Forecasting Solar Irradiance with Weather Classification and Chaotic Gravitational Search Algorithm Based Wavelet Kernel Extreme Learning Machine

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Abstract- In this work an improved KELM based forecasting model is being proposed, which attains a specific level of prediction of solar irradiance affecting PV power management. The new method is known as Wavelet KELM. A new optimization technique known as Gravitational Search Algorithm (GSA) is implemented to optimize various parameters of the kernel function. The novelty of this work is that, it focuses on a KELM learning algorithm with parameter optimization for exact solar irradiance forecasting. The exact prediction of irradiance is highly essential for system level stability and future large scale PV installations. The GSA based optimized KELM (GSA-KELM) is implemented for short term solar irradiance forecasting based on various weather conditions. A hit and trial method was used for the selection of kernel function parameters which affects the forecasting model performance. The optimized kernel structure not only minimizes the arbitrariness of the variables but also makes the process fast by extenuating the choice of parameter on the basis of the user which has to experience the repeated trial method for various kernel functions. Thus OKELM impart more accuracy in prediction within less time and outperforms the basic KELM. In this work, data collected from a photovoltaic power plant in India (the capacity being 1 MW) has been considered for forecasting model validation.

Keywords Solar Irradiance, KELM, PV power forecasting, GSA, OKELM, CGSA.

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1. Introduction

Due to scarcity of fossil fuel, environment pollution and global warming etc, the modern power system has been focused on the alternative energy sources. Thus demand for renewable energy has increased and particularly photovoltaic generation systems have gained more importance in recent days [1]. PV power penetration into the grid has led to precious solar power forecasting for stable performance of the power plant. Effectual solar irradiance prediction is needed mostly for high energy integration [2, 3, 33, 39-41]. The fluctuating character of the said radiation, affects the factors resembling stability, power quality issues and voltage oscillation etc [4]. Solar irradiance is dependent on the weather and the plant's geographical conditions which affects the output of the PV power plant. The above issues ensure the extreme importance of precise prophecy of solar irradiance. Irradiance is nothing but the measurement of solar power per unit area. The precise solar irradiation forecasting enables the power grid operators to determine the quality of the solar power and also helps in the control technique [34-36]. Hence a more definite model for solar irradiance forecasting became a key requirement as it is the fundamental for power dispatch and power regulation problems, where solar irradiance forecasting becomes the basic and most crucial step in PV power forecast.

From the literature study it is found that many scientists have applied various forecasting methods for solar irradiance forecasting, which can be generally divided into two categories, namely, linear and nonlinear forecasting methods. Predominately applied linear methods are ARMA, ARIMA and physical models such as NWP [5-8, 37, 38]. They are based on temporal persistence of solar irradiance. On the other hand, non linear forecasting models include various artificial intelligence and machine learning techniques like Fuzzy Logic systems [9], ANN systems and hybrid ANN based models [10-12]. Adaptive Neuro-Fuzzy Information System (ANFIS) is applied in solar power forecasting of an existing power plant [13]. In reference [14] a new empirical method known as numerical weather prediction model, is implemented for solar irradiance forecasting. This method is composed of four steps such as, prediction and measurement of irradiance and the data transformation into Gaussian arbitrary variables using past data observed in a modelling window. With same window data, a multivariate normal joint distribution model is estimated in the second step. The third part of the method includes a distribution of irradiance of the next day conditional on one-day-ahead forecasting. Finally, multiple confidence intervals, both temporally and spatially are estimated by using the conditional distribution [15]. However this method is not suitable for short term forecasting because it requires more input data and more computational efforts for the irradiance forecasting. The ARMA and ARIMA models are very popular for solar irradiance prediction but they suffer from inaccuracies due to their inability to handle highly fluctuating and nonlinear data. Thus the most extensively used intelligent system approach includes a variety of neural networks for solar irradiance, Artificial Neural Network (ANN) is considered to be efficient universally. Determining the number of hidden layers is a complex phenomenon in ANNs. Among the ANN based methods for irradiance forecasting, Genetic Algorithm (GA) [16-18] and Radial basis function based neural network models (RBF) [19] are known for its widespread implementation, but it suffers from problems like generalization and convergence. A method newly used for irradiance prediction is based on a hybrid autoregressive (AR) and neural network (NN) model combined with multi scale decomposition methods. This method presents a significant performance for 1 hour ahead global horizontal irradiance (GHI) forecast. This study declared that the changeability of GHI signal is not the only parameter able to influence the forecasting. It performs weak in the cloudy days and large data. This reveals the weakness of the hybrid model for these cases qualified as extreme events [20-21]. In [22-23] a Self Organizing Map (SOM) has been implemented for one day ahead solar irradiance forecasting. A Support Vector Machine (SVM) and Support Vector Regression (SVR) model have been utilised effectively for forecasting daily solar radiation. SVM is widely used forecasting method but the Mean Absolute Percentage Error (MAPE) was found to be quite high (8.94%)]. Finally a new machine learning algorithm [24-27] known as extreme learning machine (ELM) has been developed to enhance the performance of single layer neural networks (SLFNs). Due to its faster learning speed and greater accuracy, like other conventional learning algorithms, it has been applied in various fields of engineering, financial market, including power and load forecasting, wind speed forecasting etc. It is well known that the learning performance like stability and generalization of the ELM depends greatly on the choice of the number of hidden neurons and the activation function which is still an unsolved problem. Thus the kernel function can be used for stability improvement and convergence of ELM. In [28-29] the basic idea behind kernel based ELM (KELM) is described, and the hidden layer mapping is determined by the kernel matrix. In this process only the kernel function and its parameters are needed to be defined. The number of hidden nodes need not be defined. There is no randomness in KELM; hence variation in result is also reduced.

