Performance Monitoring And Prediction System For Double Slop And Pyramid Geometry Solar Still Plant

Rajeev Raghuvanshi, Dhanraj Verma, Manoj Kumar Deshpande

Abstract: This document is aimed to investigate and design two different kinds of solar still plants. Both kinds of water plants experiment with IoT devices for collecting data. The data collected from both the experimental devices are used as a dataset for developing the predictive data model. The preparation of the predictive data model aims to provide a monitoring system precisely predict the water production for different kinds of solar water stills. The proposed data model involves the linear regression technique for refining the data and computation of outlier data. The outlier data instances are removed first and then the BPN algorithm is used for training and validation of the proposed model. Besides that to optimize the algorithm running time to learn on patterns a small modification of BPN (back propagation neural network) is also proposed. The performance of the proposed modified predictive technique is compared with the previously proposed data model for justification of the work. The experimental outcomes recommend using the pyramid solar still because the production of that solar still is higher than both kinds of slop based models (i.e. single slop and double slop). Additionally, the proposed modified system reduces the running time of the learning algorithm for prediction.

Index Terms: machine learning, data mining, solar energy, water distillation, double slop, pyramid geometry.

1 INTRODUCTION

Global warming is a human-generated crisis. Additionally, after awareness, humans consistently repeating their mistakes, i.e. industrialization, reduction of forest land, transportation industries, usages of air conditioning and others [1]. That results are melting down the glaciers, increasing sea level, dry weather conditions, uneven raining, acid rain, and many more effects are we observed. In this way, if we are not taken some strong decisions and steps, we can suffer from drinking water. Water is the basic necessity of humans and other creatures [2]. Therefore we need planning and techniques for sustaining lives on earth. Thus, wastewater management, water purification techniques, etc. are needed to be optimized to deal with serious water crisis [3]. In a recent study we have proposed monitoring and predicting the water production technique for solar still plants [4]. Solar still plants can be a freshwater source for sustainability because it is low cost and easy to make. That is capable to produce water for a family's daily usages. Therefore the following objectives are proposed to accomplish.

1. Impure water is contained outside the collector where it is evaporated by sunlight shining through clear plastic or glass to implement a machine learning or data mining technique to analyze and predict the performance accurately for a solar still.
2. Identifying the factors and features which can help to improve the performance of prediction or monitoring system as well as the performance of solar still plant and.
3. they are used in areas where drinking water is unavailable so that clean water is obtained from dirty water or from dirty plants by exposting them to sunlight.
4. By using the identifiy features and factors prepare more accurate and efficient data models and data collection.

To achieve the above-listed objectives a data model and a single slope single basin solar still plant are proposed. Where two popular techniques namely BPN (back propagation neural network) [5] and LR (linear regression) [6] technique is used for prediction. Based on the obtained results performance of the predictive system is acceptable therefore, some improvements on the existing system are proposed as:

1. Solar still are used in cases where rain piped or well water is impractical, such as in remote homes or during power outages.
2. Involving two more, still plants for experimentation namely double slop and pyramid for observations and data collection.
3. Suggesting improvements on existing still plants for improving the performance of water production using three improved still plants
4. Implementing the noise reduction algorithm with the help of learning model for improving prediction performance

In this paper, an extension of the previously proposed system is provided using the hybridized BPN (back propagation neural). Besides two solar still plants are used i.e. double slop and pyramid to collect data and preparing the predictive technique. This section provides the work previously done and the extension which is performed in this paper. In next section includes the review of recent efforts. Further, both kinds of solar still plants are described and the formation of the dataset and included features are offered. Finally, the proposed predictive model is explained and a comparative performance study is included to justify the proposed work.

