Solar Mapping of India using Support Vector Machine

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Abstract. Accurate knowledge of global solar radiation (GSR) data is necessary for various solar energy based applications. However, in spite of its importance, the number of solar radiation measuring stations is comparatively rare throughout the world due to financial cost and difficulties in measurement techniques. The objective of this current study is to assess the solar energy potential and to develop solar resource mapping of India without utilizing the direct measurement techniques. GSR is predicted with commonly available meteorological parameters like minimum and maximum temperature as its inputs by using Support Vector Machine (SVM) based solar radiation model. The SVM model is validated with measured data from India Meteorological Department (IMD). This study simplifies the major challenge of preparing GSR data for various solar energy applications in a big country like India. Also the life cycle cost of Solar PV is analyzed in India. The payback period will be around 3 years for an annually solar radiation of range from 3.5 to 6 kWh/m²/day. This work eliminates the requirement of costly pyranometer to get GSR data. Solar resource mapping of India is developed without direct measurement technique thus avoids GSR data recording, daily maintenance and subsequently the increasing cost of GSR data collection.

1. Introduction

Energy crisis is one of the most important challenges faced by many countries. In this scenario, solar energy plays a vital role as a renewable energy because of its unpolluted nature and its reliability in tropical countries like India. Solar energy has an enormous potential to fulfil the energy requirements in India. Accurate knowledge of solar radiation is very essential for all solar energy based applications like optimal design such as installation of solar roof top PV system, solar energy conversion systems for heating and cooling and so on. Global solar radiation is the sum of direct and diffuse radiation. Direct normal radiation is measured by a pyrheliometer and diffuse radiation by a shaded pyranometer. Global solar radiation is measured by a pyranometer. The solar radiation measuring stations is restricted all over the world due to cost, maintenance and other technical problems in measurement. Thus the global solar radiation data is not easily available in all the sites of India. This has motivated the researchers to build various solar radiation models for the prediction of GSR. The prediction of solar radiation has generated a new attention in current years, mostly due to its significance in renewable energy and smart grid application.

There have been several works that presented various models using different meteorological data namely clear sky models, empirical models, ANN models, regression models and other hybrid models to predict GSR for the optimum site selection for solar PV plant and other solar applications [1]. Clear sky models are not suitable for cloudy sky condition [2]. In India two to three months are cloudy and clear sky models are not applicable to predict GSR during monsoon months. Hybrid regression models are restricted due to multiple meteorological parameters involved in prediction [3]. Also this statistical
regression models involves complex mathematical computations which is both time and mind consuming. Different artificial intelligence based models have also been utilized by the researchers to predict GSR [4, 5]. ANN based models need huge data set and large training time. Recently various machine learning techniques are employed for GSR prediction. SVM models are better than ANN and empirical models [6]. Global solar radiation data is considered as the chief parameter for all solar energy based applications. To find out the cost analysis of solar PV plant across different locations in India, precise knowledge of solar radiation is necessary. Temperature is the commonly measured data. Also models based on temperature are suitable for locations where the temperature is the only possible data. In the current study, a temperature-based SVM model using Sequential minimal optimization (SMO), an iterative algorithm namely SMOreg is used to predict monthly mean GSR for all Indian states. SMOreg is used for solving the regression problem which implements the SVM for regression. WEKA (Waikato Environment for Knowledge Analysis) developed at the University of Waikato in New Zealand; open source software is utilized for GSR prediction. To validate the performance metrics of the SVM solar radiation model used in this work, the measured solar radiation over different months for eight selected locations in India was obtained from IMD, Pune. The main purpose of this study is to predict the GSR with excellent prediction accuracy, also to develop solar resource mapping of India for different climatic conditions. Further to analyze the life cycle cost of the roof top solar system using the estimated GSR.

2. Solar Resource Assessment and Mapping of India
Preparation of global solar radiation data for a big country like India is a very big challenge. This work simplifies the major challenge of preparing GSR data for various solar energy applications in India. In this study, SVM based solar radiation model using SMOreg algorithm is used for assessing the solar energy potential of India. Also the results of SVM model are compared with conventional temperature based empirical models.

