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Deploying An Artificial Neural Network Model for Solar Air Heating Modelling

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Abstract

In this work, we utilize Artificial Neural Networks (ANN) to model the efficiency of solar air heaters. The underlying thermodynamic principles and factors affecting the performance of a solar air heater were considered and used for training and testing to determine the efficiency of the solar air heater.

Using an input - output mapping approach, a back propagation learning algorithm based neural network was used to train and test measurable, controlled and conditional factors as input for the modeling architecture. The output was set to be the overall efficiency and required energy by the fan used for forcing the air mass passing through the solar air heater. The network result has an efficiency of 56.17% at the highest air mass flow rate of 0.038kg/s. The variation in efficiency of the neural network was 2.032% and the neural network has reduction of 5.79% in thermal efficiency when compared with physical experimental results.

Key Words: Artificial Neural Networks, Solar Air Heater, Renewable Energy, Modelling

1. Introduction

The inexhaustible energy from the sun has been widely used in the form of renewable energy through solar air heating technologies in both homes and industries. In particular, designing of flat plate solar air heaters for higher and stable performance is of interest to engineers because of its relatively low thermal performance. To this end, engineering experiments on the conditional (uncontrollable) and un-conditional (controllable) factors of the solar air heater have been an active research focus in a bid to improve their thermal performance and the total general efficiency of the flat plate solar air heater. Conditional (uncontrollable) factors affecting the solar air heater include the ambient temperature, solar intensity, humidity and wind speed. The unconditional (controllable) components factors are length of the bed, depth of the bed, glazing material and the absorber plate. The unconditional components have had much design and modifications to help improve the convective heat transfer relation between the absorber plate, the airstreams flowing through the bed, the glazing glass and the solar radiation [1-2]. However as the conditional factors still play a vital role in solar air heater performance, there is the need for an accurate mechanism to predict their values which when incorporating the unconditional factors (obtained from real experiments) would make for a comprehensive and accurate estimation of the performance of the solar air heaters with minimal design and experimental flaws. Since these factors cannot be accurately predicted, the problem is well suited to artificial neural networks (ANN).

There have been many studies on predicting both the conditional and unconditional factors of a solar air heater. Many solar and thermodynamic related systems involve the use of programs that perform calculations using systems of complicated differential equations. These equations take into account the considered hourly values of solar radiation, ambient air temperature, wind speed and relative humidity taken from typical meteorological year. These programs are usually expensive, complicated and not within the reach of many. Moreover they are time demanding. In its place the use of artificial intelligence methods which are able to learn the key information patterns within a multi-dimensional information domain compared to complex and mathematical routines are used. The application of artificial neural networks (ANN) in many engineering problems has proven to be an accurate and cheaper alternative to tackling practical problems. These have been employed in diverse fields like power systems [3], oil price prediction [4] and financial applications [5]. Other prominent applications of ANN's are in [6]-[8]. ANNs have recently been applied in the design and performance prediction of solar air heaters incorporating both conditional and unconditional factors and easing the strain on design engineers. In [9] a modelling study of solar air heater system using ANN and wavelet neural network model is reported. In their study, a device for inserting an absorbing plate made of aluminium cans into the double-pass channel in a flat-plate solar air heater is used. They obtained as 0.0126 root mean square error value for the collector efficiency.

In [10] thermosyphon solar water heating system and simple model validation using ANN is provided. They used same random data with the performance equations obtained from experimental measurements and with the artificial neural network to predict the output parameters. From their result, they concluded that it is possible to train a suitable neural network to model a thermosyphon solar domestic water heating system which can be used to predict the performance of the system under any weather conditions. Other successful applications of ANN to solar modelling are in [11]-[13]

The purpose of this study is to use a neural network to model the performance of a solar air heater. This is done by incorporating both conditional & unconditional (via an experimental setup) parameters. We are inspired by [9] in choosing our input parameters. The data is used to train the ANN predictive tool which is able to predict the performance parameters of different configurations of solar air heaters. This would facilitate the work of design engineers in the field as it allows the prediction of the performance of hypothetical collectors designed without a need of time demanding experimentations.

