BA-PSO Based Solar Power Prediction Using Environmental Features

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ABSTRACT

Photovoltaic systems have become an important source of renewable energy generation. Because solar power generation is intrinsically highly dependent on weather fluctuations, predicting power generation using weather information has several economic benefits, including reliable operation planning and proactive power trading. This study builds a model that predicts the amounts of solar power generation using weather information provided by weather agencies. Here BA-PSO (Butterfly Algorithm Particle Swarm Optimization) Genetic Algorithm is used to predict the solar power requirement. A set of environmental variables are collected and their effect on solar power generation is evaluated by BA-PSO. This work considers a set of environmental features with their impact ratio solar power prediction. The BA-PSO was applied on dataset of Raipur city in Chhattisgarh state of India and the results show reduction in MAE, RMSE and improvement in power prediction when compared with ground truth values taken from Indian railway top roof solar installation.

Index Terms— Electric power Grid, Renewable resources-Solar.

I INTRODUCTION

Power plants based on renewable energy have increased their integration in electrical power system in recent years. The independence from foreign sources, opportunities derived from the climatic change, and the energy policies carried out in most of the developed countries have driven the construction of power plants based on renewable resources. The renewable energy with greater integration in the electric power systems are wind and solar photovoltaic energy, and the integration continues to increase. By 2050, wind and solar energies are expected to provide 12% [1] and 11% [2] of the global electricity consumption respectively.

Photovoltaic (PV) systems are the most direct way to convert solar radiation into electric power. PV systems have been used to produce electricity for low power applications in isolated areas (isolated from electric power networks) and can be easily connected to electrical grids. In recent years, large PV power plants have been built all over world, connected to medium or high voltages electric networks, with capacity of hundreds of MW (new PV plants or parks) [3]. In developed countries, which have implemented an electricity market, large scale power plants based on renewable energies can act, as any other electricity producer, providing power generation sale bids to the electricity market. The most important session for the electricity market is the daily session, in which power producer must present sale bids for the hours of the following day.

To encourage better arranging and lower the boundary for expanding the division of renewable in the framework, this work centers around the issue of consequently creating models that precisely anticipate renewable power generation by utilizing National Weather Service (NWS) climate data [4]. This work explores Butterfly PSO algorithm (BA-PSO) for prediction of solar power by utilizing NWS dataset. Hence to estimate power for small region with available information gets easy and fast. When learning of models on recorded environmental parameters with respected generated power is complete then, this works' expectation models use NWS values for a small region to predict future power production on scale of time as well. In this paper, examination is done to utilize solar based power as an intermediary for solar production, since it is relative to sun-based power harvesting [5].

II RELATED WORK

Hong et al. [6] provide an outline of various forecasting techniques used for energy forecasting. The study emphasizes that many different time series and ML techniques have been used in various energy contexts. The study shown the technique's comparison for energy forecasting and evaluates the methods used in the forecasting

Davò et al. [7] used PCA combined with the techniques ANN and Analog Ensemble (AnEn) to predict solar irradiance. With the aim to reduce the dimensionality of the dataset, PCA was used as a feature selection method. The dataset consists of the aggregated daily energy output of the solar radiation, measured over eight years. A comparison between using and not using PCA showed that using PCA in combination with ANN and AnEn enhances the prediction accuracy.

Chen et al. [8] present results on long-term (up to 100 hours) forecasting. The authors employed an ANN as their forecasting method with NWP data as input. The model was sensitive to prediction errors of the NWP input data and also showed deterioration when forecasting on rainy days in particular. During cloudy and sunny days, the ANN model produced results with MAPEs of around 8 %.

Persson et al. [9] used Gradient Boosted Regression Trees (GBRT) to forecast solar energy generation 1-6 hours ahead. The data used was historical power output as well as meteorological features for 42 PV installations in Japan. Concerning RMSE, the GBRT model performed better than the adaptive recursive linear AR time series model, persistence model and climatology model on all forecast horizons. For shorter forecast horizons, it was shown that lagged power output values had a larger predictive ability. Similarly, for longer forecast horizons, the weather forecasts increased in importance.

Yordanos et. al. in [10] Multi day-ahead, hourly mean PV control production estimating strategy dependent on a mix of genetic calculation (GA), molecule swarm enhancement (PSO) and versatile neuro-fluffy derivation frameworks (ANFIS) is displayed in this examination. Parallel GA with Gaussian procedure regression display based wellness work is utilized to decide imperative info parameters that essentially impact the measure of yield intensity of a PV production plant; and an incorporated crossover calculation consolidating GA and PSO is utilized to advance an ANFIS based PV control estimating model for the plant. The proposed displaying method is tried dependent on power production information got from Goldwind microgrid framework found in Beijing.

