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A COMPARATIVE COMPUTATIONAL INTELLIGENCE APPROACH FOR HEAT TRANSFER ANALYSIS OF CORRUGATED PLATE HEAT EXCHANGERS

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Abstract

In this paper, an application artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) are presented to predict the heat transfer rate and effectiveness in the corrugated plate heat exchangers. First, the thermal performances of the corrugated plate heat exchangers were evaluated experimentally. Experimental data were used for training and testing network. The results of the ANN are compared with the ANFIS in which the same data sets are used. The ANN model is slightly better than ANFIS. The coefficient of multiple determination (R^2) values obtained when unknown data were used to the networks were 0,999636 for heat transfer rate and 0,999565 for effectiveness, which is very satisfactory. This demonstrates that the neural network presented can help the engineers and manufacturers predict the thermal characteristics of corrugated plate heat exchangers under various operating conditions.

Key words: ANFIS, ANN, corrugated plate, heat exchanger, heat transfer

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1. Introduction

The Computational Intelligence (CI) techniques, such as Artificial Neural Networks (ANN), Fuzzy Logic (FL), adaptive neuro-fuzzy inference system (ANFIS), Genetic Algorithms (GAs) have been successfully applied in many scientific researches and engineering practices. In recent years, CI techniques have been used in analysis of heat exchangers. For example, Islamoglu (2003) used artificial neural networks to predict the heat transfer rate of the wire-on-tube type heat exchanger. Yousefi et al. (2012) presented application of imperialist competitive algorithm (ICA) for optimization of a cross flow plate fin heat exchanger. Minimization of total weight and total annual cost were considered as objectives. Tan et al. (2009) used artificial neural network models to simulate the thermal performance of a compact, fin-tube heat exchanger with air and water/ethylene glycol anti-freeze mixtures as the working fluids. Lalot and Palsson (2010) used neural network for the detection of fouling in a cross-flow heat exchanger. Diaz et al. (2001) used artificial neural network for the prediction of the dynamic behavior of a thermal system which consists of a heat exchanger working between a closed hot water and an open air loop. The network showed that the present technique performed better than conventional proportional-integral (PI) and proportional-integral-derivative (PID) control in certain cases. Najafi et al. (2011) carried out energy and cost optimization of a plate and fin heat exchanger using genetic algorithm. The multi-objective genetic algorithm was utilized for optimization of the system and achieving set of

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optimal solutions each of which is a trade-off between the highest total rate of heat transfer and the least total annual cost. Xie et al. (2007) applied Artificial Neural Network for heat transfer analysis of shell-and-tube heat exchangers with segmental baffles or continuous helical baffles. Predictions of the outlet temperature differences hot and cold sides and overall heat transfer rates were performed. Islamoglu and Kurt (2004) carried out heat transfer analysis using ANN with experimental data for air flowing in corrugated channels. Mehrabi et al. (2011) used ANFIS for modeling the effect of important parameters on heat transfer and fluid flow characteristics of helicoidal double-pipe heat exchangers. The overall heat transfer coefficient and inner and annular pressure drop were modeled. ANFIS network models and results were compared by statistical criteria. Pacheco-Vega et al. (2001) applied the ANN approach to accurately model the thermal characteristics of refrigerating heat exchangers. Peng and Ling (2008) used artificial neural networks to predict the pressure drop and heat transfer characteristics in the plate-fin heat exchangers. Duran et al. (2009) developed a model of design cost estimating for the shell and tube heat exchangers in the early design phase via the application of artificial neural networks. Peng and Ling (2008) presented application of genetic algorithm combined with back propagation neural networks for the optimal design of plate-fin heat exchangers. A procedure had been developed to run the genetic algorithm combined with back propagation neural network method and to find the global minimum weight and total annual cost of heat exchanger. Xie et al. (2009) used artificial neural network to correlate experimentally determined and numerically computed Nusselt numbers and friction factors of three kinds of fin-and-tube heat exchangers having plain fins, slit fins and fins with longitudinal delta-winglet vortex generators with large tube diameter and large number of tube rows. Hayati et al. (2009) applied an Adaptive Neuro-Fuzzy Inference System model for prediction of the heat transfer rate of the wire-on-tube type heat exchanger. Sanaye and Hajabdollahi (2010) carried out thermal economic multi objective optimization of plate fin heat exchanger using genetic algorithm.

