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Genetic Algorithm Based Optimum Solar Power Prediction by Environmental Features for Indian Railway Stations

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Abstract: Electric Power requirement is increasing with every new day. Bulk of electric power in India is consumed by Indian railways, hence green energy resources are required to reduce this load. Out of many available green energy resources solar energy is playing an important role. Hence desired optimum power output from solar plant is always of area of research. This work focuses on estimation of solar plant output with the affecting environmental variables by using genetic algorithm. Genetic algorithm predicts the ratio of environmental variables that directly increase or decrease the solar power output. Work will determine this ratio by using modified butterfly particle swarm optimization algorithm and Teacher Learning Based Optimization. Here it was obtained that proposed TLBO model is good for estimating monthly power prediction while MBAPSO estimate accurate values for daily power prediction. Proposed model experiment was done on dataset of Raipur city in Chhattisgarh state of India and the results show reduction in MAE, RMSE and improvement in Correlation Coefficient thereby accuracy 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

In India, Railways started in 1853 with steam locomotive. Gradually, diesel engines were introduced and then electric engines [1]. At present, most of railway tracks are electrified and trains are hauled by electric engines. For electric engines, power is being drawn through grid supply of State Electricity Boards. The Electricity being provided by the grid is mostly through coal based Thermal plants. The coal stocking in world is going to get depleted over a period of 15-20 years. Similarly, diesel fuel stocking all over work is also getting depleted in next 20-30 years [2].

For meeting the power requirement for hauling of trains and stations, (Traction & Non traction) only alternative remains, use of renewable sources like solar energy, wind energy, hydel energy. All these energies, called Green Energy, are renewable, available in plenty and will never get exhausted. In addition, this energy is not generating CO_2/greenhouse gases and, therefore, is clean energy [3].

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Indian Railways have undertaken a project with UNDP for improving energy efficiency in Indian Railways. Indian Railways, one of largest rail network in world, is an energy intensive organization which utilized about 2.4% of India's total Energy consumption in 2007-2008, [3]. With traffic growth project electricity demand is estimated to grow at about 9% annually [3].

Therefore, IR is developing a long-term Energy Efficiency and conservation Program to reduce energy consumption and emission of greenhouse gases by progressively introducing energy saving technologies and measures and procuring energy through Renewable sources in both traction and non-traction systems [4]. So before installing any solar plant at any railway station it is desired to find the feasibility of the power plant in terms of electricity production. As this green energy is variable in nature which makes the forecasting of power generation challenging of the environment, so this paper has introduced the estimation of solar power effecting parameters. Here work has predicted this power based on environmental parameters ratio, hence genetic algorithm will iteratively get the good set of parameter ratio [5, 6]. Here as per geo-spatial location angel of inclination is also identified. Rest of this paper was organized in few sections. Next section will inform various other approaches adopted by researcher for increasing the forecasting accuracy of solar plant power. Further paper has explained the proposed work's environmental parameters estimation by genetic algorithm. Next section explains the experimental setup with dataset; here result's values were also detailed with comparison of proposed models with existing other methods. Finally, whole paper concluded with various outcome.

II. RELATED WORK

In the literature [7], a PV power physical prediction model is established based on a four-parameter battery model, five parameter battery model and seven-parameter battery model. The results show that the forecasting accuracy of the four or five parameter models is higher. Tossa et al. [8] compared the effects of different parameters in battery models and two battery temperature models on the accuracy of the PV power prediction. The results show that the complex battery parameter model has no obvious prediction advantage. Based on the measured data of the 120 W monocrystalline silicon PV module in the southern part of Turkey, Celik and Acikgoz [9] compared the calculation accuracy of the four-parameter and five-parameter cell models. The study shows that the five-parameter model has higher accuracy than the four-parameter model, especially around solar noon.

