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SolarisNet : A deep regression network for solar radiation prediction

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सार – फोटोवोल्टेइक (PV) पौधों के प्रभावी उपयोग के लिए मौसम परिवर्तनशीलता के सुदृढ़ वैश्विक सौर विकिरण (GSR) पूर्वानुमान मॉडल की आवश्यकता होती है। हॉट्टेल द्वारा सुझाए गए यादृच्छिक मौसम की प्रक्षुब्ध घटनाओं के साथ युग्मित स्वच्छ आकाश मॉडल की मान्यताओं के परिणामस्वरूप GSR रूपांतरण दर अनुमान में पैरामीट्रिक और गैर-पैरामीट्रिक मॉडल के लिए महत्वपूर्ण चुनौतियों का पता चला है। इसके अलावा, एक अच्छे GSR आकलन के लिए महंगे उच्च-तकनीक वाले रेडियोमीटर तथा उपकरण चलाने और माप लेने वाले विशेषज्ञ की आवश्यकता होती है, जो व्यक्तिपरक हैं। अतः स्मार्ट ग्रिड पास्ट डेटा एनालिटिक्स को लगाकर फोटोवोल्टेइक (PV) पौधे की सुसंगत संक्रिया का मूल्यांकन करने के लिए एक कंप्यूटर एडेड मॉनिटरिंग (CAM) सिस्टम विकसित किया गया है। हमारा एल्गोरिथ्म, सोलेरिसनेट 6-लेयर डीप न्यूरल नेटवर्क है, जो कल्याणी मेट्रोलॉजिकल साइट, पश्चिम बंगाल, भारत के पास स्थित दो मौसम स्टेशनों से एकत्र किए गए आंकड़ों पर आधारित है। सोलेरिसनेट का उपयोग करते हुए दैनिक GSR पूर्वानुमान कौशल की मौजूदा अत्याधुनिक स्थिति और प्रभाव पिछले GSR डेटा के संदर्भ में बेहतर है। इस शोध में दैनिक और मौसमी GSR परिवर्तनशीलता को समझने हेतु अल्प अवधि पूर्वानुमान के लिए इसकी क्षमता के बारे में चर्चा की गई है।

ABSTRACT. Effective utilization of photovoltaic (PV) plants requires weather variability robust global solar radiation (GSR) forecasting models. Random weather turbulence phenomena coupled with assumptions of clear sky model as suggested by Hottel pose significant challenges to parametric &non-parametric models in GSR conversion rate estimation. Also, a decent GSR estimate requires costly high-tech radiometer and expert dependent instrument handling and measurements, which are subjective. As such, a computer aided monitoring (CAM) system to evaluate PV plant operation feasibility by employing smart grid past data analytics and deep learning is developed. Our algorithm, SolarisNet is a 6-layer deep neural network trained on data collected at two weather stations located near Kalyani metrological site, West Bengal, India. The daily GSR prediction performance using SolarisNet outperforms the existing state of art and its efficacy in inferring past GSR data insights to comprehend daily and seasonal GSR variability along with its competence for short term forecasting is discussed.

Key words – Deep neural network, Gaussian process regression (GPR), Global solar radiation (GSR), Forecasting, Time series, Meteorology.

1. Introduction

Kyoto Protocol (KP) like strategic agreements on energy resources reflects the need for long-run forecasting of renewable energy time series fluctuations and mitigate the problems of environment degradation due to emission exhausts from non-renewable resources (Protocol Kyoto, 1997). Photovoltaic systems for industrial and domestic uses require the distribution of grid connected power systems with solar radiation as the main energy source. However direct conversion of solar to electrical energy is costly and has relatively low efficiency (Mellit *et al*., 2010). Coupled with grid stability issues concerning scheduling and assets optimization for short-term (monthly) and long-term (yearly) forecasting requires guaranteed knowledge of solar radiation instabilities at local weather stations. All this information is based on satellite observations and data from ground stations, with uncertainty in geographic and time availability of data and data sampling rate posing significant forecast granularity.

