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TLBO Based Smart Grid Management Using Renewable Resources

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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 increase 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 the share of electricity produced from variable renewable resources grows, so does the need to integrate these resources in a cost-effective manner, i.e., to ensure that total electricity production from all sources including variable renewable generation equals electricity demand in real time. Also, a future electric system characterized by a rising share of renewable energy will likely require concurrent changes to the existing transmission and distribution (T&D) infrastructure. While this report does not delve into that topic, utilities, grid operators and regulators must carefully plan for needed future investments in T&D, given the lead times and complexities involved. Rather, this report focuses on the fact that variable renewable generation adds a different new component to the challenges facing system operators in maintaining system reliability. For example, the decline in solar production at the end of the day can lead to significant ramping needs for grid operators. Dispatch-able non-solar resources (existing fossil and hydro generation but also potentially demand resources) must be rapidly deployed to make up for the decline in solar PV generation at the same time that residential electricity demand is rising at the end of the day. Similar challenges can arise as a consequence of deviations in output from wind or solar facilities relative to weather forecasts over time periods ranging from minutes to hours. Dealing with Variable Generation: As work consider the variable generation characteristics of renewable energy sources, it should be noted that electric power system operations are designed to accommodate the natural (and very large) variability in load demand as well as planned and unplanned contingencies. This is done at different time-scales through load-frequency control, operational reserves, scheduling and unit-commitment, demand response, and load shedding. At deep penetration levels, renewable generation add significantly to the extent of the overall variability that must be handled.

II. RELATED WORK

In [1] Solar and wind resources are considered at variable spatial scales across Europe and related to the Swiss load curve, which serve as a typical demand side reference. The optimal spatial distribution of renewable units is further assessed through a parameterized optimization method based on a genetic algorithm. It allows us to explore systematically the effective potential of combined integration strategies depending on the sizing of the system, with a focus on how overall performance is affected by the definition of network boundaries. Upper bounds on integration schemes are provided considering both renewable penetration and needed reserve power capacity. The quantitative trade-off between grid extension, storage and optimal wind-solar mix is highlighted. This paper also brings insights on how optimal geographical distribution of renewable units evolves as a function of renewable penetration and grid extent.

In [2] Solar and wind resources are considered at variable spatial scales across Europe and related to the Swiss load curve, which serve as a typical demand side reference. The optimal spatial distribution of renewable units is further assessed through a parameterized optimization method based on a genetic algorithm. It allows us to explore systematically the effective potential of combined integration strategies depending on the sizing of the system, with a focus on how overall performance is affected by the definition of network boundaries. Upper bounds on integration schemes are provided considering

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both renewable penetration and needed reserve power capacity. The quantitative trade-off between grid extension, storage and optimal wind-solar mix is highlighted. This paper also brings insights on how optimal geographical distribution of renewable units evolves as a function of renewable penetration and grid extent.

In [16], a scalable solution for a fully decentralized micro grid, the Over grid is presented. The proposed system architecture is a peer-to-peer virtual representation of the physical grid. The nodes communicate using the Gossip protocol, and information about the overall consumption and production profiles is obtained using an average updating scheme. The performance of the network was studied using a simulator of 10,000 nodes with realistic power profiles, and achieved promising results. An experimental validation was conducted using several campus buildings. However, important aspects of decentralization are not discussed, such as Byzantine tolerance, security, and integrity of data. An automated DR program based on Message Oriented Middleware to provide an asynchronous communication paradigm between the network's components is presented in [17]. The system is not fully decentralized, since the DR programs are considered at the level of energy aggregators and not for each individual DEP part of the smart grid.

In [18], the authors propose a multi agent system aiming to provide grid decentralization leveraging on learning techniques. The presented architecture proposes each energy consumption device to be controlled by an intelligent agent which may respond to signals from the network. Each agent learns over time the most suitable set of actions to be taken according to the overall system's state and following a set of predefined polices (i.e., use available renewable energy, charge battery, etc.).

In [19], the authors define a decentralized mechanism for determining the incentive signals in a smart grid using a communication-based decentralized pricing scheme. The proposed mechanism defines and implements a decentralized method to compute the Lagrangian multiplier which is then used for computing the price signal during DR events. However, one of the most notable drawbacks is data privacy. A decentralized price based DR system is presented in [20]. The price signal is internally computed iteratively based on the forecasted energy production and demand ratio and on the user's willingness to provide load shifting on demand inside an energy sharing zone.