The sensitivity analysis of change in optimum effectiveness and total annual cost with change in design parameters of the plate fin heat exchanger was also executed and the results are noted. Selbaş et al. (2009) used neural network to obtain heat transfer rate and effectiveness values of plate heat exchanger. Zhao and Li (2013) developed an effective layer pattern optimization model for multi-stream plate-fin heat exchanger using genetic algorithm. Guo et al. (2014) carried out optimization in Plate-fin Safety Structure of Heat Exchanger Using Genetic and Monte Carlo Algorithm. Yousefi et al. (2013) carried out optimization of plate-fin heat exchangers by an improved harmony search algorithm. Numerical results indicate that the presented approach can generate optimum solutions with higher accuracy when compared to algorithms as genetic algorithms and particle swarm optimization. A systematic approach combined non-structural fuzzy decision with three-level fuzzy evaluation has been used to search for the optimal design and selection of an industrial compact heat exchanger by Zhou et al. (2014).

From the literature review mentioned above, it is seen that computational intelligence techniques are used in the analysis of heat exchangers. However, a comparative analysis between ANN and ANFIS methods has not been carried out for the heat transfer rate and effectiveness in corrugated plate heat exchangers for different chevron angles yet. This paper is focused on the applicability of ANN and ANFIS methods for heat transfer analysis.

2. Experimental procedure and heat transfer analysis

The experimental system consists of plate heat exchanger, boiler, hot water tank, valves, two heaters, two pumps, flow meter, expand box, thermocouples and data logger. The experimental system can operate in the different temperature and flow rate values. Pumps used in the experimental system can operate in different three stages (pump stage 1, pump stage 2 and pump stage 3). So, flow rate values can be adjusted. Experiments of plate heat exchangers having different chevron angles for each pump stage were carried out. The temperatures of each fluid are measured at the inlet and at the outlet with thermocouples.

Schematic diagram of experimental system is given Fig. 1. The plate heat exchangers used in experiments are in countercurrent flow. Further details of the experimental procedure can be found in Kılıç, (2013). Chevron angles of plate heat exchangers used in experiments are β=30° and β=60° (Fig. 2).The general properties of the corrugated plate are given in Table 1.

The measured variables were the inlet-outlet water temperature and the flow rate of hot and cold water. The heat transfer rate in the plate heat exchanger is defined as (Genceli, 1999; Incropera and Witt, 1990) (Eqs. 1-3):

$$\dot{Q} = \dot{m}_h . c_{ph} . (T_{hi} - T_{ho}) = \dot{m}_c . c_{pc} . (T_{co} - T_{ci}) \quad (1)$$

Heat transfer rate can also be defined as follows (Eq. 2):

$$\dot{Q} = U.A.\Delta T_{LMTD} \quad (2)$$

where A is the effective heat transfer surface area and ΔT_{LMTD} is the logarithmic mean temperature difference for countercurrent flow arrangement, given by (Eq. 3):

$$\Delta T_{LMTD} = \frac{(T_{hi} - T_{co}) - (T_{ho} - T_{ci})}{\ln \frac{(T_{hi} - T_{co})}{(T_{ho} - T_{ci})}} \quad (3)$$

