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Hydrothermal optimization of SiO_2/water nanofluids based on attitudes in decision making

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ABSTRACT

In order to avoid the costs of experimental evaluations, soft computing methods like artificial neural network (ANN) and genetic algorithm have remarkably grabbed the attentions of investigators for predicting the hydrothermal characteristics of different types of nanofluids. In this paper, the implementation of ANN and genetic algorithm for modeling and multi-criteria optimizing the hydrothermal behavior of SiO_2/water nanofluid has been investigated. Using the data obtained from the experimental analysis, an ANN model is developed to estimate the pressure drop and Nusselt number as a function of volume concentration, Reynolds number, and inlet temperature. Different network structures were assessed and it has been achieved that a network with 2 hidden layers and 6 neurons in every layer provides the most accurate prediction. It is revealed that the developed network is satisfactorily accurate to determine the Nusselt number and pressure drop of SiO_2/water nanofluid compared to the empirical correlations. To optimize the hydrothermal behavior of the nanofluid (i.e. to find the optimal cases with highest Nusselt number and the relatively least pressure drop), the genetic algorithm coupled with compromise programming approach has been implemented considering decision maker's attitude.

1. Introduction

Nowadays, various techniques for heat transfer improvement are developed to ameliorate efficiency of thermal systems. In particular, the design of heat exchangers is one of the important areas which has widely gained significant attention due to their usage in much various industries. Feasibility of nanofluid application as a working fluid instead of conventional fluids is one of the advances in this field, due to their special privileges including less clogging in conduits, long-term stability and greater thermal conductivity. In this regard, many investigations have been conducted to elaborate the applications of nanofluids in solar systems [1–3], heat transfer processes [4–10], mass transfer intensification [11,12], and thermophysical properties enhancement [13–16].

Besides the above-mentioned areas, post-processing, modeling and optimization of experimental data and their usage to design experimental techniques for exploring the impacts of different factors on the nanofluids characteristics and anticipating their various features are among the recent approaches in the field of nanofluids. Recently, artificial neural networks (ANNs) and optimization algorithms are devices which have been extensively employed to model and optimize the experimental data for finding the optimal thermophysical and hydrothermal features of nanofluids and achieving the enhanced performance of the system. ANN is a powerful tool for solving complex issues in various applications with a notable decline in time and cost due to its simplicity, extensive capacity, and high speed simulations to find the relationship between inputs/outputs. A group of the researchers that conducted several investigations to design an ANN for prediction of

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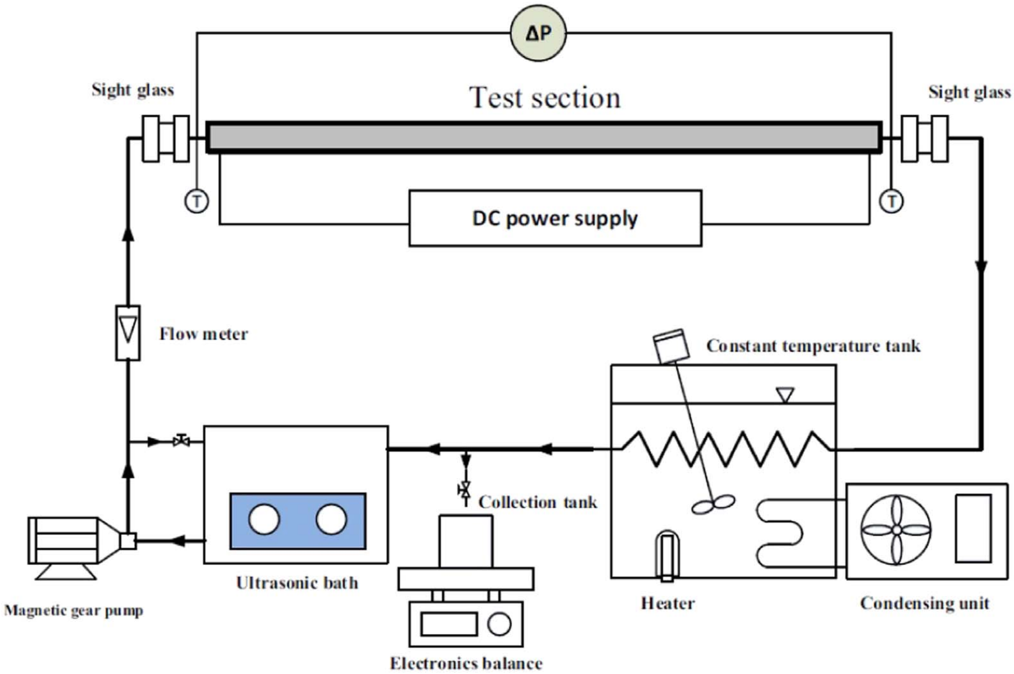

