

MODELING OF OVERALL HEAT TRANSFER COEFFICIENT OF A CONCENTRIC DOUBLE PIPE HEAT EXCHANGER WITH LIMITED EXPERIMENTAL DATA BY USING CURVE FITTING AND ARTIFICIAL NEURAL NETWORK COMBINATION

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The modeling accuracy of artificial neural networks was evaluated by using limited heat exchanger data acquired experimentally. The artificial neural networks were used for predicting the overall heat transfer coefficient of a concentric double pipe heat exchanger where oil flowed inside the inner tube while the water flowed in the outer tube. In the cases of parallel and counter flows, the experimental data were collected by testing heat exchanger in wide range of operating conditions. Curve fitting and artificial neural network combination was used for the estimation of the overall heat transfer coefficient to compensate the experimental errors in the data. The curve fitting was used to detect the trend and generate data points between the experimentally collected points. The artificial neural network was trained better from the generated data set. The feed forward type artificial neural network was trained by using the Levenberg-Marquardt algorithm. Two backpropagation network type artificial neural network algorithms were also used, and their performance were compared with the estimation of the Levenberg-Marquardt algorithm. The average estimation error between the predictions and the experimental data were in the range of $1.31e-4$ to $4.35e-2\%$. The study confirmed that curve fitting and artificial neural network combination could be used effectively to estimate the overall heat transfer coefficient of heat exchanger.

Keywords: Modeling, overall heat transfer coefficient, curve fitting, artificial neural network.

1. Introduction

Over the last decades, heat exchangers (HXs) have become increasingly important because of their roles in energy conservation, recovery, conversion, and implementation of new energy sources. HXs are widely used in air-conditioning and refrigeration, power, transportation, alternative fuels, heat recovery, cryogenic, and manufacturing industries, as well as being key components of many industrial products available in the marketplace. Although significant advances have taken place in the development of HX manufacturing technology as well as design theory [1-4], new industrial challenges require further research in HX analysis, particularly using advanced methodologies, such as artificial neural networks (ANNs).

ANNs have been applied in modeling heat transfer phenomena of different HX applications because of its ability in providing better and more reasonable solutions [5, 6]. Pacheco-Vega et al. [7]

predicted the performance of fin-tube heat exchanger and air-water HX using ANNs. Mohanraj et al. [8] reviewed the application of ANNs for thermal analysis of HXs. The use of ANN-based neuro-controllers in heat exchangers is a recently developed field. Díaz et al. [9] reported dynamic prediction and control of heat exchangers using artificial neural networks. Esfe [10] has applied the post-processing of experimental data on the flow and heat transfer in a nanofluid-based double tube heat exchanger using an artificial neural network. Naphon et al. [11] have studied on the application of artificial neural networks to analyze the heat transfer and friction factor of the horizontal double tube heat exchanger with spring insert. Fadare and Fatona [12] developed an ANN model for modeling the overall heat transfer coefficient of a staggered multi-row, multi-column, cross-flow, tube-type heat exchanger. Islamoglu [13] developed an ANN model for predicting the suction line outlet temperature and mass flow rate of a capillary tube suction line heat exchanger used in household refrigerators. Shabiulla and Sivaprakasam [14] have conducted experiments by using cold fluid (Butanol) and hot fluid (water) in constant mass flow rate of hot fluid and they have proposed ANN models for the analysis of a spiral plate HX. Xie et al. [15] set up an experimental system for investigation on performance of shell-and-tube heat exchangers and obtained limited experimental data. They predicted temperature differences and heat transfer rate for heat exchangers using the ANN. Colorado et al. [16] designed a physical-empirical model to describe heat transfer of helical coil in oil and glycerol/water solution. Patra et al. [17] have designed and developed an ANN model for process modelling of intermediate HX subsystem in nuclear reactor.

