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Genetic Algorithm Based Daily Power Prediction as per Environmental Features of Indian Railway Stations

***Sanjeev Kumar Sukalikar, **Dr. Anil Kumar Kurchania**
*Ph.D. Scholar, Department of Electrical Engineering, Rabindranath Tagore University, Bhopal
**Director & Professor, Centre for Renewable Energy, Rabindranath Tagore University, Bhopal

Abstract- Over the past few years, solar power has significantly increased in popularity as a renewable energy. In the context of electricity generation, solar power offers clean and accessible energy, as it is not associated with global warming and pollution. The main challenge of solar power is its uncontrollable fluctuation since it is highly depending on other weather variables. Thus, forecasting energy generation is important for smart grid operators and solar electricity providers since they are required to ensure the power continuity in order to dispatch and properly prepare to store the energy.This work focuses on estimation of solar plant output with the affecting environmental variables by using modified 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.Experiment was done on real geographical location environmental variables at Raipur, Chattisgarh, India. Results were compared with existing power predictions models.

Keywords:- Electric power Grid, Renewable resources-Solar.

I. INTRODUCTION

In recent years, the rapid boost of variable renewable resource energy generations particularly from wind and solar energy resources in the power generation grid has led to these generations becoming a noteworthy source of uncertainty with load behavior still being the main source of variability. Generation and load balance are required in the economic scheduling of the generating units and in electricity market trades [1].

Energy prediction/forecasting can be used to mitigate some of the challenges that arise from the uncertainty in the resource. Solar power forecasting/ prediction is witnessing a growing attention from the research community for higher efficiency [2, 3]. Increasing demand for energy is leading toward integration of renewable solar energy with the non-renewable energy resources.

Power service providers are increasing the use of solar power due to (among many factors) decreases in the cost of solar power production systems, increases in the cost of traditional energy sources, environmental concerns,and legislative requirements.

These same forces increase the prevalence of homes and small businesses with solar panels and storage that produce solar power to use in the home or business or store in battery banks or smart appliances or sell power back to power companies in tiered or real-time pricing structures.

The photovoltaic geographic information system provides climate data and the performance assessment tools of photovoltaic (PV) technology mainly for developing nation [4].Many studies are conducted to predict the level of future solar irradiance or PV power generation in solar plants using weather information [5]. Sources of weather information include both measured weather records and weather forecasts. This study finds that most previous studies have focused on exploiting only single source and that few studies have attempted to utilize both information sources [6]. Thus, this study proposes a novel two-step prediction process that finds ratio of impacting environmental features for solar power generation, as per geographical location.

II. RELATED WORK

Elias M Salilih et al [7] This paper presents modelling electrical performance of a typical PV panel/module which is Kyocera 200GT for constant electric loads which are 2O 4O 6O and 8O under weather condition of a tropical region. The specific case of the city Jigjiga 9 35°N 42 8°E located in the Eastern region of Ethiopia is considered. Electrical characteristics of the PV module are determined on the basis of detailed numerical algorithm which was designed based on tested numerical technique from reviewed articles The overall evaluation of the hourly variation in the electrical performance of the PV module is done by means of graphical technique which determines the operating point of the PV module on voltage vs current plane for each load and the performance of the PV panel is compared for each load.

B VMathisen et al in [8] launch the design of Smart Energy Systems through the 100% renewable energy system analyses and research behind the CEESA research project. The transition from fossil fuels towards the integration of more and more renewable energy requires rethinking and redesign of the energy system. Traditionally a lot of focus internationally is put on the electricity sector to solve the integration puzzle focusing on electricity storage technologies e g batteries, hydrogen storage and on electricity smart grids In Smart Energy Systems the focus is integration of the electricity heating and transport sectors and on using the flexibility in demands and various short term and long term storage in the different sectors. Such a redesign also entails that the Smart Energy System is comprised of a number of smart grid infrastructures for different sectors in the energy system i e the electricity grids, district heating, cooling grids, gas grids and fuel infrastructure.

