USING ARTIFICIAL NEURAL NETWORKS TO PREDICT THE PERFORMANCE OF A LIQUID METAL REFLUX SOLAR RECEIVER:

PRELIMINARY RESULTS

Mona M. Fowler
Department of Mechanical Engineering
North Carolina Agricultural and Technical State University
Greensboro, North Carolina

ABSTRACT
Three and four-layer backpropagation artificial neural networks have been used to predict the power output of a liquid metal reflux solar receiver. The networks were trained using on-site test data recorded at Sandia National Laboratories in Albuquerque, New Mexico. The preliminary results presented in this paper are a comparison of how different size networks train on this particular data. The results give encouragement that it will be possible to predict output power of a liquid metal receiver under a variety of operating conditions using artificial neural networks.

INTRODUCTION
In recent years, the possibility of commercializing liquid metal reflux receivers (LMRRs) has been investigated (Stine and Diver, 1994). These LMRRs are used in a dish Stirling power system as an interface between the solar concentrator and the Stirling engine to convert solar flux to thermal energy. A step in commercializing this application lies in accurately modeling the thermal performance of these receivers in order to predict output power at potential installation sites based on available LMRR and meteorological data.

Various mathematical models have been developed to predict the performance of a LMRR, but the physics involved is complicated, and various simplifying assumptions and loss correlations are required (Hogan, 1992).
Artificial neural networks (ANNs) are being considered for this problem because detailed modeling of the physical processes is not required. If an ANN trained on actual operating data from a LMRR can be shown to successfully predict output power under a variety of climatic conditions, an ANN can then be used to predict thermal performance at other sites, and also may be useful in gaining further insight into the physics of the system.

In this paper, background on the LMRR and the ANN used to model the LMRR are discussed. The data used to train the ANN has been taken from on-sun testing performed at Sandia National Laboratories, Albuquerque, New Mexico (Andraka, et al., 1992). Preliminary results from the ANN training and testing are presented.

BACKGROUND

Liquid Metal Reflux Receiver

Liquid metal reflux receivers have been designed as the interface between a solar concentrator and a Stirling engine. The receiver on which this study is based uses liquid sodium as the heat transfer fluid. Solar flux enters the receiver cavity and vaporizes the liquid sodium at a temperature of 700 - 800 C. The sodium vapor rises into the condenser where it is cooled by the water flow in the calorimeter. The condensed sodium returns to the pool by gravity, and the cycle continues.

In order to establish the thermal performance of the receiver during on-sun testing, the Stirling engine was replaced by a water cooled gas-gap calorimeter. A He/Ar gas mixture is used to control the thermal resistance in the gap between the receiver and the calorimeter, thereby affecting the operating temperature of the receiver (Figure 1). The power output of the receiver is determined from the mass flow rate and the temperature rise of the water through the calorimeter.

Artificial Neural Networks

Artificial neural networks are algorithms that can be used to model physical process. The algorithms are usually referred to as “learning algorithms” because the network modifies itself to “learn” the relationships between the values of certain input variables and one or more output variables. Once the relationships are learned from the input and output data in a training data set, the network can be used to predict the process output(s) for other input data sets.

The basic structure of an artificial neural network is inspired by biological neural networks. However, due to the lack of knowledge about the intricacy of a biological neuron, the similarity of an ANN node to the biological neuron is limited to their structural similarities (Wasserman, 1989).
Similar to a biological neuron, an ANN node has two major sections, input and output. The input section collects and selects information from other nodes or external sources. The output section modifies the result of the input section and passes the final result either out of the network or to other nodes.

The way that nodes are interconnected is known as the network architecture and is often a layered structure consisting of input and output layers separated by one or more intermediate (hidden) layers. This structure, a feed forward network, collects inputs for each layer only from the previous layer (Figure 2).

The ANN used for this paper is a feed forward network trained with the backpropagation algorithm. The backpropagation algorithm begins with inputs applied to nodes or processing elements in the input layer of the network. This layer acts as a buffer. The input nodes are connected to the next layer of nodes. As the inputs move to the next layer (hidden layer) they are multiplied by a connection weight (input section). In the next layer, at each node, the sum of the inputs multiplied by the weights (referred to as the value NET) is manipulated in a transfer function (output section). This result is the output for the node. Transfer functions come in many forms. The transfer function used in this case is a sigmoid function, given by:

\[ \text{Node output} = \frac{1}{1 + e^{-\text{NET}}} \]

This equation squashes NET to a value between 0 and 1. The sigmoid transfer function is often used for backpropagation networks because it satisfies the condition for this algorithm, that the transfer function be differentiable everywhere (Wasserman, 1989).

