Soft Load Shedding: An Efficient Approach to Manage Electricity Demand in a Renewable Rich Distribution System

Tayyab Aslam and Naveed Arshad
Department of Computer Science, Lahore University of Managment Sciences, Sector U DHA, Lahore, Pakistan

Keywords: Demand Side Management, AMI, Clustering.

Abstract: Matching demand and supply of electricity generation is difficult in a renewable-rich system. This is partly due to the long-term variability and short-term uncertainty of wind and solar. Utilities use several approaches to deal with the variations of renewable generation. Some of these include having extra fossil fuel based peaker plants, managing flexible loads using demand-side management, real-time pricing etc. In this paper, we present another approach to manage supply variations by introducing semi-flexible loads at the demand side. These semi-flexible loads are residential loads that cannot be shut down or be moved completely to another hour but have the possibility to shed a small percentage of their load for a short time. This approach called soft load shedding is challenging as residential customers have the multitude of energy usage patterns. In this paper we compare and contrast three soft load shedding techniques and discuss their strengths and shortcomings in matching the demand with available supply.

1 INTRODUCTION

Renewable sources are taking the center stage in the generation of electricity. Many countries have plans to shift to all renewable sources of electricity by 2050 (Connolly et al., 2011; Cosic et al., 2012). While renewable sources like solar and wind provide an environmentally friendly solution to the energy demand and supply, they also create challenges in the electricity distribution system. Figure 1 and 2 shows four days actual generation and forecasted power generation of Solar-PV and Wind for Belgium. It is quite noticeable that the generation is not according to the forecast. These problems mostly stem from the variability and uncertainty of renewable sources as variations in renewable sources output causes a mismatch between the demand-supply of electricity.

With the current penetration level of renewables, utilities use different approaches to handle demand and supply gap. One of the approaches is to have extra fossil fuel based standby peaker plants. But these plants are very expensive to run and maintain. Another approach is real-time pricing where prices of electricity vary hourly and customers are charged accordingly. But when prices go down real-time pricing cause a rebound effect which results in another peak demand. Another technique is demand side management (DSM). Many DSM techniques are available in the literature but the ones for residential customers mostly require direct control over high powered appliances which is very difficult to implement and may not be possible legally in some countries. Electricity storage (Roberts and Sandberg, 2011; Mohd et al., 2008; Vytelingum et al., 2010) at grid level can also be used to manage this gap but present storage technology is expensive and have limits.

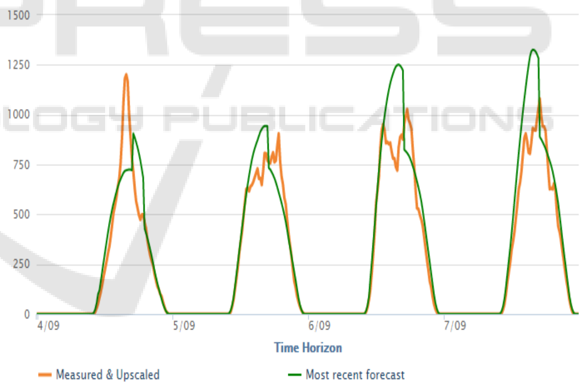

Figure 1: Solar-PV Power Forcasting for Belgium.

Another line of research uses electricity curtailment for managing the variation in supply (Aalami et al., 2010). In such programs certain financial benefits are offered to the customer for reducing their ongoing consumption up to a certain minimum percen-

Aslam, T. and Arshad, N.
Soft Load Shedding: An Efficient Approach to Manage Electricity Demand in a Renewable Rich Distribution System.
DOI: 10.5220/0006774001010107
In *Proceedings of the 7th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS 2018)*, pages 101-107
ISBN: 978-989-758-292-9

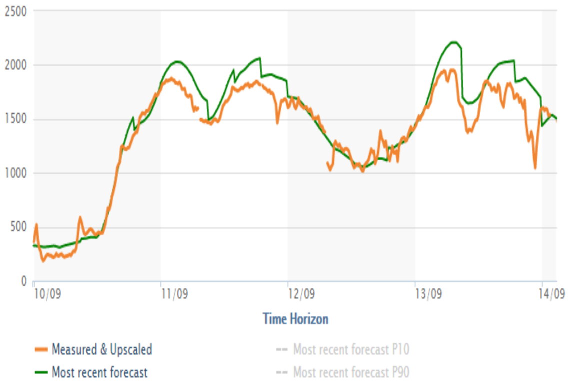

Figure 2: Wind Power Forcasting for Belgium.

