

Designing Single Slop Single Basin Solar Water Distillation Plant Performance Monitoring and Prediction System



Rajeev Raghuvanshi, Dhanraj Verma, Manojkumar Deshpande, Md. Ilyas

Abstract: *the issue of the water crisis is rising day by day, due to global warming and other environmental effects. That is not only the issue for India, but it is also for the entire world. However, the solar-based water distillation plants are not much efficient but we can use this method for producing pure and drinkable water. In this paper, we proposed to design a solar water distillation plant using the single slop method. In addition to that for monitoring and measuring the performance of the distillation plant a data mining based prediction system is implemented. The experiments are performed on the real-world implemented single slop solar water distillation plant-based observations. The observations are collected using the IoT (Internet of things) device for each five-minute time difference for each sample collection. The data samples are collected between 10:00 AM to 4:00 PM for 7 days. Additionally by using the collected samples the data mining model is trained and tested on the prepared syntactic dataset. The experimental results demonstrate accurate predictions for the solar distillation water plant. After this implementation and system model, the future directions of the research are also provided.*

Keywords: *machine learning, data mining, solar energy, water distillation, performance prediction and monitoring.*

I. INTRODUCTION

Water is the basic necessity of humans and other creatures in this world. Continuous mistakes of humans, industries, automation, transportation, and others increase the volume of various global warming factors [1]. The results are a flood, polluted water, and polluted air, dry weather conditions and many more. If we not take care about environment it becomes impossible to sustain in this world [2]. In recent years significant efforts are placed in recovering the effects of global warming.

Additionally the planning and techniques are being explored by researchers for sustaining the lives. In this context waste water management, water purification techniques etc. works to deal with water crises issues are also noticed in a significant amount [3].

The proposed work is an effort to monitoring and predicting the water production using solar still plants for sustainability as fresh water source, because the solar still plants are less expensive and can easily made using locally available materials. That is capable to generate a sufficient amount of water for a family's daily usages. Therefore the following objectives are proposed work for the complete research work.

1. To design and enhanced solar water still plant for sustaining a small family
2. To implement a machine learning or data mining technique to analyze and predict the performance accurately for a solar still
3. 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
4. By using the identified features and factors prepare more accurate and efficient data models

In this paper an initial effort for accomplishing the proposed four pints are provided. This section just provides the key objectives of the proposed work plan. In next section a review on recent efforts are provided. Further a laboratory design of solar still plant is described and the developments of dataset are provided. Moreover to predict and monitor the system performance a machine learning model is implemented with their results analysis. Finally the future prospective and work plan is also reported in this paper.

II. LITERATURE SURVEY

The desalination plants are not energy efficient. These systems consume higher energy using electricity, gas, and oil. The process releases carbon, which harm the ozone layer. It leads to global warming which is a threat to life sustainability. Solar energy is a rich source of heat. The solar desalination is a slow and low cost process with a one-time investment. Various solar desalination methods direct and indirect have been discussed by *M. Chandrashekara et al [4]*. The indirect methods are suitable for medium and large scale desalination, and direct methods are for small scale. Performance of solar stills can be improved by modification.

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* Correspondence Author

Rajeev Raghuvanshi*, PhD in Computer Science & Engineering, College of Engineering, Dr. APJ Abdul Kalam University, Indore, India.

Dr. Dhanraj Verma, Professor in Department of Computer Science & Engineering, College of Engineering, Dr. APJ Abdul Kalam University, Indore, India.

Prof. Manojkumar Deshpande, Professor & Associate Dean at MPSTME, SVKM's NMIMS-Mumbai, Shirpur Campus.

Md. Ilyas, Assistant Professor in Department of Computer Science & Engineering, Prestige Institute of Engineering Management & Research Indore, India.

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These stills can be used for daily needs of fresh drinking water and other small households living. **Miqdam T. Chaichan et al [5]** investigates the usage of thermal energy storage extracted from solar heater for water distillation. Paraffin wax selected as a phase change material and used for storing 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 about 64.07%, 112.87%, and 307.54%. **D.B. Singh et al [6]**

deals with experimental studies and performance analysis of partially covered hybrid photovoltaic thermal (PVT) flat plate collector (FPC) solar still. The model of the system has been developed and data have been collected for composite climate condition. The results have been compared and observed fair agreement between experimental and theoretical values.

