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Design of a heat exchanger working with organic nanofluids using multi-objective particle swarm optimization algorithm and response surface method

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ABSTRACT

In this study, the Pareto optimal design of COOH-MWCNTs nanofluid was investigated to reduce pressure drop and increase the relative heat transfer coefficient. Objective function modeling was based on empirical data, the solid volume fraction, and Reynolds number and then simulated with the response surface method in Design Expert software. After the objective function approximation, the regression coefficient of more than 0.9 for this study indicated the high accuracy of modeling through the RSM. To implement the optimization process, the powerful multi-objective particle swarm optimization algorithm was used. To show the correct optimization process, the results of the first and last generations of optimization are presented at the Pareto front, with all parts of it being non-dominant and optimized. Optimal results showed that to achieve a minimum pressure drop, the relative solid volume fraction should be at the minimum interval, and to achieve the maximum heat transfer coefficient, the relative solid volume fraction should be at the maximum interval. In addition, all optimal parts have the Reynolds number in the maximum range. At last, the optimum locations are presented, and the designer can select from these optimal points.

1. Introduction

Increasing heat transfer and heat transfer fluids has been the subject of much research in recent decades. Heat transfer fluids provide conditions for energy exchange in a system, and their effects depend on physical properties, such as thermal conductivity, viscosity, density, and heat capacity. Low thermal conductivity is often the most important limitation of heat transfer fluids. Among the studies conducted to overcome this limitation, Choi's proposed approach for the distribution of nanoparticles in a base fluid and for making nanofluids can be described as the best solution [1]. The impact of nanoparticles on the thermal conductivity of fluids can have a direct effect on heat transfer performance, thus increasing the heat transfer coefficient of fluids [2–8].

According to studies, the increasing temperature and solid volume fraction of nanoparticles in fluids can be called two important factors increasing the thermal conductivity of nanofluids [9–19]. In a study that Hemmat Esfe and Saedodin [3] carried out, the heat transfer characteristics of MgO/water nanofluids were tested in a heat exchanger. The results showed that a nanofluid with a higher-volume fraction and with a lower diameter of its nanoparticles has a higher Nusselt number and therefore, the higher the heat transfer coefficient. To predict the behavior of the heat transfer coefficient, pressure drop, and thermodynamic properties, such as thermal conductivity and the viscosity of nanofluids that various factors influence, mathematical relationships can be used. However, recently, software techniques, such as neural networks, have been used for this purpose. In Table 1, some of the studies in the field of modeling neural networks can be seen (Refs. [20–28]).

In a study, Hemmat Esfe et al. [29] Investigated the viscosity of TiO_2/water nanofluids using a neural network design. The

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Nomenclature

T	temperature (°C)
w	weight (gr)
k	thermal conductivity ($W\ m^{-1}\ {}^{\circ}C^{-1}$)
Re	Reynolds number
ANOVA	analysis of variance
MWCNT	Multi-Walled Carbon Nanotube
MOPSO	Multiple Objective Particle Swarm Optimization
MOO	multi-objective optimization
GA	Genetic algorithm
NSGA-II	non-dominated sorting genetic algorithm-II
RSM	Response surface methodology
DOE	Design of experiments
Greeks symbols	
ρ	density ($kg\ m^{-3}$)
φ	particle solid volume fraction
Subscripts	
Nf	nanofluid
bf	base fluid

algorithm used was a multilayer perceptron, which contains a hidden layer and four neurons. The results showed the high power of neural networks in predicting the experimental data, with the calculated regression coefficient being equal to 0.9998. Optimization between different parameters that sometimes conflict with one another has become an important issue in engineering problems in the past decade. The process that optimizes the collection of functions is called multi-objective optimization (MOO). Contrary to single-objective modeling, in MO problems, the objective is a set of points. All of these points apply the Pareto optimality definition for an optimal result at the Pareto front [30]. In recent years, studies on the algorithms of development (EAs) increased to expand MOO methods. Among famous algorithms, the genetic algorithm (GA) and non-dominated sorting genetic algorithm-II algorithm (NSGA-II) can be named [24,31–34].

Response surface methodology (RSM) is a set of mathematical methods that determine the relationship between one or more response variables with several independent variables (studied). In engineering, many phenomena can be modeled based on their related theories. In the case of the ineffectiveness of other modeling, the use of empirical modeling may work, with one of the most important of them being RSM [35–37]. For instance, Hussein et al. [38] designed a test for two nanofluids' heat transfer—SiO_2/water and TiO_2/water—in the radiator of a car. The results showed an increase in heat transfer by increasing the volumetric flow rate, inlet temperature, and solid volume fraction of the nanoparticles. Finally, they considered temperature variables, the volumetric flow rate, and the solid volume fraction as inputs and the Nusselt number as the response and designed a model. Besides MOO and response surface methods, some other methods may be used to analysis the heat exchangers which are based on entropy generation method [39,40].

In this study, to increase the relative heat transfer coefficient, and the relative pressure drop reduction of the COOH_MWCNTs nanofluid, a powerful optimization algorithm called swarm multi-objective particle was used. The objective functions were approximated using experimental data and the RSM and as the output were provided functions as polynomial objective functions.

To implement process optimization, the obtained model for objective functions connected to the multi-objective particle swarm algorithm (birds), and at each assessment, objective functions were used. After the implementation of the optimization process, to observe the optimization process, the results of the optimization of two main objectives in the first and last generations were presented in the form of Pareto front.

In this study, to increase the relative heat transfer coefficient and to reduce the relative pressure drop of COOH_MWCNTs nanofluid, the powerful multi-objective particle swarm optimization (MOPSO) algorithm was used. The objective functions were approximated using the experimental data and the RSM, and polynomial functions are presented for objective functions as the outputs. To implement the optimization process, the obtained models for objective functions were put into the multi-objective particle swarm (birds) algorithm, and at each assessment, these objective functions were used. After running the optimization process, to observe it, the results of the two objective functions' optimization in the first and last generations were presented in the form of the Pareto front.

Table 1
A summary of the studies in the field of modeling a neural network of nanofluid properties.

Author(s)	Nanofluid	Target(s)	Regression quality	Algorithm
Hemmat Esfe et al. [20]	Fe/EG	Thermal conductivity Dynamic viscosity	MSE = 0.00016 MSE = 0.00026	MLP
Hemmat Esfe et al. [21]	Al_2O_3/water	Thermal conductivity	MSE = 2.42E−6	MLP
Adham et al. [22]	SiC/water TiO_2/water	Thermal resistance & pumping power		NSGA-II
Zhao et al. [23]	Al_2O_3/water CuO/water	Dynamic viscosity	R-squared = 0.9962 R-squared = 0.9998	RBF
Mehrabi et al. [24]	TiO_2/water	Nusselt number & Pressure drop	MAE = 0.835 MRE = 8.9% RMSE = 1.01	GA-PNN & GMDH & NSGA-II
Ziaei-Rad et al. [25]	Al_2O_3/water	Friction factor Nusselt number	MRE = 0.19% MRE = 0.36%	MLP
Meybodi et al. [26]	Al_2O_3/water TiO_2/water SiO_2/water CuO/water	Dynamic viscosity	R-squared = 0.998	LSSVM
Santra et al. [27]	CuO/water	Nusselt number	MRE = 2.54 STDR = 2.46%	RPROP
Sharifpur et al. [28]	Al_2O_3/glycerol	Dynamic viscosity	R-squared = 0.9905	GMDH