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Research Article

Thermal Modeling and Performance Analysis for a Chevron Type Heat Exchanger by Using Artificial Neural Network with Limited Experimental Data

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Abstract

The problem of heat exchange between two or more fluids at different temperatures is one of the most important and most common problems of engineering applications. In order to solve this problem efficiently, the transfer of energy between two liquids at different temperatures is carried out by heat exchangers. Heat exchangers increase the energy efficiency as they can transfer the energy contained in the system to another part of the process instead of just pumping and wasting. A plate heat exchanger, a variant of heat exchanger, use a series of thin plates to transfer heat between two liquids. Thermal modelling of the heat exchanger is important due to determination of the outlet temperature of fluids depending on the system parameters. In this paper, an artificial neural network (ANN) model is used to simulate the thermal performance of a chevron type plate heat exchanger using water as working fluid. The ANN algorithms have a widely usage in thermal analysis studies of heat exchangers such as modelling of heat exchangers, estimation of heat exchanger parameters, estimation of phase change characteristics in heat exchangers and control of heat exchangers. The outer temperatures of the water are estimated depending on the cold water mass flow rate, inlet hot water temperature and inlet cold water temperature by using limited experimental data. Then the experimental results and the estimated results are compared for testing the accuracy and reliability of the developed algorithm. The results show that the experimental and estimated results have a good agreement. The developed network structure estimates the outlet temperatures with 2.58 % and 1.80 % for hot and cold water, respectively. In addition, the predicted performance of the network developed by applying untested input parameters was examined. Estimation accuracy was compared with theoretically calculated output temperatures by thermal analysis using the same inputs. According to the obtained results, it is seen that the theoretical results and prediction results are compatible with each other in determining the output for new inputs and the reliability of the developed network is proved in different inputs according to this result. After that, experimentally not obtained variations of the heat transfer rate, overall heat transfer coefficient and energy efficiency are determined depending on the inlet temperatures and mass flow rate of cold water.

Keywords: Artificial Neural Network, Chevron type, Plate heat exchanger, estimation, Thermal modelling.

Sınırlı Deneysel Verilerle Yapay Sinir Ağı Kullanılarak Chevron Tipi Isı Değiştirici için Termal Modelleme ve Performans Analizi

Öz

Farklı sıcaklıklardaki iki veya daha fazla akışkan arasındaki ısı değişimi problemi, mühendislik uygulamalarının en önemli ve en çok karşılaşılan problemlerden birisidir. Bu problemi verimli bir şekilde çözmek için farklı sıcaklıklardaki iki sıvı arasında enerji aktarma işlemi ısı eşanjörleri ile gerçekleştirilir. Isı değiştiricileri, sistemde bulunan enerjiyi sürecin başka bir kısmına aktarabildiği için enerji verimliliğini arttırırlar. Isı eşanjörlerinin bir çeşidi olan plakalı ısı değiştiricileri, ısıyı iki sıvı arasında aktarmak için bir dizi ince plaka

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kullanmaktadırlar. Isı değiştiricinin termal modellemesi, sistem parametrelerine bağlı olarak sıvıların çıkış sıcaklığının belirlenmesinden dolayı oldukça önemlidir. Bu çalışmada, çalışma sıvısı olarak su kullanılan bir Chevron tipi plakalı ısı değiştiricinin termal performansını simüle etmek için yapay bir sinir ağı (YSA) modeli kullanılmıştır. YSA algoritmaları, ısı değiştiricilerin modellenmesi, ısı değiştirici parametrelerinin ve faz değişim özelliklerinin tahmini ve ısı değiştiricilerinin kontrolü gibi termal analiz çalışmalarında yaygın olarak kullanılmaktadır. Sıcak ve soğuk suyun ısı değiştiriciden çıkış sıcaklıkları sınırlı deneysel veriler kullanılarak soğuk su kütle akış hızına, giriş sıcak su sıcaklığına ve giriş soğuk su sıcaklığına bağlı olarak tahmin edilmiştir. Daha sonra geliştirilen algoritmanın doğruluğunu ve güvenilirliğini test etmek için deney sonuçları ve tahmini sonuçlar karşılaştırılmıştır. Elde edilen sonuçlar deneysel ve tahmini sonuçların iyi bir uyuşmaya sahip olduğunu göstermektedir. Geliştirilen ağ yapısı, sıcak ve soğuk su için çıkış sıcaklıklarını sırasıyla % 2.58 ve % 1.80 yüzdelik ortalama hata ile tahmin etmektedir. Ek olarak, deneyi gerçekleştirilmemiş giriş parametreleri uygulanarak geliştirilen ağın tahmin performansı incelenmiştir. Tahmin doğruluğu ise aynı girişler kullanılarak termal analiz ile teorik olarak hesaplanan çıkış sıcaklıkları ile karşılaştırılmıştır. Elde edilen sonuçlara göre yeni girişler için çıkışın belirlenmesinde teorik sonuçlar ile tahmin sonuçlarının birbirleriyle uyumlu olduğu görülmektedir ve bu sonuca bağlı olarak geliştirilen ağın güvenilirliği farklı girişler içinde kanıtlanmış olmaktadır. Daha sonra, deneysel olarak elde edilmemiş ısı aktarım hızı, toplam ısı aktarım katsayısı ve enerji verimliliğindeki değişiklikler, sıcak ve soğuk suyun giriş sıcaklıklarına ve soğuk suyun kütle akış hızına bağlı olarak belirlenmiştir.

Anahtar Kelimeler: Yapay sinir ağları, Chevron tipi, Plakalı ısı değiştiriciler, Tahmin, Termal modelleme.

1. Introduction

Heat exchangers are often used for heat transfer between hot and cold fluids. In practice, heat exchangers used in a wide variety of engineering applications, such as automobile thermal power units, air conditioning systems, chemical and textile manufacturing operations, can be of various constructions, capacities, sizes and types according to their intended use. The design and operation of heat exchangers are determined according to several factors such as the inlet and outlet temperatures of the fluids, the operating pressure, the pressure losses that can be tolerated in the heat exchanger, the heat capacity and the types and amounts of the fluids.

