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Thermal Performance Modeling of Pulsating Heat Pipes by Artificial Neural Network

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Abstract

This paper presents a new approach for modeling pulsating heat pipes (PHPs). A vertical, closed loop, copper PHP with ethanol as the working fluid is first experimentally investigated for a range of heat inputs and fill ratios. An Artificial Neural Network (ANN) is then trained with the available test data and subsequently validated. Fully connected feed forward multi-layer ANN configuration is adopted. Standard supervised learning algorithm of back propagation with momentum is employed in this study. The ANN architecture consists of two input nodes corresponding to the heat input and the fill ratio and a single output node representing the overall thermal resistance of the PHP. The validation of the ANN predictions against experimental data is satisfactory within the domain of the total available data sets. This study also highlights that understanding of the underlying physical phenomena of the system to be modeled by ANN is an essential prerequisite for getting reasonable results. In view of the fact that there are serious limitations with conventional techniques for modeling PHPs, ANN approach seems to be very promising if sufficient data are available for covering the complete range of system operation.

Key Words: Pulsating heat pipes, Artificial neural network, Modeling

1. INTRODUCTION

Pulsating heat pipes (PHPs) are being developed for thermal control of micro electronic equipment [1]. Since the complex physical processes occurring within a PHP are not yet fully understood, the published analytical models are very limited in scope and applicability [2]. The complexity of thermofluidynamics is coupled with performance dependency on a large number of geometric, physical and operational variables. There exist no reliable tools to design a PHP for a given micro electronic cooling requirement. A contemporary technique of artificial neural networks could offer an alternative approach for modeling PHPs. ANNs have been extensively studied during the past two decades and successfully applied in different areas especially where nonlinear effects are predominant [3]. The application of ANN to thermal systems is still not very extensive and certainly needs more research. For modeling of PHPs, this approach has not been investigated so far. The main purpose of this research is to undertake this task.

2. ARTIFICIAL NEURAL NETWORKS

An ANN is a processing device, either an algorithm, or actual hardware, the design of which is motivated by the design and functioning of the human brain (biological neural cells, neurons) and components thereof. This design motivation is what distinguishes ANNs from other mathematical techniques. It is a kind of mathematical tool, similar to regression analysis. The key feature of ANNs over conventional regression analysis is that they employ nonlinear mathematics and therefore can be used to model highly complex and nonlinear systems such as PHPs.

A fully connected feed-forward multi-layer configuration using back propagation momentum learning algorithm has been employed in this study. This type of ANN has a strong ability to express complex nonlinear mapping and has already found wide ranging applications [3].

The architecture of this type of ANN usually consists of an input layer, some hidden layers and

an output layer. Each layer has some nodes representing artificial neurons. Each node is interconnected to the nodes of its preceding layer through adaptable weights and no lateral, self or back connection is allowed. Individual neurons have limited ability of calculation and expression but when they connect with each other, the whole network achieves an ability to model complex functions. A network accepts an input vector and generates a response in the form of an output vector (Fig. 1).
Training of the network involves the iterative

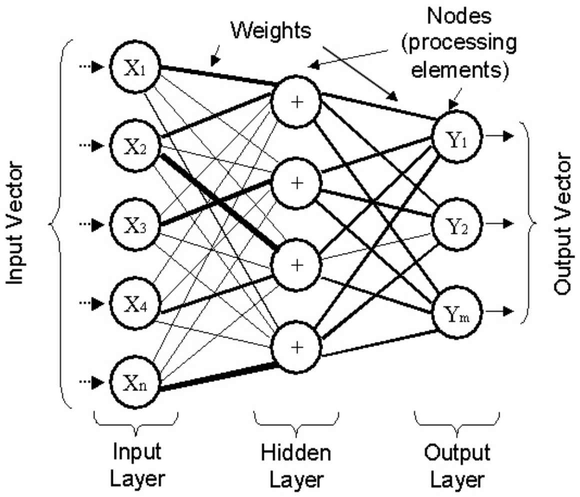

Fig 1: Basic ANN architecture

refinement of the associated 'weights' such that the pre-specified error condition is minimized. Training patterns are composed of a group of matching input and output vectors. The learning algorithm uses these sets of input and output vectors to train a network. It measures the difference between the desired output vector to the current actual output vector and the resulting error backpropagates to alter the connecting weights in the direction of reducing the error. This process runs many times until the error is within the required level. Then the network holds the weights constant and becomes a valid model for prediction.