To assess the PV plant operation dependability on global solar radiation (GSR), good measurement of GSR using a high class radiometer and correct controlling of the instrument through correct maintenance policy is essential. In order to reduce these involving costs, a solution envisaging data collected by public weather station installed near the plant but in a different location is helpful. In developing countries like India, the use of data analytics based GSR forecasting is attractive because weather station belongs public network bodies and the data are certified and free of cost. Several solar radiation prediction models (Piri and Kisi, 2015; Ferrari *et al*., 2013; Reagan *et al*., 1987; Cristaldi *et al*., 2017) from the available meteorological parameters have been developed (Piri and Kisi, 2015) from time to time, which includes both parametric and nonparametric algorithms. Razmjoo *et al.* (Wan *et al*., 2008), applied the Angstrom-Prescott (AP) methodology to estimate the monthly global solar radiation in Ahvaz and Abadan cites, Iran. Artificial Neural Network (ANN) with Multiple Regression Models (MLR) is compared by Kumar *et al*. (Chen *et al*., 2011; Yadav and Chandel, 2014; Amrouche and Le Pivert, 2014) for monthly GSR prediction and it shows the superiority of ANN models over MLR where the mean absolute percent error (MAPE) is lower in case of ANN. Mohanty *et al*. (2016) review on models categorization based on empirical and soft computing classes highlights the precision advantages of soft computing model in predicted error minimization. A lot of research has been done in this aspect of empirical and soft computing models (Piri and Kisi, 2015; Ferrari *et al*., 2013) to predict horizontal daily and monthly solar radiation.

In this contribution, a deep neural network, named SolarisNet which is particularly suited for GSR prediction is proposed for condition monitoring with minimal set of meteorological parameters like maximum temperature, minimum temperature and sunshine hour data collected at Kalyani weather station located in West Bengal, India. The comparative evaluation of SolarisNet with existing different parametric and non-parametric models is done to validate the adequacy of SolarisNet in GSR estimation.

2. Methodology

2.1. *Present status of GSR prediction model*

Based on the relationship between daily global irradiation and BSS, Angstrom proposed the first ever empirical model to estimate GSR (Angstrom, 1924). The monthly average daily irradiation to clear day irradiation at a given location and average fraction of possible sunshine hours is related through the equation. But the monthly average clear sky daily global irradiation for a location is difficult to measure and it was modified by Prescott (1940) and Page (1961). The current form of the equation is known as Angstrom-Prescott (A-P) model and has been presented as :

$$H/H_0 = a + b\,(n/N)$$

where,

H = Daily global irradiation (MJ m^{-2} day^{-1})

H_0 = Extraterrestrial radiation (same Unit as above)

a and b = Empirical constants

n = daily bright sunshine duration (hour)

N = Maximum possible daily sunshine duration (hour)

Thus, the input for GSR estimation is bright sunshine duration and it is measured at limited observatory in India. Hence there is a need to develop GSR-prediction model through air temperature, which is the most common and widely measured meteorological parameters.

2.2. *Deep Neural Net for GSR Prediction: SolarisNet*

2.2.1. *Heuristic behind SolarisNet*

The concept of deep convolutional network came from the biological connections in human body (Hinton *et al*., 2012). Every body part does not sense the same, some of them sense touch whereas some sense flavor, aroma etc. If we consider these as features of a particular specimen, then the features do not mix altogether at the beginning of the journey from the sensory organ to brain. Rather these all features travel a short length with non-linear modification and before going to decision lobe these mix altogether which discloses the property of the specimen and human take decision. In this short run, these features cross many nodes and internodes of neurons. So, we assumed that in these crossing these features independently acquires non-linearity in them. After a certain length of path, these features start mixing themselves and hence the dimensionality gets reduced which is denoted as nonlinear embedding node. These mixed features again mix with each other to form a decision.

2.2.2. *SolarisNet Architecture*

The structure of the proposed deep neural network with three inputs is shown in Fig. 1. The structural details about SolarisNet are given in Table 1. The number of mixed layer nodes should be lesser than input nodes to achieve dimensionality reduction and uniform mixture. In this network we have used hyperbolic tangent transfer (tansig) activation function in the first deep hidden layer.

