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Experimental and theoretical evaluation of a hybrid solar still integrated with an air compressor using ANN

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ABSTRACT

An experimental study has been performed to evaluate the single slope hybrid solar still integrated with heat pump (SSDHP). The purpose of this study is to determine the effectiveness of solar still and its modeling using artificial neural networks (ANNs) with the help of experimental data. Most influencing parameters (the solar radiation, glass cover temperature, basin temperature, water temperature and temperature of the evaporator) at an hour interval on the performance of hybrid solar still using ANNs model are discussed in this paper. Effect of an air compressor on the productivity of SSDHP and assess the sensitivity of the ANN predictions for different combinations of input parameters as well as to determine the minimum amount of inputs necessary to accurately model solar still a performance for the prediction of actual distiller output results. The experimental result SSDHP with air will give 100% higher yield as compared to the SSDHP without air but SSDHP dramatically maintains its lead by 25% at 9 h. While this duration maximum difference in yield of SSDHP with and without air observed that SSDHP with air gives 34.61% higher yield as compared to without air during 11 to 12 hour due to the influence of basin temperature. SSDHP with air was recorded 33.33% higher yield as compared to the SSDHP without air. For training, validation, test and all, value of R is equal to 0.99454, 0.99121, 0.99974 and 0.99374 respectively in ANNs proposed model which shows very good agreement with the experimental result. Satisfactory results for the SSDHP with air will pave the way to predict performance result for different climate regimes, with sufficient input data, the ANN method could be extended to predict the performance of other solar still designs also.

Keywords: ANN modeling; Heat and mass transfer; Hybrid solar still

1. Introduction

Clean drinkable 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. In 2013, over 17,000 people died due to the infected water, which accounts for 90% of all water-related disaster deaths globally [1]. Most of the available water purification methods are costly and easily anticipated a future increase in energy costs. Water purification such as reverse osmosis, electrolysis, multi-effect, and multi-stage are few of them. Which defiantly increase the price of water drastically, whereas costs required for pumping and transportation of purified water up to the desired location from purification unit will also boost the price. Passive solar still can be used in a view of low-cost production, as an alternative to energy-intensive approaches for getting purified water from saline, brackish or polluted water in the remote locations [2,3]. Many researchers have been reported different construction and optimization of tool and technique for enhancing the yield of single slope passive solar stills [4–6,30–32]. Present development in solar stills, daily water distiller output/yield ranges from 1 to 7 liters per square meter of still basin area [7–12], hence for feeding potable water to a small community requiring 200 m^3/d needs

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3,00,000–20,00,000 m^2 land area to meet the demand of potable water. As a high capital cost, involved in solar distillation, due to the primary land and equipment hence accurate prediction of an expected distillate production unit is essential for the success of the project and doing optimization of capital investment and maximizing the production rate. Effect on the productivity of a single slope solar still due to the internal reflector (IR) have been reported, simultaneous use of the front and side walls enhance its efficiency by 18%. However, installation of an IR on back wall it can increase the efficiency by 22% [13]. A solar still coupled with hot water tank generally doubles the distilled water output in the 24-h period, due to continuous heating of basin water from tank water. Hot water tank coupled solar stills gives higher output, in the night due to a higher temperature difference in basin water and cover temperature [14]. A comparison of forced circulation show the influence of different environmental, design, and operational parameters condition on hybrid solar still yield and efficiency have investigated and reported [15]. It has been reported that the effect of bubbling and ambient air, simultaneous air bubbling and cooling of the glass cover gives 33.5 and 47.5% higher output respectively as compared to the conventional solar still [16].

Eltawil and Omara [4] have reported a newly developed solar still which has constituted to burst air bubble at the water surface and powered by the photovoltaic system and give 51–147% more productivity as compared to the simple solar still. Considerable improvement in productivity may be obtained if the water vapor is carried away directly by the flowing air in single basin solar still, and modified factor (F) has validated with the experimental result [17]. The mathematical correlation for "Lewis number" were also reported developed for the prediction of mass flow rates [18]. Whereas experimental evaluation of simple solar distiller (SSD), and hybrid solar still connected to a heat pump (SSDHP) were also reported [19,20]. Analysis of water must be done as per the guideline of WHO before and after desalination process [21].