As stated earlier, each neuron or node performs a very simple calculation. It sums all its inputs multiplied by their respective weights, then a squashing function is applied to this value. In this study, an identity function is used for output activation. For all other nodes, a sigmoid function is used as activation function. This function can perform nonlinear input-output transformation actions and is normally used in most applications. Further details are available in [4].

3. PHP OPERATING CHARACTERISTICS

A given PHP has two operational extremities with respect to filling ratio (liquid volume / total PHP volume), i.e. 0% filled or an empty device and 100% filled equivalent to a single-phase thermosyphon [5]. It is obvious that at 0% fill ratio, a PHP structure with only bare tubes and no working fluid, is a pure conduction mode heat transfer device and obviously has a very high undesirable thermal resistance. A 100% fully filled PHP is identical in operation to a single-phase thermosyphon. Since there exist no bubbles in the tube, 'pulsating' effects are obviously nonexistent but substantial heat transfer can take place due to liquid circulation in the tubes by thermally induced buoyancy.

In between these two limits the device functions in a pulsating mode. In this pulsating operational mode, there exist three distinct regions:

Nearly 100% fill ratio: In this mode there are only very few bubbles present, the rest being all liquid phase. These bubbles are not sufficient to generate the required perturbations and the overall degree of freedom is very small. The buoyancy induced liquid circulation, which was present in a 100% filled PHP, gets hindered due to additional surface-tension-generated friction of the bubbles. Thus the performance of the device is seriously hampered and the thermal resistance much higher than for the 100% filled PHP.

Nearly 0% fill ratio: In this mode there is very little liquid to form enough distinct slugs and there is a tendency towards dry-out of the evaporator. The operational characteristics are unstable and undesirable.

PHP true working range: Between about 10% to 90% fill ratio the PHP operates as a true pulsating device. The exact range will differ for different working fluids, operating parameters and construction.

It can be clearly inferred that the underlying physics guiding the mechanism of heat transfer in a PHP is drastically different in the different modes of operation as described above. In the absence of 'a priori' knowledge of this fact, ANN modeling may prove to be quite misleading. This fact is demonstrated later.

The investigated PHP is a vertical bent tube copper heat pipe using ethanol as working fluid. The PHP is made of 10 turns as shown in Fig. 2

with parallel copper tubes of total length 1600 mm (ID: 2 mm, OD 4.2mm). The evaporator section is electrically heated by two surface mounted heaters fixed on an aluminum plate which is 5 mm thick. The PHP copper tubes are made to pass through this aluminum plate. The condenser section is air-cooled by forced air at 5m/s supplied by a fan. Thermocouples suitably placed measure the average aluminum plate temperature and air temperature. Figs. 3, 4 show the complete experimental performance data (total 76 data points on Fig. 3) of the pulsating heat pipe. The fill ratio and heat load are the chosen to be the two independent variables. Overall thermal resistance is chosen to be the parameter representing the heat pipe's thermal performance.