Mandal et al. [11] utilized wavelet change related to RBFNNs. They right off the depreciated values exceedingly fluctuating PV control time arrangement information into various time-recurrence segments. The one hour ahead disintegrated PV control yield was then anticipated utilizing the deteriorated segments, just as past solar powered light and temperature information. The last forecast was created by applying the inversed wavelet change. The outcomes demonstrated great precision, with the mix of wavelet change and RBFNN beating RBFNN without wavelets.

III METHODOLOGY

Prediction of solar power is highly dependent on the environmental conditions. This work focuses on the selection of highly affecting surrounding variables like (air, humidity, temperature, sky condition, etc.) taken from region shown in fig. 1 and 2. Whole work was divided into two module first module predicts features ratio by using Butterfly Particle Swarm Optimization algorithm. While second module predicts the solar power from the environmental parameters used in same ratio as identified in first module. Block diagram of whole work is shown in fig. 3.

Fig. 1 Climatologyenvironmental map for India[12].

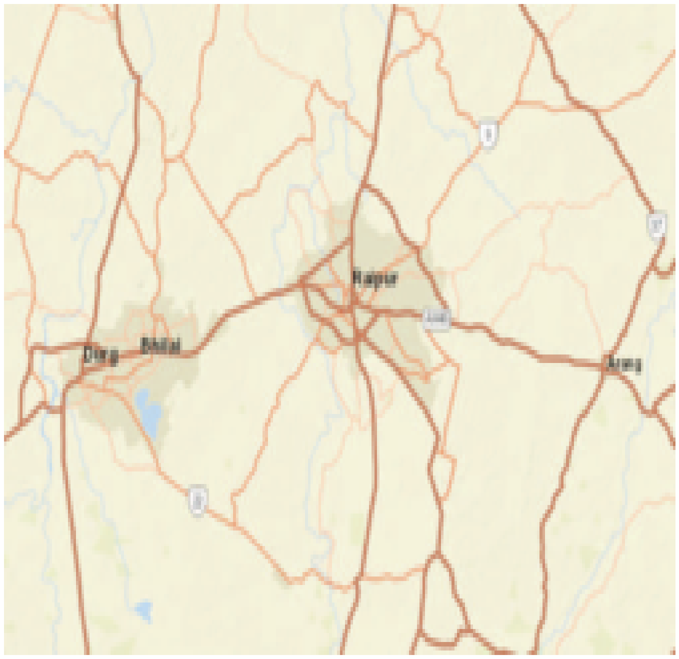

Fig. 2 Chhattisgarh environmental region [12].

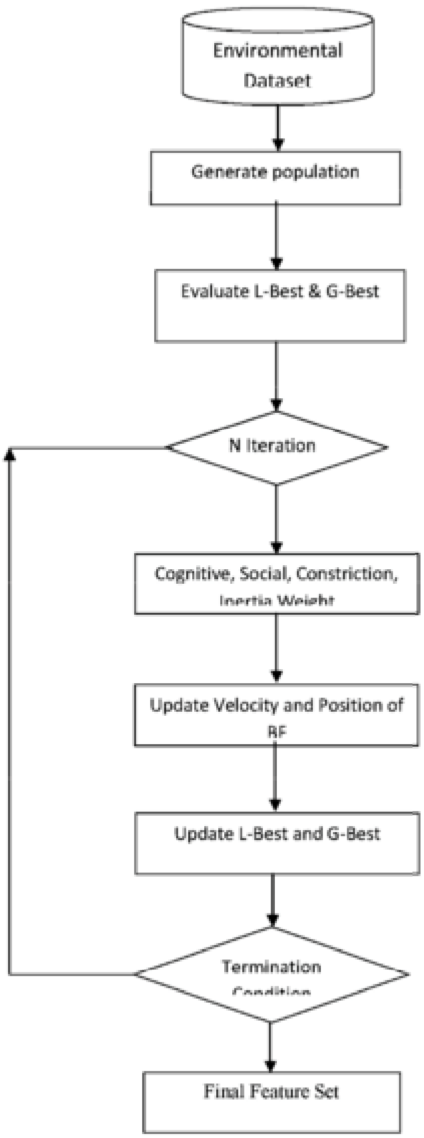

Fig. 3 Block diagram of BA-PSO genetic algorithm.