Numerous design and testing work of different researchers have given emphases on methods to improve distillate quantity; there is still a need to develop a predictive model that would be able to accurately estimate long-term distillate production. Theoretical evaluation of the hybrid solar stills needs thermal modeling, which requires a sound knowledge of the heat and mass transfer within the distiller unit and auxiliary unit. In response to this need, an artificial neural network model was considered as an alternate tool that could use more easily for the prediction of solar still performance using weather data. Multi-layer Perception (MLP) networks in artificial neural networks (ANNs) has the ability to learn the linear as well as no linear behavior between inputs and output parameters. hence it may be used for several engineering application [22]. Multiple uses of ANNs for modeling and prediction in engineering was reported by Kalogiriou [23]. He has also discussed the identification of most influencing input parameter. As ANNs network is highly data driven with the capability of capturing complex behavior of any system, learning from the input and targeted data which supplied to ANNs for training and testing purpose. After an ANNs architecture has been designed, the network must be trained in order to create the optimum set of weights and bios for each connection until there is no more change in the synaptic weights. This results in a minimized difference between the actual and predicted target variables. ANNs have a potential advantage over traditional empirical models and multivariable regression analysis because it has the ability to account the interaction between input variables [24]. The ability of solar stills to produce water for small communities is highly beneficial for remote and arid regions. With the help of advancements in computational technology, the application of ANNs in the field of passive/ active solar distillation could predict the accurate result of yield, which needs large computation in case of classical modeling techniques.

In this paper, the effectiveness of artificial neural networks in modeling the performance of solar stills is studied using experimental data is reported for SSDHP, which will pave the way to get a prediction of yield for proposed model for any other geographical condition with an input of desired input parameter.

2. Construction of experimental setup

In the present experimental work, test-rig of single SSDHP with and without air pump has been designing and constructed to investigate the effect of the air bubble and their schematic arrangement and an actual photograph of an SSDHP without air pump are shown in Fig. 1a and 1b respectively, where as Figs. 2a and 2b depict schematic arrangement with added air pump for the Tunisian condition. Figs. 1a and 2a depict different components of the experimental setups of SSDHP without and with air pump respectively. SSDHPs test rigs are made with the help of stainless steel material of 3 mm thick plate, which has 0.4 $m^2$of the basin area. Lower and higher wall of distiller units are kept 480 mm and 610 mm high to make 30º of glass cover inclination,considering latitude 33°52′53″ N and Longitude 10°05′53″ E of city Gabès in Tunisia during the summer condition. Transparent 4 mm thick glass material has used as a cover for the basin area with 90% transmittance, in both the cases of SSDHP. Gasket rubber material has used in between basin top and glass cover and further sealed with window putty to prevent the leakage of vapors from basin to ambient. The condensation water was collected in a collector channel, which is deposited at the lower end of the glass cover and small plastic pipe will be used to terminate collector channel. Fresh water was finally collected in an externally graded cylinder attached at the end of the discharge pipe. Feed raw/saline water pipes were fitted to another side wall for feeding the brackish water into a distiller unit. Fig. 2a shows that the air compressor is connected to a screen equipped with holes for diffusing air into the seawater basin of distiller unit of SSDHP. This is added in order to increase the rate of evaporation of water containing in the basin by SSDHP. The air blower connected to an air screen, further it was connected to a compressor. The flow rate of air establishes at 310^{-3} kg/s whose inlet temperature ranges from 27–30°C throughout the experimentation.

3. Experimental procedure

The experimental setup is designed and constructed in the engineers national of Gabe's (latitude 33°52′53″N and

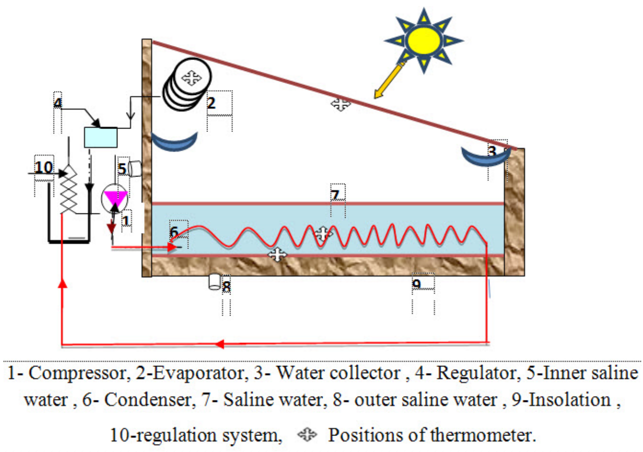

Fig. 1a. Schematic arrangement of SSDHP without air pump.

