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Solar Water Still Plant Monitoring and Maintainance using Machine Learning

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Abstract

The increasing risk of global warming also increases the risk of water and other crisis. Therefore we need to find alternate sources of natural resources for sustainability. In this paper we highlight three fold contributions; first we study recent improvements in solar water still technology, therefore an overview of solar water still plants is provided. Additionally, a review of recent improvements in still plant design is also provided. Next, we provide an experimental study of ML techniques. Thus performance of two ML models is studied for continuous value prediction. Then provide an algorithm for improving the accuracy. Finally, a system for predicting maintenance decisions for the solar still plants is proposed where we employ the enhanced algorithm to demonstrate the maintenance decision making. The proposed monitoring and maintenance system implements three Machine Learning algorithms namely Linear regression, neural network and improved neural network. The experimental results for three different kind of solar still plant have been calculated. According to obtained results the linear regression algorithm produces accuracy between 64% - 74%, NN algorithm provide accuracy between 67%-79% and the proposed algorithm we achieve higher accuracy between 87%-94%. Based on the conducted study we have found that the proposed model will able to manage the maintenance of the solar still plant and can enhance the productivity. But system requires high degree of accuracy for less false alarm thus in near future we proposed to extend this model for more accurate results.

Keywords— Solar Energy, solar still plant, RBF (Radial Basis Function), IoT (Internet of Things), Prediction system, Machine learning.

Introduction

Solar energy is a source of unlimited energy and can be utilized in various applications. It can be used in water harvesting, power generation, transportation systems, smart homes, sensor applications and others [1]. Among them water harvesting using solar water distillation is essential and life saving application. The advantage of solar water still is that it is low cost, and can produce water for utilizing in small size family. But the efficiency is the major challenge for adaptation because efficient water production needs monitoring and timely maintenance [2]. In recent studies, it is proven the predictive methods can help to enhance the productivity by automated monitoring and maintenance [3]. Thus, proposed work offers to design an automated monitoring and maintenance of solar still plants.

Water is the basic necessity of human. Human mistakes, increasing automation, industrialization, transportation and others are contributing in global warming. Due to which risk of future water crisis is rising. This paper is aimed to contribute for the problem of water crisis by offering a monitoring and maintenance model based on ML techniques. ML techniques enable us to analyze data in less time and to make decisions. The data driven decisions are requiring higher accuracy in data analysis [4]. This paper thus focused on analyzing the solar still pant parameters to predict the variation in plant's performance. The one step a-head plant performance is predicted. It is beneficial where a number of solar water plants are established to harvest water. Therefore, we proposed to develop a monitoring system which monitors performance and make decisions about maintenance. In order to keep maintain quality of service of the proposed monitoring system we also tried to implement improve neural network weight initialization technique. In addition, the sensor technology like Internet of Things (IoT) can also help in monitoring by collecting the information of plant parameters. Therefore, in this presented work we are highlighting the following key points:

- Study of recent improvements in solar water still technology: fresh water production is one of the conventional applications of solar energy. Thus an overview of solar water still plants is provided. Additionally, recent improvements in still plant design are also studied.
- An experimental study of ML techniques: first the performance of two ML models are studied which are suitable for continuous value prediction. Then appropriate model is extended for improving accuracy. This improved model is used for still plant's performance monitoring.
- A system for predicting maintenance decision: here we employ the enhanced algorithm to demonstrate the maintenance decision making, thus system architecture of the proposed model is described.

Motivation

The proposed work is motivated by two articles focused on solar energy harvesting. That suggest the monitoring system developed with prediction ability will able to improve the productivity.

In first article H. Mungad et al [5] says IoT provide the connectivity of everyday objects to exchange information. It is useful in monitoring and maintenance. They proposed to monitor and maintain the solar panels using IoT, to maximize production and rotated according to sun's direction in real time. Intensity of radiation and climate condition are also considered. They provide analysis with suitable user interface and notifications regarding dust accumulation. In second, F. A. Kraemer et al [6] in order to manage and utilize resources the solar energy prediction is essential. They evaluated different ML approaches to be used using public weather data.

Need of Study

The solar energy is a free and unlimited source of energy; additionally there are no carbon foot prints. Increasing effect of global warming motivate different government and private Non-Government Organizations (NGOs) to develop sustainable source of living resources. The proposed work is providing a study the solar water still plants, where performance of these devices is need to improve. Thus we involve a design of monitoring system of the solar still plants. The monitoring and timely maintenance will help to improve the water production performance. But decision making requires accurate prediction ability. Thus the system will provide maximum production of fresh water.