Li Y et al in [9] the authors characterize a decentralized component for deciding the motivating force motions in a brilliant lattice utilizing a correspondence based decentralized valuing plan. The proposed instrument characterizes and executes a decentralized strategy to figure the Lagrangian multiplier which is then utilized for registering the value motion amid DR occasions Be that as it may a standout amongst the most outstanding downsides is information security. A decentralized cost based DR framework is exhibited The value flag is inside registered iteratively in light of the anticipated energy generation and request proportion and on the client's ability to give stack moving on request inside a energy sharing zone 2 3 Resource Power Prediction.

Yordanos Kassa Semero et. al. in [10] author presents a hybrid approach for the forecasting of electricity production in microgrids with solar photovoltaic (PV) installations. A day-ahead, hourly mean PV power generation forecasting method based on a combination of genetic algorithm (GA), particle swarm optimization (PSO) and adaptive neuro-fuzzy inference systems (ANFIS) is presented in this study. Binary GA with Gaussian process regression model based fitness function is used to determine important input parameters that significantly influence the amount of output power of a PV generation plant; and an integrated hybrid algorithm combining GA and PSO is used to optimize an ANFIS based PV power forecasting model for the plant.

Daniel O'Leary et al in [11] Input masking an ANN tuning technique developed for acoustic signal classification and image edge detection is applied to prosumer solar data to improve prosumer forecast accuracy over traditional macrogrid ANN performance tuning techniques. ANN inputs tailor time of day masking based on error clustering in the time domain.

B Oluleye et al in [12] details the exploration and application of Genetic Algorithm GA for feature selection Particularly a binary GA was used for dimensionality reduction to enhance the performance of the concerned classifiers In this work hundred 100 features were extracted from set of images found in the Flavia dataset The extracted features are Zernike Moments ZM Fourier Descriptors FD Lengendre Moments LM Hu 7 Moments Hu7M Texture Properties TP and Geometrical Properties GP. The main contributions of this article are the development of a GA based feature selector using a novel fitness function kNN based classification error which enabled the GA to obtain a combinatorial set of feature giving rise to optimal accuracy.

III. METHODOLOGY

This section explains the proposed solar power prediction methodology where environmental parameters play an important role. Genetic algorithms were proposed and compared for findingthe ratios of local environment features. Block diagram of proposed models was shown in Fig. 1 where each block was explained under different headings of this section.

1. Generate Population:

In this step different chromosome set were generated, which have environmental feature set ratio between 0 to 1. So each environmental feature set acts as the chromosome(Cc) [13].while collection of all set is termed as population(P).

P ßRandom (n, m) ---------(1)

2. 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).

[Io W T Pr] = Cc*F---------(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 Io, W, T, Proutput 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 In. The equation of calculating solar insolation for fixed panel is,

$$In = I0 * \cos(ð) * \sin(\theta) \text{ ....(3)}$$

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×γ×T_c×P_r---------(5)

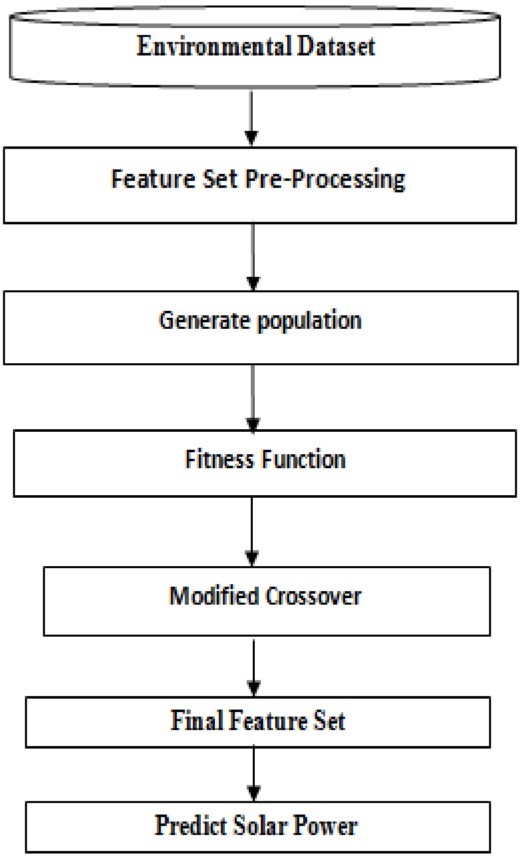


Fig 1. Block diagram of proposed genetic algorithm.

