Application of Artificial Neural Networks in predicting the thermal performance of grooved heat pipes

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Abstract. Heat pipes are versatile, relatively easy to construct, and capable of exchanging large amounts of heat between small temperature differences, even without external pumping. On the other hand, these devices have complex equations, which usually complicates their development, generating more extended periods of research and expenses. Methods that use computational intelligence, such as Artificial Neural Networks (ANN), have the ideal characteristics for use in problems of this type. ANN are algorithms that can solve complex problems using only experimental data, even without knowledge about the physics of the problem, limited only by the quality of the data used and the available computational power. In many cases, the results found using ANN have lower error percentages than those obtained using conventional methods. The database used was generated from an experimental investigation of the thermal behavior of heat pipes with a wicked structure of axial grooves and using water as the working fluid. The results were used to train two different Artificial Neural Networks. The Neural Networks used were the Multi-Layer Perceptron (MLP) and the Extreme Learning Machine (ELM). Filling ratio, slope, and dissipated power were used as inputs to the networks, and as output, we have the expected thermal resistance of the heat pipe. The results show that both ANN were able to generalize the problem, presenting errors of less than 25%. It is also possible to note that the MLP presents better results, with an error of about 18%. These values show that ANN are viable as a tool to improve the development of grooved heat pipes.

Keywords: Heat pipe, Artificial Neural Networks, thermal performance, Machine Learning.

1 Introduction

Currently, the industry faces a significant challenge arising from the dependence on processes operated at high temperatures, which result in the loss of large amounts of energy in the form of heat during the processing of various products (Agathokleous et al. [1]). These losses are especially pronounced in fossil fuel-based processes, in which the loss of heat carried by combustion gases represents a large portion of the total energy loss, and in the production and transport of electrical energy, where the loss of thermal energy during transport and power conversion represents a significant portion of the energy produced. The disadvantages range from economic due to loss of efficiency to environmental impacts resulting from the greater need for energy production (Cullen & Allwood [2]).

Heat exchangers play a crucial role in several industries requiring precise temperature controls, facilitating heat transfer between two fluids at different temperatures and separated from each other, as Bergman and Lavine [3] explained. The efficiency of these heat exchangers is directly related to the overall efficiency of the process. Therefore, optimizing and developing this equipment is extremely important to minimize the usable energy rejected.

1.1 *Heat Pipe*

Heat pipes represent highly efficient passive heat transfer devices even for small temperature differences. A heat pipe operates through the principles of evaporation and condensation of its working fluid, which is usually surrounded by an airtight casing and maintained at controlled pressures. Inside the casing, there is also a capillary structure responsible for helping to move the working fluid and, consequently, the heat inside the heat pipe. This device can be divided into three main parts, as illustrated in Fig. 1: the *evaporator*, generally located at the bottom of the heat pipe and where the working fluid is accumulated in a liquid state. Upon contact with the hot source, the fluid evaporates and moves to the *condenser* at the top of the device, and in contact with the cold source, the working fluid loses heat, returning to the liquid state. Between these two parts is the *adiabatic section*, with no heat exchange (Mantelli [4]).