(a) Generate Population: In this step different chromosome set were generated, which have environmental feature set ratio between 0 to 1. This can be understood as if any feature value is 0 than that feature is not involved.

So each environmental feature set acts as the chromosome(Cc) while collection of all set is termed as population(P). This can assume as let Cc = [r_1, r_2, ….r_m] as the chromosome set where m is number of features in a set. While P = [Cc_1, Cc_2,…Cc_n], n is number of chromosomes.

$$P \leftarrow \text{Random } (n, m) \text{ ---------(1)}$$

(b) Fitness Function: Selection of best solution from population set is done by this step where previous year environmental data were evaluated to generate power from current ratio by using equation (2) to (4).

Table 1
Notation used feature collection

Symbol	Meaning
A	Solar Panel area in m^2
η	Solar Panel Yield Efficiency
I_r	Irradiance
A^T	Ambient Temperature(C)
C^T	Solar Panel Cell Temperature(C)
Cc	Genetic Algorithm Chromosome
σ	Solar Module Efficiency
β	Maximal Power Temperature Coefficient
θ	Hour Angle
ð	Declination Angle
F	Environmental Feature Set
I_o	Clear Sky Insolation
I_n	Insolation after orientation calculation
W	Wind Speed at 10 m above ground level+ Wind Speed at 50 m above ground level mm/sec
T	Temperature Range at 2 m above ground level + Earth Skin Temperature (C)
T_c	Cell Temperature(C)
P_r	Surface Pressure (kPa)
P_s	Solar Panel Power, Watt

$$[I_o \ W \ T \ P_r] = Cc{*}F \text{---------(2)}$$

In equation (2) Cc is chromosome having ratio of m values, while F is average value of m features obtained from environmental dataset. It gives I, W, T, P_r output which is a summation of similar types of features present in F. In this work solar orientation feature was considered to get more effective values as per geographical location.

Solar Insolation value for fixed panel is denoted by I_n. The equation of calculating solar insolation for fixed panel is,

$$I_n = I_0 * \text{Cos}(ð) * \text{Sin}(\boldsymbol{\theta}) \text{ ………..}\mathbf{(3)}$$

Here, θ= Hour Angle, ð = Declination Angle

$$T_c = T + \left[\left(\frac{I_n}{I_r}\right)(C^T - A^T)\frac{C_1}{W}\left(1 - \frac{\sigma}{C_2}\right)(1 - \beta \times C_3\right] \text{--(4)}$$

$$P_s = A \times \gamma \times T_c \times P_r \text{---------(5)}$$

Output from eq. (2) are transferred in equation (3) obtained from [16], where insolation values get changed as per solar orientation. While eq. (4) obtained from [17] gives Cell temperature value. In eq. (4) c1, c2 are constant whose value range between 0-1, while C_3 range between 5 to 45.Finally, eq. (5)[13, 14]gives power of a solar panel having surface area A, with yield efficiency γ.

(c) Evaluate L-Best and G-Best : This step finds best chromosome from the population and fitness value of this best solution act as Local best and Global best value. Here it was obtained by evaluating the fitness value of each probable solution in the population. After this iteration of the algorithm starts where L-Best and G-Best update regularly.

(d) Iteration Steps: This involve calculation of Sensitivity of Butterfly by eq. (6) than cognitive values with constriction factor and inertia weight were evaluated using eq. (6) to (12) obtained from [18]. Here velocity and position of the butterfly also get update which are parameters of BA-PSO. So as per position matrix crossover is done to update population.

Table 2
Notation used in Butterfly algorithm

Symbol	Meaning
S	Sensitivity
r	Genetic algorithm Iteration
M_r	Maximum iterations
C_r	Current iteration
C_1	Cognitive parameters
C_2	Social parameters
C_{eq}	Constriction Factor
N	Number of Iteration
W_t	Inertia Weight
V	Velocity
X	Position
L_{best}	Local Best solution
G_{best}	Global Best solution
P	Probability of Nectar Selection

(i) Sensitivity of Butterfly

$$S = e^{-(M_r - C_r)/M_r} \text{----(6)}$$

Where S is sensitivity of r^{th} iteration where M_r is maximum number of iterations takes place and C_r is current iteration of this BA-PSO algorithm.

(ii) Cognitive and Social parameters

$$C_1 = y * \left(\frac{C_r}{M_r} + x\right) \text{---------------(7)}$$

$$C_2 = x * \left(\frac{C_r}{M_r}\right) \text{--------------(8)}$$

Where x, y are constant range between 0 to 1.