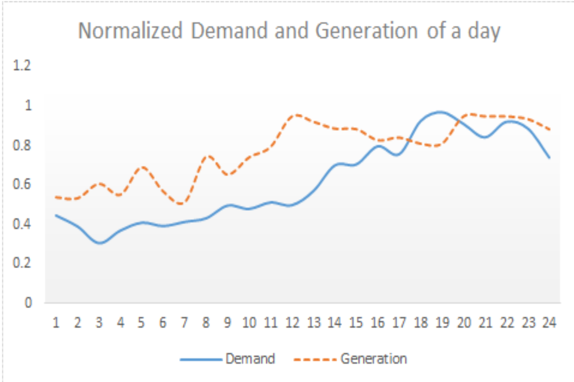

Figure 3: Normalize Demand and Generation for a Renewable Rich Electricity System.

tage. If participant customer fails to reduce their consumption within the time limit then they get a financial plenty. These programs are considered a the last choice as consumption reduction from the customer is not guaranteed. Another line of research looks at varying electricity voltage quilty along with demand-side management (Craciun et al., 2009). This could also be used to match supply and demand but compromise on electricity quality is often dangerous and can result in failure of electrical appliances. With increasing renewable penetration we need newer approaches to deal with the problems of renewable integration into the overall electricity distribution system.

To this end, we are working towards developing a Deeply Intelligent Demand Side Management System (DIDS). DIDS integrates the generation and distribution through better forecasting and planning using various optimization mechanisms. Typically utilities have flexible and inflexible loads. Flexible loads are industrial, agricultural or other loads that could be adjusted within a time window. Inflexible loads are loads that cannot be moved in such a way. We introduce semi-flexible loads that are residential loads that could not be completely shut down or moved to another hour but may shed their load by a small percentage.

One of the optimization methods that DIDS uses is Soft Load Shedding (SLS) of semi-flexible loads. SLS could be carried out on residential customers using threshold metering that comes with most AMI deployments. Of course, SLS could only be carried out if the customers' contracts allow for such provision. For this paper, we assume that such provision is available in customer contracts. Furthermore, just like peaker plants are used for only 3-5 of the time, SLS may only be carried out at times of extraordinarily high electricity demand or at the time of low renewable generation. For example, in Figure 3 a normalized demand and supply situation is presented for a 24 hours period. The demand is under the supply throughout the day except for a short period at 18:00-19:00 hours. This particular time requires some form of load shifting or load shedding.

Although semi-flexible residential loads are smaller loads, their myriad number adds up to a large share in the distribution system and could be used together to shed a certain percentage of the demand. For example, the utility distribution company we work with has a total of 4.1 million customers. Out of which 3.5 million customers are residential customers using up to around 53% of the total available electricity. One of the goals of this paper is to develop a *scalable* technique for SLS. This is important because most of the techniques we study in the literature are not scalable beyond a certain number of customers. Moreover, the SLS approach is a proactive approach like Demand Side Management (DSM) and not a reactive approach like Demand Response (DR).

To keep the demand under the supply, the idea behind SLS is that residential customers mostly use at least a handful of electric devices and household appliances. Shutting down a limited number of them may not affect customers' quality of life, but overall this step may help to keep the demand under the available renewable supply. The decision of which appliance to shut down to reduce the energy usage is left to the customer through only assigning an allocation that is based on historical load profiles.

Managing the demand for large industrial and commercial customers has been a thoroughly researched area in DSM. However, as we will see later in the paper SLS cannot be applied to residential customers in a straightforward manner using traditional DSM techniques. Soft load shedding of semi-flexible loads requires an insight of customers' electricity usage patterns to save energy.

2 APPROACH

DIDS manages the energy balance through the forecasts of energy demand and supply for a 24 hours period. Hourly generation of renewable energy, in particular, wind and solar could be predicted with a mean absolute error (MAE) of as low as 2.5% in some regions for a 24-hour forecast (Miettinen and Holttinen, 2017). Similarly, the day ahead forecasts of demand at utility-scale has considerably low MAE at around 2% as well(Ghalehkhondabi et al., 2017).