2. Description of the Solar Air Heater

The single pass solar air heater used for the experiment is made up of plywood used to construct the frame of the collector. The thickness of the plywood is 2cm and it was completely painted with black colour. The length and width of the frame is 1.5m by 1.0m respectively. Normal window glass of 0.3cm thicknesses was used as glazing while distance between the glass and the bottom of the collector duct "h", was 7cm. The air inflow into the duct was through a 2cm space created at the top of the collector by reducing the length of the cover glass to be 1.48m (Fig. 1). All sides and bottom of the collector were insulated with 2cm thick Styrofoam. The inside of the duct contains four metallic fins of 1.5m length by 7cm height. They were painted black and positioned longitudinally along the duct creating five different passage sections of air pass and each section was fixed with seven steel wire mesh layers, 0.2cm × 0.2cm in cross sectional opening. The distance between the wires mesh layers was 1cm and it was painted with black colour before installing it in the air pass channel. In this arrangement, the seven wire mesh layers acts as an absorber plate and no need to have an absorber plate at the bottom of the air pass collector.

Benefits of the modification include reduction in the total cost of the air heater because of the wire mesh's lesser cost. It also includes reducing the pressure drop through the collector because of the presence and arrangement of the porous medium. As reported by [1] who used the same experimental set up, the pressure drop is very small and can be neglected where the porosity is very high. They obtain about 0.98 for the porosity and 12.82Pa for the pressure drop using an incline manometer filled with alcohol having a density of 803 kg/m^3. The angle of the manometer was fixed at 19° when connected with the whole equipment. An 11cm diameter pipe was connected to the duct at one end and to the axial blower (Type GEC-XPEL AIR) at the other end of it. An orifice meter was design in accordance with [13] and installed into the pipe. Two air flow straightener were made and installed inside the pipe such that one was before the orifice meter and one behind it. Each of the straightener is made from plastic straw tubes with 0.595cm diameter and 3cm length and is aimed at achieving a uniform air flow through the orifice.

The outlet temperature, T_{out}, and the inlet temperature, T_{in}, was measured by using five thermocouples type T. Three thermocouples were fixed inside the pipe before the orifice meter to measure the outlet temperature of the working fluid and two fixed underneath the solar collector to measure the air ambient temperature. The temperature readings were collected by Ten-channel Thermometer ±0.5°C accuracy. An Eppley Radiometer Pyranometer was used to measure the global solar radiation incident on an inclined surface. The heater was oriented facing south and tilted with an angle of 36° with respect to the horizontal to maximize the solar radiation incident on the glass covers [15]. The procedure and recording of data from the experiment was same as reported by [1].

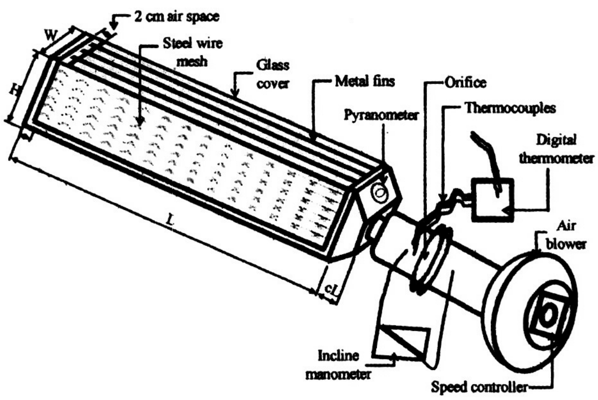

Fig. 1. Schematic View of the Constructed Single Pass Air Collector

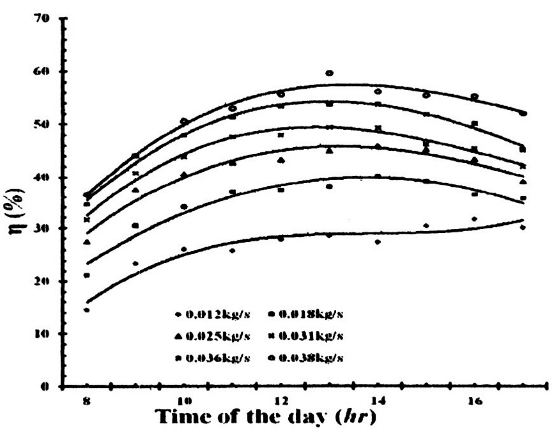

Fig. 2. Variation of Collector Efficiency with Time at Different Mass Flow Rates from Experiment [1]

