TEMPERATURE PREDICTION OF A TWO STAGE PULSE TUBE CRYOCOOOLER BY NEURAL NETWORK

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ABSTRACT

Cryocoolers are refrigerating machines which are able to achieve and to maintain cryogenic temperature, i.e. temperature below 120K. The presence of moving parts in the cold area of cryocooler makes it difficult to meet the required efficiency. Thus a new concept of cryocooler, the single stage pulse tube refrigerator (PTR) satisfied many of the requirements, but the temperature attained at the cold end side is only 30K. Thus for attaining a temperature below 30K, multistaging of PTR is an attractive option. A lot of numerical models for the two stage pulse tube have been developed during the last few decades. Unfortunately, not a single simulated model has been published that can give all the design data related to the prediction of the two stage pulse tube cold end temperature. Thus the thought of a new concept for prediction of temperature of two stage pulse tube lead to the approach of artificial neural network. The objective of this work is to train an artificial neural network to learn and predict the lowest temperature attained by a two stage pulse tube cryocooler. The training is done with input as the experimental data and its output temperature as the target. The data presented as input were, the diameter and length of pulse tubes, frequency and orifice diameters. The network output is the minimum temperature attained by the cryocooler. After successful training, the validation of the network is done with validation input. When the percentage error is within the tolerance limit, the network weights and biases are used for the prediction purposes and the predicted temperature obtained by neural network approach is within the tolerance limit.

Keywords: Cryocooler, Neural Network, Simulation, Temperature, Validation.
1. INTRODUCTION

Cryogenics is referred to the technology and science of producing low temperature, below 120K. Cryocoolers are refrigerating machines which are capable of achieving cryogenic temperature. An increased need in cryogenic temperature in many areas of science and technology during the last decades caused a rapid development of cryocoolers. But the moving parts in the cold end side of the cryocoolers makes it difficult to meet high efficiency, high reliability, low cost, low noise level etc caused for the new concept of cryocooler, the pulse tube refrigerator (PTR). This concept was introduced by Gifford [1] in the late 1964’s. The minimum temperature attained by this configuration is only 60K. It is really impossible to reach very low temperature by a single stage system. So cascading is an important option to reach very low temperature. Thus for temperature below 30K it is better to split the system into two.

The concept of two stage was first introduced by Zhou [2] and his coworkers in 1988. After that a number of experiments were taken place on this type of PTR. In 1990 E. Tward et al [3] developed a two stage pulse tube test cooler which reach 26K while rejecting heat above 300K. C.Wang and Y.L.Ju [4] developed a two stage pulse tube refrigerator with a rotating valve in 1996. The minimum temperature attained by the tube is 11.5K and produce a cooling load of 1.3W at 20K. Wang .C. [5] in 1997 developed a computer program for the numerical simulation of a 4K pulse tube cooler, which is used for the liquefaction of $^4$He. In 2001 Y.L.Ju [6] uses a mixed Eulerian-Langrangian numerical model for simulation and visualizing the internal processes of PTR operating at 4K. J.L.Shi et al [7] in 2006 developed a design model for a two stage pulse tube cryocooler. Here the differential equation associated with energy and mass conservation is solved in order to provide a detailed but one dimensional model of the pulse tube. Thus a lot of numerical models for the PTR have been developed during the last decades. Unfortunately not a single simulated theoretical model has been published that can give all the design data related to the pulse tube. Thus the unavailability of the design procedure for a two stage pulse tube causes the attempt for using neural network toolbox as a design tool for the prediction of the lowest temperature attained by a particular configuration of a two stage pulse tube cryocooler.

To date, neural network have been applied successfully to a number of engineering problems. Several researchers have demonstrated that they can be more reliable at predicting energy consumption in a building other than traditional statistical approach because of their ability to model non-linear patterns. In 2000 C.Renottee and M.Remy [8] introduced neural network for modeling and control of a heat exchanger. T.T.Chow and C.L.Song [9] introduced the use of neural network and genetic algorithm for the chiller system optimization in 2001. It was A.K Soteris and N.S Christs. [10] in 2005 introduced neural network method for computing the thermal comfort index for the heating ventilating and air conditioning (HVAC) systems. Unfortunately the researchers of the two stage pulse tube cryocoolers do not explore the utility of the neural network as a design tool for the prediction of the temperature at the cold end side and its cooling load. The aim of this study is to investigate the suitability of the neural network as a tool for the prediction of the lowest temperature attained at the cold end side of the PTR using the minimum possible set of input data.