In this work a wavelet kernel is applied for forecasting of the said irradiance of a real time solar power plant, located at Tangi, Odisha, India. Some of the parameters of the wavelet kernel function are selected randomly. Thus a new optimisation technique known as chaotic gravitational search algorithm (CGSA), has been introduced for removing the randomness of different parameters [30]. The optimized KELM result shows more accuracy than the basic KELM. In this work a modified hybrid model is designed by integrating the advantages of KELM and CGSA. The CGSA based KELM is adopted for solar irradiance forecasting in different weather conditions. The advantage of the CGSA-KELM is the reduced error, more robust and hence more efficient. The efficiency of the suggested model is verified through various test results and the best forecasted weather is established.

This work is organized as follows; Section 2 describes the significance of irradiance forecasting as the basic of solar power prediction, KELM model is proposed along with its basic model in section 3. Section 4 describes the Chaotic Gravitational Search Algorithm that has been implemented in this paper for solar irradiance prediction. Section 5 demonstrates the proposed optimized KELM based on weather forecasting and the simulation result analysis is given in section 6 for better understanding of the model, followed by conclusion and references.

2. Irradiance

Attributing to various metrological conditions, photovoltaic power output is unstable and difficult to control due to its intermittent nature and weather dependent characteristics. The solar power output varies with the solar radiation intensity, the geographical position and various season posses a random effect on the irradiance which has a relation with the weather, angular tilt, time and cloud covering. In addition to this the irradiance has a connection with the weather, angular tilt, time and cloud covering. The PV power is regularly available between 6.00 am to 6.00 pm, differing for unlike weather condition. The power output of the PV model is proportional to the temperature and irradiance, hence accurate irradiance prediction imparts to correct power forecasting. The PV panel temperature and the atmospheric temperature are different but for prediction purpose both are considered to be the same, this temperature influences the conversion efficiency of the PV module.

$$\rho = \rho_0 [1 - \lambda (T_T - T_R)] \quad (1)$$

Where T_T is the temperature at T time moment, T_R is the reference temperature which is considered to be 298 K, ρ is the conversion efficiency, R is the temperature coefficient of the batteries.

The inter relation between Power and solar irradiance is given below

$$P = i \times a \times \rho \quad (2)$$

where P represents the power, I being the irradiance and a being the area of the panel.

