Comparative gasketed plate heat exchanger performance prediction with computations, experiments, correlations and artificial neural network estimations

Selin Aradag, Yasin Genc and Caner Turk
Department of Mechanical Engineering, TOBB University of Economics and Technology, Ankara, Turkey

ABSTRACT
Gasketed plate heat exchangers (GPHEX) are popular due to their small volume, ease of cleaning and high thermal performance. Hydraulic and thermal performance of GPHEX are not as easily determined since they solely depend on the corrugation pattern of the heat exchanger (HEX) plates. Every plate needs its own correlation for Nusselt number and friction factor. Correlation development based on plate-specific experiments is one method of performance prediction. Computational fluid dynamics (CFD) is also applicable to understand the Nusselt number and friction characteristics. However, since it is difficult to observe the effects of the corrugation pattern computationally, the pattern of the plates is usually ignored and CFD is performed on flat, nonpatterned plates. In addition, correlations developed using experimental data can not exactly predict the performance. In this article, GPHEX computations are performed with corrugated plates and the results are validated via comparison with experiments performed for the same HEX plates. The use of corrugation patterns in computations is justified with the help of experimental results, and corrugated and flat-plate HEX computations. Artificial neural networks (ANNs) based on experimental findings are used as an alternative to correlations to examine the performance. The results show that ANNs can depict the experimental trends better than the correlations. The ANN results, which are composed of 12 inputs, and two hidden layers consisting of 10 and six neurons, respectively, are within 16% of the experimental results, as opposed to the correlations, which are within 40%.

ARTICLE HISTORY
Received 12 December 2016
Accepted 30 March 2017

KEYWORDS
Gasketed plate heat exchanger; experiment; correlation; CFD; ANN

1. Introduction

Gasketed plate heat exchangers (GPHEX) gained popularity due to their ease of maintenance, small volume and high thermal performance with improvements in manufacturing technology. Determination of the thermal and hydraulic performance of these types of heat exchangers (HEX) was solely based on experiments and experimentally developed correlations in the 1990s and 2000s. Computational fluid dynamics (CFD) recently gained importance in performance prediction. Thermal analysis, pressure drop prediction, the degree of nonuniformity of flow distribution (which is also known as flow maldistribution) and fouling of the HEX can be determined.

Although CFD simulations are possible, they are usually difficult and time consuming because of the intricate plate geometries. Therefore, most of the simulations in literature are either for flat plates or for very simply modified plate geometries. Piepiorka-Stepuk and Jakubowski (2012) used a plate HEX geometry composed of 20 plates and 10 flow channels in their computational study. However, the plates were taken as flat. Paras, Kanaris, Mouza, and Karabelas (2002) utilized plates with one flat side. The intricate shape of the corrugation patterns, together with the Chevron angles, corrugation heights and other geometrical parameters, have not been exactly simulated in most extant studies to date.

One other simplification in the simulations is to take only a few plates (usually three) for the computations. Wang, Liang, Zhou, and Wang (2010) used the corrugated shape of the plates in their simulations, but since they did not use several plates they modeled the problem with periodic boundary conditions. However, in actual HEX, the flow is not distributed uniformly, and this cannot be modeled with only three plates in the HEX. It is important to model the actual geometry of the HEX with a reasonable number of plates to observe the actual flow distribution over the plates for the computational results to be meaningful. Gullapalli and Sundén’s (2014) CFD results underpredicted experiments by 10–35% in terms of pressure drop. Their thermal performance values were within 20–30% of experiments. Han, Cui, Chen, Chen,
and Wang’s (2010) simulations had a 35% error when compared to experimental correlations in the literature.

Experiments are also still important. Every plate type has a different geometry that affects the Nusselt number and friction characteristics, and therefore the thermal and hydraulic performance of the HEX. Every plate needs its own correlation for Nusselt number and friction factor. Muley (1997) was the pioneer of plate HEX experiments. Akturk, Sezer-Uzol, Aradag, and Kakac (2015) and Gulenoglu, Akturk, Aradag, Sezer-Uzol, and Kakac (2014) worked on developing correlations based on experiments. However, correlations developed using experimental data usually depend on several variables, but not all variables involved, which causes an error of approximately 20% when the correlation results are compared with the raw experimental data. One way to minimize the error is to use artificial neural networks (ANNs) to predict the performance, instead of developing correlations based on the same experimental data (Turk, Aradag, & Kakac, 2016).

