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Research paper

Modelling of Two Continuous Stirred Tank Heat Exchangers in Series Using Neural Network

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Abstract

This paper presents the application of artificial neural networks (ANN) in modeling of two continuous stirred tank heat echangers in series (2CSTHEs), which is a complex non-linear process. Non-linear models of the 2CSTHEs system were developed using ANN because of ANN ability to model complex non-linear processes without requiring any explicit knowledge about input-output relationship. The ANN architecture is based on the multilayer feed forward network and it is trained using the back-propagation algorithms. Three types of back-propagation algorithms are used in the study, namely, Levenberg-Marquardt, BFGS quasi-Newton, and conjugate gradient with Polak-Ribiére updates. Two dynamic models of the system are developed: ANN model for CSTHE 1and 2. Results from the study showed that the 2CSTHEs model trained using Levenberg-Marquardt algorithm produced the best predictive performance of the system behaviour. The results confirmed that ANN can be used in the modeling of the heat exchanger 2CSTHEs, and the model obtained can predict the outputs of the system process with very high accuracy. This proves that ANN modelling method can produce accurate system models that can simulate and predict the behaviour of complex non-linear processes.

Keyword: *CSTHE; data generation; heat exchanger; modelling; neural network*

1. Introduction

Heat exchangers (HEs) are devices facilitating effective heat transfer between the two fluids by virtue of their temperature differences and widely used in engineering applications [1]. HEs are extremely complex devices for which the prediction of their operation from first principle is virtually impossible due to a large number of phenomena associated with flow and heat transfer [2]. Heat exchangers are essentially non-linear in behaviour and can be difficult to control effectively. Consequently, accurate prediction of the steady-state and dynamic performance of heat exchangers is vitally important for optimum system design and heat recovery. Among empirical models, artificial neural networks (ANNs) seem to be the most powerful mathematical tool to solve this modelling problem [3]. Artificial intelligence techniques like ANN are widely accepted as a technique that is able to deal with non-linear problem, and once trained can perform prediction and generalization at high speed [4]. ANNs were extensively used in modelling of thermal systems for the purpose of heat transfer analysis, performance prediction and dynamic control of heat exchangers [5,6,7]. The objective of this study is to develop ANN models to predict the temperatures and levels of two simulated CSTHEs in series (2CSTHEs). These two predicted variables can be utilized for controlling the temperatures and levels of the process in this case study.

2. Methodology

2.1 Mathematical model of 2CSTHEs

The 2CSTHEs system as shown in Fig. 1, including the system design parameters, is adopted from [8]. Values for the parameters used in the equations are tabulated in Table 1. The mathematical model of the system based on the conservation of heat and mass principle are as follows:

$$A_1 \frac{dh_1(t)}{dt} = f_1(t) + f_4(t) - f_2(t) \tag{1}$$

$$Ah_1 \frac{dT_1}{dt} = (f_1(t)(T_0(t) - T_1(t)) + f_4(t)(T_2(t) - T_1(t)) + \frac{UA_{c1}(T_{st1}(t) - T_1(t))}{C_p\rho} \tag{2}$$

$$C_M \frac{dT_{st1}(t)}{dt} = \lambda w(t) - UA_{C1}(T_{st1}(t) - T(t)) \tag{3}$$

$$A_2 \frac{dh_2(t)}{dt} = f_2(t) + f_3(t) - f_4(t) \tag{4}$$

$$Ah_2 \frac{dT_2}{dt} = (f_2(t)(T_1(t) - T_2(t))) + \frac{UA_{C2}(T_{st2}(t) - T_2(t))}{C_p\rho} \tag{5}$$

$$C_M \frac{dT_{st2}(t)}{dt} = \lambda w_2(t) - UA_{C2}(T_{st2}(t) - T_2(t)) \tag{6}$$

The input and output data are generated from the open loop model of the 2CSTHEs in dynamic state. Data generation is implemented using the MATLAB Simulink software. Simulink block diagrams of the open loop process for 2CSTHEs are built according to the Eqs. (1) to (6) as shown in Fig. 2 and 3.