Study of recent improvements in solar water still technology

This section provides an overview of solar water still plants. Additionally, recent improvements in still plant design are also studied.

Solar Still Plant Models

Single slop single basin

A single slop solar still is low cost but that can produce the water for daily use. We can use this model for purifying the water. The solar water still is given in figure 1. The overview of the single slope solar still is given with the key components. It is composed of a box-shaped model with a water tank and glass cover. The radiation is passed by the glass and heated into the water, the evaporation process is started. The steam condensed on the cover and walls, and the slop helps to drain the water. The Galvanized Iron sheet is used for the body. The glass cover is inclined in 15℃. Additionally, freshwater is collected by a basin using J-shape drainage to collect water. To enhance the performance walls are coated.

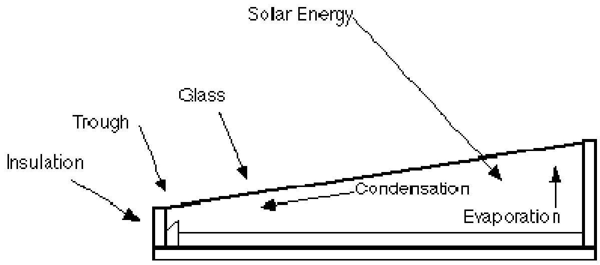


Figure 1 *Example model configuration*

Double Slop water Still plant

The aim of the Double Slope Solar Still Plant is to improvement in water production as compared to the single slop model. Such type of solar still made with mild steel plate, the minimum mass of water, and different wick materials like light cotton, sponge sheet, and waist cotton pieces. Figure 2 shows the model of the double slope Solar Still Plant. The different components of the models are also given in the diagram. The model is similar in shape and size to single slop still plant but it has two slops. Models contain a box-shaped water tank filled with water. The body of the box is designed with a Galvanized Iron sheet. This plant can be used with any side of the cover to gain direct and higher solar radiation. But another side of the cover remains at a lower temperature which enhances the property of condensation. The double slope water still is covered with glass from two sides to create two different slops. In the double slope still, plant both the slops are inclined at different angles. The generated steam condensed over the glass cover and walls is collected using a drainage system.

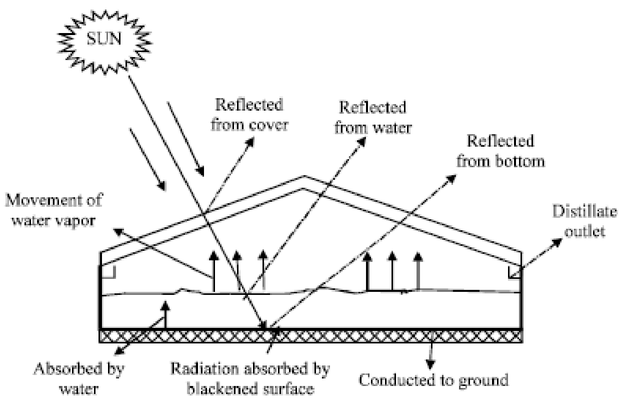


Figure 2 *double slope solar still*

Pyramid geometric water still plant

Figures 3 demonstrate a pyramid-shaped still plant. This model contains four slops to create the pyramid-like geometry. It also contains a box water tank. The key advantage of the plant is that it can observe solar energy from any side of the cover. Therefore it gains higher solar radiation. This idea enhances the property of condensation by maintaining the temperature difference between the water surface and cover. The sunlight is passed through the glass cover and heated to the water, for the evaporation process. The generated steam condensed over the glass cover and walls. Thus it is collected using a drainage system [35].

