A Novel Demand Side Management (DSM) Technique for Electric Grids with High Renewable Energy Mix using Hierarchical Clustering of Loads

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Abstract: Shortfall can occur at irregular times in an electric grid that has high a concentration of intermittent renewable energy sources. Many methods are being studied, proposed and used to change the demand in order to match the supply with the most common being Load Curtailment. New DSM techniques have evolved as a result of advancements in AMI technologies. The goal is to minimize the difference between supply and demand at the time of shortfall. Our proposed algorithm selects consumers and limits their energy consumption by profiling the commercial sites based on their historical consumption behaviour. Then, to save the required amount of energy, the sites with peak consumption levels with respect to their own daily usage are targeted. Thus, it harnesses the maximum potential of electricity deduction from a site while minimizing its effects on the residents.

1 INTRODUCTION

Due to global warming and other environmental problems associated with the fossil fuels, the whole world is trying to shift to renewable energy sources to produce electricity. For example,by 2050 the generation from wind and solar energy sources will be 2400 GW and 2700 GW respectively, which will contribute 60% to the mix of renewable energy (Zou et al., 2017). Also, recently the policies have been introduced to encourage installation of Solar PV systems among residential consumers (McKenna et al., 2018). Unlike conventional power sources, renewable energy sources are intermittent. The production of electricity from such renewable sources is dependent on factors that we cannot control, such as sunlight, intensity and speed of wind. Increasing popularity and integration of renewable energy might be a good step so solve environmental issues, but it is making generation less controllable. Due to this problem, the integration of these sources becomes difficult.

The nature of demand from renewable energy sources requires new methods from demand side management. One (old) method, as shown in figure 1, to overcome the issue is to store the extra energy at the time of extra generation and then use it at the time of need; called Electrical Energy Storage (EES). (Chen et al., 2009) However, this method is very expensive, for example it cost \$410/KWh for storage in Li-ion batteries (Obi et al., 2017). Different approaches are being used by utilities to achieve this goal and such approaches can be broadly classified into Direct Load control or indirect load control. **Direct load control** is the administered control of appliances by utility in order to shed load at certain times. While **indirect load**

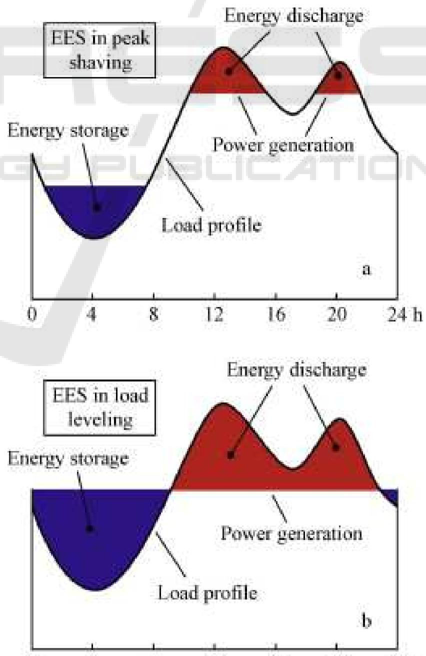

Figure 1: EES in peak shaving and load leveling.

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control involves techniques like real time pricing or incentivizing consumers to reduce their electricity usage (Allcott, 2009).

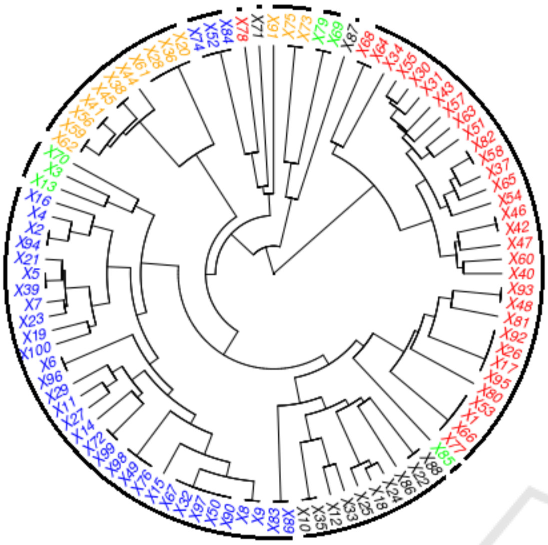

Figure 2: Different Clusters (Dendogram). Hierarchical relationship is shown within different sites based on their electricity consumption behaviour.

section − 2 represents various effective approaches proposed in the literature for the DSM. Then, *section* − 3 explains our proposed methodology after mentioning the gaps in literature while also explains its significance and mathematical formulation. At the end, *section* − 4 and *section* − 5 expands on the results and possible improvements in future research respectively.