The main aim for using a two stage pulse tube cryocooler is to attain a very low temperature and the process for attaining the very low temperature is a time consuming one and the cost for the fabrication of the two stages PTR is high. Moreover there is not a numerical equation or design method for determining the lowest temperature attained at the cold end side of the PTR. But the temperature is an important factor for the estimation of the cooling load of the PTR. Therefore the need of an alternative method for determining the temperature of the PTR is helpful for avoiding the time wastage and the huge cost for the fabrication of the PTR. Thus the recently developed technology neural network offers such an alternative method. It is widely accepted as a design technology offering an alternative way to tackle complex and ill specified problems. They can learn
from the given sets of examples and are able to deal with nonlinear problems. The network which has once trained can perform the prediction and generalization at very high speed.

2. ARTIFICIAL NEURAL NETWORKS

Artificial neural network represents a non-algorithmic, black box computational strategy. It is composed of interconnected artificial neurons; each has an input/output (I/O) characteristic and implements a local computation. Figure 1 shows an artificial neuron model with ‘p’ number of inputs. A weight ‘w’ is assigned to each input ‘p’ to describe its influence (strength). The sum of the weighted inputs and the bias ‘b’ forms the input to the activation function ‘f’, which can be either linear or non-linear differentiable. The output ‘a’ from the neuron is then given by

\[ a = f(Wp + b) \]

Figure 1: A single input neuron model

Neural network can be described as a machine learning technique which modifies the numerical values of its connection weights and biases through certain training algorithm that causes the network to approach the solution of a system model. Numerous researchers under different constraints have shown multilayer feed forward (FF) ANN which is capable of approximating any finite function to any degree of accuracy [11]. Also the multilayer feed forward (FF) [11] network structure as is so far one of the most popular and effective ANN structure. The learning ability of a neural network depends on the arbitrary choice of its architecture as well as the training algorithm. The choice of activation (\( f \)) may significantly influence the applicability of the training algorithm. Lack of success in application is likely attributable to faulty training, faulty architecture or lack of functional relationship between inputs and outputs. One of the biggest shortcomings of FF network is the limited availability of suitable training algorithms. So far back propagation (BP) [12] has been found highly successful. The standard BP algorithm is a gradient descent algorithm, which adopts an error correction based learning procedure. The Levenberg-Marquardt [11] algorithm is an alternative method for achieving fast optimization. In this process the performance of the network can be evaluated by the mean square error.

The main objective in ANN design and training is to produce network that are able to apply correctly to new unforeseen inputs. By partitioning the available data sets some testing sets are reserved for accessing the generalization performance. This is known as cross validation. Over-training might lead to memorization, and therefore pure performance when applying the testing sets.
3. TEMPERATURE PREDICTIONS USING NEURAL NETWORK

The two stage pulse tube cryocoolers is mainly used for attaining temperature less than 30K. Here the output temperature of the PTR mainly depends on the eleven input parameters of the PTR given in the table1. Thus for the training of the network data from the past experimental works were used. The training was executed systematically over a family of architecture, including single and multi layer network. It was found that all ANN architecture with single layer could not achieve in satisfactory results. The architecture from those tested, that gave the best result and finally adopted consists of a three layer network- an input layer, an output layer and a hidden layer. The input layer is mainly for receiving the input data of the training set which consists of eleven neurons, based on the eleven input parameters. The output layer of the network consists of one neuron which is mainly for giving the output of the network; here the temperature of the PTR is the output of the network. The hidden layer of the network is mainly for remapping of the input/output relation of the network, which also connects the input and output layers of the networks. The brief outline of the temperature prediction is given in Flow chart 1. The number of neurons of the hidden layer of the networks is fixed as five, after a number of training processes. The training of the network is mainly done with randomly selected learning rate coefficient and epochs. Once a satisfactory training is done with varying the

<table>
<thead>
<tr>
<th>Sl.No</th>
<th>Input variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Frequency</td>
</tr>
<tr>
<td>2</td>
<td>First orifice diameter</td>
</tr>
<tr>
<td>3</td>
<td>Second orifice diameter</td>
</tr>
<tr>
<td>4</td>
<td>First stage pulse tube diameter</td>
</tr>
<tr>
<td>5</td>
<td>First stage pulse tube length</td>
</tr>
<tr>
<td>6</td>
<td>First stage regenerator diameter</td>
</tr>
<tr>
<td>7</td>
<td>First stage regenerator length</td>
</tr>
<tr>
<td>8</td>
<td>Second stage pulse tube diameter</td>
</tr>
<tr>
<td>9</td>
<td>Second stage pulse tube length</td>
</tr>
<tr>
<td>10</td>
<td>Second stage regenerator diameter</td>
</tr>
<tr>
<td>11</td>
<td>Second stage regenerator length</td>
</tr>
</tbody>
</table>
Flow Chart. 1
Brief Outline of Temperature Prediction

