Cost Effective Bidirectional Power Transactions for Queueing Energy Requests in Smart Micro-grids

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***Abstract*—This paper investigates real time problem of cost efficient energy distribution within smart micro-grids (SMG). The aggregator announces a day-ahead price of electricity, and is most often not fully aware of on spot availability of renewable resources. Sometimes, users also encounter estimation errors in their day-ahead energy procurement. In both situations an extra cost is incurred to aggregator or the users to fulfill their needs. This cost could be minimized by intelligently balancing the real time renewable generations with users load demands. The problem is more complex when there are a number of users communicating with each other and with the aggregator at the same time through a Digital Energy Management System (DEMS) for their demand requirements. It is very challenging for DEMS to ensure comfort level for its consumers while providing low cost electricity. Hence, we establish an optimization problem of curtailing the time average cost of electricity, under certain bounds of consumers satisfactions. We introduce load scheduling and energy transaction (LSET) control policy based on Lyapunov optimization theory to develop our proposed solution.**

***Index Terms*—Smart Micro-grid, Load scheduling, Cost optimization, Demand response**

I. Introduction

For the last few years, the world's attention has moved towards promoting the boundless use of renewable energies. The main aspect behind this, is the growing scarcity of fossil fuels for producing energy and supporting independent power generating units. The substantial advantage of installing renewable generations is their low running cost, but our legacy power network is not designed to facilitate large number of these unpredictable sources. This causes a major bottleneck in balancing the system parameters while using cheap generating resources. In perfect power systems, demands and generations are balanced for all the time. To establish such a reliable system, it is necessary for generators to estimate their expected output energy a day-ahead allowing aggregators to purchase required energy accordingly. The aggregators are then committed to deliver required amount of energy to its users at real time. To ensure stability, huge penalties are imposed on those failed to deliver and this is a challenging situation when low cost operating renewable generators are involved [1]. To overcome this issue, there is a need of making energy demands controllable, to track the changeable patterns of renewable resources. To make our power grid more relaxed and prone to these intermittent resources, the ways of making power demands more dynamic and flexible are getting eminence. The system is more complex when we acknowledge that the load demands are becoming more erratic as their numbers increase. The effective cooperation of the electricity customers in power market could have resulted in balancing system parameters and reducing electricity bills. The mechanization behind making power demands more versatile is mainly known as Demand Response (DR) and Demand Side Management (DSM). One such model which incorporates this type of intelligence is the Smart Micro-grid (SMG). It includes self intelligence, monitoring and efficient control systems especially at the aggregator or utility level [2] - [3].

A number of DR and DSM programs are offered by the utilities or aggregators to their customers. This paper targets DR characteristics of SMG and we assume that our system is led by an aggregator having the capacity to generate power using its own distributed generations and can also bid in electricity market in favor of its consumers to purchase required remaining energy from central grid. An aggregator also has the capability of estimating or forecasting its day-ahead output power capacity and the electricity prices for its consumers. If there is any mismatch between forecasting and real time data experienced by an aggregator, it stabilizes its system parameters by optimizing users load demands, ensuring the cost of electricity remains low. Fig. 1 shows the conceptual model of SMG where Digital Energy Management System (DEMS) acts as an aggregator, integrating renewable energies and multiple consumers through distributed grid intelligence (DGI).