There are many studies about modelling and development of different types of heat exchangers for different applications such as plate type [Abu-Khader, 2012], ceramic based [Sommers et al, 2010], compact heat exchangers [Li et al, 2011] etc. In this study, the plate types Chevron heat exchanger is selected because of its high thermal efficiency and flexibility. Chevron type heat exchangers are extensively preferred for heating, cooling and heat-regeneration applications. There are some theoretical and experimental methods for analysing the thermal behaviour of heat exchangers in the literature such as the logarithmic mean temperature difference (LMTD), effectiveness-number of transfer units (ϵ-NTU) and computational fluid dynamics (CFD).

The theoretical analysis of heat exchangers includes more assumptions and complex calculations. However, an analysis by experimental methods is more expensive due to the initial investment needed to develop an experimental setup [Shah & Sekuliâc Duésan, 2012]. The conventional methods like LMTD and ϵ-NTU have some limitations such as constant overall heat transfer coefficient and specific heat capacity, no heat loss between the exchanger and surrounding medium, needs to steady state conditions and negligible kinetic and potential effects. However, in applications, many properties depend on time and the value of heat transfer coefficient is continuously varying [Rajapaksha, 2007]. CFD is the another method for investigating the design and optimization of heat exchangers. Also, the CFD analysis involves some assumptions and these assumptions affect the prediction performance directly. In some cases, the error between its results and experimental results is observed above %10 which is not really acceptable [Huminic & Huminic, 2012]. Hence, the assumptions are not strictly valid for the analysis of such assumptions do not allow for a realistic thermal analysis of heat exchangers. ANN overcomes these limitations of the mentioned methods and experimental approach. In the literature, there are many studies in which ANN models were developed for simulation, optimization and performance prediction of thermal systems involving heat exchangers [Yang, 2008; Sen & Yang, 2000].

ANNs are information processing system, which learn from input/output data to determine the relationships between input/output. In recent years ANN has been used in different fields of engineering because of their capability of extracting complex and nonlinear relationships. For thermal analysis of heat exchanger Multilayer feed forward network (MLFFN), radial biased function network (RBFN), generalized regression neural network (GRNN) and adaptive neuro fuzzy interface systems (ANFIS) architectures are commonly used. If ANN based modelling of plate type heat exchangers are investigated firstly, Selbas et al. [Selbaş et al, 2008] predicted the exergy and energy values of the plate type heat exchangers. The inner temperatures of the hot and cold waters and mass flow rate. The results show that the agreement between the ANN predictions and experimental data is good. Peng and Ling [Peng & Ling, 2009] developed a ANN algorithm based on the MLFFN architecture for predicting the j and f factor of plate-fin heat exchangers. The ANN predicts these factor values with mean square errors less than 1.5% and 1%, respectively. On the other hand, there are lots of studies in the literature about modelling the different types of heat exchangers such as condensers, compact heat exchangers, run-around heat exchangers, shell and tube heat exchangers and fin and tube heat exchangers. Ertunc and Hosoz [Ertunc & Hosoz, 2008] compared the prediction performances of MLFFN and ANFIS techniques on evaporative condenser. The results show that MLFFN with 7-5-4 configuration and ANFIS predictions have %5 error when they compared to experimental results and ANFIS has more successful prediction performance than MLFFN. Ermis [Ermis, 2008] predict the values of Nu, h and Δp of a compact heat exchanger by using MLFFN technique. They use 7-11-3 configuration and the results show that they predicted Nu, h and Δp values very closer to experimental results. The mean square error of all predicted data are obtained less than 6%. 5-5-3-3 configuration of MLFFN technique is used in [Vega et al, 2000] to predict to $\dot{Q}$ and sensible heat and total heat. The inputs of the network are Re, inlet air DBT, inlet air WBT, inlet Tw and fin spacing. They compared the results with the conventional correlations results and they observed that the ANN prediction error is less than 10% but the correlation predictions have more than 10% deviation.

In this paper, an ANN structure is developed for modelling the chevron type heat exchanger with limited data. These limited experimental data are obtained from experimental study in [Yildiz & Ersoz, 2015] in which they investigated the thermomechanical characteristic of the chevron type heat exchanger theoretical and experimentally. The outlet temperatures of hot and cold water are predicted depending on the inlet temperatures and mass flow rate of cold water. Then the results compared with the experimental data for proving the accuracy and reliability of the network. Furthermore, experimentally not obtained variations of the heat transfer rate, overall heat transfer coefficient and energy efficiency are determined depending on the inlet temperatures and mass flow rate of cold water.

2. Material and Methods

2.1. Experimental Setup

The Chevron type heat exchanger is a type of plate heat exchanger and the patterns on the plates are manufactured at a certain angle. Since these angles are called as chevron angle, these types of heat exchangers are also called chevron type heat exchangers in the literature. In this study, the used experimental setup is showed in Figure 1.

The material of used brazed plate Chevron type heat changer is chromium–nickel steel and its thermal conductivity, thermal expansion coefficient and specific heat are equal to $17.5\ W/mK$, $15.1x10^{-6}C^{-1}$ and $0.5\ kj/kgK$, respectively. The geometry and technical properties of this chevron type heat exchanger is showed in Fig.2 and Table 1, respectively. The technical properties in Table 1 are constant during all considered cases.