Several investigators have also focused on some research on HXs. Erdogan and Colpan [18] assessed the effect of the source temperature on the performances of the shell and tube heat exchanger heat exchanger and the organic Rankine cycle. Ali et al. [19] observed that this design feature of a counter-flow heat and mass exchanger can lead to a substantial increase of dew-point and wet-bulb effectiveness. Direk and Kelesoglu [20] presented the energy and exergy analysis of an R1234yf automotive air conditioning system. For this aim, an experimental baseline an automobile air conditioning system was developed and a double pipe internal heat exchanger was employed to the system.

Curve fitting (CF) regression analysis is used to find the best fit of curve for a series of data points. The curve fit generally produces an equation that can be used to find points anywhere along the curve. Because the experimental data always contains error, it is required to fit the data as well as possible. CF is performed to fit data sets that contain outliers.

In recent researches, some CFs were applied to the experimental data for the best fit of curve for a set of data points. CF was applied to the performance of heat pump determined by manufacture's catalog data [21]. CF was applied to experimental data of shell tube heat exchanger [22]. Mathematical information of relation between optimum exergy efficiency and the total length of the system was given by the fitted curve [23].

During experimentally the tests, some errors in the acquired data were likely to deteriorate the prediction performance of the developed model. Thus, we proposed CF and ANN combination to represent the experimental data when only limited number of readings were available. For better results of calculation, some correlations in good estimating confidence intervals for the optimal result of input values were performed by using CF. Otherwise, lack of the acquired data may lead to cause poor performance of the ANN model. Sufficient data were generated for better training and testing with the help of correlations.

A concentric double pipe oil to water heat exchanger was used for modeling of overall heat transfer coefficient. The goal of this study is to estimate the overall heat transfer coefficient (U) of the heat changer using CF and ANN combination. For this aim, an experimental setup was developed. Unlike similar ones, HX is fixed to the experimental setup with 45° inclination. The oil inlet and outlet temperatures, water inlet and outlet temperatures, and water mass flow rate were used as the input data of the ANN model, while the U was used as the output of the model. Each flow mode was performed separately by using three ANN algorithms and the obtained results were compared with the experimental values.

2. Therotical Background

2.1. Types of Flow Configuration

Heat exchangers transfer heat between two or more streams of fluid that flow through the equipment. A major characteristic of heat exchanger design is the relative flow configuration, which is the set of geometric relationships between the streams.

It must be accentuated that the configurations described represent idealizations of what truly occurs. In practice, it is never possible to make the flow patterns comply to the ideal. In a counter-flow heat exchanger, the two fluids flow parallel to each other in opposite directions.

2.2. Curve Fitting and ANN Modeling

Because experimental data always contain error, connecting the dots on a graph is not commonly preferred. Instead of connecting the dots on a graph, CF is used to find the best fit of line or curve for a series of data points. The curve fit generally produces an equation that can be used to find points anywhere along the curve [24].

ANNs comprise a multiple layers, which are termed input, hidden, and output layer, respectively. These layers consist of input nodes, hidden nodes, and output node(s), respectively [25]. The characteristics of the systems may be modeled by using CF methods and ANN methods evaluate the parameters of a theoretical or empirical equation. ANNs use the same generic equation to represent the characteristics of any system without demanding any models. The experimentally collected concentric double pipe heat exchanger data was modeled by use of ANN.

The author previously implemented a resilient backpropagation (RB), a scaled conjugate gradient backpropagation (SCG), and a Levenberg-Marquardt (LM) algorithm to estimate the faulty conditions of the vapor compression refrigeration system [26]. In this study, the same three types of ANN algorithms were used to model the considered system.

3. Description of the Experimental Setup and Testing Procedure

In this study, an experimental setup was developed for data generation. The experimental setup consisted of a heater tank, a heat exchanger, a circulation pump, a bypass and flow control valve, a proportional integral derivative (PID) controller with resistance temperature detector (RTD) and a flow meter. The heat exchanger was fixed to the experimental setup with 45° inclination. In addition, temperature measurements at 4 points were performed on the setup. The schematic diagram of the experimental setup is shown in Fig. 1.

