Soft computing techniques for a solar collector using solar radiation data

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Abstract

Prediction of solar radiation data using different soft computing approaches like Multi layer Perceptron (MLP), Artificial Neuro Fuzzy Inference System (ANFIS), and Radial Basis Function (RBF) for East coast region of India has been presented in this paper. Based on the input data like sunshine duration, temperature and humidity for the period of 1984-1999, soft computing models for a solar radiation data are analysed. The performances of these models are evaluated by comparing the predicted and measured data in terms of absolute relative error. Results obtained by ANFIS model predicted better compared to the results obtained using RBF and MLP. Based on the predicted solar radiation data, the efficiency of a solar flat plate collector is carried out. It has been found out that the soft computing approach is very promising for predicting of solar radiation and for calculation of efficiency of a solar flat plate collector. Eastern India region is considered for the present analysis due to its peculiar characteristics of solar radiation and cyclonic nature in the coastal areas.

Keywords: NPV; Profitability Index; Discounted Payback period

1. Introduction

We are awarded of the fact that solar energy is considered to be the most effective and economic alternative resource of energy. India is not far behind as the interest in application of solar energy for the growth of providing electricity especially to rural areas, solar heating and cooling processes for domestic and industrial processes.

However, it has been observed in last few years that four States of India i.e. West Bengal, Andhra Pradesh, Odisha and Tamil Nadu on the East Coast and One State i.e. Gujarat on the West Coast of India are more vulnerable to cyclone disasters. Hence solar radiation insolation in these areas is haphazard in nature as the solar radiation...
directly or indirectly generates high wind flow. Again for setting up any renewable energy systems such as a solar photovoltaic (PV), solar thermal and wind machine, the solar radiation data analysis in these areas becomes crucial. Although traditional approaches have been used to measure solar radiation in almost all Indian cities, it has been observed that most of the time no measuring equipments are used in these coastal regions due to high wind effects which cause damages to the solar radiation measuring equipments. Hence, the soft computing model based solar radiation measuring techniques can predict the solar radiation data in these coastal areas and in turn carrying out performance analysis of solar collector system. As the objective in this paper is to predict solar radiation data and thermal applications in eastern region of India, solar thermal application works related to agricultural and marine applications are need to be focused along with soft computing approaches for solar radiation prediction. Theoretical model to find global solar radiation has been mentioned in literature \[1, 2\] which is based on sunshine duration. Use of MLP and ANFIS are available in literatures \[3\] which have been used to estimate the performance of flat plate solar collectors. Solar irradiance, ambient temperature, collector tilt angle and working fluid mass flow rate have been considered as input parameter.

Soft computing approach using artificial neuro-fuzzy model \[4\] is a new method for predicting monthly clearness index \((K_t)\) in isolated areas based on geographical coordinates of latitude and longitude. This model is also applicable for sizing of stand-alone photovoltaic system. Here the model has been tested and compared with ANN architecture (MLP, RBF and RNN). Radial Basis Function (RBF) networks approach \[5\] has been used for modelling the monthly mean daily values of the global solar radiation fallen on horizontal surface and then has been compared with other models like Multilayer perceptron (MLP) in a classical regression model. The thermal performance of a solar water heating system with flat plate collectors has been carried out by researchers in the past \[6\]. Optimal performance and design of solar energy to thermal energy conversion systems \[7\] was performed. Experimental based study with soft computing has been carried out earlier for solar air heaters \[8\]. Modelling of a domestic water heating system has been used \[9, 10\]. Based on geographical needs, here we have focused on two aspects. The first one explores the use of soft computing approaches like Multi layer Perceptron (MLP), Artificial Neuro Fuzzy Inference System (ANFIS), and Radial Basis Function (RBF) for predicting solar radiation data in Eastern region of India. Second aspect of the paper is based on the prediction of solar collector performance using the results of soft computing approach. The flat plate solar collector has been considered here for performance evaluation.