Contemporary soft-computing techniques also have many real-life applications in different fields. For example, Taormina and Chau (2015) used particle swarm optimization and Extreme Learning Machines for the selection of data-driven input variables for rainfall-runoff modeling. Zhang and Chau (2009a) worked on particle swarm optimization for multiple ensemble pruning. Wang, Chau, Xu, and Chen (2015) improved the forecasting accuracy of annual runoff time series using ensemble empirical mode decomposition. Zhang and Chau (2009b) utilized semi-supervised locally linear embedding for dimension reduction for plant leaf classification. Wu, Chau, and Li (2009) used neural nets for daily flow predictions. Chau and Wu (2010) coupled a hybrid model with singular spectrum analysis for rainfall prediction.

In this work, first, computations are performed for flat-plate and corrugated-plate HEX composed of seven plates each. The effects of inlet and outlet ports are taken into consideration. The corrugation pattern is obtained through laser scanning of a commercially available plate. With the help of these computations, the effect of taking the real plate geometry into consideration, instead of using just plain plates, is shown. Since seven intricately shaped plates are involved in the computations, a computer cluster with 120 processors is used. Experiments are performed for the same plates and CFD results of the corrugated geometries are validated with the experiments.

The next part of the work involves the determination of a Nusselt number and friction factor to predict the thermal and hydraulic performance of the HEX based on experimental and computational results. Correlations are developed using experimental results. Like any other type of heat transfer correlation, our correlations cannot take every parameter into consideration. Therefore, ANN models are developed based on the same experimental results, and these models are used for performance prediction as well. Their results are compared with computations, experiments and correlations. Comparisons are presented in detail. A flow chart showing the steps of the research is presented in Figure 1.

The main contribution of the work is its demonstration of the importance of using corrugation patterns instead of flat plates in the computations of GPHEX, and using ANN estimations for hydraulic and thermal performance as an alternative to classical correlations.

2. Methodology

As summarized in Figure 1, computations are performed for flat and corrugated plate geometries. The geometrical details of the plate of tested and simulated HEX are summarized in Table 1. An image showing the definition of these geometrical parameters is also provided in Figure 2a. In Table 1 and Figure 2a, \( L_h \) and \( L_v \) are the horizontal and vertical distances between the ports, \( L_w \) is the plate width (from one port to another), \( L_p \) is the port-to-port length, \( t \) is the thickness of the plate, \( b \) is the depth of the corrugation pattern and \( D_p \) is the port diameter. The total effective corrugation area and the projected surface area are shown with \( A_t \) and \( A_{lp} \), respectively. Enlargement factor (\( \phi \)) is the ratio \( A_t \) and \( A_{lp} \). Chevron angle \( \beta \) is the angle of the Chevron pattern with the horizontal axis. The flow arrangement for the plates is shown in Figure 2b.

2.1. Experimental methodology and correlation development

The experimental setup utilizes tap water as a working fluid. A wide range of Reynolds numbers (500–5,000) can be tested with the setup. The water is heated with 38 kW resistance heaters for the hot water loop. A 3-kW pump is used to operate the system. Separate tanks are used for cold and hot water. Electromagnetic flowmeters and pressure transmitters are utilized for flow rate and pressure measurements. Figure 3 shows a schematic view of the experimental setup (Akturk et al., 2015).

The correlations developed for Nusselt number and friction factor for the HEX arrangement of these plates based on the experiments (Gulenoglu et al., 2014) are given as

\[
\text{Nu} = 0, 32867 \Re^{0.68} \Pr^{1/3} \left( \frac{\mu}{\mu_w} \right)^{0.14} \tag{1}
\]

\[
f = 259, 9 \Re^{-0.9227} + 1, 246 \tag{2}
\]
where Nu is the Nusselt number and $f$ is the friction factor. Here, Nusselt number predictions are within 40% and friction factor predictions are within 20% of the experimental results. The uncertainty in the temperature measurements is 0.45%, and for pressure drop is 0.075%, whereas it is 0.0005% in the plate geometry and 0.4% in the volumetric flow rate.

### Table 1. Details of the plate geometry.

| Geometrical parameter | Value |
|-----------------------|-------|
| Chevron angle ($\beta$) | 30°   |
| Chevron area length ($L_v$) | 0.37 m |
| Effective corrugation area, $A_t$ | 0.035 m$^2$ |
| Projected surface area, $A_{sp}$ | 0.03 m$^2$ |
| Port diameter, $D_p$ | 0.035 m |
| Port-to-port plate width, $L_w$ | 0.109 m |
| Port-to-port length, $L_p$ | 0.335 m |
| Corrugation depth, $b$ | 2.76 m |
| Plate thickness, $t$ | 0.45 m |
| Enlargement factor, $\phi$ | 1.17 |
| Hydraulic diameter, $D_h$ | 0.0047 m |
| Equivalent diameter, $D_e$ | 0.0055 m |

### 2.2. Computational methodology

A three-dimensional (3D) computer aided design (CAD) model is formed using a 3D photogrammetry scanner. The scanned data is utilized to build the CFD model of an actual-size entire plate HEX.