2.1. Temperature based Empirical Model
Bristow and Campbell [7] proposed the following equation for estimating GSR as follows:

\[ \frac{H}{H_0} = a(1 - \exp(-b \Delta T))^c \]  
(1)

Where \(H_0\) is the monthly average daily extraterrestrial radiation in kWh/m²/day which is given by

\[ H_0 = \frac{24}{\pi} I_{sc} \left[ 1 + 0.33 \cos \left( \frac{360 D_n}{365} \right) \right] \times \left[ \cos L \cos \delta \sin \omega_s + \frac{2\pi \omega_s}{360} \sin L \sin \delta \right] \]  
(2)

Where \(I_{sc}\) is the solar constant, \(D_n\) is the day of year starting from first January; \(L\) is the latitude of location:
\(\delta\) is declination angle given by

\[ \delta = 23.45 \sin \left( \frac{360(284 + D_n)}{365} \right) \]  
(3)

and \(\omega_s\) is the sunset hour angle in degree as given below

\[ \omega_s = \cos^{-1}(\tan L \tan \delta) \]  
(4)

\(a, b\) and \(c\) are empirical coefficients determined by statistical regression technique and \(H\) is the monthly average global solar radiation on horizontal surface and it is an exponential function of \(\Delta T\).
\(\Delta T = T_{\text{max}} - T_{\text{min}}\)

Where \(T_{\text{min}}\) and \(T_{\text{max}}\) are the minimum and maximum temperature.
2.2. Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning algorithm. SVM is developed in 1995 by Vapnik [8]. This machine learning algorithm is used to solve classification and regression problems. SVM can be applied with short length dataset. Artificial Neural Network (ANN) has multiple solutions associated with local minima. But SVM gives a unique solution, as the optimality problem is convex. This is an advantage of SVM compared to ANN.

Specified a set of data points \( G = \{(x_i, d_i)\}_{i=1}^{n} \) (\( n \) is the data size, \( x_i \) is input vector and \( d_i \) is the desired value), SVM approximates the function by means of Eq. (5) which is given below:

\[
f(x) = w\phi(x) + b
\]  

Where \( \phi(x) \) is the high dimensional feature space which is mapped from the input space \( x \). \( w \) and \( b \) are the coefficients determined by minimizing the regularized risk function below [8]:

\[
R_{SVMS}(C) = C \frac{1}{n} \sum_{i=1}^{n} L(d_i, y_i) + \frac{1}{2} \|w\|^2
\]  

Where \( C \frac{1}{n} \sum_{i=1}^{n} L(d_i, y_i) \) is empirical error which is measured by function \( L_\varepsilon \) as follow:

\[
L_\varepsilon(d, y) = \begin{cases} 
|d - y| - \varepsilon |d - y| \geq \varepsilon \\
0 & \text{otherwise}
\end{cases}
\]  

The term \( \frac{1}{2} \|w\|^2 \) is the regularization term. \( C \) is the penalty parameter of the error. This is utilized to manage the trade-off between the empirical risk and the regularization term. \( \varepsilon \) is the tube size and is equal to the estimate accuracy located on the training data points.

To determine the coefficients \( w \) and \( b \), Eq. (6) is altered to the primal function given by Eq. (7) by adding the positive slack variables \( \zeta_i \) and \( \zeta_i^* \) as follows [8]:

Minimize \( R_{SVMS}(w, \zeta) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} (\zeta_i + \zeta_i^*) \)

Subjected to

\[
d_i - w\phi(x_i) - b_i \leq \varepsilon + \zeta_i
\]

\[
w\phi(x_i) + b_i - d_i \leq \varepsilon + \zeta_i^*, \zeta_i^* \geq 0
\]

Finally by adding Lagrange multipliers and exploiting the optimality constraints, Eq. (5) becomes:

\[
f(x, a_i, a_i^*) = \sum_{i=1}^{n} (a_i - a_i^*) K(x_i, x_i) + b
\]

The term \( K(x_i, x_i) \) is called kernel function; the kernel function \( K(x_i, x_j) \) value is equal to the inner product of two vectors \( x_i \) and \( x_j \) in the feature space \( \phi(x_i) \) and \( \phi(x_j) \), which is given by

\[
K(x_i, x_j) = \phi(x_i) \ast \phi(x_j)
\]

In the current study, polynomial kernel function is used which is given by

\[
K(x_i, x_j) = (x_i \ast x_j + 1)^d
\]

