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Sand Bed Solar Stills for Coastal Areas: Studying Heat and Mass Transfer using ANN Model

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Abstract: **Clean potable water is a human birthright as much as clean air. Its demand increasing day by day due to several factors, viz. industrialization and human's population growth around the globe etc. Solar stills have long been recognized to have clean and potable water in remote areas. Easy-to-operate and very low maintenance may be one of the major regions behind it. In present work, the real situation near the seashores, where wet sand is available in abundance quantity containing brackish water. A laboratory scale of 1m2 basin area has been used to conduct experimentation Experimental result paves the way to have purified water on the coastal area using solar energy only with a low-cost setup. The two experimental arrangements were compared for the heat and mass transfer within the single slope solar still and the yield in the month of May at Raipur (Latitude 21.16N and longitude 81.42 E) India. It has been observed that the daily distillation yield is more in the second case where the surrounding mass of sand has been converted as heat storage that enhances heat and mass transfer. The wet sand top surface temperature that resembles the water temperature of solar still of both arrangements and a neural network model was developed to forecast the yield of solar still considering nine input parameters.**

***Keywords:*— Solar distillation; Glazing effect; Earth water still; Sand bed solar still.**

I. INTRODUCTION

Clean potable water is a birthright of the human being as much as clean air, Asia, and the Pacific is one of the most disaster-prone regions in the world [1] . In the manufacturing industry alone, the share of total water demand by 2050 is expected to increase from 7% to 22%. The water demand increase in BRICS will be sevenfold, while in developing countries it will come close to increasing by 400% [2]. Single slope passive solar stills have been recognized for the low cost potable water production and many researchers have made significant effort for enhancing the productivity of distiller units [3]–[12]. A comprehensive review of performance and optimization of single basin solar has been reported by many researchers [13]–[18]. Tiwari and Mishra [19] have been reported, solar still covering by black polythene sheet and coal powder on nearby surfaces of sand bed remains always ahead as for as yield is concerned as compared to the earth solar still whose surrounding surface in not blackened and covered with transparent polythene material. Finally in two days of observation the second still gives 12.20% more yield (6.205 lit. in comparison to 5.530 lit.) per m2 area in 48 hours of the basin in comparison to the first solar still whose surrounding area of sand was not glazed and covered(A) under consideration. The simulated performance of solar earth water still, suitable for very wet ground like beaches or swamps has been investigated. The still is essentially a single slope FRP still with a number of large holes in the bottom. It is seen that the daily distillate output of this still is almost the same as that of the conventional single slope FRP still viz. 3.06 liters/ day at Raipur, India in March Solar earth-water still's are investigated as a method for producing drinking water in an arid region [20]. This yield can be increased significantly by increasing the area of the basin. One more interesting conclusion is the fact that in still wet sand nearly behaves as a free water surface. The ability of solar stills to produce water for small communities is highly beneficial for remote and arid regions. With advancements in computational technology, the application of Artificial Neural Networks (ANNs) in the field of passive solar distillation could yield results that are not easily obtained with classical modeling techniques. In this paper, the effectiveness of artificial neural networks in modeling the performance of solar stills is studied using experimental data. This study will evaluate the overall performance of an ANN model in predicting solar still production and will also identify the effect that each input variable has on ANN model performance.

II. MATERIAL AND METHOD

The concept of artificial neurons was first introduced in 1943 [21], and applications of ANNs in research areas begin with the introduction of the back-propagation training (BP) algorithm for feed forward ANNs in 1986 [22]. An ANN is an information-processing system that roughly replicates the behavior of a human brain by emulating the operations and connectivity of biological neurons. ANNs represent complex, non-linear functions with many parameters that are adjusted (calibrated or trained) in such a way that the ANN's output becomes similar to measured output on a known data set.

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ANNs need a considerable amount of historical data to be trained, upon satisfactory training, an ANN should be able to provide output for previously ‘‘unseen” inputs. The main differences between the various types of ANNs involve network architecture and the method for determining the weights and functions for inputs and neuron’s (training) [23]. The monthly averages of the daily weather data is used as an input for the artificial neural network analysis (ANN). The performance as well as the total operating days for each solar still represented in Table 1. In order to advance the field of solar distillation system, this study pave the way to replace traditional heat and mass transfer modeling by using local data recorded at sub-hourly frequencies with ANNs.