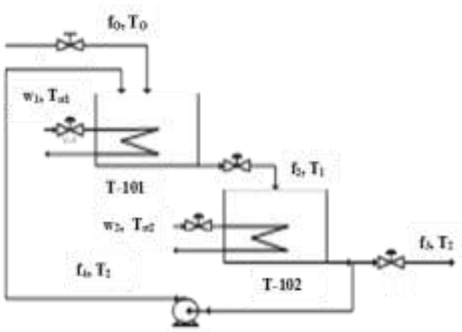

Fig. 1: Two Stirred Tank Heat Exchanger in Series

TABLE 1: Parameter values for CSTHE system

Parameter	Meaning	Value
A	Tannk cross section area	0.196 m^2
UAc_1	Heat transfer term x Effective heat transfer area of coil	12.52 $kJ/kg.m^3$
UAc_2	Heat transfer term x Effective heat transfer area of coil	98.21 $kJ/kg.m^3$
λ	Latent heat of vaporization of steam	2260 kJ/kg
ρ	Water density	1000 kg/m^3
C_p	Water heat capacity	4.187 kJ/kg.K

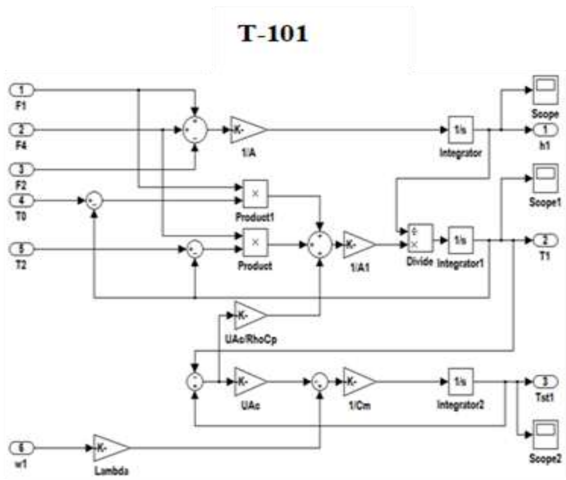

Fig 2: Simulink open-loop model for tank T-101

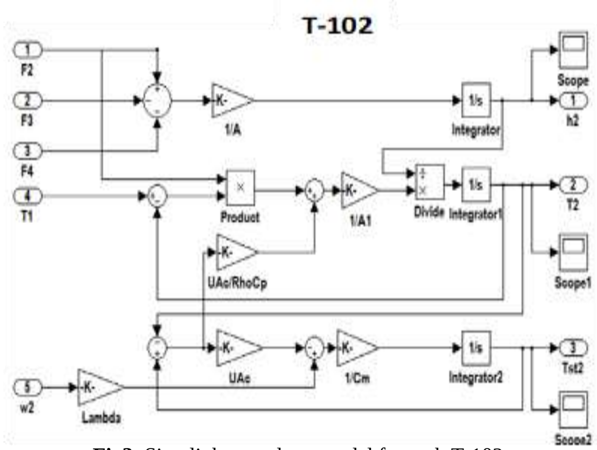

Fig3: Simulink open-loop model for tank T-102

Simulations of the Simulink data generation block as shown in Fig. 4 were run to generate the process data. Data collected is taken as real process data, and is used for system identification of the 2CSTHEs, where the data is supplied in the training of the network. In the simulation, 3300 data sets were generated for the 2CSTHEs system at dynamic state.