Where \( d \) is the kernel parameter. The kernel parameter should be vigilantly selected as it completely states the organization of the high dimensional feature space \( \phi(x) \) and thus controls the complication of the concluding solution.
2.3. Data Set
The input data set consist of geographical parameters namely the latitude and longitude and month numbers and commonly available meteorological parameters namely the minimum and maximum temperature. The measured data for this work namely the monthly mean maximum temperature, minimum temperature and daily GSR in MJ/m²/day for different locations of India were collected from India Meteorological Department, Pune. Monthly average GSR data collected from IMD for few Indian locations namely Bhubaneswar, Chennai, Hyderabad, Mangalore, Nagpur, New Delhi, Trivandrum and Patna is used to train the SVM solar radiation models to predict the GSR for other Indian locations where the GSR data is unavailable. The minimum and maximum temperature data for India in states are taken from National Aeronautics and Space Administration (NASA)[9]. The data set is export to a CSV file (Comma-Separated-Value). Solar resource mapping of India is developed using SVM model with the help of WEKA. "WEKA" is a collection of machine learning algorithms for solving real-world data mining jobs. The machine learning algorithms are applied straight to the input dataset.

2.4. Performance Metrics of the solar radiation model
The performance of the SVM model is examined using correlation coefficient (R) and Root Mean Square Error (RMSE) which is present in WEKA classifier output. RMSE is given by:

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (H_{im} - H_{ip})^2} \]  (9)

where \( H_{ip} \) is the \( i \)th predicted value, \( H_{im} \) is the \( i \)th measured value of solar radiation and \( n \) is the total number of observations.

Correlation Coefficient (R): Correlation Coefficient ‘R’ measures the degree of linear relationship between the predicted value and the measured value. The value of correlation coefficient ‘R’ varies between -1 to +1 and if R value is +1, then the correlation between the predicted value and the measured value is said to be perfect and positive.

3. Life cycle cost analysis of Solar PV in India
In this work, a roof top PV grid tied system has taken for the estimation. In roof top solar system installers have the right to feed solar electricity into the public grid and therefore obtain a rational premium tariff per generated kWh reflecting the profit of solar electricity to reimburse for the current additional cost of PV electricity. Also by installing a roof top solar system the shading effect and obstacles on the PV solar system is eliminated and therefore, can receive solar radiation without any obstacle. The key factors to be considered in cost estimation are the available solar radiation, cost of electricity from the utility provider, area, efficiency of the PV panel, hardware and installation costs.

The power from the solar radiation can be calculated as follows:

\[ P = H_{av} \times Area \times Efficiency \ (Watts) \]  (10)

Where P is the power, \( H_{av} \) is the annual averaged GSR.

Energy per year is given by

\[ E = (\frac{P \times 365 \times 24}{1000}) \ kWhr \]  (11)

Solar power cost is calculated as follows:

\[ Solar \ power \ cost = E \times utility \ cost \ per \ unit \]  (12)
Installation cost for 1kW roof top PV system without battery is assumed as 1 lakh rupee. Installation cost for 1kW roof top system with battery would add 25,000 rupees that is, 1.25 lakh rupees. Thus the payback period of the roof top solar system is given by the fraction of installation cost to the solar power cost.

\[
\text{Payback Period} = \frac{\text{Installation Cost}}{\text{Solar Power Cost}}
\]

Precise estimation of the yearly energy obtainable from PV panels makes it possible to estimate the lifecycle cost of PV energy. This study depends on global solar radiation, area, panel efficiency and utility cost per kW. In this cost estimation study, a roof top PV grid tied system installation is considered. The area is assumed as 500 square feet and solar panel is from the product sun power X series solar panel X21-335 BLK monocrystalline whose efficiency is 21.1%. Also the installation cost with battery is assumed.