In [10] author study the motion of cloud over a photovoltaic (PV) power station that directly cause the change of solar irradiance, which indirectly affects the prediction of minute-level PV power. So in order to improve the computation accuracy, a pattern classification and particle swarm optimization optimal weights based sky images cloud motion speed calculation method for solar PV power forecasting (PCPOW) is proposed. The method consists of two parts. First, was k-means clustering method and texture features based on a gray-level co-occurrence matrix to classify the clouds. Second, for different cloud classes, build the corresponding combined calculation model to obtain cloud motion speed.

The authors in [11] propose an adaptive hybrid predictor subset selection (PSS) strategy to obtain the most relevant and non-redundant predictors for enhanced short-term forecasting of the power output of distributed PVs. In the proposed strategy, the binary genetic algorithm (BGA) is applied for the feature selection process and support vector regression (SVR) is used for measuring the fitness score of the predictors. In order to validate the effectiveness of the proposed strategy, it is applied to actual distributed PVs located in the Otaniemi area of Espoo, Finland. The findings are compared with those achieved by other PSS techniques.

Padovan and Col [12] measured the global and diffuse horizontal irradiance and the PV array irradiance of different surface tilt angles and orientations. After that, he discussed the combined models of three decomposition models and four transposition models (one isotropic and three anisotropic).

Lave et al. [13] measured global horizontal irradiance and coincident measured PV array irradiance from 12 meteorological stations within the USA. Then, the combination of three decomposition models and four transposition models were evaluated. The results suggest that the Erbs and Dirint decomposition models showed the best performance, and the model combined with the Hay–Davies transposition model had the smallest mean bias difference. In order to evaluate the influence of different combined models on PV forecasting, Pelland et al. [14] explored 12 combination models by combining each of the decomposition models and transposition models. The results show that different combination models have little effect on the accuracy of PV power forecasting.

III. METHODOLOGY

This section explains the proposed solar power prediction methodology where environmental parameters play an important role. Here two genetic algorithms were proposed and compared for finding the ratio of local environmental features set shown in Table 1. This estimation increases the plant installment reliability as amount of power generated by solar can be estimated in advance. Block diagram of proposed models is shown in Figure 1 where each block was explained under different headings of this section.

(a) Initialization Phase: This is common phase for both type of genetic algorithm. In this phase dataset explanation with pre-processing was detailed, with population generation. Both algorithms use common fitness function hence fitness value calculation is also detailed here.

Environmental Dataset: Collection of different geographical parameters values was done from [15]. Global access of different solar affecting parameters is present at [15], so passing the longitude and latitude values, dataset can be generated. Experimental region for this paper is shown in fig. 2.

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 = $[r_1, r_2, \ldots r_m]$ as the chromosome set where m is number of features in a set. While P = $[Cc_1, Cc_2, \ldots Cc_n]$, n is number of chromosomes.

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

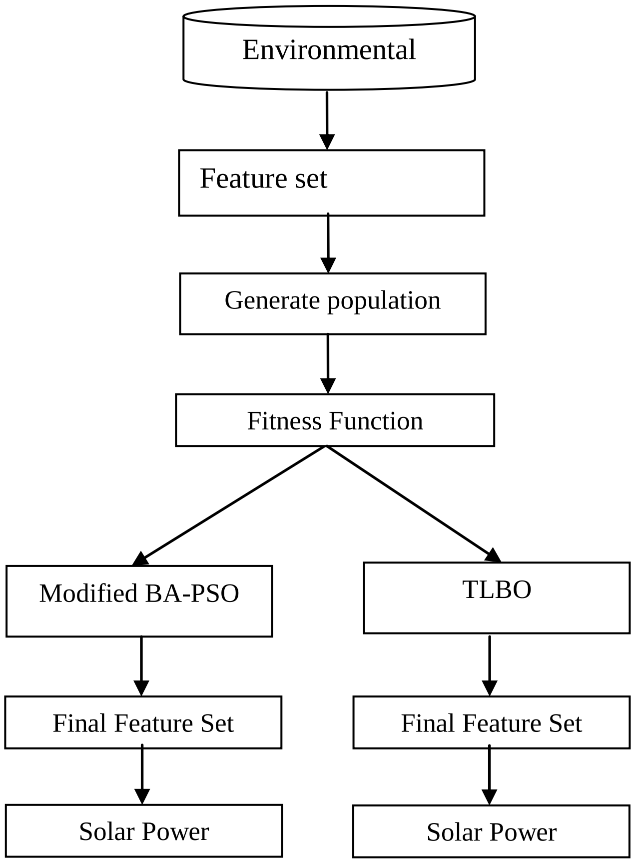

Fig. 1 Block diagram of proposed genetic algorithm.

