Forecasting of Global Solar Insolation Using Ensemble Kalman Filter Based Clearness Index Model

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***Abstract*— This paper describes a novel approach in developing a model for forecasting of global insolation on a horizontal plane. In the proposed forecasting model, constraints such as latitude and whole precipitable water content in vertical column of that location, have been used. These parameters can be easily measurable with global positioning system (GPS). The aforesaid model has been developed by using the above datasets generated from different locations of India. The model has been verified by calculating theoretical global insolation for different sites covering east, west, north, south and central region with the measured values from the same locations. The model has also been validated on a region, from which data has not been used during the development of the model. In the model clearness index coefficients (K_T) are updated using ensemble Kalman filter (EnKF) algorithm. The forecasting efficacies using K_T model and EnKF algorithm have also been verified by comparing two popular algorithms namely recursive least square (RLS) and Kalman filter (KF) algorithms. Minimum mean absolute percentage error (MAPE), mean square error (MSE) and correlation coefficient (R) value obtained in global solar insolation estimation using EnKF in one of the location is 2.4%, 0.0285 and 0.9866 respectively.**

***Index Terms*— Forecasting, Global solar insolation, Extra-terrestrial irradiance, Ensemble Kalman Filter, Clearness index**

I. Introduction

INTERMITTENT and variable nature of renewable generations poses new challenges to power system operation and control. With high penetration of solar irradiance in a photovoltaic (PV) system, more acute problems such as voltage and frequency fluctuations occur resulting in additional requirement of ancillary generations and challenges in the electricity markets. Hence, devising accurate forecasting methods has attracted more attention to researchers, for resolving the aforesaid issues with intermittency in PV power system. Since majority of generation units are associated with output of day ahead market, day ahead forecasting is important. A new model proposed [1] to estimate solar insolation, on comparing with numerical simulation and the climatology measured data. Results show accurate evaluation of solar radiation for any day of a year with inputs such as altitude, longitude and latitude. However, main concern is that in order to collect utmost solar energy, the orientation and inclination of receiver are to be varied, as per the variation of solar declination angle. The diffuse ratio (*k*) vs. clearness index (K_T) was reviewed [2] for hourly, daily, monthly and yearly frequency regression models. From the regressor equation, the averaged diffuse irradiation values have been estimated from averaged global irradiation values. A method [3] has been developed for calculation of total solar radiation from the evaluated direct and scattered solar radiation. In this method, the bias, which is the difference between the estimated and calculated values of diffuse and direct solar irradiance, act as an offset in estimation of global solar insolation. It was also found that temperature and relative humidity are the considered factors influencing the bias for direct and diffuse solar radiation, and finally the assessment of global solar insolation is limited using this model. A rigorous review [4] has been made for the development and analysis of different models for estimating diffuse horizontal solar radiation during the day for different baroscopic places in China. System Advisor Model (SAM) [5] is used to get the past solar generation information, on giving the input data from Solar anywhere. Using MATLAB software and System Identification Toolbox, the model has been validated. Main concern here is that when forecast horizon increases, both persistence and Auto Regressive Moving Average (ARMA) models provide erroneous results. In [5] because of geographical differences, for prediction of irradiance, each location requires one model and construction of model requires two phases i.e for finding out orders and co-efficients of ARMA. For a country covering a vast geographical location, a single model cannot accurately forecast the solar power. A simple theoretical model has been developed in [6] for assessment of total solar insolation on a horizontal plane. The said model is developed considering the latitude and the quantity of entire precipitable water content in the vertical

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column of the desired site as input constraints. However, the main lacunae in [6] is that the perfect estimation of clearness index K_T, is not achievable which plays a major role in the forecasting of global solar irradiance. A two-stage technique [7], where at first a statistical regulation of the lunar power has been carried out using a clear sky model. Then adaptive linear time series model is used for forecasting the regulated solar power. The main disadvantage lies in the model is on the dependency of two types of inputs such as for forecasts up to 2 h ahead solar power, while for longer horizons Numerical Weather Predictions (NWP) are the most important inputs. A hybrid model based on the mesoscale meteorological Weather Research and Forecasting (WRF) model [8] and the clearness index-based Kalman filter has been developed for day-ahead solar radiation prediction and has been validated for two sites in Japan and China. This model has the drawback that the forecasting accuracy is more in clear sky than overcast condition. Solar irradiance forecasting by employing artificial neural network (ANN) is suggested in [9]. In the ANN model, Multilayer Perceptron MLP-model is found to be reasonably good to estimate the 24 hours based solar irradiance by applying the daily temperature of air and mean solar irradiance. The main issue lies in the complexity of the MLP-forecasting is owing to huge computing time involved for attaining a decent performance. Authors propose the power output forecasting [10] that is based on 24 hours leading insolation forecasting for a PV system by utilizing weather testified statistics, fuzzy theory, and ANN. In this model also more complexity is involved in training NN by output power information created on fuzzy theory and weather reported information. A comparative study [11] has been carried out among empirical models and ANN models and it is found that empirical models perform better as compared to ordinary ANN models. However, when ordinary ANN models are coupled with Genetic Algorithm, their performance improved. But taking into account all the factors such as skill, processing time and equipment, empirical model is a better choice for evaluation of day-to-day total solar insolation in the climatic condition of Iran. A feedforward backpropagation model [12] and its application in predicting the daily global solar radiation has been presented. Proposed neural network runs with ten neurons and the log-sigmoid transfer function of the hidden. Fifteen numbers of different Geographical and meteorological parameters have been used as input variables and daily global solar radiation as outputs variables. After accessing neural network-based method [13-14], people have done experiments on machine learning based methods [15] such as random forest, gradient boosting, regression tree and many others, for prediction of solar irradiance. In machine learning [15], the construction and study of systems can be learnt from data sets, giving computers the ability to learn without being explicitly programmed. Machine learning models find relationships between input and output even without any possible representation. Before using machine learning models for forecasting problem, classification and data mining are of prime importance because one has to work with big datasets and the task of pre-processing, data protection and transmission can be taken care of by machine learning models, so forecasting model using machine learning requires more skill and computational time as compared to other conventional methods. It was difficult to rank those methods as per their performance because of the data set diversification, forecasting horizon, time step and performance indicators. For improving prediction performance, they have suggested for hybrid models. Another solar irradiance forecasting method [16] built on Markov Switching Model has been established. Above technique has been applied to only remote locations where cloud based and other numerical prediction technique may not be used.