Two plates are arranged with the chevron pattern pointing in opposite directions to form the cross-corrugated channel shown in Figure 2, and the plates are assembled to construct a complete plate HEX, as illustrated in Figure 4. It includes distribution areas at the inlet and outlet ports and 15 cm inlet and outlet ports, as is the case with experiment.

3D Reynolds-averaged Navier–Stokes equations are solved utilizing Ansys-CFX software for the simulations. Reynolds-averaged Navier–Stokes equations are shown below:

$$\frac{\partial}{\partial x_i}(U_i) = 0$$  \hspace{1cm} (3)
Here, Reynolds stresses are given as:
\[
\tau'_{ij} = -\rho u'_i u'_j
\] (6)

A \( k-\omega \) Shear Stress Transport (SST) turbulence model is utilized in the simulations. This model is one of the two-equation models that is composed of standard \( k-\epsilon \) and standard \( k-\omega \) models. The \( k-\epsilon \) model is accurate and robust; however, it may not always be reliable for flow over curved surfaces or prediction of boundary-layer separation. The standard \( k-\omega \) model is based on turbulence kinetic energy \( (k) \) and turbulent frequency \( (\omega) \). It does not involve the nonlinear damping functions of \( k-\epsilon \), which makes it more suitable for boundary layer flows. In the \( k-\omega \) SST model, transport effects are included in the formulation of eddy viscosity; therefore, separation of flow is modeled more accurately. It does not need extra wall treatment or wall functions as in \( k-\omega \). This turbulence model is usually recommended for boundary layer simulations. The model switches to \( k-\epsilon \) for the free stream flow. Therefore, the model combines the best properties of \( k-\omega \) and \( k-\epsilon \) turbulence models. Ozkaya, Gulenoglu, Aradag, and Kakac (2014) performed a turbulence model study for GPHEX simulations and \( k-\omega \) SST was found to be the most suitable for this kind of simulation.

The continuity, momentum and energy equations are solved using a high-order advection scheme, whereas the turbulence equations are solved using a first-order upwind scheme.

The main assumptions pertaining to the utilized model are summarized as: there is no heat transfer between the fluid and the surroundings. Conduction is assumed to take place only in the normal direction to the heat transfer surfaces. Flow maldistribution is not taken into consideration in the computations, which means the flow is equally distributed to all plates. Fluid properties are dependent on the temperature inside the HEX. The overall heat transfer coefficient is independent of location. The flow is 3D, turbulent and steady. The fluid is single phase and does not change its phase inside the HEX. The velocity of the fluid is constant at the inlet ports.

Plate HEX geometry consisting of three cold and three hot fluid channels is formed using seven plates of known dimensions (Figure 2). All fluid channels are connected to each other with ports of diameters 15 cm.

As boundary conditions, mass flow rate is used at the inlet ports and pressure outlet is used at the outlets. The static pressures are specified. The mass flow rate is 0.1 kg/s for the inlet ports and the static pressure is taken as 0 for the outlet. With the help of this static pressure boundary condition, the working pressure of the HEX is defined as 101 kPa, which is same as the experiments. The
Figure 4. CAD models for the HEX with (a) seven flat plates and (b) seven corrugated plates.

Table 2. Boundary conditions.

| Boundary    | Condition and value          |
|-------------|------------------------------|
| Hot inlet   | Temperature = 90°C           |
| Hot inlet   | Mass flow rate = 0.1 kg/s    |
| Hot outlet  | Static pressure = 0 atm       |
| Cold inlet  | Mass flow rate = 0.1 kg/s    |
| Cold inlet  | Temperature = 20°C           |
| Cold outlet | Static pressure = 0 atm       |
| Wall        | No slip wall = Smooth wall    |
| Plate       | No slip wall = Smooth wall, Thin material = 0.45 mm steel |

Inlet temperatures of the hot and cold fluids are 90°C and 20°C. Water density is taken as 998 kg/m³ in the simulations. The metal plates are specified as smooth, thin walls with the thermal resistance of a 0.45 mm stainless steel wall where no slip wall boundary condition is applied. Conservative interface heat flux is applied for heat transfer with a steel material thickness of 0.45 mm. Exterior walls are modeled as adiabatic. No periodic boundary condition is used because of the complex geometry of the plate HEX. The boundary conditions are summarized in Table 2. The boundaries are shown in Figure 5. Monitoring points for temperature and pressure values are used to ensure the simulation results reach a steady state.