3. Kernel Extreme Learning Machine (KELM)

In later stage a new technique known as the Extreme Learning Machine (ELM) is being used by researchers for different applications because of its learning speed and accuracy. ELM is basically a single hidden layer neural network. The output matrix Γ can be written as layer feed forward network (SLFNs) in which the hidden layer need not be tuned. In ELM the input weights and hidden layer is chosen randomly. The output function of the ELM can be written as

$$f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) \quad (3)$$

β is the vector of the output weights between the hidden layer of L nodes and the output node

$$h(x) = [h_1(x), \ldots . h_L(x)] \quad (4)$$

Where $h(x)$ is the output of the hidden layer with respect to x input. The hidden layer output matrix H can be written as

$$H = \begin{bmatrix} h_1(x) & \cdots & h_L(x) \\ \vdots & \vdots & \vdots \\ h_1(x_N) & \cdots & h_L(x_N) \end{bmatrix} \quad (5)$$

$$\Gamma = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix} \quad (6)$$

Now β can be now rewritten as

$$\beta = H^T \Gamma \quad (7)$$

Where H^T is the Moore-Penrose generalized inverse of matrix

But in case of KELM the feature mapping $h(x)$ is not required and the kernel matrix can be defined as following

$$\mathrm{K}_{ELM} = HH^T \quad (8)$$

Now the output function can be written as

$$f(x) = h(x) H^T \left(\frac{1}{C} + HH^T \right) \Gamma \quad (9)$$

In order to decrease the training error and make it more generalized, the output weight is minimized and written as

$$f(x) = [\mathrm{K}(x, x_1), \ldots, \mathrm{K}(x, x_N)] \left(\frac{1}{C} + HH^T \right)^{-1} \Gamma \quad (10)$$

Here Γ is the output and $\mathrm{K}(x, y)$ is the kernel function of the hidden neurons and C is the regulation coefficient which is basically a user defined parameter that further improves the performance.

Finally the output function can be written as

$$f(x) = \begin{bmatrix} K(x, x_1) \\ \vdots \\ K(x, x_N) \end{bmatrix} \left(K_{ELM} + \frac{1}{C} \right)^{-1} \Gamma \quad (11)$$

There are various kernel function that has been already implemented in various fields, the different types of kernel functions are polynomial, Gaussian, RBF, wavelet etc. In this paper the wavelet kernel based ELM is chosen for performance analysis purpose for best predicted weather. The wavelet kernel ELM is defined in equation 12, where d, e and f are the user specified variables.

$$K(x, y) = Cos\left(d \left| \frac{x - y}{e} \right| \right) \exp\left(- \frac{|x - y|^2}{f} \right) \quad (12)$$

4. Gravitational Search Algorithm.

The GSA optimization is population based algorithm developed by E.Rashedi 2009. The theme of this technique is simulating the mainly general trend of gravitation in nature. In this process the gravitational force between any two particles is evolved for searching the optimal solution.

Definition 1. The inertial mass represents fitness of the particle, which is calculated as following.

$$\begin{cases} m_i(t) = \dfrac{fit_i(t) - worst(t)}{best(t) - worst(t)} \\ M_i(t) = \dfrac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \end{cases} \tag{13}$$

Where $fit_i(t) =$ fitness of the particles.

$best(t) =$ Optimal solution at time t.

Worst(t)= worst solution at time t.

$M_i(t) =$ mass of particle x_i at time t .

Definition 2. The gravitational force between i_{th} and j_{th} particle in k dimension is given by

$$F_{ij}^k(t) = G(t)\frac{M_{bj}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon}\left(x_j^k(t) - x_i^k(t)\right) \tag{14}$$

Where ε is a small constant and M_{aj}, M_{bi} represents the inertial mass of object j and i respectively. The universal gravitational constant is given by

$$G(t) = G_0 \times e^{-\frac{\alpha}{T}} \tag{15}$$

$G_0 =$ the value of gravitational constant initially, and set to 100. $\alpha = 20$, T is the maximum number of iteration and $R_{ij}(t)$ is the Euclidean distance between the particles i and j .

Definition-3: the acceleration due to gravity between the particles i and j is calculated by the following

$$a_i^k(t) = \frac{F_i^k(t)}{M_i(t)}$$

Here $M_i(t)$ is inertial mass.

Using the following formula the velocity and position of the object i is updated according to the acceleration.

$$v_i^k(t+1) = rand_i \times v_i^k(t) + a_i^k(t)$$
$$x_i^k(t+1) = x_i^k(t) + v_i^k(t+1) \tag{16}$$

Pseudo Code of Chaotic Gravitational search Algorithm.