2 RELATED WORK

Load Curtailment has previously been done on regional/feeder level due to underdeveloped metering infrastructure. However, with the development of smart electric grids and advance metering infrastructure (AMI) , it is now possible to target individual consumers.One such approach, called soft load shedding, is presented by (Aslam and Arshad, 2018). Their approach makes use of clustering the consumers based upon the amount of electricity foretasted and limiting their usage through Cluster-based Incremental Reduction (CBIR) algorithm. Also, (Bashir et al., 2015) have proposed Direct Load Control (DLC) system that administers the devices of the site to limit the overall consumption. However, for this technique, every major device should be controllable by utility. Additionally, due to the lack of authority over control of these devices for consumers, many consumers may not want to enroll into the program. Another problem is the complexity of the system. For millions of consumers, this method can get very complex. (Stenner et al., 2017) have shown that customer distrust can reduce willingness to participate in Direct load Control (DLC) programs. Utilities have to develop the trust among consumers, which is a problem in itself.

(Erdinc et al., 2018) have proposed an incentive model to attract more users to the DLC program. But this method was only developed for Heating, ventilation, and air conditioning (HVAC) systems. Again, this method requires utility companies to set the temperature level of HVAC systems of the consumers, and thus is impractical and also expensive(as explained earlier). (Xia et al., 2017) have also proposed an incentive-based model to increase the effectiveness of DSM programs. (Chrysikou et al., 2015) state that people start losing interest in these kinds of programs with time and hence, are no longer effective. In 2005, Rocky Mountain Power -a company based in Utah, USA, evaluated the use of their differential pricing-based tariffs. They found that in opt-out schemes, up to 98% of participating consumers chose to leave the program after the mandatory period had been completed (Holyhead et al., 2015)

(Chandan et al., 2014) described a demand response control by the utility that maximizes the users convenience. However, this approach requires data at the granularity of each appliance in site. (Hussain et al., 2015) present a review of several demand response techniques with a view on pricing signals, appliance scheduling, optimization and their benefits. (Lu et al., 2018) proposed an artificial intelligence based dynamic pricing demand response algorithm. (Allcott, 2009) presents different schemes of real time pricing in electricity markets.

The complexity and cost associated with DLC systems makes it difficult to be deployed on large scale while dynamic pricing has its own drawback. Our proposed algorithm is not only inexpensive and easily deployable but also it eliminates the uncertainty in consumer behaviour (as would have been observed through peak pricing) by limiting their consumption levels in advance.

