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Artificial Neural Network Modeling of a Closed Loop Pulsating Heat Pipe

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Abstract**—**Technological innovations in electronic world demand novel, compact, simple in design, less costly and effective heat transfer devices. Closed Loop Pulsating Heat Pipe (CLPHP) is a passive phase change heat transfer device and has potential to transfer heat quickly and efficiently from source to sink. Thermal performance of a CLPHP is governed by various parameters such as number of U-turns, orientations, input heat, working fluids and filling ratio. The present paper is an attempt to predict the thermal performance of a CLPHP using Artificial Neural Network (ANN). Filling ratio and heat input are considered as input parameters while thermal resistance is set as target parameter. Types of neural networks considered in the present paper are radial basis, generalized regression, linear layer, cascade forward back propagation, feed forward back propagation; feed forward distributed time delay, layer recurrent and Elman back propagation. Linear, logistic sigmoid, tangent sigmoid and Radial Basis Gaussian Function are used as transfer functions. Prediction accuracy is measured based on the experimental data reported by the researchers in open literature as a function of Mean Absolute Relative Deviation (MARD). The prediction of a generalized regression ANN model with spread constant of 4.8 is found in agreement with the experimental data for MARD in the range of ±1.81%.

Keywords**—**ANN models, CLPHP, filling ratio, generalized regression, spread constant.

I. Introduction

CLPHP is a novel wickless passive device works on the phase change phenomena and effectively transfers heat from the source to sink [1]. It is typically a serpentine copper tube as shown in Fig. 1. The diameter of a copper tube is selected to surpass the surface tension force over the gravitational force. Evaporator acts as a source through which heat is supplied to the device while condenser acts as a sink through which heat is rejected from the device. The CLPHP is partially filled with the working fluid. The working fluid converts into gas-liquid two-phase flow and attains the pulsating/oscillating motion in a CLPHP due to the pressure difference between evaporator and condenser. Adiabatic section facilitates the pulsating/oscillating motion of liquid slugs and vapor plugs. As CLPHP involves intricate gas-liquid two-phase heat and mass transfer and multivariate operating mechanism, a complete understanding of the complex thermo-hydrodynamics mechanism of CLPHP is still lacking [2].

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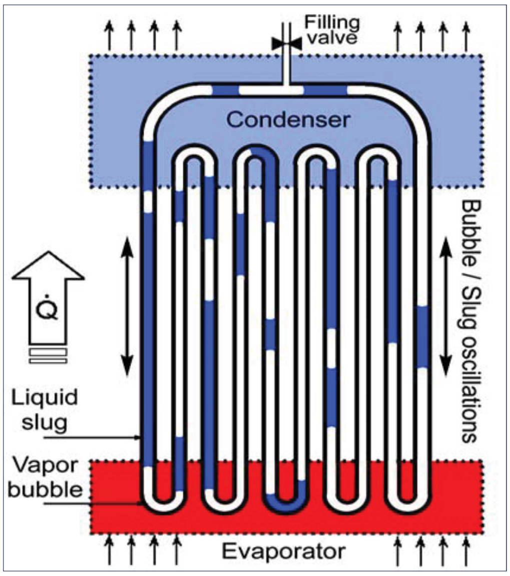

Fig. 1 Pulsating heat pipe [1]

Thermal performance of a CLPHP is influenced by several parameters involving number of U-bends, evaporator location in different planes, input heat flux, type of working fluids and filling ratio. Literature review of experimental work on CLPHP including authors' work on CLPHP [3], [6] shows significant impact of these parameters on the thermal performance of a CLPHP. Hence, it is essential to carry out a systematic analysis of a CLPHP to develop a mathematical model. ANN is widely used for the qualitative and quantitative analysis of two-phase flow data. The possibility of using a neural network based technique to identify gas-liquid two-phase flow pattern and pressure drop is reported by Mehta et al. [7], [8]. The present research paper aims to predict the thermal performance of a CLPHP by developing various ANN models and to recommend the accurate prediction model. The experimental data reported by Shafii et al. [9] are used for neural network training, validation and testing. The input parameters to all ANN models are set as Filling ratio and input heat while thermal resistance is considered as output parameter.