Output from eq. (2) are pass in equation (3) obtained from [15], where insolation values get changed as per solar orientation. While eq. (4) obtained from [14]gives Cell temperature value. In eq. (4)c1, c2 are constant whose value range between 0-1, while C3 range between 5 to 45.Finally, eq. (5) [16]gives power of a solar panel having surface area A, with yield efficiencyγ.

3. 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, congnitive and social feature values. While PSO velocity specify the crossover position in chromosome. As MBAPSO use position parameter to shuffle the chromosome environmental ratio parameter, this work do not modify chromosome as per position value.

4. 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.

Following eq. 6 to 12, were obtained from [17].

4. Sensitivity of Butterfly:

S=e^(-(M_r-C_r)/M_r)----(6)

Where S is sensitivity of rth iteration where Mr is maximum number of iterations takes place and Cr is current iteration of this MBAPSO algorithm.

5. Cognitive and Social parameters:

C_1=y*(C_r/M_r)+x)---------------(7)

C_2=x*(C_r/M_r)--------------(8)

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

6. Constriction Factor Ceq:

α=C_1+C_2

C_eq=1-α-√(α^2-4α)----(9)

7. Inertia Weight:

W_t=y+((M_r-C_r))/M_r ----- (10)

8. 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 V values crossover operation were performed.

9. Modified Crossover:
MBAPSO use velocity parameter to crossover the chromosome environmental ratio parameter, this work do not modify chromosome as per position value.

10. 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.

11.. Modified MBAPSO Solar Power Prediction:
In this phase features of geographical location are read where solar poweris predicted for that location. Here feature ratio is multiplied with environmental values and obtained valuesare 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 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.

1.Dataset:
Analysis done on actual dataset (Ground Truth Values) for Raipur city in Chhattisgarh state of India having Lattitude: 21.2514° N, Longotude: 81.6296° E. Various environmental features used in the calculation are given in Table 3 and it was obtained from [18] for Raipur.

2.Results:
The generated power is compared with required daily power, so less difference between daily power and generated power is desired.

From table 1 it is observed that MBAPSO MAE value corresponding to daily data from Aug-2018 to July-2019 for real requirement of power was low as compared to other existing TLBO [19] and GA-PSO-ANFIS [10] algorithm. This reduction of error was achieved by modifying the Butterfly algorithm for crossover operation.

From table 2. it is observed that MBAPSO execution time value for power prediction corresponding to daily data from Aug-2018 to July-2019 for real requirement of power was low as compared to other existing TLBO [19] and GA-PSO-ANFIS [10] algorithm.

This reduction of time was achieved by modifying the Butterfly algorithm for crossover operation.

Table 1. MAE of daily required power and generated power.

Month	GA-PSO-ANFIS [10]	TLBO	MBAPSO
Aug-2018	1020.1	822.05	515.18
Sep-2018	1215.5	906.9554	621.2275
Oct -2018	1024.2	665.8292	539.2022
Nov 2018	2439	738.34	442.7299
Dec 2018	679.8342	440.3329	376.5370
Jan 2019	763.1120	487.3723	429.5392
Feb 2019	1538.6	679.5651	664.5498
Mar 2019	1158.3	857.2905	819.2984
Apr 2019	1631.7	926.2459	925.7026
May 2019	1525.2	799.7867	742.4832
Jun 2019	1032.8481	630.5391	566.8467
July 2019	1786	1340.2	674.0437

Table 2. Execution Time (Second) of Prediction of Generated power.

