International Journal of Scientific Research & Engineering Trends
Volume 5, Issue 2, Mar-Apr-2019, ISSN (Online): 2395-566X

Smart Grid Load Balancing Using Renewable Resources and Genetic Algorithm

Research Scholar Manish Verma
Electrical Engineering Department
Mandsaur Institute Of Technology,
Mandsaur India

Asst Prof. Ashish Sethiya
Electrical Engineering Department
Mandsaur Institute Of Technology,
Mandsaur India

Asst Prof. RP Kumawat HOD
Electrical Engineering Department
Mandsaur Institute Of Technology,
Mandsaur India

***Abstract*- With increase in load Smart Electrical Grids are required for proper distribution of electrical load. Here this balancing is not straight switching because of random electric requirements. Considering these facts work has focus on developing a smart grid for balancing the renewal load distribution, by using genetic algorithm. Here propose work will utilize Teacher Learning Based optimization algorithm, where two phase learning is done. Here proper set of solar or wind mill generators are assigned for fulfilling particular load requirement is estimate by this genetic algorithm. In this work proper fitness function was used where distance of source plant is also consider for loss of power dissipation and reduce it. This work increases the resource utilization with minimum loss. Experiment was done on real dataset from authentic datasets and result shows that proposed work is better as compared to previous other approaches n various evaluation parameters.**

***Keywords* – Electric power Grid, Dynamic load balancing, Renewable resources.**

I. INTRODUCTION

A number of factors are contributing to increases in renewable energy production in the United States (and beyond). These factors include rapidly declining costs of electricity produced from renewable energy sources, regulatory and policy obligations and incentives, and moves to reduce pollution from fossil fuel-based power generation, including greenhouse gas emissions. While not all renewable energy sources are variable, two such technologies – wind and solar PV – currently dominate the growth of renewable electricity production. The production from wind and solar PV tries to capture the freely available but varying amount of wind and solar irradiance.

As a result, today's grid is able to accurately plan in advance which generators to dispatch, and when, to satisfy demand. The problem with substantial renewable integration is that the electricity renewable generate is not easily predictable in advance and varies based on both weather conditions and site-specific conditions. While utilities may take the time to manually develop accurate prediction models for large scale solar farms that produce multiple megawatts, manually developing specialized models that predict the power output from distributed generation at many small-scale facilities at smart homes and buildings throughout the grid is infeasible. This fact is evident in current net metering laws for most states, which allow consumers to sell energy produced from on-site renewable back to the grid, but typically places low caps on both the total number of participating customers and/or the total amount of energy contributed per customer [3]. As one example, Massachusetts caps the total number of participating customers at 1% of all customers. Utilities restrict the contribution from renewables, since, unlike electricity demand, renewable generation is not easily predictable, and complicates advance planning of the grid's generator dispatch schedule.

To facilitate better planning and lower the barrier to increasing the fraction of renewable in the grid, we focus on the problem of automatically generating models that accurately predict renewable generation using National Weather Service (NWS) weather forecasts. Specifically, we experiment with a variety of machine learning techniques to develop prediction models using historical NWS forecast data, and correlate them with generation data from solar panels. Once trained on historical forecast and generation data, our prediction models use NWS forecasts for a small region to predict future generation over several time horizons. Our experiments in this paper use solar intensity as a proxy for solar generation, since it is proportional to solar power harvesting [4]. Importantly, since we generate our models from historical site specific observational power generation data, they inherently incorporate the effects of local characteristics on each site's capability to generate power, such as shade from surrounding trees. Since local characteristics influence power generation, individual sites must tune prediction models for site-specific characteristics. We view automatic model generation as critical to scaling distributed generation from renewable to millions of homes throughout the grid.