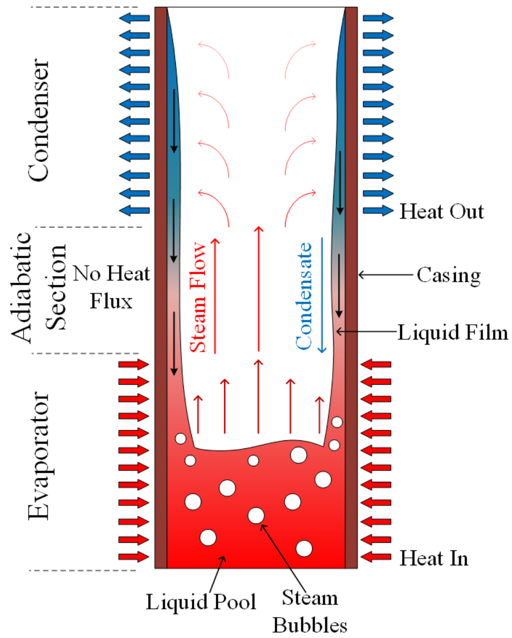

Figure 1. Operation of a Heat Pipe

The construction of a heat pipe involves the use of a hollow tube, usually made of metallic material due to its good thermal conductivity, necessary for heat to flow between the working fluid and the environment with the minimum possible thermal resistance, and also because these materials have good mechanical resistance, ideal for withstanding differences between internal and external pressure. The casing material must not react chemically with the working fluid to avoid unwanted effects. Working fluid selection is based on specific characteristics required for heat pipe design, such as thermal conductivity, vapor pressure, and critical point temperature. Furthermore, the filling ratio, which represents the proportion between the amount of working fluid and the volume of the evaporator, is an important parameter in heat pipe manufacturing (Zohuri [5]).

The selection of the capillary structure in the heat pipe is an essential factor as it significantly impacts its operation. The various available capillary structures vary greatly in properties and results. However, the decision on the ideal structure is often unclear since the mathematical equations that govern their functioning within a heat pipe are very complex and sometimes have inaccurate results (Reay et al. [6]).

In this context, using computational models, such as Artificial Neural Networks (ANN), can play an important role in reducing the main problems caused by the difficulty encountered in modeling these and other thermal devices.

1.2 *Artificial Neural Networks*

Artificial Neural Networks are computational models developed based on the nervous system of higher organisms, such as animals, with the aim of predicting different behaviors of complex problems without the need for in-depth knowledge about the theory behind it. The functioning of ANN is based on using previously obtained experimental data. Therefore, it is possible to "teach" the Neural Network about the behavior of complex problems (Haykin [7]). These algorithms are formed by connecting small modules, usually called neurons, distributed in different layers, as represented in Fig. 2. These neurons simulate the behavior of organic neurons, receiving input data and performing simple mathematical operations to obtain new values that will be transmitted to the following layers until, finally, obtaining results from the output layer.

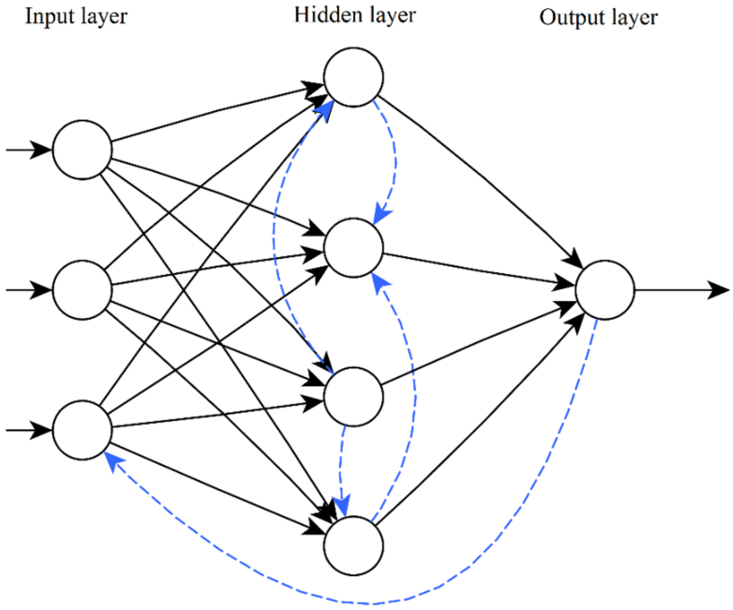

Figure 2. Neural Network Architecture

Multilayer Perceptron. The Multilayer Perceptron (MLP) is one of the most used ANN architectures. It can be defined as a Feedforward Multilayer Network with one or more hidden or intermediate layers in addition to one output and one input layer. The number of neurons in the intermediate layers directly impacts the mapping quality of the MLP network, and a reduced number of neurons can lead to an insufficient approximation of the desired function, generating high errors. In contrast, an excessive number of neurons can lead to another problem: overfitting. In this case, the network reduces its error relative to the training group. However, it has a lower generalization capacity, that is, to predict the behavior of new data, as it adapts excessively to the specific training group. Each neuron in the input layer receives one of the data applied to the network as input. Each hidden layer neuron will normally receive all data from the previous layer multiplied by its respective connection weight. These values are then added together with the bias value, which can be considered an input with value 1. The sum of the values is then applied to an activation function. Different functions, such as the hyperbolic tangent or the sigmoid function, can be used. The activation function's resulting value is the neuron's output, which is then passed to the next layer. For some functions, the network inputs must be normalized within the function's valid range. Several algorithms have been developed for MLP training. Among them, the most used and well-known is the Backpropagation Algorithm, which is based on the error correction learning rule which consists of two phases: a) *propagation*: input data is applied to the network input, propagating through the following layers and producing a set of outputs. In this step, there is no change in weights; b) *backpropagation*: the response obtained in the propagation step is used together with the known output data to produce an error signal, which is then backpropagated through the network and used to modify the weights (Haykin [7]).