Fig. 1. Schematic diagram of the experimental apparatus [Jumpholkul et al. [39], with permission from Elsevier].

thermal conductivity and viscosity of different types of nanofluids from input experimental data are Hemmat Esfe et al. [17–26]. They evaluated the thermophysical properties of various nanofluids such as Fe/water, Cu-TiO_2/water-EG, Al_2O_3/water, $Mg(OH)_2$/EG, Al_2O_3/water-EG (40:60), MgO/water-EG (60:40), MWCNT/water, TiO_2/water, ZnO/EG, and MgO/EG in their studies separately. The comparison between the performance of the ANN model and the results obtained from experimental data disclosed that the neural network can more accurately predict the thermophysical properties of studied nanofluids. Afrand et al. [27–30] investigated thermophysical properties of water-based Fe_3O_4, MgO, MWCNT, and MWCNTs-SiO_2/AE40 over a wide range of concentrations and temperatures and proposed the ANNs to precisely predict the experimental results. Ahmadloo and Azizi [31] studied the application of a 5-input ANN model to predict the 776 experimental data points of thermal conductivity ratio of fifteen various nanofluids. The input variables considered in this study were some appropriated numbers for both base fluid and nanoparticle, temperature, thermal conductivity, volume fraction, and average diameter of nanoparticles. They developed a model with 1.26% and 1.44% mean absolute percent errors for training and testing data sets, respectively. Many other studies are available in this field concerning the application of ANN modeling for prediction of thermophysical properties of nanofluids such as the oxide-based nanofluids dynamic viscosity [32], the thermal radiative properties CNT nanofluids including extinction and transmittance coefficients [33], the convective heat transfer and pressure drop of nanofluids in a jacked reactor [34] or in a microchannel heat sink [35].

However, investigations on the optimization of experimental data are still scarce and more researches are need to be conducted. Using the modified non-dominated sorting genetic algorithm (NSGA-II), Hemmat Esfe et al. [36,37] optimized the ND-Co_3O_4 aqueous nanofluid and Al_2O_3/water-EG (40:60) nanofluids in order to minimize the viscosity and maximize the thermal conductivity of nanofluids. Accordingly, they provided the Pareto Front and the corresponding optimum points. Their results revealed that the most optimal conditions can be achieved at the highest temperature. Another group of researchers investigated the application of particle swarm optimization (PSO) to mathematically model and optimize the thermophysical properties of Al_2O_3 nanofluid for a biomass plant [38]. They employed the modified PSO with multi leaders instead of the conventional PSO for evolution process. The results showed that about 56.6% reduction in the annual cost can be achieved in an optimum configuration containing 2% nanoparticles. Amani et al. [13] evaluated the application of ANN, empirical correlations and genetic algorithm for modeling and multi-criteria optimization of the thermophysical properties of clove-treated MWCNTs nanofluid which has been synthesized through a facile and eco-friendly procedure. The revealed that the optimal ANN model is a more precise and accurate way to predict the thermal conductivity and viscosity of ecofriendly nanofluids compared to empirical correlations obtained from nonlinear regression method. Moreover, the final optimal solutions opted from several distinguished procedures of decision-making including the Bellman-Zadeh, TOPSIS and LINMAP approaches.

In spite of extensive applications of water-based SiO_2 nanofluid, there is no available ANN modeling for prediction and optimization of the hydrothermal properties of these nanofluids. In this regard, this study aims to employ the multilayer perceptron neural network to model the Nusselt number and pressure drop of SiO_2/water nanofluid at different temperatures, concentrations and Reynolds numbers. The experimental data used in this article are presented by Jumpholkul et al. [39]. Different numbers of neuron and hidden layer have been examined to obtain the optimal network structure. The models obtained from the ANN are employed as the objectives in the optimization method. This research reports the optimum values of effective parameters to obtain the highest heat transfer and the relatively least pressure drop. In this regard, different viewpoints of the decision maker are also considered in the optimization by implementing a compromised programming approach with capability of decision-making.