Study of previous works in the field of forecasting in solar irradiance exhibit shortcomings (Sh) and weaknesses, which are divided into the following categories:

1. Sh-1: Problem lies in the variation of receiver as per the variation of solar declination angle and modelling for accuracy of clearness index K_T, which play vital roles in forecasting of global solar insolation ([1], [2], [6], [7]).
2. Sh-2: Temperature and humidity, affect the bias for direct and diffuse solar irradiance and finally affect the forecasting performance of global solar insolation ([3], [4]).
3. Sh-3: Model developed for solar irradiance forecasting is not uniform for any location in world i.e it is location specific and also when forecast horizon increases, accuracy in forecasting decreases ([5], [16]).
4. Sh-4: Main concern in neural network (NN) and hybrid model-based forecasting lies in training of NN by huge amount of weather data, involvement of more skill, computation time and equipment in forecasting of solar irradiance ([8] - [12]).

Solar insolation forecasting is now-a-days more important because of more inclusion of PV in conventional power system. Statistical methods of forecasting give good results for forecast horizon of upto 6 hours but for greater than 6 hours forecast horizon, numerical weather prediction (NWP) method is preferred. However, in this paper, a clearness index model based Ensemble Kalman Filtering has been used, for accurate forecasting of global solar insolation on a horizontal plane. Performance of the proposed method has also been compared with recursive least square (RLS) and Kalman filtering (KF) method.

The model developed in this work for forecasting direct insolation depend on two dominant measured constraints, such as latitude and precipitable water in the vertical column of the desired site. By using a global positioning system GPS receiver or a geographical map, latitude of desired site can be found. The source of insolation data for different locations of India is the Indian Meteorological Department, Pune i.e https://imdpune.gov.in/ site. From the data related to daily relative humidity provided by the climatological department, precipitable water at that place can be found, or can be measured using radiosonde or GPS receivers. In the developed model for calculating clearness index (i.e K_T), Fourier coefficients are updated using ensemble Kalman filter (EnKF) algorithm. So, a model, based on few input parameters will aid fast and easy estimation of insolation for any place for any specified day.

The major contributions of this paper are concised below:

1- Solar irradiance forecasting has been performed based on two important parameters (latitude and precipitable water in the vertical column of the desired location). Environmental condition and solar angles are also taken into account during the development of model (tackling Sh1, Sh2).

2- In the developed model K_T, Fourier coefficients are updated using ensemble Kalman filter (EnKF) algorithm, which provides more accuracy in estimation for K_T (tackling Sh1).

3- In the proposed model, few input parameters used for fast and easy estimation of insolation for any place for any specified day (tackling Sh3, Sh4).

The paper has been arranged as follows: the development of Ensemble Kalman Filter based clearness index model for global solar insolation forecasting is explained in section II. The test and validation results are discussed in section III. Section IV concludes the paper.

II. Ensemble Kalman Filter (EnKF) Based Clearness Index Model

The schematic for forecasting of global solar insolation is given in Fig. 1. First K_T modelling has been carried out and then final estimate of K_T has been done using EnKF/RLS/KF algorithm, Finally, global solar insolation value has been forecasted.

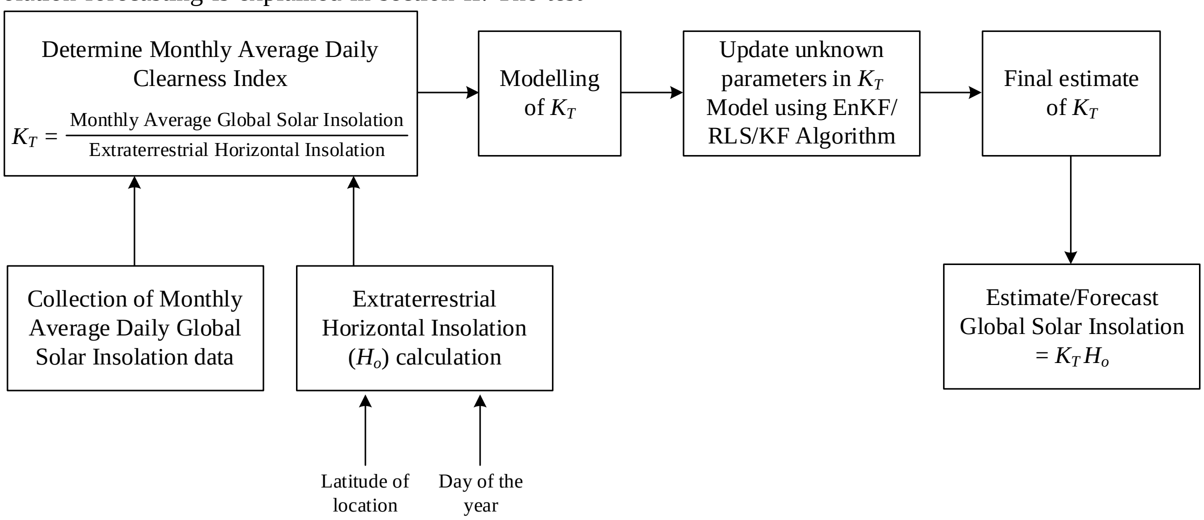

Fig. 1. Schematic for forecasting of global solar insolation

The average monthly data for daily global solar insolation is usually accessible for various places in a given region. The data must be collected in a way that covers a large area of latitudes. These data are then reduced to an index of average monthly daily clearance (i.e. K_T) by taking the global solar radiation to the estimated extra-terrestrial horizontal insolation, at a specified site. Extra-terrestrial horizontal insolation per day is an insolation on the horizontal surface without atmospheric influences. Extra-terrestrial horizontal insolation is expressed in terms of latitude and day of the year. It can be estimated for any site and for any day as described below.

The extra- terrestrial horizontal insolation, H_o is given by

$$H_0 = \frac{24 I_0}{\pi}[\cos\phi.\cos\delta.\sin\omega_{sr} + \omega_{sr}.\sin\phi.\sin\delta] \text{ kWh/m}^2 \quad (1)$$

where

H_0 = Extra – terrestrial horizontal insolation in kWh/m^2

$$I_0 = I_{sc}\left[1 + 0.033\left(\frac{360N}{365}\right)\right] \quad (2)$$

I_0 = Extra-terrestrial insolation in kW/m^2

I_{sc} = Solar constant=1.367 kW/m^2

N = Day of the particular year

ϕ = Latitude of the location in degrees

$$\delta = 23.45\sin\left[\frac{2\pi(N-80)}{365}\right] \quad (3)$$

δ = Declination angle in degrees [13]

ω_{sr} = Hour angle during Sunrise in radians

$$\omega_{sr} = \cos^{-1}(-\tan\phi.\tan\delta) \quad (4)$$

From above equations, it can be observed that extra-terrestrial horizontal insolation can be determined for each location and day of the year as it depends on day of the year and latitude only. But in the above calculations, atmospheric effects had not been taken into account.