1. Initialization: let t=1 and select a random set of feasible solution and a set of velocities.

   $x^t = \{x_1^t, x_2^t..........x_N^t\}$, $v^t = \{v_1^t, v_2^t.......v_N^t\}$

2. While stopping criterion is not satisfied do.
3. Fitness evaluation: The objective function $f(x_i^t)$ is evaluated for each resolution (mass) in the present population x^t .
4. $G^t or G^t_{chaotic}$, $best^t$, $worst^t$ and M_i^t are updated using the above equations.
5. Computation of total force: Compute F_{ij}^k and F_i^k .
6. Update : Compute a_i^t, v_i^{t+1} and x_i^{t+1}
7. End while

4.1 Irradiance Forecasting Model Based on Weather Forecasting

Irradiance of PV panel is one of the vital factor of solar plants because of it is intermittent in nature and varies with environmental condition. In this paper the PV system data is divided into four parts based on weather conditions like sunny, foggy, cloudy and rainy weather. The irradiance plays important role in solar power forecasting. Figure 1 shows various irradiance levels in different weather condition for 1 month, solar irradiance forecasting is very vital for changing atmospheric condition. In this paper a novel optimized Kernel function based extreme learning machine (KELM) technique is applied for irradiance forecasting which is highly intermittent in different weather conditions.

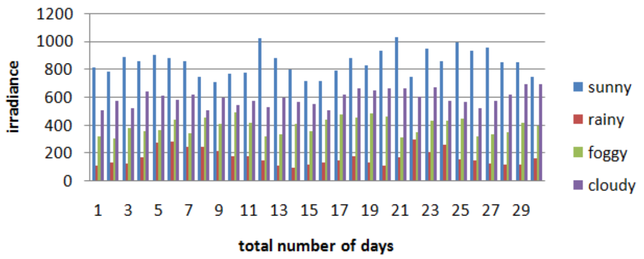

Figure1.Solar irradiance under different weather condition

4.2 Data Collection

The radiation angle and geographical location of a solar plant is assumed to be fixed. In this work solar system of capacity 1 MW situated at Bhubaneswar, Odisha, India (20^0.25, N and $85^0$85 E). A one year historical data is collected for forecasting purpose. The test time is taken from a period of 1st January 2010 to 31st December 2010. Different time horizon has been considered for error calculation. Every day solar irradiance assortment is done between 6.00 AM to 6.00 PM. The solar power plant comprises of total 64 strings, 25 SCBs and the frequency is noted between 50.02- 50.04 Hz, the details of the solar power plant is mentioned in table 1.

Table-1: summery of solar power plant.

Location	Tangi, Odisha, India		
Coordinates	19.924°N, 85.3966° E		
Capacity	1 MW		
Data accumulation	Irradiance, atmospheric temperature, Current, Power		
Time Horizon	5min	30 min	1hour
Time Period	1st January 2015-31st December 2015		

4.3 Data Pre-processing and Precision index

The previous recorded data irradiance data (ranges from 0 to 1200 W/m^2) is taken as input to the KELM model. The main objective of pre assignment the data into a smaller space is to increase the precision level by confining the values within a certain range and hence maintaining a correlation among the set of data. One way of preventive the values is by the process of normalization, in this work the normalized value is controlled within a range of 0-1. Equation 17 gives the normalization equation

$$D_N = \frac{D_A - D_{\min}}{D_{\max} - D_{\min}} \tag{17}$$

Where D_N is the normalized value, D_A is the actual data, D_{max} is the maximum value in the actual data and D_{min} is the minimum value in the actual data set. There are various methods for the appraisement of the forecasting result, in this paper the error calculation techniques that has been implemented are Mean Absolute Percentage Error (MAPE) as given in equation 18, Mean Absolute Error (MAE) is shown is equation 19, RMSE (Root Mean Square Error) is illustrated in equation 20 followed by Correlation Coefficient Error (CC^2) in equation 21. The above mention error calculation demonstrates the effectiveness of the proposed model.

$$MAPE = \frac{1}{n_0}\sum_{i=1}^{n_0}\left(\frac{|A_c - F_c|}{A_c}\right)*100 \tag{18}$$

$$MAE = \frac{1}{n_0}\sum_{i=1}^{n_0}\left|A_c - F_c\right| \tag{19}$$

$$RMSE = \sqrt{\frac{1}{n_0}\sum_{i=1}^{n_0}\left(A_c - F_c\right)^2} \tag{20}$$

$$CC^2 = \frac{\left(n_0\sum_{i=1}^{n_0} F_c(x_i)T_r(x_i) - \sum_{i=1}^{n_0} F_c(x_i)\sum_{i=1}^{n_0} T_r(x_i)\right)^2}{\left(n_0\sum_{i=1}^{n_0} F_c(x_i)^2 - (\sum_{i=1}^{n_0} F_c(x_i))^2\right)\left(n_0\sum_{i=1}^{n_0} T_r(x_i)^2 - (\sum_{i=1}^{n_0} T_r(x_i))^2\right)} \tag{21}$$