II. RELATED WORK

Li et al. [5], developed a simple non-linear regression model of the Multivariate Adaptive Regression Splines (MARS) to forecast solar power output for 24-h ahead. The MARS model was applied on the daily output of grid-connected 2.1 kW PV system. The MARS model is a data-driven approach without assuming the relationship between the power output and predictors. It processes

© 2019 IJSRET

the capability of handling nonlinearity while maintaining the simplicity of the classical multiple linear regression models. Based on the result analysis, the MARS models show the best results in terms of RMSE, followed by ARMAX, MLR, kNN, SVR, CART, ANN, and ARIMA models.

Massidda et al. [6], forecasted the power output of a 1.3 MW PV plant in Borkum, Germany by integrating the Multilinear Adaptive Regression Splines and NWP. The proposed model forecasts the power production of a PV plant for one day ahead. Past historical power output data and the available weather forecasts of the GFS NWP model were used by the developed regression model. Based on the simulation analysis, the results were favorable even though only a relatively low number of samples and features were considered.

Sharma et al. [7], proposed a 15-min and hour-ahead solar irradiance prediction approach by introducing a mixed Wavelet Neural Network (WNN) in a tropical region in Singapore. The Morlet wavelet and Mexican hat wavelet were used in the WNN architecture with LM backpropagation approach. The performance of the developed WNN model was validated by assessing MBE and NRMSE. The proposed WNN model gives the lowest MBE and NRMSE values.

Hossain et al. [8], proposed an Extreme Learning Machine (ELM) model to forecast PV output power of three grid-connected PV plant installed on the rooftop of PEARL laboratory in University of Malaya for 1-h and 1-day ahead. Based on the simulation analysis, the proposed ELM model shows more reliable results than ANN and SVR models in terms of the forecasting capability and accuracy.

Ramli et al. [9], presented a solar radiation forecast on PV panel surfaces with specific tilt angles by using SVM and ANN methods at Jeddah and Qassim in Saudi Arabia. The direct, diffuse, and global solar radiation data on the horizontal surface were utilized in solar radiation prediction. The performance and the comparison of the developed models were evaluated using RMSE, Coefficient Correlation (CC), Mean Relative Error (MRE), and computation speed.

Wolff et al. [10], developed PV power forecasting for 15-min to 5-h ahead via statistical learning model Support Vector Regression (SVR). This developed model was evaluated and served as an alternative to complement other physical prediction models via PV power measurement, NWP, and Cloud Motion Vector (CMV) irradiances. The RMSE and BIAS metrics were determined between measurement and forecasts of PV power. The prediction of PV measurement for SVR indicates good results in prediction up to 1-h ahead, while NWP-based predictions produce better period forecast starting at 3-h ahead, and CMVs emerged as the best amongst them. The combination of these three input sources has provided the best result.

Bhardwaj et al. [11], developed a solar radiation prediction technique by using a combination of Continuous Density Hidden Markov Model (CDHMM) with Generalized Fuzzy Model (GFM). CDHMM with Pearson R was applied to extract the shape-based clusters from the meteorological variables. Then, GFM was used to predict solar radiation accurately. The meteorological variables used in this estimation process are wind speed, relative humidity, temperature, sunshine hour, atmospheric pressure, and solar radiation data.

III. PROPOSED WORK

Prediction of solar power is highly depend on the environmental condition. So this work focus on selection of highly effecting surrounding variables like (air, humidity, temperature, sky condition, etc.). Whole work was divide into two module first module predict features ratio by using Teacher Learning Based optimization algorithm. While second module predict the solar power from the environmental parameters are used in same ratio as identified in first module.

TLBO (Teacher Learning Based Optimization)
In this model TLBO (Teachers Learning Based Optimization Algorithm was used for selection of weather feature set value. In this work genetic algorithm TLBO is use because this takes two phase learning. Main motive of this model is to identify balance ratio of the environmental parameters. Here iteration of teacher and student phase was done while two similar solutions were not obtained.

Generate Population: In this step different chromosome set were generate, which have set environmental feature ratio between 0 to 1. This can be understand as if any feature value is 0 than that feature is not involve.
So each environmental feature set act as the chromosome while collection of all set is term as population. This can be assume as let Cc = [c1, c_2, ….c_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.

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

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

Table Notation table.