Effect of the atmosphere somewhere on insolation is determined by the clearness index, K_T. But, K_T is a stochastic parameter, that depends on time of year, climatic state, season and geographical position. So, in order to take into account, the effects of the atmosphere on the insolation of a place, a model of the clearness index is needed. For modelling of K_T, the data on the insolation on a horizontal surface over a time interval covering each seasons and atmospheric situations, for a few locations are to be measured. Utilizing Eq. (1), the H_0 can be estimated for desired sites, which provides measured global insolation. In the calculated value, atmospheric effect has not been taken into account. After calculation of H_0 for specific locations and the measured global horizontal insolation for the same locations, K_T for these locations are calculated. Then a graph is plotted by taking K_T vs month of the year as shown in Fig. 2. It is found from the graph that the variation of K_T is a periodic function having a periodicity of one-year. Thus, for modelling of K_T, the Fourier series are regarded as suitable curve fitting method.

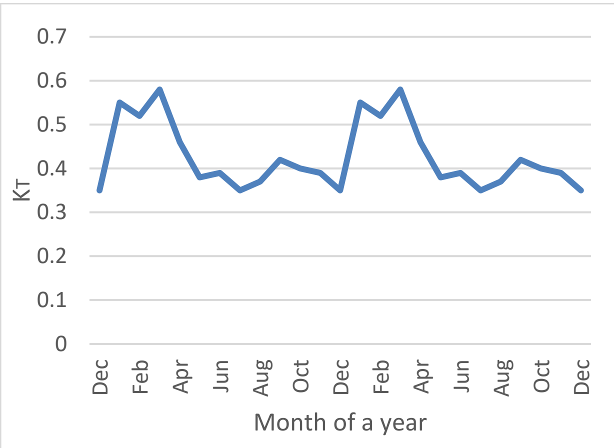

Fig. 2 Variation of K_T throughout year

K_T can be represented by the Fourier series:

$$K_T = f(x,w,t) + e \tag{5}$$

$$f(x,w,t) = A_1 + A_2 \sin t + A_3 \sin 2t + A_4 \sin 3t + A_5 \cos t + A_6 \cos 2t + A_7 \cos 3t \tag{6}$$

Trigonometric terms (t) are functions of the day of the particular year (N)

$$x = \phi - 35 \tag{7}$$

$\phi =$ Latitude in degrees

$w =$ Total precipitable water vapor in gm/cm^2

$$t = (2\pi / 365)(N - 80) \tag{8}$$

$e =$ error

$$e = K_T - f(x,w,t) \tag{9}$$

x has been updated based on best fit of the available data. Since all the used data have been collected from India only, we have found that an offset value of 35-degree latitude gives the best fit for the sub-continent. In this way, the function of x given in eq. (7) has been determined.

$A_1, A_2, ..., A_7$: Functions of (ϕ) and (w)

Fourier coefficients are evaluated from the succeeding equation:

$$A_i = a_{i1} + a_{i2}x + a_{i3}x^2 + a_{i4}w + a_{i5}w^2 \tag{10}$$

Now replacing A_i in the Eq. (6) for $f(x,w,t)$

$$\begin{aligned} f(x,w,t) = {} & (a_{11} + a_{12}x + a_{13}x^2 + a_{14}w + a_{15}w^2) \\ & + (a_{21} + a_{22}x + a_{23}x^2 + a_{24}w + a_{25}w^2)\sin t \\ & + (a_{31} + a_{32}x + a_{33}x^2 + a_{34}w + a_{35}w^2)\sin 2t \\ & + (a_{41} + a_{42}x + a_{43}x^2 + a_{44}w + a_{45}w^2)\sin 3t \\ & + (a_{51} + a_{52}x + a_{53}x^2 + a_{54}w + a_{55}w^2)\cos t \\ & + (a_{61} + a_{62}x + a_{63}x^2 + a_{64}w + a_{65}w^2)\cos 2t \\ & + (a_{71} + a_{72}x + a_{73}x^2 + a_{74}w + a_{75}w^2)\cos 3t \end{aligned}$$

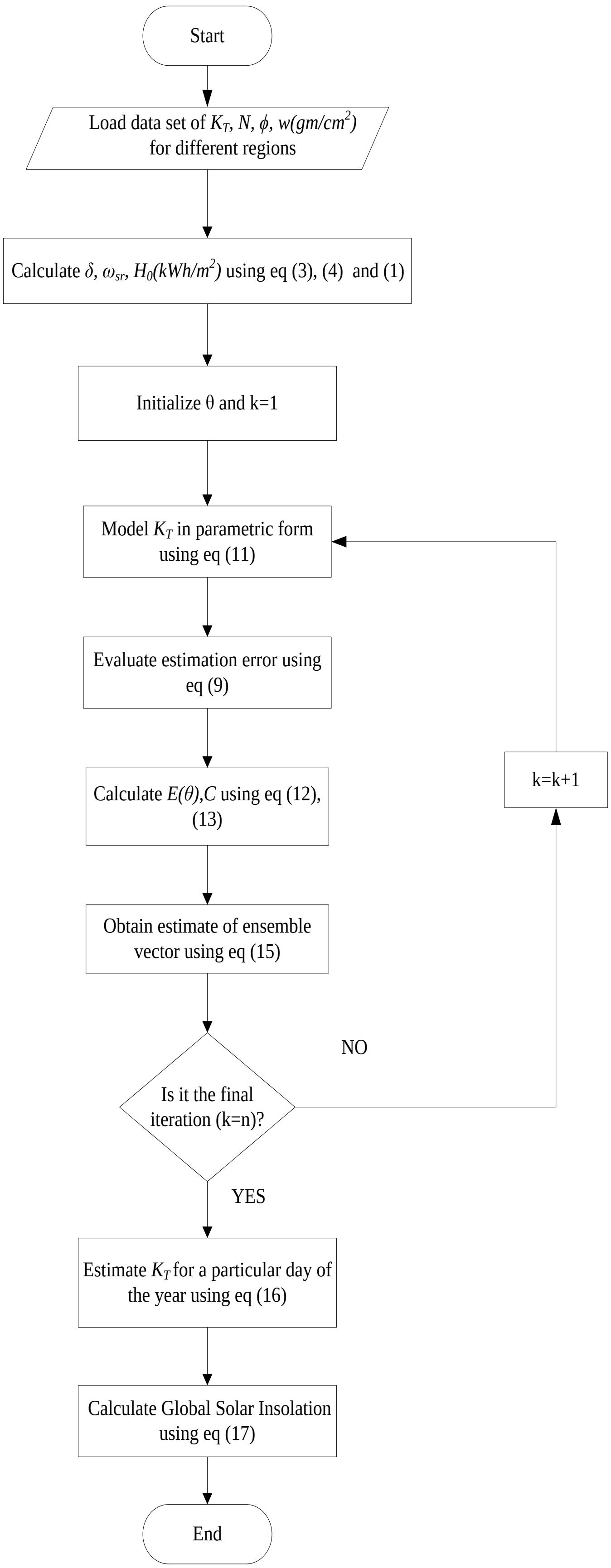

Fig. 2. Flow chart for estimation of global solar insolation using EnKF algorithm.