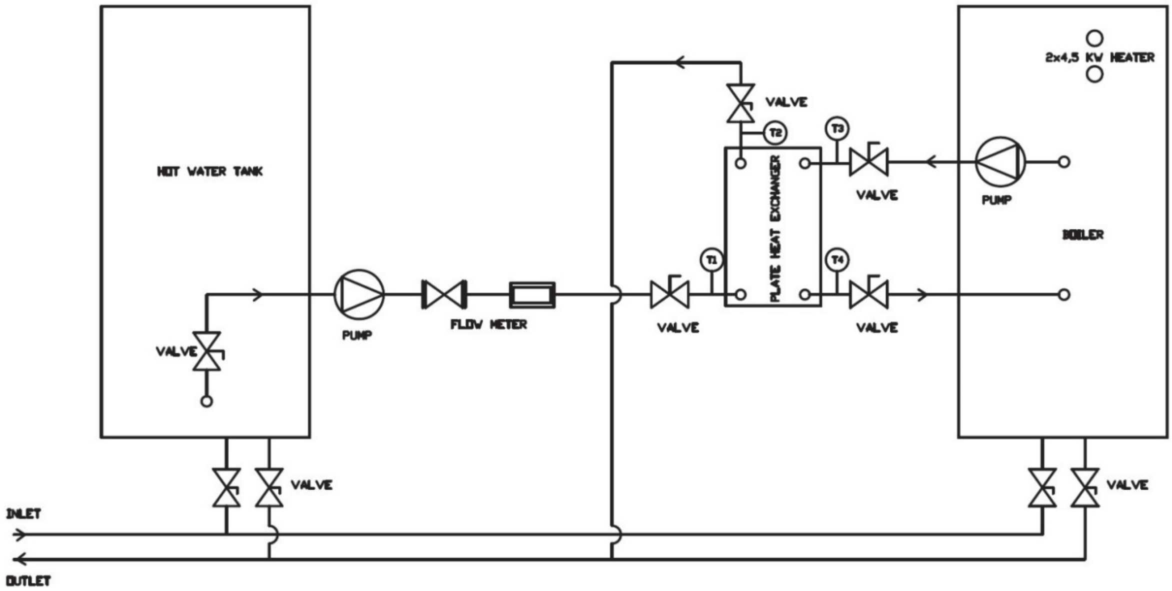
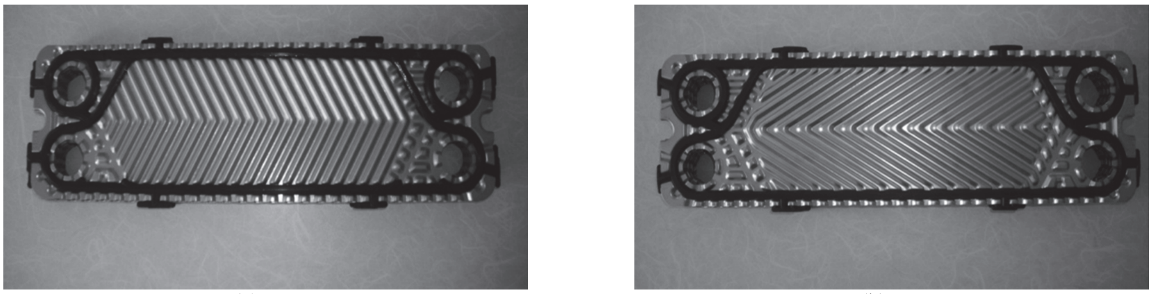


Fig. 1. Schematic diagram of experimental system



(a) 30°　　　(b) 60°

Fig. 2. Plate heat exchangers having different chevron angles: (a) 30° and (b) 60°

Table 1. General properties of a corrugated plate used in present study

Property	*Value*
Plate length (mm)	431
Plate width (mm)	125.5
Total number of plates	10
Heat transfer area (m^2)	0.032
Plate material	0.5 mm SS AISI 316
Chevron angles	30° and 60°
Gasket material	EPDM per.
Design temperature (°C)	145
Design pressure (bar)	10

Total heat transfer coefficient can also be defined as follows (Eq. 4):

$$\frac{1}{U} = \frac{1}{\alpha_1} + R_{f1} + \frac{L_1}{\lambda_1} + R_{t,1-2} + \frac{L_2}{\lambda_2} + R_{t,2-3} + \frac{L_3}{\lambda_3} + R_{f2} + \frac{1}{\alpha_2} \tag{4}$$

where R_f is the dirtiness resistance and R_t is the contact resistance for countercurrent flow arrangement.

Heat capacity for hot and cold fluids (Genceli, 1999; Incropera and Witt, 1990) (Eqs. 5-6):

$$C_{hot} = \dot{m}_h . c_{ph} \tag{5}$$

$$C_{cold} = \dot{m}_c . c_{pc} \tag{6}$$

The effectiveness of heat exchanger is given as (Genceli, 1999; Incropera and Witt, 1990) (Eq. 7):

$$\varepsilon = \frac{\dot{Q}}{\dot{Q}\mathrm{max}} \tag{7}$$

Here the maximum possible heat transfer rate $\dot{Q}_{max}$ is determined as (Genceli, 1999; Incropera and Witt, 1990) (Eq. 8):

$$\dot{Q}_{max} = C_{min}(T_{hi-}T_{ci}) \tag{8}$$

where C_{min} represents the smaller of heat capacity between hot and cold fluids.

3. Artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS)

Artificial neural network is a calculation tool which is used to test the data and to create a model by these data. When artificial neural network applies the training data for learning latent patterns existing within the data, it may use them to access to the outputs (Mehrabi et al., 2011). Artificial neural network process is described in the Fig. 3. Detailed information about ANN can be found in literature (Fu, 1994; Haykin, 1999; Kalogirou, 2000; Selbas et al., 2009; Tasdemir et al., 2011; Veelenturf, 1995).

ANFIS system uses two neural network and fuzzy logic approaches. Since ANFIS combines both neural network and fuzzy logic, it is capable of handling complex and nonlinear problems. ANFIS is a class of adaptive multi-layer feed-forward networks that is functionally equivalent to a fuzzy inference system. It implements a Takagi Sugeno fuzzy inference system and has a five layered architecture as shown in Fig. 4 (Hayati et al., 2009). ANFIS have been used in many applications. Some of these have been given in literature (e.g. Alasha'ary et al., 2009; Esen et al., 2008; Soyguder and Alli, 2009).