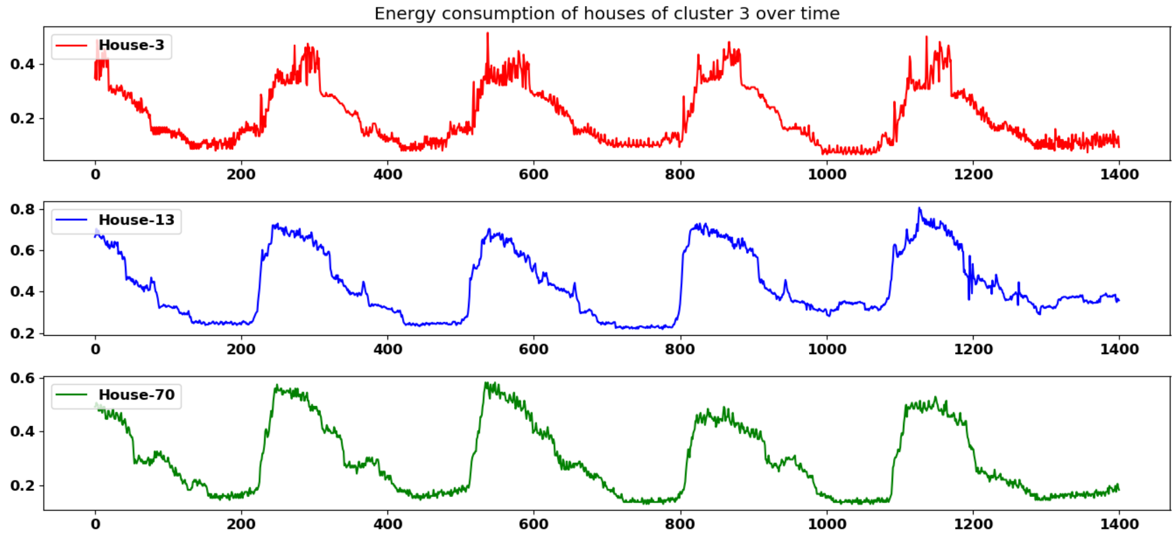

Figure 3: Same cluster Commercial sites.

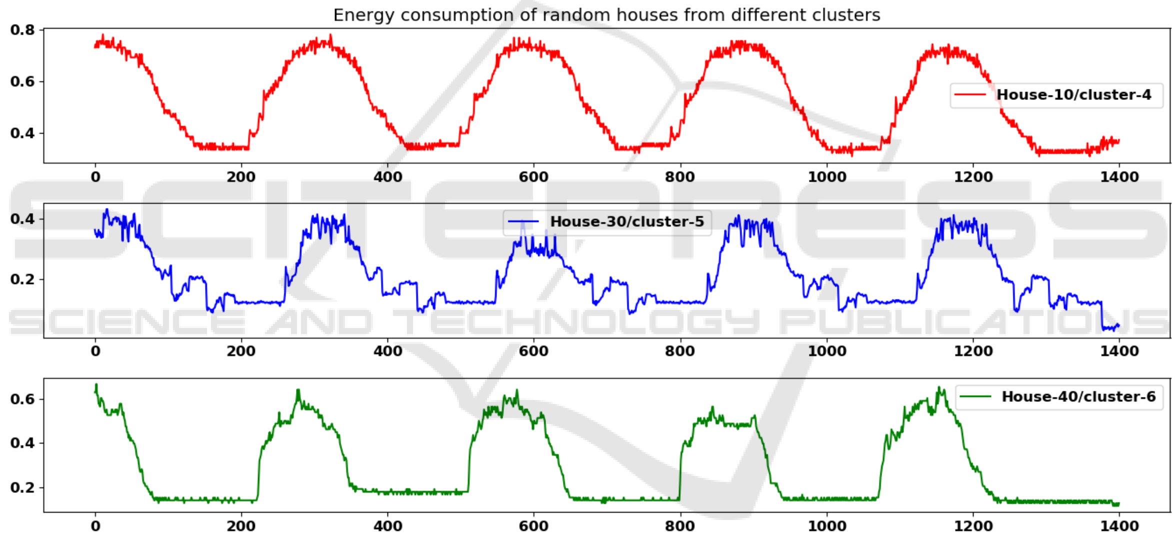

Figure 4: Different cluster Commercial sites.

3 METHODOLOGY

The ultimate goal is to allocate quota to users to limit their electricity usage. It can be thought of as a hybrid of indirect and direct load control programs, as the utility has the control over maximum limit of electricity usage, while consumers have the choice of how they want to use their allocated quota. After sites with similar consumption behaviours are clustered, then at the time of shortfall the cluster with maximum contributions to the grid load is selected and each site within it is allocated a quota.

3.1 Assumptions

The first assumption is that the shortfall is given or in other words the demand and supply for the next day is known in advance (without forecasting).Here it is important to note that the commercial sites have a predictable usage routine which could be predicted using various Time Series forecasting techniques. In case the sites do not show a trend and have a lot of variance in its usage behavior then our proposed strategy is not applicable and we might need to devise a fix quota allocation for those outliers. Secondly, the consumption behaviors of people are assumed to remain same throughout selected time frame.