A. Muthu Manokar et al [7] work is an effort to study the performance of a PV panel integrated solar still to generate power and desalination. Performance is experimentally investigated from different aspects. Results show that maximum distillate output of 7.3 kg when inclined solar panel basin with sidewall and bottom insulation. **Francisco Suarez et al [8]**, the performance of a direct contact membrane distillation (DCMD) system driven by salt-gradient solar ponds were investigated. A mathematical model was developed and validated. Using this model performance of system in different geographical locations and operational conditions was studied. Results show that when system used to meet future needs of energy and water. The performance of an inclined type solar still was investigated by **R. Samuel Hansen et al [9]** using different wick materials on absorber plate configurations. New materials are characterized for absorption, capillary rise, porosity, water repellence and heat transfer co-efficient to select a suitable material. Performances were compared with wick materials i.e. wood pulp paper, wicking water coral fleece fabric and polystyrene sponge. To solve issues of drinking water solar desalination method is promising. **Ravishankar Sathyamurthy et al [10]** communicate a review of different geometrical shapes of solar still. They conclude that geometry in solar still significantly influences the yield of fresh water. **Bhupendra Gupta et al [11]** communicate the design of modified single slope solar still. The enhancements include walls painting inside with white color, inclusion of water sprinkler with a constant water flow on glass cover. The performance of modified still has been evaluated and compared with conventional still. **Kuldeep H. Nayi et al [12]** review development in the field of pyramid solar still and techniques to improve the performance. It has been found that pyramid solar still is more efficient and economical. Thus, it will assist the researchers to understand the fundamentals of pyramid solar still.

A compact solar-thermal membrane distillation system with three features: highly localized solar-thermal heating, effective cooling strategy, and recycling the latent heat, is proposed by **Guobin Xue et al [13]**. The steam generation rate is 0.98 kg in the open system, while water productivity could be 1.02 kg with a two-level device. Outdoor experiments show water productivity of 3.67 kg with salt rejection over 99.75% on a cloudy day. **Hayder Al-Madhhachi et al [14]** investigates the key factors that affect water production in a distillation system. Experiments

were performed to find influence of evaporation temperature, vapor volume, Peltier current and input power. Experiment shows that an increase in the sample water temperature from 30 °C to 60 °C led to an increase in total water production by 47% and an increase in total water production by 58% by reducing vapor volume from 600 cm³ to 400 cm³ during a 3-h operation. **Ruh Ullah et al [15]** review introduces central energy parameters for MD (e.g., energy efficiency, gained output ratio, etc.) and discusses the reported impacts of membrane properties, mass and heat transfer, feed water properties. **Liangliang Zhu et al [16]** discuss photo-thermal conversion processes of various solar absorber materials and designs of different interfacial photo-thermal evaporation pertaining to judicious optical, thermal and wettability management, and finally current progress in scalable saline water desalination, wastewater purification, and energy generation applications. The aim is to provide a summary of the recent development in interfacial photo-thermal evaporation. Additionally, an inexpensive cellular carbon sponge that has a broadband light absorption and inbuilt structural features to perform solitary heat localization for in situ photo-thermic vaporizations is reported by **Liangliang Zhu [17]**. By isolating from bulk water, the solar-to-vapor conversion efficiency is increased by 2.5-fold. The performance of corrugated solar still (CrSS) and conventional solar still (CSS) is investigated experimentally. **Z. M. Omara et al [18]** concerns with double layer wick material and reflectors together inside the CrSS. Additionally, the influence of water depth (1, 2, and 3 cm) on performance. Results indicated enhancement in total productivity and efficiency of CrSS. The productivities of CrSS with wick and reflectors are about 145.5% higher than the CSS.

III. EXPERIMENTAL SETUP

This section explains the devices and experimental data which are collected for measuring the performance of the solar still plant.

A. Solar still plant

The aim of the work is to first design a solar distillation water plant that purifies the Sewage into drinkable water. In this context, a model that is already available in our laboratory is used. This model is a single slop single basin solar water distillation plant model. These models are very basic and low cost in nature but that can produce the water for daily use which is pure and drinkable. Thus in conditions of huge water crisis, we can use this model for purifying the water. The model of a single slope single basin solar water distillation plant is given in "Fig. 1".