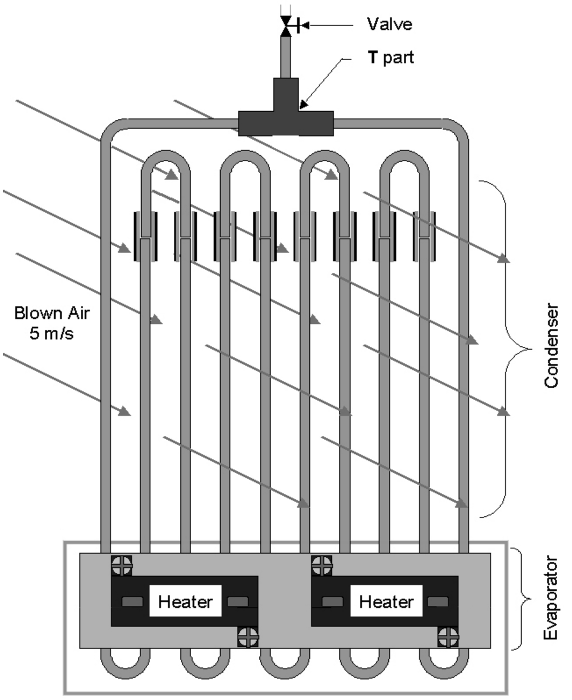

Figure 2: Schematic of the fabricated PHP

4. ANN MODELING PROCESS

4.1 Model for the typical working range

A total of 76 sets of data, for fill ratios from 0%~100%, is recorded. Among these data, 52 sets of data for fill ratios between 20 %~85 % are in the typical range in which the device works as a true PHP. Since the fill ratio and the heat load affect the thermal resistance simultaneously, both were considered as inputs to the network. The overall thermal resistance, based on heater temperature and the cooling air temperature, is the network output. 41 sets of data in the typical working range are used for training the network model, 11 sets of data are used for testing. The Stuttgart Neural Network Simulator is used for this study [4].

Since available theory to choose network architecture is scarce, it is more a skillful art. In actual applications, a common method is to train various network architectures and then to choose the one which gives most accurate predictions for a given CPU time. Some of the suggested recommendations are:

Kolmogorov equation (for one hidden layer) [3]:

$$N_h = 2J_i + 1 \quad (1)$$

Rogers and Jenkins equation [3]:

$$N_t = 1 + N_h(J_i + J_o + 1) / J_o \quad (2)$$

Kalogirou equation [6]:

$$N_h = 1/2(J_i + J_o) + \sqrt{N_t} \quad (3)$$

where,

J_i : input neuron number

J_o : output neuron number

N_h : hidden neuron number when there is only one hidden layer

N_t : number of training sets

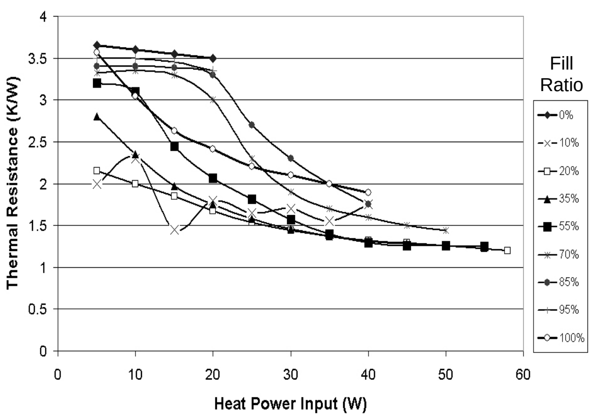

Figure 3: Experimental results for vertical PHP orientation with ethanol as working fluid