II. ANN Modeling

The basic structure of ANN applied to a CLPHP is shown in Fig. 2. Filling ratio and heat input are placed as input parameters for predicting thermal resistance as targeted output. Sometimes neural network predicts the accurate output for known input data which are used for training the network model but it cannot give a good estimation for new data. This problem occurs due to over-fitting or over training. In order to avoid over-fitting, all data are divided into three parts: Training (70%), validation (15%) and testing (15%). Training data are used to develop the accurate neural network model by adjusting weight and bias. Therefore, the majority of data (70%) should be assigned to the training process. Validation data (15%) are used to judge the accuracy and generalization of trained network. It stops the network training process at some epochs in order to avoid over-fitting. Testing data (15%) are used to examine the final behavior of the network. Out of 47 experimental data, 42 data (89%) are used for training, validation and testing process during ANN modeling. Remaining 5 data (11%) are used for testing the final models.

The neural networks considered in the present study are radial basis, generalized regression, linear layer, cascade forward back propagation, feed forward back propagation, feed forward distributed time delay, layer recurrent and Elman back propagation. The various transfer functions used in the modeling are Linear, logistic sigmoid, tangent sigmoid and Gaussian RBF. The arrangement of networks and transfer functions provide diverse network models which are tabulated in Table I. The intention of the present work is to propose the suitable ANN model which predicts the thermal resistance in agreement with the actual experimental resistance reported by Shafii et al. [9].

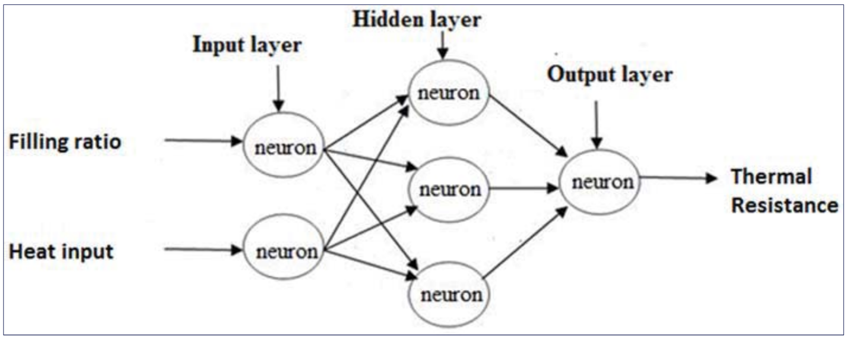

Fig. 2 Generalized ANN structured

TABLE I
DIFFERENT ANN MODELS

Neural Network	Transfer Function	Model Notation
Cascade forward back propagation	TANSIG	A
	LOGSIG	B
	PURELIN	C
Elman back prop	TANSIG	D
	LOGSIG	E
	PURELIN	F
Feed forward back-propagation	TANSIG	G
	LOGSIG	H
	PURELIN	I
Feed forward distributed time delay	TANSIG	J
	LOGSIG	K
	PURELIN	L
Generalized regression	**Gaussian RBF**	**M**
Layer Recurrent	TANSIG	N
	LOGSIG	O
	PURELIN	P
Linear layer (design)	PURELIN	Q
Radial basis (exact fit)	Gaussian RBF	R

III. EXECUTION PROCEDURE

Procedure for neural network modeling in MATLAB is given below. Following steps are common for every neural network model.

1. Prepare excel data sheet for input data, output data and test data.
2. Import these data without any headings or labels into MATLAB workspace.
3. Type nntool command in command window of MATLAB.
4. Import input and test data as "input data" and output data as "target data" in nntool box.'
5. Click on New option. Select proper network, input-target data, training-performance function with a suitable number of layer and neurons.
6. Hit create button for the development of new network as per chosen parameters.
7. Open this network and Train the network for given input and target data by pressing the Train Network button.
8. Use simulate button for testing the neural network. Predicted result and error are generated in the output window and error window in the nntool box.
9. Export these data into again MATLAB workspace. After that, paste them into excel sheet for post processing.