This process continues through all the layers until the output layer is reached. At the output layer, the output of the network is compared to the output value from the training data set. The error between these two values is sent backward (backpropagated) through the network and used to update the weights. Another set of inputs are applied to the network and the process is repeated. Thus, the network “learns” by adjusting its weights so that the desired output is produced for all input/output pairs in the training data set. The final set of connection weights for the network, that exists after the training, is the neural network model for the training data set.

NEURAL NETWORK TRAINING DATA

The data used for this work were recorded at The National Solar Thermal Test Facility at Sandia National Laboratories in Albuquerque, New Mexico. The tests were performed between August 31, 1989 and May 23, 1990. The object of this training is to show that an ANN has the ability to successfully train on a set of data which reflects the quasi-steady performance of the receiver at full operating temperature. Training for data that includes start-
up and shut-down of the system and large cloud induced transients is the topic of on-going work. The data used in this training include tests at: 1/2, 3/4, and full power, where full power output is approximately 65 kW. The 1/2 and 3/4 power data were achieved by covering 50 and 25 percent, respectively, of the mirrors on the concentrator.

The variables used for training include: solar elevation angle, solar azimuth angle, ambient temperature, wind speed, wind direction, sodium pool temperature, actual solar input power, and receiver power output.

The test data were recorded at an average of 3 second intervals, for as long as the weather permitted during each day's test.

TRAINING RESULTS

The training for this example was performed using the Neural Wave software by Neural Wave Inc.

For training purposes, the data from several days tests, representing a variety of operating conditions including full, half, and three-quarter power tests, are randomly divided into three data sets. The first and largest data set is used for the training data. The second data set is used to test the generalization ability of the network during training (Wasserman, 1989). The third data set is used as a final independent test of the network. The network will not previously have seen the third data set, and the agreement between the measured power output and the power output predicted by the network for this set is an indication of the accuracy of the trained network when used as a prediction tool.

The first network used for this training was composed of three layers, the input layer, one hidden layer, and the output layer. The input layer has seven nodes, the hidden layer has 30 nodes and the output layer has one node. The number of hidden layer nodes is arrived at by trial and error. The number of nodes chosen for this training was initially set as twice the number of input variables and was then increased in subsequent trials to improve the predictive capability of the network. Another network, that has produced better results, consists of four layers, including input and output layers, identical to the first network, and two hidden layers. The first hidden layer has 15 nodes (about twice the number of input nodes) and the second hidden layer has 7 nodes (equal to the number of input nodes).

Figure 3 presents the results obtained with the one-hidden-layer network and Figure 4 gives the results from the two-hidden-layer network. These figures include test data from three different days, including tests at full power, one-half power, and three-quarter power. Figures 5 and 6 are the error histograms for the one- and two-layer networks respectively. The use of two hidden layers clearly improved the network's ability to accurately predict the power output of the LMR. Figure 6 shows that 67 percent
of the points tested against the trained network agreed within 5 percent, and 85 percent of the points agreed within 12 percent.

CONCLUSIONS
Using artificial neural networks as a means to model the performance of a liquid metal reflux solar receiver appears to be feasible. After training a one-hidden-layer network with several combinations of network variables and number of hidden layer nodes, a two-hidden-layer network was trained. The use of two hidden layers improved the accuracy of the network prediction compared to a single-hidden-layer network. Researchers tend to limit the number of hidden layers to one or two layers because it can be proven that a one-hidden-layer backpropagation network can approximate any function (Kreinovich, 1991) although additional hidden layers with fewer nodes are sometimes used to achieve a more compact network.

Additional network architectures and combinations of input variables are being explored to improve the prediction accuracy of the network.

This work is continuing with the goal of further improving the ability of artificial neural networks to predict the performance of a liquid metal reflux receiver under a variety of operating conditions including transient operation. A key question to be answered is: Can an artificial neural network accurately predict power output of a liquid metal reflux solar receiver during start-up and shut-down periods, and how important is this to predicting annual performance and losses of the system?

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Figure 1. Schematic Diagram of the Liquid Metal Receiver

Figure 2. Schematic Diagram of a Three-Layer Neural Network with a Seven-Node Input Layer, a N-Node Hidden Layer and a Single-Node Output Layer.
Figure 3. Graph of Actual Receiver Output Power and Neural Network Output Power in kW from the One-Hidden-Layer Network.

Figure 4. Graph of Actual Receiver Output Power and Neural Network Output Power in kW from the Two-Hidden-Layer Network.
Figure 5. An Error Histogram for the Test Performed with the One-Hidden-Layer Network.

Figure 6. An Error Histogram for the Test Performed with the Two-Hidden-Layer Network.