Start

Give input and target (actual output) to the neural network

Create initial weights and biases

Perform ANN training by learning law

If stopping criteria met met

Network output and compare with actual output

% error within tolerance

Save weights and biases

Provide validation input

Compare validation output with actual output

% error in tolerance limit

YES

Save weights and biases for prediction

Stop

No

No

% error within tolerance

Save weights and biases

Provide validation input

Compare validation output with actual output

% error in tolerance limit

YES

Save weights and biases for prediction

Stop

learning rate coefficient and epochs, the weights and the biases are fixed. Then the network having fixed weights and biases are used for the prediction purposes whose results and training results are given in the next section.
IV. RESULTS/VALIDATION

The training of the network is mainly done by the three layer network by varying the learning rate and epoch. Initially the training is done with learning rate less than 0.1 and various epoch. Thus for a learning rate of 0.0988 and epoch 18 the network output is obtained. The percentage error between the target and network output of the above training are less than 10%. When validation input is given to the trained network, the network predicts the output but the maximum error between the target temperature and the network output temperature is 11.2% and the aim was to get an error less than 10% in the validation process. Thus it causes for taking the decision for training the above network further. Then the network training is done with learning rate 3. For the above learning rate the network gives a better output for an epoch 14 where the maximum percentage error between the target and network output is around 5%. Thus the network weights and biases are used for the validation purposes but the result obtained from the validation makes the percentage error greater than 10. Therefore the network is not yet suitable for the prediction purposes because the learning rate greater than one makes the weights and biases vector to overshoot from the ideal position there by the result of the validation is not in the accurate form. Now the training of the network for the input and its target is done with learning rate which is randomly selected from 0.1 to 1. Thus for a learning rate of 0.920 and epoch 24, the network gives the output temperature which is close to the target temperature, where two of the percentage error is zero and most of the percentage error was very small. These are because of the overtraining of the network which causes for the memorization of input data’s by the network. So the network does not give the exact output for the simulation. The training is continued for various learning rate and epoch and finally for a learning rate of 0.96985 and epoch 13, a good result is obtained which is shown in the table 2. Here the maximum percentage error is 3.5 and that of minimum is 0.3. This percentage error of the result is within the tolerance limit of +5% to-5%. Now the input weights, layer weights, input biases and layer biases are used for the validation purposes whose result is given in table.3. The percentage errors obtained by the validation are within the tolerance range +10% to -10%; also it is one of the best results of the ever training process for this work and also for the validation. Thus this results shows that the neural network approach is more suitable for the prediction of the lowest temperature attained by a two stage pulse tube cryocoolers.

<table>
<thead>
<tr>
<th>Target Temp (K)</th>
<th>7.7</th>
<th>4.6</th>
<th>6.2</th>
<th>7.2</th>
<th>14</th>
<th>5.1</th>
<th>4.5</th>
<th>6.6</th>
<th>4.3</th>
<th>4.4</th>
<th>4.8</th>
<th>8.5</th>
<th>3.3</th>
<th>12.3</th>
</tr>
</thead>
<tbody>
<tr>
<td>N/O Temp (K)</td>
<td>7.68</td>
<td>4.76</td>
<td>6.14</td>
<td>7.15</td>
<td>13.88</td>
<td>5.07</td>
<td>4.39</td>
<td>6.53</td>
<td>4.35</td>
<td>4.38</td>
<td>4.82</td>
<td>8.55</td>
<td>3.25</td>
<td>12.27</td>
</tr>
<tr>
<td>% error</td>
<td>0.30</td>
<td>-3.5</td>
<td>1.0</td>
<td>0.7</td>
<td>0.86</td>
<td>0.6</td>
<td>1.11</td>
<td>1.1</td>
<td>-1.2</td>
<td>0.5</td>
<td>-0.42</td>
<td>-0.6</td>
<td>1.5</td>
<td>0.3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Target Temp:(K)</th>
<th>7.9</th>
<th>5.5</th>
<th>8.8</th>
<th>3.7</th>
</tr>
</thead>
<tbody>
<tr>
<td>N/O Temp: (K)</td>
<td>8.64</td>
<td>5.10</td>
<td>7.94</td>
<td>3.91</td>
</tr>
<tr>
<td>% error</td>
<td>-9.3</td>
<td>7.2</td>
<td>9.8</td>
<td>-5.6</td>
</tr>
</tbody>
</table>
5. CONCLUSION

Once trained, the network predicts the lowest attainable temperature of a particular configuration of a two stage pulse tube cryocooler. At this stage the work was confined at primarily investigating the suitability of artificial neural network for the prediction of temperature. In order for the network to be of significant use of cryogenic engineers it needs to be enriched with more training cases and diverse constructional and environmental parameters. Furthermore, it is estimated that the performance will improve with use, since the network has the capability of learning from moderate data. As these become available and more data, they may be used to retain the network and hence to improve the accuracy. This method may also be applied for the cooling load estimation, a job which is much harder.

REFERENCES