Eight different meshes are used for the computations with flat plates, and two different meshes are used for the computations with corrugated plates. Table 3 shows the mesh properties for the eight meshes used for the flat plate GPHEX computations. The results for temperature difference and pressure drop are presented for these meshes in Figure 6 and Figure 7, respectively. Based on the results, Mesh 7 is selected for further flat plate GPHEX computations.

For the corrugated GPHEX geometry, two different meshes are generated with a total of 8 million and 12
Table 3. Mesh properties for flat plate GPHEX computations.

| Mesh | Hot flow volume | Cold flow volume |
|------|----------------|-----------------|
|      | Number of grid points | Number of elements | Number of grid points | Number of elements |
| 1    | 268550          | 1135399         | 273416          | 1158673         |
| 2    | 805204          | 3695783         | 802515          | 3682539         |
| 3    | 712761          | 1779909         | 715567          | 1797288         |
| 4    | 1302103         | 2935452         | 1307637         | 2958453         |
| 5    | 1930523         | 4622963         | 1960013         | 4708368         |
| 6    | 3351088         | 7439001         | 3395718         | 7544543         |
| 7    | 4762938         | 10248839        | 4812841         | 10373041        |

Figure 6. Mesh refinement study results for flat plate GPHEX (temperature difference).

Figure 7. Mesh refinement study results for flat plate GPHEX (pressure drop).

The corrugated plates require meshes with a higher number of elements than the flat plates because of their more complex geometry. Therefore, even the coarse mesh for the corrugated plate geometry has more elements than the flat plate geometry does. Since experimental data for comparison is available for the corrugated plate geometries, only two meshes are used for the grid refinement study of corrugated plates, instead of eight as in flat plate geometry. Unstructured tetrahedral meshing with maximum spacing of 0.96 cm is applied to the fluid volumes as a final mesh used in the computations presented herein. The total number of grid points is 6 million, while the total number of elements is around 12 million for each of the hot and cold fluid zones. The results are presented for the second mesh and compared with the experimental results.

Mean \( y^+ \) (nondimensional first cell height) values of all the meshes are around 3.5. A comparison of \( y^+ \) and number of mesh elements is made with the study of Aradag, Kakac, and Ozkaya (2017). In their study, when 10 million mesh elements were used, the \( y^+ \) value changed between 1 and 5, and the results for temperature difference were less than 5%. Therefore, a \( y^+ \) value of 3.5 is used for all meshes in the computations presented herein.

2.3. Artificial neural network-based performance prediction methodology

ANNs are a combination of interconnected neurons. The concept started from the human brain. The artificial neurons are connected via weights that pass information from one neuron to the other. The network is constructed in such a way as to learn and connect information when necessary, like the human brain. ANNs are used in several fields, such as physics, mathematics and engineering, to detect and process data quickly. They are usually an alternative for solving complicated problems. An input and output layer must both exist in an ANN. The inputs take the data from outside of the network and pass it to the neurons. The input data is usually random. The weights determine the effect of each input on the neurons. The output layer is where the interaction results are passed out of the network. There is also at least one more layer, called a hidden layer. The number of hidden layers and neurons in a network are determined by trial and error. There are many studies in the literature that consider neural networks. For engineering applications, a feed-forward type of network is commonly used (Xie, Wang, Zeng, & Luo, 2007). In this study, the ANN toolbox of Matlab is utilized. The feed-forward Levenberg–Marquardt back propagation algorithm is also used.
To construct an ANN, data is necessary to train the configuration. This data can either be experimental or computational. The network is then tested using the test data. In most cases, approximately 75% of the data is used for training and the rest for test purposes. Once the network has been trained with a suitable amount of data, it can be used for estimations of test data. A flow chart for the ANN estimation process is shown in Figure 8.

For training of the ANNs in this work, the experimental data obtained for the same plate are used as in the development of correlations. The Nusselt number and friction factor are predicted using separately trained and tested network configurations. The total number of data points is 52, while 36 random points are chosen to train the data, and the rest is used for testing. The inputs are mass flow rate, inlet and outlet temperature, Reynolds number, Prandtl number, and viscosity for both the hot and cold sides, all for the network that has the Nusselt number as the output. Furthermore, 68 data points, 51 of which are for training, are used for friction factor prediction. The inputs are Reynolds number, mass flow rate, viscosity, inlet temperature, outlet temperature, pressure drop, and number of plates. Seven inputs are used in the input layer of the network. The output is the friction factor.