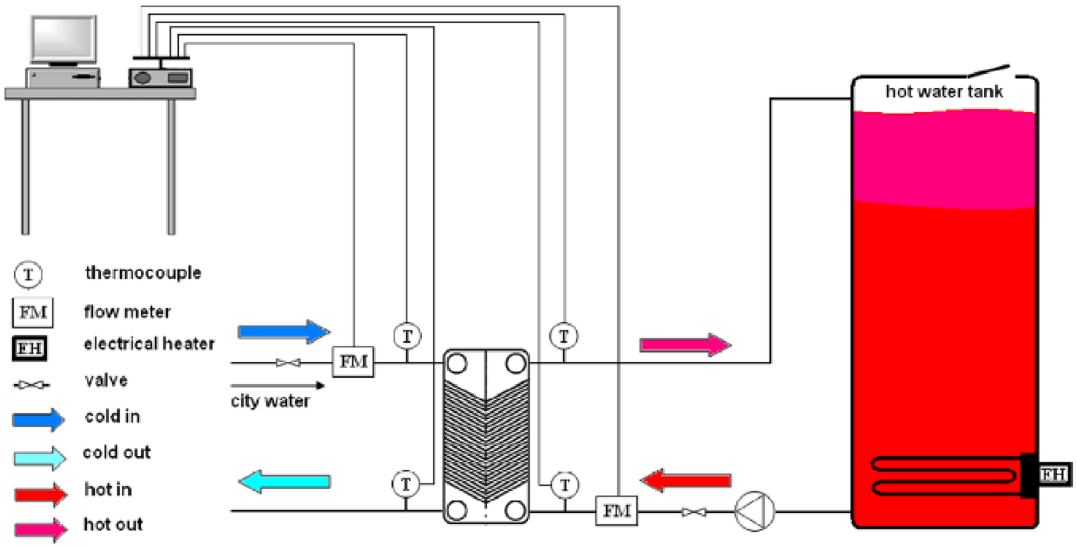

Figure 1. Schematic diagram of the experimental setup [Yildiz & Ersoz, 2015]

As seen in the Figure 1 the experimental setup consists of cold water and hot water flow loops. 2kW immersion heaters are used in the hot water tank which has 50 L water capacity. Flow maters are used to measure the flow rates of the hot and cold waters which are controlled by the valves. The temperatures of the water are measured by PT-100 thermocouples and a water pump helps circulation of the hot water through the heat exchanger. Cold water is supplied by city water supply. On the other hand, cold water was supplied from the waterworks in the setup. In the experiment, the mass flow rate of cold water is varied from 0.0277 kg/s to 0.0833 kg/s when mass flow rate of hot water is equal to 0.083 kg/s. It was kept constant during all considered cases. On the other hand, the temperatures of hot and cold waters were varied from 35 °C to 60 °C and from 21 °C to 25.35 °C, respectively. Therefore, ANN predictions was limited in these temperature values.

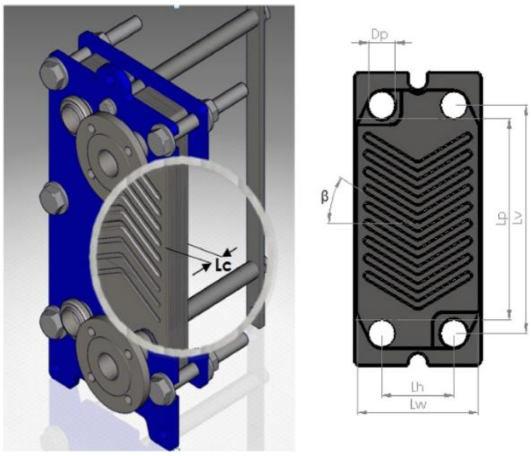

Figure 2. Geometry of the Chevron type heat exchanger [Yildiz & Ersoz, 2015]

Table 1. Technical properties of the used chevron type heat exchanger [Yildiz & Ersoz, 2015]

Plate thickness, mm (t)	0.3
Chevron angle, degrees (β)	45
Total number of plates	15
Vertical port distance, m (Lv)	0.154
Compressed plate pack length, m (Lc)	0.05
Effective channel width, m (Lw)	0.08
Total effective area, m2 (A)	0.1968
All port diameters, m (Dp)	0.016
Number of passes	1
Thermal conductivity of the plate material (W m-1 K-1)	17.5
Enlargement factor (ϕ)	1.273

2.2. Architecture of ANN

ANNs are an information processing system that is inspired by biological neural networks and contains some performance characteristics similar to biological neural networks. In other words, they are computer systems which are developed with the purpose of realizing the ability to derive new information, learn and derive new information through learning from the characteristics of the human brain automatically without any help. Artificial neural networks are physical cell systems that receive, store and use experimental knowledge. This is a widely used method for modelling complex and non-linear systems using these experimental data. Applications of ANNs are generally used for prediction, classification, data association, data interpretation and data filtering. There are basically three steps in the artificial neural network learning process; i) to calculate the output, ii) compare outputs with target outputs and calculate the error, iii) repeat the process by changing weights. As a result of the training process, it is expected that the error calculated in artificial neural network reduces to an acceptable error rate. In most network types, a neuron in the hidden layer only receives signals from all neurons of the previous layer. After neuron processing, it sends the output to all the neurons of the next layer. The output signal of each neuron is determined by applying activation function to its input data. The information flow takes place with the connection links from one neuron to the other neuron, and each link has a weights to create the desired input-output relationship. These weights are updated based on the error margin between the net output and the expected output. [Haykin, 1998; Beale et al, 2017].

The correct selection of the topology of the network affects directly the generalization ability of the artificial neural network. Therefore, the most appropriate architecture is selected by making optimizations. Initially, the randomly assigned weight values are revised along with the learning process to produce the expected outputs based on the given inputs. The learning process of the network aims to minimize the error and to produce the most accurate results for previously untested inputs. Therefore, some of the experimental data is used for training the network, while the other part tests for the success of the network. The flow diagram of the learning and test processes for the designed network is given in Figure 3.