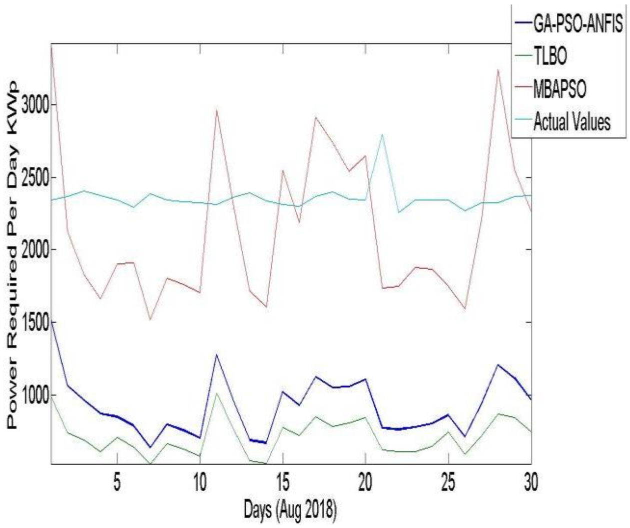
Month	GA-PSO-ANFIS [10]	TLBO	MBAPSO
Aug-2018	5.0561	1.2745	1.0938
Sep-2018	5.0682	1.0136	1.1238
Oct -2018	5.2861	1.0365	1.0253
Nov 2018	6.0253	1.2233	1.1225
Dec 2018	5.0361	1.225	1.0235
Jan 2019	5.1225	1.203	1.1214
Feb 2019	6.3621	1.3621	1.0232
Mar 2019	5.8639	1.1061	1.1122
Apr 2019	6.3263	1.0963	1.0365
May 2019	5.8362	1.2352	1.1022
Jun 2019	5.6398	1.1025	1.0965
July 2019	5.2813	1.0838	1.0993

From table 3. it is observed that MBAPSO Error percentage value corresponding to daily data from Aug-2018 to July-2019 for real requirement of power was low as compared to other existing TLBO [19] and GA-PSO-ANFIS [10] algorithm. This reduction of error was achieved by modifying the Butterfly algorithm for crossover operation.

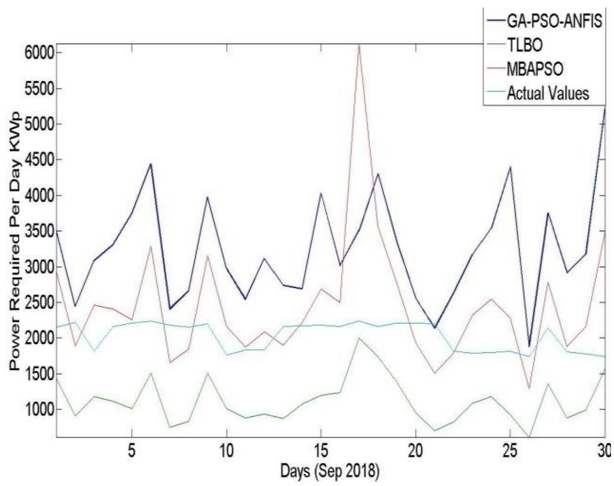
Table 3. Error Percentage of daily required power and generated power.

Month	GA-PSO-ANFIS [10]	TLBO	MBAPSO
Aug-2018	50.27	40.51	25.3894
Sep-2018	59.9009	44.6970	30.6156
Oct-2018	50.4752	32.8137	26.5732
Nov 2018	135.73	41.0906	24.6390
Dec 2018	41.2188	26.6976	22.8297
Jan 2019	43.4361	27.7411	24.4492
Feb 2019	78.7369	34.7769	34.0084
Mar 2019	39.9362	29.5575	28.2476
Apr 2019	56.2577	31.935	31.9162
May 2019	51.1647	26.8298	24.9075
Jun 2019	36.002	21.9750	19.7552
July 2019	75.7227	56.8206	28.5785