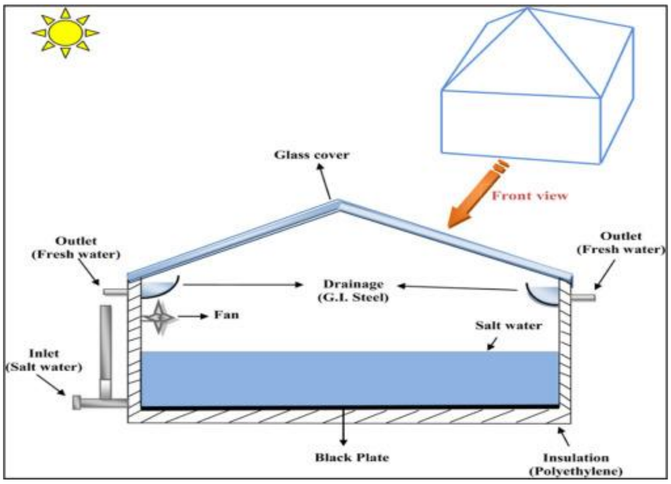


Figure 3 *pyramid geometry solar still*

Review of Solar Water Still Plant Improvement

Solar energy can be used as an efficient source of heat but it is a time-consuming process. M. Chandrashekara et al [7] discussed different methods of solar desalination. The indirect methods are utilizable for large scale, and direct methods are for small scale water production. That can be improved by locally available materials and can produce daily need of fresh water. M. T. Chaichan et al [8] examine thermal energy storage used for water distillation. Solar energy is stored during the day, and used later. There are four scenarios studied. The working time increased about 5h with tracker and PCM. D. B. Singh et al [9] studied the performance of partially covered hybrid photovoltaic thermal (PVT) flat plate collector (FPC) solar still. The system has been developed and the data collected. It is found there is a relationship between experimental and theoretical values.

A. M. Manokar et al [10] are studying the performance of a PV panel-based solar still. That shows 7.3 kg is maximum output, using an inclined basin, and insulation of the walls and bottom has improved the performance. F. Suarez et al [11], investigate a direct contact membrane distillation system for salt-gradient ponds. A model was developed and experimented with different locations, and circumstances. Consequences demonstrate system can fulfill the water and energy demand. The parameters influence water production rates such as air pressure and thermal efficiency. The inclined still's performance was examined by R. S. Hansen et al [12] for wick materials used. The aim is to suggest materials for absorption, porosity, capillary rise, water repellence, and heat transfer. According to findings water coral fleece material is the most suitable material.

R. Sathyamurthy et al [13] reviewed various solar still geometrical shapes and found that the geometry of still influences performance. B. Gupta et al [14] design a modified single slope still. It includes painted white color walls and (ii) a water sprinkler. The water output was found enhanced from 2940 ml and 3541 ml. K. H. Nayi et al [15] studied the development of the pyramid still to improve. It is efficient and economical. This study helps to conceptualize pyramid solar still, challenges, and issues to improve cost and performance. G. Xue et al [16] a compact solar-thermal membrane still system with features like localized thermal heating, cooling, and recycling of heat is proposed. The rate of steam generation is 0.98 kg and productivity is 1.02 kg found. A water generation of 3.67 kg salt rejection over 99.75% recorded.

H. A. Madhhachi et al [17] evaluate factors that influence the production of water. Observation parameters are evaporation temperature, volume, and current power. Experiments show that sample water temperatures from 30 °C to 60 °C increase total water production by 47% and total production by 58%. R. Ullah et al [18] review energy parameters such as energy efficiency, and output. Additionally, discusses the impacts of membrane properties. The application of MD is also explained. This analysis establishes its strengths and limitations. L. Zhu et al [19] discuss conversion steps of photo-thermal solar absorber materials and designs for scalable water desalination, purification, and energy. The aim is to provide recent development in evaporation and to inspire on large-scale water production. According to L. Zhu [20] a low-cost carbon sponge has good light absorption ability and structural properties to better heat localization. Solar-to-vapor conversion efficiency is increased by 2.5 times. Z. M. Omara et al [21] investigate double-layer wick material and reflectors. The influence of water depth is described. Results show improvement in efficiency and productivity up to 145.5% higher.

A. F. Mashaly et al [22] present a forecasting system using adaptive neuro-fuzzy inference, neural networks, and multiple regressions. The dataset composed with different operational and meteorological variables. The low errors, high predictability, and feasibility are found with ANN. M. S. Yousef et al [23] done performance enhancement of solar still. Pin fins heat sink (PF) is used to enhance conductivity. Steel mesh fibers are employed in the basin. The finding shows total daily cumulative yield with PCM, PCM-PF, and PCM-SWF is higher. The inclusion of the fins sinks increases the daily energy and efficiency. The efficiency of PCM-PF is higher than PCM. The SWF with PCM improves enhances daytime efficiencies. The total daily evaporative energy of PCM-SWF is higher. T. Parkinson et al [24] evaluate the low-cost IEQ monitoring system. Data from 100 devices were used. Performance was evaluated using Monte Carlo simulation. The result shows it is not as accurate as laboratory models. That system is better for long-term performance.