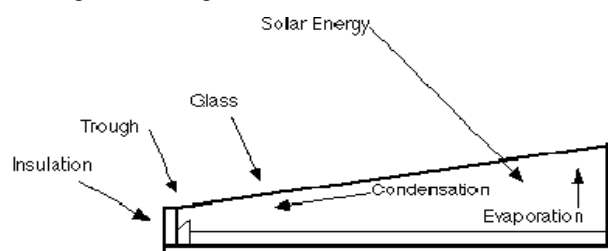


Fig. 1. Example model configuration.



“Fig. 1” demonstrates a basic overview of the single-slope single basin solar still plants. Additionally, the different key components of the models are also given in this diagram. It is a box-shaped model which consists of a water tank, and a glass cover. The sunlight radiation is passed through the glass cover and heated the water, by which the evaporation process is started. The prepared steam condensed over the glass cover and walls, and the slop helps to drain or pour the water into a basin. The laboratory model for performing the experiments is given in “Fig. 2”. The entire box dimension of the obtained experimental plant is 120*85*25 cm. The body of experimental box is designed with the help of the GI (Galvanized Iron) sheet of 3.5 MM thickness. That thickness is verified using a Vernier caliper device. In order to cover the GI box, the used glass is made with 5 MM thick.



Fig. 2 Laboratory model

The glass cover of the still plant is inclined in 15° . Additionally, to collect the freshwater the basin is designed with a metal sheet of GI (Galvanized Iron). But to prepare drain water in basin J-shape drainage is available which helps to collect distillate water as output. The basin also consists of a measuring jar. Additionally to enhance the absorption of solar radiation the walls of the box are coated with black paint.

B. Data collection & Observation

The above-described model is used for conducting the experiments. The model needs a significant amount of temperature or heat for evaporation purposes. Therefore the timing between 10:00 AM to 4:00 is suggested for conducting the experiment. An IoT (internet of thing) device is also established with the plant for measuring the different parameters of the solar water still plant. These parameters are basin temperature, condensing cover temperature, water temperature, solar radiation intensity, and ambient temperature. The device collects these parameters in each 5 minute time difference, additionally communicated over a database. Thus observation is made in a total of 72 samples. But it is not a significant amount of data to learn with a data mining or machine learning model. Therefore, we enable this model to collect the sample for a total of 7 days, thus we have a total of $72 * 7 = 504$ samples for learning with their distilled water yield or efficiency and the instantaneous performance of the system in terms of percentage (%).

IV. PROPOSED MODEL

This section demonstrates how the proposed data mining model is working for providing the prediction about the

instrument instant efficiency. That process can also be used to monitor the performance of large scale production of solar distillation plants. This section includes a description of the proposed algorithms for prediction and monitoring.

A. Methodology

The proposed data model for predicting the solar water still plant performance is demonstrated in “Fig. 3”. Additionally, the description of involved components is also reported in the same section.

The process of the given data model is to start with producing the **Input dataset**. According to the previous discussion in section III (B), the collected observations from the single slope solar still plant are used as the training data for the proposed monitoring and prediction system. The dataset includes the basin temperature, condensing cover temperature, water temperature, solar radiation intensity, and ambient temperature as the attributes for learning. Additionally, the water production yield and instantaneous efficiency of the plant is the predictor variables. Thus first the collected samples of all the seven days are accepted as input datasets for learning and validation of the prediction performance.

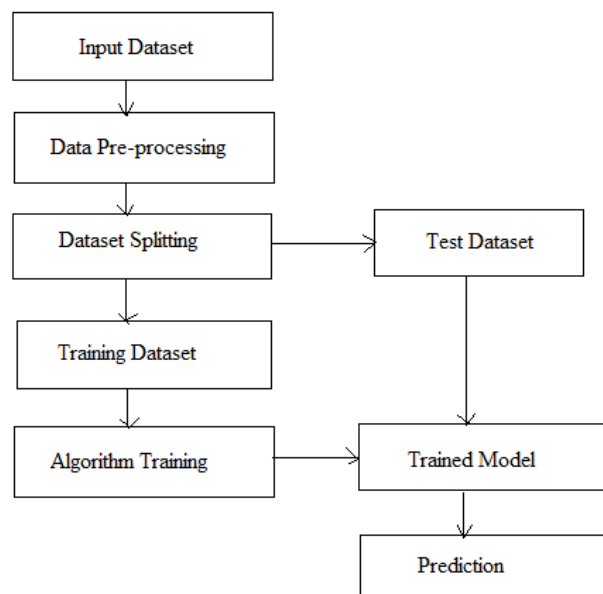


Fig. 3: Proposed system

After acceptance of input data, the **preprocessing** of the data is performed. The aim of preprocessing is to improve the quality of data. Additionally, it makes effective learning with the target algorithms. In this context following process is used for improving the quality of data.

