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Applicability of connectionist methods to predict thermal resistance of pulsating heat pipes with ethanol by using neural networks

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ABSTRACT

Pulsating heat pipes (PHPs) are compact and efficient devices in heat transfer which are applicable for several purposes. The thermal resistance of PHPs depends on several parameters. In the present study, four models including multilayer perceptron (MLP), radial bias function (RBF), conjugated hybrid of particle swarm optimization and adaptive neuro-fuzzy inference system (CHPSO ANFIS) are applied to predict the thermal resistance of pulsating heat pipes filled with ethanol. The obtained results indicated that the radial bias function (RBF) model had the highest accuracy among the applied models and can predict the thermal resistance of the PHPs precisely. The R-squared and root mean squared error (RMSE) values for this model were 0.9892 and 0.0650, respectively.

1. Introduction

Heat pipes are effective heat transfer devices that are utilized for several applications [1–3]. There are several kinds of heat pipes such as wick heat pipes, rotating and pulsating [4–8]. Pulsating heat pipes (PHPs) are compact types of heat pipes which consist of a capillary tube bent into several turns [9]. The size of PHPs is smaller in comparison with other types of heat pipes which makes them more applicable for several purposes [10]. PHPs can be used for various applications such as renewable energy systems, and electronic device cooling [8,11–13].

Various parameters affect the thermal performance of PHPs [14,15] and inclination angle, heat input, working fluid and filling ratio are among the most important parameters [16–18]. The inclination angle of PHPs affect their thermal performance because the gravity has influence on the fluid motion inside the tube. Heat input is another parameter which is influential, since two-phase heat transfer exists in PHPs. Working fluid thermophysical properties have significant impact on heat transfer capability of PHPs [19,20]. Filling ratio is another important factor [21] and at low filling ratios, it is more possible for dry-out occurrence since there is no adequate liquid for evaporation. On the other hand, increase in filling ratio would impede fluid motion inside the tubes.

The performance of PHPs have been predicted by some proposed correlations and models [22]. In addition to correlations, other approaches can be used to model PHPs thermal performance. There are various models used for modeling engineering systems [23–27]. Artificial neural networks are among the most appropriate approaches that are broadly used in recent years to model different systems [28–30]. In this work, four algorithms including multilayer perceptron (MLP), radial bias function (RBF), conjugated hybrid of particle swarm optimization and adaptive neuro-fuzzy inference system (CHPSO ANFIS) models are applied to predict thermal resistance of PHPs filled with ethanol as working fluid.

2. Methods

2.1. Multilayer perceptron neural network

Neural network (NN) is a conventional practice to model various systems. Multilayer perceptron (MLP) networks are type of

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Nomenclature

AARD	average absolute relative deviation
CHPSO ANFIS	conjugate hybrid-PSO ANFIS
Di	inner diameter
Do	outer diameter
GA	genetic algorithm
La	length of adiabatic section
Lc	length of condenser section
Le	length of evaporator section
LSSVM	least square support vector machine
MLP	multilayer perceptron
MNN	maximum number of neurons
MSE	mean square error
NN	neural network
PHP	pulsating heat pipe
PSO	particle swarm optimization
Q	heat input
R^2	correlation coefficient
RBF	radial bias function
RMSE	root mean squared error
STD	standard deviation

NNs which are feed-forward. Three layers exist in a MLP network, including input layer, hidden layer and the output layer. Each mentioned layer has multiple neurons [31,32]. The number of layers depend on the input variables and output data of the problems. It is possible to have one or more layers in hidden section of the network [33]. The neurons in hidden and output layers are fed in from the neurons exist in previous layers. Each neuron had summing and activation functions. In first stage, the inputs multiplied by a weighting factor and were added together while a bias factor was added to the obtained number. Afterwards, the obtained number in previous step was used in the activation function as input data. There are three types of activation functions which are common [34,35].