DIDS compares the forecasted demand with the available forecasted supply. If the demand exceeds the generation for any set of hours, DIDS employ various mechanisms to keep the demand under the supply. Some of these methods include moving flexible loads to another hour where supply is adequately available, using backup renewable generation sources such as stored hydro, or biomass, etc. The details of these methods will be presented at another venue. However, if all these methods fall short of meeting the demand for a particular hour, the systems resorts of SLS. To develop an SLS schedule, the traditional techniques of load shedding cannot be applied as these techniques are mostly designed for utility scale(Laghari et al., 2013). Moreover, an important goal of SLS is to minimize customer inconvenience which requires insight into the energy usage behavior of individual customers before being able to shed any load.

To get an insight into the energy consumption behavior, we utilize AMI data to build profiles for each customer using historical usage data at hourly intervals. This historical data combined with temperature forecast provides the forecasted individual energy profile of each customer. Similar profiles have been studied by other colleagues as well(Iyengar et al., 2016). However, since energy usage profiles at finer levels have variabilities across days and seasons, in DIDS we have used the PARX method of finding customer energy demand profiles (Ardakanian et al., 2014). The PARX method requires up to three days of historical data that is used in conjunction with temperature readings to forecast day ahead individual customers' demand profiles. Weekdays and weekends are forecasted separately in the PARX method. For the hour(s) where the demand exceeds supply SLS provides a way to assign an allocation of energy for each customer based on their forecasted usage. In the subsequent section, we discuss three ways of carrying out SLS.

3 SLS METHODS

To discuss the SLS methods, we use data set of hourly consumption from a city in Sweden. This dataset consists of 1436 customers. We simulate a 20% shortfall of energy supply for a single hour i.e. 18:00-19:00. Thus the goal in the following SLS methods is to reduce the demand by 20% to keep it under the available supply. To deal with any changes in forecasted demand or generation, in a real distribution system the amount of shedding may be slightly higher than 20%. However, for simplicity sake, we assume that shedding of 20% is enough to keep the demand under the supply.

Figure 5 shows the 24 hours forecasted usage profiles of a subset of customers on a Saturday. Some customers have a pretty constant usage of electricity while for some the usage vary quite a lot during the day. To keep usage in perspective, we plot the forecasted usage of the SLS hour with the total forecasted usage of the day. This analysis is depicted in Figure 6. Except for a few outliers, this figure shows two trend lines. The first line shows a linear behavior which means that most customers' total usage of energy is proportional to their usage in a particular hour. The second trend line is a horizontal line that shows customers whose energy usage is concentrated mostly in a particular hour. As the data is on a Saturday, these could be customers who may spend their day outside and used energy only at a certain time during the day.

3.1 Equal Allocation / Equal Reduction

The first SLS method is Equal Allocation, that is equally distributing the available energy to the customers. Thus if the available energy during the hour is around 2772 units each of the 1436 dwellings will get 1.93 KWH for the hour. Apparently, such allocation seems fair, but on a deeper look, this allocation may create the following problem. The low-end customers whose requirement is less than the 1.93 KWH are given more electricity as using this method 570 units are allocated beyond the need of such customers. On the other hand, 730 customers are the ones on which SLS will be carried out.

Thus, for the low-end customer, if the electricity is not utilized the utility will face a loss of earnings and for the high-end customers, the utility will face an opportunity loss. Thus equal allocation will not get the true benefits of SLS as we will not get the energy savings needed for this particular hour.

A similar method is an Equal Reduction where we calculate the shortfall which is the difference between demand and supply. The shortfall number is equally