The components of the experimental setup are explained below: *a) heat exchanger*: A concentric double pipe HX has been designed with the goal of accomplishing maximum heat transmission at minimum pressure drop. The outer spiral-formed space leads water in a flow counter to the flow of oil in the inner space. Built into the inner space are offset fin sections [27]. The HX was manufactured from brass and copper, and has very small dimensions in relation to its heat transmission capacity. The spiral formed outer space forces the hot refrigerant liquid over the entire heat transmission surface and prevents the formation of condensate on the outer space. The built-in offset fin sections in the inner space produce turbulent flow in the refrigerant vapor. Thus, the heat transmission from liquid to vapor is very effective. At the same time, pressure drop is kept down to a reasonable level. The detail of the HX is given in Table 1.

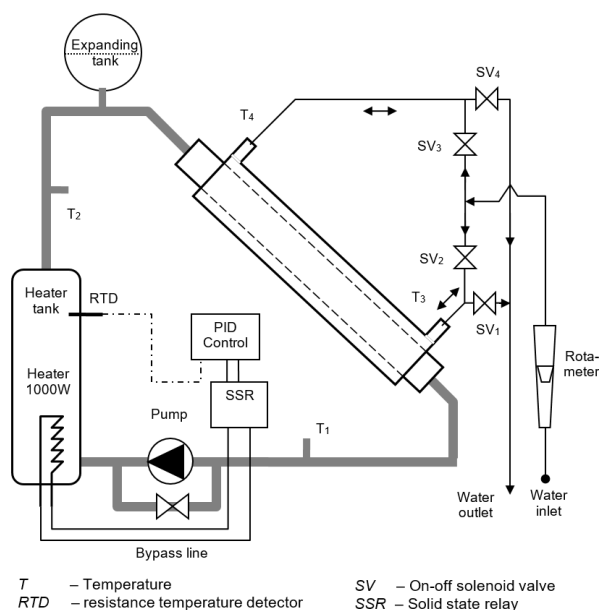


Figure 1. Schematic diagram of the laboratory type heat exchanger unit

Table 1. Characteristics of the HX

Characteristic	Value
Weight, [kg]	1.692
Outer diameters of tubes, [mm]	41.3
Wall thickness of tubes, [mm]	1.27
Tube length, [mm]	310
Inlet size, [mm]	28
Max. Working Pressure, [bar]	21.5
Outlet size, [mm]	12

This HX was manufactured for the liquid-vapor lines of refrigeration systems. *b) heater*: The electric resistance type heater is placed near the bottom side of a steel tank, and has a capacity of 1000 W. *c) PID controller*: Heater is controlled by a PID temperature controller using SSR. It has self-tuning feature. *d) temperature sensor*: A RTD is used as a temperature sensor (PT100), and it is located in the middle of the heater tank. *e) circulation pump*: The pump has 5.6 mWC head pressure, and 3.4 m³/h flow rate. *f) multi temperature selector and display*: Oil inlet and outlet temperatures, where are located at the oil inlet (point 1) and outlet (point 2) of the heater tank, are measured by RTD type sensor. Water inlet and outlet temperatures, where located at the inlet (point 3) and outlet (point 4) of the HX water line, are measured by NTC type thermistors. Some features of the instrumentation are summarized in Table 2.

Table 2. Characteristics of the instrumentation.

<i>Measured variable</i>	<i>Instrument</i>	<i>Range</i>	<i>Accuracy</i>
Oil temperature, [°C]	RTD type sensor	-50 to 200	0.3 °C
Water temperature,[°C]	NTC type thermistor	-20 to 100	0.2 °C
Water mass flow rate, [Lh ⁻¹]	Variable area flow meter	50 -500	5%

The ANN modeling approach for parallel flow and counter flows has been applied to the experimental setup shown in Fig. 1. The oil is pumped into the central tube and comes in contact with the counter-flowing water, which is supplied from the city water line into the annular space. The oil is heated by electric resistance and its temperature is controlled by PID controller and a solid state relay (SSR). A control valve is provided to adjust the flow rate of the water. Various transport properties of the oil is given in Table 3. Measurements were taken in the range of 100 L/h to 500 L/h with 20 L/h increments. In the experimental study, totally 21 different steady state test runs for parallel flow and counter flow have been conducted to gather data for training the proposed ANN model and testing its performance. The ranges of measured variables for parallel flow and counter flows are shown in Table 4.