Table 1 List of features (F).

Feature Name
Clear Sky Insolation Clearness Index
All Sky Insolation Incident on a Horizontal Surface ($kW\text{-}hr/m^2/day$)
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 above ground level (degree C)

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Earth Skin Temperature (degree C)
Wind Speed at 10 m above ground level (m/s)
Wind Speed at 50 m above ground level (m/s)
Surface Pressure (kPa) at earth's surface

Fitness Function

Selection of best solution from population set is done by this step where previous years environmental data were evaluated to generate power from current ratio by using equation (2) to (5).

Table 2 Notation used from eq. 2 to 5.

Symbol	Meaning
A	Solar Panel area in m^2
γ	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 m/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. For solar power prediction learning was done as in [21].

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

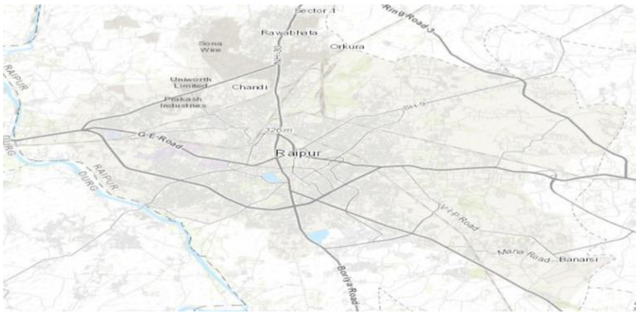
$$I_n = I_0 * \text{Cos}(ð) * \text{Sin}(\boldsymbol{\theta}) \ldots\ldots\ldots\ldots\mathbf{(3)}$$

Here, θ= Hour Angle, ð = Declination Angle

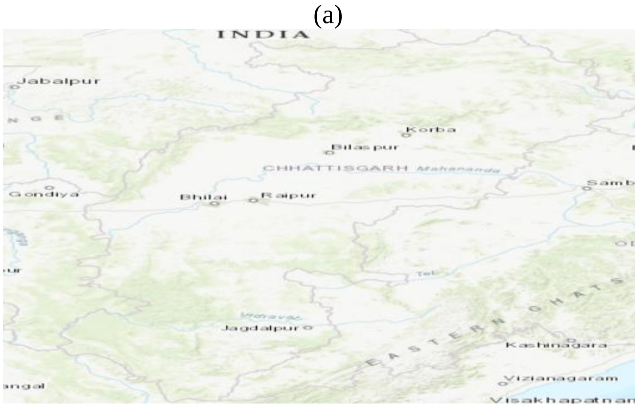
$$T_c = T + \left[\left(\frac{I_n}{I_r}\right)(C^T - A^T)\frac{C_1}{W}\left(1 - \frac{\sigma}{C_2}\right)(1 - \beta \times C_3)\right] \text{--(4)}$$

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

Output from eq. (2) are pass 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) [19, 20]gives power of a solar panel having surface area A, with yield efficiency γ.



(a)



(b)

Fig. 2 Power regional Data Access map for Raipur (a), Chhattisgarh (b) [15].

(b) Modified BA-PSO

This genetic algorithm is a hybrid combination of Butterfly and Particle swarm optimization. Here work has applied crossover operation as per butterfly sensitivity, cognitive and social feature values. While PSO velocities specify the crossover position in chromosome. As BAPSO use position parameter to shuffle the chromosome environmental ratio, this work does not modify chromosome as per position value.