2 LITERATURE SURVEY

This section is providing a study about the solar still plants which are being used in experimentation and the relevant efforts recently contributed by different researchers. The desalination plants are not energy efficient. Additionally, global warming is the long term rise in the average temperature of the earth's climate system. Global warming is a threat to life sustainability. Solar energy is a rich source of heat. The solar desalination is a low-cost process. Solar desalination methods are direct and indirect. According to M. Chandrashekara et al [7], indirect methods are suitable for medium and large scale desalination, in this method of measurement the unknown quantity is directly compared with the standard quantity the result of the quantity is expressed is number. And direct methods are for small scale Hitesh N. Panchal et al [8], an attempt has been made to evaluate the impact of different design, climate and operational parameters that still affect solar performance. Miqdam T. Chaichan et al [9] investigates the usage of thermal energy extracted from solar heater for water distillation. Paraffin wax selected as a phase change material and to store energy. Solar energy stored and retrieved for later use. Water's temperature measured in a definite interval of time. The system concentrating, heating, and productivity, has increased. Kamel Rabhi et al [10] present a modified solar still with pin fins absorber and external condenser. A comparative study is carried out between the modified still and conventional still. That is conducted to evaluate the thermal behavior and water production performance. D.B. Singh et al [11] conducted a study and analysis of partially covered hybrid photovoltaic thermal flat plate collector solar still. The model has been developed and data have been collected for climate conditions. The results have been compared and obtained a clear relationship between experimental values and theoretical values. Wael M. El-Maghlany [12] represents the optimum inclination angles of the glass cover of the double slope solar still, and orientation for maximum collected solar energy that could be captured by the solar still glass cover. The inclination angle is changed from 10 to 60 on both sides of the glass cover to get independently the optimum inclination angles for each side that not necessary to be the same. A. Muthu Manokar et al [13] study the performance of a photoVolatic panel integrated solar still to generate power and water. Results show that maximum distillate output of 7.3 kg when inclined solar panel basin with sidewall and bottom insulation. Francisco Suarez et al [14], the performance of a direct contact membrane distillation system driven by salt-gradient solar ponds was investigated. A model was developed and validated. The performance of the system in different locations and operational conditions was studied. Results show that the system can be used to meet future needs. A.E. Kabeel et al [15] analyze the effect of various heat exchange mechanisms adopted to augment water production from different solar still designs. The performance of inclined type solar still was investigated by R. Samuel Hansen et al [16] using different wick materials. Wicking material are modern technical material which draw moisture away from the day. New materials are suggested for absorption, capillary rise, porosity, water repellence, and heat transfer co-efficient to select a suitable material. Performances were compared with other traditional wick materials. Ravishankar Sathyamurthy et al [17] communicate a review of different geometrical shapes of solar still. They conclude that geometry in solar still influences the yield of water. Bhupendra Gupta et al [18] offer the design of modified single slope solar still which includes walls white painting inside, the inclusion of water sprinkler. The performance still has been evaluated and compared with conventional still. Kuldeep H. Nayi et al [19] review development in the field of pyramid solar still and techniques to improve performance. The pyramid solar still is more efficient and economical. Hayder Al-Madhhachi et al [20] investigates the factors that affect water production. Experiments were performed to find the influence of evaporation temperature, vapor volume, Peltier current and input power. The experiment shows that an increase in the sample water temperature can increase water production. Ruh Ullah et al [21] introduces energy parameters for MD and reported impacts of membrane properties, mass and heat transfer, feed water. Z. M. Omara et al [22] concerns with double layer wick material and reflectors inside CSS. Additionally, the influence of water depth on performance is recorded. Results indicate enhancement in total productivity and efficiency

3 EXPERIMENTAL SETUP

This section explains the design of both the solar still plant devices (i.e. double slop and pyramid) and data collection for experiments.

3.1 Double Slop and Pyramid geometric Solar Still Plant

The work aims to investigate the performance improvement in water production by using the two different kinds of solar still plants. Thus two designs of the solar still plants are considered in this experiment i.e. Double Slop and Pyramid geometric Solar Still Plant. The solar distillation water plant purifies the Sewage into drinkable water. A basin type double slope sola still with mild steel plate was fabricated and tested with minimum mass of water and different wick materials like light cotton cloth sponge sheet coir mate and waist cotton pieces in the basin.