Weather data can be used as an input to simulated ANN model and the total daily distillate production as the target (output) variable. Selection of input variable are selected as per their influence of energy gains and loss on solar still. Daily average ambient air temperature, daily total incident solar radiation, average cloud cover, daily average wind direction, and daily average wind speed were recorded at energy park station. The recorded daily operating distillate volume has been incorporated as an input into the ANN model. Since the saline water volume and depth of water are related by a constant factor of basin area, either variable could be used for neural network analysis. However, in terms of operation, the user will be more likely to use the saline water volume as a means of determining how much it has to be used to flush and operate the solar still. The original series of data were collected with the help of serious of various experiments at Raipur for two set of experimental setups A (modified single slope solar still integrated with the earth) and B (modified single slope solar still integrated with the earth and nearby surfaces of sand covered with the black polythene), they had an effective rectangular basin area of $0.98m^2$.

Table 1: Solar still data summery

Solar still type	Days of available data	Maximum daily production (L/m^2)	Minimum daily production (L/m^2)
Solar still “A”	100	5.530	1.23
Solar Still “B”	100	6.205	2.50

A maximum and minimum recorded value for both the experimental setup is tabulated in Table 1.

Figure1 gives an example ANN architecture composed of one input, ten hidden and one output layer. The input layer consists of the various weather variables and saline water volume with the output layer consisting of the target (actual yield observed experimentally) distillate production. The hidden layer consisted of thirty thee processing units. The transfer function used for all processing units was the tangent sigmoid function due to its superior performance compared to alternative transfer. The most common training algorithm used in the ANN literature is called Back Propagation (BP). General Regression Neural Networks (GRNNs) is used to predict continuous outputs. GRNN nodes require two main functions to calculate the difference between all pairs of input pattern vectors and estimate the probability density function of the input variables. The difference between input vectors is calculated using the simple Euclidean distance between data values in attribute space. Weighting the calculated distance of any point by the probability of other points occurring in that area yields a predicted output value.

$$E_{Y/X}(X) = \int y * f_{XY}(x,y)dy \Big/ f_{XY}(x,y)dy; \qquad (1)$$

A one-hidden-layer network is commonly adopted by most ANN modelers in case of linear behavior where as in multilayer hidden layers are chosen in case of non linear behavior of input to target values (output) [24]. The ANN has been created with a set of weather data and saline water volume data as an inputs and a set of daily distillate yield as a target (output) variable. Before proceeding to the training process, the input and target variables were normalized between 0 and 1 through dividing by the maximum value in each variable’s range. It will accelerate the training process and enhances the network’s generalization capability. Eighty percent of the entire solar still performance data set was used for training purposes and the remaining 20% was used to test/validate the network’s predictive ability. The training data set for solar still ‘A’ and ‘B’ included data from 03/03/2016 to 20/11/2016 and the validation and testing data set included data from 22/11/2016 to 30/12/2016.

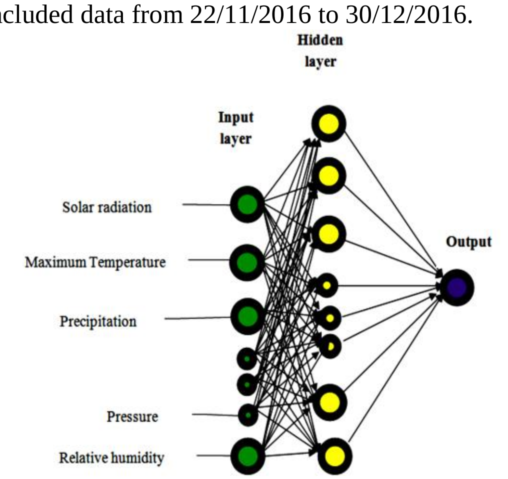

Fig.1 Artificial neural network example architecture

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For network generalization and to stop training validation data were used, when ever generalization stops improving. The testing data set consists of data not previously included in training and validations are used to provide an independent measure of network performance. Solar still 'A' and 'B' data set consisted of 100 data points with 70 points used for training, 10 points for validation, and 20 for testing the trained network. Training/testing process of the ANN model was repeated with different combinations of weather variables to found out the best performing combination of input weather variables. Incident radiation (isolation) and ambient temperature plays very important role in the radiation and convection of the distiller units as a source of energy. Rate of condensation and heat removal rate will depends on the glass surface temperature and wind velocity, as glass surface temperature influence due to the ambient and wind velocity hence both parameters are also considered as an input parameter for ANN model.

III. RESULT AND DISCUSSION

Various combination of the input data for ANN model were tested and optimum one is presented for solar still "B" as its performance maintains its lead throughout the year of the experimentation.

