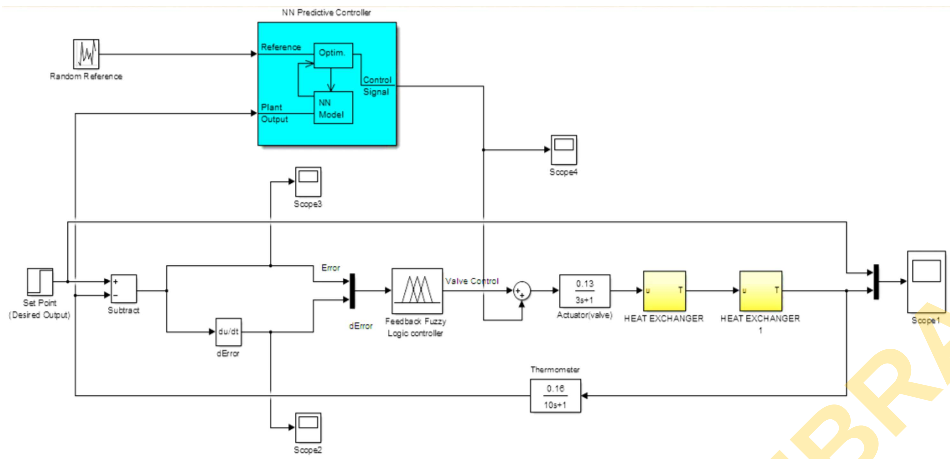

Fig. 1. Control diagram of coupled shell and tube heat exchangers in series with neural network and fuzzy controller

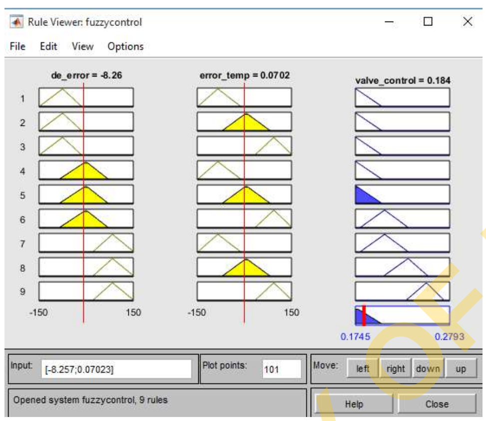

Fig. 2. Fuzzy logic controller with rule viewer

D. Design of the Neural Network Controller

The neural network controller architecture is made up of the input, hidden and output layers, which contain 2 neurons, 7 neurons and 1 neuron, respectively. The Tansig and Purelin transfer functions were used in the construction of the controller setup's hidden and output layers, respectively. The Levenberg-Marquardt algorithm was chosen as the optimisation subroutine for training the network using the random input and output data from the plant model. The network was trained by varying some predictive parameters until the desired output of the plant model was achieved. The cost and control horizons, control weighting factor, and search parameter were all eventually set at 7, 2, 0.05, and 0.001 accordingly.

E. Performance Parameters

The error indices used in evaluating the performance of the controllers are the integrated absolute error (IAE), integrated square error (ISE), integrated time absolute error (ITAE) and integrated time square error (ITSE), and they are obtained as indicated in equations 3 – 6.

$$\text{IAE} = \int_0^{\infty} |e(t)|\,\partial t \qquad (3)$$

$$\text{ISE} = \int_0^{\infty} e^2(t)\,\partial t \qquad (4)$$

$$\text{ITAE} = \int_0^{\infty} t\,|e(t)|\,\partial t \qquad (5)$$

$$\text{ITSE} = \int_0^{\infty} te^2(t)\,\partial t \qquad (6)$$

III. RESULTS AND DISCUSSION

In comparison of control system results using series connections of heat exchangers, it can be observed from Table 3 that application of neuro-fuzzy controller produced no significant overshoot (0.505%), though the rise time (80.33 s) is higher when compared to what was produced by other controllers. Likewise, the settling time (12.74 s) for neuro-fuzzy controller is considerably lower than what was generated by other controllers used in comparison. Interestingly, PI plus feedforward controlled system has the lowest rise time of 28.38 s. Whereas, as presented in Table 4, for the parallel connection of heat exchangers, the neuro-fuzzy controller shares the same overshoot of 0.505% with

PI and PIDF controllers, having less settling time of 11.37 s but with rise time of 113.48 s.