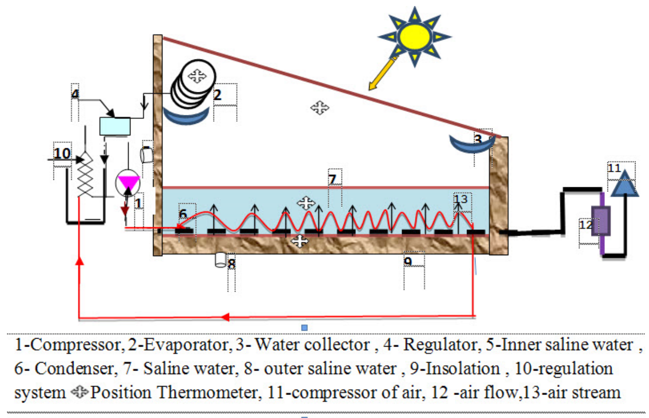

Fig. 2a. Schematic arrangement of SSDHP with air pump.

Fig. 1b. Actual photograph o SSDHP without air pump.

Fig. 2b. Actual photograph o SSDHP without air pump.

longitude 10°05′53″E) to investigate the effect of air bubbles on developed distiller unit and its comparative study with the similar SSDHP unit without air. The starting time of the work was October 2013 and continued to September 2014, during the period of July 2014. While the experimentation temperature of the glass cover, water, and evaporator was measured with the help of K type thermocouple, the flow rate of air was recorded with the help of rotameter and distillate output was measured and recorded with the help of graduated cylinder on an hourly basis.

2.1. Uncertainty analysis

The measurements of the parametric variables, air flow rate, water temperature, water level and relative air humidity and temperature at the basin inlet and water surface, have been recorded during the experiments. Details of all measuring equipment are tabulated in Table 1. Rotameter with a range of 5–2000 L/h and an uncertainty of 4.6% is used for measuring air flow rate. The water temperature in the basin is measured using the thermometer-Pt100 which works in the range from −20 to +26°C with an uncertainty of 2.6%. The relative humidity and temperature of air streams are measured using 2 thermo-hygrometers which work in the range from 0 to 100% RH and from −40 to +12°C and its uncertainty is 1.4%.

Table 1
Range and accuracy of different measuring equipment

Instrumentation	Number	Range	Accuracy
K-type thermocouple	5	–200–1250°C	±2°C
Digital differential pressure manometer	2	(+–)2bar	±2%
Digital thermohygrometer	2	0–100% RH	±1.4%RH
Rotameter	2	5–2000 L/h	±4.6%
Thermometer-Pt100	4	–20 – +26°C	2.6%

2.2. Structure of neural network model

The concept of artificial neurons was first introduced in 1943 [25], and applications of ANNs in research areas begin with the introduction of the back-propagation training (BP) algorithm for feed forward ANNs in 1986 [26]. 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, nonlinear 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. 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) [27]. The multilayer perceptrons (MLP) neural network has been designed to function well in modeling nonlinear phenomena. A feed-forward MLP network consists of an input layer and output layer with one or more hidden layers in between. Each layer contains a certain number of artificial neurons. An artificial neuron in a typical ANN architecture (Fig. 3) receives a set of inputs (signals (x) with weight (w), calculates their weighted average (z), using the summation function), and then uses some activation function to produce an output

$$o = f(z), \tag{1}$$

$$\text{where } Z = \sum_{i=1}^{n} x_i w_i \tag{2}$$

The connections between the input layer and the middle or hidden layer contain weights, which usually are determined through training the system. The hidden layer sums the weighted inputs and uses the transfer function to create an output value. The transfer function (local memory) is a relationship between the internal activation level of the neuron called the activation function and the outputs. A typical transfer function is a sigmoid function $f(z)$, which varies from 0 to 1 for a range of inputs [28]. In time series prediction, supervised training is used to train the ANN in such a way as to minimize the difference between the network output and the measured target. Therefore, training a process of weight adjustment that attempts to obtain a desirable outcome with least squares residuals. The most common training algorithm used in the ANN literature is called BP. General Regression Neural Networks (GRNNs) predicts 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.

