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Energy Demand Side Management with supply constraints: Game theoretic Approach

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Abstract

The management of energy supply and demand is becoming more challenging in regions where the demand continues to grow rapidly and more intermittent renewable supply sources are added to the energy infrastructure. In this context, Demand Side Management (DSM) can be employed to improve reliability of supply and stretch the capacity limits of the existing grid infrastructure. A game theoretic approach for DSM model incorporating storage components is suggested in this paper for environments with supply constraints. The proposed model is able to not only reduce the Peak-to-Average ratio to benefit the electric grid, but also smoothen the dips in load profile caused by supply constraints.

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Keywords: Demand Side Management; Game theory; Storage; Supply constraints.

1. Introduction

Currently, the developing world is facing a major energy crisis. Over the recent years, there has been a rapid increase in the demand for electricity, and a similar trend is expected to continue in future with a 20% increase in demand in next 10 years [1]. However, access to adequate, reliable and affordable energy remains a major problem. In many cases the growth in demand is much faster than the increase in energy supply due to the time required to build new

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generation capacity, lack of funding and socio-political reasons [2]. Consequently, many developing countries in Asia and Africa are facing severe supply shortfalls that have resulted in massive rolling black outs, which has caused huge economic loses and devastating influences on citizens' lifestyles. Along with funding constraints the lack of secure and stable energy infrastructure is a result of poor planning, management and maintenance of resources [3]. Distributed renewable energy sources serve as a promising solution to deal with the energy access and scarcity issues. However, when formed as a micro-grid to power demand through renewable resources, it faces many operational challenges to guarantee the reliable and efficient supply, especially in standalone mode not connected to the electrical grid [4].

Demand side management (DSM) techniques are highly relevant and beneficial in the given context. By using DSM demand can be manipulated to match the supply and hence the existing infrastructure can be utilised more efficiently [5]. The energy system is of heterogeneous nature consisting of multiple consumers each having their own energy usage which makes the system diverse and adds greater flexibility to the system in terms of load scheduling. Game Theory modelling is ideally applied to describe this problem as it considers the different energy scheduling strategies and payoffs of each player and provides a more holistic approach to analyse the problem [6]. Furthermore, solving the problem in a centralised fashion becomes increasingly challenging due to the wide scope of the problem involving numerous customers and a diverse range of electrical devices. Game theory turns the nature of the problem from centralised to distributed, thereby making it computationally easy [7]. Moreover, ICTs and smart metering technologies have enabled the automation of DSM programs making the process user friendly, and easier to manage. At the same time, it enables data collection that can be used for effective planning and development of the energy sector [8].

Active work is being done in this area. [5], [7], and [9] have introduced frameworks mainly aimed to reduce the peak to average ratio (PAR) along with the costs for consumers using different pricing incentives. [10] and [11] incorporate storage devices into their DSM models. Whereas, [12] and [13] introduced renewable generation into their analysis of the energy demand management. Nevertheless, these models normally assume sufficient energy supply is available from the grid to meet all the demand regardless of costs. This is not applicable in the developing countries where supply is constrained and energy sector is marked by supply shortfalls and load shedding, or in a micro-grid environment where the supply from distributed renewable resources can be frequently interrupted due to the inherent intermittency and uncertainty.

The modelling research on the resource-constrained and infrastructure-limiting supply under the developing country context remains a gap; this could be tackled by an extended DSM framework and optimised strategy which help consumers reduce their electricity bills, and provide them with greater flexibility in terms of scheduling load under supply constraints. This study presents a new game theoretic DSM framework to model the supply constrained environments and complexity of individual consumer's utility and the integrated system performance through demand side management strategies. The model aims to reduce PAR while trying to lessen the impact of supply constraints and providing cost savings for customers. By reducing the peaks in the system, it will reduce the overall stress on the system and therefore reduce the requirement for building extra generation capacity. The storage units incorporated in the model provide additional energy to drive demand management under load shedding/supply constraints as per consumers' preferences. Thus, it gives consumers more freedom to schedule their loads and lowers their discomfort. The connection of the storage elements to small scale renewables generation such as rooftop solar PV can pave way for a more distributed and efficient energy system. A case study is included in this paper to demonstrate the model functionality, followed by conclusions and future work.