Table 3. Transient response of the controllers for series arrangement of heat exchangers

Controller	Rise time (s)	Settling time (s)	Overshoot (%)
PI	70.34	102.46	10.345
PIDF	65.83	123.22	10.565
PI + feedforward	28.38	162.45	41.282
PIDF + feedforward	40.83	53.46	20.385
Neural network + Fuzzy logic	80.33	12.74	0.505

Table 4. Transient response of the controllers for parallel arrangement of heat exchangers

Controller	Rise time (s)	Settling time (s)	Overshoot (%)
PI	39.84	62.77	0.505
PIDF	30.92	146.47	0.505
PI + feedforward	2.63	143.26	41.280
PIDF + feedforward	0.26	153.82	16.060
Neural network + Fuzzy logic	113.48	11.37	0.505

From the error responses of all the controllers as summarized in Tables 5 and 6, it is observed that neuro-fuzzy controller has the lowest error value for all the error indices considered. Low error index is an indicator of better performance of neuro-fuzzy controller when compared with other controllers.

Table 5. Error indices of the controllers for series arrangement of heat exchangers

Controller	IAE	ITAE	ISE	ITSE
PI	68.7	4.563e+04	94.9	7.525e+04
PIDF	72.5	6.638+04	87.6	5.12e+04
PI + feedforward	95.45	8.212e+04	82.48	4.56 +04
PIDF + feedforward	82.51	7.534e+04	74.56	4.485e+04
Neural network + Fuzzy logic	54.23	2.473e+04	54.24	3.512e+04

Table 6. Error indices of the controllers for parallel arrangement of heat exchangers

Controller	IAE	ITAE	ISE	ITSE
PI	116.70	6.433e+04	144.90	8.335e+04
PIDF	135.70	7.551+04	197.70	1.150e+04
PI + feedforward	82.69	4.216e+04	72.35	3.575e+04
PIDF + feedforward	77.27	4.114e+04	63.24	3.404e+04
Neural network + Fuzzy logic	86.09	4.537e+04	78.34	4.128e+04

IV. CONCLUSION

In this study, the temperature control model of coupled shell and tube heat exchanger systems in series and parallel were carried out using the combined neural network and fuzzy logic control system and compared with variant of PID controllers. The transient characteristics and error indices are used to evaluate the performances of different controllers.

Simulation results showed that the combined neural network controller and fuzzy logic controller are stable and performs better than well-known classical PID control approaches. The combined neural network and fuzzy logic control system drastically decreases overshoot and has a controllable settling time compared to the traditional PID controller, which exhibits a larger degree of overshoot and settling time. The hybrid neural network and fuzzy logic control system produced lower values of IAE and ISE for both the series and parallel connections of heat exchangers, which confirms its superiority over the traditional PID controller and ease of use when comparing set point tracking using IAE and ISE values.

V. REFERENCES

[1] A. Vasičkaninová and M. Bakosova, “Control of a heat exchanger using neural network predictive controller combined with auxiliary fuzzy controller,” *Appl. Therm. Eng.*, pp. 1–8, 2015, doi: 10.1016/j.applthermaleng.2015.02.063.

[2] T. R. Neethu, P. Kalaichelvi, and V. Vetriselvi, “Control of a heat exchanger using neural network predictive controller combined with auxiliary fuzzy controller,” *Int. J. Instrum. Control Syst.*, vol. 8, no. 2, pp. 11–17, 2018.

[3] J. Richalet, T. Darure, and J. Mallet, "Predictive functional control of counter current heat exchangers," in *19th IFAC World Congress*, 2014, vol. 47, no. August 24-29, pp. 5345–5350. doi: 10.3182/20140824-6-ZA-1003.02828.

[4] D. Bogale, "Design and Development of Shell and Tube Heat Exchanger for Harar Brewery Company Pasteurizer Application (Mechanical and Thermal Design)," *Am. J. Eng. Res.*, vol. 3, no. 10, pp. 99–109, 2014.