IV. RESULTS AND DISCUSSION

The experimental data reported by Shafii et al. [9] are used for ANN modeling of a CLPHP. Shafii et al. [9] considered total five turn copper tube of 1.8 mm internal diameter, 3 mm outer diameter and 4 m overall length for their experiments. The length of the evaporator (heating section) and condenser (cooling section) was kept as 60 mm while the adiabatic section was set as 150 mm. The width was 250 mm. The orientation was set as vertical bottom heating position. The inside volume of CLPHP was 12 Cubic Centimeter (CC). Filling Ratio (FR) was considered as 30%, 40%, 50%, 70%

and 80%. Water was used as working fluid. Heat input varies in the range of 5 to 70 Watt with an incremental step of 5 Watt. For each combination of heat input and FR, average evaporator and condenser temperatures were recorded under steady state condition. Thermal resistance is calculated using (1):

Thermal resistance = (Average evaporator temperature – Average condensation temperature)/(Total heat supply) (1)

The Training function and Adaption learning function are considered as TRAINLM and LEARNGDM. Total two number of hidden layer are considered. Total number of neurons considered is 10. Learning rate is considered as 0.01. MATLAB R2015a is used for ANN modeling. The prediction accuracy of various ANN models (Table I) is estimated using MARD through (2):

$$MARD = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P(i)_{predicted} - P(i)_{experiment}}{P(i)_{experiment}}\right| \quad (2)$$

Fig. 3 shows the prediction accuracy of various ANN models as a function of MARD. Generalized regression with Gaussian RBF model is found to have least MARD among all tested models. Generalized regression with Gaussian RBF model takes default spread constant value as 1. Optimization is carried out for different spread constant value. MARD obtained for different spread constant in generalized regression with Gaussian RBF model is plotted in Fig. 4. The optimum spread constant is found between 4 to 5. In order to carry out further optimization of spread constant, Mean Absolute Error is calculated and compared for spread constant 4.5 to 5.5. The spread constant 4.8 is found to have least Mean Absolute Error as shown in Fig. 5. The performance prediction using generalized regression with Gaussian RBF model having spread constant 4.8 is compared with experimental data as shown in Fig. 6 and found in the error range of 1.81%.