Table 3. Transport properties of oil

<i>Transport properties</i>	<i>Test standards</i>	<i>Value</i>
Density, at 20°C, [kgm ⁻³]	DIN 51757	0.869
Viscosity, at 40°C,[mm ² s ⁻¹]	DIN 51562	33
Flame point, [°C]	DIN 51584	220
Working temperature, [°C]		350
Specific heat, at 45 °C, [kJkg ⁻¹ K ⁻¹]		1.977
Thermal conductivity, [Wm ⁻¹ K ⁻¹]		0.12
Freezing point, [°C]	ISO 3016	-16
Boiling point, [°C]	DIN 51582/ISO 3733	360

Table 4. Range of measured variables in the experiments for parallel flow and counter flows

<i>Measured variable</i>	<i>Instrument</i>	<i>Parallel flow</i>	<i>Counter flow</i>
Oil input temperature, [°C]	RTD type sensor	55.7 – 45.3	52.3 – 42.8
Oil output temperature, [°C]	RTD type sensor	55.8 – 45.9	52.5 – 43.3
Water input temperature, [°C]	NTC type thermistor	15.2 – 13.8	15.2 – 13.7
Water output temperature, [°C]	NTC type thermistor	25.5 – 15.9	24.4 – 15.6
Water mass flow rate, [L/h]	Variable area flow meter	100 – 500	100 – 500

4. Data Generation and ANN Modeling

Due to measurement errors, the acquired data had error. The accuracy of the data was improved by using the curve fitting method which reduced the errors by smoothing the curve. This approach reduces the possible ANN representation errors when the number of hidden nodes is increased. To fix or reduce errors in experimental data, curve fitting equations of Polynomial and Exponential series models were used to do the best fit of data.

The curve fitting equation of Polynomial series [29] y in a single indeterminate can be expressed as

$$y = \sum_{i=1}^{n+1} p_i x^{n+1-i} \quad (1)$$

where i , n , p , and x are iteration number, number of term in the series, constant value, and variable respectively.

Water input data ($T_{c,in}$) and output data ($T_{c,out}$) for counter flow were calculated by using Polynomial equations (1) with third degree and with fourth degree, respectively. However for parallel flow they were calculated by using equationd with third and first degree, respectively. The best fit of $T_{c,in}$ and $T_{c,out}$ for counter and parallel flows were acquired. Oil input data ($T_{h,in}$) and output data ($T_{h,out}$) for parallel flow were calculated by using a Polynomial equations with fourth degree. However for parallel flow, they were calculated by using with first degree, and the best fit of $T_{h,in}$ and $T_{h,out}$ was acquired. Water mass flow rate (\dot{m}_w) was calculated by using a Polynomial equation with first degree and the best fit of \dot{m}_w was acquired.

After acquiring data by using calculations, the Logarithmic Mean Temperature Difference (LMTD) method was tested to calculate the overall heat transfer coefficient (U). This methods can be explained as follows [2-4].

Because the temperature difference between the oil (T_h) and water (T_c) streams varies along the length of the concentric double pipe HX, it is essential to derive an average temperature difference from the heat transfer calculations.

Let T_h and T_c , respectively denote the temperature of the hot and cold fluids. Furthermore, let ΔT_1 and ΔT_2 stand for the temperature difference at each terminal side of the HX, i.e.,

$$\Delta T_1 = \begin{cases} T_{h,in} - T_{c,out} & \text{if counter flow,} \\ T_{h,in} - T_{c,in} & \text{if parallel flow,} \end{cases} \quad (2)$$

$$\Delta T_2 = \begin{cases} T_{h,out} - T_{c,in} & \text{if counter flow,} \\ T_{h,out} - T_{c,out} & \text{if parallel flow,} \end{cases} \quad (3)$$

where, $T_{c,in}$ and $T_{c,out}$ are input and output temperatures of the cold fluid and $T_{h,in}$ and $T_{h,out}$ are input and output temperatures of the hot fluid respectively.