2. Methodology

This section discusses a game theory based model suggested for DSM under different supply constraints. It provides detailed mathematical formulation of the model and states the assumptions taken.

2.1. System Model

The model consists of n consumers, who are connected to the grid, owning two types of load: 1) Electrical appliances - a and 2) Storage components - b. The model accounts hourly loads for a day, thus the time vector is defined from 1-24 hours. Furthermore, for each consumer an hourly energy scheduling vector is defined as $\boldsymbol{l_n^t}$in Eq. (1), which is the sum of energy consumption profile of appliances $\boldsymbol{x_{n,a}^t}$ and hourly energy discharge/charge profile for storage component $\boldsymbol{s_{n,b}^t}$.

$$l_n^t = \sum_{a=1}^{A_n} x_{n,a}^t + \sum_{b=1}^{B_n} s_{n,b}^t \tag{1}$$

The scheduling vectors have energy constraints given by the power limits and daily energy consumption defined by consumers' usage of different devices. Each appliance will have a time interval for scheduling starting at $\alpha_{n,a}$and ending at $\beta_{n,a}$as user-defined parameters. The difference between the two parameters must be equal to or greater than the normal operating hours O to guarantee all tasks fully done. For the non-shiftable appliances, the interval is equal to $\boldsymbol{O}$. Outside this interval the devices are off and within this interval the devices can operate at standby power P_{min}or maximum power limit P_{max}. The daily energy sum of each appliance must be equal to its daily energy consumption level $\boldsymbol{E}_{n,a}$ defined by the user. Similarly, the storage components are bounded by their maximum energy capacity $\boldsymbol{E_{max}}_{\,n,b}$, so $\boldsymbol{s_{n,b}^t}$ can take any value between -$\boldsymbol{E_{max}}_{\,n,b}$ and +$\boldsymbol{E_{max}}_{\,n,b}$ (negative sign indicates that the storage component is in discharging state). Furthermore, the storage components should follow these given bounds, where q represents the initial state-of-charge of battery Eq. (2).

$$0 \leq q_{n,b}^0 + \sum_1^t s_{n,b}^t \leq E_{max}n,b \tag{2}$$

The sum $\sum_{t=1}^{H} \boldsymbol{s_{n,b}^t} = 0$ implies that at the end of the day the storage component has the same state as the start of the day. Although not necessary in the 24-hour analysis, this assumption is useful when the spatial and temporal scales of the studied system increase to protect the storage systems. Also, at any given point the battery cannot discharge more energy than needed by the devices, as denoted by Eq. (3):

$$\sum_{a=1}^{A_n} \boldsymbol{x}_{n,a}^t + \sum_{b=1}^{B_n} \boldsymbol{s}_{n,b}^t \geq 0 \tag{3}$$

The aggregated load profiles of all consumers can be used to determine the Peak-to-Average load ratio Eq. (4) on the grid. This represents imbalance in load demand profile. Reducing this ratio can help lower the stress on the grid.

$$PAR = L\_peak / L\_avg \tag{4}$$

2.2. Cost Model

The costs on consumers can be defined by a sum of the price of electricity $\boldsymbol{P_t}(L_t)$ (Eq.(5)) and cost of discomfort $\boldsymbol{D_{n,t}}(l_n^t)$ (Eq.(6)) that the users face when they shift their loads. The adopted price is an increasing function of the aggregated load in the system, while the discomfort cost depends on the difference between the initial schedule $\boldsymbol{l\_sch_n^t}$ specified by the consumer and the optimized schedule followed after load shifting. $\boldsymbol{w_{n,a}}$ represents the willingness of consumers to shift the load of various appliances, a lower value means higher willingness to shift load.