2. Experimental setup and procedure

An important step in employing nanoparticles to improve the heat transfer performance of a system is preparation process of the nanofluid. The SiO_2 nanoparticles used in this research were purchased from Degussa with 7 nm mean diameter (Aerosil 380) [39]. 0.5, 1 and 2% nanoparticle concentrations were prepared by dispersing the desired amount of nanoparticles measured by the electronic mass balance into the DI-water without any surfactant. Moreover, ultrasonication was conducted for 2 h before using the nanofluids samples to guarantee stable dispersion of the nanoparticles.

The schematic of the apparatus is depicted in Fig. 1 [39]. The length, inner and outer diameters of the test tube (made of SS 304) were 200, 0.7 and 0.95 cm, respectively. A uniform heat flux was implemented on the pipe using a DC power supply with a voltmeter to control the voltage. The experimental data of wall temperatures were attained by using 9T-type thermocouples (with the precision of ± 0.1 °C) which were equally placed from each other along the test section. In addition, the bulk temperatures of nanofluids at the inlet and outlet of the test section were measured using 2 further T-type thermocouples placed inside the nanofluid flow at these positions. A rubber insulation and fiberglass cloth were used to insulate the test section for preventing heat loss in a radial direction. In order to measure the pressure drop, a differential pressure transmitter is employed between the inlet and outlet of the test section. After reaching the steady state condition, a data logger was used to record the experimental data of temperatures every 10 min.

3. Artificial neural network

To model the Nusselt number and pressure drop of the SiO_2/water nanofluid flowing in a tube in turbulent regime in terms of Reynolds number, nanoparticle fraction and inlet temperature, a multilayer perceptron ANN is defined as depicted in Fig. 2.

The MLP-ANN is consisting of several neurons in multiple layers. Weight coefficients have the connecting role between neurons. Biases and weights have to be updated to determine the connection between outputs and inputs. Furthermore, in order to generate the neuron output, an activation function is established on the summation of bias and weighted inputs of neurons in each layer.

A standard approach in nonlinear optimization for training purpose called Levenberg-Marquardt (LM). In this method, the Hessian matrix is expressed as:

$$H = J^T J \tag{1}$$

where J represents the Jacobian matrix. And the gradient is calculated by:

$$g = J^T e \tag{2}$$

in which e represents the network errors. A standard backpropagation technique can be used to solve the Jacobian matrix, which provides less complicated calculation. In LM approach, the following estimation for Hessian matrix is employed:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{3}$$

where x_k denotes is a vector of biases and weights.

Accordingly, μ is considered as a large value which results in conversion of the estimation into gradient descent with a minor step size. Note that if $\mu = 0$, it would be Newton's approach, which is highly desirable due to its minimum errors and high speed. Thus, μ is better to increased only when the performance function is needed to be increased.

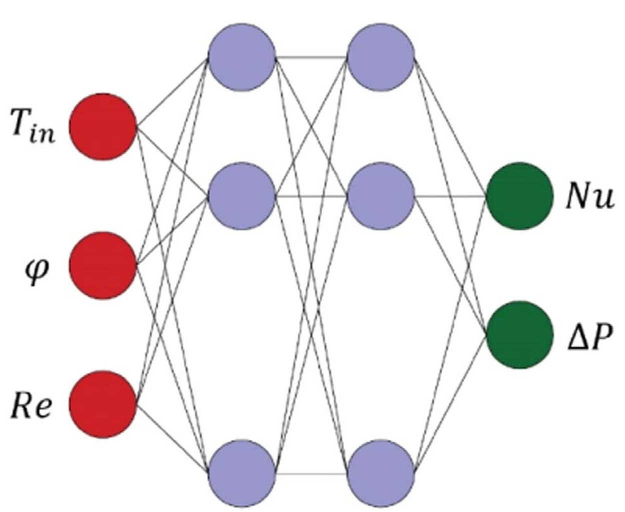

Fig. 2. Configuration of the ANN.