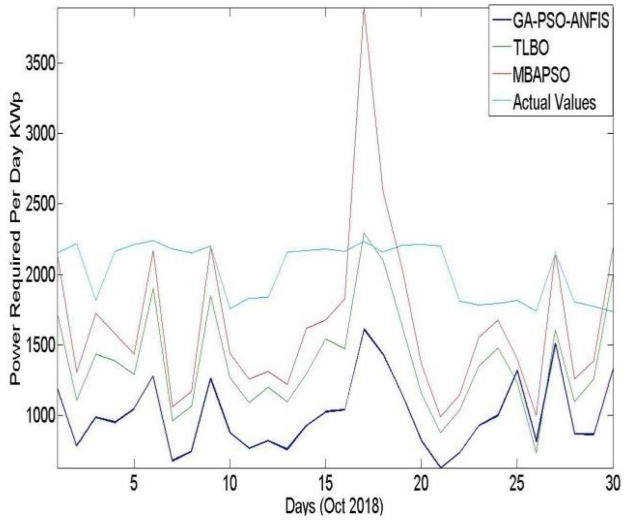
Comparison of Real Requirement and predicted value from different algorithm-



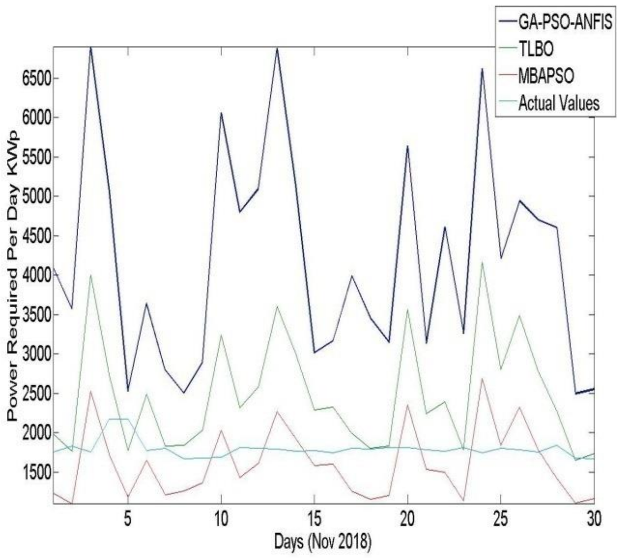
(a)



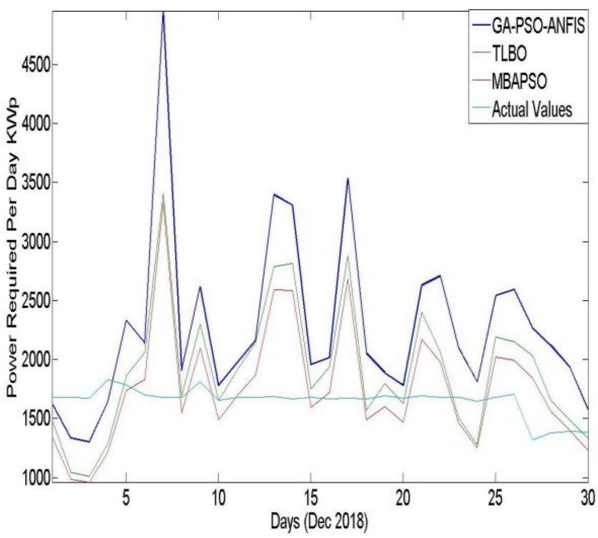
(b)


GA-PSO-ANFIS
TLBO
MBAPSO
Actual Values
Power Required Per Day KWp
Days (Oct 2018)

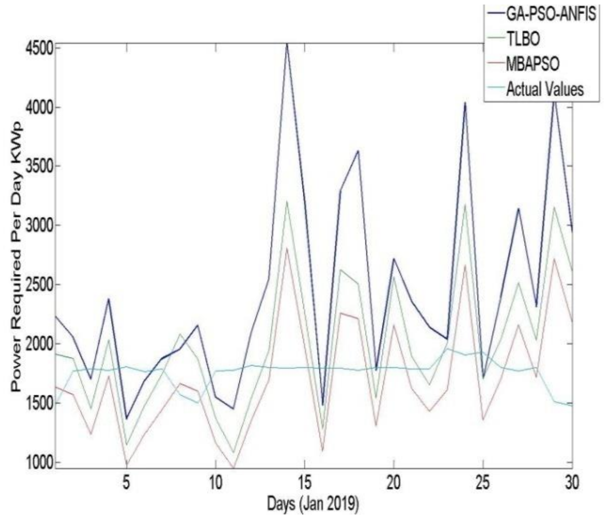
(c)