$$P_t(L_t) = g * L_t^2 \tag{5}$$

$$D_{n,t,a}(l_n^t) = ((l_n^t - l\_sch_n^t)\verb|^|2) * w_{n,a} \tag{6}$$

2.3. Load constraints

In an environment with supply constraints due to load shedding, the above energy consumption profiles will bear additional constraints. Let $\boldsymbol{Z_t} \triangleq \{z_1^t, \ldots, z_h^t\}$ define the loading shedding schedule, in which the time slots denote the hours of scheduled power cuts by the utility. During this period, the battery can only operate in two states; discharge or stay idle as depicted by Eq. (7):

$$s_{n,b}^{t} \leq 0\ ,\ t \in Z_t \tag{7}$$

Meanwhile, the appliances can just get their energy supply from the storage components as denoted in Eq. (8).

$$\sum_{a=1}^{A_n} x_{n,a}^{t} \leq \sum_{b=1}^{B_n} s_{n,b}^{t}\ ,\quad t \in Z_t \tag{8}$$

Furthermore, the cost functions will change in a supply-constrained environment. The electricity price, $P_t(L_t)$ will take the form of a piece-wise function given in Eq. (9), defined by an increasing quadratic function during electricity provision hours and equal to 0 during the power cut hours.

$$P_t(L_t) = g * L_t^2 t \mathrel{\bar{\in}} Z_t \quad ; \qquad P_t(L_t) = 0 \ \ t \in Z_t \tag{9}$$

2.4. Game Theory Model

A Game Theory model is proposed in this work, which is defined by all involved players, their strategies and the corresponding payoffs. In this model, the consumers act as players and thus n defines the set of players going from 1,2…, N. The strategies are the energy scheduling vectors $x_{n,a}^{t}$and$s_{n,b}^{t}$that the players desire to optimize in order to increase their payoffs, i.e. reduce their costs. As each player is concerned about their own payoffs, the aggregated load can be broken into load of the *n*th consumer and load of all other consumers in the system. Thus the payoffs for consumer n can be defined as Eq. (10)

$$C(l_n^t) = \sum_{t=1}^{T} \left(\left(g * (l_n^t + l_m^t) \right) + \sum_{a=1}^{A_n} w_{n,a} * (l_n^t - l_{sch_{n,a}}^{\ t})^2 \right)_n^{t\,2} \tag{10}$$

2.5. Implementation

At the start of the day, the utility company will gather the schedules from all consumers and based on that it will forward the aggregated load for each hour to consumers. Having this information beforehand, the gaming algorithm will be run at each consumer's end to optimize their energy scheduling profiles. If they make changes to the schedule, they will submit any variations to the utility. Thus, utility will keep forwarding the updated aggregated load to all consumers until no further changes are made and an optimum solution is reached for all.

3. Case study and results discussion

In this illustrative case study, a data set for 10 consumers was used, each having 6 appliances, among which 4 are shiftable (e.g., dishwasher, washing machine, refrigerator and boiler) and 2 non-shiftable (e.g., lights, and TV). Furthermore, each user owns a battery with a capacity of 4KWh for energy storage. The model was built and solved in GAMS24.7.4 using IPOPT solver.

Figure 1. and Figure 2. represent the load profiles from the grid and consumers' perspectives, respectively. Figure 1. first illustrates the reduction of PAR for DSM model with respect to the original load profile. When storage is included there is a PAR reduction of 43%, compared to 35% reduction without storage. Figure 2. further highlights the importance of energy storage for consumers. Storage load can be scheduled during power cut hours and hence dips in the profile are reduced.