[5] A. A. A. Emhemed, A. Alsseid, and D. Hanafi, "Modelling and Controller Design for Temperature Control of Power Plant Heat Exchanger," *Univers. J. Control Autom.*, vol. 5, no. 3, pp. 49–53, 2017, doi: 10.13189/ujca.2017.050302.

[6] J. García-Morales, M. Cervantes-Bobadilla, J. A. Hernandez-Perez, Y. I. Saavedra-Benítez, M. Adam-Medina, and G. V. Guerrero-Ramírez, "Inverse artificial neural network control design for a double tube heat exchanger," *Case Stud. Therm. Eng.*, vol. 34, no. 102075, pp. 1–12, 2022, doi: 10.1016/j.csite.2022.102075.

[7] A. Sahoo, T. K. Radhakrishnan, and C. S. Rao, "Modeling and control of a real time shell and tube heat exchanger," *Resour. Technol.*, vol. 3, pp. 124–132, 2017, doi: 10.1016/j.reffit.2016.12.001.

[8] A. Panbude and M. Sharma, "Implementation of Neural Network for PID Controller," *Int. J. Comput. Appl.*, vol. 2, pp. 31–34, 2015.

[9] R. Zhang, S. Wu, and F. Gao, "Improved PI controller based on predictive functional control for liquid level regulation in a coke fractionation tower," *J. Process Control*, vol. 24, pp. 125–132, 2014, doi: 10.1016/j.jprocont.2014.01.004.

[10] D. Kishore, G. Jalalu, A. Sumalatha, and K. Prasanti, "Control of Heat Exchanger Using Hybrid Fuzzy-Pi," *Int. J. Eng. Res. Appl.*, vol. 3, no. 7, pp. 9–15, 2013.

[11] R. Naik, Suraksha, V. A. Bhat, N. Rao, and R. Rao, "Review of Speed Control of DC Motor using Various Controllers," *Int. J. Recent Res. Asp.*, vol. Special Is, pp. 76–79, 2018.

[12] A. Singh and S. S. Sehgal, "Thermohydraulic Analysis of Shell-and-Tube Heat Exchanger with Segmental Baffles," *ISRN Chem. Eng.*, pp. 1–5, 2013, doi: 10.1155/2013/548676.

[13] M. Tamilselvan, N. Thirumarimurugan, and E. S. Manikandan, "Study on various control strategies of plate type heat exchanger for non - Newtonian fluids," *J. Ambient Intell. Humaniz. Comput.*, vol. 12, pp. 7253–7261, 2021, doi: 10.1007/s12652-020-02401-4.

[14] G. Charan, D. Sampath, R. S. Rao, and Y. P. Kumar, "ANN-based self-tuned PID controller for temperature control of heat exchanger," in *Research and Applications in Artificial Intelligence*, 2021, pp. 149–161.

[15] N. Srivastava, D. K. Tanti, and M. A. Ahmad, "MATLAB simulation of temperature control of heat exchanger using different controllers," *Autom. Control Intell. Syst.*, vol. 2, no. 1, pp. 1–5, 2014.

[16] B. P. Kumar, J. Manoj, M. F. Qureshi, and G. K. Agrawal, "Intelligent Optimal Control of a Heat Exchanger using ANFIS and Interval Type-2 Based Fuzzy Inference System," *Int. J. Innov. Res. Sci. Eng. Technol.*, vol. 3, no. 9, pp. 6072–16082, 2014, doi: 10.15680/ijirset.2014.0309042.

[17] A. Jamal and R. Syahputra, "Heat exchanger control based on artificial intelligence approach," *Int. J. Eng. Res.*, vol. 11, no. 16, pp. 9063–9069, 2016.

[18] A. Mangal, "Optimize heat exchanger installations," *Hydrocarb. Process. (International ed.)*, vol. 89, no. 12, pp. 53–56, 2010.

[19] M. A. Ravagnani, A. P. Silva, and C. A. Jose, "Optimal Shell and Tube Heat Exchangers Design," *Heat Anal. Thermodyn. Eff.*, vol. 129, 2011.

[20] D. Strusnik and J. Avsec, "Artificial neural networking and fuzzy logic exergy controlling model of combined heat and power system in thermal power plant," *Energy*, vol. 80, pp. 318–330, 2015, doi: 10.1016/j.energy.2014.11.074.