4. Application

In this study, the heat transfer rate and effectiveness in the corrugated plate heat exchangers are predicted using ANFIS and ANN approaches. The training data for ANFIS and ANN approaches were provided from the experimental data (Kılıç, 2013). Inputs for network are the mass flow rate, chevron angle, hot and cold water inlet temperature; outputs are heat transfer rate and effectiveness. The ANN and ANFIS models developed according to these parameters are shown in Fig. 5 and Fig. 6.

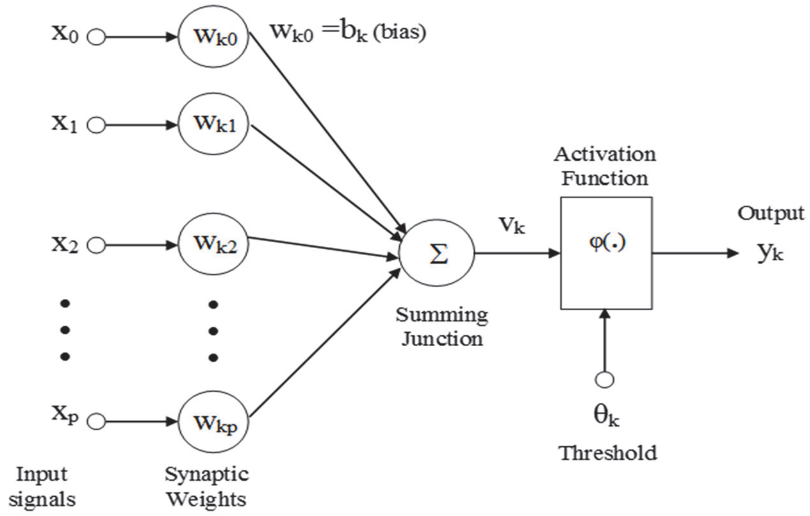


Fig. 3. Artificial neural network process

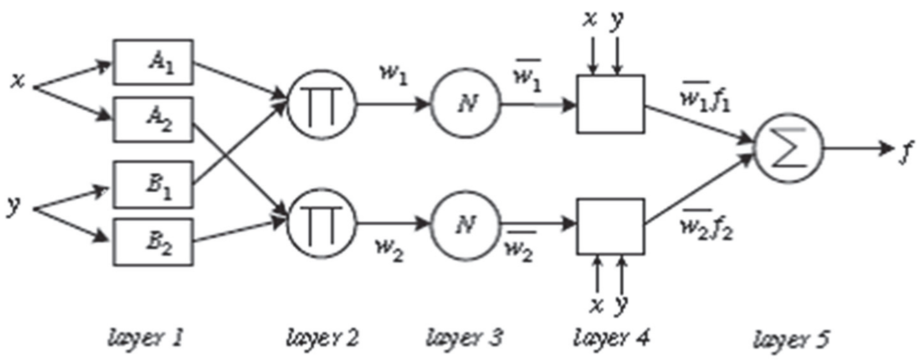


Fig. 4. ANFIS architecture based on Takagi–Sugeno

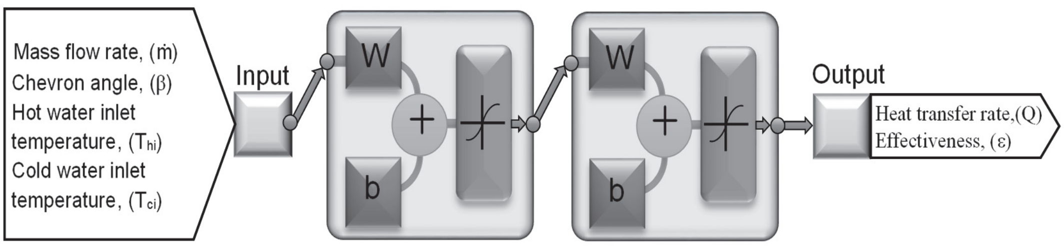


Fig. 5. The ANN model

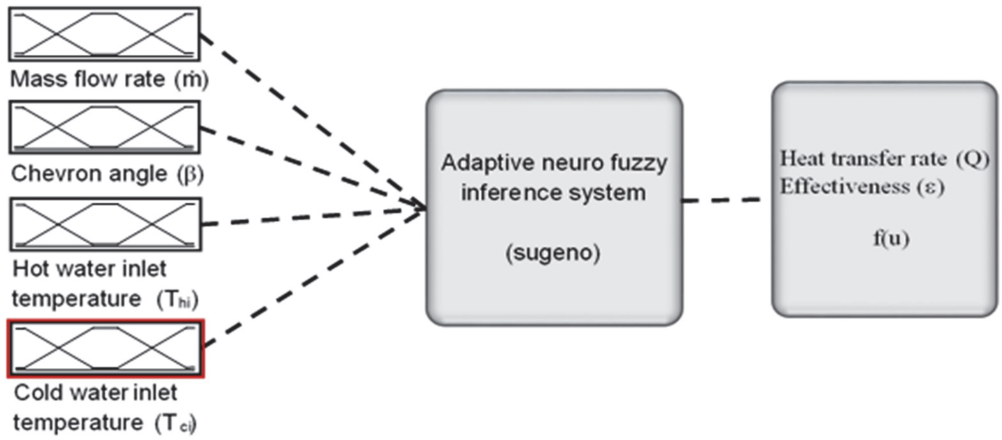


Fig. 6. The ANFIS model

Table 2. Statistical values for the heat transfer rate

Algorithm	*RMSE*	*cov*	R^2
LM-3	53.5148	0.02003	0.999618
LM -4	52.7873	0.01975	0.999628
LM -5	**52.2255**	**0.01954**	**0.999636**
LM -6	58.6761	0.02196	0.999540
LM -7	54.9293	0.02056	0.999597
LM -8	63.3763	0.02372	0.999464
LM -9	57.5448	0.02153	0.999558
LM -10	60.1653	0.02251	0.999517
LM -11	58.8812	0.02203	0.999537
LM -12	129.645	0.04852	0.997758
SCG-3	95.9341	0.03590	0.998772
SCG-4	76.4545	0.02861	0.999220
SCG-5	75.8600	0.02839	0.999232
SCG-6	61.0010	0.02283	0.999503
SCG-7	71.3101	0.02669	0.999321
SCG-8	61.6170	0.02306	0.999493
SCG-9	63.3772	0.02372	0.999464
SCG-10	54.6721	0.02046	0.999601
SCG-11	62.3508	0.02333	0.999481
SCG-12	59.8349	0.02239	0.999522

The computer program was performed under MATLAB environment using the neural network toolbox. The back propagation learning algorithm has been used in a feed forward, single hidden layer neural network. The data set for the heat transfer rate and effectiveness of in the corrugated plate heat exchangers available included 227 data patterns. From these, 185 data patterns were used for training the network and the remaining 42 patterns were randomly selected and used as the test data set. Epoch numbers for the heat transfer rate and effectiveness was selected as 1000.The variants of the