2. Prediction of solar radiation data

As discussed previously, solar radiation data in the coastal region are haphazard in nature due to the effect of humidity and constant cyclone. As a result, measurement of solar data is a tedious in the coastal region of eastern India. Hence we are proposed here a soft computing approach as a better option for predicting solar radiation data. In this section, various soft computing approaches have been used to predict solar data. Three important coastal station of India i.e. Bhubaneswar, Kolkata and Vishakhapatnam have been considered regions of eastern India for predicting average monthly global solar radiation. Data mentioned in these regions from 1984-1999 has been used as training data. The input parameters used in this model are \((S/S_0)\) i.e. ratio of sunshine duration \((S)\) to maximum sunshine duration \((S_0)\), \((T/T_0)\) i.e. ratio of average temperature \((T)\) to maximum temperature \((T_0)\) and \((R/R_0)\) i.e. ratio of relative humidity \((R)\) to maximum humidity \((R_0)\). The output parameter is the clearness index \((H/H_0)\), where \(H\) is the daily solar radiation and \(H_0\) is the maximum solar radiation on daily basis or extraterrestrial radiation. Following four models have been devised to get the required output.

Model I: Estimates the global solar radiation from average Temperature, Relative Humidity and Sunshine duration as represented by Eq (1).

\[
\frac{H}{H_0} = f\left(\frac{S}{S_0}, \frac{R}{R_0}, \frac{T}{T_0}\right)
\]  \[(1)\]

Model II: Estimates the global solar radiation from Relative Humidity and Sunshine duration as represented by Eq (2).

\[
\frac{H}{H_0} = f\left(\frac{S}{S_0}, \frac{R}{R_0}\right)
\]  \[(2)\]

Model III: Estimates the global solar radiation from average Temperature, Relative Humidity as represented by Eq
(3).
\[
\frac{H}{H_0} = f\left(\frac{R}{R_0}, \frac{T}{T_0}\right)
\]

Model IV: Estimates the global solar radiation from sunshine duration and temperature as represented by Eq (4).
\[
\frac{H}{H_0} = f\left(\frac{S}{S_0}, \frac{T}{T_0}\right)
\]

Following section gives the brief insight into the different tools used in this paper for prediction of solar radiation data. The results of these models are compared with measured values for predicting the best model.

2.1 NEURAL NETWORKS MODEL (Multi-layer Perceptron)

The model consists of an input layer having three inputs, an output layer having one output and one or more hidden layer. Fig.1 shows a MLP network. The function \(\alpha\) here may be a simple threshold function or a sigmoid, hyperbolic tangent function. To obtain the optimal structure of the MLP neural network, we conducted several training by varying the network parameters such as the activation function, number of hidden layers, number of neurons in each layer, the learning parameters, the no of iteration.

The best performance for Kolkata has been obtained with maximum regression (0.96886) with Mean Square Error (MSE) (0.000650) is obtained at epoch 2000, iteration 6 using 10 hidden layer neurons. For Bhubaneswar the maximum regression coefficient (0.82582) and MSE (0.00868) is found at epoch 2000 and iteration 6 and for Vishakhapatnam the regression coefficient (0.97908) and MSE (0.00113) is found at epoch 2000 and iteration 6.

2.2 ARTIFICIAL NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is the implementation of fuzzy Inference system (FIS) to adaptive networks for developing fuzzy rules having some membership functions. The basic structure of a FIS consists of three components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions (MF) used in the fuzzy rules and a reasoning mechanism, ANFIS is a multilayer feed-forward network which uses neural network learning algorithms and fuzzy reasoning to map inputs into output.

A general adaptive neuro-fuzzy network shown in Fig.2. A five layer Anfis structure is constructed having three inputs at input layer, and one output at output layer.
Fig. 2. ANFIS model

Using ANFIS, several simulations are carried out and it is found that the model gives better accuracy at epoch 3. The ANFIS model uses triangular membership function (trimf) for input and linear type function for output.

2.3 RADIAL BASIS FUNCTION NETWORKS (RBF)

A radial basis function network is an artificial network whose activation function is radial basis function. A radial basis function (RBF) network contains three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. The second layer /hidden layer performs non-linear mapping from the input space into a higher dimensional space by using a Gaussian kernel function. Output layer/the final layer performs a weighted sum with a linear output. The model is shown in Fig. 3.