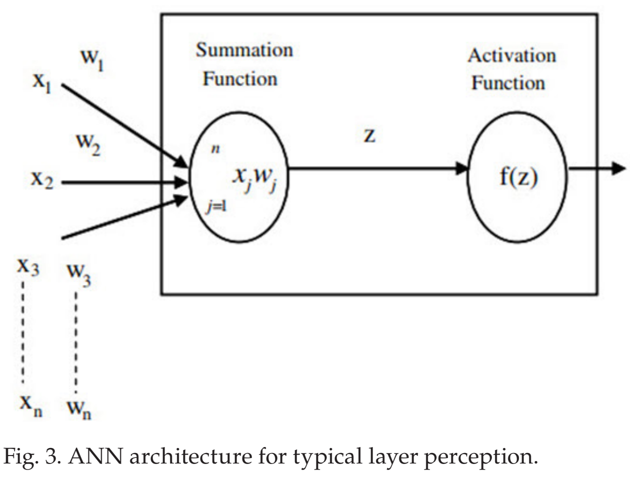

Fig. 3. ANN architecture for typical layer perception.

$$E_{Y/X}(X) = \int y * f_{XY}(x,y)dy \big/ f_{XY}(x,y)dy; \tag{3}$$

A one-hidden-layer network is commonly adopted by most ANN modelers in case of linear behavior whereas in multi-layer hidden layers are chosen in case of nonlinear behavior of input to target values (output); the number of hidden nodes M in this model is between I and 2I + 1 [29], where I is the number of input nodes. As a guide, M should not be less than the maximum of I/3 and the number of output nodes O. The optimum value of M is determined by trial and error. Networks with fewer hidden nodes are generally preferable because they usually have better generalization capabilities and fewer over fitting problems [30–32]. If the number of nodes is not large enough to capture the underlying behavior of the data, however, then the performance of the network may be impaired. In this study, a trial and error procedure for hidden node selection was carried out by gradually varying the number of nodes in the hidden 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 twenty-three 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 ANN model is created with a set of weather and saline water volume data as inputs and a set of daily distillate production as the 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 is used for training purposes and the remaining 20% is used to test/validate the network's predictive ability. For the training, validation and testing record data set from October 2013 to September 2014 is used.

For network generalization and to stop training validation data is used, whenever generalization stops improving. The testing data set consists of data not previously included in training or validation and are used to provide an independent measure of network performance. Solar still 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 play very important role in the radiation and convection of the distiller units as a source of energy. The rate of condensation and heat removal rate will depend on the glass surface temperature and wind velocity, as glass surface temperature influence due to the ambient and wind velocity hence both parameters is also considered as an input parameter for ANN model.

4. Results and discussion

While the experimentation variation in incident radiation on the inclined cover surface of the experimental setup has been recorded on 24th July 2014 with the help of Precision Spectral Pyranometer and represented in Fig. 4, which shows that it's a sunny day. At our latitude, the maximum value of incident radiation was recorded 1000 W/m^2 between 12–13 h on a clear day at solar noon in the summer months. The variation of basin temperature of SSDHP with and without air pump with respect to time is shown in Fig. 5 basin temperature of the SSDHP with air will maintain its superiority throughout the experiment as compare to the SSDHP without air, just after half hour interval of the experimentation, it suppressed to SSDHP without air by 3.85%. In both the cases initially it increases linearly but basin temperature of SSDP maintains its lead by 27.74%, before SSDHP without air temperature starts the decline. Whereas maximum temperature of SSDHP recorded 88°C, which is 41.93% higher as compared to the basin temperature of SSDHP without air at 13 h as it receives. However basin temperature of SSDHP with air gradually decreases from 88°C to 73°C by 17% between 13 to 17 h, but basin temperature of SSDHP with air reduce more rapidly from 69°C to 50°C by 27.53% between 10 h to 17 h. At the end of experimentation basin temperature of SSDHP with air is recorded 46% higher as compared to SSDHP without air due to the influence of air bubble in basin air. Fig. 6 depicts the variation of water and glass surface temperature with respect to time, the water temperature is higher than that of the air in, therefore heat transfer from the water to the air occurs during this process. At the same time a transfer of material in the same direction occurs, the phenomenon of vaporization has the effect of decreasing the temperature of the water on the one hand and of increasing the humidity and the temperature of the air of other Share. It is shown that the water temperature is of the order of 85°C without air and does not exceed 75°C with air. The same applies to glass, which does not exceed 40°C with air. Comparisons of productivity of SSDHP with and without air is illustrated in Fig. 7, which shows that SSDHP with air will give higher yield as compared to the SSDHP without air due to the influence of air discharge in its basin area. At the beginning of experimentation SSDHP with air will give 100% higher yield as compared to the SSDHP without air but SSDHP dramatically maintains its lead by 25% at 9 h, which further reduced from 10 h onwards up to 14 h. While this duration maximum difference in yield of SSDHP with and without air observed that SSDHP with air gives 34.61% higher yield as compared to without air during 11–12 h due to the influence of basin temperature