3.2 Data Acquisition And Synthesis

The data used to apply the technique consisted of 100 commercial/ industrial sites with 5-minutes energy usage granularity obtained from the Greenbutton. The data consisted of different attributes but the consumption over time of all the sites was compiled. After compilation, to simulate the shortfall present at a point in time, some attributes of the data were also synthesized with a definite scheme. At each point, the probability of a shortfall was considered 16%. If the shortfall happens then the value of shortfall will be under 20% of the cumulative demand of all sites at that time.

3.3 Clustering And Algorithm Development

The primary motivation of the work is to be able to allocate a fair amount of quota to each site by exploiting similar trends in consumption patterns of different sites. To make different clusters machine learning technique of hierarchical clustering was used. R was used to synthesize data and apply clustering using HClust package. After clustering, the cumulative usage of each cluster was calculated. Different numbers of sites were accompanied in each cluster which reflected the consumption patterns similarity in a more granular way. However, this presented challenge in cluster selection for soft-load shedding since now, the cumulative consumption of a cluster does not reflects that the sites in that cluster are consuming electricity at their peak. To overcome this issue, the values were normalized so that we should be able to check which cluster contributes the most with respect to its own consumption behavior and irrespective of other people's behavior. After this a Global Deduction Rate (GDR) is defined which implies how much of the power will be deducted from the usage value of a particular consumer (as represented in figure 5).
The selection of site within the cluster is considered to be random. After this a point is selected where the shortfall is present and the above mentioned steps are performed until the shortfall is met. In every next allocation, previous sites are white-listed and a round robin method is used to traverse through the clusters.We have used Hierarchical clustering and its respective algorithm is represented in Algorithm 1.

Algorithm 1: Hierarchical clustering.

```
procedure SIMPLE HAC(d1,...,dN)
    for n ← 1 to N do
        for i ← 1 to N do
            C[n][i] ← SIM(dn,di)
            I[n]                ▷ keeps track of active clusters
    A ← []                      ▷ Clusters as sequence of merges
    for k ← 1 to N − 1 do
        i,m ← argmax_{<i,m>:i≠mAI[i]=1AI[m]=1} C[i][m]
        A.APPEND (< i,m >)      ▷ Store merge
        for j ← 1 to N do
            C[i][j] ← SIM(i,m,j)
            C[j][i] ← SIM(i,m,j)
        I[m] ← 0                ▷ Deactivate cluster
    return A
```

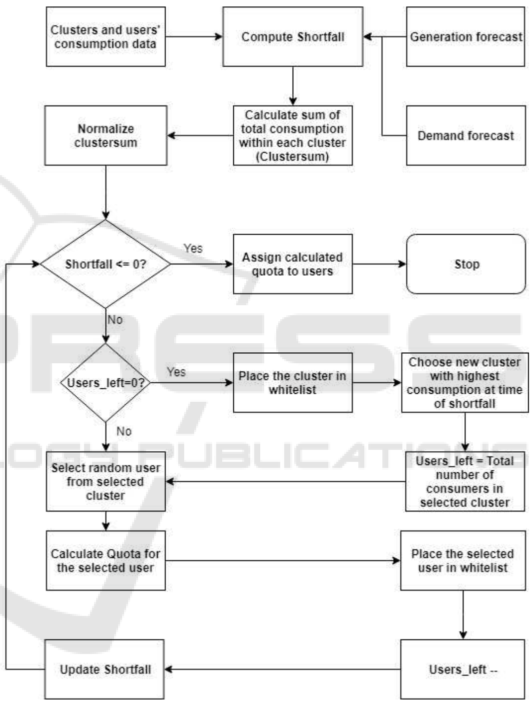

Figure 5: Flow Chart of Algorithm.