Depending on the experimental setup, ANN algorithm has three inputs such as mass flow rate of the cold water and inner temperatures of hot and cold waters. The outputs of the networks are determined as outer temperatures of hot and cold waters. The neural-network model was developed using similar 25 experimental data sets for training, validation of the network. The network uses a back propagation algorithm which is the classical feed-forward artificial neural network and it uses to calculate the error contribution of each neuron after a batch of data is processed. One hidden layer is used in the network with 12 neurons in the network. This neuron numbers in the hidden layer is obtained at the end of the several trials to maximize the correlation coefficient R.

Figure 4 shows the architecture of developed the neural network structure for predicting the water temperatures at the outlet of the heat exchanger. Wij and Woj denote the synapse weights of the network. The desired input/output relation is getting better by adjusting these connections weigths during the training process. Some of the experimental results not used in training have been used to measure the prediction performance of the trained network.

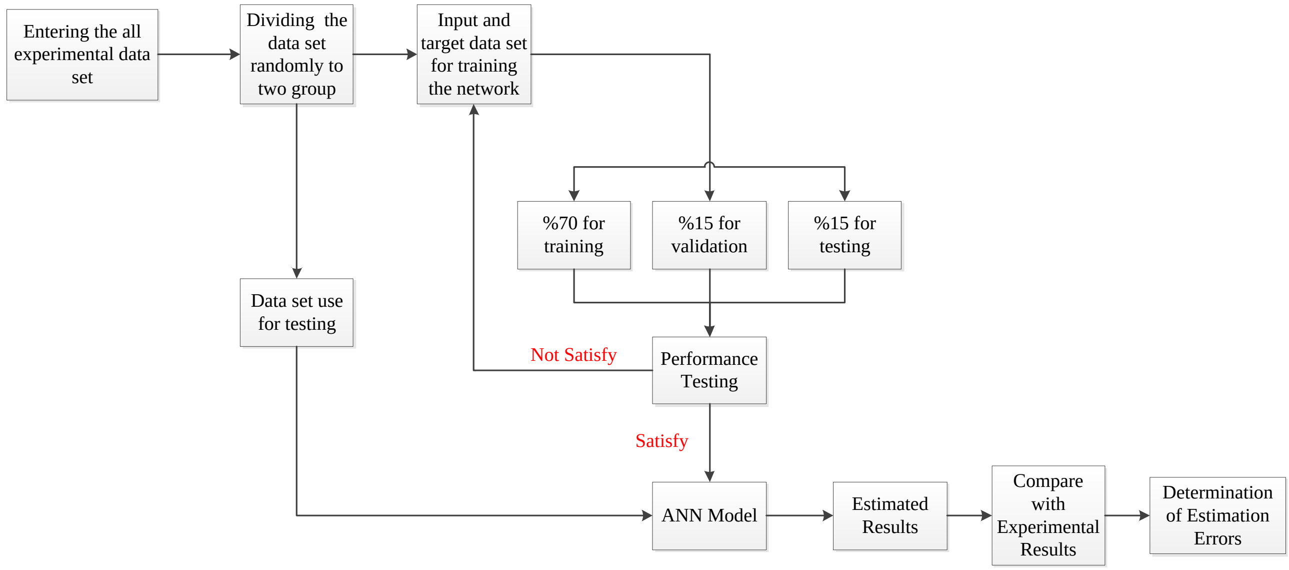

Figure 3. The flow diagram of ANN network developing process

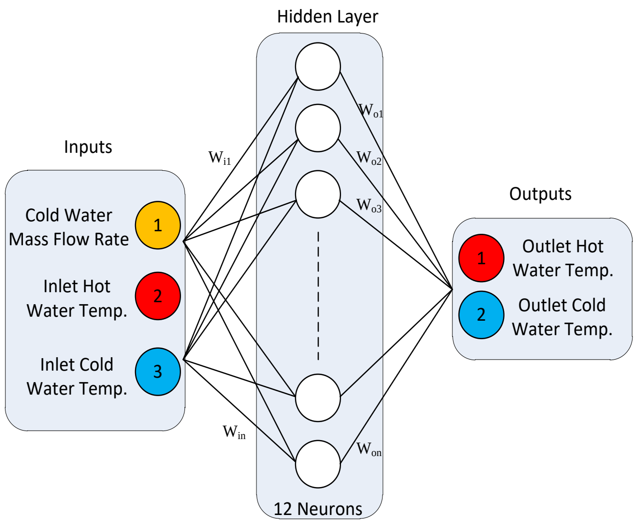

Figure 4. The architecture of the ANN

2.3. Thermal Analysis

During the energy and exergy analyses, following assumptions have been taken into consideration. The heat exchanger operates under steady-state flow conditions. Heat transfer to the surroundings is negligible and no heat generating in the exchanger. The dead state conditions are taken as $T_0 = 25$ °C. There is no temperature difference along the cross-section of the chevron type plate heat exchanger. The heat resistance of the plates is constant along the chevron type plate heat exchanger.

In the energy analysis, the heat transfer rate is calculated by using

$$\dot{Q} = UA\Delta T_{LMTD} \tag{1}$$

where U, A and $\boldsymbol{T_{LMTD}}$ are overall heat transfer coefficient, total effective area and logarithmic mean temperature difference, respectively. The overall heat transfer coefficient is obtained by Eq. (2).

$$\frac{1}{U}=\frac{1}{h_{cf}}+\frac{t}{k_p}+\frac{1}{h_{hf}} \tag{2}$$

t, $\boldsymbol{k_p}$, $\boldsymbol{h_{cf}}$ and $\boldsymbol{h_{hf}}$ are plate thickness, thermal conductivity of plate material, heat transfer coefficients for cold and hot waters, respectively and they are calculated by using following equations.

$$h_{cf}=\frac{Nu_c k_{cf}}{D_c}, \qquad h_{hf}=\frac{Nu_h k_{hf}}{D_h} \tag{3}$$

The logarithmic mean temperature difference term in Eq. (1) defined as

$$\Delta T_{LMTD}=\frac{\left(T_{h_{in}}-T_{c_o}\right)-\left(T_{h_o}-T_{c_{in}}\right)}{\ln\left(\frac{T_{h_{in}}-T_{c_o}}{T_{h_o}-T_{c_{in}}}\right)} \tag{4}$$

The used chevron type heat exchanger's chevron angle is equal to 45^o. Therefore, some flow characteristic and chevron angle dependent constants are determined using Table 2.