| Table 1. Predicted monthly mean global solar radiation values in kWh/m²/day for Indian states |
|------------------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Months/Indian States   | Jan | Feb | Mar | April | May | June | July | Aug | Sep | Oct | Nov | Dec | Annual GSR |
| Andhra Pradesh         | 6.14 | 6.38 | 6.43 | 6.43 | 6.42 | 5.91 | 5.47 | 5.52 | 5.49 | 5.16 | 5.10 | 5.16 | 5.80 |
| Arunachal Pradesh      | 3.39 | 3.56 | 3.93 | 4.32 | 4.29 | 4.26 | 3.89 | 3.90 | 3.86 | 3.76 | 3.34 | 3.29 | 3.82 |
| Assam                  | 3.45 | 3.92 | 4.47 | 4.43 | 4.44 | 4.28 | 3.86 | 3.87 | 3.91 | 3.79 | 3.60 | 3.33 | 3.95 |
| Bihar                  | 4.31 | 5.49 | 6.09 | 6.12 | 6.12 | 5.34 | 4.57 | 4.37 | 4.09 | 4.62 | 4.61 | 4.09 | 4.99 |
| Chattisgarh            | 5.12 | 6.06 | 6.27 | 6.32 | 6.31 | 5.73 | 4.19 | 4.13 | 4.35 | 5.03 | 4.95 | 4.36 | 5.24 |
| Goa                    | 6.00 | 6.38 | 6.38 | 6.41 | 6.34 | 4.84 | 3.98 | 4.14 | 4.85 | 5.06 | 5.16 | 5.14 | 5.39 |
| Gujarat                | 6.04 | 6.22 | 6.28 | 6.30 | 6.24 | 5.77 | 5.11 | 5.12 | 5.28 | 5.32 | 5.36 | 5.32 | 5.70 |
| Haryana                | 3.59 | 3.97 | 5.80 | 6.09 | 6.09 | 5.68 | 5.03 | 4.91 | 4.99 | 5.00 | 4.18 | 3.53 | 4.91 |
| Himachal Pradesh       | 3.39 | 3.56 | 3.58 | 3.58 | 3.80 | 4.01 | 3.74 | 3.69 | 3.41 | 3.41 | 3.39 | 3.35 | 3.58 |
| Jammu & Kashmir        | 3.41 | 3.58 | 3.59 | 3.60 | 3.73 | 4.27 | 4.23 | 3.67 | 3.47 | 3.41 | 3.39 | 3.35 | 3.64 |
| Jarkhand               | 4.34 | 5.57 | 6.14 | 6.19 | 6.20 | 5.29 | 3.99 | 4.03 | 4.17 | 4.29 | 4.42 | 4.04 | 4.89 |
| Karnataka              | 6.19 | 6.35 | 6.38 | 6.41 | 6.35 | 5.31 | 4.80 | 4.85 | 5.16 | 5.41 | 5.40 | 5.38 | 5.67 |
| Kerela                 | 5.78 | 6.18 | 6.18 | 5.69 | 5.03 | 4.33 | 3.99 | 4.65 | 4.73 | 4.71 | 4.61 | 5.03 | 5.08 |
| Madhya Pradesh         | 5.33 | 6.29 | 6.44 | 6.49 | 6.41 | 5.88 | 4.86 | 4.44 | 5.03 | 5.32 | 5.20 | 4.65 | 5.53 |
| Maharashtra            | 6.05 | 6.21 | 6.27 | 6.29 | 6.26 | 5.81 | 4.88 | 4.78 | 5.16 | 5.36 | 5.36 | 5.26 | 5.64 |
| Manipur                | 3.68 | 3.93 | 4.76 | 5.29 | 4.86 | 4.49 | 3.84 | 3.85 | 3.88 | 3.84 | 3.75 | 3.33 | 4.13 |
| Megalaya               | 3.89 | 4.59 | 5.53 | 5.48 | 5.25 | 4.53 | 4.06 | 4.07 | 4.19 | 4.18 | 3.83 | 3.68 | 4.44 |
| Mizoram                | 3.83 | 4.43 | 4.34 | 5.64 | 5.33 | 4.45 | 4.03 | 4.05 | 4.21 | 4.31 | 3.86 | 3.66 | 4.35 |
| Nagaland               | 3.54 | 3.97 | 4.74 | 5.14 | 4.80 | 4.54 | 3.85 | 4.09 | 3.88 | 3.87 | 3.63 | 3.33 | 4.11 |
| Orissa                 | 5.35 | 6.12 | 6.23 | 6.27 | 6.23 | 5.17 | 4.03 | 3.96 | 4.26 | 4.39 | 4.87 | 4.79 | 5.14 |
| Punjab                 | 3.40 | 3.76 | 4.60 | 5.95 | 6.08 | 5.71 | 5.02 | 4.70 | 4.70 | 4.59 | 3.58 | 3.39 | 4.62 |
| Rajasthan              | 4.33 | 5.44 | 5.91 | 6.11 | 6.08 | 5.68 | 5.08 | 5.03 | 5.11 | 5.12 | 4.94 | 4.34 | 5.26 |
| Sikkim                 | 3.39 | 3.56 | 3.57 | 3.77 | 3.54 | 3.82 | 3.72 | 3.63 | 3.57 | 3.36 | 3.34 | 3.29 | 3.55 |
| Tamil Nadu             | 5.84 | 6.41 | 6.44 | 6.49 | 6.43 | 5.69 | 5.43 | 5.52 | 5.49 | 5.09 | 4.79 | 4.84 | 5.71 |
| Telangana              | 6.04 | 6.44 | 6.48 | 6.51 | 6.43 | 5.88 | 5.12 | 5.01 | 5.12 | 5.36 | 5.34 | 5.31 | 5.75 |
| Tripura                | 4.47 | 5.53 | 6.01 | 5.76 | 5.41 | 4.52 | 3.98 | 3.92 | 4.07 | 4.16 | 4.34 | 4.23 | 4.70 |
| Uttar Pradesh          | 3.79 | 5.28 | 6.12 | 6.19 | 6.18 | 5.67 | 4.96 | 4.73 | 4.75 | 5.04 | 4.70 | 3.99 | 5.12 |
| Uttarkhand             | 3.40 | 3.57 | 3.58 | 3.87 | 4.41 | 4.62 | 3.95 | 3.91 | 3.71 | 3.41 | 3.39 | 3.36 | 3.76 |
| West Bengal            | 5.16 | 6.09 | 6.21 | 6.25 | 6.06 | 5.11 | 4.23 | 4.00 | 4.11 | 4.21 | 4.83 | 4.69 | 5.08 |
### Table 2 Comparison of error statistics between Empirical and SVM model