5. Optimized Kernel Extreme Learning Machine

In KELM the regulation coefficient *C* and various kernel parameters needs to be selected appropriately for satisfying the generalization performance of neural network. For better accuracy it is tedious to select the suitable kernel parameters. The parameters needs to be tested within a wide range of values and therefore time consuming, in order to mitigate the trial and error method this paper proposes a new method.

In this study the wavelet kernel function is used for forecasting purpose. In order to achieve good generalization performance the regulation coefficient *C* and wavelet kernel parameter *d, e* and *f* needs to be chosen appropriately. In the study of SVM and LS-SVM the parameters *C* and *γ* are selected empirically or by going through a wide range of values as given in [31]. Various hybrid kernel function are proposed for getting better the generalization performance of the KELM; nevertheless the fundamental query is of how to select the optimal values of the parameter has not been determined. In this paper an artificial electric field algorithm optimization technique has been introduced to KELM to determine the optimal parameters of the wavelet Kernel.

In this model the dimension of the searching space is four (D=4) corresponding to the four variable parameters used in wavelet kernel (*C, d, e, f*). The main aim of CGSA for parameter optimization is to achieve the finest generalised performance of KELM.

6. Simulation and Performance Analysis

All the simulations of this work is carried out in MATLAB 2015 a. Here 15 min, 60 minutes and one day time horizons have been considered to test the robustness and capability of KELM in different weather condition. The entire one year data is classified as per the weather condition such as such as sunny weather, cloudy weather, foggy weather and rainy weather. ELM is fast and simple but with an issue of unstable output, this problem is solved by KELM which shows a greater generalization performance along with being stable but had a disadvantage of un-optimized parameter this is mitigated by an optimization technique. In this paper CGSA optimization technique is considered as a new powerful optimization and the results are depicted in table-2 for sunny weather. The ELM and KELM based rainy weather forecasting is given in table 3, the KELM and ELM based cloudy weather and foggy weather forecasting is represented in table- 4 and table- 5 respectively. Figures 2,3,4 represents the actual and predicted values of the sunny weather for three time horizons which is found to be the best predicted weather using the basic KELM , rainy season shows more error as compared to the sunny weather and figures 5,6,7 presents the forecasted error for three different time interval. The forecasted errors in cloudy weather are depicted in figures 8,9,10 and from figures 11, 12, 13 it is observed during that of the foggy weather.

The irradiance data set used in this study is of the same origin, the variations in result are basically ascribed to variation of weather pattern. The solar plant data considered in this paper is located in Eastern India where mainly two weather conditions are realized.

That is sunny and rainy climate. Thus total number of samples for summer season surpasses other seasons along with more consistent irradiance and hence results in more accurate prediction. The best weather forecasted condition is further optimized to obtain more accurate prediction result in order to solve the various power quality issues that mainly occurs during the summer season due to load fluctuation and thus can be helpful for load shading also. Table 6 shows the different values of the parameter before and after the application of optimization technique. The comparison of different methods of ELM, KELM and OKELM for solar irradiance forecasting in different time zone is shown in table 7, 8 and 9 in summer season, and a summary of different forecasting technique in previous literatures and the proposed model has also been given in table-10.

The forecasting graphs are zigzag in nature because it compares with the original output pattern of photovoltaic cell. As it is well known that the pv output is intermittent in nature because it depends on the factors like irradiance. The solar irradiance depends on temperature, humidity and position of sun in the sky and other atmospheric factors. This work focuses on the forecasting of pv output, which obviously follow the original zigzag pattern of irradiance.