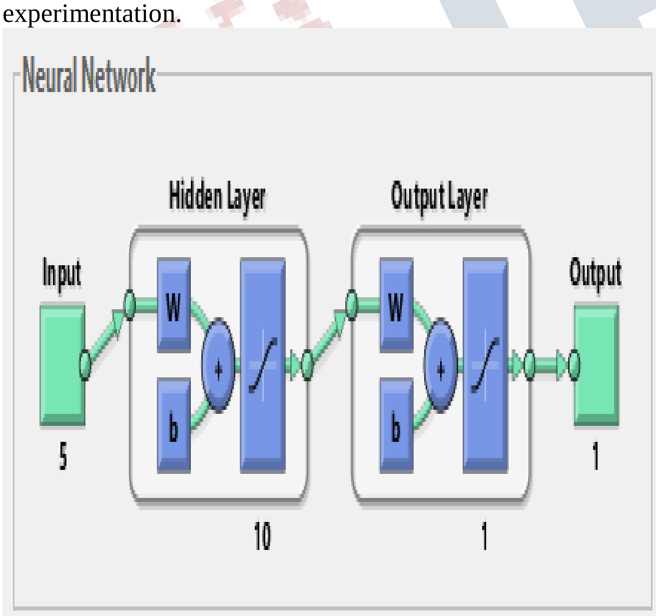

Fig.3 Developed ANN model for solar still 'B'

Developed ANN model has five input parameter and ten hidden layer and one output layer.

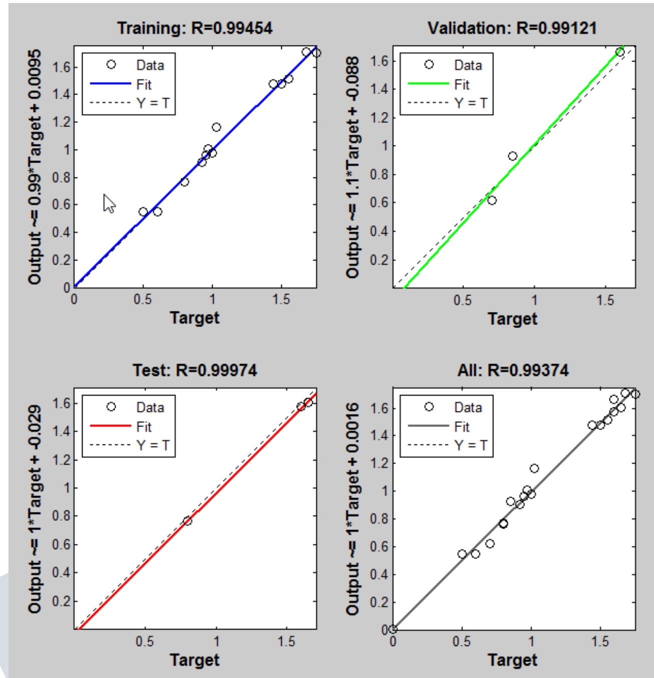

Fig.4 Training, testing and validation results of ANN model for earth solar still 'B'

Figure 4 gives good agreement between output and target values of training, validation and testing, whereas correlation coefficient for training, testing and combined is tabulated in Table 2 for the developed ANN Model of solar still 'B'.

Table 2: Coefficient of determination (r2) for ANN predictions for solar still 'B'

	Solar still 'B'
Training	0.9945
Testing	0.9997
Combined	0.9937

The criteria for evaluating the performance of different combination of input data for ANNs model prediction within the 10% of the actual daily yield of solar still "B". Plot of the relationship between ANN predicted and actual daily yield is shown in Figure 5.

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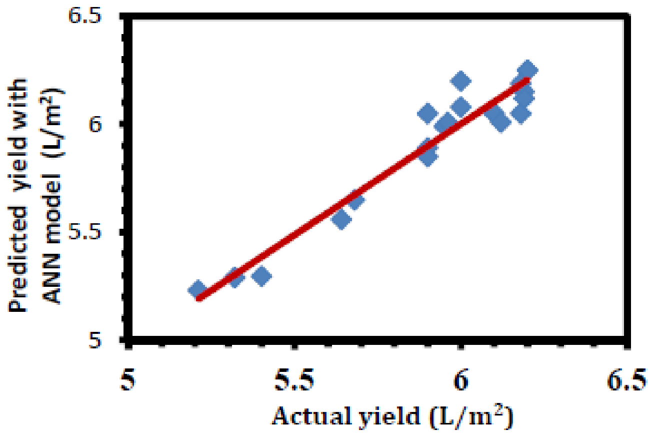

Fig.5 Behavior of predicted yield with respect to the actual yield Solar still 'B'

A result obtaining from ANN model indicates that the distillate yield of solar still can be easily predicted by knowing local weather parameter of any location on globe. It also avoids lot of computational effort and time which desired for evaluation of any distiller unit by using heat and mass transfer theories available.

IV. CONCLUSION

This study has shown that daily weather observations can be used with artificial neural networks (ANNs) in order to accurately predict daily solar still distillate production. Results shows that artificial neural network is a viable tool that can both predict performance and can be used to determine the combined effect of individual input variables also.

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