Fig. 3. RBF model

The best performance is obtained at epoch 2 with spread is 2.0. The MSE for Kolkata is 0.00414128. Similarly, for Bhubaneswar and Vishakhapatnam MSE is 0.0061278 and 0.0075529 respectively. From the above three models, it is found that the result of ANFIS gives better performance in comparison to other soft computing techniques such as Multi layered Perceptron (MLP) and Radial Basis Function (RBF).

3. Thermal modelling of flat plate collector

This section focuses on thermal modelling of solar collector. Mainly a flat plate collector has been considered here for modelling and its performance analysis. A typical flat plate collector as shown in Fig. 4. Consists of an absorber, transparent cover sheets and an insulated box. The absorber is usually a sheet of high-thermal-conductivity metal with tubes or ducts either integral or attached. Its surface is painted or coated with selective coating to maximize radiant energy absorption and to minimize radiation heat loss emission. The insulated box provides structure and sealing and reduces heat loss from the black or sides of the collector. The transparent cover sheets
usually made of glass cover allow sunlight to pass through to the absorber and simultaneously minimize convective heat losses. Metallic tubes are soldered, brazed or pressure bonded to the bottom of the absorber plate. Usually water, air are kinds of fluid is circulated in tubes which carry the absorbed heat. The steady state useful energy of the collector is given by Eq. (5)

\[ q_u = \dot{m} c_p \left( T_{fo} - T_{fi} \right) = F \eta_s A_s \left[ S_s - U_L \left( T_a - T_f \right) \right] \]  

(5)

Where \( q_u \) is useful heat absorbed by the fluid, \( m \) is rate of mass flow. \( T_{fo} \) and \( T_{fi} \) are outlet and inlet temperature of fluid flowing through tubes. \( F \) is hat removal factor and \( U_L \) is overall heat loss coefficient. \( T_a \) is atmospheric temperature. Heat absorbed by absorber plate is calculated using Eq. (6)

\[ S_t = I_r \eta_{optical} \]

(6)

Where \( I_r \) is total radiation on horizontal surface and \( \eta_{optical} \) is optical efficiency of the thermal system. \( I_r \) and \( H \) are related by the following equation assuming tilt factors are almost unity.

\[ H = \frac{180}{15\pi} \sum_{\omega} I_r d\omega \]  

(7)

Where \( \omega \) is called as hour angle, being 15° per hour. And the instantaneous thermal efficiency of the collector is given by \( \eta_i = \frac{q_u}{A_s I_r} \)  

(8)

4. Simulation

Computer codes for different models are developed in the MATLAB® software to find the monthly solar radiation data. For testing purpose, data for 16 years at Kolkata, Bhubaneswar and Vishakhapatnam from (1984-1999) have been considered [13]. The measured monthly averaged data such as ratio of sunshine hour, temperature ratio, relative humidity ratio and clearness index for the mentioned three cities are mentioned in Table 1.

| Month | Kolkata | Bhubaneswar | Visakhapatnam |
|-------|---------|-------------|---------------|
|       | S/So    | T/To        | R/R0          | H/H0          |
|       | S/So    | T/To        | R/R0          | H/H0          |
|       | S/So    | T/To        | R/R0          | H/H0          |
| Jan   | 0.78    | 0.751       | 0.641         | 0.58          | 0.747 | 0.728 | 0.508 | 0.617 | 0.87  | 0.844 | 0.621 | 0.622 |
| Feb   | 0.8     | 0.791       | 0.843         | 0.533         | 0.741 | 0.825 | 0.517 | 0.616 | 0.962 | 0.894 | 0.681 | 0.634 |
| March | 0.682   | 0.825       | 0.536         | 0.557         | 0.647 | 0.935 | 0.496 | 0.588 | 0.79  | 0.916 | 0.683 | 0.617 |
| April | 0.557   | 0.845       | 0.843         | 0.556         | 0.637 | 0.999 | 0.553 | 0.599 | 0.821 | 0.938 | 0.706 | 0.603 |
| May   | 0.679   | 0.879       | 0.711         | 0.521         | 0.601 | 0.996 | 0.67  | 0.559 | 0.77  | 0.951 | 0.749 | 0.568 |
| June  | 0.635   | 0.907       | 0.731         | 0.428         | 0.355 | 0.974 | 0.779 | 0.575 | 0.628 | 0.959 | 0.766 | 0.448 |
| July  | 0.551   | 0.922       | 0.838         | 0.38          | 0.263 | 0.942 | 0.819 | 0.67  | 0.648 | 0.959 | 0.784 | 0.412 |
| Aug   | 0.556   | 0.929       | 0.667         | 0.406         | 0.328 | 0.937 | 0.825 | 0.36  | 0.723 | 0.949 | 0.779 | 0.428 |
| Sept  | 0.677   | 0.918       | 0.869         | 0.424         | 0.416 | 0.921 | 0.803 | 0.415 | 0.654 | 0.941 | 0.795 | 0.472 |
| Oct   | 0.734   | 0.886       | 0.626         | 0.498         | 0.623 | 0.874 | 0.734 | 0.516 | 0.829 | 0.926 | 0.744 | 0.542 |
| Nov   | 0.808   | 0.827       | 0.767         | 0.528         | 0.66  | 0.802 | 0.581 | 0.574 | 0.87  | 0.908 | 0.643 | 0.571 |