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.

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 (11) obtained from [18]. Here velocity and position of the butterfly also get update which are parameters of MBAPSO. So as per position matrix crossover is done to update population.

Table 3 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

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 MBAPSO algorithm.

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 ranging between 0 to 1.

Constriction Factor C_{eq}

$\alpha = C_1 + C_2$

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

Inertia Weight

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

Update velocity V and position X of each probable solution

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

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 V values crossover operation were performed.

Crossover

In this work population P is updated as per V value. Hence random change in column value either increases or decreases V^{th} feature ratio in crossover [18]. This operation is repeated with all other set of chromosomes. This updated chromosome is further evaluated for finding the fitness value. If fitness is better as compared to previous chromosome than new chromosome is included in population.

Update G-Best

After each iteration values of G-Best get optimized if new probable solution fitness function values are better than previous G-Best values. Hence, if two successive iterations show same values than iteration will stop or if N number of iterations are complete.

Modified MBAPSO 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).

(c) TLBO

In this phase Teacher Learning Based Optimization (TLBO) genetic algorithm was detailed. Population generation and fitness function of this algorithm was common as done in phase one. Here two step population update was done first was teacher and other was student. In teacher phase one best solution perform crossover operation with all set of chromosomes and in student step group of chromosomes were involved for crossover.

Teacher: This phase was used for the crossover of the chromosomes by the single best solution from the population. So as per P_s which was used to find distance from the required power, Cc which have minimum distance was considered as best solution in the population set [21]. Here best solution $Cc_{teacher,i}$ act as a teacher and its selection is based on the fitness value. Top possible solution after sorting will act as the teacher for other possible solutions. Now selected teacher will teach other possible solution $Cc_{student,i}$ by replacing environmental ratio as present in teacher solution. By this all possible solution which act as student will learn from best solution which act as teacher. In order to do crossover operation random position feature value is copied from the teacher chromosome and it was replaced to the non teacher chromosome by eq. 12. This improved the population quality.

$$Cc_{new,i} \leftarrow Cc_{teacher,I}\ i \in \{1, 2, \ldots \ldots m\} \text{---------Eq(12)}$$

Where $Cc_{new,i}$ is the updated value of $C_{student,i}$.

Student Phase: In this phase some random group of chromosomes were made automatically and then each group was used for the crossover of the chromosomes by the single best solution in that group. Here best solution act as a trainer among other chromosomes and its selection is based on the fitness value. In order to do crossover operation random position weather feature value is copied from the trainer chromosome and it was replaced to the non-teacher chromosome. Here each new chromosome was cross verified that either its fitness value improved than previous, if fitness improves then new chromosome is included in the population and older one gets removed. Vice-versa, if fitness value does not improve.

TLBO Solar Power Prediction

After 't' numbers of iterations, for teacher and student phase, algorithm gets final geographical feature ratio.

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Hence in this phase features of geographical location were read where solar power was predicted for that location. Here feature ratio is multiplied with environmental values and obtained value is 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.

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 2 and it was obtained from [15] for Raipur.

Results

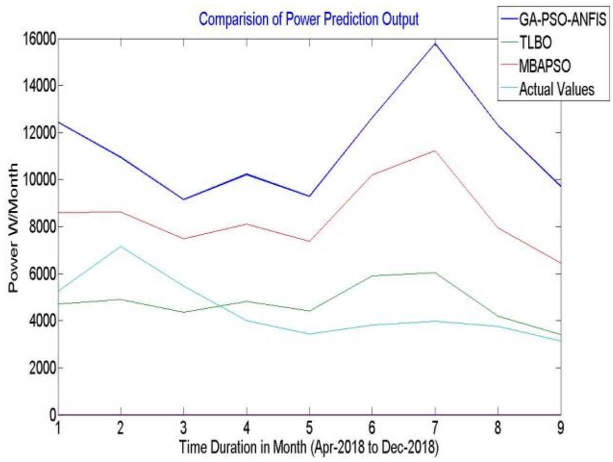

Fig. 3 Comparison of Prediction and actual power output.