3. Data And Artificial Neural Network Model

Experimental data used to study the performance of the single pass solar air heater packed with steel wire mesh as absorber was used to train the network. The input parameters and output parameters of the solar air heater neural network are similar to [9]. Input parameters were Time (hr), T-in, T-out, I (w/m^2) and temperature difference (°C). For the sake of network simplicity the output parameter is the efficiency. The ANN experiments were carried out using a 2.2 GHz PC with 2 GB of RAM, Windows XP OS and MATLAB v 7.9.0 (R2009b). In this work an equal training to testing (50:50) ratio was used. The idea is to ensure that the ANN is not exposed to more training results than testing results thereby biasing the results (over fitting). Thus since we had 68 instances, 34 instances were used for network training while the remainder was used for network testing. The ANN has 5 input neurons according to the number of input parameters, 12 hidden neurons and 1 output neuron. The input parameters are normalized to a range of 0-1 prior to feeding to the ANN. The initial weights of the ANN were randomly generated with values between -0.5 and +0.5 and the neural network learning algorithm used is the back propagation learning algorithm. Variations were attempted with the number of hidden neurons (from 1 to 50), learning coefficient ($\acute{\eta}$) and the momentum rate (α) adjusted with various values. The final training parameters for this neural model were: learning coefficient (0.0495) and momentum rate (0.41). During training, a total of 18,208 iterations was carried with a back propagation learning algorithm neural network and was stopped once a target training mean square error (MSE) goal of 0.001 was attained. After an appropriate training of the network with experimental data, the training efficiency obtained was compared with the experimental efficiency. Then new unseen data is presented to the trained ANN model to evaluate its performance and the obtained testing efficiency value is again compared to the experimental setup values. Table.1 shows the final parameters of the solar air heater ANN modelling scheme. Fig.3 presents the efficiency against the standard local time from training the network while Fig.4 presents the efficiency against the standard local time from testing the network and both figures show similar trends as the performance from experimental result shown in Fig.2. These ANN training (Fig.3) and testing (Fig.4) and comparison with experimental setup (Fig.2) are done at different mass flow rates as can be seen from the figures. The efficiency of the solar collector, η, is defined as the ratio of energy gain to solar radiation incident on the collector plane.

$$\eta = \frac{mC_p(T_{out} - T_{in})}{I\,A_c} \tag{1}$$

where, m is the air mass flow rate, C_p is the specific heat of the fluid; A_c is the area of the collector.

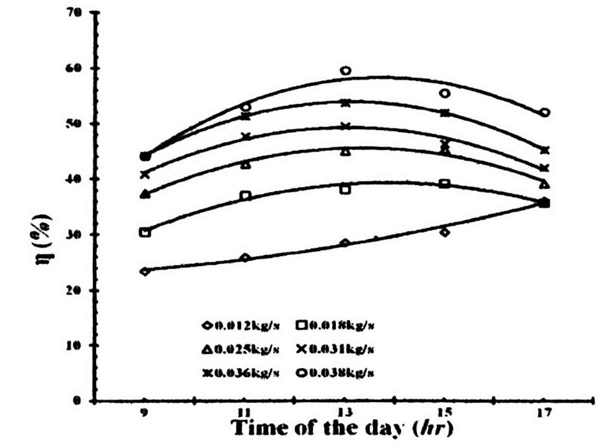

Fig. 3. Efficiency performance with time at different mass flow rate from training the network