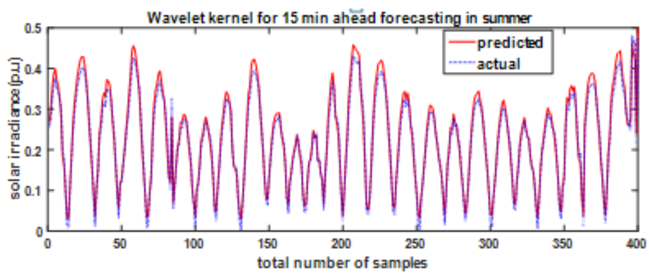

Figure 2. wavelet kernel for 15 min ahead forecasting for summer season

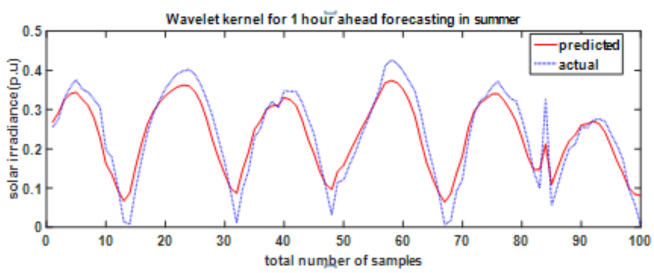

Figure 3.wavelet kernel for 1hour ahead forecasting for summer season

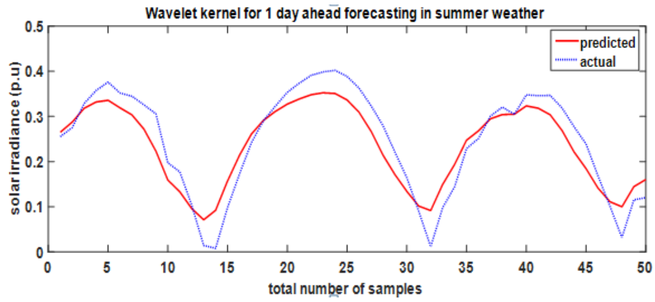

Figure 4: wavelet kernel for 1day ahead forecasting for summer season

Table 2. Test result for sunny weather forecasting

Algorithm	Time Horizon	MAPE (%)	RMSE	MAE	CC^2
ELM	15 min	1.537	0.029	0.015	0.978
	1 hour	3.990	0.056	0.039	0.963
	1 day	5.478	0.075	0.054	0.904
KELM	15 min	1.448	0.0168	0.0145	0.984
	1 hour	3.346	0.040	0.0347	0.909
	1 day	3.721	0.0428	0.0372	0.906

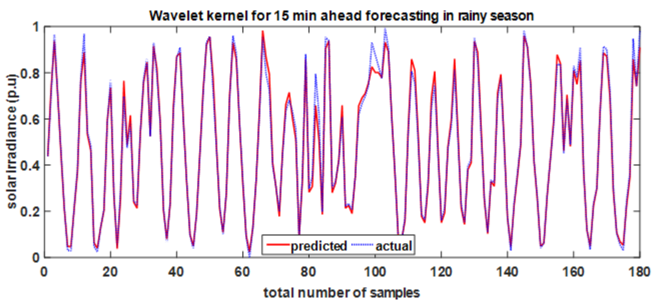

Figure.5: wavelet kernel for 15min ahead forecasting for rainy season

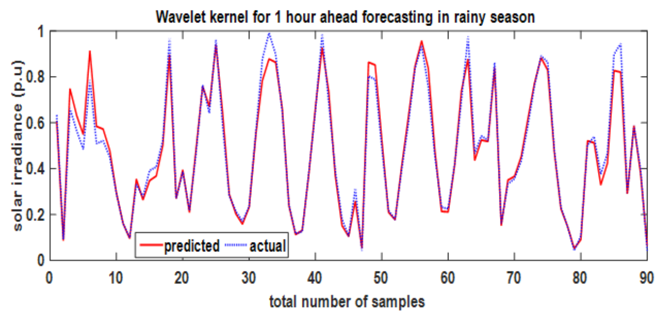

Figure 6: wavelet kernel for 1hour ahead forecasting for rainy season

Table 3: Test result for rainy weather forecasting

Algorithm	Time Horizon	MAPE (%)	RMSE	MAE	CC^2
ELM	15 min	2.915	0.047	0.029	0.987
	1 hour	4.428	0.062	0.044	0.988
	1 day	5.417	0.074	0055	0.916
KELM	15 min	2.138	0.0315	0.0214	0.918
	1hour	2.914	0.0412	0.0291	0.976
	1 day	3.545	0.0502	0.0355	0.970