Table 2. Constant for single phase heat transfer in chevron type heat exchangers [Kakac et al, 2012]

Angle	C_h	n	Re
45^o	0.718	0.349	Re<10
	0.4	0.598	10<Re<100
	0.3	0.663	Re>100

After that, firstly Nusselt number, which is a dimensionless number that expresses the relationship between the convection heat transfer coefficient and the ratio to the transmission heat transfer coefficient, is determined by using

$$Nu=C_h\left(\frac{D_h G}{\mu}\right)^n\left(\frac{C_p\mu}{k_f}\right)^{\frac{1}{3}}\left(\frac{\mu_b}{\mu_w}\right)^{0.17} \tag{5}$$

Then, Reynolds number is found by using channel mass velocity, equivalent diameter and dynamic viscosity as follows

$$G_{ch}=\frac{\dot{m}_{ch}}{N_{cp}bL_w}, \qquad Re=\frac{G_{ch}D_h}{\mu} \tag{6}$$

Calculations are performed with the experimental data by using the basic heat transfer equations.

$$T_{c_m}=\frac{(T_{c_{in}}-T_{c_o})}{2}, \qquad T_{h_m}=\frac{(T_{h_{in}}-T_{h_o})}{2}, \qquad T_w=\frac{(T_{c_m}-T_{h_m})}{2} \tag{7}$$

The formulas of thermo-physical properties of water depending on the bulk temperatures at cold and hot side and the wall are given in Eqs. (12-15) in [Yildiz & Ersoz, 2015].

The energy performance in the heat exchanger is calculated by using following equation.

$$\varepsilon_1=\frac{\dot{Q}}{\dot{Q}_{max}}, \quad \dot{Q}_{max}=C_{min}\left(T_{h_i}-T_{h_o}\right) \tag{8}$$

where C_{min} is the smaller of $C_c=\dot{m}_c C_{p_{cf}}$ and $C_h=\dot{m}_h C_{p_{hf}}$. The heat removed from the hot water, $\dot{Q}_h$, and the heat absorbed by the cold water, $\dot{Q}_c$ are calculated by:

$$\dot{Q}_h=\dot{m}_h C_{p_{hf}}\left(T_{h_i}-T_{h_o}\right) \tag{9}$$
$$\dot{Q}_c=\dot{m}_c C_{p_{cf}}\left(T_{c_i}-T_{c_o}\right) \tag{10}$$

3. Results and Discussion

The main goal of this study to modelling of the chevron type heat exchanger for estimation of its outlet temperatures depending on its inlet temperatures and mass flow rate of cold water without the need for any experiments. Therefore, a neural network architecture was developed and Table 3 shows the values of ANN inputs, the related predicted outlet temperatures and experimental results and the percent error rates of cold and hot waters.

The five different input combinations on the table were selected from the data with experimental results that were not used in network training. The results show that the percentage errors for the temperatures of hot and cold waters predictions are less than 5% for all considered cases. The average errors for estimation of cold and hot water temperature at the output of the heat exchanger are determined as 2.58 and 1.80, respectively. As a results, the predicted values and experimental values have a good agreement and therefore, the accuracy of developed ANN structure is proved. Furthermore, it is indicated that the developed network has higher estimation performance for predicting the cold water output temperature. After that, the estimation performance of developed ANN is tested by comparing its results with the theoretical results for different cases which are not considered experimentally. In the theoretical analysis, due to the fact that outlet temperatures of hot and cold water are not known, the analysis requires an iterative process. Initial values are chosen for the outlet temperatures and Eqs. (1)–(8) and Eqs. (12-15) in [Yildiz & Ersoz, 2015] are solved. Then, these values are introduced into Eqs. (9) and (10) so as to calculate the new values for the outlet temperatures. The process is repeated until the difference between successive values of each quantity is less than 0.01%.

Table 3. Comparison of the estimated temperatures and experimental results

INPUTS			ANN		Experiment		Errors (%) Mean Percentage Absolute Error	
$\dot{m}_c$	T_{h_i}	T_{c_i}	T_{h_o}	T_{c_o}	T_{h_o}	T_{c_o}	e_h	e_c
0.0277	45	21.02	41.6751	38.95	40.59	39.49	2.67	1.33
0.0416	40	22.08	35.8426	33.6927	35.36	32.88	1.36	2.47
0.0555	55	25.03	45.198	42.1646	45.86	41.19	1.44	2.36
0.0694	50	24.07	37.5837	37.8079	38.78	38.77	3.07	2.48
0.0833	35	23.49	29.96	29	28.72	28.9	4.34	0.36
					Average Error (%)		2.58	1.80

Figure 5 and Figure 6 show the variations of the hot and cold water outlet temperatures as a function of cold water inlet temperatures when the mass flow rate of cold water equal to 0.0277 kgs-1. The hot water inlet temperature is changed from 35 °C to 60 °C with 5 °C increment. The results show that the outlet temperatures of hot and cold water are increased linearly for all considered hot water inlet temperatures when the cold water inlet temperature is increased. It can be seen in Fig. 5 that the estimation error between the results of ANN and theoretical calculations is less for higher hot water intel temperature than lower ones. However, Fig. 6 shows an opposite behaviour for cold water outlet temperature. The prediction error increases when the inlet temperature of the hot water is increased.