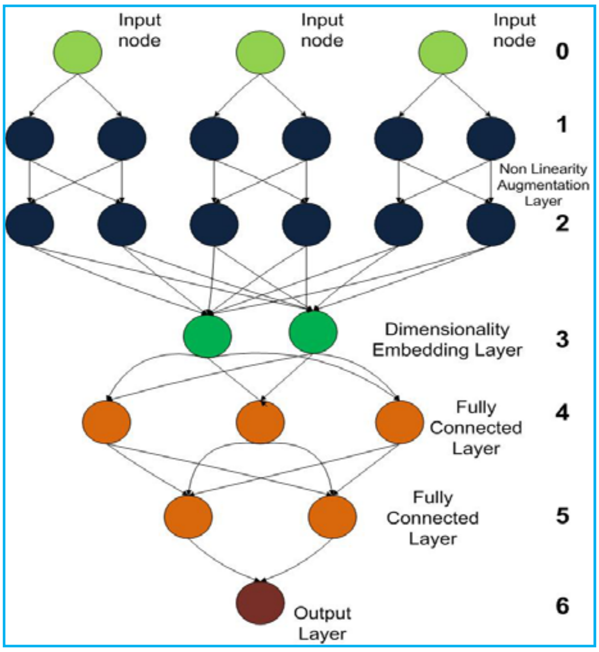

Fig. 1. SolarisNet Architecture

From the Non-linear embedding node to second hidden layer log-sigmoid (logsig) activation function is used to increase the correlation within the target data. The following activation functions are used in the SolarisNet layers and are given below:

$$\text{Log sig}(n) = \frac{1}{1+e^{-n}},$$

$$\tan \text{sig}(n) = \frac{2}{1+e^{-2n}} - 1$$

The training of the network is done by Levenberg-Marquardt (LM) back propagation technique (Levenberg, 1944). LM algorithm uses second order training speed. For the sum of squares performance function the Hessian matrix can be approximated as $H = J^T J$ and the gradient can be computed as, $g = J^T e$, where J is the Jacobean matrix that contains first derivatives of the network errors with respect to the weights and biases and e is a vector of network errors. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update (Hinton *et al.*, 2012):

$$X_{k+1} = X_k \left(J^T J + \mu I\right)^{-1} J^T e$$

μ is decreased after each step and increased whenever there is an increase in the performance function.

TABLE 1

Details of SolarisNet structure

Layers	Layer type	No of neurons	Activation function
0-1	Input	1 × 3	Direct connection
1-2	Non-linearity augmentation	2 × 2 × 3	tan sigmoid
2-3	Dimensionality Embedding	1 × 2	log sigmoid
3-4	Fully connected	3	log sigmoid
4-5	Fully connected	2	log sigmoid
5-6	Output	1	Direct connection

2.2.3. *Gaussian Process Regression (GPR) model*

Standard regression model involves training a data set, $D = [(x_i, y_i), I = 1, 2\ldots n]$ where, x_i and y_i represents the input and output vectors. In the GPR model, it is assumed that the noise is additive, independent and of Gaussian type. Hence, the regression formulation becomes, $y = f(x) + \varepsilon$, where $f(x)$ is some unknown latent function operated element wise on the inputs. $\varepsilon = (\varepsilon_n)\, \varepsilon\, R^N$, is a constant power Gaussian noise given by, $\varepsilon_n \sim N\left(0, \sigma_n^2\right)$ (Rohani *et al.*, 2018; Salcedo-Sanz *et al.*, 1936-1940). The GPR assigns a Gaussian process (GP) prior to the unknown function, $f(.)$, represented by $f(x) \sim \mathcal{GP}[\mu_x, k(x,\tilde{x})]$. Here, μ_x and $k(x,\tilde{x})$ signifies the mean and the covariance functions respectively. Moreover, GPR is a better choice when underlying model parameters are unknown. With GP being represented as a set of random variables, it is formulated as:

$$\begin{bmatrix} y \\ y_* \end{bmatrix} \sim N\left\{0, \begin{bmatrix} \left(C(x,x)+\sigma_n^2 I\right) & C(x,x_*) \\ C(x,x_*) & C(x_*,x_*) \end{bmatrix}\right\}$$

where, x_* is the test data and $\mathcal{C} \epsilon R^{N \times N}$ is generated from the squared-exponential covariance function,

$$k(x,\tilde{x}) = \sigma_f^2 \exp\left(-\frac{|x-\tilde{x}|^2}{2l^2}\right)$$

Here, l is the length-scale, characterizing the distance metric. For short length scales, all estimates are less correlated and the predictive variance increases rapidly away from the data points. The vectors, y and y_* are conditionally distributed as, $y_*\left[y \sim N\left(\mu_f, \text{cov}(f_*)\right)\right]$, where, $\mu_f = k_*^T(\mathcal{C}(x,x) + \sigma_n^2 I)^{-1} y$ represents the matrix