M. S. Yousef et al [25] is studying the performance of a single slope still with phase change materials. The investigation involves (1) still based on PCM (2) coupled with PCM (3) with hollow cylindrical pin fins (4) with PCM and steel wool fibers (5) with only steel wool fibers. The finding says the presence of PCM affects productivity. Also, still based on PCM and pin fin achieves the best performance. A smart temperature monitoring system was developed by N. M. Mokhtar et al [26]. The aim is to monitor and capture the temperature to control the flow of the water pump. The real-time data was displayed and saved. The highest temperature attained based on the experiments was above 60°C. A fluctuation in energy consumption was observed. The system also demonstrates a moderate separation efficiency and salt rejection of 93.96%.

An experimental study of ML techniques

This section provides the performance of two ML models, which are suitable for continuous value prediction. Then appropriate model is extended for improving accuracy. This improved model is used for still plant’s performance monitoring.

ML Algorithms

The following two ML techniques are used for predicting the performance:

Neural network (NN)

The continuous prediction is the main aim of the neural network. During the process of training the data is provided as input and network take training by adjusting network weights. For termination a fixed epoch cycles is used. The trained model is used for predicting the values [27]. The NN consists of multiple layers and each layer is defined using multiple neurons. The neurons are connected densely throughout[28]. The weights are denoted as W_{ij} and the neurons are denoted as y_i. The weights are initialized using the random values between 0 and 1. By using eq. (1) the inputs values and weights the output is calculated:

$$x_j = \sum_{i=0} y_i W_{ij} \,.\,(1)$$

Where, y_i is the input of the j^{th} unit in the previous layer, W_{ij} is the weight of connection between i^{th} and the j^{th} unit.

To produce the output y_i an activation function is used such as sigmoid function. Finally, when outcomes for all output units have been measured to calculate error (E) using eq. (2):

$$E = \frac{1}{2}\sum_{i}(y_i - d_i)^2 \; (2)$$

Where, y_i is output of the j^{th} unit and d_i is actual output.

Finally, to adjust the error an Error Derivative (EA_j) is calculated to modify the weights using eq. (3):

$$EA_j = y_j - d_j (3)$$

Linear Regression

The regression is also used for prediction. In this technique we are estimating a function that fit the given series of data [41]. The regression equation requires to understanding the nature of data and the number of inputs. In linear regression usage a line equation (4):

$$f(x) = y \; = \; mx \; + c(4)$$

That maps the linear relationship among the variables x and y. Thus for each x we calculate the values of y and represented as eq. (5):

$$\emptyset \; = \; \delta \; + \; \mu x. (5)$$

According to above equation $\emptyset$ is a dependent variable, x is independent, additionally μ is slope of line and δ is the intercept. To calculate δ and μ we can use the eq. (6) and (7):

$$\delta = \frac{(\sum \emptyset)(\sum x^2) - (\sum x)(\sum x\emptyset)}{n(\sum x^2) - (\sum x^2)} (6)$$

$$\mu = \frac{n(\sum x\emptyset) - (\sum x)(\sum \emptyset)}{n(\sum x^2) - (\sum x^2)} (7)$$

Where, n are the samples involved in observations.

Improved NN model

The dataset is collected using three different solar still plants. The dataset includes basin temperature, cover temperature, water temperature, solar radiation, and ambient. The water production yield and instantaneous efficiency are the predictable variables. Each datasets contains a total of 2160 instances. The data is collected using an automatic process; therefore the mistake in the dataset is possible. Thus, first the prepossessing is adopted for verifying the data quality. The preprocessing steps are given in table 1.

Table 1 *data preprocessing*

Input: dataset D **Output:** pre-processed data P
Process: 1. $[row, col] = readDataset(D)$ 2. $for(i = 1; i \leq row; i++)$ a. $temp = D_i$ b. $for(j = 1; j \leq col; j++)$ i. $if(D_{i,j} == null)$ 1. $removeRow(i)$ ii. Else 1. $P_i.Add(temp)$ iii. $end\ if$ c. $end\ for$ 3. End for 4. $return\ P$

Before utilizing the data we apply the linear regression for identifying outliers in data [43]. The MATLAB is used for regression analysis. That function can be written as eq. (8):

$$[\beta_0, \beta_1, R, R_i, stat] = Regress(X, F) \ldots\ldots\ldots (8)$$

According to this function if the interval R_i for an observation has not pass through zero, then it is recognized as outlier. In order to remove them the following algorithm is used as given in table 2.

