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Smart Grid Management by Genetic Algorithm and Renewable Resources

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Abstract- **As power requests are expanding day by day causing unbalance in the present grid framework which brings about different causes like load shedding, unbalance voltage and so on which at last influences the end users. Presently to stay away from every such circumstance the main alternative is to take care of the demand by generation but, world are additionally slacking with the conventional sources so producing more power is not helpful by traditional ways. The power industry has adopted "smart" grids that use information and communication technologies, which may make electric power systems more reliable and efficient. This paper has proposed a grid load balancing by modified genetic algorithm and renewable resources. Genetic algorithm provides a combination of renewable resource with non-renewable power resources. Experiment was done on different environmental condition to get better comparisons.**

Keywords- **Genetic algorithm, Dynamic load balancing, Renewable resources, power Grid.**

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. Dispatchable 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.

1. 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 [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 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 [3], a scalable solution for a fully decentralized microgrid, the Overgrid 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 [4]. 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 [5], 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 [6], 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 [7] 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

Explanation of proposed work is done by two method first is by block diagram so it act as graphical representation of whole work while in second explanation of each step is done in word form. So reading this part make clear understanding of whole work in detail.

1. After School learning Genetic Algorithm:
In this work a genetic approach was adopt to predict the best combination of renewable resources from available set of wind and solar plants. Here whole work was depends 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. Modified After school learning genetic algorithm finds the best set of power resources for particular set of demands.

2. Feature Generation:
Various parameters from the renewable resources are calculated for the power contribution estimation from the solar and wind power plant. In this work two type of renewable resource was consider. So wind power is estimate by finding the average air density of area with velocity of the air. These parameters are natural an depend on the location while in order to get maximum utilization of the plant some artificial approach will increase the output power such as frontal area of wind mill. It is the use of air flow through wind turbines to mechanically power generators for electricity.

$$P_w = 0.5*C*p*A*V^3$$

Where C is coefficient of performace,
p is air density
A is frontal area
V is air velocity

Here air density is calculate by below formula

$$p = P / R*T$$

Where: p =air density, kg/m3
P = pressure, Pascals (multiply mb by 100 to get Pascals)
R = specific gas constant, J/ (kg*degK) = 287.05 for dry air
T = temperature, deg K = deg C + 273.15

Solar panel refers to a panel designed to absorb the sun's rays as a source of energy for generating electricity.

$$Ps= Ap * ý* T*PR$$

Total Solar Panel Area (In M^2) = 1.61 m2
Solar Panel Yield Efficiency is depend on the number of cell in the panel

Cell Number in Plate	Yield Efficiency
200	12.42
225	13.98
250	15.53

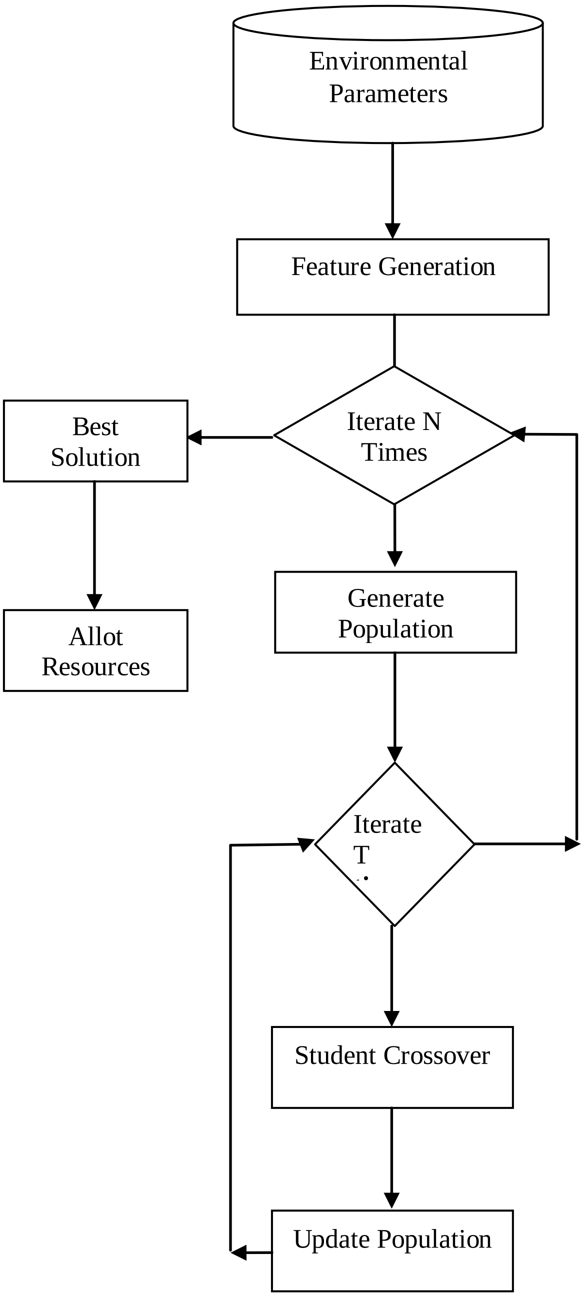

Fig 1. Block diagram of proposed work.

Annual Average Temperature Radiation On Tilted Panel is T. Performance Ratio is value which range between [0.5 to 0.9].