Fig. 2. Field measurement of global solar radiation using pyranometer located at from Kalyani meteorological site, WB, India

of regression coefficients and $cov(f_*) = \mathcal{C}(x_*, x_*) - k_*[\mathcal{C}(x,x) + \sigma_n^2 I]^{-1} k_*$ is the Schur complement. Hence, $cov(f_*)$ depends only on the inputs, $x \epsilon R^N$. In GP model both the prior and likelihood are Gaussian, *i.e.*, $f|x \sim \mathcal{N}(0, \mathcal{C})$ and $y|f \sim \mathcal{N}(f, \sigma_n^2 I)$. The marginal likelihood is given by,

$$p(y|x) = \int p(y|f,x)p(f|x)df$$

The log marginal likelihood is the sum total of the data-fit term, regularization terms and a normalization constant and is given by,

$$\log[p(y|x)] = -\frac{1}{2} y^T \tilde{C}^{-1} y - \frac{1}{2}\log(|\tilde{C}|) - \frac{n}{2}\log(2\pi)$$

where, $\tilde{\mathcal{C}} = \mathcal{C}(x,x) + \sigma_n^2 I$

More details about the existing parametric models like Angstrom-Prescott and non-parametric methods like GPR, SVR and ANN can be traced from (Wan *et al*., 2008; Rohani *et al*., 2018; Salcedo-Sanz *et al*., 2014; Chen *et al*., 2011; Yadav and Chandel, 2014).

3. Experimental data and pre-processing

3.1. *Acquisition of Global Solar Radiation (GSR) Field Data and Pre-processing*

The incoming GSR time series data was measured using a thermopile pyranometer (Make National Instrument and Calibrated by India Meteorological Department, Pune). The thermopile pyranometer is designed to measure the broadband solar radiation flux density with 180° field view and its measurable wavelength ranges from 0.3 µm to 3 µm (Fig. 2). The instrument does not require any power to operate and gives output voltage in mili-volt range, which was converted to radiation flux units (Wm^{-2}) by suitable standardisation. The hourly interval measurement throughout the day was cumulated to obtain the daily solar radiation in MJ m^{-2} day^{-1}. Table 2 summarizes the descriptive statistics of the two datasets (DS) used for proposed deep learning based method validation. The GSR range, total number of samples in each dataset and along with mean and variance of each one of the meteorological parameters are given. Dataset-1 (DS1) is taken from meteorological site with coordinates 22°87′ N 88°20' E while, dataset-2 (DS2) is taken from coordinates 22°87' N 88°20' E.

3.2. *Significance of the considered meteorological parameters*

The significance of the three parameters can be estimated from the log length scale *vs*. length scale number plot. Low log length scale value has high influence to the response of the model. A total number of eleven meteorological parameters (300 observations) from the dataset are given as input in GPR model which discloses length scale number 9 (sunshine hour) has the highest sensitivity to predict the GSR. The second, third and fourth highest sensitive length numbers are 3 (Dry Bulb Temperature I), 2 (minimum temperature), 1 (maximum temperature) respectively. As we are considering for the simplicity of the model as well as the requirement of meteorological instruments we are taking length scale numbers 1, 2 and 9 as input meteorological parameters to the GPR model.

The sensitivity (SA) analysis of the data is done to show the relevancy of the input features. The SA of the GPR for the dataset reveals that sunshine hour is the most sensitive feature. It is obvious that if the sunshine hour changes then the incoming solar radiation will change rapidly, hence the GSR will get affected. The effect of whole day GSR is sensed at night. Decrease in daily GSR causes higher min, temp. which is evident for observations made for cloudy and partially-cloudy day. The SA is shown in Fig. 3.

3.3. *Training and test data splitting*

We have trained different statistical models for the corresponding datasets. In all cases, we standardized the input features. In VMD and GPR combined model the mean was removed from observed GSR data. The data is split in 80% training set and 20% test or holdout set. Hyper-parameters for GPR and GPR+ denoised combined model were optimized by maximizing the marginal log-likelihood using the training set. Best results of each model are shown in Table 3. In terms of the statistical measures like mean absolute error (MAE),