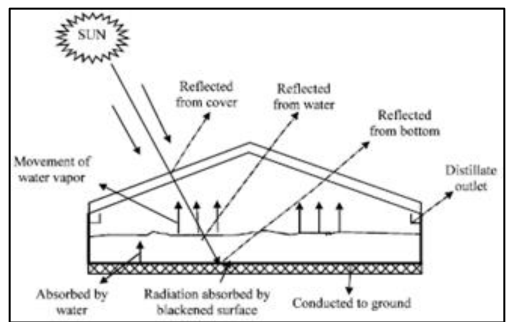

Figure 3.1 double slope solar still

Figure 3.1 and the model of Pyramid geometric Solar Still Plant is given in figure 3.2 respectively. Both the figures demonstrate an overview of the double-slope and pyramid-shaped still plant. The different components of the models are also given in the diagram. Both the models are similar in shape and size additionally one has two slops and another includes four slops to create the pyramid-like shape. Both models contain a box-shaped water tank filled with water. The box dimension of the experimental plant is 120*120*25 cm for both the plants. The body of the box is designed with the help of a GI (Galvanized Iron) sheet of 3.5 MM thickness.

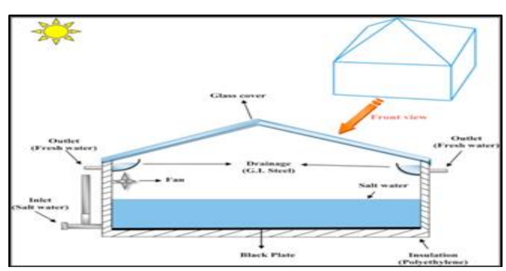

Figure 3.2 *pyramid geometry solar still*

The pyramid solar still any one side of cover directly gain the direct and higher solar radiation than other side. So other side remains at lower temperature than this one idea which enhances the property of condensation that accrue on these sides due to gig her temperature different between water surface and cover. That the double slope water still plant is covered with a glass from two sides to create two different slops. Similarly in a pyramid, the four side slopes are prepared with the help of glass cover. The used glass cover is made with 5 MM thickness. In the double slope still plant both the slops are inclined in different angles first is 〚15〛^° and the second slope is created at 〚30〛^°. On the other hand in the pyramid still, all the four slops are having 〚45〛^°inclined. The sunlight is passed through the glass cover and heated the water, for the evaporation process. The generated steam condensed over the glass cover and walls. Thus it is collected using a drainage system. Additionally, all the water is poured into a basin outside the plant. The basin to collect the freshwater is developed with a metal sheet of GI (Galvanized Iron). The basin also consists of a measuring jar which is used to find the water production.

3.2 Data collection & observation

Both kinds of models are used here for experimentation. Additionally, the firebase database is prepared for storing the captured data from IoT sensors. The requirements of higher temperature or heat for evaporation we experiment with the model between 10:00 AM to 4:00 PM. During these experiments, the previously used features basin temperature, cover temperature, water temperature, solar radiation intensity, and ambient temperature are used. Additionally, some more parameters are included such a weather temperature, wind direction, wind speed, and weather conditions are also considered. The device collects these parameters in each 5 minute time interval and updates to the firebase database. Every day we capture a total of 72 samples. Thus to prepare a dataset using these attributes we conduct the experiments for 30 days. Using these experiments we found a total of 72 * 30 = 2160 samples for both the prepared dataset. Also, that distilled water yield or efficiency and the instantaneous performance of the system in terms of percentage (%) is measured and associated with the data instances as a predictive variable. The outcome of these experiments is the preparation of two datasets with 2160 data instances for double slop and pyramid-shaped still plants.

4 PROPOSED MODEL

The proposed model is working for functional aspects of the proposed data mining based predictive model. The prediction process is used to monitor the performance of solar distillation plants.

4.1 Methodology

The proposed model for predicting the performance of the solar still plant is demonstrated in figure 4.1.