Extreme Learning Machines. The Extreme Learning Machine (ELM) is a learning algorithm proposed by Huang et al. [8] for Feedforward Networks with only one hidden layer that uses constant random weights in the intermediate layer and an analytical method to determine the weights of the output layer, not needing iterative methods based on gradient descent. The analytical method utilized is the Moore Penrose inverse. The advantage of using this method in contrast with other ANN is its training speed, which, according to Huang et al. [9], can be thousands of times faster than training via Backpropagation, in addition to avoiding several other problems, such as convergence to local minima and overfitting. The most significant difference in ELM training is that the hidden layer is not adjusted, only the output layer, speeding up the training process.

2 Methodology

The data used to train the Artificial Neural Networks used in this work were obtained from experimental work by Nishida et al. [10] referring to heat pipes with axial grooves. The heat pipes used were made using the wire electrical discharge machining (wire-EDM) process on copper tubes. With this, three different models of axial microgrooves were manufactured, which can be seen in Fig. 3.

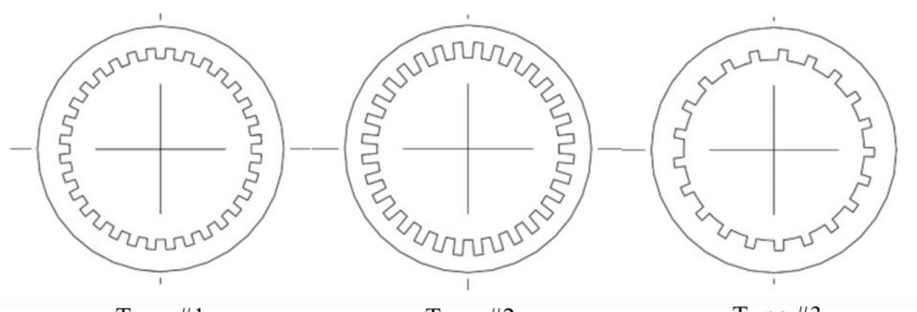

Figure 3. Axial grooved heat pipes tested for the database

2.1 *ANN Training*

Two different ANN were used to evaluate the heat pipes: the Multilayer Perceptron (MLP) and the Extreme Learning Machine (ELM). Each network was built from scratch using the Python® programming language, without pre-made libraries, to increase understanding of how each network works and to have more control over the parameters used.

The data found in the experimental tests were used to train each of the ANN used. Training has different methods for each of the networks used. The MLP Network was trained following the methodology presented in Haykin [7] using Backpropagation for both layers. ELM training used the method proposed by Huang et al. [8].

In training each ANN, some variable parameters are usually found by testing a wide range of possibilities, such as the number of neurons used in the hidden layer. These properties were evaluated during training in an initial stage that used fewer training epochs to search for these parameters. The combinations of parameters that generated results with the lowest Mean Square Error (MSE) in relation to the test data were selected. Some important parameters used during ANN training are the number of hidden layers, the number of neurons in each hidden layer, and the activation functions used. The parameters of each Neural Network used are listed in Tab. 1. Each ANN is trained several times for each configuration, and the average value among all values obtained is the result to be evaluated. For the MLP, once the best combination of parameters for this case was found, the network was trained again using a greater number of epochs to obtain the final results. The number of epochs used was 1,000 for the initial training phase and 10,000 for the final phase.