GA-PSO-ANFIS
TLBO
MBAPSO
Actual Values
Power Required Per Day KWp
Days (Nov 2018)

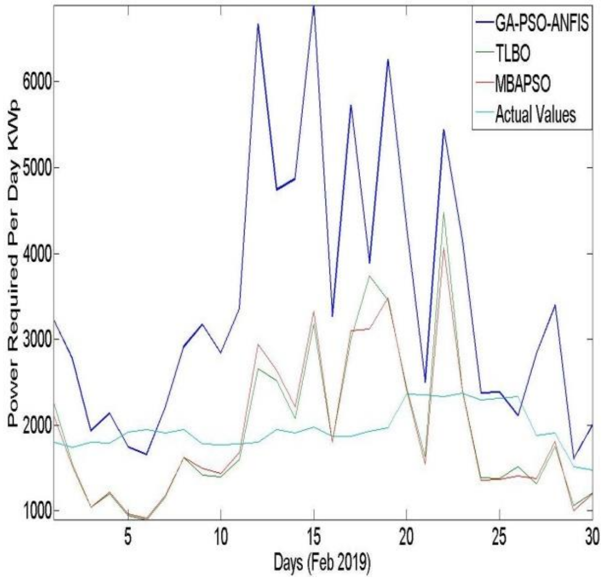
(d)


GA-PSO-ANFIS
TLBO
MBAPSO
Actual Values
Power Required Per Day KWp
Days (Dec 2018)

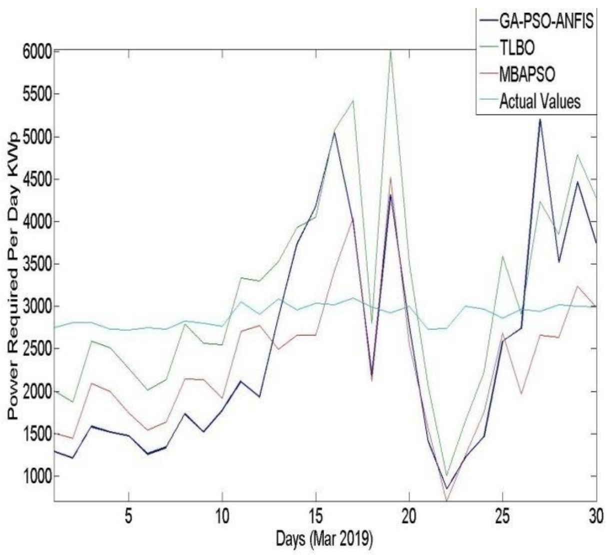
(e)


GA-PSO-ANFIS
TLBO
MBAPSO
Actual Values
Power Required Per Day KWp
Days (Jan 2019)

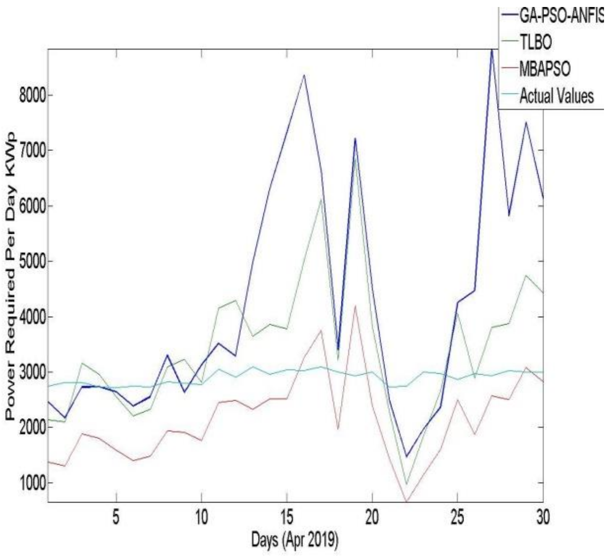
(f)


GA-PSO-ANFIS
TLBO
MBAPSO
Actual Values
Power Required Per Day KWp
Days (Feb 2019)