Symbol	Meaning
A	Area in m^2
γ	Yield Efficiency
I_r	Irradiance
A^T	Ambient Temperature
C^T	Cell Temperature
σ	Module Efficiency
β	Maximal Power Temperature Coefficient
F	Feature Set
I	Isolation
W	Wind Speed
T	Temperature
P_r	Pressure

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

$$\boldsymbol{T_c = T + \left[\left(\frac{I}{I_r}\right)(C^T - A^T)\frac{c_1}{W}\left(1 - \frac{\sigma}{c_2}\right)(1 - \beta \times C_3\right]}\text{--Eq(3)}$$

$$P_s = A \times \gamma \times T_c \times P_r\text{---------Eq(4)}$$

So as per P_s which is find distance from the required power, now Cc which have minimum distance is consider as best solution in the population set.

Teacher Phase: This phase was used for the crossover of the chromosomes by the single best solution from the population. 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 weather feature value is copied from the teacher chromosome and it was replaced to the non teacher chromosome by eq. 5. This improve the population quality.

$$Cc_{new,i} \leftarrow Cc_{teacher,i}\ i \in \{1,2, \dots \dots m\}\text{---------Eq(5)}$$

Where Cnew,i is the updated value of $C_{student,i}$. Accept $C_{teacher,\ i}$ value.

Student Phase: In this phase some random group of chromosome 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 teacher 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 teacher chromosome and it was replaced to the non teacher chromosome. Here each new chromosome was cross verified that either its fitness value improved then previous, if fitness improves than new chromosome is include in the population and older one get removed. Vice versa if fitness value not improves.

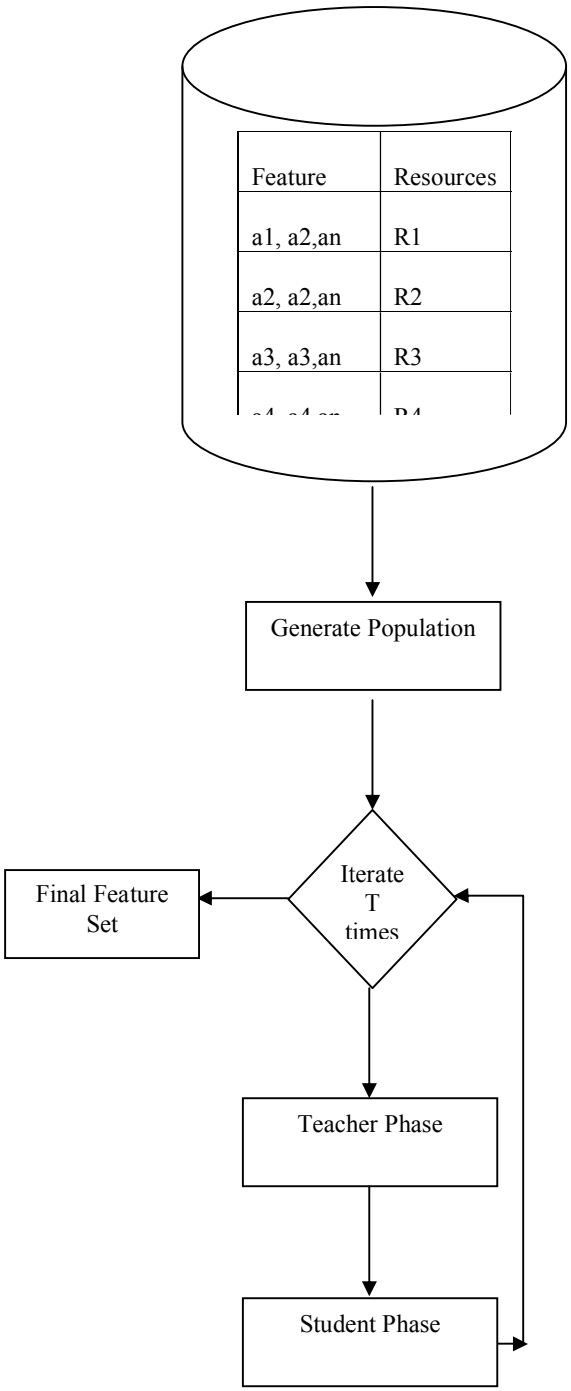

Fig. 1 Block diagram of TLBO genetic algorithm.