From Figure 3 it is observed that TLBO power estimation value corresponding to monthly data from April-2018 to December 2018 of Raipur region is more nearer (Actual) to ground truth values as compared to MBAPSO, GA-PSO-ANFIS values [22]. Use of two step population updates increase the closer power forecasting for monthly data.

Evaluation Parameters:

Root Mean Square Error

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

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

Mean Average Error

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

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

Correlation Coefficient (R): This parameter value ranges from -1 to 1, where 1 means good relation and -1 is very poor relation between observed and model values.

$$R = \frac{n \sum X_{obs} - \sum X_{obs} \times X_{model}}{\sqrt{\left(n \sum X_{obs}^2 - \left(\sum X_{obs}\right)^2\right) \times \left(n \sum X_{model}^2 - \left(\sum X_{model}\right)^2\right)}} \text{---(15)}$$

i) MEA and RSME Monthly based comparison

Table 4. MAE based monthly comparison of solar power forecasting models.

MAE Based Comparison			
Months Year 2018	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
Apr-Jun	4890.7	1289.1	2283.9
Jul-Sep	6955.3	1294.1	4807.5
Oct-Dec	8961.7	924.3	4909.6

From Table 4 it is observed that MAE for MBAPSO value was lower than other existing method GA-PSO-ANFIS [22], while TLBO further reduces this error. Hence, power forecast is more accurate in TLBO work as compared to MBAPSO algorithm. This accuracy was achieved by introducing all environmental parameters in some ratio, instead of selecting or rejecting as done in [22].

Table 5. RMSE based monthly comparison of solar power forecasting models.

RMSE Based Comparison			
Months Year 2018	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
Apr-Jun	5159.6	1474.2	2417.7
Jul-Sep	7078.1	1409.9	4932.7
Oct-Dec	9216.5	1229.5	5189.5

From Table 5 it is observed that MBAPSO RMSE value was lower than method adopted in [22], while TLBO further reduces this error by using two step population updation. Hence monthly power forecasting values are more accurate in TLBO work as compared to MBAPSO algorithm. This accuracy was achieved by introducing all environmental parameters in some ratio, instead of selecting or rejecting as done in [22].

ii)Execution Times based Monthly Comparison

Table 6. Execution time based monthly comparison of solar power forecasting models.

Execution Time (second) Based Comparison			
Months Year 2018	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
Apr-Jun	2.3256	0.8180	1.0387
Jul-Sep	3.0987	1.0287	1.3376
Oct-Dec	2.8976	1.1123	1.789

From Table 6 it is observed that TLBO execution time for finding the environmental parameters ratio was less as compared to method used in [22], and MBAPSO. This high execution time in MBAPSO was due to its calculation for two set of algorithms first for Butterfly while other for PSO. Although MBAPSO execution time was less as compared to GA-PSO-ANFIS.

iii) Weekly Based comparison

Table 7. MAE based Weekly comparison of solar power forecasting models.

April 2019 Week based MAE Comparison			
Week	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
1st Week	802.9	797.5033	505.6348
2nd Week	1661.7	596.2753	322.0830
3rd Week	1441.5	501.9027	276.9975
4th Week	622.7	895.9576	192.1373
May 2019 Week based MAE Comparison			
Week	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
1st Week	594.4610	432.2772	441.0856
2nd Week	579.3428	480.8351	520.0989
3rd Week	449.7148	277.8925	211.6136
4th Week	431.0381	318.2540	351.1325
June 2019 Week based MAE Comparison			
Week	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
1st Week	1018.9	696.5651	616.7929
2nd Week	793.3	348.9293	326.4959
3rd Week	352.5	554.2177	646.6564
4th Week	828.8	809.2465	816.3754

From Table 7 it is observed that average MAE for all weeks of different months (April, May, June) MBAPSO is better as compared to TLBO and GA-PSO-ANFIS [22]. under MAE evaluation parameters. As MBAPSO 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 8. RMSE based weekly comparison of solar power forecasting models.