Table 2 *outlier removal*

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

After that, we find a linearly fit dataset, which can be used for better learning. Therefore, during neural network training in place of random initialization of network, we proposed a weight initialization process. First we use the min-max normalization and correlation coefficient. The Min-Max Normalization is defined in eq. (9):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (9)$$

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

And Correlation coefficient is given using eq. (10):

$$C_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i-1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i-1}^{n}(y_i - \bar{y})^2}} \ldots\ldots\ldots (10)$$

Where, n = number of sample, 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 the dataset attributes are normalized using the min-max technique, and then correlation coefficient is used for selecting the optimal weights to be initialize the neural network. The process of neural network initialization is demonstrated in table 3.

Table 3 *weight selection algorithm*

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

The selected weights are used for the initialization of the neural network. After the initialization, the normalized values are used for learning. In addition, last layer of neural network has modified with RBF (radial basis function) to update the weights. The RBF kernel is defined in eq. (11). The RBF kernel is used for distance computation between predicted and actual values.

$$RBF = exp\left(\frac{\|x - x'\|^2}{2\sigma^2}\right) (11)$$

The data is subdivided into two subsets i.e. **training and testing dataset.** The training dataset is containing 70% of samples and the testing data is 30%. The training dataset is used with Linear Regression (LR), Neural Network (NN) and Improved Neural Network (INN). The models are takes training using the training data. The process of training is summarized in table 4.

Table 4 *proposed algorithm*

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

The algorithm in table 4 accepts a dataset D as input and read it. The dataset has stored in a vector $\mathrm{R_n}$, which is preprocessed to clean, and stored in a new variable $\mathrm{P_n}$. The liner regression has used with preprocessed data for outlier identification and removal. Then normalization is preformed and stored in a variable $\mathrm{O_n}$. The $\mathrm{O_n}$ have used for creating the test datasets $\{\mathrm{T_1}, \mathrm{T_2}, \mathrm{T_3}, \mathrm{T_4}\}$. Now the modified BPN have used. Then $\mathrm{O_n}$is used to train BPN which results as $\mathrm{T_{model}}$. Finally the $\mathrm{T_{model}}$ used with the test datasets and predict the values and the accuracy has measured. The mean accuracy $\mathrm{A} = \frac{\mathrm{A}}{4}$ is results as validation consequences. The P as the predicted outcome is also returned.

A system for predicting maintenance decision

In this section we employ the enhanced algorithm for simulation of the maintenance decision making task. Thus we describe system architecture of the required system.

System Overview

The proposed model is providing a Machine learning model for maintenance task. In this context, the entire system can be divided into three parts.

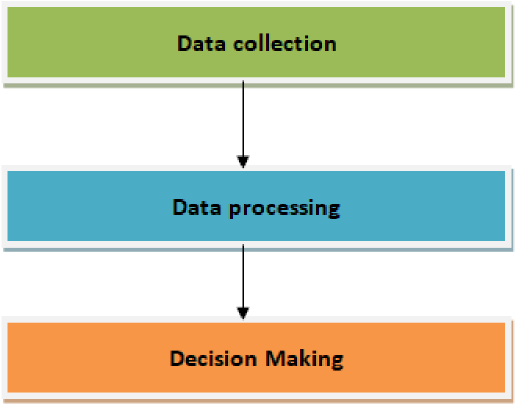


Figure 4 *Layers of proposed model*

The figure 4 describes the components of proposed experimental model. We explain each of them as:

Data collection

In this experiment we have collected data from local laboratories of Bhopal, Madhya Pradesh. Additionally the solar radiation data set available online has been used for experiment. However, we can use the Internet of Things (IoT) enabled devices for data collection. That helps to collect data and send the data to a base station for data processing. After data processing the model will perform a call for maintenance.