$$f(x,w,t) = H(x,w,t)\theta \tag{11}$$

$H(x,w,t)$: system structure matrix

θ: vector of unknown parameter

Here the unknown parameters are estimated using Ensemble Kalman Filter (EnKF) [18] algorithm. The EnKF is a Monte Carlo approximation of the conventional Kalman Filter (KF). Rather developing the covariance matrix of probability density function of the state vector, it uses distribution characterized by a sample of state vector *x*, called an ensemble.

θ is updated using Ensemble Kalman Filtering (EnKF) as given below:

Take the ensemble matrix θ and data matrix as f.

Ensemble mean and covariance are

$$E(\theta) = \frac{1}{Q}\sum_{n=1}^{Q}\theta_n \tag{12}$$

Q: No. of Ensembles

$$C = \frac{GG^T}{Q-1} \tag{13}$$

Where

$$G = \theta - E(\theta) \tag{14}$$

$$\hat{\theta}(k) = \theta(k-1) + CH^T(HCH^T + R)^{-1}(f - H\hat{\theta}(k-1)) \tag{15}$$

After finding the updated values of θ, i.e. $a_{11}, a_{12}........a_{75}$

These coefficients are utilized to find the Fourier coefficients $A_1, A_2, ...A_7$

Which leads to the following model for K_T

$$\begin{aligned} K_T &= A_1 + A_2 \sin t + A_3 \sin 2t + A_4 \sin 3t + A_5 \cos t \\ &+ A_6 \cos 2t + A_7 \cos 3t \end{aligned} \tag{16}$$

Now for a particular location and for a particular day of the year, K_T can be estimated by applying the above Equation.

$$H_{tf} = K_T . H_0 \tag{17}$$

H_{tf} = Estimated/forecasted value of Global solar insolation on a horizontal surface at a particular location for a particular day. The EnKF algorithm, for estimation of daily global solar insolation is given as flow chart in Fig.3.

III. RESULTS AND DISCUSSIONS

The model validation has been carried out in a two steps method. In the first stage, measured daily median values of global insolation data for 12 different locations covering a large range of latitude across India have been collected. The model has been developed using measured data from 12 different locations in India covering whole area of the country over a period of 5 years. Based on these data, a model for K_T has been developed. From the model, theoretical global insolation has been calculated and then compared with the measured value for validation.

In the second stage, the conceptual global insolation has been estimated for another location in India, whose latitude lies inside the range of latitudes considered for development of model. The estimated and measured insolation curves are studied for validation of the proposed model. Table I gives the measured and forecasted values of global solar insolation at five different locations covering north, south, east, west and central parts in India. In the table, Inso stands for Insolation, *Htm* is the measured value of global solar insolation in kWh/m^2 and H_{tf} is the forecasted value of global solar insolation in kWh/m^2.

Fig.4 represents the measured and calculated global solar irradiance at region A, which is located in the northern part of India. From this Fig., it is found that estimation of global solar irradiance, using RLS is comparatively better than using KF. But estimation using EnKF outperform over RLS and KF in estimation of global solar insolation. Fig.5 shows the comparison of estimation accuracy using all the three discussed algorithms at region B, located at southern part of India and it has been found that in this case also estimation accuracy is more in case of EnKF estimation as compared to RLS and KF algorithms. Fig. 6 shows the comparative estimation of global solar irradiance using the three algorithms in region C, which is at the eastern part of India. In this region the measured and estimated irradiances almost match with each other with more accuracy in estimation using EnKF algorithm.

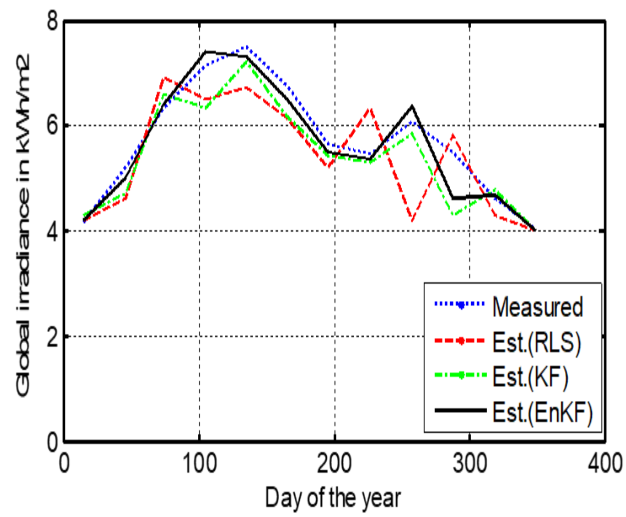

Fig. 4. Measured and estimated global solar irradiance for region A (North).