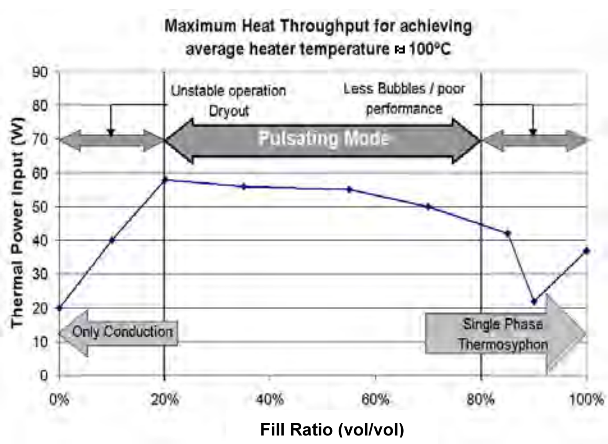

Figure 4: Result showing various operational regimes of the PHP

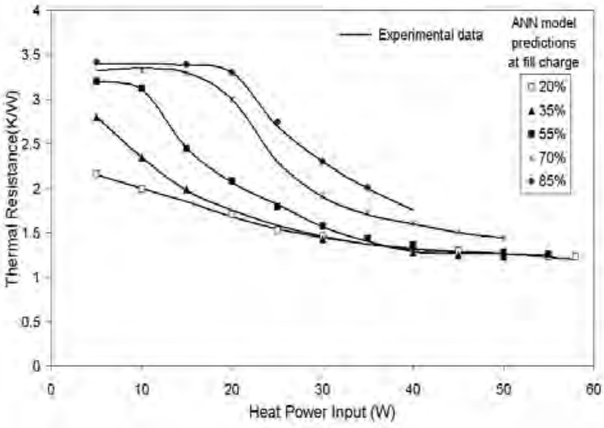

Figure 5: ANN output data after training in the typical working range of 20% to 85% fill ratio.

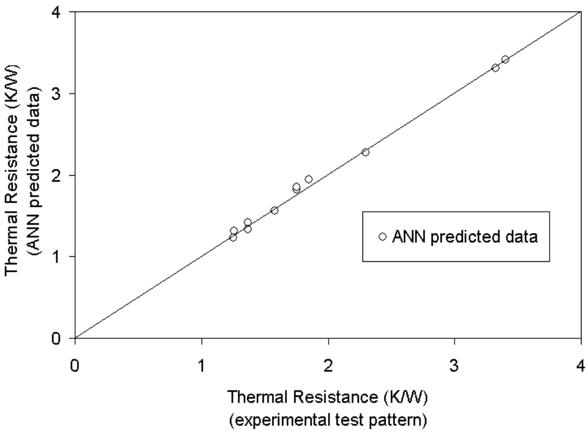

Figure 6: Validation of ANN model (2-6-2-1) with experimental test data.

According to the recommendatory equations, ten different configurations are studied as follows:

Input node – Hidden Node(s) – **Output Node**
(in one or more layers)

2-5-**1**	**2**-8-**1**
2-5-3-**1**	**2**-3-5-**1**
2-1-7-**1**	**2**-7-1-**1**
2-6-2-**1**	**2**-2-6-**1**
2-4-4-**1**	**2**-3-2-3-**1**

The best one with the least errors between the ANN trained output data and the experimental data after the same cycle training is 2-6-2-1. This configuration has two input nodes corresponding to the heat load and the fill ratio, two hidden layers: the first has six nodes; the second has two, and a single node in the output layer for the thermal resistance.

The ANN was trained with the data representing the typical pulsating working range and the result is shown in Fig.5. Fitted experimental curves are also indicated for comparison. It is significant to note that the average scatter of the data is only within 5.3% although the number of total data is really not large enough.

Validation of the model is the next important step and this is done by testing the network with new sets of data which have not been used for training. If the output data generated by the ANN model are close to the test data, the network model is successful.

Validation is done by the 11 data sets already kept aside for this purpose. A comparative graph of the ANN test data and the experimental data is shown in Fig.6 where it can be seen that the matching is satisfactory. The largest relative error between the predicted and experimental data is 6.9%.

4.2 Model for the entire data range

An attempt was made to investigate the effect of training the ANN with the entire range of 76 data sets covering the complete fill ratio range from 0% to 100%. It has been mentioned earlier in section 3 that the heat transfer mechanism is different for the different fill ratio ranges. The same 11 sets of data mentioned previously are used for model validation. The rest of the 65 data sets formed the training set of the network. Five different configurations i.e. 2-5-5-1, 2-6-4-1, 2-4-6-1, 2-3-7-1, 2-7-3-1 as per the guidelines were studied. The configuration giving the best result was found to be 2-5-5-1 as shown in Fig. 7.