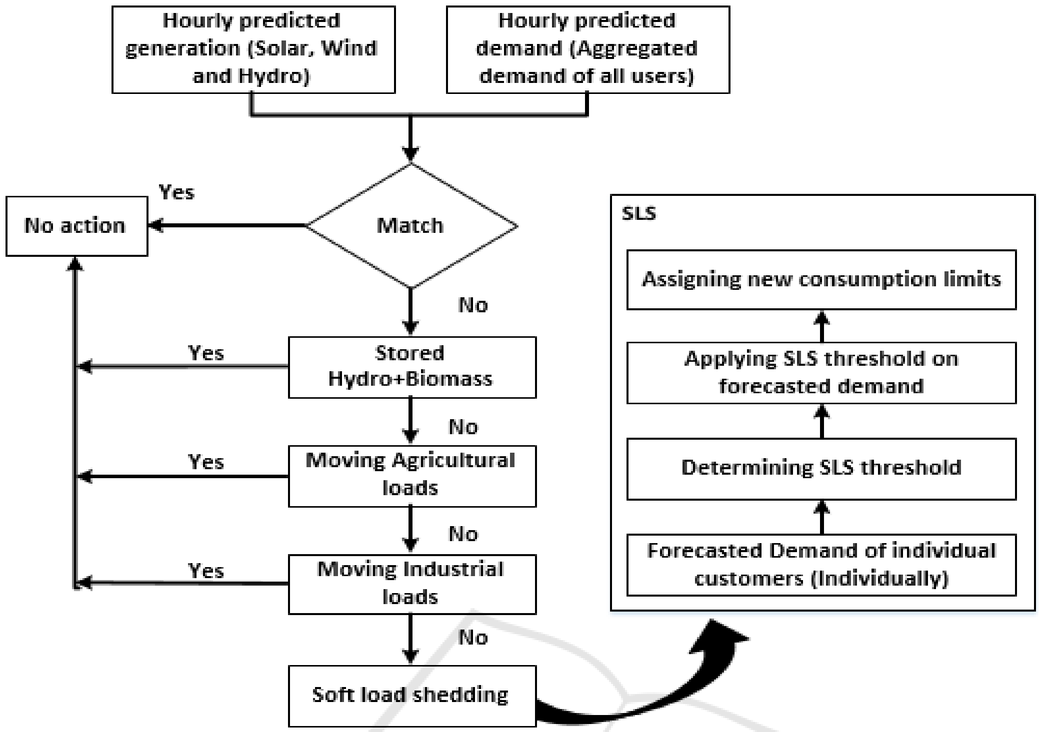

Figure 4: DIDS.

divided across the customer base. For example, if the shortfall is 693 KWH, each member of the community will face a reduction of 0.47 KWH each to make up the demand and supply equation. This method again seems fair, but on a deeper look it may be a good solution for a high-end customer, but for 77 low-end customers decreasing 0.47 KWH may mean shutting down the complete supply for the SLS hour. Thus this method favors the high-end customers while deals with the low-end customers unfairly.

3.2 Percentage Reduction

In this method instead of allocating/reducing load based on KWH, a percentage of the total forecasted load is reduced from allocation. This means that if the shortfall is 20%, each customer will get a 20% reduction in their allocation of electricity based on their forecasted demand. Again this method may seem fair but it favors the high-end customers as 20% reduction for a lower end customer may mean not be able to operate a critical appliance during that hour.

3.3 Clustering Based Incremental Reduction

The Clustering Based Incremental Reduction (CBIR) method uses the customer profiling performed through PARX method as described previously. Instead of just looking at the hour where the SLS is to be carried out it takes into account the total energy used by a customer in the whole 24 hours forecasted period. We group this data using K-means clustering with a threshold of 0.2, and K=3.

We show the results of clustering in Table 1. Customers are put in three clusters called low usage, medium usage, and high usage. The low usage customers are around 815 and their average demand in 1.41 KWH with a total share of 33.4%. The medium usage customers are 489 and their average usage is 2.9 KWH with a total share of 40.9%. The high-end usage customers are 132 and their average usage is 6.72 with a total share of 25.6%.

The total predicted demand for 1436 houses is 3465 KWH for the SLS hour i.e. 18:00-19:00. With 20% less supply we have to cap the demand at 2772 KWH.

In CBIR our first goal is not to carry out SLS on customers whose usage is below a given threshold. This exemption is to ensure fairness to customers who are already frugal in their energy usage. Table 2 shows customers whose energy consumption is less than 1 KWH for the SLS hours. Around 221 customers are in the low usage cluster but a small number are in medium usage cluster as well. Other than fairness, carrying out SLS on these customers yields