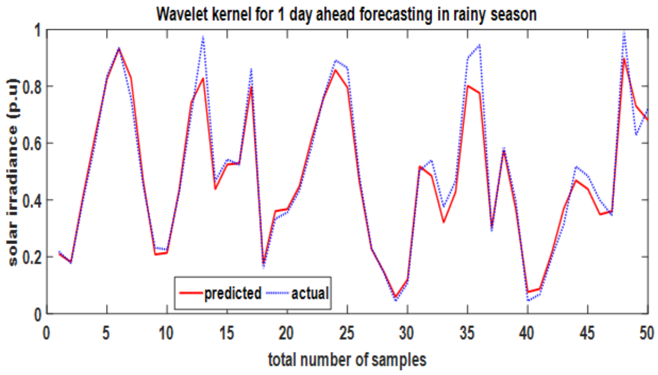

Figure 7: wavelet kernel for 1 day ahead forecasting for rainy season

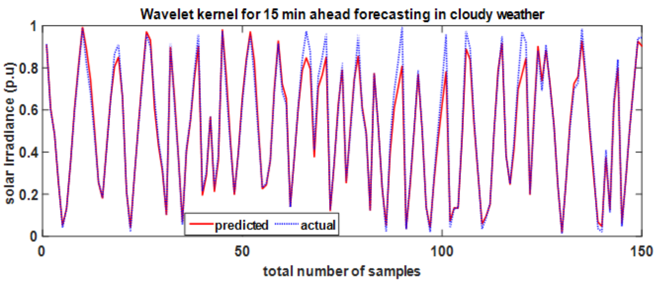

Figure 8: wavelet kernel for 15min ahead forecasting for cloudy weather

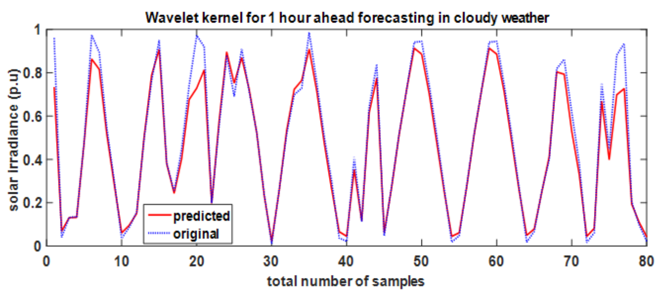

Figure 9: wavelet kernel for 1hour ahead forecasting for cloudy weather

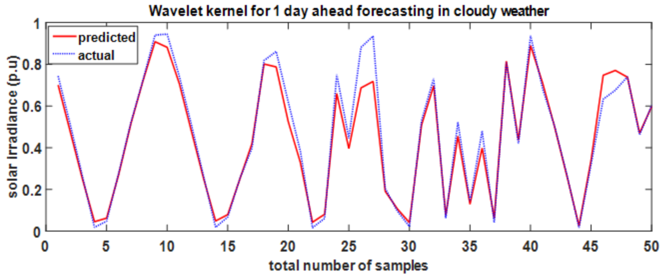

Figure.10: wavelet kernel for 1day ahead forecasting for cloudy weather

Table 4. Test result for cloudy weather forecasting

Algorithm	Time Horizon	MAPE (%)	RMSE	MAE	CC^2
ELM	15min	3.342	0.052	0.033	0.965
	1 hour	5.189	0.058	0.052	0.924
	1 day	6.450	0.081	0.064	0.916
KELM	15min	2.779	0.042	0.0278	0.983
	1 hour	3.262	0.0575	0.0326	0.974
	1 day	3.757	0.0580	0.0376	0.969