Figure 9 shows the network (including input, output, hidden layers and connections) for the Nusselt number predictions. The reason for selecting these 12 input variables is that all these parameters play a role in the determination of heat transfer characteristics, and therefore
the Nusselt number. They are also the main parameters used in the experiments for Nusselt number determination. For example, the inlet and outlet temperatures and mass flow rates determine the heat transfer rate. The viscosities change with temperature; therefore, they have to be included as input parameters in the network. Usually, the number of plates is not taken into consideration when correlations are developed. However, based on the experimental results, it is determined that the Nusselt number changes when a different number of plates is used, so that it is also taken as a parameter for predictions. The same parameters are used, including the pressure difference for friction factor predictions. Pressure drop is the main parameter that determines the friction factor and hydraulic performance. However, since the pressure drops for hot and cold sides are usually similar, we decided not to separate the hot and cold side friction factors, and instead determine only one friction factor as output based on the input data for both the hot and cold sides.

3. Results

3.1. Computational fluid dynamics results and comparison with experimental findings

Thermal and hydraulic characteristics of full-size HEX composed of seven corrugated plates and seven flat plates are predicted with computational, experimental and ANN-based methods. As a test case for CFD, hot and cold fluid temperatures are specified as 90°C and 20°C at inlet ports and mass flow rates for hot and cold fluids are defined as 0.1 kg/s. Table 4 shows the comparison of the results for HEX simulations with flat plates and corrugated plates, as well as the experimental results for the corrugated plates.

When we examine the difference between the CFD results of flat plate and corrugated plate HEX, it is obvious that narrow and corrugated fluid channel geometry helps to enhance the heat transfer characteristics of HEXs, but increases the pressure drop, and therefore the required power to operate the HEX. The most important finding
Table 4. Comparison of numerical simulation results with experimental findings and the results for flat and corrugated plate heat exchangers.

| Plate type | Heat load (W) | Reynolds number | Pressure drop, CFD (Pa) | Pressure drop, experiment (Pa) | Nusselt number – CFD | Nusselt number – experiment |
|------------|---------------|-----------------|------------------------|--------------------------------|----------------------|-----------------------------|
| Hot Fluid  | Corrugated    | 12,153          | 1363.5                 | 839.6                          | 805.01               | 59.0                        | 56.8                        |
|            | Flat          | 5400.7          | 1508.4                 | 130.9                          | –                    | 21.7                        | –                           |
| Cold Fluid | Corrugated    | 12,225          | 705.75                 | 866.9                          | 926.9                | 63.6                        | 50.7                        |
|            | Flat          | 5389.3          | 593.62                 | 131.0                          | –                    | 23.9                        | –                           |

Figure 10. HEX hydraulic performance comparison.

Figure 11. HEX thermal performance comparison.

The results from this comparison show that there is no point in taking the corrugated plate surfaces as flat in CFD simulations as a simplification, since the results are completely different from each other.

Several simulations are performed for a Reynolds number range of 400 to 5,000. Figure 10 shows the hydraulic performance comparison of CFD and experimental results for pressure drop changes with the mass flow rate, and Figure 11 shows the thermal performance comparison in terms of the Nusselt number changing with the Reynolds number. CFD results are in the uncertainty range of experiments. The mean deviation of the heat transfer results for CFD simulations from the experimental findings is about 10%, and the pressure drop is 13%, and hence underpredicted by CFD.

By using the available correlations in the literature for the same chevron angle and similar geometrical properties, a comparison is made with recent numerical findings for friction factor and Nusselt number varying with Reynolds number, as can be seen in Figure 12. Focke, Zacharides, and Oliver (1985) derived Nusselt and friction factor correlations for plates with an enlargement factor of 1.464 and chevron angle of 30° for a wide range of Reynolds number from 150 to 16,000. Okada et al. (1972) developed a Nusselt number correlation based on the experimental data for plates having a surface enlargement factor of 1.147 and the same chevron angle as in this study. This correlation is valid for Reynolds numbers from 400 to 15,000. Kumar (1984) used plates with the same chevron angle. Correlations in the literature have the same trend; however, they deviate from each other, which proves that every plate needs its specific correlation.

Figure 13 shows the flow structure inside the channels of the corrugated plate and flat plate HEX in terms of streamlines. The flow in both the hot and cold domains are clearly shown in the figure. The streamlines mainly follow the surface of the plate in the flat plate HEX because of the absence of any pattern on the plate, such as the distribution channels. On the other hand, the distribution channels of the corrugated plate HEX let the flow be uniformly distributed.

The temperature variations on the plate surfaces are shown in Figures 14 and 15. The heat exchange between
the hot and cold fluid streams is clear in the figures. A gradual change in temperature values from the first to the last channel, as well as from inlet to outlet ports of each channel, is clearly shown.