| Solar Radiation Models - Comparison | R | RMSE |
|-----------------------------------|---|------|
| Bristow and Campbell [6]          | 0.8908 | 1.5171 |
| Chen et al. models [6]            | 0.8876 | 1.5365 |
| Current study SVM model           | 0.8938 | 1.5000 |

### Table 3 Cost estimation and payback period

| Location                  | Estimated annual GSR (kWh/m²/day) | Utility cost per KW (Rs) | Solar power cost (Rs) | Installation cost (Rs) | Payback period (Years) |
|---------------------------|-----------------------------------|--------------------------|-----------------------|------------------------|------------------------|
| West Bengal               | 4.99                              | 8.92                     | 3.78,902              | 6,11,334               | 1.6                    |
| Uttarakhand               | 3.70                              | 4.50                     | 1,42,950              | 4,53,293               | 3.1                    |
| Uttar Pradesh             | 5.03                              | 5.00                     | 2,15,928              | 6,16,234               | 2.8                    |
| Tripura                   | 4.62                              | 7.20                     | 2,85,591              | 5,66,004               | 1.9                    |
| Telangana                 | 5.65                              | 8.50                     | 4,12,324              | 6,92,192               | 1.6                    |
| Tamil Nadu                | 5.61                              | 6.60                     | 3,17,891              | 6,87,291               | 2.1                    |
| Sikkim                    | 3.48                              | 4.57                     | 1,79,309              | 5,59,879               | 3.1                    |
| Rajasthan                 | 5.17                              | 6.70                     | 2,97,397              | 6,33,386               | 2.1                    |
| Punjab                    | 4.54                              | 6.04                     | 2,35,431              | 5,56,203               | 2.3                    |
| Orissa                    | 5.05                              | 5.30                     | 2,29,793              | 6,18,684               | 2.6                    |
| Nagaland                  | 4.04                              | 6.50                     | 2,25,458              | 4,94,947               | 2.1                    |
| Mizoram                   | 4.27                              | 5.00                     | 1,83,303              | 5,23,125               | 2.8                    |
| Meghalaya                 | 4.36                              | 5.30                     | 1,98,396              | 5,34,151               | 2.6                    |
| Manipur                   | 4.05                              | 5.10                     | 1,77,336              | 4,96,173               | 2.7                    |
| Maharashtra               | 5.54                              | 10.91                    | 5,18,927              | 6,78,715               | 1.3                    |
| Madhya Pradesh            | 5.43                              | 6.30                     | 2,92,083              | 6,61,564               | 2.2                    |
| Kerala                    | 4.99                              | 6.20                     | 2,92,770              | 6,73,815               | 2.3                    |
| Karnataka                 | 5.57                              | 7.30                     | 3,44,713              | 6,73,815               | 1.9                    |
| Jarkhand                  | 4.08                              | 3.60                     | 1,64,844              | 5,88,057               | 3.5                    |
| Jammu & Kashmir           | 3.57                              | 4.00                     | 1,28,212              | 4,88,791               | 3.8                    |
| Himachal Pradesh          | 3.51                              | 5.10                     | 1,56,318              | 4,37,367               | 2.7                    |
| Haryana                   | 4.82                              | 6.30                     | 2,60,711              | 5,90,507               | 2.2                    |
| Gujarat                   | 5.60                              | 4.90                     | 2,50,013              | 6,86,066               | 2.7                    |
| Goa                       | 5.30                              | 4.50                     | 2,04,765              | 6,49,312               | 3.2                    |
| Chhattisgar               | 5.15                              | 5.40                     | 2,38,766              | 6,30,936               | 2.6                    |
| Bihar                     | 4.90                              | 8.00                     | 3,36,556              | 6,00,308               | 1.7                    |
| Assam                     | 3.88                              | 7.90                     | 2,66,498              | 4,75,546               | 1.7                    |
| Arunachal Pradesh         | 3.75                              | 4.00                     | 1,28,784              | 4,59,419               | 3.5                    |
| Andhra Pradesh            | 5.70                              | 7.98                     | 3,93,563              | 7,10,909               | 1.8                    |
Figure 1. Solar Resource Maps for different seasons of India developed using SVM model