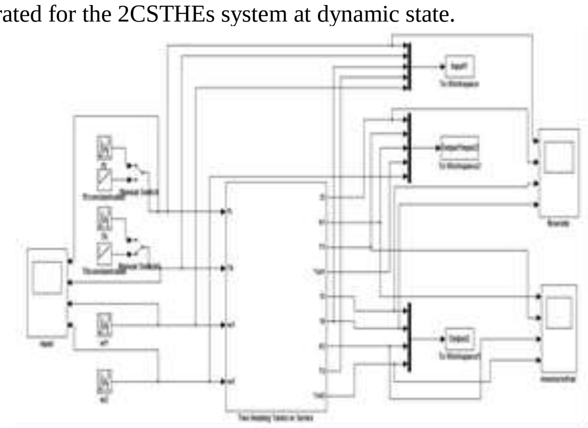

Fig.4: Simulink data generation block for 2CSTHEs at dynamic state

2.2 ANN modelling of 2CSTHEs

Neurons are processing units in an ANN where a set of neurons grouped together in layers which inter-relate with others by parameter called weights and these weights are used to model complex relationships between inputs and outputs by adjusted their values. The neural network consists of three layers: The first layer is the inlet layer which receives input data, the second layer may made up of one or more layers known as ‘hidden’ layer and the third layer is the output layer which propagates the information from network back to the outside as predicted output [9]. In the present study, the hidden layer neuron applied differentiable transfer function in the form of the hyperbolic tangent sigmoid (TANSIG) to predict the outputs with respect to the generated data. In the output layer the linear transfer function (PURELIN) was used. The transfers are given by the following [10]:

$$\mathrm{TANSIG} = \frac{2}{1+\exp(-2n_S)} - 1 \qquad (7)$$

$$\mathrm{PURELIN} = n_S \qquad (8)$$

where n_S is the sum of the weighted inputs and bias. Then, the output $y_{(k)}$ for the general function is given by [11]:

$$y_{(k)} = \mathrm{PURELIN}\left(\sum_{j=1}^{J}[LW_{(k,j)}V + b2_{(k)}]\right) \qquad (9)$$

$$V = \mathrm{TANSIG}\sum_{r=1}^{R} IW_{(j,r)}P_r + b1_{(j)}$$

where J is the neuron number in the hidden layer, IW are the weights in the input-hidden layer, *b1* are the biases in the hidden layer. LW are the weights in the hidden output layer, *R* is the input-neuron number and *b1*, *b2* are the biases in the output layer. Two ANN models of 2CSTHEs at dynamic state are developed; ANN model for tank T-101 and T-102. The multilayer feed-forward network or MLFFN is used in this study using the MATLAB software. Fig. 5 and 6 show the MLFFN network structures, with its input and output variables, for tanks T-101 and T-102, respectively.

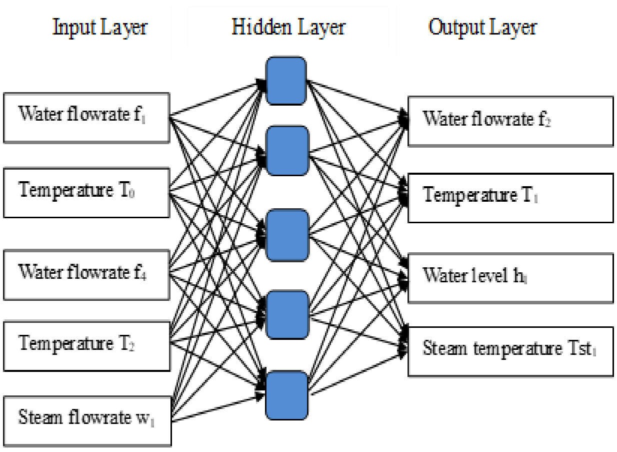

Fig.5: MLFFN network for T-101 at dynamic state

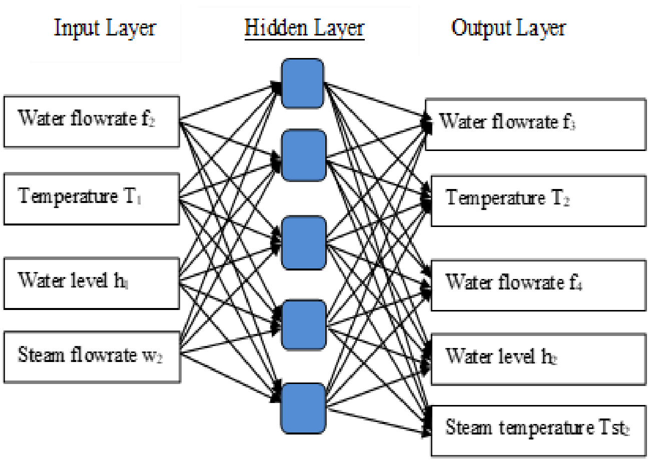

Fig. 6: MLFFN network for T-102 at dynamic state

In the training of MLFFN, a number of parameters of the network need to be determined, like the number of hidden layers in the network, number of neurons in the hidden layer, and distribution of data between training, validation, and testing of network. In the study, the main method used to determine the performance of the ANN models are the mean squared error, mse. The mse value is obtained using Eq. 10:

$$mse(t) = \frac{1}{N_p} \sum_{i=1}^{N} \sum_{k=1}^{k=p} [(d_k^i)^2 - (y_k^i)^2] \qquad (10)$$

where; t = Number of completed training epochs, y_k^i = Value of k^{th} output predicted by the network for i training pattern, d_k^i = Value of k^{th} output of real system for i training pattern, N = Total number of training pattern. Three different back-propagation training algorithms were used in the training of neural network; Levenberg-Marquardt back-propagation (LM), BFGS Quasi-Newton backpropagation (BFG), and conjugate gradient back-propagation with Polak-Ribiére updates (CGP). The network training was carried out using the MATLAB Neural Network Toolbox.

3. Results and discussion

The optimum ANN structures for every ANN model for tank T-101and T-102 are tabulated in Tables 2 and 3, respectively.

TABLE 2: Optimum ANN structures of tank T-101 for every training algorithm

Parameter	Structure 1	Structure 2	Structure 3
Training algorithm	Levenberg Marquardt	BFGS quasi-Netwon	Conjugate gradient backpropagation
Number of hidden layers	2	2	2
Number of neurons in hidden layers	First – 8, Second – 7	First – 10 Second – 6	First – 6 Second – 6
Data distribution during training	Training – 70% Validation – 15% Testing – 15%	Training – 70% Validation – 15% Testing – 15%	Training – 60% Validation – 20% Testing – 20%

TABLE 3: Optimum ANN structures of tank T-102 for every training algorithm

Parameter	Structure 1	Structure 2	Structure 3
Training algorithm	Levenberg Marquardt	BFGS quasi Netwon	Conjugate gradient backpropagation
Number. of hidden layers	2	2	2
number of neurons in hidden layers	First – 9 Second – 8	First – 9 Second – 8	First – 9 Second – 2

Data distribution during training	Training – 80% Validation– 10% Testing – 10%	Training – 80% Validation – 10% Testing – 10%	Training – 60% Validation – 20% Testing – 20%

The results of the ANN training are shown in Table 4. From the results, the *mse* values obtained were able to be minimized down to 0.01, with the exception of tank T-102 ANN models trained using the BFG and CGP algorithms. ANN models with structure 1 which trained using LM algorithm produces the best *mse* values, showing the best prediction performance of the 2CSTHEs system. After the optimum numbers of neurons for every model are determined, the designed ANN models are tested for their prediction performance of the 2CSTHEs system behavior

TABLE 4: Results of ANN training of the 2CSTHEs ANN Models

Training ANN Model	**Parameter**	Structure		
		1	**2**	**3**
Tank T-101	Mean squared error	0.0100	0.0213	0.0849
Tank T-102	Mean squared error	0.0356	0.1042	0.4588

Tank (Green – real output; Blue – Predicted output)

T-101

T-102

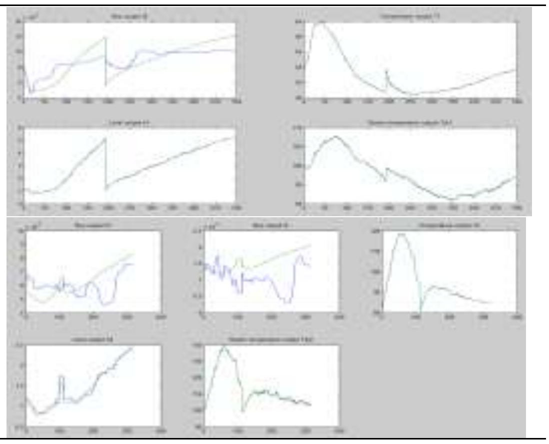

Fig.7: The predicted outputs and real process outputs for structure 1

These prediction outputs are compared with the testing data of the real system outputs [12,13]. Fig. 7 shows the graph of predicted outputs and the real system outputs for structure 1 for every ANN model tested for tank T-101 and T-102, respectively. In general, all the models are able to predict the system outputs with good accuracy. LM-trained ANN models are shown to produce the best predictions of the system output, with the least errors in the prediction.