April 2019 Week based RMSE Comparison			
Week	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
1st Week	1058.7	848.3993	657.5501
2nd Week	1736.7	616.7679	375.9816
3rd Week	1512.5	524.8904	362.0192
4th Week	754.1	902.0695	241.3562
May2019 Week based RMSE Comparison			
Week	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
1st Week	630.3307	478.2410	486.8154
2nd Week	630.5033	525.1446	552.9998
3rd Week	484.8603	343.3321	317.8497
4th Week	485.7819	342.5805	370.8301
June 2019 Week based RMSE Comparison			
Week	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
1st Week	37.1	759.5	661.8
2nd Week	810	417.4	361.1
3rd Week	470.2	628.0	540.1
4th Week	922.3	1019.4	891.3

From Table 8 it is observed that average RMSE for all weeks of different months (April, May, June) MBAPSO is better as compared to TLBO and GA-PSO-ANFIS [22], under RMSE evaluation parameters. As MBAPSO genetic algorithm has generated different combinations which perform two type of learning, first was sensitivity of butterfly while second was particle velocity and position.

iv) Corelation coefficient based comparison

Table 9. Correlation coefficient (CC) based weekly comparison of solar power forecasting models.

April 2019 Week based CC Comparison			
Week	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
1st Week	-0.1879	0.2070	0.2590
2nd Week	0.2755	0.4954	0.5055
3rd Week	0.6371	0.6695	0.6543
4th Week	0.3105	0.4831	0.5289
May 2019 Week based CC Comparison			
Week	**GA-PSO-ANFIS[22]**	**TLBO**	**MBAPSO**
1st Week	0.0891	0.1048	0.1218
2nd Week	-0.5446	-0.3573	-0.2552
3rd Week	0.2238	0.3980	0.4325

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4th Week	-0.1761	-0.0968	-0.0374
June 2019 Week based CC Comparison			
Week	**GA-PSO-ANFIS [22]**	**TLBO**	**MBAPSO**
1st Week	-0.2566	-0.2691	-0.2401
2nd Week	0.5255	0.5061	0.4994
3rd Week	-0.3059	-0.3671	-0.3145
4th Week	-0.8765	-0.8689	-0.8724

From Table 9 it is observed that average Correlation Coefficient (CC) value for all weeks of different months (April, May, June) MBAPSO is better as compared to TLBO. As MBAPSO 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 result obtained in short time and iteration loop gets break.

v) Comparison of TLBO and MBAPSO for three months

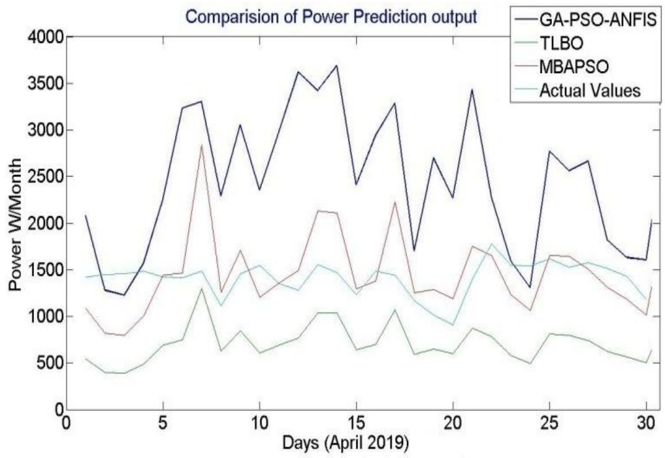

Fig. 4 Comparison of power forecasting techniques for month of April- 2019.