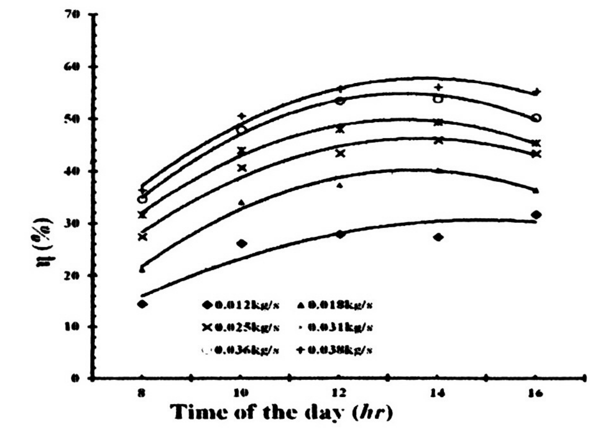

Fig. 4. Efficiency performance with time at different mass flow rate from testing the network

The highest efficiency obtained from the original experimental data was 59.62% at the highest air mass flow rate (m= 0.038kg/s at 13:00 hour). This was obtained at the same air mass flow rate from training the network with original experimental. The data inputs for T-in, T-out, I, and ΔT were 34.25°C, 56.02°C, 913.5, 21.77°C respectively (See Fig.3). The performance of the network when tested with different values used as inputs shows an efficiency value of 56.17% for m = 0.038kg/s at 14:00 hour (the highest mass flow rate) (See Fig.3). The T-in, T-out, solar incidence, I, and ΔT inputs were 37.00°C, 55.82°C, 892.5, 18.82°C respectively.

4. Discussion of Results

Comparing efficiency from the tested neural network to the efficiency obtained from the experimental result, it shows a difference of 3.45 in values and represents 5.79% reduction in total percentage of experimental result. Calculated mean average of 43.720%, average standard deviation of 2.032% in efficiency and mean square error (MSE) of 0.0036 were obtained from testing the network. The mean and standard deviation in efficiency obtained from testing network was carried out and obtained separately using the following equations [14].

$$X_m = \frac{1}{n}\sum_{i=1}^{n}(X_i) \tag{2}$$

$$\sigma = \left[\left(\frac{1}{n-1}\right) * \sum_{i=1}^{n}(X_i - X_m)^2\right]^{1/2} \tag{3}$$

where, X_i is the individual reading recorded, n is the number of readings, X_m is the arithmetic mean and σ is the standard deviation. The mean square error (MSE) is defined as [3]:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(A-T)^2 \tag{4}$$

where MSE is the mean square error, A is the networks actual output and T the desired output.

Table 1. Final Parameters of the ANN Modelling Scheme

Number of Input Neurons	5
Number of Hidden Neurons	12
Number of Output Neurons	1
Weights Values Range	-0.5 to +0.5
Learning co-efficient	0.0495
Momentum Rate	0.41
Training MSE Error	0.001
Testing MSE Error	0.0036
Performed iterations	18208
Training time (s)[1]	186
Testing Time (s)[1]	0.3×10^{-4}

1. Using a 2.2 GHz PC with 2 GB of RAM, Windows XP OS and MATLAB v 7.9.0 (R2009b)

6. Conclusions

This study shows that neural network can be successfully applied to the modelling problem of solar air heaters. In this work a host of conditional parameters were used with some unconditional parameters (experimental data) to model the efficiency of solar air heaters. In training and testing of the network, a total number of 5 input parameters were selected out of a possible 12 input parameters. Furthermore an equal training to testing ratio was utilized in a bid to prevent network over fitting.

For the tested network, obtained mean average efficiency was 43.720% with an average standard deviation of 2.032% and a MSE of 0.0036. The authors feel the results are very encouraging and show promise for further practical implementations and research.

Nomenclature

A_c Area of the collector (m^2)
C_p Specific heat of the fluid (kJ/kg. K)
h Fluid deflection inside the incline manometer (m)
I Solar radiation (W/m^2)
m Air mass flow rate (kg/s)
T_{in} Inlet temperature (K)
T_{out} Outlet temperature (K)
ΔT Temperature difference (T_{out} - T_{in}) (K)

Greek Letters

η Efficiency of the solar collector
ρ Density of air (kg/m^3).
ΔP Pressure difference, $\Delta P = \rho g h \sin 19^0$ (N/m^2).
σ Standard deviation

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