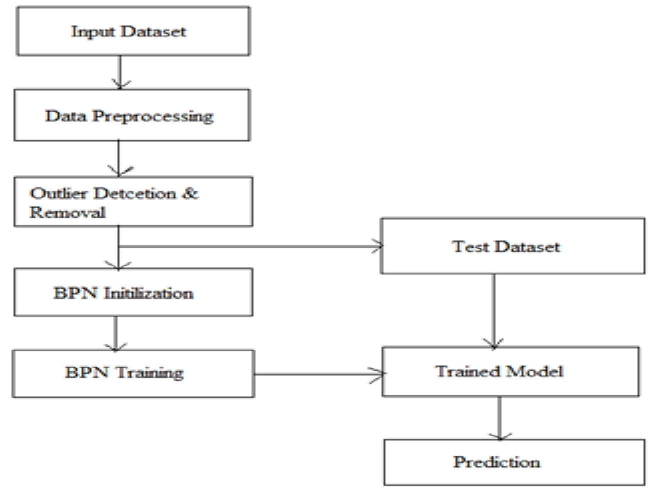

Figure 4.1 *predictive data model*

The proposed data model contains several computational components that are being used for computing the intermediate objectives. In this experiment, we utilized two different datasets one for double slop based observations and second for pyramid solar still plants. Each of the datasets contains a total of 2160 data instances with the values of performance. Both the datasets have 9 attributes and 2 class variables which are needed to be predicted. However, the data is collected in the automatic process; therefore the mistake in the dataset is possible. Therefore, the prepossessing is adopted for verifying the data quality. Additionally if any mistake or issue in any instance of data we found then we remove it. Thus a similar process as applied in [4] is used for preprocessing of the data. After preprocessing the data is cleaned and it is ready to be used with the proposed model. But before consuming the data we apply the linear regression technique for enhancing the data more effectively [24].

$$[\beta_0, \beta_1, R, R_i, stat] = Regress(X, F)$$

The outlier estimation using linear regression requires R_i. That is recognized as Intervals to diagnose outliers in MATLAB, it is a numeric matrix. If the interval $R_i(i:)$ for an observation I do not pass through zero, is suggesting an outlier. The obtained points are identified as the outliers are removed in the next step. The following algorithm is used for the outlier removal purpose.

Input: Preprocessed dataset D *Output: outlier removed dataset O*

Process:
1. $D_{m,n} = ReadAttributes(D)$
2. $C_n = ReadClassValues(D)$
3. $[\beta_0, \beta_1, R, R_i, stat] = Regress(D_{m,n}, C_n)$
4. $for(i = 1; i \leq n; i++)$
   a. $if(R_{i,1} \leq 0 \; \&\& \; R_{i,2} \geq 0)$
      i. $O.Add(D_i, C_i)$
   b. $else$
      i. $D_i.remove$
   c. *End if*
5. *End for*
6. *Return O*

Table 4.1 *outlier removal*

To find and remove the outlier points from the dataset we apply the linear regression and by using the previously discussed property of regression analysis we eliminate from the dataset and remaining data points are keep preserved for further use. The process of outlier removal is used for removal of those data instances that are not much suitable for learning and these patterns can disturb the performance of learning. Thus the optimized data is used for further process. Before using the entire data for learning we select 4 different sets as the test dataset by using the random process. Therefore 4 times 30% of random data instances are selected as test datasets additionally the performance of the learning algorithm is tested based on these four-fold test set. The obtained performance, mean value is used as a performance indicator. After that process, we find the complete linearly fit dataset which can be used for accurate classification but to improve the running time of neural network in place of random initialization we proposed a different technique. Those concepts usages the min-max normalization and correlation coefficient based methodology to be used. Both techniques are first needed to be introduced.

Min-Max Normalization

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where X = existing value of attribute
X'= new value of X
X_{min}= minimum value of that attribute
X_{max} = maximum value of that attribute

Correlation coefficient

$$C_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i-1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i-1}^{n}(y_i - \bar{y})^2}}$$

Where
n = number of samples
x_i, y_i are the individual i^{th} samples
$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ and similar for $\bar{y}$

First of all the dataset attributes are normalized using the min-max technique after scaling the values between 0-1. Further, the correlation coefficient is used for optimizing the values for selecting the weights to be initialized. Thus the following process is used.