LMTD (logarithmic mean temperature difference) can be calculated from

$$\Delta T_m = \frac{(\Delta T_2 - \Delta T_1)}{\ln(\Delta T_2/\Delta T_1)} \quad (4)$$

with ΔT_1 and ΔT_2 as defined in (2) and (3).

U can be calculated from

$$U = \frac{\dot{Q}_e}{A_s \Delta T_m} \quad (5)$$

where, \dot{Q}_e is heat transfer rate which is emitted from hot liquid and A_s is heat transmission area.

Followings are the assumptions made in the thermal analysis of heat exchanger by LMTD:

- U is constant over the length of fluid.
- The specific heat is constant over entire length of path.
- There are no partial phase changes in the system.
- Heat losses to the surrounding air are negligible because pipe, heater tank and circulation pump are insulated by rockwool.

After acquiring and calculating all necessary data, the network architecture of CF and ANN model has been applied to predict optimal results of the counter flow and the parallel flow for the overall heat transfer coefficient (U). Input nodes which are oil input temperature ($T_{h,in}$), oil output temperature ($T_{h,out}$), water input temperature ($T_{c,in}$), water output temperature ($T_{c,out}$), and water mass flow rate (\dot{m}_w) were used and output node which is the overall heat transfer coefficient (U) was used. The different number hidden nodes were used to predict an optimal result of counter and parallel mass flow rates.

The performance of the ANN is evaluated by assessing the estimation errors on the training data. Then, the estimation error on the testing data is recalculated after the ANN predicts the output(s). The estimation errors on the testing data are generally higher compared to the training data. Respect to range of target data, average percentage error of every predicted output of training and testing data was defined by

$$R_{ave} = \frac{1}{N} \frac{\sum_{i=0}^n |A^e - A^p|}{|A_{max}^e - A_{min}^e|} \quad (6)$$

where A^e is the experimental data, A^p is the predicted result, and N is the number of data. The network architecture of this ANN model with curve fitting is shown in Fig. 2.

Furthermore, one-way analysis of variance (ANOVA) were employed for determining the means of groups. ANOVA uses F -statistic to statistically test the equality of means. The F -statistic simply a ratio of the mean squared errors. The sources of variance on experimental values of the two or more groups can be separated into constituent parts and accurately measured. ANOVA returns to the p -value for a balanced one-way ANOVA by group. The p -value is the probability that the test statistic may take a value greater than the value of the computed test statistic [30].

5. Limitations of ANN Modeling for Heat Exchanger and Uncertainty Analysis

The major limitations of ANN for heat exchanger analysis consist of over training errors, extrapolation errors and optimization of network configuration [31]. In this study, the network consisted of one input layer with 5 neurons, one hidden layer, and one output layer with one node (Fig. 2). The number of hidden nodes increased from 1 to 40. the LM, RB, and SCG type ANN were trained and tested by using the generated data. The LM had the best estimations in all the cases after 40 trials and 1000 training iterations for each cases when the results of estimating errors were compared. For compact representation and consistency, the LM type ANN with 8 hidden nodes was selected. Due to the best performance, the LM type ANN was selected to represent ANNs. The ANN parameters for LM type ANN were shown in Table 5.

Data The uncertainty analysis for the overall heat transfer coefficient (U) for the counter and parallel flows was performed using by Moffat (1997) [28]. According to this method, the function R is presumed to be computed from a set of the totally N measurements represented by