algorithm used in the study are the Levenberg–Marquardt (LM) and scaled conjugate gradient (SCG) algorithms. Inputs and outputs are normalized in the (0.1) range. A logistic sigmoid (logsig) transfer function has been used for both the hidden layer and the output layer. In order to achieve the optimal result, different algorithms and different numbers of hidden neurons were used. Statistical values such as the Root-Mean-Squared Error (*RMSE*), the coefficient of multiple determinations (R^2) and the coefficient of variation (*cov*) are given in Table 3 for the heat transfer rate and in Table 4 for the effectiveness.

During learning the error is estimated by RMSE defined as Eq. (9):

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n}\left(y_{p,m} - t_{m,m}\right)^2}{n}} \tag{9}$$

In addition, the coefficient of multiple determination (R^2) and coefficient of variation (*cov*) in percent are defined as follows (Eqs. 10, 11):

$$R^2 = 1 - \frac{\sum_{m=1}^{n}\left(t_{m,m} - y_{p,m}\right)^2}{\sum_{m=1}^{n}\left(t_{m,m} - \bar{t}_{m,m}\right)^2} \tag{10}$$

$$\text{cov} = \frac{RMS}{\left|\bar{t}_{m,m}\right|}100 \tag{11}$$

Table 3. Statistical values for the effectiveness

Algorithm	*RMSE*	*cov*	R^2
LM -3	0.0102575	0.022758	0.999475
LM -4	0.0096802	0.021477	0.999532
LM -5	0.0134191	0.029773	0.999101
LM -6	0.0097002	0.021522	0.999530
LM -7	0.0099292	0.022030	0.999508
LM -8	0.0097623	0.021660	0.999524
LM -9	0.0100210	0.022234	0.999498
LM -10	0.0096225	0.021350	0.999538
LM -11	0.0109986	0.024403	0.999396
LM -12	**0.0093323**	**0.020706**	**0.999565**
SCG-3	0.0124508	0.027625	0.999226
SCG-4	0.0109349	0.024261	0.999403
SCG-5	0.0129422	0.028715	0.999164
SCG-6	0.0114423	0.025387	0.999346
SCG-7	0.0121871	0.027040	0.999258
SCG-8	0.0118729	0.026343	0.999296
SCG-9	0.0112524	0.024966	0.999368
SCG-10	0.0101688	0.022562	0.999484
SCG-11	0.0109066	0.024199	0.999406
SCG-12	0.0113416	0.025164	0.999358

where n is the number of data patterns, $y_{p,m}$ indicates the predicted, $t_{m,m}$ is the measured value of one data point m, and $\bar{t}_{m,m}$ is the mean value of all measure data points (Dincer et al., 2008).