Since ANN is a typical ‘Black Box’, unaware of the physical phenomena guiding the system dynamics, due to fully connected configuration, the results from the trained ANN model may tend to get adversely affected by those training data sets which represent different phenomenological regimes of the system. Thus, the ANN model trained with the data sets of the typical pulsating range of operation gives better results than the model trained with the entire range of data as seen in Figure 8. For example, in Fig. 7 the ANN predictions of 20% fill ratio are affected by the unsteady, partial dryout conditions at 10% fill ratio (the oscillating curve). Also, predictions for points lying near phenomenological boundaries, e.g. 2%, 5%, 98% etc. were found to be quite unreasonable. However the predictions for the fill ratio range of 20% to 80% were satisfactory. It is therefore very important that the ANN designer is well aware of the different physical processes of the system under study. Analysis of data is thus an essential prerequisite. The quantity of data representing the desired physical and phenomenological system dynamics should be sufficient enough to have a dominating effect on the model output.

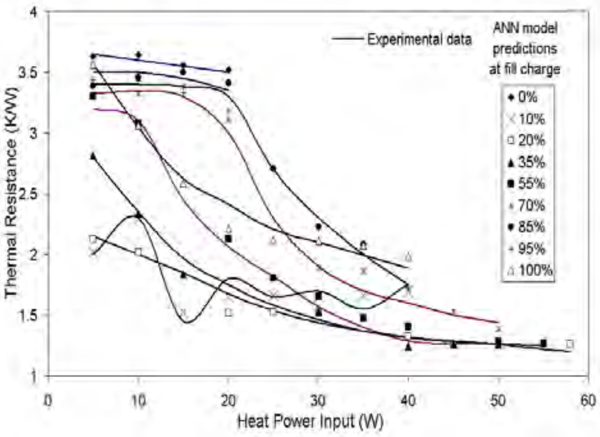

Figure 7: ANN output data (2-5-5-1 model) for the complete experimental range.

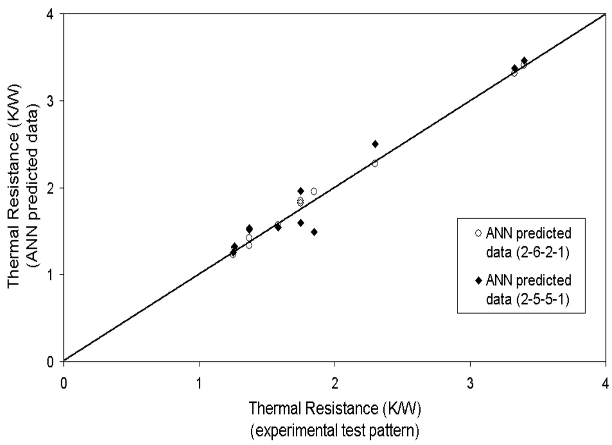

Figure 8: Comparison of validation for ANN configurations (2-6-2-1) and (2-5-5-1).

5. CONCLUSIONS

ANN modeling has been successfully applied to predict the performance of a PHP with acceptable accuracy. Since modeling PHP behavior is rather difficult by traditional analysis, ANN based methods appear to be good tools albeit with certain inherent limitations. Also, in some aspects subjectivity cannot be avoided, e.g. the user has to face with several uncertain choices which include the number of hidden layers, the number of nodes in each layer, the minimum number of training data sets, the initial assignment, the choice of test data, the data reduction and decomposition etc. Such choices are by no means trivial and are critical in achieving good ANN based models.

In this study only two parameters i.e. the heat power input and the fill ratio, were used as the input parameters. In reality there exist various other parameters which affect PHP operation like diameter of the tube, number of tube windings, length of the tube, inclination angle, and physical properties of the working fluid, to name a few [7]. To include all these parameters, reliable and ample experimental data are required. Here, there seems to be an inherent contradiction in the fact that while ANN can effectively model highly complex and non linear systems, it is increasingly difficult to obtain reliable and abundant experimental data for such complex systems. Analysis of experimental data and understanding subtleties of the underlying phenomena can help network design, training and selection of learning algorithms. All of these are important for good quality ANN models.

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