On the other hand, overfitting has to be considered in such problems. It occurs when notable errors are obtained in verifying the performance of network by test data, although the network satisfactorily predicts the training data. To address this issue, a generalized network learning algorithm has to be employed. In this regard, a regularization is implemented which enhances the network generalization.

The mean sum of squares of the errors (MSE) is used for examining the training performance of the network. The MSE can be expressed as:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (e_i)^2 \tag{4}$$

where e_i denotes the difference between the experimental and predicted values. Moreover, mean sum of squares of the network weights (MSW) is defined so as to elevate network generalization by producing smaller biases and weights.

$$\mathrm{MSE}_{\mathrm{new}} = \gamma \mathrm{MSE} + (1-\gamma)\mathrm{MSW} \tag{5}$$

where γ is the performance ratio, and

$$\mathrm{MSW} = \frac{1}{n}\sum_{j=1}^{n} (w_j)^2 \tag{6}$$

in which w_j denotes the weights of the network.

In regularization, the accuracy of trained data prediction would be decreased when the optimum performance ratio is very small. On the other hand, very large ratio would result in overfitting. The Bayesian framework is a procedure which can be employed to train the network for determining the optimum regularization parameters. In this framework, specified distribution is considered for the random variables assigned for the weights and biases.

The problem under study is solved using the Bayesian regularization-based Levenberg-Marquardt training (LM-BR) method. Thus, the network is trained by the LM approach and its generalization is improved by implementation of the Bayesian regularization.

For the network training, the objective function is defined as:

$$F = \alpha \times \mathrm{MSW} + \lambda \times \mathrm{MSE} \tag{7}$$

where α and λ are regularization parameters. The network responses would be smoother if $\alpha \gg \lambda$, while the training algorithm errors would be smaller if $\alpha \ll \lambda$. Further description on the Bayesian regularization is presented in Refs [40,41].

For evaluation of ANNs accuracy, mean relative error (MRE) and coefficient of determination (R^2) are calculated, according to Eq. (8) and Eq. (9), as follows.

$$\mathrm{MRE} = \frac{1}{M}\sum\nolimits_{i=1}^{M} \frac{|y_{exp} - y_{pred}|}{y_{exp}} \tag{8}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_{exp} - y_{pred})^2}{\sum_{i=1}^{n} (y_{exp})^2} \tag{9}$$

4. Multi-objective optimization

A genetic algorithm is used to obtain the optimum states and the relative objective functions were the models obtained from the ANN. The optimization procedure was conducted to maximize the heat transfer as well as achieving the least pressure drop. It should be noted that in a multi-objective optimization, there is more than one optimum point and in fact, a series of optimal states are commonly achieved which have no preference over each other. Regarding to consider the decision maker's attitude, in this research, a compromise decision making method is employed along with genetic algorithm for facilitating the selection process among various optimal cases. Accordingly, the problem changes into a single-criteria optimization by combination of the objective functions.

In this approach, Eq. (10) must be minimized. In Eq. (10), the objective functions are reflected in Z and W which have to be maximized and minimized, respectively.

$$D = \sum_{k=1}^{1} \alpha_k^b \left[\frac{Z_k^* - Z_k(x)}{Z_k^* - Z_k^-}\right]^b + \sum_{s=1}^{1} \alpha_s^b \left[\frac{W_s(x) - W_s^*}{W_s^- - W_s^*}\right]^b \tag{10}$$

In Eq. (10), superscript "$^-$" and "*" represent the worst and the best values for the relative objective functions. The relative importance of each objective function compared to the other one is reflected in coefficients α. In fact, based on the decision maker's attitude, the relative importance of objective functions can be adjusted via changing these coefficients before conducting the optimization. Moreover, in this research, the distance coefficient (b) was considered equal to 1 (it can be ranged from 1 to ∞).

5. Results and discussion

Affecting parameters on the Nusselt number and pressure drop of water-based SiO_2 nanofluids were inlet temperature, concentration and Reynolds number for the turbulent flow regime in a circular tube [39]. It was observed that the heat transfer as well as pressure drop were increased when the nanofluid concentration and Reynolds number were augmented. Therefore, it can be understood that maximizing the convective heat transfer along with minimization of the pressure drop would be a critical finding. In this regard, ANN has been employed for the developments of the objective functions (Nu and ΔP) based on input effective variables including inlet temperature, concentration and Reynolds number.