4. Conclusion

Mathematical modeling of 2CSTHEs in series has been conducted, and the Simulink model of the system was built and used in the data generation for ANN training. The ANN models were trained using three different training algorithms. The designed ANN models were able to predict the behavior of 2CSTHEs system with very high accuracy and produces small errors despite the fact that the process is highly non-linear. From the three ANN training algorithms, the LM is found to be the best algorithm for the modeling of 2CSTHEs. The prediction performances of LM-trained models are the most accurate of the three, and the rate of convergence is the fastest during network training.

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References

[1] Mohanraj M, Jayaraj S, and Muraleedharan C (2015), Application of Artificial Neural Networks for Thermal Analysis of Heat Exchangers. International Journal of Thermal Sciences. 90,150-172.

[2] Diaz G, Sen M, Yang KT, and McClain RL (2001), Dynamic prediction and control of heat exchangers using artificial neural networks. International Journal of Heat and Mass Transfer, 44,1671-1679.

[3] Lazrak A, Boudehem F, Bannot S, Fraisse G, Leconte A, Papillon & Souyri B (2016), Development of a dynamic artificial neural network model of an absorption chiller and its experimental validation. Renewable Energy, 86, 1009-1022.

[4] Mikulandric R, Loncar D, Bohning D, Bohme R & Beckmann M (2014), Artificial neural network modelling approach for biomass gasification. Energy Conversion and Management, 87, 1210-1223.

[5] Al-Dawery SK, Alrahawi AM, and Al-Zobai KM (2001), Dynamic modelling and control of plate heat exchanger. International Journal of Heat and Mass Transfer, 55, 6873-6880.

[6] Bakosova M, Oravec J (2014), Applied Thermal Engineering. Robust model predictive control for heat exchanger network. Applied Thermal Engineering, 73, 924-930.

[7] Lazrak, A, Boudehem F, Bannot S, Fraisse G, Leconte A, Papillon P & Souyri B (2016), Development of a dynamic artificial neural network model of an absorption chiller and its experimental validation. Renewable Energy, 86, 1009-1022.

[8] Kiu MY, Thesis: Optimal control design of two continuous stirred tank heaters is Series. Bangi: National University of Malaysia (UKM), (20120).
[9] Alvarez EM, Hernandez JA & Bourous, M (2016), Modelling the performance parameters of a horizontal falling film absorber with aqueous (lithium, potassium, sodium) nitrate solution using artificial neural networks. Energy, 102, 313-323.
[10] Morales LI, Conde-Gutierrez R A, Hernandez JA, Huicochea A, Juares-Romero D, Siqueiros J (2015), Optimisation of an absorption heat transformer with two-duplex components using inverse neural network and solved by genetic algorithm. Applied Thermal Engineering. 85, 322-333.
[11] Morales LI, Conde-Gutierrez R A, Hernandez JA, Huicochea A, Juares-Romero D, Siqueiros J (2015), Optimisation of an absorption heat transformer with two-duplex components using inverse neural network and solved by genetic algorithm. Applied Thermal Engineering, 85:322-333.
[12] Annuar MH. Thesis: Modelling of two heaters in series using neural networks. Bangi, National University of Malaysia (UKM), (2015) Malaysia.
[13] Ahmad ZAG, Norliza AR & Faezah Esa*.2014. Pembangunan Kawalan Logik Kabur dalam Reaktor Lapisan Terpadat. Jurnal Kejuruteraan, 26(2014): 55-61.