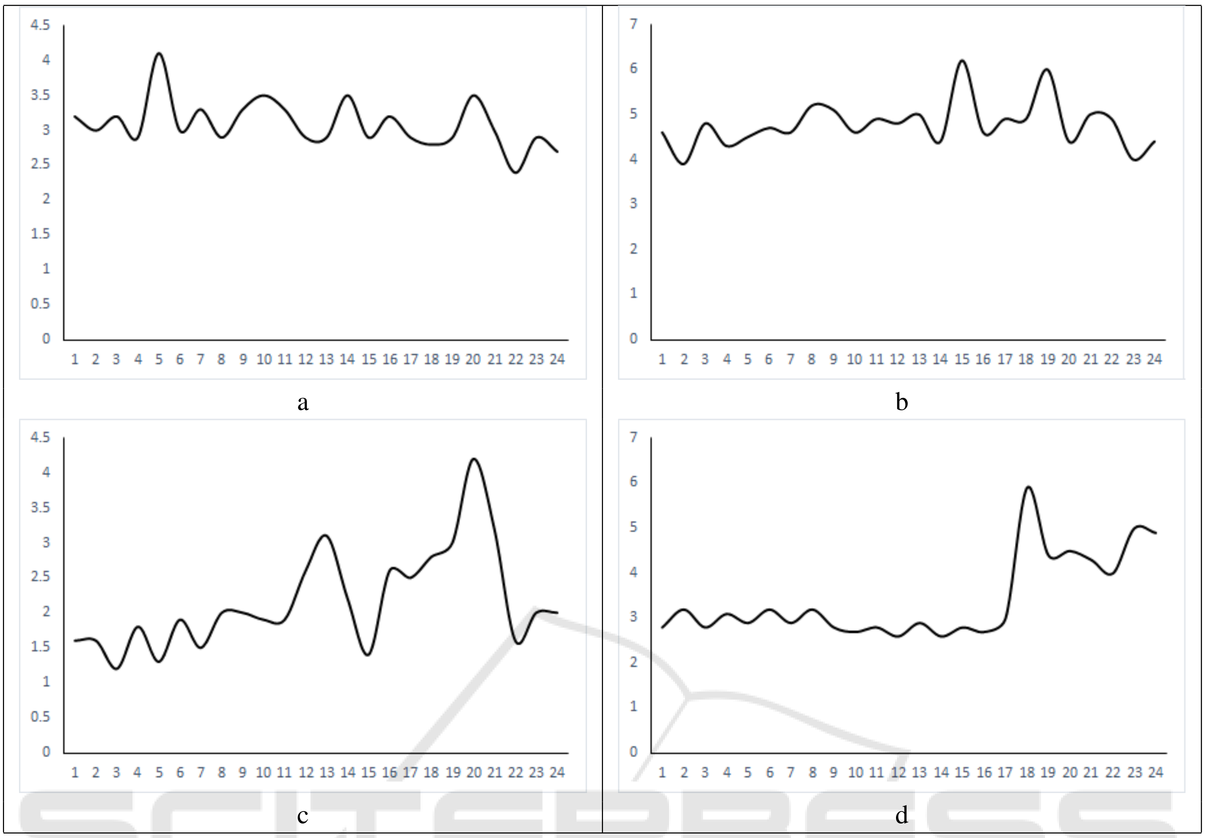

Figure 5: Sample predicted demand profiles of cutomers.

Table 1: Clustering Result: Demand for SLS Hour.

Cluster	Customers	Demand (KWH)	Demand %	Avg Demand
Heigh	132	889	25.6 %	6.72
Medium	489	1420	40.9 %	2.9
Low	815	1156	33.4 %	1.41

Table 2: SLS Analysis with 1 KWH Threshold.

Cluster	Cutomers	Customers under 1 KWH	SLS (KWH)
Heigh	132	0	0
Medium	489	7	0.9
Low	815	221	24.66

only 25.56 kWh in energy savings. Thus in CBIR, we do not carry out any reduction to these selected low usage customers.

Beyond these customers, we apply the SLS to all other customers in the following manner: As shown in Table 3, the low usage customers will get 19.5% percent reduced allocation in their expected usage for saving around 201 units. Similarly, for the medium usage customers, the allocation is reduced by 21% except for the seven customers who are exempted from SLS. This reduction saves around 297.2 KWH from this category. Finally, the high-end customers are allocated 22% reduction allocated saving around 195.6 KWH from this cluster.

In total, CBIR manages to reduce the energy usage by 694.42 KWH while ensuring that the allocation is carried out as fairly as possible.

4 DISCUSSION

The implementation of AMI with threshold metering allows SLS on residential customers. In this paper,

Table 3: SLS percentage for clusters.