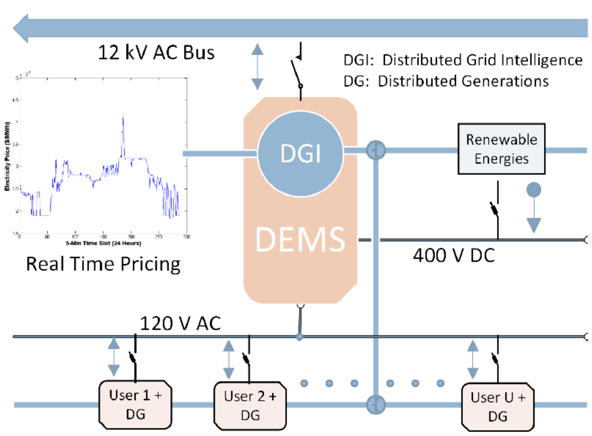


Fig. 1: Smart Micro-grid conceptual model

A. Related Work

The recent advancement in the theory of DR is the real time load scheduling, depending on more sophisticated variable constraints. A lot of work has been done in this field, which helps in determining how deferrable demands can help in balancing the power networks in the presence of uncertain and unpredictable renewable resources [4]- [5]. In [6] and [7] time-of-use price (TOU) indicators are used to smoothen daily load curve but they do not provide sufficient support for the integration of stochastic resources. Although, by using real time price (RTP) one can deal with the changeable nature of distributed generations, it can also lead to disturbance in system because of price instability [8]. Some work is also referred as Home Energy Management (HEM) where the deferrable loads are helping out in balancing the system parameters within the consumers premises by using its own renewable resources [9] - [10]. Yet the use of renewable generation has been proven to lessen the electricity cost but there are many complications regarding balancing the power flow. Most of the literature just describe the integration of distributed resources for reducing electricity cost e.g. [11]- [13], but they do not consider the losses incurred during shifting of loads to these distributed generations. Some illustrate only the power flow policies to balance the system such as [14]- [16]. While in [17] and [18], a concept of AC/DC smart micro-grid is introduced only to minimize the average cost of electricity. Our work deals with both of the above concepts of balancing the power system and lowering the total electricity cost.

B. Our Contribution

In this paper, a new concept of Hybrid Demand Response (HDR) is introduced, heavily dependent on digital computation and a sophisticated communication infrastructure. A conception of day-ahead energy procurement is used to stabilize the users demands and electricity prices under any unstable condition. For example, when there is any real time indication of low electricity prices, the users may rush to get that energy slot for its load demands, results in system instability and elevated prices instead. So with the help of day-ahead procurement procedure the users are forced to stick their procured plan. But usually most of the users do not follow their day-ahead procurement plan exactly, results in load estimating errors. These errors are sometimes called excess energy which the user does not use but already paid for it and sometimes called excess demand whenever a user tries to get energy from the system for its unregistered loads. Likewise, real time energy generation through renewable resources also differ from the predicted one. The utilities or the aggregators displaying day-ahead electricity prices also suffer from price forecasting errors. This paper deals with these estimation errors of energy procurement and the electricity pricing encountered by the consumers and an aggregator, respectively. Moreover, this work is based on real time problem of modeling and scheduling user load demands. It allows an ingenious approach of solving the problem of energy management in SMG. We assume, that users have both deferrable and non-deferrable load demands.

Excess demands are fulfilled by the central grid at any cost if renewables are not available. Whereas, excess energy can be utilized by DEMS for low cost energy operations. One way to use this excess energy is, by storing it in the Energy Storage Devices (ESD) and can be supplied to user load demands whenever requested. But it is not an economical way, because of the high cost of ESD and their inefficiencies, which eventually induce high electricity cost to the users. So a solution has been proposed to utilize this excess energy with the help of deferrable loads. User can schedule its load demands by using this excess energy at merely low price than determined by the central grid. In this way a user can minimize its electricity cost without involving any wasteful components like ESD.

A Load Scheduling and Energy transaction (LSET) policy has been proposed for the above mention procedure. The load demands participating in HDR must send their job requests as a digital energy message to DEMS for further processing. The main task of DEMS is the real time load scheduling operation for deferrable and non-deferrable load demands by using real time price signals. In the proposed algorithm the concept of penalty has been introduced for the users who acquire excess energy ahead of their requirements and a concept of incentive to the users who operate their deferrable loads for this excess energy. In our work, three different cases of scheduling load demands have been compared using Lyapunov optimization benchmark. First case reflects our optimum policy of load scheduling and energy transaction (LSET), in which we consider all the three types of energies i.e. user own excess energy (energy can be used by the user itself for its deferrable loads without penalty), other users excess energy (if the energy is not used by the user itself then it may be penalized and this energy can be available for any other user at lower rates) and the grid energy (energy available from central market at high rates). The second case named as load scheduling without user's own excess energy (LSUE). Here, we assume that the user do not use its own excess energy but it can schedule its deferrable loads through DEMS. The last case includes only grid energy and we assume that the excess energy from users is unavailable and the users deferrable loads need to be operated at any price. This case is known as load scheduling with grid energy (LSGE).