4. Results and Discussion
Support vector machine solar radiation model is used to predict the GSR for all the 29 states of India using WEKA software. Table 1 shows the predicted annual average GSR by SVM model for all the Indian states in kWh/m²/day. From Table 1, it is found that tremendous solar energy potential is available in the following states namely Tamil Nadu, Telangana, Madhya Pradesh, Maharashtra, Karnataka, Gujarat and Andhra Pradesh (above 5.5 kWh/m²/day). Least solar radiation is available in Uttarkhand, Sikkim, Nagaland, Manipur, Jammu and Kashmir, Himachal Pradesh, Arunachal Pradesh and Assam in the range of 3 to 4 kWh/m²/day. Figure 1 displays the solar resource map with estimated
GSR by SVM model for four different seasons namely summer, winter, north east monsoon and south west monsoon. Overall the estimated GSR varies between 3.5 and 6 kWh/ m²/day (See Table 1). These predicted GSR values are in excellent agreement with GSR values of NREL, India solar resource map [10]. From the results it is observed that huge solar energy potential is available in India for different solar energy applications particularly in southern states covering Tamil Nadu. The result of SVM model is compared with the Chen et al. and Bristow and Campbell empirical models for the site Patna [6]. Table 2 shows the performance comparison between the empirical models and the SVM machine learning model. The value of Correlation coefficient R should be nearer to one and error value should be small for better modelling. R value is closer to one and RMSE value is small for SVM model. Hence it is proved that SVM Machine learning model is best in GSR prediction. The estimated GSR values by SVM model confirmed that superb solar potential is available in India. This radiation can be converted into electricity by installing roof top solar PV system. The cost analysis of solar roof top depends on global solar radiation, area, PV panel efficiency and utility cost per kW. Equations (10) to (13) are used to perform the cost analysis. Table 3 summarizes the solar power cost, installation cost and payback period for the study sites. The payback period will be around 3 years for Indian locations.

5. Conclusion
Through this work, global solar radiation is estimated using SVM model for all the 29 states of India by using with WEKA software. The SVM model is validated with measured solar radiation data of IMD, Pune. The results developed by SVM model is compared with empirical models namely Chen et al. models and Bristow and Campbell model. The results proved that the SVM machine learning model is more accurate in the prediction of GSR. Hence the SVM model can be implemented worldwide to predict GSR wherever the ground measured data is unavailable. Solar resource map is developed for India for different months and seasons using predicted GSR values without using direct radiation measurement data. Life cycle cost of solar PV is analyzed in India using the predicted GSR values. It is concluded that, for an annually solar radiation of range from 3.5 to 6 kWh/m²/day, the payback period will be around three years. Thus this work eliminates the requirement of costly pyranometer to get GSR data thus avoids data recording, daily maintenance and subsequently the increasing cost for the collection of solar radiation data. Also this work simplifies the major challenge of preparing GSR data for various solar energy applications in India.

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