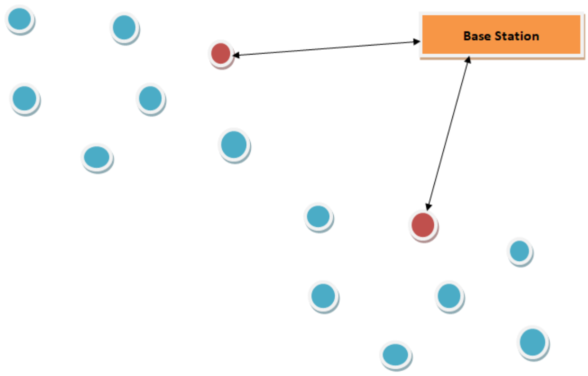


Figure 5 *Example of Required IoT Network*

Figure 5 demonstrates an IoT based network for supporting the monitoring and maintenance of solar still plants. The figure consists a network made with three types of nodes. Blue nodes are demonstrating the IoT device fixed on solar still for collecting the still plant parameters. Node represented using red color are used for collecting the data from their member nodes. These nodes are working as cluster head. Finally the base station node is receiving the information from the cluster head for processing.

Data processing and decision making

The data collected from the network source will be utilized for analysis in this phase. The data is stored on base station, additionally the data processing and decision making process is also implemented on it. The figure 6 provides the functional overview of the proposed model for experimental study.

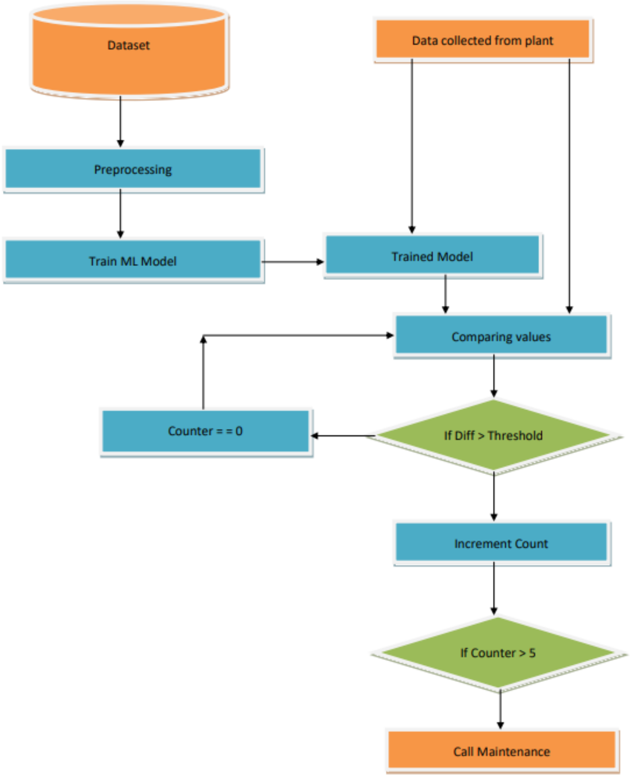


Figure 6 *Data Analysis and maintenance System*

The proposed model first takes training for making predictions. Therefore, we utilize the previously collected data of different laboratories for performing the training of the model. The experimental data preprocessed before utilizing with the machine learning algorithms.

Table 5 *Performance of three predictive algorithms*

Dataset	LR			NN			INN		
	Single Slope	Double Slop	Pyramid Shape	Single Slope	Double Slop	Pyramid Shape	Single Slope	Double Slop	Pyramid Shape
300	59.35	56.79	58.93	71.25	70.58	72.31	80.21	81.37	79.45
500	61.73	58.41	63.27	71.98	76.31	73.22	82.38	83.82	81.61
800	63.92	59.35	61.41	73.15	72.43	74.59	81.42	84.11	83.19
1000	62.86	61.42	62.96	72.63	74.32	75.15	83.65	85.35	85.16
1500	63.53	60.53	61.47	74.38	75.11	76.44	84.42	86.42	87.28
2160	65.88	64.29	66.21	75.31	76.42	77.38	86.59	88.33	89.13
Mean	62.87	60.13	62.37	73.11	74.19	74.84	83.11	84.9	84.3

Therefore we utilize the preprocessing as demonstrated in table 1. After that we have trained three ML algorithms namely LR, NN and INN. The trained model then used for prediction of the solar water still performance one step ahead. Here for prediction value we use the symbol P. on the other hand we also obtain actual value of solar still plants, which is denoted as A. Using both the values P and A we calculate the difference. This difference is demonstrating the difference between predicted value and actual value of solar still plant performance.

Now we need a threshold value to identify the abnormal performance variation. In this context, we first need to identify a threshold value. The threshold value for the proposed model is described using eq. (12).

$$Th = \frac{1}{N}\sum_{i=1}^{N} ||P - A|| \ (12)$$

Additionally the difference between P and A is denoted by eq. (13).

$$Diff = ||P - A|| (13)$$

If difference between predicted value and actual value is increased then threshold then we increases a counter. When the counter reaches to the maximum of 5 times in a series then the system recognize a maintenance call. On the other hand if the model provides difference less than 5 times then system reset the counter.