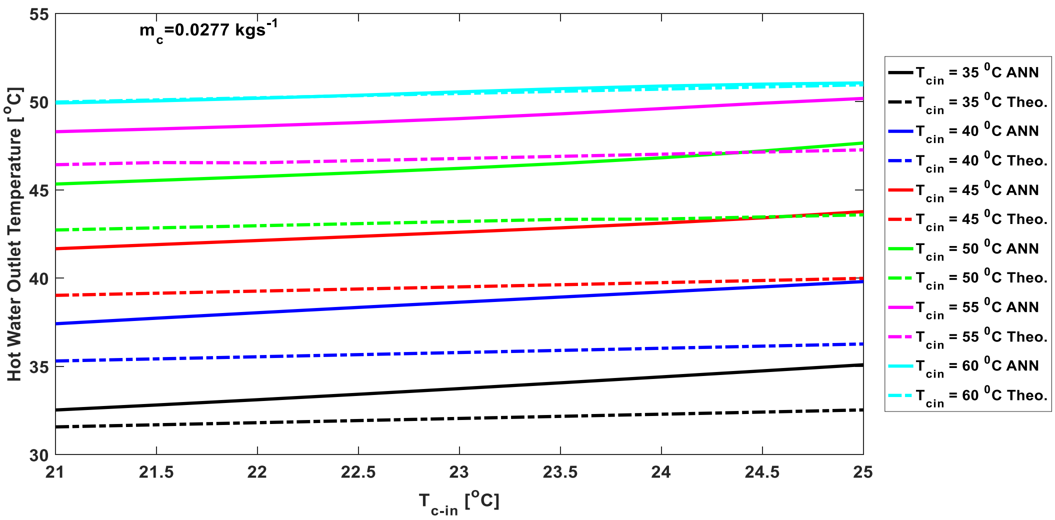

Figure 5. The comparison between the ANN predictions and the theoretical calculations for hot water outlet temperature at specific values of T_{h-in} *and* $\dot{m}_c = 0.0277\ kgs^{-1}$

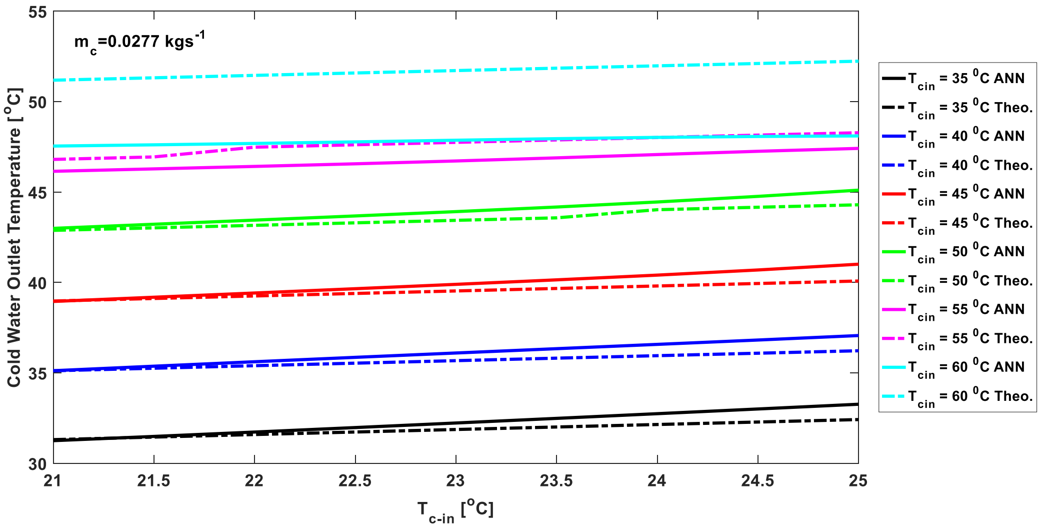

Figure 6. The comparison between the ANN predictions and the theoretical calculations for cold water outlet temperature at specific values of T_{c-in} *and* $\dot{m}_c = 0.0277\ kgs^{-1}$

These mean percentage errors and the performance of ANN is summarized in Table 4 for all considered cases. On the other hand, Figure 5 and Figure 6 show that the prediction performance of ANN decreases when the cold water inlet temperature is increased for all considered cases. These results were determined separately for all considered cold water mass flow rates. Table 5 shows the performance of ANN when the mass flow rate of the cold water is equal to 0.0555 kgs-1. When we compare the results in Table 4 and Table 5, the results show that the estimation performance of ANN is better for the case in which $\dot{m}_c = 0.0555\ kgs^{-1}$.

Table 4. The error between the estimated and calculated results for hot and cold water outlet temperatures at $\dot{m}_c = 0.0277\ kgs^{-1}$

$\dot{m}_c = 0.0277 kgs^{-1}$ / T_{h-in}	Error for T_{h-out} Estimation (%)	Error for T_{c-out}. Estimation (%)
35 °C	5.3470	1.2043
40 °C	7.9220	1.1767
45 °C	7.9433	1.0163
50 °C	7.3072	0.99
55 °C	4.9677	1.9001
60 °C	0.1849	7.4725

Table 5. The error between the estimated and calculated results for hot and cold water outlet temperatures at $\dot{m}_c = 0.0555\ kgs^{-1}$

$\dot{m}_c = 0.0555\ kgs^{-1}$ / T_{h-in}	Error for T_{h-out} Estimation (%)	Error for T_{c-out}. Estimation (%)
35 °C	1.6467	0.6087
40 °C	2.7678	0.1011
45 °C	4.3464	0.5415
50 °C	2.4633	2.8316
55 °C	1.5164	3.6023
60 °C	2.0548	2.3484

On the other hand, based on the predicted data, the variations of the heat transfer rate, $\dot{Q}$, calculated by Eq. (1), are given in Figure 7 and Figure 8 as a function of hot and cold water inlet temperatures, respectively. Figure 7 show the change of the heat transfer rate for the combinations of the hot water inlet temperature, T_{h-in}, such as 35°C, 40°C, 45°C, 50°C, 55°C and 60°C and specific values of cold water mass flow rate, $\dot{m}_c$, as 0.0277 kgs-1 and 0.0555 kgs-1. The results in Figure 7 show that increase in the cold water inlet temperature leads to decrease in heat transfer rate for all considered cases. Moreover, it is observed that the heat transfer rate increases for a specific cold water temperature value when the hot water inlet temperature or the mass flow rate of the cold water are increased.