© 2019 IJSRET

Solar Power Prediction

In this phase features of geographical location were read where solar power were predict for that location. Here feature ratio is multiply with environmental values and obtained value is used in equation 3 and 4.

IV. EXPERIMENT AND RESULTS

This area exhibits the experimental assessment of the proposed procedure for management of smart grid system. All calculations and utility measures were executed by utilizing the MATLAB apparatus. 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 the standard dataset for India region where values for the calculation was obtained from the https://power.larc.nasa.gov/data-access-viewer/

Table 2. Feature Set used in grid balancing.

Feature Name
Clear Sky Insolation Clearness Index
Temperature Range at 2 Meters
Earth Skin Temperature
Wind Speed Range at 10 Meters
All Sky Insolation Incident on a Horizontal Surface
Insolation Clearness Index
Wind Speed Range at 50 Meters
Specific Humidity at 2 Meters
Clear Sky Insolation Incident on a Horizontal Surface

Results:

Table 3. MAE Based Comparison between proposed and previous work.

MAE Based Comparison		
Requirements (Hours)	**Proposed Work**	**Previous Work**
3	1.23E+05	5.92E+04
4	3.57E+03	7.06E+04
6	5.23E+04	6.84E+04

From table 3 it is obtained that under ideal condition proposed work is better as compare to previous work in [1]. under MAE evaluation parameters. As TLBO genetic algorithm has generate different combination and perform two level learning. So this reduces the MAE value of the proposed work.

Table 4. Comparison of Difference of required and supplied power.

Difference of Required Power Generation (kW) Based Comparison		
Required Power	**Proposed Work**	**Previous Work**
703681	612.3080	-5.5146e+04
685132	4.1717e+03	-6.2077e+04
513732	6.9161e+03	7.9652e+04
569908	2.5983e+03	8.5683e+04

From table 4 it is obtained that under ideal condition proposed work is power requirement fulfillment is more nearer to the previous work in [1]. under required power evaluation parameters. In this work initial solution generation and crossover operation increase the accuracy of the work.

© 2019 IJSRET

Table 5. Execution time Based Comparison between proposed and previous work.

Execution time (second) Based PSNR Comparison	
Proposed Work	**Previous Work**
1.8522	2.5115
1.6764	1.7369
1.6365	1.7381
1.5326	1.85262

From table 5 it is obtained that under ideal condition proposed work is execution time of proposed TLBO approach is quit less as compared to the previous approach. This less time requirement is due to the two stage learning in TLBO single iteration, so based on same number of initial population earlier result will be appeared.

Table 6. Power plant resource requirement comparison between proposed and previous work.

Required power plant number Based SNR Comparison	
Proposed Work	**Previous Work**
28	28
25	26
20	26
24	28

From table 6 it is obtained that under ideal condition proposed work is execution time of proposed TLBO approach is quit less as compared to the previous approach. This less time requirement is due to the two stage learning in TLBO single iteration, so based on same number of initial population earlier result will be appeared.

V. CONCLUSION

In this paper, studied of a fundamental problem of using a microgrid system central controller to optimally schedule the demand and supply profiles so as to minimize the fuel consumption costs during the whole time horizon. Here renewable resources are arrange for the demand of power where genetic algorithm TLBO was used for finding the best solution as per required power. In this work distance of the renewable resource from the smart grid is also consider for selection or rejection. Experiment was done on read dataset obtained from www.eosweb.larc.nasa.gov for India region and results shows that MAE for the system is quit low as compared with previous approach. Here execution time for the algorithm is also less. So this proposed solution find suitable combination of renewable resources from the smart grid. As research is never ending process so one can consider other technique and feature for assigning resources.