Table 1. Parameters used in training each ANN

Model	**Number of Neurons**	**Hidden layers**	**Activation Function**	
			Hidden	**Output**
MLP	3 - 200	1-2	Logistic	Linear
ELM	3 - 200	1	Logistic	Linear

3 Results

The comparison between values found by theoretical equations and experimental values for devices such as heat pipes is not frequently addressed in the literature. Thus, a value acquired based on experiments is used as a basis for evaluating the results obtained. The value used to define an acceptable result is 30% Mean Absolute Percentage Error (MAPE). Higher values represent a variation in the expected thermal resistance that generates significant losses from an experimental point of view.

In addition to MAPE, where also used the Mean Absolute Error (MAE), which represents the average of the absolute value of the errors found, and the Square Root of the Mean Square Error (RMSE), which is similar to the MAE, but is more punitive for larger values of absolute error. Different error assessment methods are important since, in many cases, just one metric cannot clearly express the results. Using different methods to understand the values obtained is essential in these cases.

From the experimental database, the ANN were applied and generated the results presented in Tab. 2. The best result for the MAPE Error was obtained using the MLP Network, with an error percentage close to 18%. The ELM Network also has a great result, of around 24%, showing that the two Neural Networks adapted well to the problem. The values were obtained from the average of errors between 30 independent tests.

Table 2. Results for each ANN

Model	***NN***	**Hidden layers**	***MAE***	***RMSE***	***MAPE* [%]**
MLP	6	1	0.232	0.323	18.3
ELM	30	1	0.514	0.742	24.0

The results show that the MLP and ELM Networks can generalize the problem, generating consistent errors between tests and within the expected levels. It is also possible to see that the MLP Network presents better results in relation to MAPE, RMSE, and MAE errors in this problem. The MAPE found for the MLP Network is around 27% lower than that presented by the ELM Network. At the same time, the MAE is around 54% smaller, and the RMSE is 56% smaller. These values show a more stable result for the MLP that, besides having better average results, also has less absolute error, shown by the smaller MAE, and fewer outliers, shown by the smaller RMSE.

Figure 4 shows the relationship between MAPE and the number of neurons in the hidden layer of the ELM Network. A clear trend can be noted, which begins in the region of 3 neurons where the error quickly drops until 6 neurons when a trend of error growth begins. After this the error keeps increasing util 70-80 neurons where it stabilizes. The region of minimum can be clear seem and agrees with the information in Tab. 2 (6 neurons).

Figure 5 shows the variation in MAPE about the number of neurons for the MLP Network in the region with the lowest error found. The results show that unlike the other ANN tested, there is a clear stability region between 3-42 neurons where the error suddenly grows exponentially. It is also possible to notice a region with the smallest error between 21 and 36 neurons. The best result is found with 30 neurons.