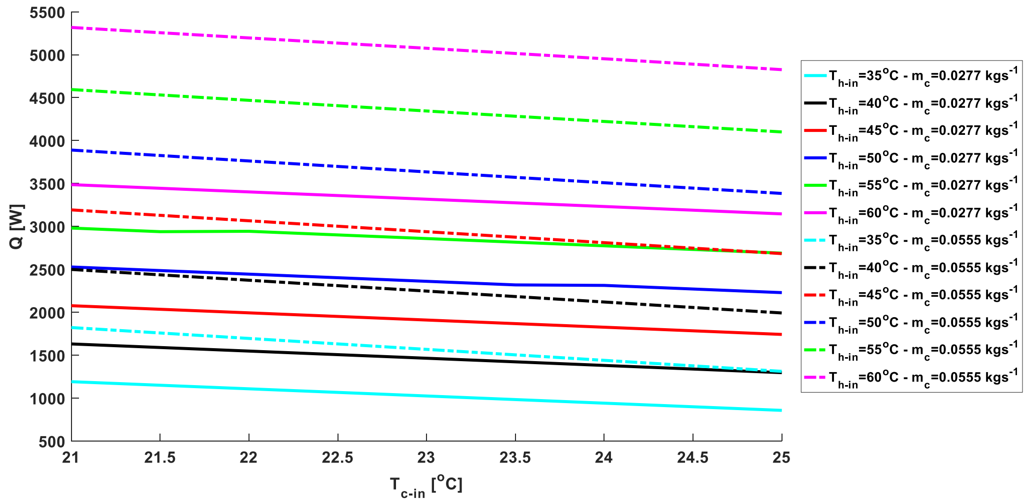

Figure 7. The variation of heat transfer rate value with respect to cold water inlet temperature for $\dot{m}_c = 0.0277\ kgs^{-1}$ *and* $\dot{m}_c = 0.0555\ kgs^{-1}$ *at specific hot water inlet temperatures*

In Figure 8, the variations of the heat transfer rate are shown for the cases in which the combinations of the cold water inlet temperature, T_{c-in}, such as 21°C, 22°C, 23°C, 24°C and 25°C and same cold water mass flow rate values in previous figure. It can be seen that the heat transfer rate increases when the value of T_{h-in} is increased. On the other hand, increase in cold water inlet temperature leads to decrease in $\dot{Q}$ for a specific value of T_{h-in}. Moreover, the slope of the linearly varying curve increases when the cold water flow rate is increased and it leads to increase the heat transfer rate, similarly.

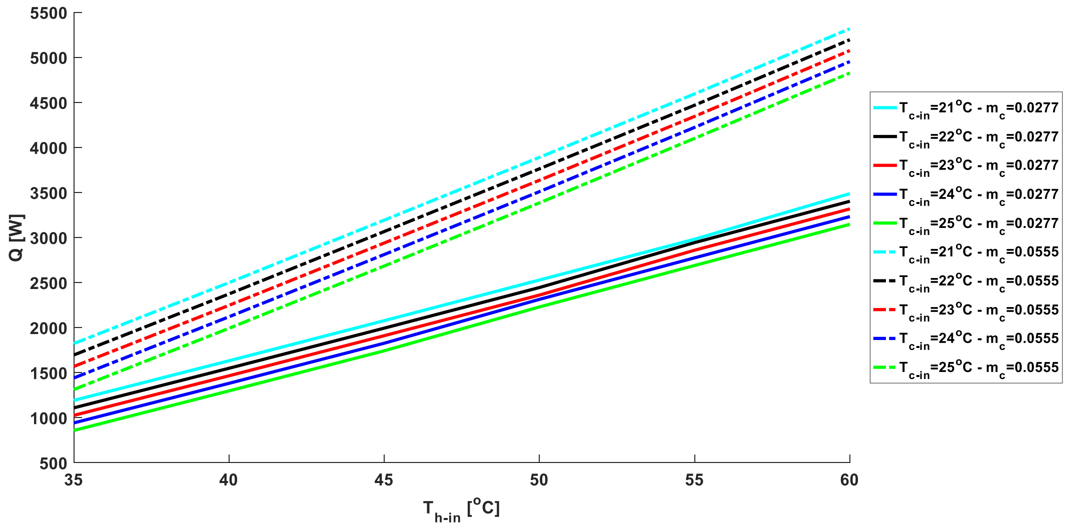

Figure 8. The variation of heat transfer rate value with respect to hot water inlet temperature for $\dot{m}_c = 0.0277\ kgs^{-1}$ *and* $\dot{m}_c = 0.0555\ kgs^{-1}$ *at specific cold water inlet temperatures*

Figure 9 show the variation of overall heat transfer coefficient, U, as a function of T_{c-in} for combinations of the specific values of T_{h-in} and $\dot{m}_c$. Similarly, the values of $\dot{m}_c$ are equal to 0.0277 kgs-1 and 0.0555 kgs-1 and the values of T_{h-in} are equal to 35°C, 40°C, 45°C, 50°C, 55°C and 60°C. The results show that U changes linearly and it increases depending on increasing in T_{c-in} for all considered cases. Increasing in T_{h-in} leads to increase in U for the both cold water mass flow rates. Moreover, increase in $\dot{m}_c$ has similar effect on the overall heat transfer coefficient for a specific values of T_{c-in} and T_{h-in}.