Summarizing, this work deals with the common problem of day-ahead and real time mismatching of load demand and generation characteristics of a power network. LSET policy is proposed for scheduling user load demands under certain delay bounds. This proposed scheme reflects effective switching strategy for efficient power flow within SMG. It also provides an optimal electricity price with high customer satisfaction level to its users, while promising SMG sustainability and reliability. In the beginning of paper some background knowledge on DR is presented. Section II describes proposed cost and load models. Cost minimization problem is formulated in section III, which addresses the DEMS ability of queuing load demands and supplying them energy at specific time. The optimization solution is illustrated in section IV putting constraints and minimizing accumulative electricity cost. Section V presents simulation results of the proposed solution and finally, Section VI concludes this work.

II. System Model

A scenario of Smart Micro-grid (SMG) is assumed, consisting of multiple users and an aggregator (DEMS) containing distributed generations. SMG at the other side is also interlinked with central grid, so that it can fulfill its energy shortage requirements from the external electricity market as shown in Fig. 1. Let $\mathcal{U}$ donate the set of users attached with DEMS making transactions of energy within SMG. Each user representing one household and the number of these users is $U \triangleq |\mathcal{U}|$. Real time electricity price is shown in Fig. 2a. While in Fig. 2b, excess energy (+ve residuals) and excess demands (-ve residuals) are presented for every time slot t.

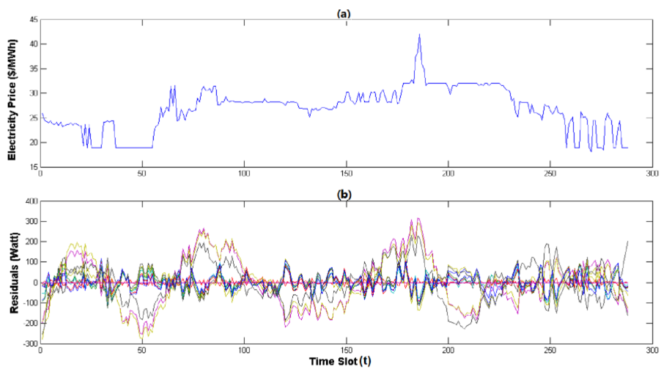


Fig. 2: (a) Market clearing price of electricity for the day of 19/11/2014 from IESO, (b) Residuals generated due to mismatching of day-ahead procured and real time load demands

For each user $u \in \mathcal{U}$, let $d_u^{DA}(t)$ is the day-ahead procured energy at any time t. Whereas, $d_u^{RT}(t)$ represents real time energy demand of the same user. This can be formulated as:

$$d_u^{DA}(t) = \lambda_u^B(t) + \lambda_u^C(t), \quad \forall t \tag{1a}$$

$$d_u^{RT}(t) = d_u^{DA}(t) + \hat{\lambda}_u^B(t) + \hat{\lambda}_u^C(t), \quad \forall t \tag{1b}$$

Where, $\lambda_u^B(t)$ represents non-deferrable loads. While, $\lambda_u^C(t)$ shows deferrable loads. However, hat above the notation shows changing behavior of the additional load demands at real time. The difference between day-ahead procured energy and the real time usage of energy by a user engenders residuals at time t and is shown in Fig. 2b. These residuals for any user can also be modelled as:

$$R_u(t) = d_u^{DA}(t) - d_u^{RT}(t), \quad \forall t \tag{2}$$

It is assumed that additional non-deferrable loads $\hat{\lambda}_u^B(t)$ are served through central grid if excess energy is not available on real-time, so these loads are not considered further. However, deferrable loads should be served using excess energy or renewable energy in the system. The load consists of a random number of appliances of an individual user attached with the user's smart meter. Excess energy to DEMS is denoted as $A_u(t)$ and excess load demands are expressed as $\hat{\lambda}_u^C(t)$. Hence the total excess energy at every time slot from all users in DEMS will be *E(t)* and the total load demand at each time slot is *L(t)* and can be written as:

$$E(t) = \sum_{u=0}^{U} A_u(t), \quad L(t) = \sum_{u=0}^{U} \hat{\lambda}_u^C(t), \quad \forall t \tag{3}$$

Furthermore, the loads are served through the power delivered by the DEMS *P(t)*. This power includes excess power from users and regular power from grid *G(t)*, e.g.

$$P(t) = G(t) + E(t), \quad \forall t \tag{4}$$

Whereas, the power above should be greater than or equal to the real time loads ($P(t) \geq L(t)$). Real time Market clearing price (MCP) indicator taken from [20] shown in Fig. 2a is considered for this problem to make it more real and challenging. The cost of electricity at any time is denoted as *C(t)*. In each time slot DEMS gathers information, related renewable resources, users excess energy and the load demands. Users and DEMS interlink with each other and update their demand and energy status, respectively.