Input: Dataset O, number of input neurons IN, number of hidden neurons HN, number of output neurons ON, number of cycles NC *Output: selected weight for initialization W*

Process:
1. $R_n = readDataset(O)$
2. $N_n = NormalizeData(R_n)$
3. $for(i = 1; i \leq NC; i++)$
   a. $D = IN * HN$
   b. $S = Select(D, O, Random)$
   c. $CC = CorrCoff(S, Class)$
   d. $if(CC_i \leq CC_{I-1})$
      i. *Terminate*
   e. *Else*
      i. *Go to step 3*
   f. *End if*
4. *End for*
5. *W=S*
6. *Return W*

Table 4.2 *weight selection algorithm*

The selected optimum weights are used for the initialization of the back-propagation neural network (BPN). After the initialization of the network, the normalized values are used for learning with the predictive variables. After learning the four-fold test datasets are applied and using the cross-validation technique the performance of the learning system is demonstrated. This section explains the technique used for learning and predicting the water production capacity and instantaneous efficiency for both the solar water still. The next section includes a summary of the entire process adopted as a proposed algorithm.

4.3 Proposed algorithm

The above-given process is summarized in this section as the algorithm steps. Table 4.3 contains all the required steps of the system functioning.

Input: dataset D, test datasets $T = \{T_1, T_2, T_3, T_4\}$ *Output: predicted data P, Accuracy A*

Process:
1. $R_n = ReadDataset(D)$
2. $P_n = preProcessData(R_n)$
3. $O_n = NormalizeDataset(P_n)$
4. $\{T_1, T_2, T_3, T_4\} = createtestData(30\%, random, O_n)$
5. $W = selectWeights(O_n, BPN)$
6. $BPN = BPN.initilize(W)$
7. $T_{model} = BPN.Train(O_n)$
8. $for(i = 1; i \leq 4; i++)$
   a. $P = T_{model}.Predict(T_i)$
   b. $A_i = P.Accuracy$
   c. $A = A_{I-1} + A_i$
9. $end\ for$
10. $A = \frac{A}{4}$
11. $return\ A, P$

Table 4.3 *proposed algorithm*

According to the above-discussed algorithm the dataset D is produced as input to the system and in the first step, it is read and prepared a vector R_n. The R_n is used with the preprocessing technique for cleaning the dataset, after preprocessing of the data it becomes P_n. The preprocessed data is used in with the linear regression algorithm for finding the outlier points thus in this phase the normalization and outlier is removed from data and O_n is prepared for the further learning process. The O_n is further used for preparing the test datasets $\{T_1, T_2, T_3, T_4\}$.Additionally, the weights for the BPN initialization process are selected. After weights initialization, the data is used with the BPN algorithm and the trained model is prepared the trained model is demonstrated here as T_{model} The trained data model usages the test datasets four times and predict the values based on predicted values the accuracy of the system is measured. Additionally, the mean accuracy $A = \frac{A}{4}$ is returned as a system performance validation outcome. Moreover, the P which is the predictive outcome is also returned as an outcome of the system.

5 RESULTS ANALYSIS

The proposed solar still plant performance prediction technique is described in the previous section. After the implementation of the system, the performance is measured and reported in this section. The aim of conducted experiments is to achieve higher accuracy as compared to previously proposed data models [4]. Additionally identifying the obtained performance improvement over the traditional model after modification of the proposed model the impact on algorithm running time and memory usages is also measured and compared with the lastly introduced method of BPN algorithm. The experimentation based obtained results and their comparison with the existing model is described in this section.