Input: dataset D
Output: preprocessed data P

Process:

```

1. [row,col] = readDataset(D)
2. for(i = 1; i ≤ row; i++)
    a. temp = Di
    b. for(j = 1; j ≤ col; j++)
        i. if(Di,j == null)
            1. removeRow(i)
        ii. Else
            1. Pi.Add(temp)
        iii. end if
    c. end for
3. End for
4. return P
    
```

Table-I: Data preprocessing

After that process data is subdivided into two subsets namely training and testing dataset. The training dataset is the set of 70% of the entire dataset and the testing data is 30% of the total data samples normally. But to identify the effect of data over the learning performance the different sizes of sets are created for training data 30, 50, 80, 100, 200 and 500. Additionally, for the testing purpose, 30% of data among the selected data samples as a training set is extracted. The training dataset is used with two data models namely linear regression and back-propagation neural network. Both the techniques are explained as:

Back propagation neural network (BPN)

To implement the neural network training method utilizes data and trained with the data. During this process, the continuous data is produced and weights of the neural network are adjusted for finding the desired outcome. To regulate the termination condition number of training cycles is used to stop the training process. After completing the input number of training cycles the network is trained and can be used for predicting the values by producing the required attribute values [19]. So, first need to create two vectors first is used for defining the input and hidden unit and second is used to store the output. The two-dimensional vector is denoted here as W_{ij} and a one-dimensional vector is defined as Y_i . Now the weights are initialized using the random values between 0 and 1. Further by using the inputs and the associated weights the output for the neurons is calculated using the following equation.

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

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

Finally to produce the actual values y_i is estimated using a sigmoidal function.

$$y_i = \left(\frac{e^x - e^{-x}}{e^x + e^{-x}} \right) \quad (2)$$

Finally, when outcomes for all output units have been measured the network calculates error (E). To calculate the error of network we can use the following equation.

$$E = \frac{1}{2} \sum_i (y_i - d_i)^2 \quad (3)$$

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

Now to adjust the error in different training cycles Error Derivative (EA_j) is calculated to modify the weights. That can be computed using

$$EA_j = y_j - d_j \quad (4)$$

Additionally Error Variations of total input received by an output changed is measured using

$$EI_j = EA_j y_j (1 - y_j) \quad (5)$$

Additionally Error Fluctuations over connection into output unit is calculated using

$$EW_{ij} = EI_j y_i \quad (6)$$

And overall Influence of the error is calculated by using

$$EA_i = \sum_j EI_j W_{ij} \quad (7)$$

Linear Regression

In a number of data analysis techniques, the regression is used. That is a manner by which we can estimate an effective function that can fit the given series of data. Therefore to provide effective and accurate predictive outcomes need to establish a regression equation [20]. The regression equation requires understanding the nature of data and the number of input variables and based on these two factors the regression equation is designed. In this work, we use a simple linear regression method.

In linear regression, the concept of line is used for fitting the data. The line is defined using

$$f(x) = y = mx + c \quad (8)$$

That helps to map the linear relationship among the independent variable x and a dependent variable y . Thus for each x in the given data sample, we have to calculate the values of y . in terms of linear regression the equation can be used.

$$\phi = \delta + \mu x \quad (9)$$

It is also used to model the relationship among two variables according to the above equation ϕ is a dependent variable, and x is independent, additionally, μ is the slope of the line and δ is the intercept. To calculate the next values of δ and μ we can use these formulas:

$$\delta = \frac{(\sum \phi)(\sum x^2) - (\sum x)(\sum x\phi)}{n(\sum x^2) - (\sum x)^2} \quad (10)$$

$$\mu = \frac{n(\sum x\phi) - (\sum x)(\sum \phi)}{n(\sum x^2) - (\sum x)^2} \quad (11)$$

Where n is the sample involved in observations.

Both models are takes training using the training data and the trained model is developed. That accepts the raw input and produces the predictive outcomes for water yield performance and instantaneous efficiency.