3. Generate Population:
Here assume some cluster from the different resource set. This is generating 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 utilizing for creating initial population matrix.
ST[x] □Random(N, Cn)

4. Fitness Function:
For finding difference between two renewable resource Eludician Distance formula was used. The Euclidean distance d between two solution X and Y feature vector 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 values final fitness value of each chromosome or probable solution is given. This is considering as final rank of the work.

5. Normalize:
So fitness of the probable solution was done on the base of the power obtained from wind and solar plants. Fitness value obtained from both resources are normalize into single value by below formula from eq. 5.6:

$$Fitness = C1* Ps + C2* Pw$$

6. Student Crossover:
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.

- For i = 1: Pn
- Randomly select two learners Xi and Xj, where i is not equal to j
- If f (Xi) < f (Xj) // f is the fitnees value of the selected population.
- Xj,x = Difference (Xi,x, Xj,x) // x: position of the cluster center in population vector.
- Else
- Xi,x = Difference (Xj,x, Xi,x)
- End If
- End For

Accept Xnew if it gives a better function value. Once student phase is over then check for the maximum

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iteration for the teaching if iteration not reach to the maximum value then GOTO step of teacher phase else stop learning and the best solution from the available population is consider as the final centroid of the work. Now images are cluster as per centroid.

7. 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 is generating. So in this phase user has submitted various requirement of power at different time duration as the input in the system. Here as per the requirement of power different renewable resource combination are prepared in genetic population. Finally by the end of iteration good solution is obtained where required power supply from the renewable source is arranged.

IV. EXPERIMENT AND RESULTS

In this section values are shown with there explanation for different evaluation parameters which were discussed above. Here evaluation was done for testing of different power load requirement. Experiment was done on MATLAB tool. Input environmental data was collect from [10]. Results were compared with algorithm proposed in [1] (Previous work).

1. Results:

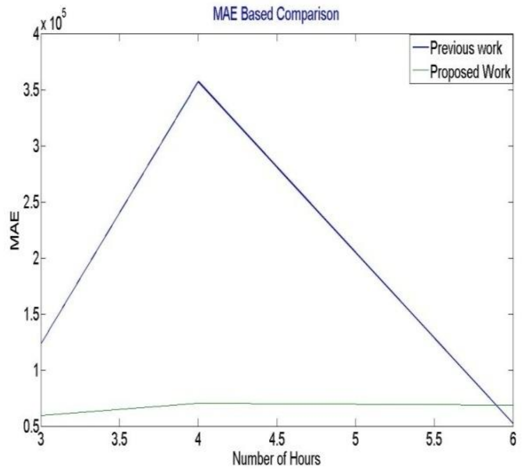

Fig 2. MAE Based Comparison between proposed and previous work.

From fig. 2 it is obtained that under ideal condition proposed work is better as compare to previous work in [8]. Under MAE evaluation parameters. As AFTER SCHOOL LEARNING genetic algorithm has generate different combination and perform two level learning. So this reduces the MAE value of the proposed work.

Table 1. Required power comparison and differences.

Required Power	Proposed Work	Previous Work
560963	89200	28000
558078	52900	56000
563334	85500	107000
639461	21000	42000
695700	20100	26300
659748	1130	79800
568102	22700	65900

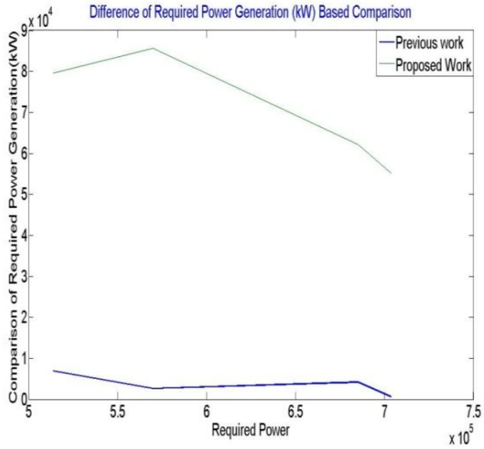

Fig 3. Comparison of Difference of required and supplied power.

From fig. 2 and table 1 it is obtained that under ideal condition proposed work is power requirement fulfillment is more nearer to the to previous work. Under required power evaluation parameters. In this work initial solution generation and crossover operation increase the accuracy of the work.

Table 2. Execution time Based Comparison between proposed and previous work.

Execution time (second) Based Comparison	
Proposed Work	Previous Work
1.822	3.115
1.764	2.369
1.5365	2.381
1.4326	2.5262

Table 3. Power plant number Based Comparison between proposed and previous work.

Required power plant number Based Comparison		
Required Power	Proposed Work	Previous Work
560963	27	24
558078	26	25
563334	28	27
639461	26	27
695700	26	20
659748	26	25
568102	28	23

From table 2 and 3 it is obtained that under ideal condition proposed work is execution time of proposed AFTER SCHOOL LEARNING approach is quit less as compared to the previous approach. This less time requirement is due to the two stage learning in AFTER SCHOOL LEARNING 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 arranged for the demand of power where genetic algorithm AFTER SCHOOL LEARNING was used for finding the best solution as per required power.

In this work distance of the renewable resource from the smat grid is also consider for selection or rejection. Experiment was done on read dataset results shows that MAE for the system is quit low as compared with previous approach. So this proposed solution finds 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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