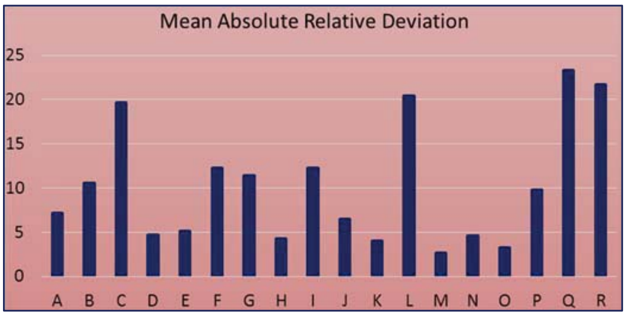

Fig. 3 Comparison between different ANN models by MARD

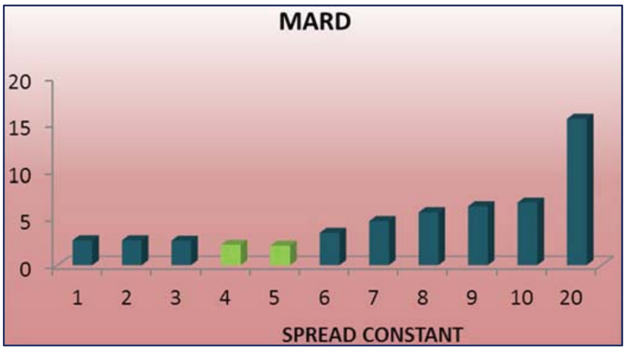

Fig. 4 MARD for different spread constant in generalized regression model

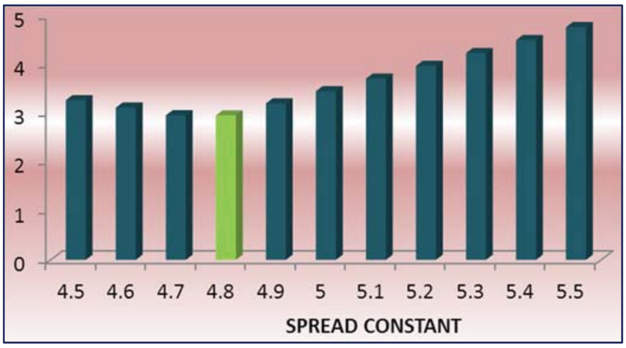

Fig. 5 MARD for spread constant (4.5-5.5) in generalized regression model

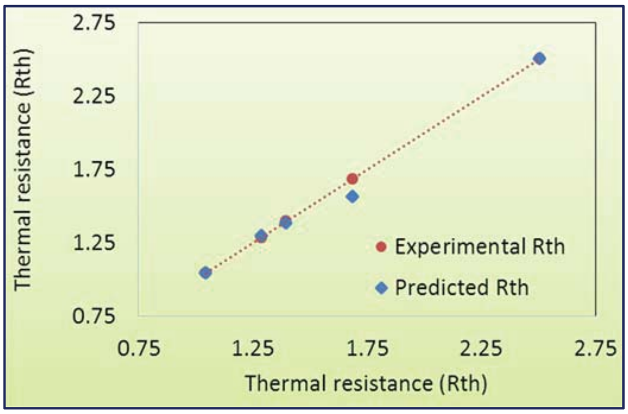

Fig. 6 Experimental versus Predicted thermal resistance by generalized regression model with spread constant of 4.8

V. Conclusion

ANN modeling of a CLPHP is performed in the present paper. A total of 18 ANN models involving different transfer functions is considered to predict the thermal performance of a CLPHP. The neural network models are trained and tested using experimental data collected from the literature. Heat input supplied to the evaporator and FR is used as an input parameter of the neural network and thermal resistance of pulsating heat pipe is selected as an output parameter. It is concluded that generalized regression neural network with

Gaussian RBF having spread constant 4.8 gives minimum MARD among all models and predicts the thermal performance of a CLPHP in the error range of ±1.81%.

REFERENCES

[1] Charoensawan, P., Khandekar, S., Groll, M., and Trenton, P. (2003). ‘Closed loop pulsating heat pipes-Part A: Parametric experimental investigations’. Applied Thermal Engineering, 23(16), 2009–2020.
[2] Zhang, Y., and Faghri, A. (2008). ‘Advances and Unsolved Issues in Pulsating Heat Pipes’. Heat Transfer Engineering, 29(1), 20–44.
[3] Patel, V., M., Gaurav, and Mehta, H., B. (2017). ‘Influence of working fluids on startup mechanism and thermal performance of a closed loop pulsating heat pipe’. Applied Thermal Engineering, 110, 1568–1577.
[4] Patel, V., M., and Mehta, H., B. (2016). 'Influence of Gravity on the Performance of a Closed Loop Pulsating Heat Pipe '. World Academy of Science, Engineering and Technology, International Science Index 109, International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering, 10(1), 219 - 223.
[5] Patel, V., M., and Mehta, H., B. (2016). ‘Start Up Mechanism of Pulsating Heat Pipe’. National Conference on Thermal Fluid-science and Tribology Application, S.V. National Institute of Technology, Surat, ISBN: 978-93-5265-440-6, 1-8.
[6] Gamit, H., More, V., Bade, M., and Mehta, H., B. (2015). ‘Experimental Investigations on Pulsating Heat Pipe’. The 7th International Conference on Applied Energy, ICAE2015, Energy Procedia, 75, 3186-3191.
[7] Mehta, H. B., Patel, V., M., and Banerjee, J. (2016). 'Prediction of Air-Water Two-Phase Frictional Pressure Drop Using Artificial Neural Network'. World Academy of Science, Engineering and Technology, International Science Index 109, International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering, 10(1), 210 - 213.
[8] Mehta, H., B., Pujara, M., P., and Banerjee, J. (2013). ‘Prediction of Two-Phase Flow Pattern using Artificial Neural Network’. International Conference on Chemical and Environmental Engineering (ICCEE-2013) Johannesburg (South Africa), April 15-16, 2013.
[9] Shafii, M., B., Arabnejad, S., Saboohi, Y., and Jamshidi, H. (2010). 'Experimental Investigation of Pulsating Heat Pipes and a Proposed Correlation'. Heat Transfer Engineering, 31(10), 854–861.