From the data presented in Table 2 for the heat transfer rate, the LM algorithm with five neurons in the hidden layer (LM-5) appeared to be the most optimal topology. As can be seen from Table 3 for the effectiveness, the LM algorithm with twelve neurons in the hidden layer (LM-12) appeared to be the most optimal topology.

Different ANFIS architectures were tried and the appropriate model structure was determined for predicting of the heat transfer rate and effectiveness. Hybrid learning rule was used to train the model. The final ANFIS architecture being used in this study has been shown in Table 4. The computer program was performed under MATLAB environment using anfis editor (anfisedit).

Table 4. Optimal architecture and specification of proposed ANFIS model

Type	*Sugeno*
Input/Output	4/1
Number of training data	185
Number of test data	42
Input membership function types	Triangle
Rules Weight	1
Number of fuzzy rules	81
Number of epochs	500

5. Results and discussion

The performances of ANN and ANFIS models developed in this study were assessed using various standard statistical performance evaluation criteria. Table 5 presents a comparison of statistical performance evaluation criteria values such as R^2, RMSE, and *cov* between ANN and ANFIS techniques for the heat transfer rate and effectiveness estimation of corrugated plate heat exchanger. As can been seen in Table 5, ANN model is slightly better than ANFIS for the heat transfer rate and effectiveness estimation.

Table 6 gives a comparison of the experimental results with the results of ANN and ANFIS models for the heat transfer rate of the corrugated plate heat exchanger. Table 7 gives a comparison of the experimental results with the results of ANN and ANFIS models for the effectiveness of the corrugated plate heat exchanger.

Table 5. Comparison of statistical measures between ANN and ANFIS techniques for the heat transfer rate and effectiveness estimation

Property	*Method*	*Comparison Parameters*		
		R^2	*RMSE*	*cov*
Heat transfer rate	ANN	0.999636	52.2255	0.01954
	ANFIS	0.999602	54.5643	0.02042
Effectiveness	ANN	0.999565	0.0093323	0.020706
	ANFIS	0.999461	0.0103911	0.023055

Fig. 7 and Fig. 8 give a comparison of the experimental results with the results of ANN model of the corrugated plate heat exchanger for the β=30° and β=60° respectively. As can be seen in Fig.7 and Fig.8, the experimental heat transfer and effectiveness values for both chevron angles agree with the results of ANN model. Fig. 9 and Fig. 10 give a comparison of the experimental results with the results of ANFIS model of the corrugated plate heat exchanger for the β=30° and β=60° respectively. As can be seen in Fig. 9 and Fig. 10, the experimental heat transfer and effectiveness values for both chevron angles agree with the results of ANFIS model. Heat transfer rate and effectiveness values increase with increasing hot water inlet temperature.

Table 6. Comparison of experimental and ANN and ANFIS estimated heat transfer rate of the corrugated plate heat exchanger

T_{hi} (°C)	T_{ci} (°C)	T_{ho} (°C)	T_{co} (°C)	m (kg/s)	β (°)	Experimental Q (W)	Obtained Q from ANN (W)	Obtained Q from ANFIS (W)
27.4	20	24.4	24.4	0.167	30	2098	2066	2042
44.6	37.1	41.5	42	0.167	30	2167	2144	2160
51.1	43.6	48	48.6	0.167	30	2167	2166	2176
58.1	50.1	54.7	55.5	0.167	30	2377	2354	2340
39.3	34	37	37.3	0.239	30	2295	2284	2274
37.9	34.3	36.3	36.8	0.321	30	2144	2115	2117
45.5	41.9	43.9	44.6	0.321	30	2144	2159	2164
19.2	15.7	17.6	16.9	0.39	60	2608	2609	2642
26.4	21.9	24.4	23.6	0.39	60	3259	3254	3234
37.5	33.1	35.4	35	0.39	60	3422	3421	3446
45.2	40.8	43	42.9	0.39	60	3585	3572	3548
32.1	29	30.7	30.2	0.517	60	3023	3055	3046
45.7	42.5	44.1	44	0.517	60	3455	3419	3454
54.3	51	52.6	52.8	0.517	60	3671	3606	3657