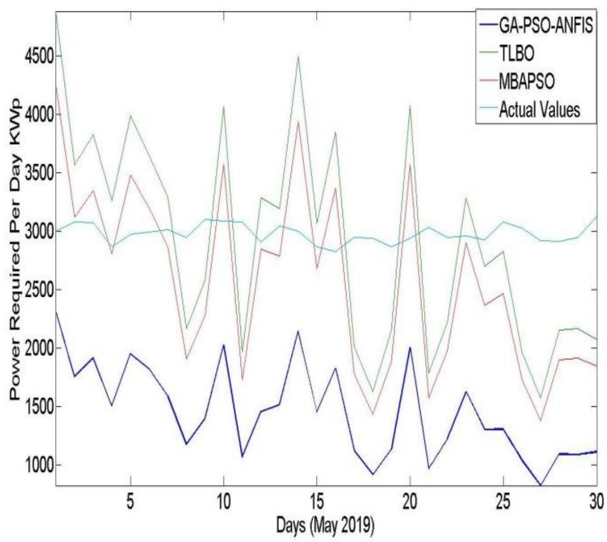
(g)


GA-PSO-ANFIS
TLBO
MBAPSO
Actual Values
Power Required Per Day KWp
Days (Mar 2019)

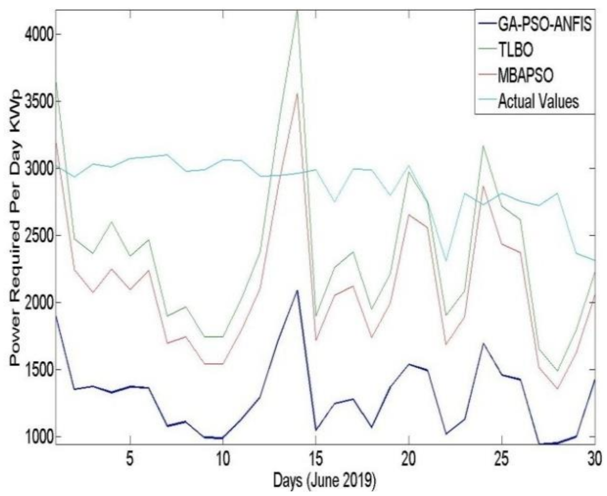
(h)



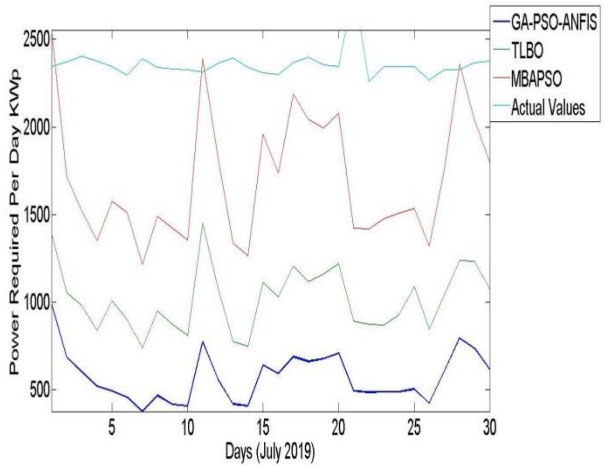
(i)



(j)



(k)



(l)

Fig 2. Comparison of Real Requirement and predicted value from different algorithm.

Above figure 2 shows for 12 month from Aug-2018 to July-2019 for real requirement of power to prediction of power from MBAPSO, TLBO[19] and GA-PSO-ANFIS [10] algorithm.

By MBAPSO, reduction of error was achieved by modifying the Butterfly algorithm for crossover operation.

V. CONCLUSION

Installation of solar panels for a small or large power generation unit need to be verified by solar forecasting algorithms. This paper has proposed solar power prediction model that utilize geographical environment variables.

Hybrid genetic algorithm Butterfly and PSO was used for identifying the geographical feature ratio that impact solar power generation. It was found that predicted power by the model was almost close to real required power. Experiment was done on real dataset. Results values shown that proposed model has increased the prediction accuracy. In future some leaning model need to be developed that learns the feature ratio.

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