Trial and error or intelligent methods can be applied to calculate the number of hidden layers and neurons in each layer. To obtain the optimal condition, a parameter which is known as MSE (mean square error) was used. Various trial and error steps were employed to find the optimal number of weight and bias. It was necessary to consider step numbers to prevent obtaining an improper model [36].

2.2. Radial basis function neural networks

Radial bias function (RBF) is another feed-forward neural network which is like MLP networks. Similar to MLP network, RBF networks have three layers. In these types of networks, there is just one hidden layer which results in simpler structure and working principle. In addition, the learnability of RBF networks is higher in comparison with MLP networks. Another advantage of these networks is their better reactions against the inputs used as test data [37–39].

Multiple neurons are used in the hidden layer of RBF networks which consist of both summing and activation functions. The activation function in RBF networks is a radial-based function. Learning process is applied to optimize both weight and bias values. A cost function should be used to be minimum amongst the actual and the output data [40–44].

2.3. Least square support vector machine (LSSVM)

The least square support vector machine (LSSVM) is a model which is generated based on utilizing support vector machine (SVM) and modifying it [45–47]. The model was more complete compared with SVM. By applying LSSVM, it was possible to model complicated problems. This approach was operated based on statistical learning theory [48,49]. Two parameters, σ^2 and γ, are required to tune in the procedure of LSSVM completion. By tuning the mentioned parameters, the achieved model would have more appropriate functions [49]. Various algorithms can be utilized to optimize and tune the parameters, including GA, PSO or CSA. Similar to previous methods, a cost function was required to be minimized between the input and output data [50–53].

2.4. Conjugate hybrid-PSO ANFIS (CHPSO ANFIS)

In this work, the fuzzy logic which was applied to describe process by utilizing a number of *if-then* rules [54,55] was used. To obtain favorable results, it was necessary to utilize other models including artificial neural networks in addition to the fuzzy logic. Adaptive neuro-fuzzy inference system (ANFIS) is a model that was obtained by integrating ANN and fuzzy logic. In ANFIS model, a predefined structure existed which was known as FIS for which a number of *if-then* rules and special functions called membership functions were defined. Afterwards, the membership functions were improved via using NN by considering the issue which was used for modeling [56].

2.5. Data acquisition

Obtaining an appropriate dependable model requires valid data in wide ranges [44,57,58]. Several factors are involved in thermal performance of PHPs. Among the various influential parameters, heat input plays a key role because of two-phase heat transfer occurrence in PHPs. Since increase in heat input results in enhancement in boiling heat transfer, which in turn, leads to a low thermal resistance of PHPs. Figs. 1 and 2 show the thermal resistance based on power input for 40% and 50% filling ratios.

In addition to heat input, the filling ratio is another influential parameter on the heat transfer of PHPs. Most of the studies have shown that the filling ratio must be in the range of 20–80% to achieve the best performance. The influence of the filling ratio and the heat input on the thermal resistance of a PHP is shown in Fig. 3.

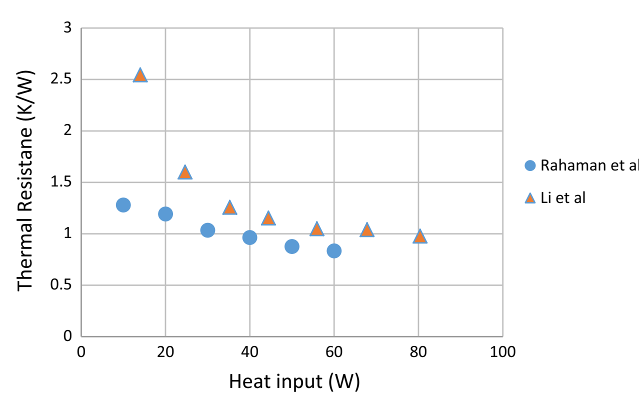

Fig. 1. Thermal resistance vs heat input in 40% filling ratio in vertical orientation [60,61].