Table 7. Comparison of experimental and ANN and ANFIS estimated effectiveness values of the corrugated plate heat exchanger

T_{hi} (°C)	T_{ci} (°C)	T_{ho} (°C)	T_{co} (°C)	m (kg/s)	β (°)	Experimental ε	Obtained ε from ANN	Obtained ε from ANFIS
21.2	15.4	18.9	18.9	0.167	30	0.40	0.396	0.409
44.6	37.1	41.5	42	0.167	30	0.41	0.409	0.414
51.1	43.6	48	48.6	0.167	30	0.41	0.407	0.418
31.8	26.6	29.6	29.6	0.239	30	0.42	0.423	0.425
22.4	18.9	20.9	21	0.321	30	0.43	0.426	0.433
29.1	25.5	27.6	27.8	0.321	30	0.42	0.423	0.421
59.5	55.9	57.8	58.8	0.321	30	0.47	0.466	0.462
28	21.8	25.4	24.2	0.263	60	0.42	0.426	0.423
34.8	28.4	32	31	0.263	60	0.44	0.445	0.443
41.4	34.9	38.5	37.7	0.263	60	0.45	0.453	0.444
53.3	46.8	50.2	50	0.263	60	0.48	0.477	0.479
26.4	21.9	24.4	23.6	0.39	60	0.44	0.439	0.438
37.5	33.1	35.4	35	0.39	60	0.48	0.478	0.476
45.7	42.5	44.1	44	0.517	60	0.50	0.505	0.500