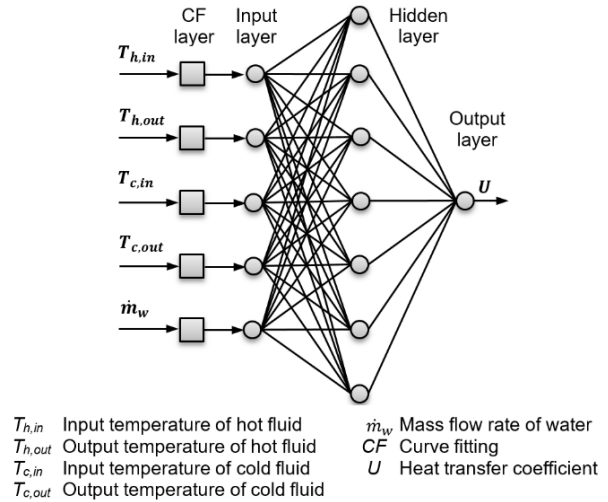


Figure 1. Network architecture of CF and ANN model

$$R = R(m_1, m_2, m_3, \dots, m_N) \quad (7)$$

Then the uncertainty of the result R can be calculated from

$$\delta R = \sqrt{\sum_{i=1}^N \left(\frac{\partial R}{\partial m_i} \delta m_i \right)^2} \quad (8)$$

Using the accuracies for the measured variables denoted in Table 2, the uncertainty of the calculated U was determined with the evaluation of Eq. (7) in Eq. (8). The total uncertainty of U for the counter and parallel flows was 6.95% and 6.18%, respectively.

Table 5. Neural network parameters for LM type ANN

<i>Parameter</i>	<i>Value</i>	<i>Description</i>
net.trainParam.epochs	1000	Maximum number of epochs
net.trainParam.goal	0	Performance goal
net.trainParam.max_fail	1000	Maximum validation failures
net.trainParam.min_grad	1e-20	Minimum performance gradient
net.trainParam.mu	0.001	Initial mu
net.trainParam.mu_dec	0.1	mu decrease factor
net.trainParam.mu_inc	10	mu increase factor
net.trainParam.mu_max	1e20	Maximum mu
net.trainParam.show	25	Epochs between displays
net.trainParam.time	inf	Maximum time to train in seconds

6. Results and Discussion

In this section, the characteristics of the data and the need for CF will be discussed. Next, the empirical model for representation of the experimental data was introduced. Then, data generation for training of the ANN will be outlined. Finally, the performance of the ANNs will be discussed.

Experimental data were collected with parallel flow and counter flow studies. Measurements were taken in the range of 100 L/h to 500 L/h with 20 L/h increments. Therefore, 21 different measurements were taken in each case (mode). The U for parallel and counter flows was calculated by the LMTD method. The calculated U for the parallel flow was in range of 297.683 to 309.906. However, for the counter flow the calculated U was in range of 324.365 to 369.228. The ANN had one input layer with 5 nodes, one hidden layer, and one output layer with single node. The LM, SCG and RB type ANNs were trained with 14 cases while the number of hidden nodes was increased from 1 to 40. The performances of the ANNs were evaluated by using the 7 cases which they never saw before. The average estimation percentage errors (R_{ave}) without CF for testing were in the range of 31.1% to 0.75% when the LM type of ANNs was used. Due to measurement errors, the acquired data had error. The accuracy of the data was improved by using the curve fitting method which reduced the errors by smoothing the curve. This approach reduces the possible ANN representation errors when the number of hidden nodes is increased.

Secondly, sufficient data was generated by CF for better training of the ANNs. Polynomial series models were used to fit a curve to the experimental data and to generate the training cases for the ANN. The curves generated by the empirical models were always within the 95% confidence bounds of the data. The water input ($T_{c,in}$) temperatures for counter flow were derived from Eq.(1) with third degree. However the water output ($T_{c,out}$) were derived from Eq.(1) with fourth degree. The R^2 of $T_{c,in}$ and $T_{c,out}$ were 0.9996 and 0.9993, respectively. Water input ($T_{c,in}$) temperatures for parallel flow were derived

Eq.(1) with third degree. But, the water output ($T_{c,out}$) were derived from Eq.(1) with one term. The R^2 of $T_{c,in}$ and $T_{c,out}$ were 0.9986 and 1, respectively. Oil input ($T_{h,in}$) and output ($T_{h,out}$) temperature for the counter flow were derived from the Polynomial equation with fourth degree and R^2 of $T_{h,in}$ and $T_{h,out}$ were 0.9992 and 0.9991 respectively. However, oil input ($T_{h,in}$) and output ($T_{h,out}$) temperatures of parallel flow were derived from the Polynomial equation with one term. The R^2 of $T_{h,in}$ and $T_{h,out}$ were 0.9993 and 0.9983 respectively. The mass flow rate of water was derived from polynomial equation, and R^2 of \dot{m}_w was 1.