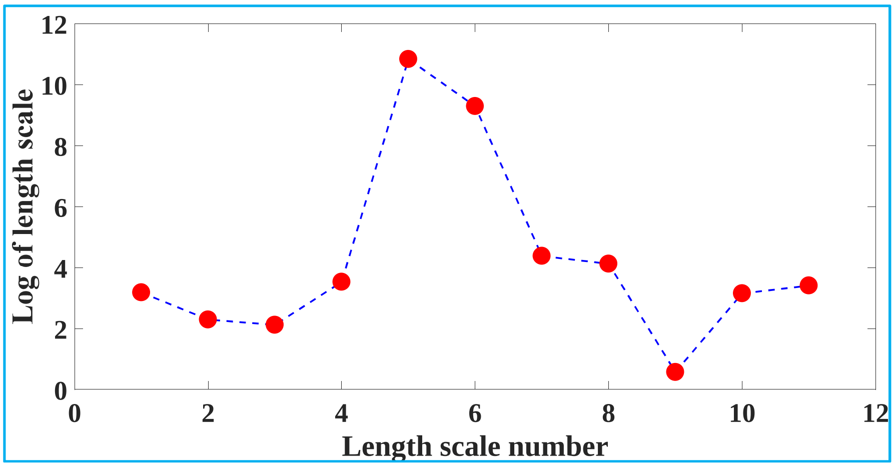

Fig. 3. Log-log plot of the length scale *vs* length scale number. A total of eleven meteorological parameters are given as input in the GPR model, out of which parameter 9 (sunshine hour), parameter 2 (Minimum temperature) and parameter 1 (maximum temperature) are the most statistical significant parameters to the GPR response

TABLE 2

Descriptive statistics of Dataset1 and dataset 2

Dataset (DS) [No. of samples]			Max. Temp.		Min. Temp.		Sunshine hr	
			μ	σ^2	μ	σ^2	μ	σ^2
DS1 (1461)	GSR range (MJ/m^2)	9.69 to 25.70	31.92	4.49	21.11	6.30	6.42	3.11
DS2 (1064)	GSR range (MJ/m^2)	5.60 to 23.50	32.23	4.41	23.29	5.08	5.13	2.98

TABLE 3

Comparison of selected studies in daily global solar radiation prediction

	Method	RMSE	MAE	MBE	ρ
DS1	Angstrom Eqn. (Wan *et al.*, 2008)	2.6710	2.0035	-1.5431	1.1250
	SVR (Chen *et al.*, 2011)	2.7930	2.1032	-1.7618	1.0810
	GPR (Rohani *et al.*, 2018)	2.3560	1.7367	-1.1626	1.1478
	ANN (Yadav and Chandel, 2014)	2.0821	1.7855	-0.0224	1.2909
	GPR + (denoised + GPR)	2.2913	1.8149	-1.0127	1.1935
	Proposed SolarisNet	1.7661	1.7249	-0.3682	1.2376
DS2	Angstrom Eqn. (Wan *et al.*, 2008)	3.4731	2.7886	1.0342	0.8712
	SVR (Chen *et al.*, 2011)	1.5961	1.3245	-0.0209	1.3847
	GPR (Rohani *et al.*, 2018)	1.3713	1.0966	-0.0300	1.1839
	ANN (Yadav and Chandel, 2014)	1.3983	1.1191	-0.2116	1.1392
	GPR + (denoised + GPR)	1.2972	1.0054	-0.0879	1.1756
	Proposed SolarisNet	1.0492	0.7868	0.1270	1.0956

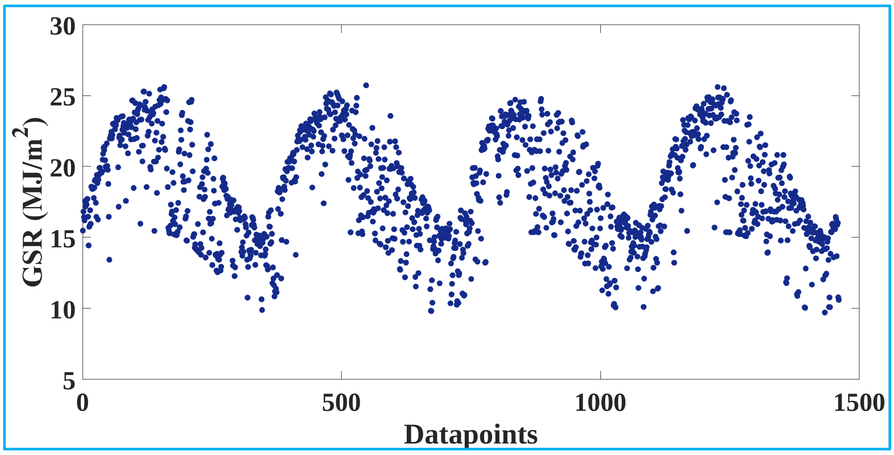

Fig. 4. Daily global solar radiation data pattern

Pearson correlation coefficient (ρ), mean bias error (MBE) are compared for each model.