TABLE I
MEASURED AND FORECASTED VALUES OF GLOBAL SOLAR INSOLATION

Loc	Ins	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
A	*Htm*	4.15	5.19	6.34	7.13	7.51	6.76	5.66	5.45	6.07	5.5	4.6	4.02
	Htc(RLS)	4.2	4.61	6.92	6.48	6.72	6.15	5.2	6.33	6.33	5.25	4.3	4.01
	Htc(KF)	4.3	4.7	6.6	6.32	7.2	6.16	5.42	5.31	5.86	4.3	4.77	4.00
	Htc(EnKF)	4.2	5.0	6.4	7.4	7.3	6.5	5.5	5.35	6.36	5.63	4.68	4.00
B	*Htm*	6.17	6.58	6.89	6.48	5.58	5.58	5.2	5.75	6.23	5.59	5.24	5.62
	Htc(RLS)	6.48	7.23	6	6.15	5.46	5.44	5.47	4.8	6.6	5.49	5.3	5.69
	Htc(KF)	6.05	7.54	6.2	7.8	6.92	5.12	5.04	5.3	6.0	4.98	6.04	5.4
	Htc(EnKF)	6.1	7.5	6.3	6.85	6.2	5.3	5.06	5.5	6.1	5.53	5.8	5.5
C	*Htm*	4.24	5.26	6.09	6.59	7.01	5.14	4.71	4.36	4.62	4.64	4.3	4.07
	Htc(RLS)	4.6	4.18	6.7	6.74	6.3	5.27	3.96	4.4	4.62	4.59	4.35	3.84
	Htc(KF)	4.77	4.89	6.91	6.73	7.26	5.0	4.83	4.2	4.5	4.3	3.8	4.2
	Htc(EnKF)	4.5	4.94	7.0	6.4	6.7	5.2	5.0	4.3	4.4	4.4	4.6	4.02
D	*Htm*	5.08	5.77	6.58	7.13	7.42	5.8	4.17	4.09	5.2	5.66	5.23	4.83
	Htc(RLS)	4.9	5.5	5.83	6.16	6.63	5.62	4.32	4.88	4.81	4.92	5.0	4.75
	Htc(KF)	4.78	5.86	5.15	6.4	6.5	5.27	4.54	4.9	5.4	5.63	5.32	4.35
	Htc(EnKF)	5.2	5.6	6.78	7.13	7.48	5.56	4.86	4.8	5.5	5.33	5.1	4.5
E	*Htm*	5.03	5.78	6.43	6.97	7.12	6.01	4.41	4.22	5.38	5.87	5.3	4.85
	Htc(RLS)	4.32	5.84	6.07	7.20	6.74	6.64	4.51	3.53	5.28	5.87	4.78	5.02
	Htc(KF)	5.24	6.2	6.8	7.5	6.86	6.4	4.43	5.21	4.32	5.6	5.32	5.01
	Htc(EnKF)	5.1	6.4	6.24	7.3	7.1	5.85	4.5	4.3	5.0	5.3	5.4	5.00

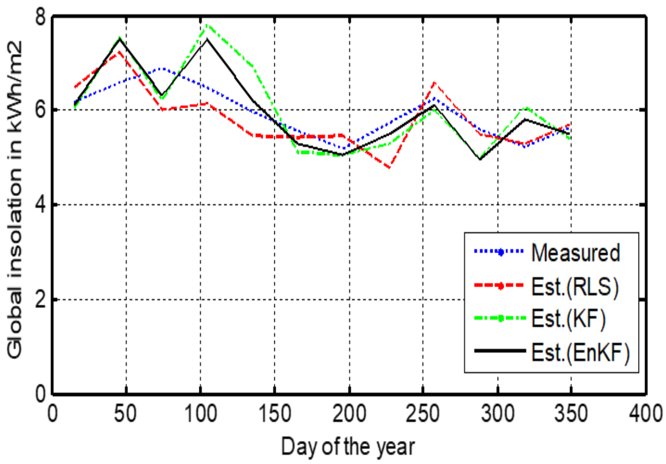

Fig. 5. Measured and estimated global solar irradiance for region B (South).

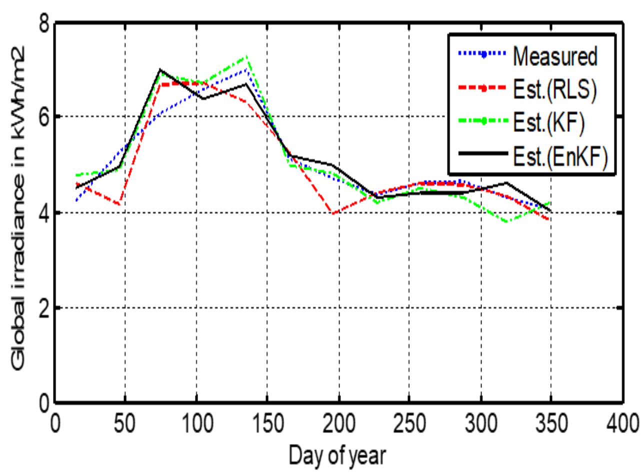

Fig. 6. Measured and estimated global solar irradiance for region C (East).

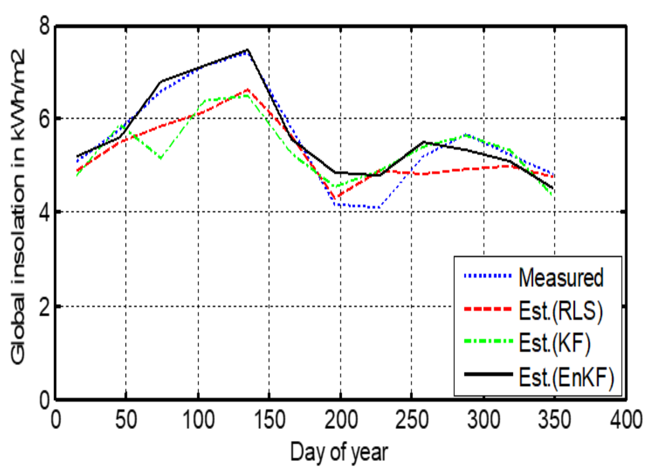

Fig. 7. Measured and estimated global solar irradiance for region D (West).

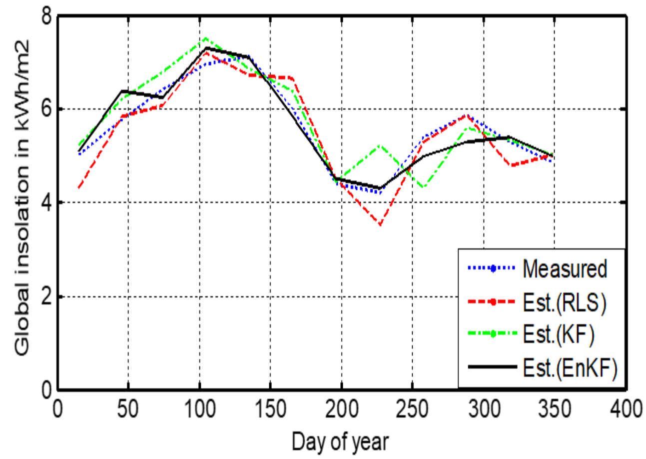

Fig. 8. Measured and estimated global solar irradiance for region E (Central).

For verification of the proposed EnKF based estimation of global solar irradiance, in rest of the two regions, Fig, 7 and Fig. 8 show the comparative estimation of global solar irradiance in region D and E, located in western and central part of India. In both the Figs., estimation performance of global solar irradiance using EnKF is comparatively better as contrasted to RLS and KF.