3.2. Artificial neural network predictions and comparison with correlations obtained from the same experimental data

The relative error ($E_r$) of every predicted value is defined by

$$E_r = \frac{|A^e - A^p|}{A^e} \times 100\%$$

Here, $A^p$ is the ANN prediction, whereas, $A^e$ is the corresponding experimental value. The performance of an ANN estimation is shown by the root mean square (rms) value of the error, where $M$ is the number of data points.

$$\text{rms} = \sqrt{\frac{1}{M} \sum_{i=1}^{M} \left( \frac{A^e - A^p}{A^e} \right)^2}$$

Another error definition used is shown below (Xie et al., 2007)

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( R - R_i \right)^2}$$

where

$$R = \frac{1}{N} \sum_{i=1}^{N} R_i = \frac{1}{N} \sum_{i=1}^{N} \frac{A^e}{A^p}$$

Here, $R$ shows the average certainty of the predictions. Obtaining an $R$ value that is as close to $R = 1$ as possible is the best-case scenario. $\sigma$, on the other hand, shows how the error diffuses or is scattered. Therefore, for an ideal case this value should be as close to zero as possible.

Eleven ANN configurations studied for the same plate to estimate the Nusselt number are shown in Table 5. First number for the network configurations for example for the 12_10_4_2 network, (12) is the number of inputs in the input layer. The last number (2) is the number of outputs. The numbers between first and last number represent the number of neurons of hidden layers. There can be more than one hidden layer. For example, for the 12_10_4_2 network, the configuration has two hidden layers, the first with 10, and the second with four neurons. In order to select the best network that provides results closer to the experimental results, all the error definitions, including the maximum deviation from the experimental findings, rms error, and $\sigma$ and $R$ definitions as explained above, are used together. When the training data is first used for network training purposes, an rms error value is obtained for each configuration. This is the first error definition that needs to be taken into account for optimization of the network parameters. Once acceptable estimations have been obtained with some network configurations that have only one hidden layer, the next step is to reduce the uncertainty and scatter of the predictions using $R$ and $\sigma$ as a basis for comparison, by changing the number of hidden layers. The number of hidden layers is increased to have an $R$ value that is as close to 1, and a $\sigma$ value that is as close to 0, as possible. A good
network is selected (meaning the number of hidden layers and neurons is determined) using these parameters as a comparison basis based on training data. The networks selected are confirmed and the best one is selected by using the test data in the same network and obtaining \( \sigma \) values for the test data. The configuration that has
Figure 15. Temperature distribution over flat plates.
the best result in terms of the optimization procedure explained here is 12_10_6_2.

It should be noted here that the network that provides the best value for an average rms error for the hot and cold sides is not selected. A network configuration that gives acceptable rms errors for both the hot and cold sides is the selected network from the training data. For example, when the rms error results for the training data are examined (see Table 5), it is seen that the lowest rms errors for the hot side are obtained with the 12_8_2, 12_10_2, and 12_10_6_2 networks, and with the 12_10_8_2, 12_12_2, 12_10_4_2 and 12_10_6_2 networks for the cold side. However, the 12_10_6_2 network is selected even though it does not have the lowest rms average but it has low enough rms values for both hot and cold side training data.

Overfitting is also an important problem for statistical models. When the network is trained with more data than necessary, it may start to memorize the training data instead of truly being trained. Whether overfitting exists can be observed from the performance of the network on the test data. In an overfitted network the performance drops drastically for the test data, although it is

### Table 5. Comparison of Nusselt number errors for the prediction by different ANN configurations and correlation.

| Networks   | Nu, hot side | Nu, cold side |
|------------|--------------|---------------|
|            | Max relative error (%) | rms         | Max relative error (%) | rms         |
| Correlation| 92.15         | 0.37371       | 343.35          | 0.88569     |
| 12_12_2    | 81.18         | 0.26692       | 46.44           | 0.19271     |
| 12_10_2    | 82.97         | 0.25248       | 82.97           | 0.21127     |
| 12_8_2     | 64.90         | 0.23058       | 72.67           | 0.20750     |
| 12_6_2     | 66.68         | 0.26052       | 78.16           | 0.26466     |
| 12_4_2     | 132.46        | 0.31010       | 66.84           | 0.23203     |
| 12_10_8_2  | 77.41         | 0.28292       | 122.59          | 0.40535     |
| 12_10_6_2  | 105.21        | 0.29032       | 54.39           | 0.19435     |
| 12_10_8_6_2| 202.89        | 0.75858       | 268.24          | 0.80002     |