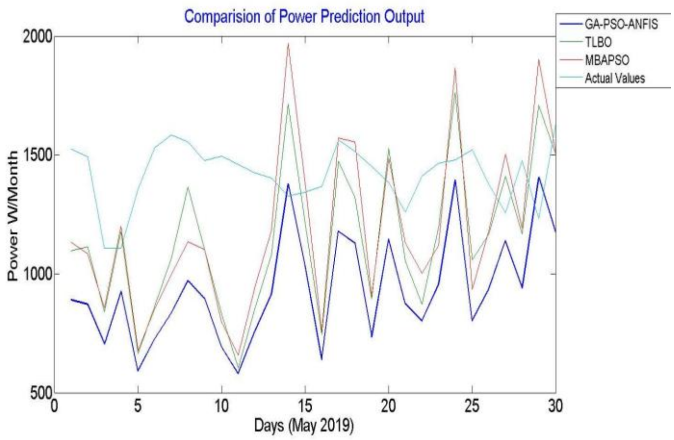

Fig. 5 comparison of power forecasting techniques for month of May- 2019.

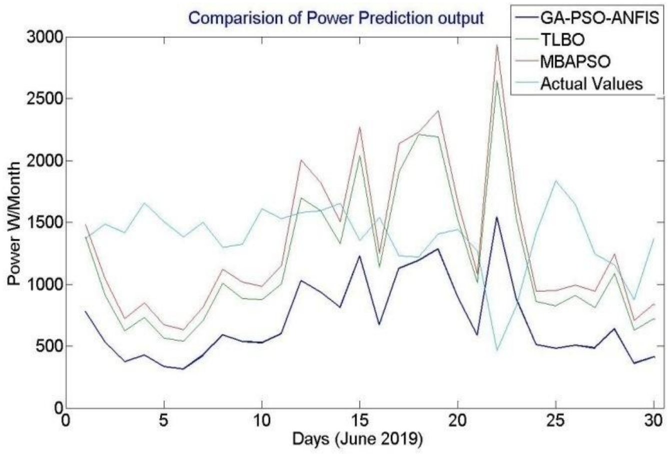

Fig. 6 Comparison of power forecasting techniques for month of June- 2019.

From fig. 4, 5 and 6, it is observed that TLBO power estimation value corresponding to daily data from April-2019 to June 2019 of Raipur region is more nearer (Actual) to actual values as compared to GA-PSO-ANFIS values [22], but MBAPSO has further increase this closeness with actual power values. Hence, it was concluded that MBAPSO is better for daily power forecasting method.

V. CONCLUSION

Solar is a promising renewable source that has experienced a fast 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 facilitate smooth integration with the power grid. Thus, this work proposed two genetic algorithms that forecast solar power based on 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, RMSE for the MBA-PSO systems of daily dataset was reduced by 44.74% and 45.41% as compared to GA-PSO-ANFIS. While TLBO reduced values of MAE by 5.93 times, and RMSE values were reduces by 5.21 times as compared to GA-PSO-ANFIS.

REFERENCES

1. Dolf Gielen, Ricardo Gorini, Nicholas Wagner, Rodrigo Leme, Laura Gutierrez & Gayasthri Prakash. "Global Energy Transformation". International Renewable Energy Agency (Irena), Isbn 978-92-9260-059-4, Apr, 2018.
2. Eswara Arun Kishore. "Carbon emissions from Indian Railways An estimation for transportation of goods during 2010-2011". https://www.irfca.org/docs/Indian_railways_carbon_emissions.pdf published by Ministry of Railways 2012.
3. http://www.indianrailways.gov.in/Indian%20Railways%20Whistling%20Ahead-%20%20Story%20of%20Growth%20and%20Modernisation-Booklet.pdf
4. Alexandra Solovieva. "Global Environment Facility Project Document". United Nation Development Program India, 2012.
5. K. Arul Kumar, K. Palanisamy, D. Vijaya Kumar. "Recent Advances and Control Techniques in Grid Connected PV System – A Review". International Journal Of Renewable Energy Research, Vol.6, No.3, 2016.
6. Yang HT, Huang CM, Huang YC, Pai YS. A weather-based hybrid method for 1- day ahead hourly forecasting of PV power output. IEEE Trans Sustain Energy 2014; 5:917–26.