In order to measure the accuracy of the estimation, the errors between the estimated values and measure data are examined here. In this paper, mean absolute percentage error (MAPE), mean square error (MSE) and correlation co-efficient (*R*) as defined in Eq. (18), (19) and (20) respectively, are used as the error indices to verify the forecasting technique.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{H_{tm}(t)-H_{tf}(t)}{H_{tm}}\right| \tag{18}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(H_{tm}(t) - H_{tf}(t)\right)^2 \tag{19}$$

$$R = \frac{n\sum H_{tm}H_{tf}-(\sum H_{tm})(\sum H_{tf})}{\sqrt{[n\sum H_{tm}^2-(\sum H_{tm})^2][n\sum H_{tf}^2-(\sum H_{tf})^2]}} \tag{20}$$

where n is the number of measurements

From the table II, it is seen that for all the cities, the MAPE and MSE using EnKF method is minimum as compared to other two methods. It can also be seen from the table II that correlation co-efficient (*R*) for most cases of forecasting lies between 0.7 – 1, which shows strong association between measured and forecasted values. In majority of cases for *R* values in EnKF estimation is very close to 1, which shows that EnKF estimation has strongest association between measured and estimated values as compared to other two algorithms

The MAPE in the estimation of global solar insolation using different methods has been shown in Fig. 9, it is seen that for all the cities, the MAPE error using EnKF method is minimum as compared to other methods. Minimum MAPE using EnKF method is found as 2.4 % for city A and maximum MAPE value using EnKF is 5.6% for both city B and D, which can be accepted for getting accuracy in forecasting. Fig. 10 shows the comparison of MSE in the assessment of global solar insolation applying various methods. It has been found that MSE value in case of EnKF estimation for all the five cities is minimum as compared to RLS and KF. Minimum value of MSE is 0.0285 in EnKF estimation for city A. Maximum value of MSE is 0.1858 for city B, which can be accepted for estimation accuracy. Fig.

11 shows a comparison of correlation coefficient (*R*) value in global solar insolation assessment using various methods and it is seen that there is strongest association between measured and estimated value in each city using EnKF algorithm as compared to other two methods.

TABLE II
COMPARISION OF MAPE, MSE AND R OF DIFFERENT PLACES WITH DIFFERENT METHODS

City	Methods	MAPE (%)	MSE	*R*
A	RLS	7.5	0.2750	0.8868
	KF	6.4	0.2527	0.9228
	EnKF	2.4	0.0285	0.9866
B	RLS	6.6	0.2153	0.7082
	KF	10.3	0.5419	0.6118
	EnKF	5.6	0.1858	0.7661
C	RLS	6.5	0.2361	0.8841
	KF	5.9	0.1357	0.9528
	EnKF	5	0.1183	0.9361
D	RLS	8	0.3059	0.9359
	KF	8.8	0.4063	0.8317
	EnKF	5.6	0.0893	0.9418
E	RLS	6.1	0.168	0.9336
	KF	7.4	0.255	0.8634
	EnKF	3.7	0.0897	0.9462

In each case of estimation, it is seen that estimated and measured values of insolation are following very closely and the estimation using EnKF is giving more accuracy as compared to others.

TABLE III
PERFORMANCE COMPARISON OF PROPOSED EnKF ALGORITHM WITH ALGORITHMS [13], [14]

Papers	**Locations**	**Model/ Algorithms**	R^2	**RMSE**	**MAPE**
[13]	Algeria	AR	0.6706	1.29	-
		NAR	0.6651	1.28	-
		SVR	0.6753	1.26	-
		RF	0.6759	1.25	-
		PER	0.5217	1.54	-
[13]	Ghardia	AR	0.6989	1.08	-
		NAR	0.6645	1.10	-
		SVR	0.6849	1.08	-
		RF	0.7001	1.07	-
		PER	0.5738	1.26	-
[14]	Jaisalmar	Multi step	-	0.445	6.193
	Barmer		-	0.365	7.977
	Bikaner		-	0.333	6.968
	Jodhpur		-	0.367	0.474
This paper	City A	EnKF	0.9733	0.168	2.4
	City B		0.5869	0.431	5.6
	City C		0.8762	0.344	5
	City D		0.8869	0.298	5.6
	City E		0.8952	0.299	3.7

Table III shows on performance comparison of proposed EnKF algorithm with the methods used in [13] and [14]. On comparing R^2 values using EnKF algorithm with the methods employed in [13] for day ahead forecasting, it has been found that proposed EnKF forecasting outperforms over the algorithms used in [13] in most of the cases of forecasting with maximum R^2 value of 0.9733 in city A. RMSE performance of forecasting using proposed EnKF algorithm has also been compared with [13] and [14] and it has been found that EnKF outperforms over the methods used in above two papers, with minimized RMSE value of 0.168 in city A. Comparison of MAPE using EnKF with [14] shows that it has very less MAPE error in all cases of forecasting as compared to [14] except in Jodhpur. Overall comparison from Table II shows that forecasting using proposed EnKF method outperforms over the methods used in [13] and [14].

However, since the model has been developed on taking the data from the above five locations out of other locations, the accuracy in the above results required to be again validated. For that the measured values and estimated values of insolation for a location has been chosen, whose data has not been taken during the model development. Place Z, is one such location whose data has not been considered during model development and its latitude lie within the range of latitudes for the model. The measured and estimated insolation values of place Z for a year using three estimation algorithms are given in table IV. Here also the insolation estimation performance of EnKF is better as compared to rest of the two. We have found out from Fig. 12 that the measured values and estimated values are very close to each other in case of estimation using EnKF. Table V shows the MAPE, MSE and *R* values comparison using different methods for region Z and it is also found that, EnKF outperforms over other two methods. Fig. 13 shows the MAPE comparison using different methods for city Z and it is also found that, in case of EnKF estimation, MAPE is minimum i.e 4% as compared to other two methods. Fig. 14 gives a comparison of MSE values in global solar insolation estimation for city Z and it is seen that in this case also, MSE is minimum (0.0872) using EnKF estimation. Fig. 15 shows a comparison of correlation coefficient (*R*) of city Z with different methods and it is found that, *R* value in case of EnKF estimation is 0.9486, which shows a stronger association of measured and estimated values as compared to other two methods. Above results definitely validate not only the developed model but also the used methodologies.