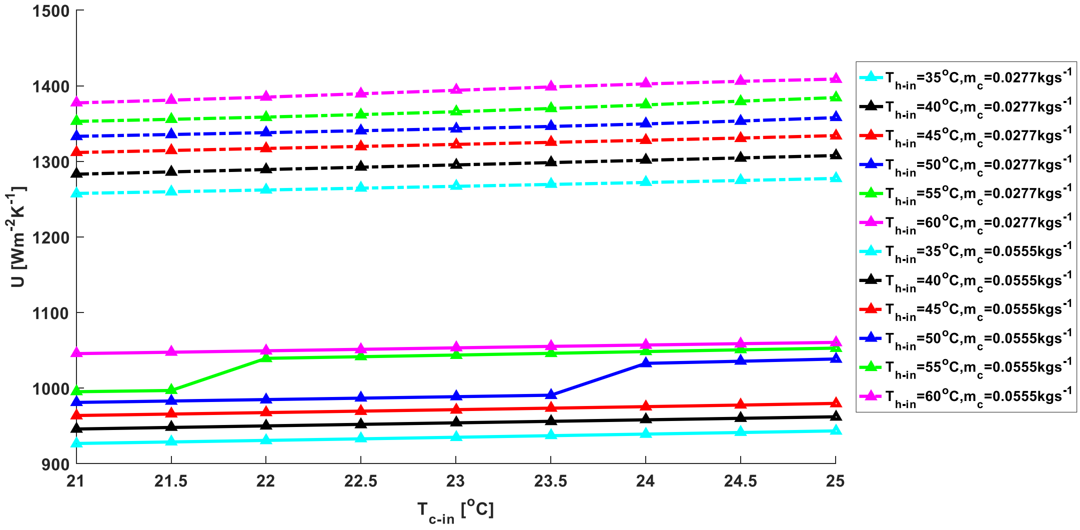

Figure 9. The variation of overall heat transfer coefficient value with respect to cold water inlet temperature for $\dot{m}_c = 0.0277\ kgs^{-1}$ and $\dot{m}_c = 0.0555\ kgs^{-1}$ at specific hot water inlet temperatures

Figure 10 shows the variation of the energy efficiency as a function of cold water inlet temperatures for specific values of $\boldsymbol{T_{h-in}}$ and $\boldsymbol{\dot{m}_c}$. The results indicated that the energy efficiency increases linearly depending on increase in $\boldsymbol{T_{c-in}}$. Similarly, increase in $\boldsymbol{T_{c-in}}$ cause to increase the overall efficiency for the specific values of $\boldsymbol{T_{c-in}}$ and $\boldsymbol{\dot{m}_c}$. However, the energy efficiency decreases when the mass flow rate of cold water is increased.

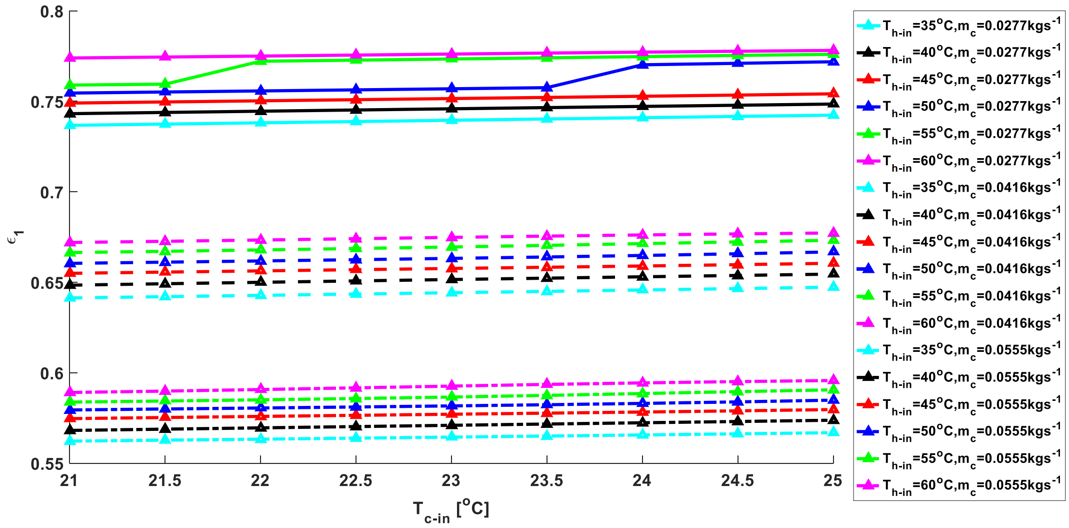

Figure 10. The variation of energy efficiency with respect to cold water inlet temperature for $\dot{m}_c = 0.0277\ kgs^{-1}$, $\dot{m}_c = 0.0416\ kgs^{-1}$ and $\dot{m}_c = 0.0555\ kgs^{-1}$ at specific hot water inlet temperatures

4. Conclusions

In this study, a ANN is developed for prediction of the outlet temperatures of the chevron type heat exchanger depending on the inlet temperatures and mass flow rate of cold water when the mass flow rate of hot water is assumed to be constant for all cases. Developing ANN is important in applications because the experiments take very long time and ANN allows us to get fast results between the values trained without doing these long experiments. The predicted results of ANN show very good agreement with experimental data used as testing. The developed network structure estimates the outlet temperatures with 2.58 % and 1.80 % for hot and cold water, respectively. Therefore, this developed ANN model presents satisfactory performance to estimate the outlet temperatures. In addition, theoretically obtained outputs were compared with the predicted outputs by applying untested input parameters. According to the results, it is seen that the theoretical results and the estimation results are compatible with each other in determining the outputs for the new inputs. This also proves the reliability of the developed network in different inputs. This inexpensive technique, which can determinate the outlet temperatures quickly, will reduce the total cost operations and save time. Therefore, the variations of heat transfer rate, overall heat transfer rate and energy efficiency are determined for specific cases with experimental data not included in [Yildiz & Ersoz, 2015].

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