### Table 6. Comparison of friction factor errors for the prediction by different ANN configurations and correlation.

| Networks   | R          | σ           | R          | σ           |
|------------|------------|-------------|------------|-------------|
| Correlation| 1.14847    | 0.50182     | 0.98115    | 1.02101     |
| 12_12_2    | 1.11668    | 0.35672     | 1.04776    | 0.39133     |
| 12_10_2    | 1.04091    | 0.28165     | 0.96468    | 0.34082     |
| 12_8_2     | 1.04716    | 0.31832     | 1.02620    | 0.34082     |
| 12_6_2     | 1.00125    | 0.31423     | 0.94705    | 0.22778     |
| 12_4_2     | 0.99420    | 0.23954     | 0.94705    | 0.22778     |
| **12_10_6_2** | **0.99182** | **0.25580** | **0.97633** | **0.24600** |
| 12_10_4_2  | 1.71925    | 0.90022     | 1.02966    | 0.30368     |
| 12_10_8_2  | 0.93414    | 0.38146     | 1.03442    | 0.34431     |
| 12_10_6_2  | 0.94023    | 0.23539     | 1.04051    | 0.28265     |
| **12_10_6_4_2** | **1.20626** | **0.88151** | **1.36740** | **0.85500** |
superior for the training data. Here, to avoid overfitting, and to select the best network configurations, not only the training but also the test data is used.

The selected networks are confirmed both for Nusselt number and friction factor predictions based on σ values of the test data, to avoid overfitting and to ensure that the networks work well for new test data, which is totally different than the data for training. The σ and R values obtained for training and test data for both Nusselt number and friction factor predictions show that the selected network is converged.

For friction factor predictions, 10 different configurations are studied. The results are shown in Table 6. The (7_7_1) configuration is superior to the others. The error results are lower than others; therefore, this configuration can be chosen to estimate the friction factor, and it can be concluded that ANN provides better results than correlations for the friction factor based on these results.

Figure 16 shows the relative errors for the best configuration (12_10_6_2) and experimental correlation for the training data. The accuracy of the ANN estimations is higher than the correlations. Mean relative errors for hot and cold side Nusselt number predictions are 17.04%
and 15.26%, respectively, while the mean relative errors for the correlation are 28.65% and 53.10%. Figure 16 also shows that the results for ANN

(Figure 17) show relative errors for the 12_10_6_2 configuration and experimental correlation for the test data points. After obtaining the network, it is important to test its accuracy for different data points than the training data. In other words, it is essential to use new data instead of that used for training the network.

Figure 18 shows the Nusselt number estimations for the tested points based on ANN and correlations. When the results are examined, ANNs are clearly superior to correlations, provided a suitable network is utilized.

4. Discussion and conclusion

Thermal and hydraulic performance of GPHEX is determined using CFD and experiments by using Nusselt number and friction factor as a comparison basis. Full size HEX composed of seven flat plates and seven corrugated plates are simulated. The effects of inlet and outlet ports are also taken into consideration. The simulation results include outlet temperatures, temperature distributions for the plate surfaces, velocity and pressure distribution inside the plate heat exchanger channels and streamlines. The CFD results are in good agreement with the experimental findings. The mean deviation of the heat transfer results for CFD simulations from the experimental findings is about 10% and pressure drop is 13%, which was underpredicted by CFD. These values are promising based on the literature. For example, Gullapalli and Sundén’s (2014) CFD results underpredicted experiments by 10–35% in terms of pressure drop. Their thermal performance values were within 20–30% of experiments. Han et al.’s (2010) simulations had a 35% error when compared to experimental correlations in the literature.

With the help of these computations, the effects of taking real plate geometry into consideration, instead of using just flat plates, is shown. By using seven plates instead of only one plate, the flow maldistribution, which causes a different flow distribution for each plate rather than a uniform flow, is also examined.

The next part of the work involves determination of the Nusselt number and friction factor to predict the thermal and hydraulic performance of the HEX based on experimental and computational results. Hydraulic and thermal performance of GPHEX are not as easily determined as the performance of other types of HEX, since they solely depend on the corrugation pattern of the plates of the HEX. Therefore, every plate needs its own correlation for Nusselt number and friction factor. Correlations are developed using both experimental and computational results for performance prediction. ANN models are developed based on the same experimental results. The results show that ANNs can depict the experimental trends better than the correlations. The mean relative error for Nusselt number predictions is around 16%, while the mean relative error for the correlation is 40% based on the correlation developed by Gulenoglu et al. (2014).

Computational results also show agreement with the experiments and prove the importance of the inclusion of corrugation patterns in the simulations. The next step in this research is to apply the computational and experimental experience gained from the application of nanofluids or other new fluids in plate HEX. Plate design based on performance predictions is also a subject that needs to be investigated.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Funding

This research was financially supported by Tubitak (Turkish Scientific and Research Council) under grant number 112M173, and the Turkish Academy of Sciences Distinguished Young Scientist Award grant. The computations presented were performed using the computational facilities of the ETU Hydro Energy Research Laboratory, financially supported by the Turkish Ministry of Development.