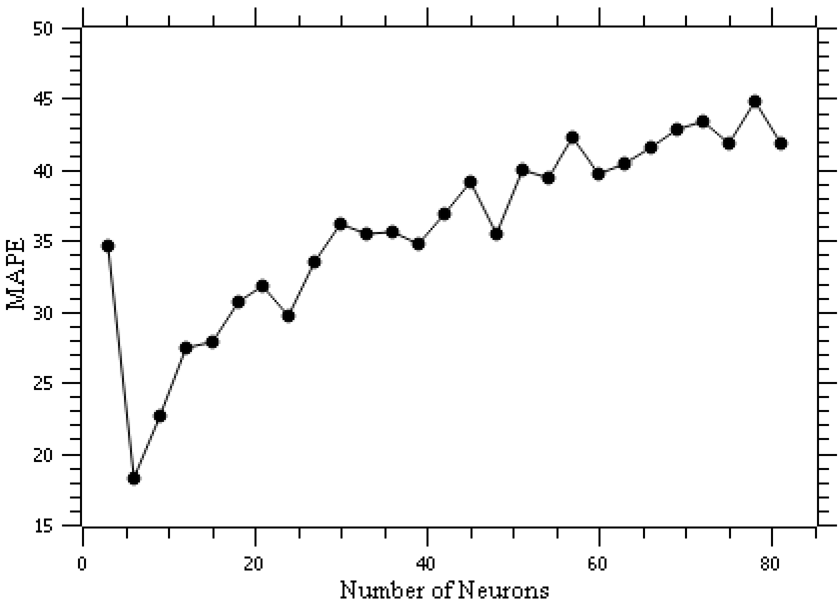

Figure 4. Variation of the average MAPE with the number of neurons for the MLP

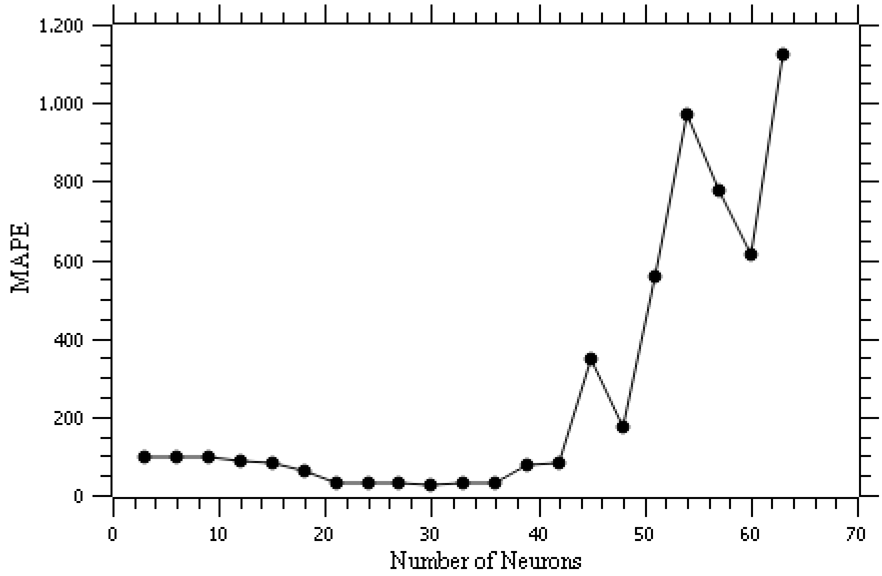

Figure 5. Variation of the average MAPE with the number of neurons for the ELM

Figure 6 and 7 compares the thermal resistances of the heat pipes obtained experimentally and the values obtained using ANN for one iteration. It is possible to see that, in addition to generating good average error values, the neural networks generate consistent results for the individual values obtained. It can be seen that most of the results obtained are within the 30% error range, in addition to being concentrated close to the central line for both networks, which represents the optimal values. In this case, both neural networks have similar behaviors, although the ELM Network presents some discrepant points (outliers).