5.1 Accuracy

The accuracy is also termed as precision. The precision is measured infraction and the accuracy is conversion in terms of percentage (%). it is the rate of correctly predicted samples concerning total samples predict. To implement with the model the following equation can be used.

$$Accuracy = \frac{Total\ correctly\ predicted\ samples}{of\ total\ samples\ to\ predict} X100$$

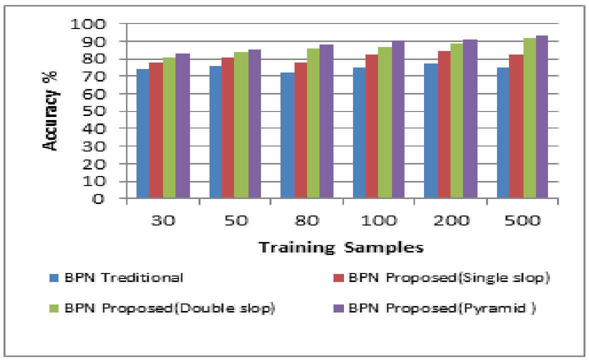

Figure 5.1 *Accuracy (%)*

The accuracy of the implemented algorithm is demonstrated using figure 4. First, the traditional data model and proposed data model is applied for predicting the performance of single slop water still. The prediction ability of the system is improved as compared to the traditionally implemented model. In further the proposed data model is applied to predict the performance of double slop and pyramid based solar water still. Thus all four experimental outcomes are reported in figure 4. The line graph is used for reporting the performance of the proposed system where the X-axis provides the details about the training samples involved for training and Y-axis shows the corresponding accuracy of prediction. The accuracy is measured and denoted in terms of percentage (%). According to the obtained results, the proposed technique optimizes the performance as compared to the traditional model which is introduced by us. Additionally, the involvement of additional features also helps to understand the patterns in different kinds of conditions (i.e. weather, and wind). Thus the proposed model can improve the performance of the system for predicting the time series values.

5.2 Memory usages

The memory usages are also termed as space complexity or memory consumption of the algorithm. That is measured based on the requirements of the main memory to store data and instructions in memory. However, the memory used in JAVA based systems is measured on the basis of processes running. Therefore the memory assigned by the system and the amount of available free memory difference is used for computing the memory requirement of the algorithm. To calculate the memory the following equation can be used.

$$memory\ usages = Assigned\ memory - free\ memory$$

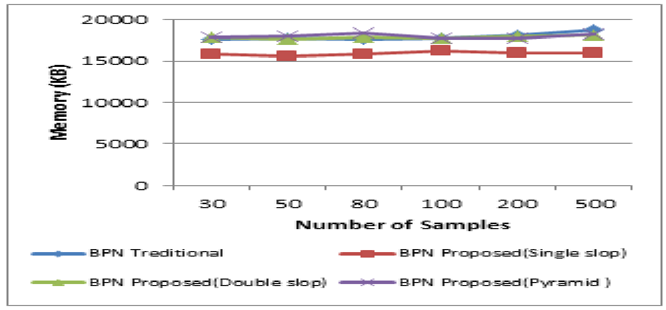

Figure 5.2 *memory usages (KB)*

The memory usages for all the scenarios i.e. first the traditionally used single slop water still plant with previously developed BPN, the enhanced BPN with traditional data attributes for single slop, the proposed BPN for double slop and pyramid geometry-based model is described using the figure 5.2. The memory usages of the implemented models are measured in terms of KB (kilobytes). The demonstrated line graph contains a number of data objects for training in X-axis and the Y-axis shows the measured memory consumption. According to the simulated results the proposed data model reduces the training memory usages, but for the double slop and pyramid solar still plant the attributes are increases, additionally, the memory usages directly depend on the amount of data produced for processing. Thus the model is able to reduce the computational efforts.