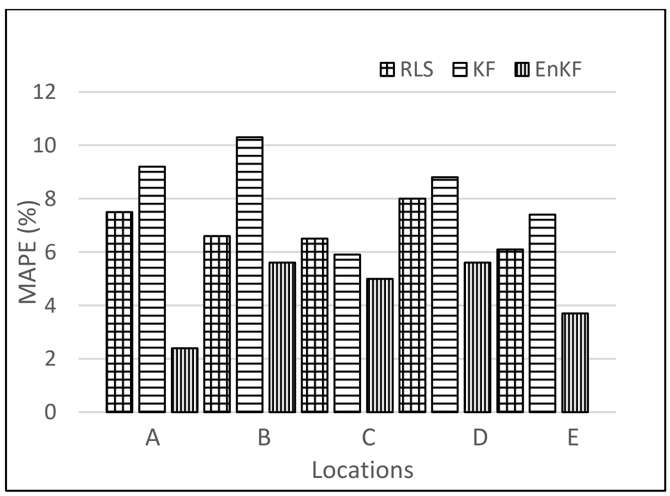

Fig. 9. Comparison of MAPE of different places with different methods

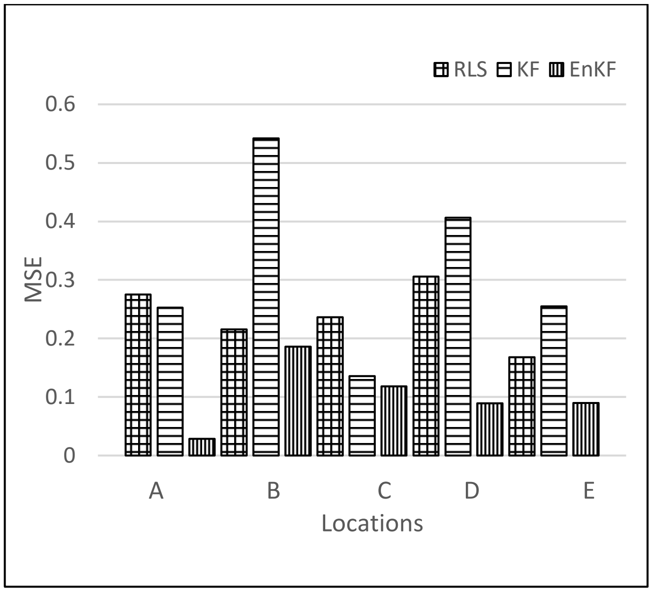

Fig. 10. Comparison of MSE of different places with different methods

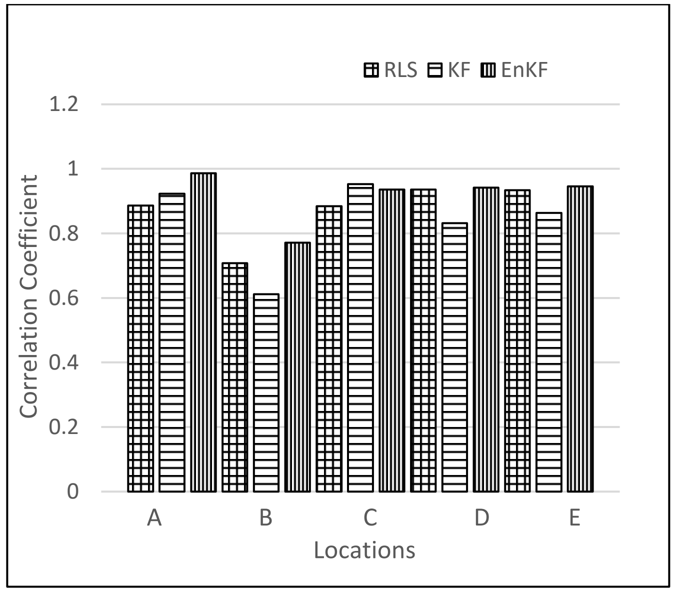

Fig. 11. Comparison of Correlation Coefficient (*R*) of different places with different methods

TABLE IV
CITY Z (WHOSE DATA HAS NOT BEEN INCLUDED IN MODEL)

Place	Inso	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Z	*Htm*	5.74	6.41	6.83	7.03	7.00	5.04	3.93	5.05	5.81	5.91	5.85	5.58
	Htc (RLS)	5.56	6.75	6.35	6.5	6.67	5.7	3.44	5.7	5.5	6.7	6.76	4.48
	Htc (KF)	6	6.64	6.2	6.8	6.4	5	3.85	5.72	4.5	6.5	5.34	4.43
	Htc(EnKF)	5.6	6.8	6.9	7.0	6.84	5	3.85	5.5	5.25	6.1	6.06	5.09

TABLE V
COMPARISION OF MAPE, MSE AND R OF CITY Z WITH DIFFERENT METHODS

City	Methods	MAPE (%)	MSE	R
Z	RLS	10	0.3853	0.7862
	KF	8.8	0.4178	0.7780
	EnKF	4	0.0872	0.9486

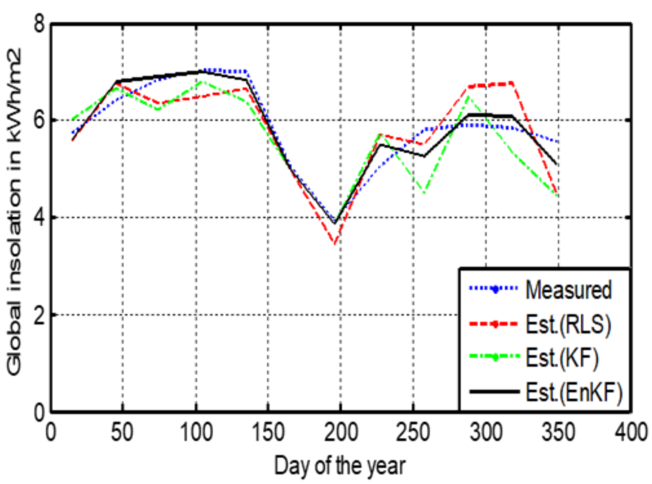

Fig. 12. Measured and estimated global solar irradiance for region Z (Data not included during model development)