Cluster	Customers	SLS %	Demand (KWH)	SLS (KWH)
H with SLS	132	22 %	889	195.6
M with SLS	475	21 %	1415.6	297.2
M w/o SLS	7	0 %	4.5	0
L with SLS	594	19.5 %	1032.7	201.4
L w/o SLS	221	0 %	123.3	0
Total	1436	-	3465	694.42

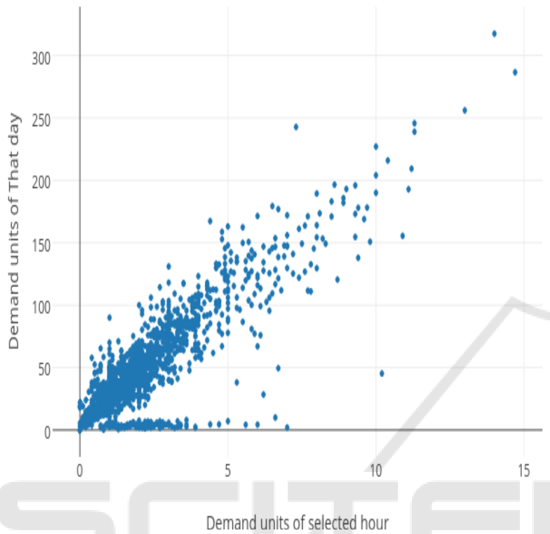

Figure 6: Data for forecasted demand of 1436 customers. SLS Hour vs. 24-hrs Demand.

we have merely scratched the surface of evaluating methods in carrying out SLS.

In CBIR we limit the number of clusters to three. This number is only a demonstration, and in reality, the number of clusters may vary according to the need. Similarly, we fixed the threshold to 1 KWH while in a real distribution system this may vary from feeder to feeder, area to area and may also have a dynamic value. Stemming from this the percentage reduction for each cluster also requires further investigation. For this paper, we choose an arbitrary percentage while in reality, it will depend on the actual gap between demand and supply and the customer contracts. The actual implementation of SLS is also an important question. How will the customers get the information of the assigned allocation? What to do if the customer does not follow the allocation and use more energy? Should we shut down the customer's connection for a brief period which seems harsh or we should have enough energy buffer in the system to allow usage beyond her SLS allocation?

Finally, SLS is a technique that we will need in future to reduce costs associated with the variability and uncertainty of renewables. The negative energy prices in Germany and US in recent months due to overproduction from renewables requires us to resort to SLS-like methods to manage the growth of renewable generation in a controlled manner.

5 RELATED WORK

Managing load shedding has been an area of interest in the power engineering community. However, so far this interest is mostly focused on utility-scale load shedding at feeder levels. Recently some work has been carried out that takes us towards large-scale SLS. Chandan et al. described a DR control from the utility that maximizes the user convenience(**?**). However, this approach requires deep insight into the appliance level usage of the customers while in our approach we only utilize the meter data from the last few days to develop SLS schedule. While their technique may be more beneficial for the customer convenience, it requires a lot of data at the appliance level from the customers which may not be possible for all customers at utility scale. Moreover, their technique is more of a DR technique while ours is more of a DSM one.

Bashir et al. have proposed Direct Load Control (DLC) system that can enforce several user-defined low-power states. It directly controls the devices of the house to manage the load. (Bashir et al., 2015). While this may be a good solution, the DLC method is only applicable when all major appliances have this control capability. Secondly, for millions of customers, this means managing tens of millions of devices. Such control may not be possible without incurring a huge extra cost. Chandan et al. provided the designing for demand response event by analyzing customers data of smart meter and weather. (Chandan et al., 2014)

On customer profiling, Ardakanian et al. proposed customer profiling using autoregression based on data from three days, separately for weekdays and weekends(Ardakanian et al., 2014). Srinivasan et al. grouped data from a utility into eight consumption patterns(Iyengar et al., 2016). Albert and Rajagopal proposed a technique to similar group customers for forecasting their energy profiles (Albert and Rajagopal, 2013).

Queuing-Based energy consumption management system for residential smart gird is proposed by Yi Liu et al. (Liu et al., 2016). Mainly there are two types of demands, essential and flexible demands. Flexible demands includes delay-sensitive and delay-tolerant loads. These loads can be controled by residential smart grid directly and scheduled accordingly. Which means they need extra resources for controlling these appliances, for millions of customer it's not a feasible solution.

6 CONCLUSION AND FUTURE WORK

We have introduced SLS to overcome the issues with conventional DR and DSM techniques and to manage the variability factor of renewable energy resources. The main idea behind SLS is to manage the variability factor of renewable resources while keeping fairness and customer inconvenience in view. Our future work involves finding the most suitable balance between forcing and requesting the customers to shed their energy usage at the time of need. Moreover, since SLS depends on the forecasting of individual customers' energy profiles, we will be working to improve this forecasting. While consumer level forecasting techniques claim to have 80% accuracy, our goal is to use contextual information from customers to improve forecasting further. Smart grid testbed (Tushar et al., 2016) could be use to test our solution and will help us to imporve our technique.