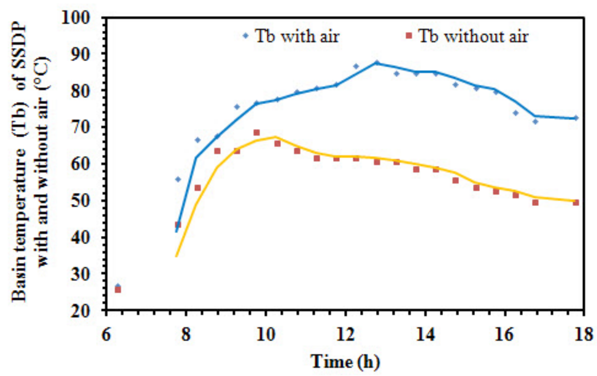

Fig. 5. Variation of basin temperature of SSDHP with air and without air with respect to time.

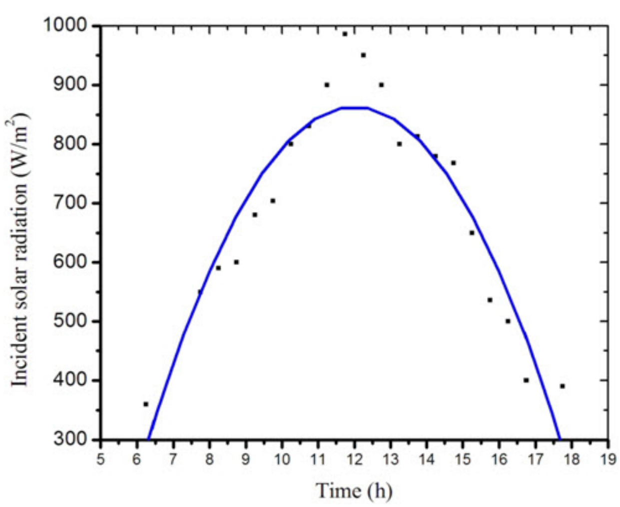

Fig. 4. Behavior of incident solar radiation with respect to time.

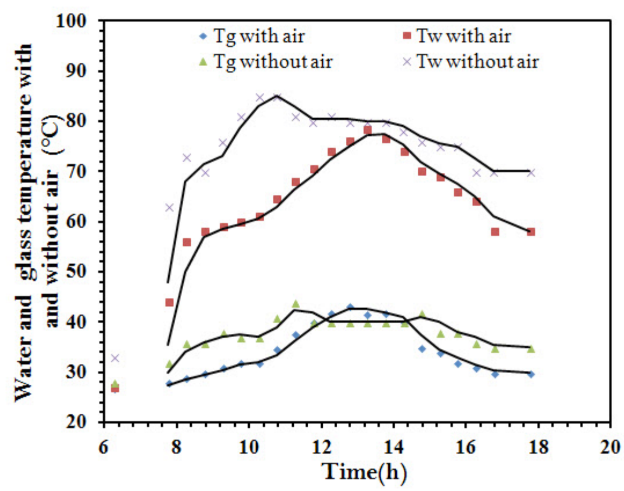

Fig. 6. Variation of water and glass temperature of SSDHP with air and without air with respect to time.