The authors of [21] propose algorithms for shifting the individual energy consumption profiles from peak load periods. The centralized approach implements an algorithm for an automation controller that is responsible for inferring the standby consumption of several Sensors 2018, 18, 162 5 of 21 devices and then computing the maximum monetary reduction. The decentralized algorithm runs in a distributed manner on each smart device, where each device is responsible for its own optimization, without having overview information about the entire system.

III. PROPOSED WORK

Hybrid Genetic Algorithm

In this work a hybrid approach is adopt for finding the shortest path Algorithm is embedded with Teacher leaning Based optimization algorithm. Here whole work is depend on the random condition of the available power generation resources like wind, solar, etc. In this work power obtained from the resources are supplied to the required load area. TLBO algorithm find the best set of power resources for particular set of demands.

Generate Population

Here assume some cluster from the different resource set. This is generate by the random function which select fix number of resource in cluster. This can be understand as let the number of cluster be Cn, then one of the possible solution is {C1, C2, ...Cn}. In the similar fashion other possible solutions are prepared which can be utilize for creating initial population matrix.

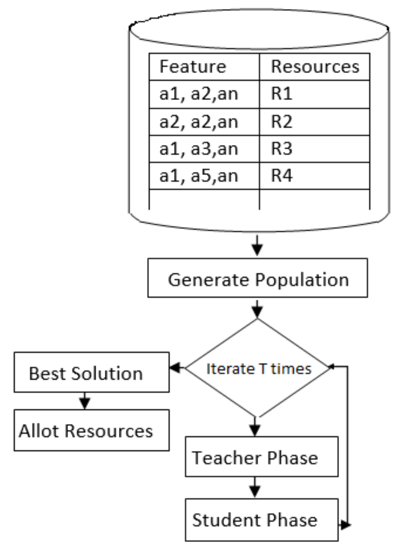

Fig. 1Block diagram of proposed work.

Fitness Function

For finding difference between two chromosomes Eludician Distance formula was used. The Euclidean distance d between two solution X and Y is calculated by

d = [SUM ((X-Y). ^2)] ^0.5

Here two parameter are user in X first is distance of the renewable power plant from the smart grid and second is power generated by the resource. Based on these two value final fitness value of each chromosome or probable solution is given.

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Teacher Phase

For finding difference between clusters Eludician Distance formula is use for evaluating the load matching requirement between the resources in cluster. The Euclidean distance d between two features of the resource is calculated by Top possible solution after sorting will act as the teacher for other possible solutions. Now selected teacher will teach other possible solution by replacing fix number of cluster as present in teacher solution. By this all possible solution which act as student will learn from best solution which act as teacher. This difference modifies the existing solution according to the following expression.

Xnew, i = Xold, i + Replacing Cluster value

Where Xnew, i is the updated value of Xold, i. Accept Xnew, i if it gives better function value.

Accept Xnew if it gives a better function value. Once this phase is over then check for the maximum iteration for the teaching if iteration not reach to the maximum value then GOTO step of student phase else stop learning and the best solution from the available population is consider as the final centroid of the work.

Student Phase

In this phase all possible solution after teacher phase are group for self-learning from each other. This can be understand as let group contain two student then each student who is best as compare to other will teach other solution. Teaching is similar as done in teacher phase, here replacing fix number of centroid is done which is similar as in best student of the group.

Final Solution

In this work after sufficient number of iteration cluster are obtained and assign resource to specific requirement load. Here each load is represent by its cluster. So as per the different number of resource type available in the dataset number of clusters are generate.

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://eosweb.larc.nasa.gov/sse/global/text/10yr_wspd50m. Wind data: https://eosweb.larc.nasa.gov/sse/global/text/22yr_T10M.

Results:

Table 1. 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 1 it is obtained that under ideal condition proposed work is better as compare to previous work in [8]. 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 2. 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 2 it is obtained that under ideal condition proposed work is power requirement fulfillment is more nearer to previous work in [1], under required power evaluation parameters. In this work initial solution generation and crossover operation increase the accuracy of the work.

Table 3. Execution time Based Comparison between proposed and previous work.

1.8522	2.5115
1.6764	1.7369
1.6365	1.7381
1.5326	1.85262

From table 3 it is obtained that under ideal condition proposed work is execution time of proposed TLBO approach is quit less as compared to the previous

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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 4. Power plant number Based 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 4 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 micro grid 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 quite 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.

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