After implementation of the proposed model using the python technology we have conducted experiments with the system. The experiments are carried out with the dataset and the performance has been calculated and reported in next section.

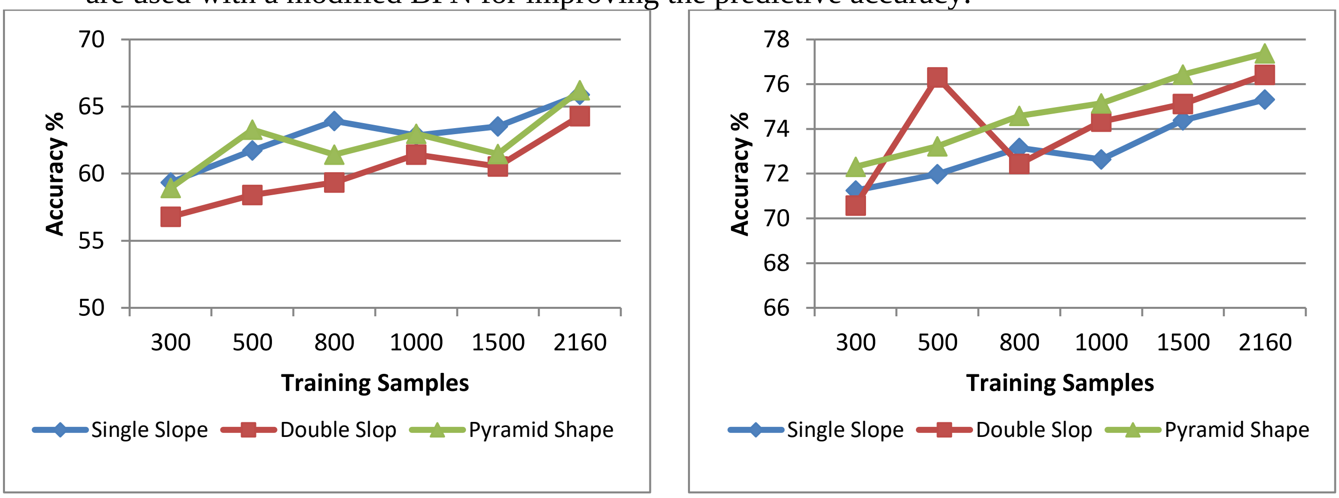
Results analysis

The experimental analysis of proposed predictive method for monitoring and maintaining the solar still plant performance is discussed in this section. Therefore experimental scenario and obtained results are described.

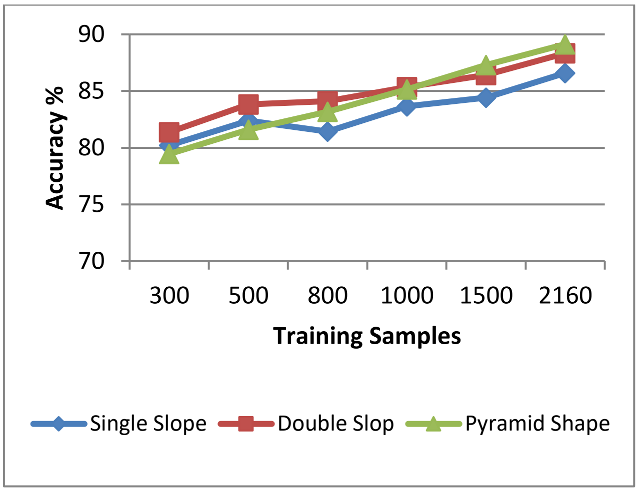
Experimental Scenarios

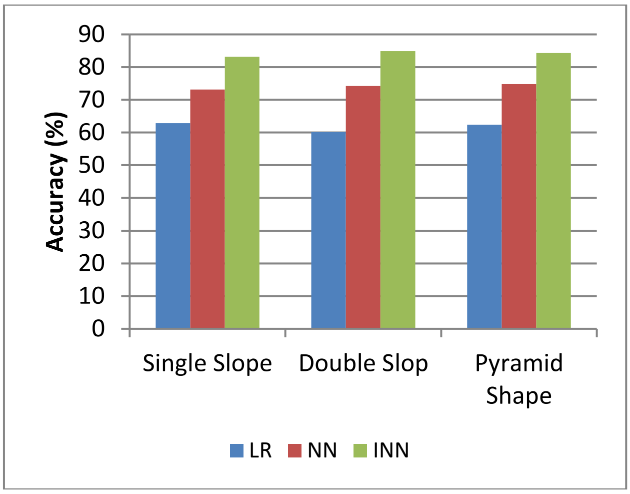
The performance of the proposed monitoring and maintenance model is depends on accuracy of prediction. Inaccurate prediction can impact on entire monitoring system performance. In this context the following experimental scenario is proposed for experiments:

1. Experiment with linear regression based model: in this experiment the linear regression algorithm is used for conducting experiments with the collected data from all three kinds of samples.
2. Experiment with classical NN: the traditional NN algorithm is utilized with the datasets and obtained results are compared to linear regression model.
3. Implementing improved INN to predict the solar water still performance**:** the datasets are used with a modified BPN for improving the predictive accuracy.



(A) (B)





(C) (D)

Figure 6 *Accuracy of the prediction for three types of solar still plants using (A) Linear Regression (B) traditional Neural Network (C) improved Neural Network and (D) mean accuracy of models*

Performance analysis of single slop solar water still

Mainly we have evaluated the accuracy of the models, which is used to demonstrate the success rate for prediction. That can be measured using the following equation (14).

$$\text{Accuracy} = 100 - \frac{1}{n}\sum_{i=1}^{n}|A - P|\,X10014)$$

The accuracy of the implemented algorithms namely NN, LR and INN is computed and demonstrated in figure 6 and table 5. The figure 6(A) shows the prediction accuracy using LR for three kinds of solar still, similarly 6(B) contains the accuracy of classical NN, and the proposed algorithm's accuracy is given in 6(C). Finally there mean performance is demonstrated using 6(D) in a bar graph. In the line graphs X axis includes the sample size and Y axis represents the accuracy in percentage (%). According to the obtained results the accuracy of the classical algorithm is unexpectedly low due to outliers. Then the proposed modified INN model works more accurately.

Conclusion and future work

The proposed work is motivated to employ ML technology over life saving application for sustainable leaving. In this context we studied the different ML techniques, sensor technology, solar water still plants and their applications with their performance improvement techniques. Based on theoretical and experimental experience we found the essential facts which are discussed in terms of conclusion and future work.

Conclusion

The proposed work involves a number of tools and technology for preparing the required model. Therefore we conclude the entire work in two major parts:

Study of solar energy harvesting as solar still plants and their improvement techniques: here we include the solar water still plants for study. This study involve single slop solar water still, double slop solar water still and the pyramid geometric solar water still. Additionally, we investigate the different research articles for finding the trends and improvement methods of solar water plants productivity. According to the findings we conclude the improvements in the following facts:

a. Solar water still plants can produce significant amount of water to drink and basic utility
b. Solar water plants are low cost and easy to built in basic materials
c. Small changes such as inclusion of fan and sprinkler improve the performance
d. Paint on walls, inclusion of insulation martial, and phase change martial can improve productivity of plant
e. The single slop produces lower, double slop middle and pyramid shaped plant provides higher productivity
f. The plant productivity is influencing with weather conditions such as wind speed, clouds, radiation, positions and angle of sun
g. The productivity is also influencing with number of slops and angle of cover

2. The design of a predictive monitoring system using ML algorithms: the communication and computation technologies can improve the productivity of the systems. Therefore we can improve the solar still performance by monitoring and maintaining them. In this context we implement three experiments as follows:

a. In first experiment the ML models based on linear regression, neural network and an improved neural network has been implemented. The experiments with these models demonstrate that the INN algorithm produces higher accurate results.
b. The inclusion of outlier detection and removal from the training dataset, and normalization, for weight initialization of the neural network improves the overall performance the monitoring system.
c. The model contains the properties of the NN, additionally includes the RBF kernel for improvements. The model improves accuracy.
d. By using the experiments we find it the quality of data seriously impact on the performance of predictive algorithm's performance.
e. Pre identified weight can also help to improve the training time, and the accuracy of the learning algorithms.

Future Work

The proposed work is enhancing the productivity of solar water still plants. Therefore maintenance and mentoring techniques using predictive method is proposed. The model has developed and experimented successfully and based on which the following work has been proposed for future extension.

- Develop the proposed model with real time system.
- Generalize the system to employ with different applications to support in monitoring

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