(iii) Constriction Factor C_{eq}

$\alpha = C_1 + C_2$

$$C_{eq} = 1 - \alpha - \sqrt{\alpha^2 - 4\alpha} \text{----(9)}$$

(iv) Inertia Weight

$$W_t = y + \frac{(M_r - C_r)}{M_r} \text{----- (10)}$$

(v) Update velocity V and position X of each probable solution

$$V_{i+1} = C_{eq} * (W_t * V_i + S \quad * (1 - P) * R * C_1 * (L_{best} - C_r) + P * R' * C_2 * (G_{best} - C_r) \text{-------------(11)}$$

$$X = R*P*V_{i+1} \text{-----(12)}$$

In above equation V is velocity, X is position while R and R` are random number whose values range between 0-1. Pis probability of nectar for the butterfly selection. So as per X and V values crossover operation were performed.

(e) Crossover: In this work population P is updated as per X column wise and V values update P row wise. Change in column help to assign new position for the cluster center in same probable solution [15]. While changes in row value as per L_{best}(where is L-best)solution increase the chance of generation of better fitness probable solution.

(f) Update G-Best : After each iteration values of G-Best get optimize if new solution probable solution fitness function values are better than previous G-Best values. Hence if two iteration shows same values than iteration will break or if N number of iteration complete.

(g) Solar Power Prediction

In this phase features of geographical location are read where solar power is predicted for that location. Here feature ratio is multiplied with environmental values and obtained values are used in equation (4) and (5).

IV RESULTS AND DISCUSSION

This area exhibits assessment of the proposed procedure for management of smart grid system. All calculations and utility measures were executed by utilizing the MATLAB 2012a software. The tests were performed on a 2.27 GHz Intel Core i3 machine, outfitted with 4 GB of RAM, and running under Windows 7 Professional.

(a) Dataset: Analysis done on actual dataset (Ground Truth Values) for Raipur city in Chhattisgarh state of India having Longitude: 21.2514° N, Latitude: 81.6296° E. Various environmental features used in the calculation are given in Table 3 and it was obtained from [12] for Raipur.

Table 3
List of features used (F).

Feature Name
Clear Sky Insolation Clearness Index
All Sky Insolation Incident on a Horizontal Surface (kW-hr/m^2/day)
Insolation Clearness Index
Clear Sky Insolation Incident on a Horizontal Surface (kWh/m^2/day)
Declination Angle, Hour Angel (Degree)
Temperature Range at 2 m height (degree C)
Earth Skin Temperature(degree C)
Wind Speed Range at 10 m above ground level(m/s)
Wind Speed Range at 50 m above ground level(m/s)
Surface Pressure(kPa)

(b) Results : From fig. 4 it is observed that BA-PSO power requirement values is more nearer (Actual) to ground truth values as compared to GA-PSO-ANFIS values [10], under required power evaluation parameters. In this work initial solution generation and crossover operation increases the accuracy of the work.

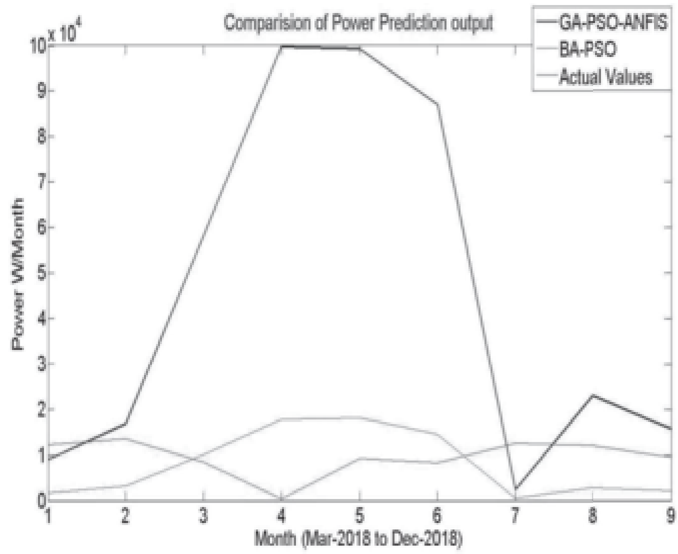

Fig. 4 Comparison of predicted and actual power output

(c) Evaluation Parameters:

(i) Root Mean Square Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} X_{obs,i} - X_{model,i}}{n}} \text{--------(13)}$$

where X_{obs} is observed (ground truth values) values and X_{model} is predicted power by modelfor n instances.The smaller the root means square error, the closer to the ground truth values.