3.4. *Evaluation metric : Statistical measures*

Performance assessment of GSR forecasting models is evaluated using four statistical measures which are defined as:

Root mean square error (RMSE) is defined as

$$\mathrm{RMSE} = \left[\Sigma_n \left(H_{\mathrm{pred}} - H_{\mathrm{actual}}\right)^2 / n\right]^{0.5}$$

Mean absolute error (MAE) is defined as

$$\mathrm{MAE} = \frac{1}{n}\sum_n \left|H_{\mathrm{actual}} - H_{\mathrm{pred}}\right|$$

Pearson correlation (**ρ**) is defined as

$$\rho = \frac{\sum_n \left(H_{\mathrm{pred}} - \overline{H}_{\mathrm{pred}}\right)\left(H_{\mathrm{actual}} - \overline{H}_{\mathrm{actual}}\right)}{\sqrt{\sum_n \left(H_{\mathrm{pred}} - \overline{H}_{\mathrm{pred}}\right)^2}\sqrt{\sum_n \left(H_{\mathrm{actual}} - \overline{H}_{\mathrm{actual}}\right)^2}}$$

Mean bias error (MBE) is defined as

$$\mathrm{MBE} = \sum_n \left(H_{\mathrm{pred}} - H_{\mathrm{actual}}\right) / n$$

where, H_{pred} and H_{actual} are the predicted and the actual values of GSR, $\overline{H}_{\mathrm{pred}}$ and $\overline{H}_{\mathrm{actual}}$ are the average values of predicted and actual GSR. In general, a low RMSE is desirable, a positive MBE shows over estimation while a negative MBE indicates under estimation.

4. Results and discussion

We developed our deep neural net, SolarisNet in MATLABR2016a and have trained it on AMD FX-8320 Octa-core system with 3.50 GHz processor and 16GB RAM. Some of the heavy-duty processes were written in C MEX file to speed up calculation. Moreover, the proposed net requires 1-Dconvolutions and therefore implementation wise economical and requires simple hardware. It took an average of 14.034 sec to complete one set of training. Both parametric (Angstrom Eqn.) and non-parametric models (GPR, ANN and SVR) are trained with the field dataset and compared with the proposed SolarisNet based prediction. Two meteorological sites near Kalyani, India is selected for the training and validation of global solar radiation (GSR). The study area is situated under tropical climatic region with humid summer and high amount of rainfall. A high fluctuation of temperature is observed throughout the year. It can be seen from Fig. 4, that a periodicity exists in the global solar radiation pattern over the year for this particular area. Moreover, GSR reaches to peak around April to May and thereafter it goes down due to the cloud cover during monsoon season. Value of GSR remains lower during December to January. However, the variation in the intermediate days is high which introduced stochastic characteristics in the data.

Neural network (NN) based algorithms are better in solving stochastic problems. However, fully connected NN induces high degree of non-linearity with the stack of input data which might not be the necessary for the prediction a target. Therefore, we introduced a NN architecture which is not fully connected at initial stage to preserve the non-linearity of the input parameter itself.