Third, the performances of the CF methods were compared and the best model was selected. Smoothened data were generated with the best model for training of the ANN. The average estimation percentage errors (R_{ave}) with CF for testing were in the range of 6.332% to 0.003% when the LM type of ANNs was used. Due to unsatisfactory performance of ANN after training and testing with 21 cases, 101 cases were generated with the selected empirical model. The LM, SCG and RB type ANNs were trained with 67 cases, while the number of hidden nodes increased from 1 to 40. The performances of the ANNs were evaluated by using the remaining 34 cases which they never saw before. By using trial and error method with different ANN configurations, it was decided to have the network consisting of one input layer with 5 neurons, one hidden node, and one output node.

Table 6. Average estimation errors of U during counter flow with LM, RB, and SCG type ANNs

Hidden Nodes	LM [%]		Hidden Nodes	SCG [%]		Hidden Nodes	RB [%]	
	Training	Testing		Training	Testing		Training	Testing
6	0.000551	0.000782	8	0.005562	0.006034	32	0.052081	0.060628
7	0.000151	0.000223	9	0.003698	0.004322	33	0.071212	0.068304
8*	0.0001771	0.000121	10*	0.002583	0.002664	34*	0.041575	0.043573
9	0.000212	0.000373	11	0.009559	0.010338	35	0.10671	0.11832
10	0.000241	0.000564	12	0.009125	0.010833	36	0.15567	0.16574

*Best result

Finally, the R_{ave} was calculated for all the ANNs after 40 trials and 1000 training iterations for each cases. Table 6 showed that in case of the counter flow, the best estimations were obtained when the hidden nodes were selected 8, 10, and 34 with the LM, RB, and SCG type ANN when the LMTD method were used respectively. The LM gave the best estimations in all the cases. For the counter flow the most accurate U value estimations were obtained with the LMTD method when 8 hidden nodes were used according to Table 6. According to Table 7, for the counter flow the best estimations were obtained when the hidden nodes were selected 19, 7, and 37 with the LM, RB, and SCG type ANN when the LMTD method were used respectively.

For compact representation and consistency, the LM type ANN with 8 nodes was selected. The R_{ave} value was 0.000121% which means that the LM type ANN was capable to learn at high accuracy. R-square error (R^2) for the training, the testing, and the validation was 1 when the LM type ANN for counter flow and parallel flows were trained. Furthermore, ANOVA was employed to determine differences between the predicted U for 21 cases without CF, 21 cases with CF, and the generated 101 cases. F-statistic was $F= 0.0044$ ($p=0.9473$) when 21 cases without CF and with CF were used. F-statistic was $F= 0.0051$ ($p = 0.9431$) when 21 cases without CF and generated 101 cases were used. F-statistic was $F= 3.36e-4$ ($p = 0.9854$) when 21 cases with CF and generated 101 cases were used. F-statistic was 0.003 ($p=0.997$ when all cases were used.) F-statistic for all cases indicated that all groups have no significant difference. All type of test indicate that the generated 101 cases have more accuracy

than 21 cases without CF and with CF. For the counter flow mode, the predictions of the ANN were compared with the experimental results in Fig 3. The estimations were very close to the experimental data. According to the generated U (U_g) and the predicted U (U_p), the 3D plot in Fig. 4 illustrated the U prediction performance of the LM type ANN respect to three inputs: the temperatures of the water at the entrance, at the outlet, and the mass flow rate of water. For the counter flow, the maximum value of U was obtained with LMTD method was 369.23 (Fig. 4).