Generation of the data required to train the ANN is the most substantial step of ANN modeling, which is highly important to develop the model for proper prediction of the problem under study. The experimental data which has been previously published by Jumpholkul et al. [39] has been adopted for the ANN modeling and accordingly, three inlet temperatures (T_{in} = 25, 30, and 35 °C) and four concentrations (φ = 0, 0.5, 1, and 2 vol%) at ten Reynolds numbers (Re = 3800–12,000) have been considered for conducting the experimental analysis. 90 data points out of 120 were employed to train the ANN and the rest of data were allocated to validate the model. To enhance the predictive capacity of the ANN, all the data were scaled in the range of [0 1]. Also, the linear activation function and sigmoid activation function are employed on the output and hidden layers respectively.

In order to find the network with the highest prediction ability, different configurations were assessed and it has been achieved that a network with 2 hidden layers and 6 neurons in every layer provides the most accurate prediction. Table 1 presented the performance of ANNs with various structures based on the test data, indicating the achievement of minimum errors in the network with above-mentioned structure which has been bolded.

For the test data, the optimum structure (2 hidden layers and 6 neurons in every layer) predicted the Nusselt number with R^2 and MRE values of 0.9992 and 0.017, respectively. Moreover, the values of R^2 and MRE associated with the pressure drop were 0.9996 and 0.009, respectively. For better illustration, Figs. 3 and 4 exhibits the comparison of experimental data and those obtained from the ANN modeling based on the training and test data. As can be seen the ANN modeling is highly reliable due to the consistency of the results.

New correlations in a form of dimensionless variables have been proposed by Jumpholkul et al. [39] to predict the Nusselt number and friction factor as follows:

Table 1
Performance of the ANN with different structures.

Number of hidden layers	Number of neurons in each layer	R^2		MRE	
		Nu	Δ*P*	*Nu*	Δ*P*
1	2	0.9970	0.9975	0.044	0.026
1	4	0.9968	0.9972	0.046	0.018
1	6	0.9985	0.9990	0.029	0.013
1	8	0.9955	0.9959	0.081	0.034
1	10	0.9978	0.9982	0.042	0.010
1	12	0.9962	0.9967	0.052	0.008
2	2	0.9959	0.9965	0.066	0.022
2	4	0.9965	0.9970	0.048	0.009
2	**6**	**0.9992**	**0.9996**	**0.017**	**0.009**
2	8	0.9947	0.9955	0.155	0.047
2	10	0.9974	0.9979	0.043	0.017
2	12	0.9981	0.9987	0.035	0.021

The bold line presents the optimum structure of ANN, corresponding the most accurate prediction.