REFERENCES

Aalami, H., Moghaddam, M. P., and Yousefi, G. (2010). Demand response modeling considering interruptible/curtailable loads and capacity market programs. *Applied Energy*, 87(1):243–250.

Albert, A. and Rajagopal, R. (2013). Smart meter driven segmentation: What your consumption says about you. *IEEE Transactions on power systems*, 28(4):4019–4030.

Ardakanian, O., Koochakzadeh, N., Singh, R. P., Golab, L., and Keshav, S. (2014). Computing electricity consumption profiles from household smart meter data. In *EDBT/ICDT Workshops*, volume 14, pages 140–147.

Bashir, N., Sharani, Z., Qayyum, K., and Syed, A. A. (2015). Delivering smart load-shedding for highly-stressed grids. In *Smart Grid Communications (SmartGridComm), 2015 IEEE International Conference on*, pages 852–858. IEEE.

Chandan, V., Ganu, T., Wijaya, T. K., Minou, M., Stamoulis, G., Thanos, G., and Seetharam, D. P. (2014). idr: Consumer and grid friendly demand response system. In *Proceedings of the 5th international conference on Future energy systems*, pages 183–194. ACM.

Connolly, D., Lund, H., Mathiesen, B., and Leahy, M. (2011). The first step towards a 100% renewable energy-system for ireland. *Applied Energy*, 88(2):502 – 507. The 5th Dubrovnik Conference on Sustainable Development of Energy, Water and Environment Systems, held in Dubrovnik September/October 2009.

Cosic, B., Krajacic, G., and Duic, N. (2012). A 100% renewable energy system in the year 2050: The case of macedonia. *Energy*, 48(1):80 – 87. 6th Dubrovnik Conference on Sustainable Development of Energy Water and Environmental Systems, {SDEWES} 2011.

Craciun, D., Ichim, S., and Besanger, Y. (2009). A new soft load shedding: Power system stability with contribution from consumers. *PowerTech, 2009 IEEE Bucharest*, pages 1–6.

Ghalehkhondabi, I., Ardjmand, E., Weckman, G. R., and Young, W. A. (2017). An overview of energy demand forecasting methods published in 2005–2015. *Energy Systems*, 8(2):411–447.

Iyengar, S., Lee, S., Irwin, D., and Shenoy, P. (2016). Analyzing energy usage on a city-scale using utility smart meters. In *Proceedings of the 3rd ACM International Conference on Systems for Energy-Efficient Built Environments*, pages 51–60. ACM.

Laghari, J., Mokhlis, H., Bakar, A., and Mohamad, H. (2013). Application of computational intelligence techniques for load shedding in power systems: A review. *Energy Conversion and Management*, 75:130 – 140.

Liu, Y., Yuen, C., Yu, R., Zhang, Y., and Xie, S. (2016). Queuing-based energy consumption management for heterogeneous residential demands in smart grid. *IEEE Transactions on Smart Grid*, 7(3):1650–1659.

Miettinen, J. J. and Holttinen, H. (2017). Characteristics of day-ahead wind power forecast errors in nordic countries and benefits of aggregation. *Wind Energy*, 20(6):959–972. WE-15-0321.R2.

Mohd, A., Ortjohann, E., Schmelter, A., Hamsic, N., and Morton, D. (2008). Challenges in integrating distributed energy storage systems into future smart grid. In *Industrial Electronics, 2008. ISIE 2008. IEEE International Symposium on*, pages 1627–1632. IEEE.

Roberts, B. P. and Sandberg, C. (2011). The role of energy storage in development of smart grids. *Proceedings of the IEEE*, 99(6):1139–1144.

Tushar, W., Yuen, C., Chai, B., Huang, S., Wood, K. L., Kerk, S. G., and Yang, Z. (2016). Smart grid testbed for demand focused energy management in end user environments. *IEEE Wireless Communications*, 23(6):70–80.

Vytelingum, P., Voice, T. D., Ramchurn, S. D., Rogers, A., and Jennings, N. R. (2010). Agent-based micro-storage management for the smart grid. In *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems: Volume 1-Volume 1*, pages 39–46. International Foundation for Autonomous Agents and Multiagent Systems.