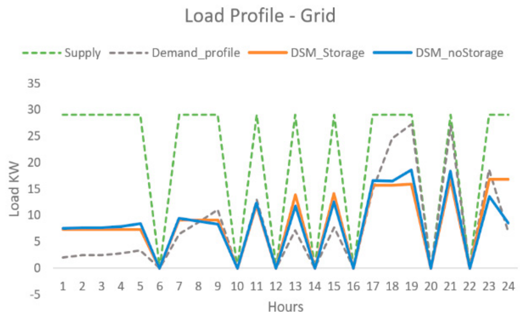

Figure 1. Load profiles as seen by grid

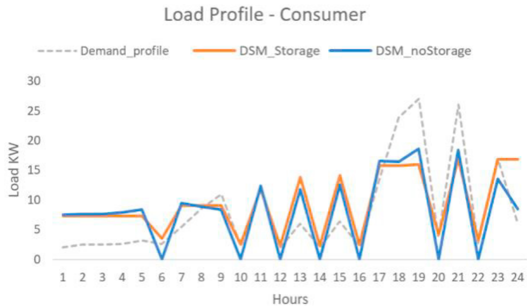

Figure 2. Consumers load profile

Depending on priority of appliances, captured by the willingness parameter and the storage capacity, load is scheduled as per consumer preferences. In Figure 2, it can be seen that the dips are shallower for DSM model with storage.

The model gives consumers power to schedule their loads under outage hours using their storage devices and hence their discomfort costs are significantly reduced as they are able to schedule the entire load in outage hours as per demand. This is shown in Figure 2, where the lower bound of demand profile is closely tracked by the model with storage. Figure 3 highlights the reduction in bills for the consumers for the same scenario shown above, note this does not show the total payoffs, as payoff is both the bills and discomfort costs combined. Figure 4 provides a summary of all the payoffs for three different scenarios namely, 5, 7, and 9-hoursof power cuts respectively. It is demonstrated the Peak-to-Average ratio and overall bill reductions decrease with increasing power outages, as the overall flexibility to manipulate load reduces. In addition, the third benefit to smoothen the dips is met. Figure 4, shows the extra load scheduled in each scenario.

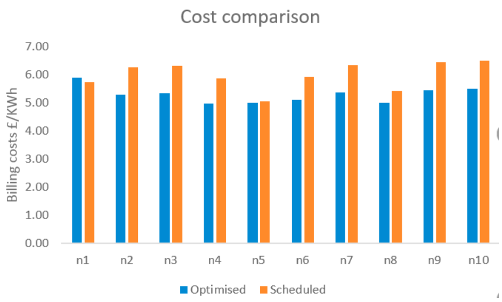

Figure 3. Cost comparison

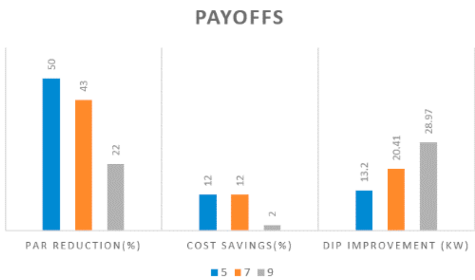

Figure 4. Payoff gains

4. Conclusion

We have presented a game theoretic model for DSM that incorporates storage components and takes into account the supply constraints in the form of power outages. In context of developing world, smart energy control and demand side management can be vital to bridge the continuously increasing supply and demand gaps. Not only is DSM a meaningful approach for maintaining the supply and demand balance and reduce stress on grid, it also delivers benefits to customers by reducing their utility bill. The game theoretic approach captures the needs of every individual and helps to exploit the diversity of load profiles of the consumers set. Furthermore, the storage elements are used to supply power at load shedding hours. This delivers additional benefits to the consumers by lessening the impact of power cuts through scheduling load via storage devices. The results of the model demonstrate the PAR reduction along with the decrease in the load dips for consumers, hence making the overall load profile smoother. DSM is proved to be a useful tool to cater for the growing demand meanwhile the new generation capacity is built.

The storage components were also modelled in a grid connected mode, and they can be combined with renewable generation sources to help reduce the stress on grid further. In future work, we will adapt the methodology to be combined with our previously studied hybrid renewable energy powered micro-grid to show its wider applicability. We will also scale up the current analysis to a real-world context and obtain a comprehensive costs and benefits analysis for the whole society.

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