The users with excess energy are penalized of their extra procured energy a day-ahead by transferring the energy to other users without paying back, forcing efficient utilization of energy. If the user consumes this excess energy through its own deferrable loads then it will be charged with zero penalty and the cost of using its own excess energy will be:

$$C_{a,u}(t) = 0, \quad \forall t \tag{5}$$

Moreover, if a user has activated its real time load (which is not scheduled a day-ahead) and have not its own excess energy available then it requests DEMS to supply low cost energy. The DEMS then search out for available excess energy units from other users and supply it to the target user after adding some incentive. The cost will be:

$$C_{s,u}(t) = C(t)(1-\beta), \quad \forall t \tag{6}$$

Where β represents incentive. In addition, if DEMS fails to get enough energy from the other users then it requests energy from the central grid. The grid uses its conventional generators to generate the required energy and incurred real time cost of energy units (the market price) denoting as:

$$C_{s,g}(t) = C(t), \quad \forall t \tag{7}$$

The consumers participating in HDR programs are directly and indirectly get advantage of lessening their electricity costs either by getting low price energy or by using deferrable loads. The deferrable loads are operated with the help of queues installed at the user's premises or with the DEMS. The DEMS keeps the queue buffer updated for each users demands and the queue backlog for time slot t is denoted as N_u^t.

III. Real Time Scheduling Problem

For each time slot, DEMS examine its decision of energy allocation for a particular user by certain decision variables. Such as:

$$D_u^A(t) \in \{0,1\}, \;\; D_u^E(t) \in \{0,1\}, \;\; D_u^G(t) \in \{0,1\}, \quad \forall t \tag{8}$$

These variables indicates that the requested demands are fulfilled either by users own excess energy $D_u^A(t) = 1$ or other users excess energy $D_u^E(t) = 1$ or by central grid $D_u^G(t) = 1$. The net requested energy for the load demands for any user that will be served within SMG at any time slot *t* can be written as:

$$P_u(t) = D_u^A(t)A_u(t) + D_u^E(t)E_u(t) + D_u^G(t)G_u(t), \quad \forall t \tag{9}$$

Whereas, maximum power reserve for any user demand is limited to $P^{max}(t)$ at each time slot. i.e.

$$0 \le P_u(t) \le P^{max}(t), \quad \forall t \tag{10}$$

In our work FIFO (First-In-First-Out) queue is used for serving user load demands. The net demand requests from *U* consumers in the queue at any time is denoted by $N_u(t)$ and the requested energy units updating equation is as follows:

$$N_u(t+1) = max[N_u(t) - P_u(t), 0] + \hat{\lambda}_u^C(t), \quad \forall t \tag{11}$$

Where $\hat{\lambda}_u^C(t)$ represents user demand arrival rates and is upper bounded by:

$$0 \le \hat{\lambda}_u^C(t) \le \hat{\lambda}^{max}(t), \quad \forall t \tag{12}$$

The expected time average queue backlog is defined as,

$$\bar{N_u} \triangleq \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{t-1} \mathbb{E}\{N_u(T)\} \tag{13}$$

Where *T* represents average time function. To make users queues stable, the expected time average queue length of a single user should be less than infinity, such that:

$$\mathbb{E}\{N_u(T)\} < \infty \tag{14}$$

To establish a worst case delay threshold to the demand arrivals the approach of delay aware virtual queue $S_u(t)$ is applied, developed in [11]. The delay aware virtual queue for user *u* is modeled as,

$$S_u(t+1) = max[S_u(t) - P_u(t) + \epsilon 1_{N_u(t)>0}, 0], \tag{15}$$

The variable ϵ is used to handle delay and $1_{N_u(t)>0}$ is an indicator function with the value *1* when $N_u(t) > 0$ and *0* otherwise. So, the delay conscious queue of user *u* evolves whenever demands are not served. With the induction of delay conscious virtual queue, the queue backlog of each user is confined maximally by the Lemma described as:

Lemma: When $S_u(t) \le S_u^{max}$ and $N_u(t) \le N_u^{max}$, then the load demands of all users ensure the worst case delay is limited by W_{max} at any time *t* such that:

$$W_{max} \triangleq \frac{S_{max} + N_{max}}{\epsilon} \tag{16}$$

Where $N_{max} \le VC^{max} + \hat{\lambda}^{max}$ and $S_{max} \le VC^{max} + \epsilon$ and $C^{max} = max\ [C_{a,u}^{max}, C_{s,u}^{max}, C_{s,g}^{max}]$. A user defined parameter *V* is used to impose cost-delay tradeoff. The total cost given by the DEMS at time *t* is:

$$\begin{aligned} \mathcal{C}(t) \triangleq \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{t-1} \mathbb{E}[C_{a,u}(t)D_u^A(t)A_u(t) \\ + C_{s,u}(t)D_u^E(t)E_u(t) + C_{s,g}(t)D_u^G(t)G_u(t)] \end{aligned} \tag{17}$$

The objective of this research is to lessen the time average expected cost of power supplied by DEMS, which introduces the following constrained optimization problem.

$$\mathcal{P}_1 = \min_{D^A(t), D^E(t), D^G(t)} \lim_{T\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\{\mathcal{C}(T)\} \tag{18}$$

s.t. *ref, eq (8),(9),(10),(11),(12),(14),(15),(16),(17)*

IV. Real Time Solution

The problem is a non-convex optimization problem based on binary decision parameters of using users excess energy or the grid energy. The decision criterion and the problem, both are timely coupled. The real time solution is established on Lyapunov algorithm. Let $\Theta(t) = \{\Theta_1(t), \cdots, \Theta_U(t)\}$ where $\Theta_u(t) \triangleq (S_u(t), N_u(t))$ act as a concatenated vector of real and virtual queues of user *u*. To estimate congestion in the queues we define the following Lyapunov function: $\mathcal{F}(\Theta(t)) \triangleq \frac{1}{2}[S_u(t)^2 + N_u(t)^2]$. Conditional 1-slot Lyapunov drift is modeled as:

$$\Delta(\Theta(t)) \triangleq \mathbb{E}\{\mathcal{F}(\Theta(t+1)) - \mathcal{F}(\Theta(t))|\Theta(t)\} \tag{19}$$

A control variable $V > 0$ is useful in effecting performance-delay tradeoff and is needed to force the expected cost to remain within $O(1/V)$ of the optimal value of $\mathcal{C}$. It also ensures the optimal user satisfaction within *O(V)* of worst case delay. The following drift plus penalty function is achieved by using drift plus penalty framework developed in [11],

$$\Delta(\Theta(t)) + V\mathbb{E}\{\mathcal{C}|\Theta(t)\} \tag{20}$$

As stated in framework [11], the above function must be bounded by the following expression:

$$\begin{aligned} \Delta(\Theta(t)) + V\mathbb{E}\{\mathcal{C}(t)|\Theta(t)\} \le B + V\mathbb{E}\{\mathcal{C}(t)|\Theta(t)\} \\ + \sum_{u=0}^{U} N_u(t)\mathbb{E}\{(\lambda_u^C(t) - D_u^A(t)A_u(t) - D_u^E(t)E_u(t) - D_u^G(t)G_u(t))|\Theta(t)\} \\ + \sum_{u=0}^{U} S_u(t)\mathbb{E}\{(\epsilon - D_u^A(t)A_u(t) - D_u^E(t)E_u(t) - D_u^G(t)G_u(t))|\Theta(t)\} \end{aligned} \tag{21}$$

Where *B* is constant and the RHS of the above function is minimized which gives us,

$$\begin{aligned} \mathcal{D}(t) = \min V[\sum_{u=0}^{U}\{\mathcal{C}_{a,u}(t)D_u^A(t)A_u(t) + \mathcal{C}_{s,u}(t)D_u^E(t)E_u(t) + \mathcal{C}_{g,u}(t)D_u^G(t)G_u(t)\} \\ - \sum_{u=0}^{U}\{N_u(t) + S_u(t)\}\{D_u^A(t)A_u(t) + D_u^E(t)E_u(t) + D_u^G(t)G_u(t)\}] \end{aligned} \tag{22}$$