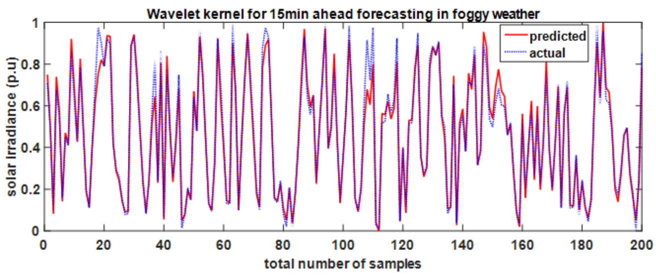

Figure.11: wavelet kernel for 15min ahead forecasting for foggy weather

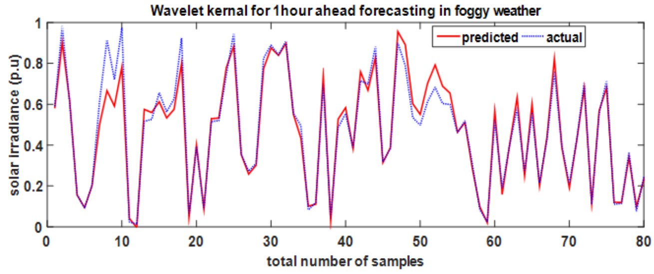

Figure.12: wavelet kernel for 1hour ahead forecasting for foggy weather

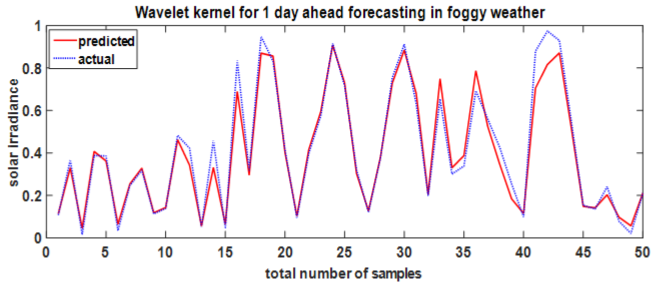

Figure. 13: wavelet kernel for 1day ahead forecasting for foggy weather

Table 5. Test result for foggy weather forecasting

Algorithm	Time Horizon	MAPE (%)	RMSE	MAE	CC^2
ELM	15min	3.911	0.047	0.039	0.977
	1 hour	4.428	0.062	0.044	0.988
	1 day	5.471	0.074	0.055	0.916
KELM	15min	2.961	0.0463	0.0296	0.974
	1 hour	3.539	0.0536	0.0354	0.962
	1 day	3.821	0.0564	0.0382	0.966

Table 6. Parameter Specification for OKELM

Parameter	Specification	
	Optimized	Un optimized
C	4	16
d	1.2	5
e	1	3
f	1	3

Table 7. Comparison of performance by ELM, KELM and OKELM for summer season in 15 minutes ahead prediction

Learning Algorithm	MAPE	MAE	RMSE	CC^2
ELM	1.537	0.029	0.015	0.978
KELM	1.448	0.0168	0.0145	0.984
OKELM	0.709	0.007	0.0093	0.995

Table 8. Comparison of performance by ELM, KELM and OKELM for summer season in 1 hour ahead prediction

Learning Algorithm	MAPE	MAE	RMSE	CC^2
ELM	1.837	0.037	0.026	0.978
KELM	1.348	0.021	0.013	0.912
OKELM	0.809	0.008	0.004	0.983

Table 9. Comparison of performance by ELM, KELM and OKELM for summer season in 1 day ahead prediction

Learning Algorithm	MAPE	MAE	RMSE	CC^2
ELM	2.537	0.067	0.038	0.926
KELM	1.436	0.038	0.026	0.919
OKELM	0.875	0.016	0.007	0.916

Table 10. Comparison of establishments associated with the solar irradiance prediction employing various learning methods and the proposed method.

Reference	Model Type	Location	MAPE Error (%)
[31]	Persistence	Portugal	13.43
[31]	ARIMA	Portugal	11.03
[32]	SVR	China	6.02
[32]	EMD-PSO-SVR	China	3.43
[31]	FNN	Portugal	9.84
This paper	Proposed CGSA-KELM	India	0.71

Conclusion

The primary contribution of this study focuses on a novel optimized OKELM technique (Chaotic Gravitational Search Algorithm Optimization based Kernel Extreme Learning Machine). The parameters of the kernel function are optimized which reduces the trial and error method based parameter selection. As shown from the simulation result, the generalization performance of the proposed OKELM algorithm in terms of irradiance forecasting is found to be significantly improved compared to KELM and the basic

ELM. For validating the proposed CGSA-ELM different accuracy measurement has been calculated, table 10 gives the comparison with other forecasting methods and it is found that forecasting in the summer season gives the minimum error. This precise method can be implemented in various other forecasting purposes because of its robustness without any premature convergence and improved performance.

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