ORCID

Selin Aradag © http://orcid.org/0000-0002-2034-0008

References

Akturk, F., Sezer-Uzol, N., Aradag, S., & Kakac, S. (2015). Experimental investigation and performance analysis of gasketed plate heat exchangers. *Isı Bilimi ve Tekniği-Journal of Thermal Science and Technology*, 35(1), 43–52.

Aradag, S., Kakac, S., & Ozkaya, E. (2017). Utilization of numerical methods and experiments for the design and tests of gasketed plate heat exchangers. *Numerical Simulation of Heat Exchangers: Advances in Numerical Heat Transfer Volume V*, CRC Press.

Chau, K. W., & Wu, C. L. (2010). A hybrid model coupled with singular spectrum analysis for daily rainfall prediction. *Journal of Hydroinformatics*, 12(4), 458–473.

Focke, W. W., Zacharides, J., & Oliver, I. (1985). The effect of the corrugation inclination angle on the thermohydraulic performance of the plate heat exchangers. *International Journal of Heat and Mass Transfer*, 28, 1469–1479.

Gulenoglu, C., Akturk, F., Aradag, S., Sezer-Uzol, N., & Kakac, S. (2014). Experimental comparison of performances of three different plates for gasketed plate heat exchangers. *International Journal of Thermal Sciences*, 75, 249–256.

Gullapalli, V. S., & Sundén, B. (2014). CFD simulation of heat transfer and pressure drop in compact brazed plate heat exchangers. *Heat and Mass Transfer*, 35(4), 358–366.
Han, X.-H., Cui, L.-Q., Chen, S.-J., Chen, G.-M., & Wang, Q. (2010). A numerical and experimental study of chevron, corrugated-plate heat exchangers. *International Communications in Heat and Mass Transfer, 37*, 1008–1014.

Kumar, H. (1984). *The plate heat exchanger: Construction and design*. 1st UK National Conference on Heat Transfer, Inst. Chem. Symposium series, United Kingdom, 86, 1275–1286.

Muley, A. (1997). *Heat transfer and pressure drop in plate heat exchangers* (PhD Dissertation). University of Cincinnati.

Okada, K., Ono, M., Tomimura, T., Okuma, T., Konno, H., & Ohtani, S. (1972). Design and heat transfer characteristics of a new plate heat exchanger. *Heat Transfer Japanese Research, 1*, 90–95.

Ozkaya, E., Gulenoglu, C., Aradag, S., & Kakac, S. (2014). *CFD simulations and experimental validation for gasketed plate heat exchangers*. Convective heat and mass transfer (CONV 2014) conference.

Paras, S. V., Kanaris, A. G., Mouza, A. A., & Karabelas, A. J. (2002). *CFD code application to flow through narrow channels with corrugated walls*. 15th international Congress of Chemical and Process Engineering, 1–12.

Piepiorka-Stepuk, J., & Jakubowski, M. (2012). Numerical studies of the fluid flow between the plates of the heat exchanger in the analysis of CIP cleaning conditions. CIGR-AGENG 2012.

Taormina, R., & Chau, K.-W. (2015). Data-driven input variable selection for rainfall–runoff modeling using binary-coded particle swarm optimization and extreme learning machines. *Journal of Hydrology, 529*(3), 1617–1632.

Turk, C., Aradag, S., & Kakac, S. (2016). Experimental analysis of a mixed-plate gasketed plate heat exchanger and artificial neural net estimations of the performance as an alternative to classical correlations. *International Journal of Thermal Sciences, 109*, 263–269.

Wang, D., Liang, Z., Zhou, J., & Wang, H. (2010). The simulation research on the performance of chevron-type corrugated plate heat exchanger. *ICEEAC 2010, 11*, 298–301.

Wang, W.-C., Chau, K.-W., Xu, D.-M., & Chen, X.-Y. (2015). Improving forecasting accuracy of annual runoff time series using ARIMA based on EEMD decomposition. *Water Resources Management, 29*(8), 2655–2675.

Wu, C. L., Chau, K. W., & Li, Y. S. (2009). Methods to improve neural network performance in daily flows prediction. *Journal of Hydrology, 372*(1–4), 80–93.

Xie, G. N., Wang, Q. W., Zeng, M., & Luo, L. Q. (2007). Heat transfer analysis for shell-and-tube heat exchangers with experimental data by artificial neural networks approach. *Applied Thermal Engineering, 27*, 1096–1104.

Zhang, J., & Chau, K. W. (2009a). Multi-layer ensemble pruning via novel multi-sub-swarm particle swarm optimization. *Journal of Universal Computer Science, 15*(4), 840–858.

Zhang, S. W., & Chau, K.-W. (2009b). Dimension reduction using semi-supervised locally linear embedding for plant leaf classification. *Lecture Notes in Computer Science, 5754*, 948–955.