7. N. Sharma, J. Gummeson, D. Irwin, and P. Shenoy, "Cloudy Computing: Leveraging Weather Forecasts in Energy Harvesting Sensor Systems," in SECON, June 2010.
8. Tossa, A.K., Soro, Y.M., Azoumah, Y., et al.: 'A new approach to estimate the performance and energy productivity of photovoltaic modules in real operating conditions', Sol. Energy, 2014, 110, pp. 543–560.
9. Celik, A.N., Acikgoz, N.: 'Modelling and experimental verification of the operating current of mono-crystalline photovoltaic modules using four- and five-parameter models', Appl. Energy, 2007, 84, (1), pp. 1–15.
10. Zhao Zhen; Shuaijie Pang ; Fei Wang ; Kangping Li ; Zhigang Li ; Hui Ren ; Miadreza Shafie-khah . "Pattern Classification and PSO Optimal Weights Based Sky Images Cloud Motion Speed Calculation Method for Solar PV Power Forecasting". IEEE Transactions on Industry Applications (Volume: 55 , Issue: 4 , July-Aug. 2019).
11. Abinet Tesfaye Eseye , Matti Lehtonen , Toni Tukia, Semen Uimonen, and R. John Millar "Adaptive Predictor Subset Selection Strategy for Enhanced Forecasting of Distributed PV Power Generation". IEEE Access July 24, 2019.
12. Padovan, A., Col, D.D.: 'Measurement and modeling of solar irradiance components on horizontal and tilted planes', Sol. Energy, 2010, 84, (12), pp. 2068–2084.
13. Lave, M., Hayes, W., Pohl, A., et al.: 'Evaluation of global horizontal irradiance to plane-of-array irradiance models at locations across the United States', IEEE J. Photovoltaics, 2015, 5, (2), pp. 597–606.
14. Pelland, S., Galanis, G., Kallos, G.: 'Solar and photovoltaic forecasting through post-processing of the global environmental multiscale numerical weather prediction model', Progress Photovoltaics Res. Appl., 2013, 21, (3), pp. 284–296
15. https://power.larc.nasa.gov/data-access-viewer/
16. Kamrul Islam Chowdhury, Md.Iftekhar-ul-Alam, Promit Shams Bakshi"Performance Comparison Between Fixed Panel, Single-axis and Dual-axis Sun Tracking Solar Panel System". BRAC UNIVERSITY 2017.
17. C. Schwingshackl, M. Petitta, J.E. Wagnera, G. Belluardo, D. Moser, M. Castelli, M. Zebisch and A. Tetzlaff. "Wind effect on PV module temperature: Analysis of different techniques for an accurate estimation". Elsevier, European Geosciences Union General Assembly 2013.
18. Aashish Kumar Bohre1, Dr. Ganga Agnihotri,Dr. Manisha Dubey, Jitendra Singh Bhadoriya. "A Novel Method To Find Optimal Solution Based On Modified Butterfly Particle Swarm Optimization". International Journal Of Soft Computing, Mathematics And Control (Ijscmc), Vol. 3, No. 4, November 2014.
19. Rudy Schoenmaker. "Developing a Smart Grid Simulation model from an end-users perspective". Rijksuniversiteit, Groningen, January 27, 2014.
20. Joseph Amajama. "Effect of Air Pressure on the Output of Photovoltaic Panel and Solar Illuminance". International Journal of Scientific Engineering and Applied Science (IJSEAS) – Volume-2, Issue-8, August 2016 ISSN: 2395-3470.
21. Mohan Allam, M. Nandhini. "Feature Optimization using Teaching Learning Based Optimization for Breast Disease Diagnosis". International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-7 Issue-4, November 2018.
22. YordanosKassaSemero, Jianhua Zhang and Dehua Zheng. "PV Power Forecasting Using an Integrated GA-PSO-ANFIS Approach and Gaussian Process Regression Based Feature Selection Strategy". csee journal of power and energy systems, vol. 4, NO. 2, JUNE 2018.

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