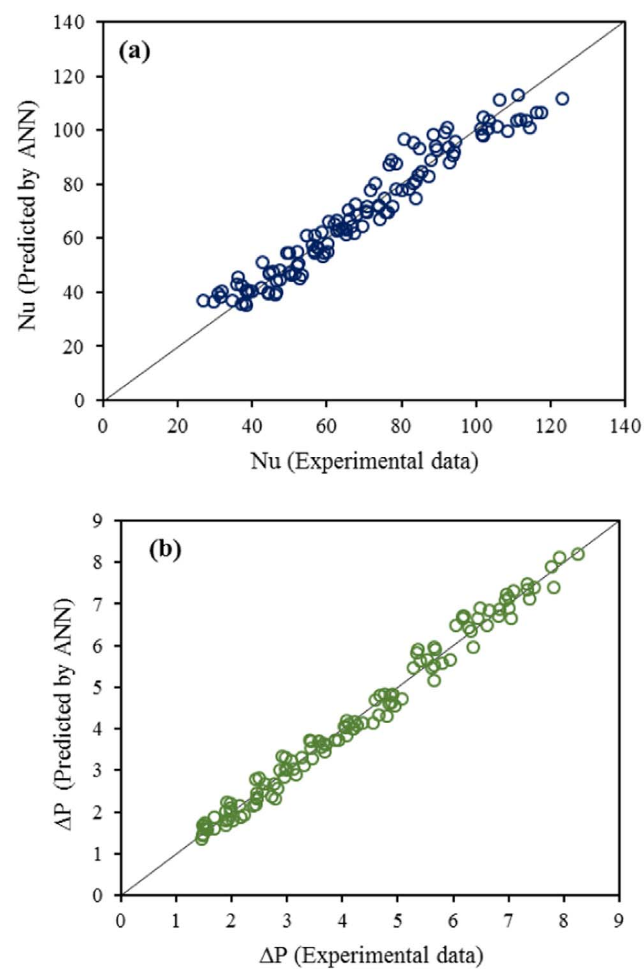

Fig. 3. Correlation between experimental work of Jumpholkul et al. [39] and those obtained from ANN model; a) Nusselt number, b) pressure drop.

$$Nu_{nf} = 0.001142\mathrm{Re}_{nf}^{1.26}\mathrm{Pr}_{nf}^{-0.19}(1+\varphi)^{14.45}\left(\frac{T_{in}}{25}\right)^{-0.4} \tag{11}$$

$$f_{nf} = 0.527\mathrm{Re}_{nf}^{-0.3}(1+\varphi)^{4.892} \tag{12}$$

The scope of Eqs. (11) and (12) is in temperature range of 25–35 °C and volume concentration between 0 and 2% at Reynolds numbers between 3800 and 12,000. The MRE and R^2 coefficients for the Nusselt number correlation are 0.0692 and 0.9941 and the corresponding

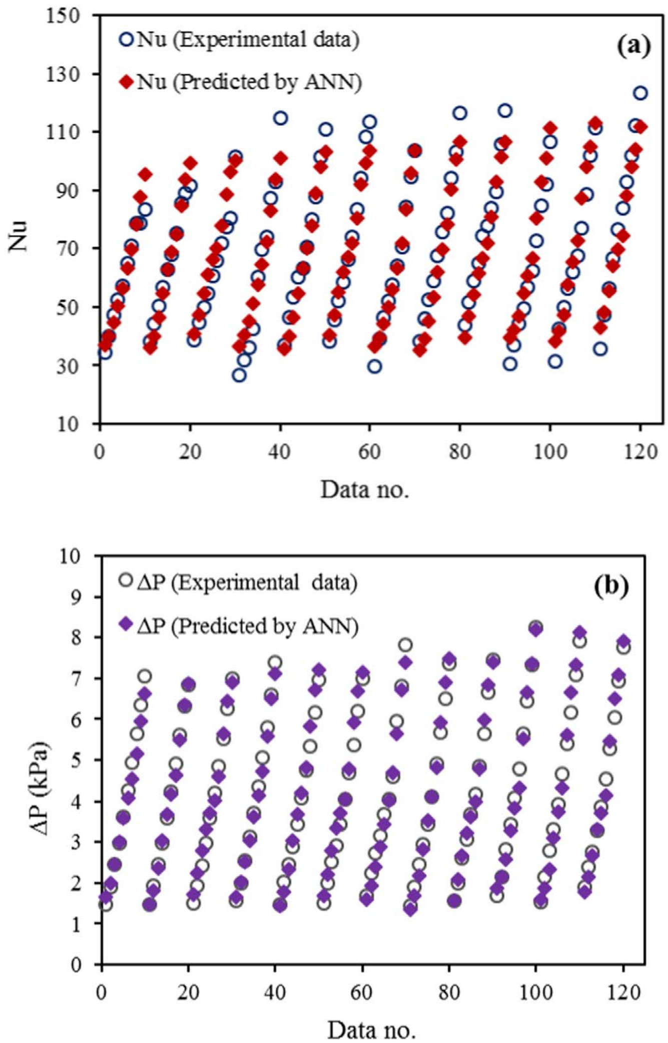

Fig. 4. Comparison between experimental work of Jumpholkul et al. [39] and those obtained from ANN model; a) Nusselt number, b) pressure drop.

values for the friction factor correlation are 0.0569, and 0.9949 respectively. The comparison between the error values of the proposed correlations and the optimal ANN model revealed that the ANN is much powerful tool for determination of the hydrothermal properties in the problem under study.