5.3 Time Required

The time requirements of the algorithm execution are also known as time complexity. That is known as the time expense to execute the algorithm for processing data is known as time usages or consumption. In a java based implemented system that is computed on the basis of the time difference among algorithm initialization and finalization. The following formula can be used to measure the time.

$$Time\ Required = Algorithm\ End\ time - start\ time$$

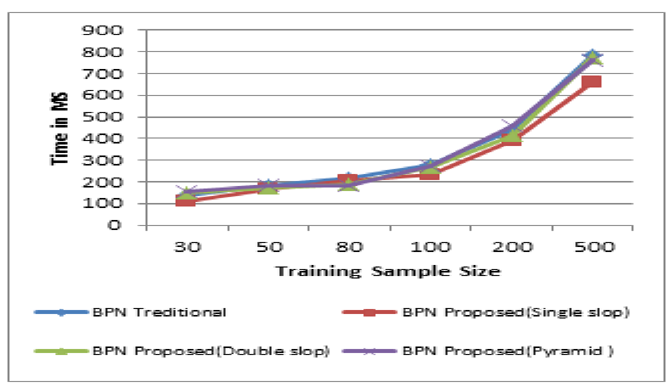

Figure 5.3 *time consumption*

The performance of the implemented experimental scenarios is reported using figure 5.3. That is the line graph where the training samples are used are given in X-axis and Y-axis contains the time requirements. The measured time is given here in terms of MS (milliseconds). The blue line shows the performance of traditional BPN based single slop solar water still plant, additionally for the same data set the proposed data model is used and the performance is reported using the red color line. The line of performance in green color demonstrates the performance of a double slope solar still plant with improved BPN. Finally, the purple color line shows the performance of the pyramid-shaped water still plant. According to the obtained results, the time requirements of the system are reduced when we use the proposed BPN model for predictive data analysis.

6 CONCLUSION & FUTURE WORK

This section provides a summary of the proposed work for improving the performance of solar still plant and their monitoring and prediction systems. On the basis of obtained experimental results, the conclusion of the work is prepared and the future extension is also reported.

6.1 Conclusion

This paper is focused on two major concerns first is finding the way of efficient solar water distillation and second is to provide an effective methodology to observe and predict the performance of solar water still plants. In this context, the proposed work first provides a study about the two solar still plants namely double slop and pyramid-shaped solar water still plant. During experiments, we observe the double slop model is efficient than the single slop water still plants in normal conditions. We found 30% additional water production in double slop water still plants as compared to single slop water still plant. In addition to the pyramid-shaped solar still is efficient than the double slop water. The performance of the pyramid-shaped solar still plant is 23% higher than the double slope solar still plant. In addition to that, a predictive monitoring system is also contributed to this paper. That model is based on the back-propagation neural network. That model is a supervised learning approach that learns from the collected data from solar still plants and predicts the water distillation yield and instantaneous efficiency. In this context first, the data is preprocessed and refined. The preprocessed data is further used with the linear regression algorithm for computing the outliers in data. Thus an outlier detection and removal algorithm is also implemented for optimizing the data linearity. After that the data is used for learning purpose thus BPN algorithm is implemented. The initialization process of the BPN algorithm is modified using the correlation coefficient and min-max normalization. After that BPN learns on the patterns and predicts the data. based on performance and other factors are computed. The implementation of the proposed data model is performed using the JAVA technology and to store and prepare the performance results the MySql server is used. The performance summary of the comparison between the currently proposed and traditional data model is given in table 6.1.

S. No.	*Parameters*	*BPN Traditional*	*Modified BPN*
1	*Accuracy*	*Low*	*High*
2	*Error rate*	*High*	*Low*
3	*Memory usages*	*High*	*Low*

Table 6.1 *performance summary*

According to the described performance of the developed system, the proposed model is able to regulate the performance of the predictive system. In addition to that, it is also capable to minimize the time and memory resource consumption during the algorithm processing or learning.

6.2 FUTURE WORK

The proposed work is motivated to find a sustainable and efficient way of solar still plant design. In this context, the first, single slop model is proposed and then doubles slop and pyramid-shaped models are also used for experimentation. During these experiments, we proposed a BPN based model previously which is extended and enhanced for accurate performance prediction. In order to make it more efficient and accurate the following work is proposed.

1. Involving the ensemble learning techniques for improving the model prediction ability
2. We found that the pyramid based model is efficient for producing distilled water, but some small modifications can improve the performance more which is implemented in the near future.

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