B. Proposed Algorithm

This section summarizes the process of the entire system modeling. “Table-II” includes the steps of the proposed algorithm for analyzing and predicting the required parameters.

The proposed algorithm is given in “Table-II”, in this table all the required steps are demonstrated. According to the given process steps, the system accepts the input dataset for learning and prediction of required variables. The system read the dataset instances and stores the data in variable D_n , where n is the number of instances to learn. In the next step, the data is preprocessed as defined in algorithm 1 given in “Table-I”. The preprocessed data is stored over the variable PP_n . The dataset further splitter in two parts $Train_m$ and $Test_o$. Both the subsets of data consist of m and n numbers of instances respectively.

Input: input dataset D, Selected Data-model M = {BPN, LR}
Output: Predicted Value [P, Acc]
Process: <ol style="list-style-type: none"> 1. $D_n = readDataset(D)$ 2. $PP_n = PreprocessData(D_n)$ 3. $[Train_m, Test_o] = PP_n.Split$ 4. $T_{model} = M.Train(Train_m)$ 5. $for(i = 1; i \leq o; i++)$ <ol style="list-style-type: none"> a. $P = T_{model}.Predict(Test_i)$ b. $A = Test_i.LastIndex$ c. $if(P - A \rightarrow 0)$ <ol style="list-style-type: none"> i. $Acc += 1$ d. End if 6. End for 7. Return [P, Acc]

Table-II: Proposed algorithm

Now using the selected data model M and the training dataset $Train_m$ the learning is performed after learning the system results in the T_{model} as the trained data model. The T_{model} and test dataset $Test_o$ is used for validation of the learned model. During this using the predicted variable P and actual observation A the prediction accuracy of the data model is decided. Finally, the system produces the final outcome as predicted outcome and model accuracy.

This section describes how the proposed algorithm processes the data. In the next section obtained performance of the system is delivered.

V. RESULTS ANALYSIS

After the successful implementation of the proposed data model the performance of the system is measured and reported in this section.

A. Accuracy

The accuracy or precision is the rate of correctly predicted data samples over the total data samples produced for prediction. That can be measured using the following equation.

$$Accuracy = \frac{\text{Total correctly predicted samples}}{\text{total samples to predict}} \times 100$$

The accuracy of the implemented algorithms namely BPN and LR is computed and demonstrated in “Fig. 4”. The performance of distilled plant prediction system is demonstrated in demonstrated using line graph in this diagram where X-axis indicates a number of training samples involved for prediction algorithm training and Y-axis represents the accuracy of prediction in percentage (%) The accuracy of both the algorithm is unexpectedly low because of outliers and other influences over the observations. The accuracy of the BPN algorithm is efficient as compared to the LR algorithm.

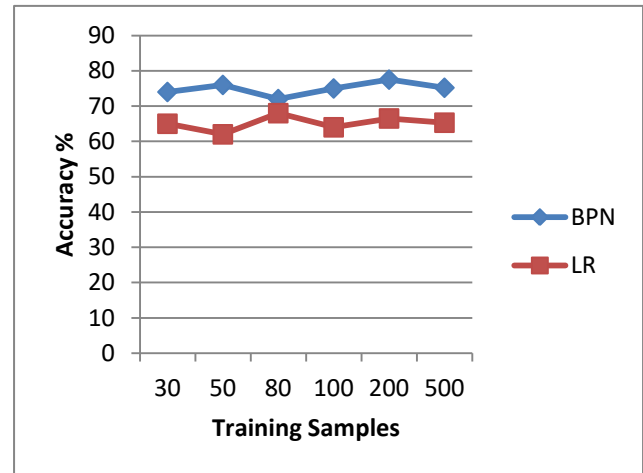


Fig. 4 Accuracy (%)

B. Memory usages

The algorithm execution for processing the input data needs an amount of main memory to host the data. This size of memory storage is measured as memory usages is termed here as the memory usages. In JAVA technology it is computed on the basis of process execution where the system assigns a fixed amount of main memory to a particular process and process return the amount of free amount of main memory, using these two parameters we can calculate the memory usages using the following equation.