REFERENCES

[1] Tim Mareda, Ludovic Gaudard, and Franco Romerio. “A Parametric Genetic Algorithm Approach to Assess Complementary Options of Large Scale Wind-solar Coupling”. IEEE/CAA JOURNAL OF AUTOMATICA SINICA, VOL. 4, NO. 2, APRIL 2017.

[2] B. V. Mathisen, H. Lund, D. Connolly, P.A. stergaard, B. Moller. “The Design of Smart Energy System with 100% renewable resources and Transportation Solutions”. 8th conference in sustainable development of energy, water and environment system, 2013.

[3] M. Barnes, J. Kondoh, H. Asano, J. Oyarzabal, G. Ventakaramanan, R. Lasseter, N. Hatziargyriou, T. Green, Real-world microgrids-an overview, in: IEEE International Conference on System of Systems Engineering, IEEE, 2007, pp. 1–8.

[4] Sanmukh R. Kuppannagari , Rajgopal Kannan, Viktor K. Prasanna. “Optimal Net-Load Balancing in Smart Grids with High PV Penetration” arXiv:1709.00644v2 [cs.DS] 8 Sep 2017.

[5] Mohsen Einan, Hossein Torkaman and Mahdi Pourgholi. “Optimized Fuzzy-Cuckoo Controller for Active Power Control of Battery Energy Storage System, Photovoltaic, Fuel Cell and Wind Turbine in an Isolated Micro-Grid”. doi:10.3390/batteries3030023 www.mdpi.com/journal/batteries, 5 August 2017

[6] Croce, D.; Giuliano, F.; Tinnirello, I.; Galatioto, A.; Bonomolo, M.; Beccali, M.; Zizzo, G. Overgrid: A Fully Distributed Demand Response Architecture Based on Overlay Networks. IEEE Trans. Autom. Sci. Eng. 2017, 14, 471–481. [CrossRef]

© 2019 IJSRET

[7] Giovanelli, C.; Kilkki, O.; Seilonen, I.; Vyatkin, V. Distributed ICT Architecture and an Application for Optimized Automated Demand Response. In Proceedings of the IEEE ISGT-Europe, Ljubljana, Slovenia, 9–12 October 2016; pp. 1–6.
[8] Dusparic, I.; Taylor, A.; Marinescu, A.; Cahill, V.; Clarke, S. Maximizing Renewable Energy Use with Decentralized Residential Demand Response. In Proceedings of the 2015 International Smart Cities Conference, Guadalajara, Mexico, 25–28 October 2015.
[9] Sakurama, K.; Miura, M. Communication-Based Decentralized Demand Response for Smart Microgrids. IEEE Trans. Ind. Electron. 2017, 64, 5192–5202.
[10] Liu, N.; Yu, X.; Wang, C.; Li, C.; Ma, L.; Lei, J. An Energy Sharing Model with Price-based Demand Response for Microgrids of Peer-to-Peer Prosumers. IEEE Trans. Power Syst. 2017, 32, 3569–3583.
[11] Siebert, L.C.; Ferreira, L.R.; Yamakawa, E.K.; Custodio, E.S.; Aoki, A.R.; Fernandes, T.S.P.; Cardoso, K.H. Centralized and Decentralized Approaches to Demand Response Using Smart Plugs. In Proceedings of the 2014 IEEE PES T&D Conference and Exposition, Chicago, IL, USA, 14–17 April 2014; pp. 1–5.
[12] Bin Dong, Xiuqiao Li, Qimeng Wu, Limin Xiao, Li Ruan, “A dynamic and adaptive load balancing strategy for parallel file system with large-scale I/O servers”, J. Parallel Distribution Computing. 72 (2012) 1254–1268.
[13] Yunhua Deng, Rynson W.H. Lau, “Heat diffusion based dynamic load balancing for distributed virtual environments”, in: Proceedings of the17th ACM Symposium on Virtual Reality Software and Technology, ACM, 2010, pp. 203–210.

© 2019 IJSRET