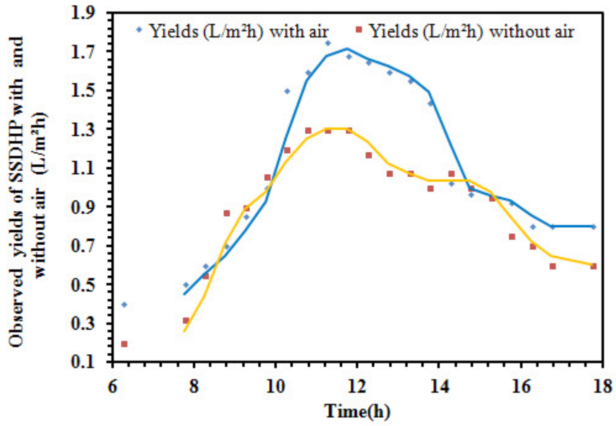

Fig. 7. Variation of actual observed yield of SSDHP with and without air with respect to time.

and mix gradient. Between 14–15 h SSDHP without air further increases slightly as compare to SSDHP with air and further reduces from 15 h till the experimentation, at the end of experiment SSDHP with air will give 33.33% higher yield as compared to the yield obtained from SSDHP without air. Artificial neural network modeling results of training validation and test for the SSDHP with air done with the help of MATLAB software. The Pearson correlation coefficient (R^2 value) is also calculated to measure the correlation between predicted and actual yield, represent in Fig. 8. Where, top performing architecture uses the temperature of the glass surface (T_g), water (T_w), Basin (T_b), evaporator (T_e) and incident solar radiation (I) as an input parameter for the training and evaluation. Artificial neural network modeling result for the SSDHP with air is presented in Fig. 9, which shows the variation of actual yield obtained while experimentation with respect to the yield obtained through the ANN model on