$memory\ usages = Assigned\ memory - free\ memory$
The memory usages of the implemented two-time series based prediction algorithms i.e. BPN and LR is given in “Fig. 5”. The memory is sometimes also known as space complexity of algorithm which is also an essential parameter for measuring the system performance. The memory usages of the implemented data models are given here in terms of KB (kilobytes). The X-axis of the diagram indicates the number of training samples is involved for prediction algorithm training and the Y-axis shows the measured memory consumption. According to the observations, the BPN shows consistent performance as compared to the LR algorithm because as the size of training increases the LR memory requirements increase.

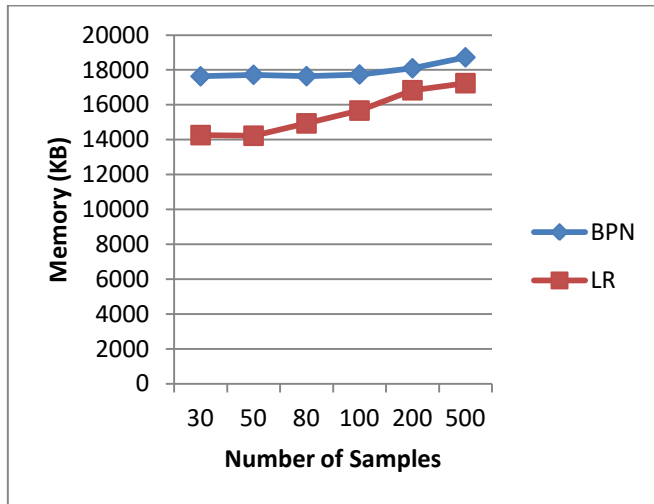


Fig. 5 Memory usages (KB).

C. Time required

In order to report the performance of any algorithm, the time requirement of data analysis is an essential parameter. That is also known as the time complexity of the algorithm. Basically it is the amount of time required to processing the supplied data for analysis. The following formula can be used for computing the time requirements.

$$\text{Time Required} = \text{Algorithm End time} - \text{start time}$$

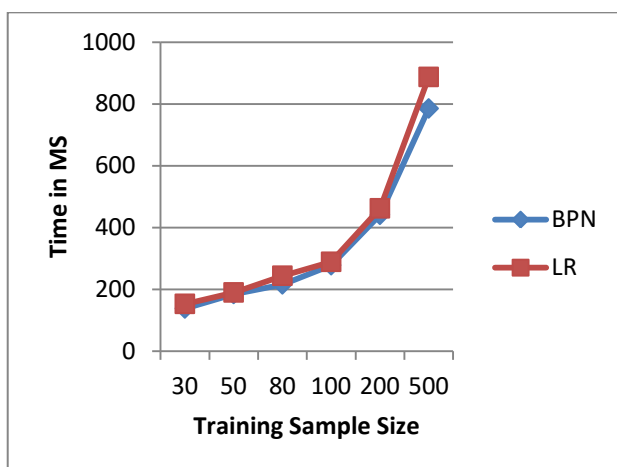


Fig. 6 Time consumption

Here the time series data is needed to be analyzing thus two popular data models linear regression (LR) and back-propagation neural network (BPN) are implemented and compared for finding the performance of prediction. The number of training samples is used are given here in X-axis and Y-axis contains the time requirements for prediction using the algorithms. The measured time given here in terms of MS (milliseconds), the results show the performance of the implemented algorithms is similar in both the algorithms but BPN is efficient as compared to the LR model.

VI. CONCLUSION & FUTURE WORK

The proposed work is intended to accurately predict and monitor the solar still water plant performance for producing the drinking water. In this context, a significant amount of

literature is collected and analyzed. According to the researchers and contributors of solar water still plants the performance of a drinking water plant can be influenced by various factors such as the number of slops, the direction of radiation, insulation materials, condensing system, weather, flow of air, temperature, coating, dimensions, surface type, thickness, and others. Therefore first we use a laboratory-based single slop single basin solar water still plant additionally based on experimental observations of 7 days a dataset prepared. This dataset is further used with the two predictive data models namely LR (linear regression) and BPN (back-propagation neural network). Using these data-models we analyze and predict the relevant performance and instantaneous efficiency of solar still. Both the data models are frequently used for time series data analysis and complex data prediction. The implementation of the data model is offered using JAVA technology. After that the performance of the implemented models is measured and reported in "Table-III", using the mean performance of the system.