4 RESULTS AND DISCUSSION

4.1 Case Study

Based on the similar trends in their usage patterns sites were divided into fifteen clusters. The division of clusters and how much they differ from each other according to previously mentioned criteria can be observed in figure 2.
Radial phylogenetic tree in figure 2 shows that each site is represented at its leaf and the arrangement describes the similarity between their usages. The

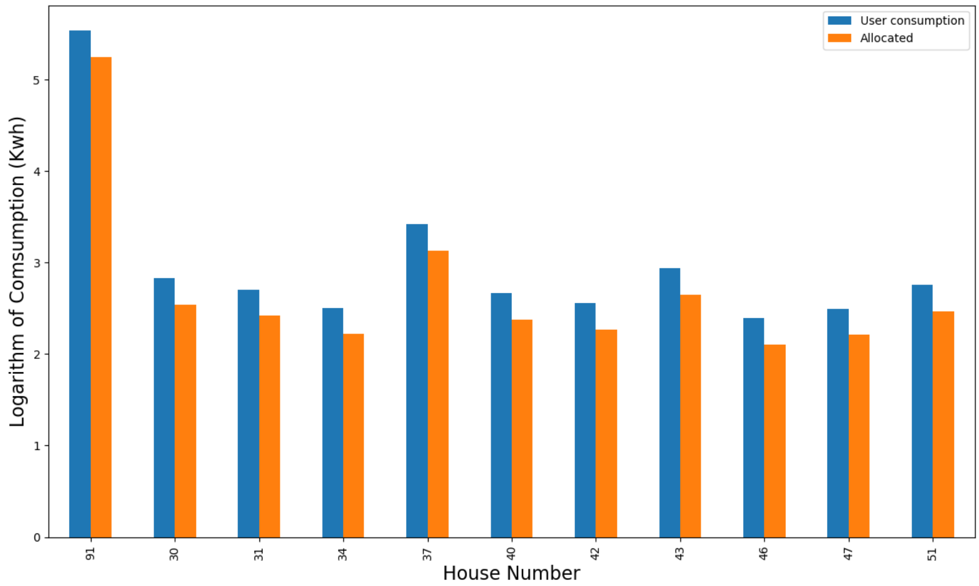

Figure 6: User consumption Vs allocated quotta at shortfall.

credibility of this technique can be illustrated if we draw the normalized value of their usage across a day and observe the difference between the usage trends of sites in a single cluster vs. sites in different clusters. The three sites in figure 3 represent a single cluster. It can be seen how they show load peaks at almost the same time, show increase/decrease in consumption within same time period and mostly show a single peak along a day. In contrast, if we look at figure 4 then there is no clear relation between usage pattern of these three sites which have been selected randomly (site number 10, 20 and 30 belonging to cluster 4, 5 and 6 respectively). Each site has its own peak time, different trend for increase/decrease in consumption, and shows multiple peaks differing from each other.
The algorithm presented in the paper provides an end to end solution for allocating quota to each site. Let's look into the scenario where a shortfall is present with GDR equal to 25%. The results from simulations and the allotted quota to each consumer is displayed in figure 6

4.2 Communication with Smart Meters

The proposed algorithm requires the forecast of electricity twenty-four hours in advance. Based on the forecasted values of generation and consumption of electricity, the algorithm is triggered. Then, based on those figures, recommendations will be made by the system to limit the consumption of electricity for particular users. Having the values in advance enables us to inform the users prior to the demand response actions. This notification system can possibly add to the convenience of the users, leading to voluntary actions by them to limit the electricity consumption. Also, currently the granularity level is just one hour but the planning can be made better by increasing the granularity to 15 minutes level. For the prediction of next fifteen minutes, mean bias error (MBE) of just 1.3% could be achieved (Raza et al., 2016).It is advised to use the spinning reserves as the buffer to accommodate the user's energy demand. It will ensure the stability of the grid in case of a wrong forecast circumstances.

5 CONCLUSION AND LIMITATIONS

The presented algorithm exploits the existing functionality of advance metering infrastructure to carry DSM, thus reducing the cost and making the solution feasible. In future we plan to improve the algorithm by making the value of GDR dynamic instead of fixed. Also, the forecasting modules will be implemented with the algorithm to make an end to end solution. The system relies on the forecasted values and does not takes into account the validity of such forecasts. So, the scenarios where the demand becomes lower than the generation or vice verse needs to be accommodated. Also, to understand the consumer's perspective we plan to conduct an on-site experiment in near future.

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