Fig. 4. Schematic layout of Flat plate collector [11]
The model is trained and tested by using different soft computing technique such as MLP, ANFIS and RBF. The best performance for Kolkata has been obtained with maximum regression (0.96886) with Mean Square Error (MSE) (0.000650) is obtained at epoch 2000, iteration 6 using 10 hidden layer neurons. For Bhubaneswar the maximum regression coefficient (0.82582) and MSE (0.00868) is found at epoch 2000 and iteration 6 and for Vishakhapatnam the regression coefficient (0.97908) and MSE (0.00113) is found at epoch 2000 and iteration 6. Using ANFIS, several simulations are carried out and it is found that model give better accuracy at epoch 3. The ANFIS model uses triangular membership function (trimf) for input and linear type function for output. Similarly, several simulations have been carried using RBF, and the best performance is obtained at epoch 2 with spread is 2.0. The MSE for Kolkata is 0.00414128. Similarly, for Bhubaneswar and Vishakhapatnam MSE is 0.0061278 and 0.0075529 respectively. The overall performances of the models are calculated on the basis of absolute relative error in percentage which is given in Table 2. By calculating absolute relative percentage error for all models, it is found that ANFIS seems to be more effective compared to other soft computing technique (MLP and RBF).

Table 2. Absolute relative errors for given three cities using different soft computing techniques

| Month | Kolkata       | Bhubaneswar  | Vishakhapatnam |
|-------|---------------|--------------|----------------|
|       | MLP | ANFIS | RBF | MLP | ANFIS | RBF | MLP | ANFIS | RBF |
| Jan   | 0.0165 | 0.0016 | 0.0691 | 0.9494 | 0.0055 | 3.8024 | 0.117 | 0.0135 | 1.709 |
| Feb   | 4.2324 | 0.0381 | 3.5534 | 5.3647 | 0.0035 | 6.4643 | 2.5307 | 0.0044 | 0.006 |
| March | 3.476 | 0.0053 | 5.6596 | 5.6702 | 0.0077 | 4.0527 | 0.862 | 0.0049 | 8.46  |
| April | 2.7738 | 0.0426 | 7.5107 | 0.9199 | 0.0012 | 3.4472 | 0.3502 | 0.0355 | 4.645 |
| May   | 2.8363 | 0.0158 | 6.1261 | 3.1333 | 0.0024 | 6.5792 | 1.199 | 0.0064 | 5.458 |
| June  | 1.1139 | 0.0059 | 7.4124 | 0.8544 | 0.0047 | 3.7042 | 6.18  | 0.0066 | 4.464 |
| July  | 1.5638 | 0.0036 | 6.193  | 8.7102 | 0.0044 | 6.834  | 6.02  | 0.0089 | 6.795 |
| Aug   | 4.2362 | 0.0091 | 3.6189 | 0.4637 | 0.0253 | 9.029  | 6.701 | 0.0119 | 8.180 |
| Sept  | 4.3099 | 0.0044 | 6.9943 | 8.9104 | 0.0063 | 8.346  | 1.112 | 0.0232 | 6.036 |
| Oct   | 4.5103 | 0.0082 | 0.8281 | 6.4035 | 0.0089 | 0.307  | 3.702 | 0.0004 | 5.870 |
| Nov   | 0.3375 | 0.0066 | 2.3547 | 0.9799 | 0.0062 | 3.755  | 9.040 | 0.0067 | 6.293 |
| Dec   | 1.8914 | 0.0066 | 2.7157 | 6.7407 | 0.00053 | 5.180  | 2.360 | 0.0065 | 0.515 |