In the following, the optimization on the hydrothermal characteristics of SiO_2/water nanofluid is conducted using genetic algorithm connected with the ANN modeling to find the optimal points with the highest heat transfer and the relatively least pressure drop. Accordingly, the problem would be a two-objective optimization with a maximizing objective of *Nu* number and a minimizing objective of ΔP. As previously mentioned, several optimal conditions can be achieved in a multi-objective optimization while they have no particular preference over each other and selecting the best condition depends on the decision maker. In this regard, selection among the optimum cases has been facilitated by using genetic algorithm coupled with a compromise programming technique. Therefore, the multi-criteria optimization would be converted to a single-criteria optimization, according to the following equation:

$$D = \alpha_1\left[\frac{Nu^* - Nu}{Nu^* - Nu^-}\right]^2 + \alpha_2\left[\frac{\Delta P - \Delta P^*}{\Delta P^- - \Delta P^*}\right]^2 \tag{13}$$

where coefficients α represent relative importance of the objective functions. Based on Eq. (13), the problem can be solved for various combinations of α_1 and α_2 and consequently, the new objective function *D* have to be minimized. It has to be mentioned that the sum of α_1 and α_2 which are the relative importance of the objective functions related to the Nusselt number and pressure drop, should be equal to 1.

Table 2
Optimal conditions obtained in this analysis.

No.	α_1	α_2	Re	φ (vol%)	T_{in} (°C)
1	0	1	3830	0	35.0
2	0.1	0.9	4700	0.18	34.2
3	0.2	0.8	5574	0.39	34.8
4	0.3	0.7	6431	0.60	35.0
5	0.4	0.6	7352	0.85	34.2
6	0.5	0.5	8185	1.03	33.8
7	0.6	0.4	9048	1.17	35.0
8	0.7	0.3	9934	1.35	35.0
9	0.8	0.2	10,787	1.66	34.7
10	0.9	0.1	11,671	1.87	35.0
11	1	0	12,570	2.0	35.0

Different combinations of coefficients *α*, which corresponds the various situations of the decision maker's attitude, have been considered to solve the problem. The optimal parameters including *Re*, *φ* and T_{in} are provided in Table 2. The observations indicated that the maximum Nusselt number along with minimum pressure drop can be obtained at the elevated inlet temperature (T_{in} = 35 °C). Moreover, it was revealed that in the case of assigning all the significance to the pressure drop, nanoparticles content and Reynolds number would have their least values (see the first row of Table 2). It is due to the fact that when nanoparticles content and Reynolds number are increased, the pressure drop is incremented. On the other hand, in the case of assigning all the significance to the heat transfer, inverse conditions for nanoparticles content and Reynolds number would occur (i.e., nanofluid concentration and Reynolds number have their highest values - see the last row of Table 2). It can be referred to the direct relationship between the heat transfer of nanofluid and the Reynolds number as well as concentration of nanofluid.

From Table 2, one can observe that when the relative importance of the heat transfer increases, among the other parameters, the Reynolds number and concentration quickly increment towards their highest values (i.e., by moving from the top to down of the table). Therefore, it can be concluded that the Reynolds number and content of nanoparticles highly affect the heat transfer and the significance of its influence on heat transfer is much greater compared to that on the pressure drop. Moreover, it can be seen that the inlet temperature moderately stable at its maximum amount (35 °C), by increasing the relative importance of the heat transfer. It indicates that the inlet temperature is a parameter which almost equally affects the both objectives.

6. Conclusion

A model for estimation of the Nusselt number and the nanofluid pressure drop in terms of Reynolds number, volume concentration, and inlet temperature has been developed via ANN using the data obtained from the experimental analysis. It is obtained that a network with 2 hidden layers and 6 neurons in every layer provides the best predicting performance. The comparison between the error values of the proposed correlations and the optimal ANN model revealed that the neural network is much powerful tool for determination of the hydrothermal characteristics in the problem under study. This model estimated the outputs accurately, and it was utilized in the optimization process as objective function. In order to consider the decision maker's attitude in optimizing the problem, genetic algorithm was coupled with compromise programming decision making method to obtain the optimal cases. The optimum values, which present the highest heat transfer along with the relatively least pressure drop, were eventually obtained for several levels of relative importance of the objective functions.

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