Fig. 13. Comparison of MAPE of city Z with different methods

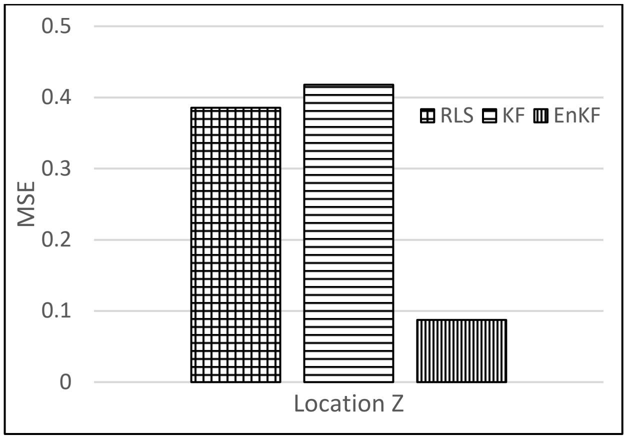

Fig. 14. Comparison of MSE of city Z with different methods

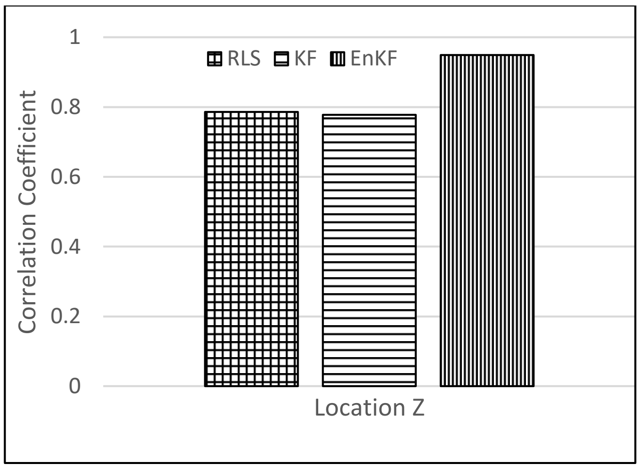

Fig. 15. Comparison of Correlation Coefficient (*R*) of city Z with different methods

IV. Conclusion

A method on development of solar insolation model for certain region has been explained. As, forecasting of global solar insolation mainly depend on K_T value and using EnKF algorithm, more accuracy in updated K_T value has been obtained, so accuracy in forecasting is more in the estimation using this algorithm. From the obtained results, it is found that the forecasted value of insolation using EnKF method is more closely matching with measured values (minimum MAPE of 2.4 %, MSE of 0.0285 and R of 0.9866), this method can be used for any region in world for forecasting solar insolation. For getting more accuracy in forecasting, measured data should be taken covering a large range of latitudes of the region. Also data available should be as accurate as possible to obtain a low error model, in order to calculate global solar insolation for a specific day and for a specific location. Now-a-days with the help of satellites, data for certain region can be taken with good accuracy. With more accurate data, using proposed EnKF algorithm, more accurate Fourier's Co-efficients can be obtained to forecast the global solar insolation. Since accuracy on forecasting of global solar insolation depends on both K_T and H_0 value, proper modeling for getting K_T and accurate calculation for H_0 value of the desired location are very much essential, so more accurate modeling for K_T and less input parameters model for H_0 calculation can be used in future.

References

[1] Y. El Mghouchi , A. El Bouardi, Z. Choulli, T. Ajzoul "New model to estimate and evaluate the solar radiation" *International Journal of Sustainable Built Environment*, vol.3, pp.225-234,2014.

[2] S. E. Berrizbeitia, E. J. Gago, and T. Muneer "Empirical Models for the Estimation of Solar Sky-Diffuse Radiation. A Review and Experimental Analysis" *Energies 2020*, vol. 13, no. 3, 2020.

[3] M. Xiao, Z. Yu, and Y. Cui, "Evaluation and estimation of daily global solar radiation from the estimated direct and diffuse solar radiation", *Theoretical and Applied Climatology*, vol. 140, pp. 983-992, 2020.

[4] Fan J, Wu L, Zhang F, Cai H, Ma X, and Bai H "Evaluation and development of empirical models for estimating daily and monthly mean daily diffuse horizontal solar radiation for different climatic regions of China" *Renewable Sustainable Energy Rev*. vol. 105, pp.168–186, 2019.

[5] R. Huang, T. Huang, and R. Gadh "Solar Generation Prediction using the ARMA Model in a Laboratory-level Micro-grid" IEEE Smart Grid Symposium, 5-8 Nov. 2012, Taiwan.

[6] R. Kumar, and L. Umanand "Estimation of global radiation using clearness index model for sizing photovoltaic system" *Renewable Energy*, vol. 30, pp. 2221–2233, 2005.

[7] P. Bacher, H. Madsen, and H. A. Nielsen "Online short-term solar power forecasting" *Solar Energy*, vol. 83, pp. 1772–1783, 2009.

[8] Y. Che, L.Chen, J.Zheng, L. Yuan and F. Xiao " A Novel Hybrid Model of WRF and Clearness Index-Based Kalman Filter for Day-Ahead Solar Radiation Forecasting" *Applied Sciences*, vol. 9, no. 3967, 2019.

[9] A. Mellit, and A. M. Pavan, "A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy" *Solar Energy*, vol. 84, pp. 807–821, 2010.

[10] A. Yona, T. Senjyu, T. Funabashi, and CH. Kim" Determination Method of Insolation Prediction with Fuzzy and Applying Neural Network for Long-Term Ahead PV Power Output Correction" *IEEE Transactions on Sustainable Energy*, vol. 4, no. 2, pp. 527-533, 2013.

[11] Jahani B, and Mohammadi B, "A comparison between the application of empirical and ANN methods for estimation of daily global solar radiation in Iran". *Theor Appl Climatol* vol.137: pp.1257–1269,2019.

[12] Brahim Belmahdi, Mohamed Louzazni, Mohamed Akour, Daniel Tudor Cotfas, Petru Adrian Cotfas and Abdelmajid El Bouardi "Long-Term Global Solar Radiation Prediction in 25 Cities in Morocco Using the FFNN-BP Method" *Frontiers in Energy Research*, vol. 9, no. 833842, 2021

[13] A. Takilalte, S. Harrouni & J. Mora "Forecasting global solar irradiance for various resolutions using time series models - case study: Algeria" *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, DOI: 10.1080/15567036.2019.1649756, 2019

[14] Deeksha Chandola, Harsh Gupta, Vinay Anand Tikkiwala, Manoj Kumar Bohra "Multi-step ahead forecasting of global solar radiation for arid zones using deep learning" *Procedia Computer Science*, vol. 167, pp. 626–635, 2020

[15] C. Voyant, G. Notton, S. Kalogirou ML. Nivet, C. Paoli, F. Motte, and A. Fouilloy "Machine learning methods for solar radiation forecasting: A review", *Renewable Energy*, vol. 105, pp. 569-582, 2017.

[16] A. Shakya, S. Michael, C. Saunders, D. Armstrong, P. Pandey, S. Chalise, and R. Tonkoski "Solar Irradiance Forecasting in Remote Microgrids Using Markov Switching Model" *IEEE Transactions on Sustainable Energy*, vol. 8, no. 3, pp. 895 – 905, 2017.

[17] RHB. Exell "A mathematical model for solar radiation in Southeast Asia (Thailand)" *J. Solar Energy*, vol. 26, pp. 161-168, 1981.

[18] P. K. Ray, and B. Subudhi "Ensemble Kalman Filter Based Power System Harmonics Estimation" *IEEE Trans. on Instrumentation and Measurement*, vol. 61, no. 12, pp. 3216-3224, 2012.

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