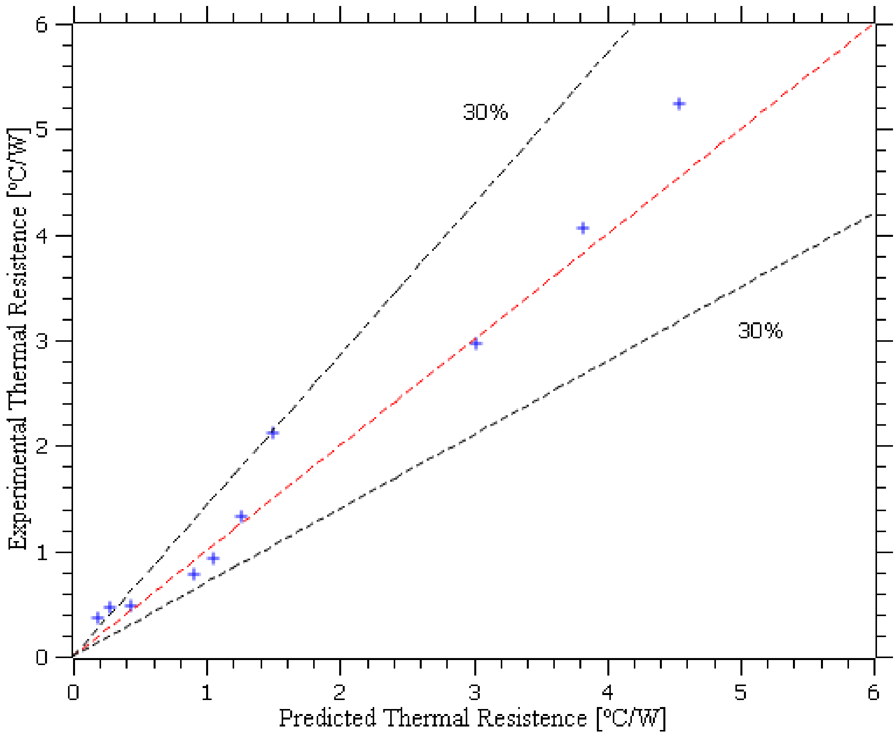

Figure 6. Experimental X Predicted thermal resistance MLP

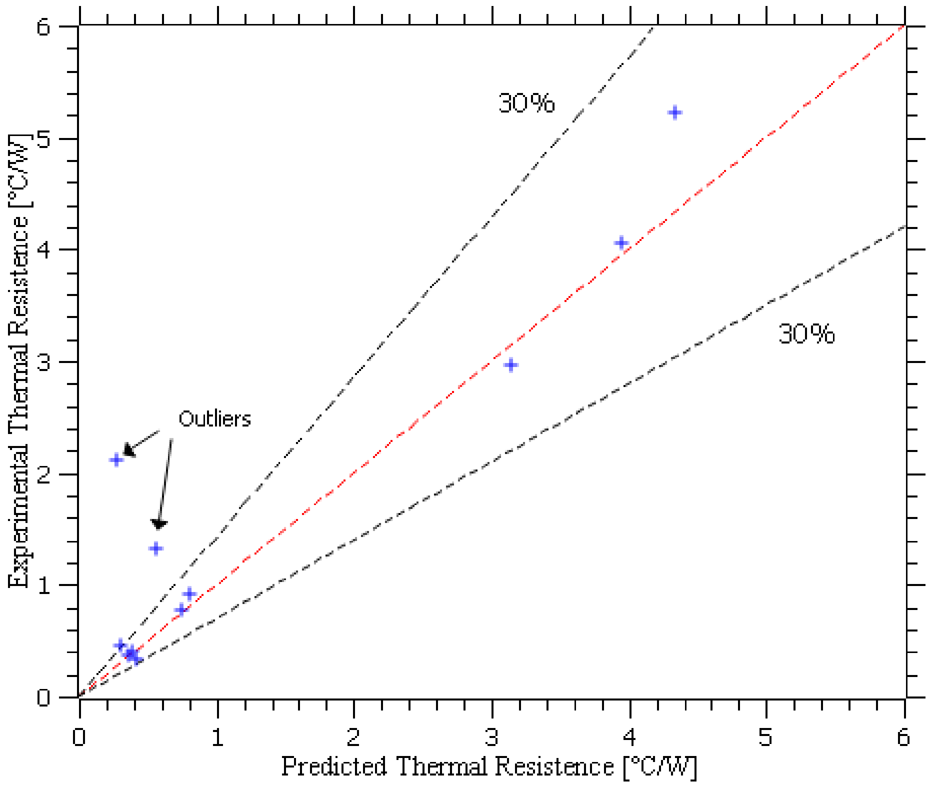

Figure 7. Experimental X Predicted thermal resistance ELM

4 Conclusions

In this work, an experimental investigation of the thermal performance of a copper heat pipe with axial grooves wick structure under different inclinations using water as the working fluid and cooled through forced air convection was used. The heat pipe was tested at inclinations of 0, 45, and 90° to the horizontal, with thermal load dissipation between 5 and 50W, with a step of 5W. The data of the thermal resistance of the heat pipes, which, together with the heat pipe properties, were used as a database for the training of two Artificial Neural Networks: Multilayer Perceptron (MLP) and the Extreme Learning Machine (ELM). After training the ANN, their results were compared with those obtained experimentally. The results showed that the Neural Networks were able to generalize the proposed problem, achieving results with less than 24% for both ANNs and error close to 18% for the MLP Network. With the values obtained, it is possible to conclude that Artificial Neural Networks can be used to aid in the process of developing heat pipes with axial grooves and, most likely, other types of wick structures. It is also necessary to point out the need for new experiments to confirm the results acquired. The small number of samples, although sufficient for use in initial work, limits the quality of the results. It is also essential to evaluate the use of different methods, such as other Machine Learning Methods, more modern versions of the applied networks, and analytical results for comparison.

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