(ii) Mean Average Error

$$MAE = \frac{\sum_{i=1}^{n} | X_{obs,i} - X_{model,i} |}{n} ---(14)$$

where X_{obs} is observed (ground truth values) values and X_{model} is predicted power by model for n instances. The smaller the means average error, the closer to the ground truth values.

Table 4
MAE Based Comparison between BA-PSO and GA-PSO-ANFIS.

MAE Based Comparison		
Months Year 2018	**BA-PSO**	**GA-PSO-ANFIS**[10]
Feb-Apr	7479	18649
May-Jul	10913	89386
Aug-Oct	9405	9169

From Table 4 it is observed that BA-PSO is better as compared to GA-PSO-ANFIS[10], under MAE evaluation parameters. As BA-PSO genetic algorithm has generated different combinations and performed two type of learning, first was sensitivity of butterfly while second was particle velocity and position.

Table 5
RMSE Based Comparison between BA-PSO and GA-PSO-ANFIS.

RMSE **Based Comparison**		
Months Year 2018	**BA-PSO**	**GA-PSO-ANFIS** [10]
Feb-Apr	8545	28720
May-Jul	11900	89779
Aug-Oct	9608	9404

From table 5 it is observed that BA-PSO is better as compared to GA-PSO-ANFIS [10], under RMSE evaluation parameters. As BA-PSO genetic algorithm has generated different combinations which perform two type of learning, first was sensitivity of butterfly while second was particle velocity and position.

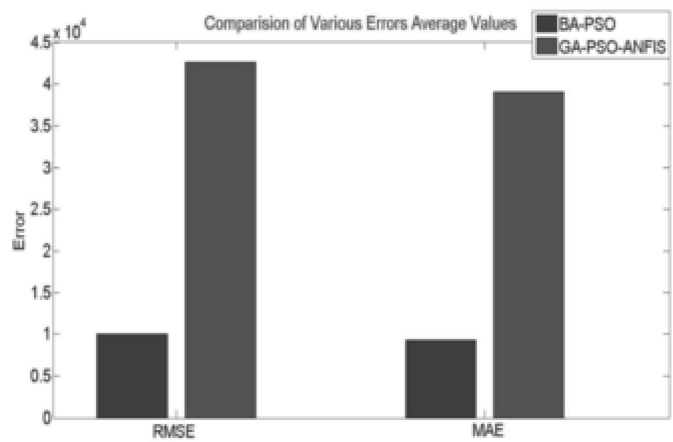

Fig. 5. Average error Comparison of solar power prediction.

From fig. 5 it is observed that BA-PSO feature selection ratio involved each environmental parameter for solar PV power prediction, so average error for various months was less as compared to [10]. While selection of some features was done in GA-PSO-ANFIS[10],which reduces its accuracy. As BA-PSO genetic algorithm has generated different combinations which perform two type of learning, first was sensitivity of butterfly while second was particle velocity and position.

Table 6
Execution time Based Comparison between BA-PSO and GA-PSO-ANFIS.

Execution time (seconds) Comparison		
Iteration	**BA-PSO**	**GA-PSO-ANFIS** [10]
10	1.245	1.8765
20	1.7921	3.0678
30	2.0976	3.7803

From Table 6 it is observed that BA-PSO is better as compared to GA-PSO-ANFIS [10], under execution time evaluation parameters. As BA-PSO genetic algorithm has generated different combinations and performed two type of learning, first was sensitivity of butterfly while second was particle velocity and position. So better results obtained in short time and iteration loop get break.

V CONCLUSION

Solar is a promising renewable source that is experiencing a fast pace of growth in the recent years. An inherent feature of these resources is that the energy production capacity is not fully controllable, thus necessitating the use of proper forecasting and management techniques to ensure smooth integration with the power grid. So this work proposed a genetic algorithm that forecast solar power as per environmental parameters like, insolation, solar orientation, temperature, etc. Real dataset obtained from NASA resource library for Raipur, India, Chhattisgarh region is used. The results show that MAE and RMSE for the BA-PSO system is quite low as compared with previous approaches. BA-PSO has reduced the RMSE value 4.255 times, while MAE was reduced by 4.21 times as compared to GA-PSO-ANFIS. This high reduction in error was obtained by estimating proper ratio of the environmental parameters. In future research can be pursued to further minimize the error in a day-ahead prediction.

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