Table 3. Geometrical and operating data of the flat plate collector under consideration

| Items                              | Value | Items                              | Value |
|------------------------------------|-------|------------------------------------|-------|
| Length of absorber plate           | 2 m   | Tube pitch                         | 0.113 m |
| Width of absorber plate            | 1.13 m| Absorptivity of glass cover        | 0.88  |
| Plate to cover distance            | 0.025 m| Emissivity of glass cover          | 0.88  |
| Thermal conductivity of plate      | 350 W/mK | Thickness of glass cover           | 0.04 m |
| Thickness of plate                 | 0.00015 m | Thermal diffusivity of adhesive   | 0     |
| Absorptivity of plate              | 0.94  | Water flow rate                    | 70 kg/s|
| Emissivity of plate                | 0.14  | Water Inlet temperature            | 60 c  |
| Outer diameter of the tube         | 0.0137 m | Ambient temperature                | 25 c  |
| Inner diameter of the tube         | 0.0125 m | Heat transfer coefficient above glass cover | 16.4 W/m²K |

Fig.5. - Fig.7. depict the monthly averaged solar data comparison of different soft computing tools for Kolkata, Bhubaneswar and Vishakhapatnam respectively. It has been observed that results from ANFIS matches quite well with the measured values. However, the data from NN and RBF are within 10% error band with that of measured value. The Parity plot showing measured data and predicted data using different soft computing techniques is shown in Fig. 8., which confirms the well match between two. Based on the predicted value (H) for mentioned locations, hourly radiation data (Iₜ) has been obtained using Eq. 7. Solar insolation data on the absorber plate can be found from Eq. 6 with consideration of approximate optical efficiency value as 0.85. Eq. 5 and Eq. 8 are used to measure the outlet fluid temperature and efficiency respectively.

Fig.9. depicts the instantaneous efficiency of solar collector with respect to solar radiation absorbed by the absorber plate. It can be seen the efficiency value increases from 31% to 71% as the solar radiation increases from 500 to 900 W/m². Similarly, the efficiency value increases as the atmospheric temperature increases but at a slower rate. Fig.10. shows the outlet fluid temperature for various solar radiation absorbed by plate and atmospheric temperature levels. The trend is linear for the both cases. As the solar radiation and atmospheric temperature increases, the outlet fluid temperature also goes on increasing.
Fig. 5. Measured data and predicted data using different Soft computing approaches for Kolkata

Fig. 6. Measured data and predicted data using different Soft computing approaches for Bhubaneswar

Fig. 7. Measured data and predicted data using different Soft computing approaches for Vishakhapatnam

Fig. 8. Parity plot showing measured and predicted solar irradiance

Fig. 9. Variation of Efficiency with respect to Incident solar heat flux and atmospheric temperature
Fig.10. Variation of outlet fluid temperature with respect to solar heat flux atmospheric temperature

5. Conclusion

This paper presented a comparison of mean monthly global solar radiation data of Eastern India using different soft computing techniques like MLP, ANFIS and RBF. The measured average monthly global solar radiation was compared with measured values of Kolkata, Bhubaneswar and Vishakhapatnam. Due to frequent cyclonic effects in these places considered are much useful to study the feasibility of use of soft computing approaches for measurement of solar data. It was seen that the mentioned ANFIS predicts much well with measured values. It can be concluded that, with sunshine duration data, temperature data, and/or humidity data, solar radiation can be estimated with soft computing techniques. Hence this tool seems to be promising to estimate solar data for the places where costly equipments for measuring solar data cannot be installed. Furthermore, the results obtained from the soft computing approaches were used to study the performance of the solar flat plate collector. It has been found that this approach is suitable and hence this soft computing approach can be adopted for feasible study and setting up solar thermal system in the coastal. Future work can be made of sizing, rating and economic analysis of photovoltaic system and thermal systems.

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