Table 7. Average estimation errors of U during parallel flow with LM, RB, and SCG type ANNs

Hidden Nodes	LM [%]		Hidden Nodes	SCG [%]		Hidden Nodes	RB [%]	
	Training	Testing		Training	Testing		Training	Testing
17	0.00070805	0.0015117	5	0.003944	0.004041	35	0.16044	0.17488
18	0.00023498	0.00034189	6	0.019334	0.021156	36	0.13307	0.15055
19*	0.00022498	0.00013071	7*	0.00217	0.002512	37*	0.027766	0.031096
20	0.00025861	0.00035	8	0.012609	0.014893	38	0.10287	0.10698
21	0.00011526	0.00018744	9	0.012872	0.014098	39	0.16836	0.19903

*Best result

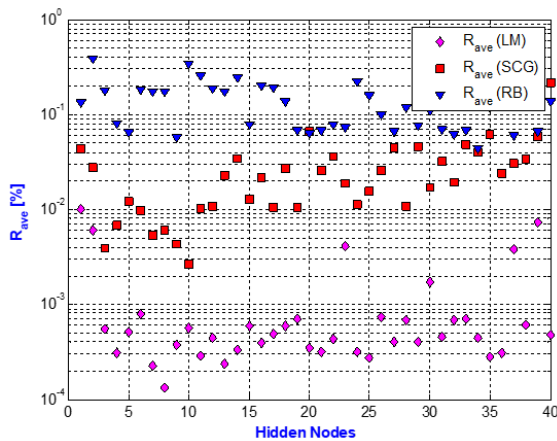


Figure 3. Comparison of R_{ave} error for LM, RB, and SCB testing data

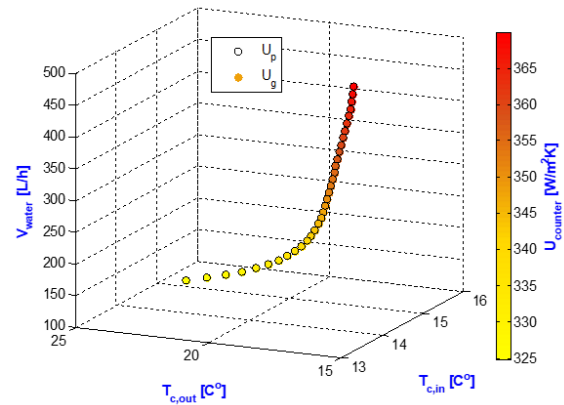


Figure 4. 4D Plot out of U for LM algorithm.

7. Conclusions

In the paper, CF and ANN combination was proposed to represent the experimental data when only limited number of readings is available. The curve fitting increased the data points with the help of the selected empirical model without creating extreme deviations between the data typically observed at the estimations of over fitted ANN models.

In the study, empirical equations were used to smoothen the experimental data and to increase of the cases for the training and testing data. The performances of the empirical equations varied from case to case. The prediction of the LM, RB, and SCG type ANN, which were trained and tested by using the generated data, were compared when the LMTD method were used respectively. The results have been discussed in term of astimating errors. The LM type ANN gave the minimum estimation errors.

The results indicated that CF and LM type ANN combination may be used to represent the experimental data when limited number of test points were obtained experimentally. The performances of the curve fitting methods were very close to each other in the considered cases, and any of them could be used to smoothen the data and to generate training and test cases for the ANNs.

Nomenclature

ANN – artificial neural network
As – heat transmission area, [m²]
CF – curve fitting
HX – heat exchanger
i – iteration number
LM – Levenberg Marquart
LMTD – logarithmic mean temperature difference
m – independent variable
min – minimum
mWC – meter of water column
N – number of data
 \dot{Q}_e – heat transfer rate emitted from hot liquid, [W]
p – constant value
PID – proportional + integral + derivative
PT100 – temperature sensor
NTC – negative temperature coefficient
RTD – resistance temperature detector
R – a function of independent variables
R_{ave} – average percentage error, [%]
R² – adjusted R-squared
RB – resilient backpropagation
SCG – scaled conjugate gradient
SSR – solid state relay
SV – solenoid valve
T – temperature, [°C]
U – overall heat transfer coefficient, [W/m²K]

Greek symbols
 ΔT – temperatures differences, [°C]

Subscripts and superscripts
c – cold
e – experimental
g – generated
h – hot
in – inlet
m – mean
n – number of term in the series
out – outlet

p – predicted

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