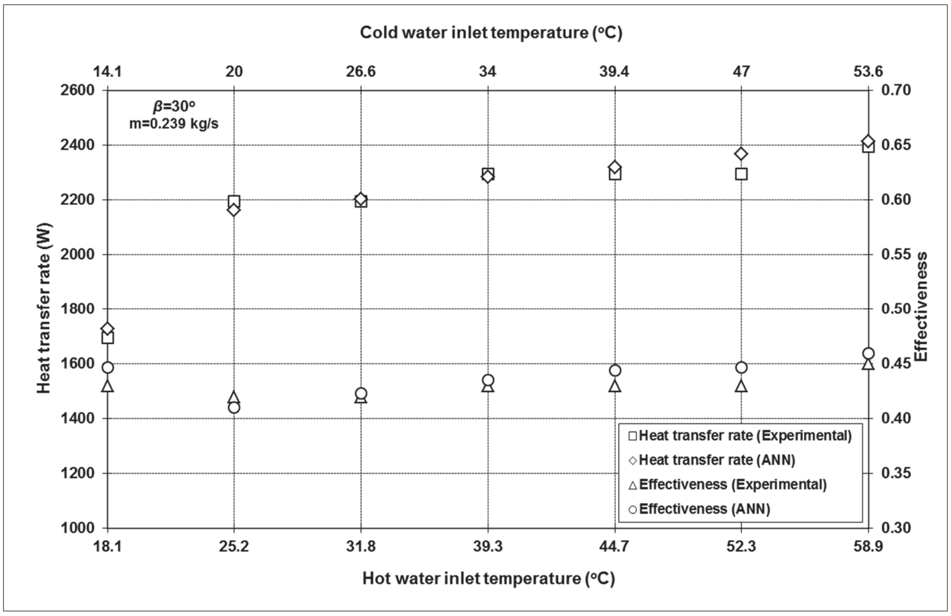


Fig. 7. Comparison between experimental and ANN results for β=30°

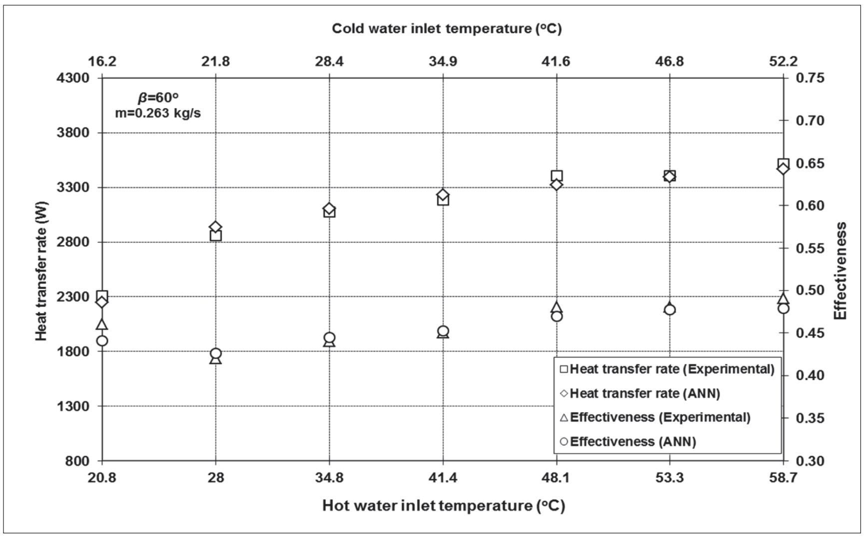


Fig. 8. Comparison between experimental and ANN results for β=60°

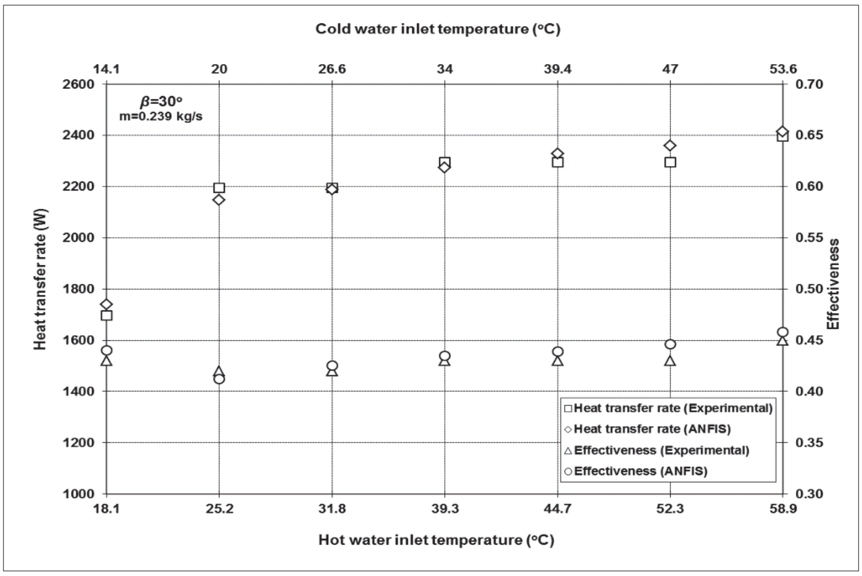


Fig. 9. Comparison between experimental and ANFIS results for β=30°

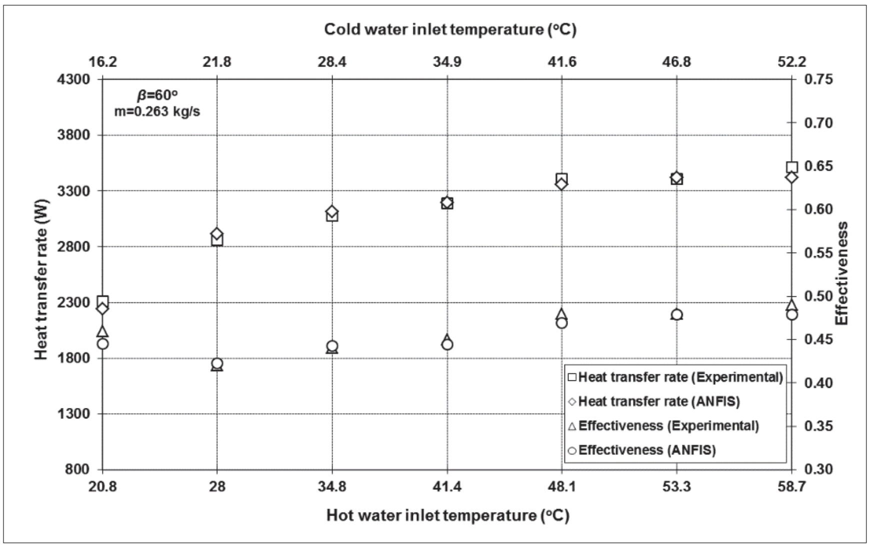


Fig. 10. Comparison between experimental and ANFIS results for β=60°

6. Conclusions

In this study, an experimental system for investigation on performance of the corrugated plate heat exchanger is set up, and limited experimental data are obtained. The ANN and ANFIS are applied to estimate heat transfer rate and effectiveness for the corrugated plate heat exchanger. The ANN model is slightly better than ANFIS.

The comparison between experimental and predicted values of proposed ANN and ANFIS models shows that there is a good agreement between the predicted heat transfer rate and effectiveness and the experimental results with least error. Both of the models are a suitable tool for use in the prediction of heat transfer rate and effectiveness. It is recommended that ANN and ANFIS can be applied to simulate thermal systems, especially for engineers to model the complicated heat exchangers in engineering applications.

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