S. No.	Parameters	BPN	LR
1	Accuracy	74.95 %	65.13 %
2	Memory usages	17927.16 KB	15529.33 KB
3	Time complexity	340.5 MS	370.8

Table-III Mean performance

The measured performance of the system is acceptable but needs to be enhanced. Therefore, the following improvements to the existing system are proposed for work.

- 1) Involving two more still plants for experimentation namely double slop and pyramid for observations and data collection
- 2) Suggesting improvements on existing still plants for improving the performance of water production using three improved still plants
- 3) Involving more attributes in the existing dataset for obtaining precise relationships among predictable variables
- 4) Implementing the noise reduction algorithm with the learning model for improving prediction performance.

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Security, Cloud Security and Privacy, Big Data Analytics, Data Mining, IoT and Computational Intelligence based education. He has 18 years of teaching experience and 6 years of Research Experience..



Prof. Manojkumar Deshpande has joined PIEMR Indore, as Director, in Jan 2018. In short time, his reforms at various levels, enhanced academic standard of engineering and management education. Before he was having additional charge of Vice Chancellor at Symbiosis University of Applied Sciences, Indore. In SUAS, due to his tireless effort and networking, Technology and Management education boosted.

He has also worked as Professor & Associate Dean at MPSTME, SVKM's NMIMS-Mumbai, Shirpur Campus. He spent 12 years in Mumbai and worked with Best Engineering Colleges such as D J Sanghvi College of Engineering. He was also Member, Board of Studies of SVKM's NMIMS University, Mumbai.

He has received Doctoral Degree in Computer Engineering from SVKM's NMIMS University, Mumbai in 2011. He is alumnus of formerly CEDTI, NIELET, Aurangabad (M.Tech.) and, SSGMCE, Shegaon (B.E.) Maharashtra, India.

He is having 27 years of academic experience at various positions. He is guide for Ph.D. & M.Tech in Computer Engineering. There are 28 publications One Patent (Applied) at his credit. His research focus is Big Data Analytics, Artificial Intelligence, Software Engineering and Multimedia Systems and STEM Education. He is recipient of recipient of Education Leadership Award: Dewang Mehta Education Award, June 2019 & Top Retail Minds Awards, Mar 2019

He is Member of ISTE and involved in conducting Conferences, Workshops, Industrial Consultancies and Social Activities. He was also member of ASEE, CSI, ACM etc. He visited Kingston University, London, UK, University of Oslo, Norway, Microsoft & Washington State University, Seattle, USA.



Md. Ilyas Bachelor of Engineering from IET Devi Ahilya Vishwa Vidhyalaya (DAVV) Indore, 2009 and Master of Engineering from Sushila Devi Bansal College of Engineering Indore in Year 2015. Currently presently working as an Assistant Professor in Department of Computer Science & Engineering, Prestige Institute of Engineering Management & Research Indore. He has published more than 8

Research paper National / international journals including. His main research work focuses on Artificial intelligence, Cloud Computing, IoT, Big Data Analytics, Data Mining, MANET, Privacy Preserving Data and Computational Intelligence based education. He has 9.8 years of teaching experience. He has Microsoft Technology Associate (MTA) Certificate with 94%.

AUTHORS PROFILE



Rajeev Raghuvanshi Bachelor of Engineering from IET Devi Ahilya University Indore, 2009 and Master of Engineering from Medicaps Institute of Technology and Management, Indore in Year 2013. Pursuing Ph.D. (CSE) from Dr. APJ Abdul Kalam University, Indore from year 2017. Currently presently doing PhD in Computer Science & Engineering, College of Engineering,

Dr. APJ Abdul Kalam University, Indore. He has published more than 9 Research paper National / international journals including. His main research work focuses on Network Security, Wireless Network, Big Data Analytics, Data Mining, IoT, Solar Energy and Computational Intelligence based education. He has 9.7 years of teaching experience..



Dr. Dhanraj Verma Bachelor of Science from Vikram University of Ujjain, 1997 and Master of Technology from Devi Ahilya University, Indore in Year 2007. Ph.D. (CSE) from BU University in year 2013. Currently Presently working as a Professor in Department of Computer Science & Engineering, College of Engineering, Dr. APJ Abdul Kalam University, Indore. He is a member

of IEEE & IEEE Computer Society Since 2012, Life member of the CSI since 2012, He has published more than 24 Research paper National / international journals including. His main research work focuses on Network