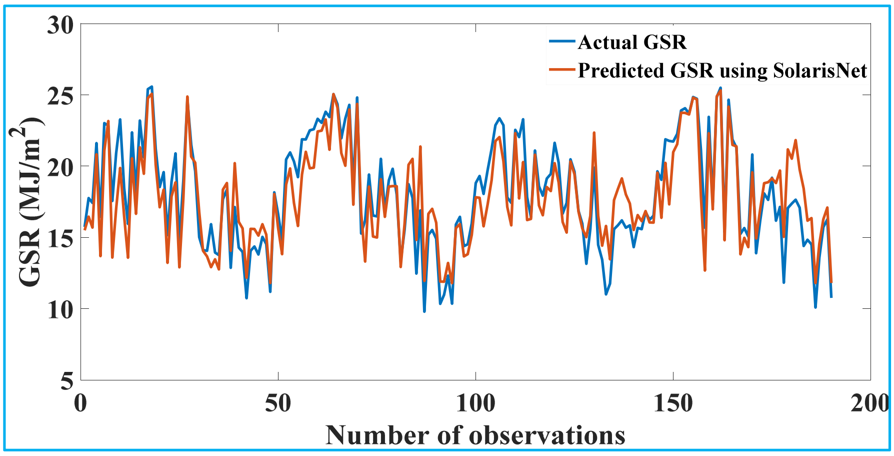

Fig. 5. Representative plots for predicted GSR using SolarisNet

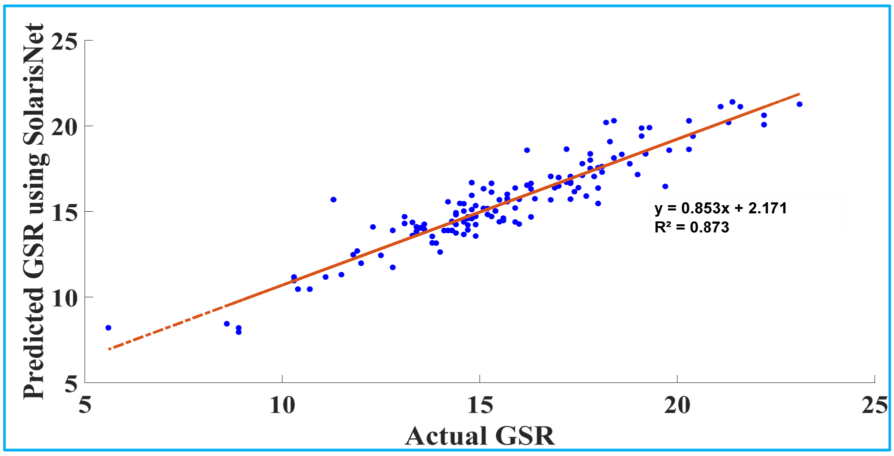

Fig. 6. Observed *vs* predicted GSR for DS1 using SolarisNet using most relevant features only

Table 3 illustrates the results of different algorithms in comparison with proposed Solarisnet architecture. As the GSR data set holds the form of skewed normal distribution with a noise floor, GPR (2.35) and denoised GPR (2.29) shows better RMSE values than Angstrom (2.67) and SVR (2.79) algorithms for DS1. Also, similar results hold for DS2. The RMSE for Angstrom and SVR models were 3.47 and 1.59, respectively. Whereas, for GPR and denoised GPR the values are 1.37 and 1.29, respectively. In case of simple ANN model the RMSE fluctuates from 1.39 to 2.08 from DS2 to DS1. In comparison, our proposed SolarisNet produced an accuracy of 1.76 for DS1 & 1.04 for DS2. Hence, a high improvement of accuracy is observed using the proposed architecture. The improvement in accuracy might be due to the effective capture of inherent non-linearity in both the data sets.

In the mean absolute error (MAE) values an improvement of 5% and 22% is observed for SolarisNet architecture than denoised GPR model. Also, the mean bias error (MBE) for SolarisNet (-0.3682) is much lower and comparable to simple ANN model (-0.0224) for DS1. However, all the models under-predict GSR for DS1. In case of DS2, the mean bias error of SolarisNet is 0.1270 which shows over-prediction of GSR. Fig. 5 shows the plots of actual GSR and predicted GSR. The predicted GSR using SolarisNet follows the pattern of actual GSR. Also, a high correlation and high r-squared value can be observed in between actual GSR and predicted GSR from Fig. 6. Hence, our proposed SolarisNet architecture outperforms other existing models in the literature for the prediction of GSR.

5. Conclusions

We developed a neural network based architecture, SolarisNet for global solar radiation (GSR) prediction. SolarisNet exceeds the performance of standard existing algorithms in predicting GSR from experimental solar radiation field data. Further, the sensitivity analysis on

GPR mean and variance shows the relevancy of minimum temperature and sunshine hour is higher than maximum temperature in GSR forecasting. The presence of non-linear interrelationship among the feature variables is exploited by employing a non-linear mapping layer in the SolarisNet which helps in lowering the RMSE for predicted and measured GSR values. This model can further be extended globally for fast and accurate retrieval of GSR. Alternatively, the authors are considering the exploitation of short term temporal and meteorological information in designing long short time networks (LSTN) to improve the robustness of model parameters in estimation.

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