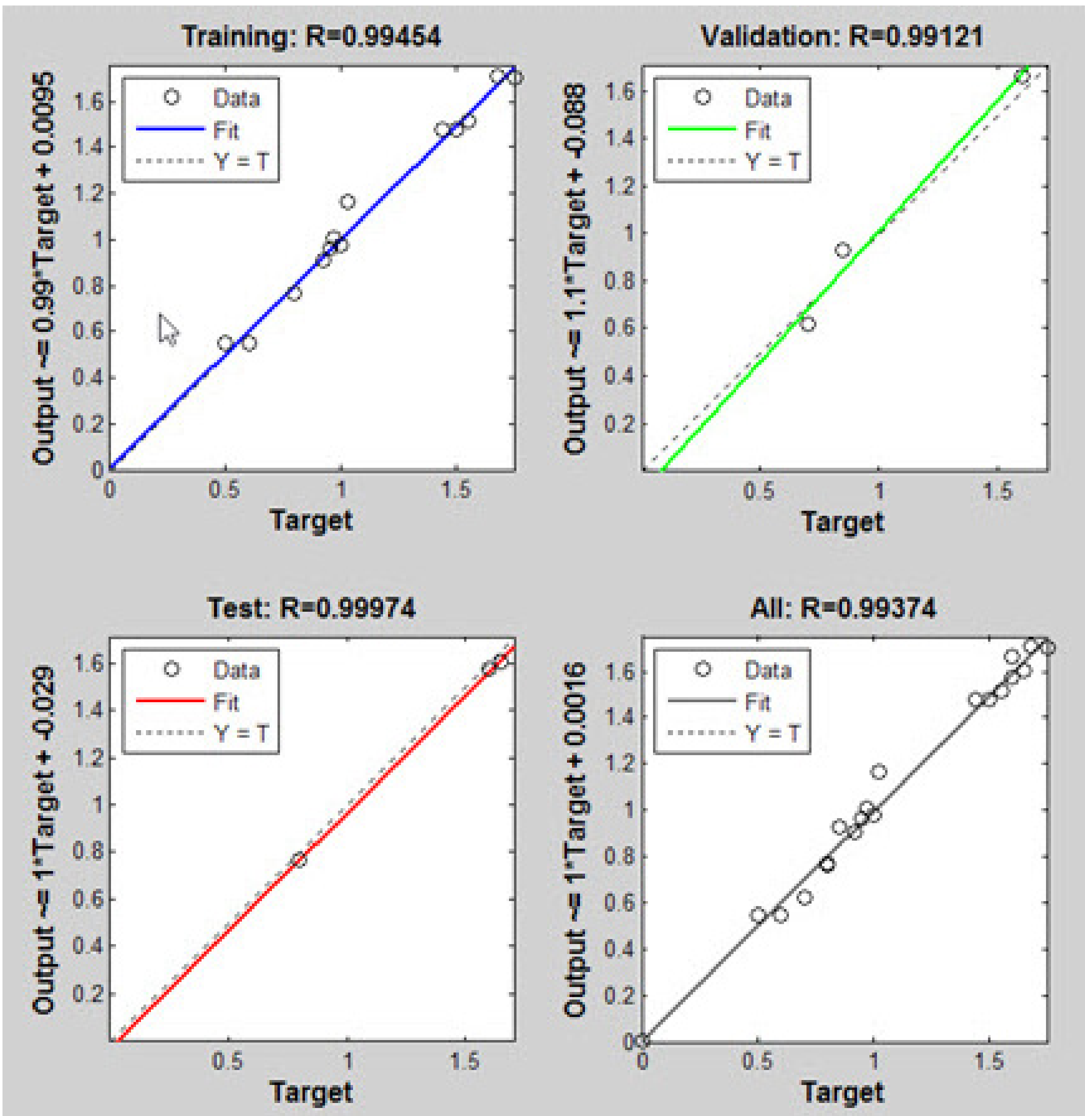

Fig. 8. Variation of ANN mode result as an output with respect to target data.

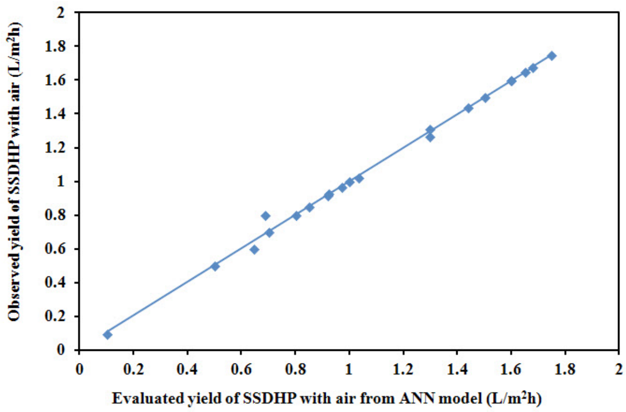

Fig. 9. Variation of actual yield of SSDHP with air with respect to yield predicted through ANN Model.

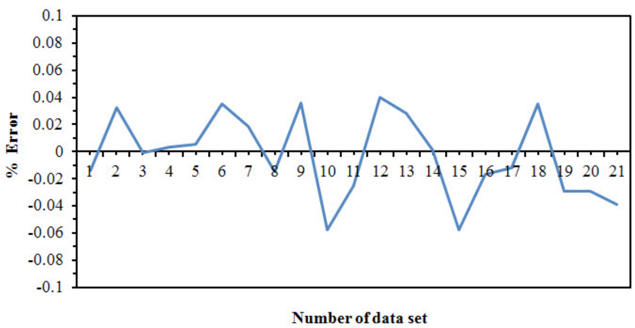

Fig. 10. Variation of % error of ANN Model with respect to concern set of input data.

a linear trend line. The primary criteria for evaluating the performance of different combinations of input data architectures are the percentages of model predictions which is within 10% of actual daily distillate production of SSDHP with air represented in Fig. 10.

5. Conclusion

Following conclusions are drawn on the basis of outdoor experimental results and theoretical evaluation did with the help of ANN Model:

- The SSDHP with air will give higher yield as compared to SSDHP without air due to the enhancement of heat mass transfer rate and newly design ANN network model for SSDHP can be used for the estimation of its output for different conditions and a different set of the input parameter.
- Trained ANN model predicts actual daily distillation of SSDHP less than 10% variation of actual yield for both the cases.
- With the help of input parameters, ANN model easily evaluates SSDHP with and without air. It will give more relevance for the construction and installation for large scale production.

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