The cost can be reduced by achieving real time decision making policy without knowing any future statistical information. At time *t* DEMS observes users own excess energy cost, other users excess energy cost, grid energy cost and the queue backlog of each user. Using Lyapunov optimization mechanism, scheduling decisions are made. DEMS initially runs users own excess energy policy to satisfy the target demand requirements, but if the target demands cannot be fulfilled then DEMS scans for other users low cost excess energy. If the energy requirements still persist then eventually it can ask the grid for low cost power. And if the queue length is approaching to its limits then it purchases easily available energy from any source on priority basis and updates the queue to next time slot. However, the priority shall be given to the source exhibiting low cost power. If the DEMS completely scan the available low cost users excess energy for a given time slot and no demands are present to serve or if the target demands of users are already satisfied then the algorithm will update the queue backlog and move to the next time slot. The excess energy available at this time might be a loss to a user, which is very rare in case of deferrable load operations.

By re-arranging and solving the eq.(22) we can get our scheduling decisions mentioned below as:

$$\begin{aligned}\mathcal{D}(t) = \min[&\sum_{u=0}^{U}\{D_u^A(t)A_u(t)(VC_{a,u}(t) - (N_u(t) + S_u(t)))\} \\ &+ \sum_{u=0}^{U}\{D_u^E(t)E_u(t)(VC_{s,u}(t) - (N_u(t) + S_u(t)))\} \\ &+ \sum_{u=0}^{U}\{D_u^G(t)G_u(t)(VC_{g,u}(t) - (N_u(t) + S_u(t)))\}]\end{aligned} \tag{23}$$

So the decision parameter is based on the comparison between price and queue backlog bounds. The achieved target energy constraints are set by the following rules:

$$P_u^{target}(t) = \begin{cases} \min(N_u(t), P^{max}), & if D_u^A(t) or D_u^E(t) or D_u^G(t) = 1 \\ 0, & otherwise \end{cases} \tag{24}$$

V. Numerical Results

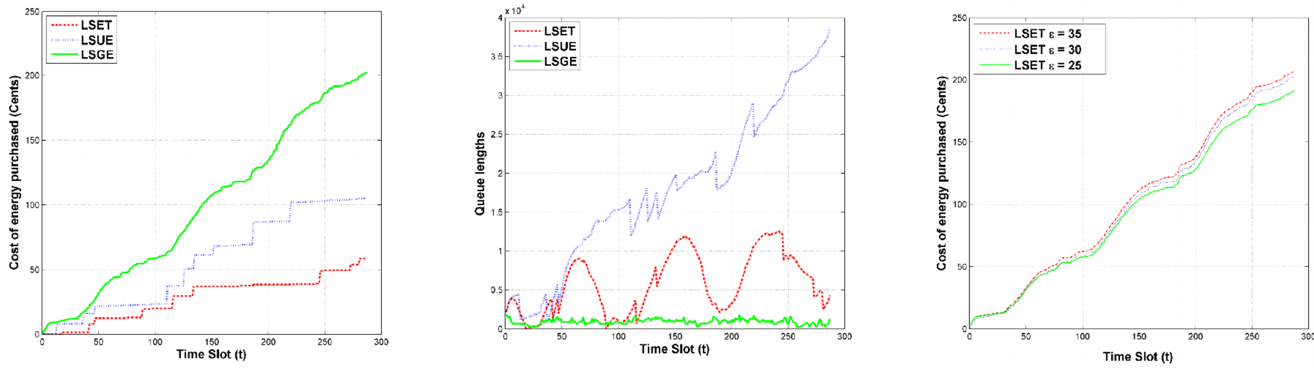
In this section, the results of the three scheduling cases applied on the proposed conceptual model are compared. A scenario of a Smart micro-grid is taken consisting of DEMS and Distributed grid intelligence (DGI), controlling the load demands of about 15 users. The effectiveness of the proposed scheduling polices is measured by introducing three different cases. The first one introduces the distributed scheduling control both at user and DEMS level, enabling power supply from users own excess energy free of cost. The second one puts the control of scheduling demands at DEMS forcing the users to send their excess energy back to aggregator. While, in third case it is assumed the DEMS is not working for the social welfare or if there is no bidirectional flow of power among aggregator and the users. The DEMS will then schedule the demands on energy taken from the grid. Yet, all of these cases include the intelligence of cost-delay tradeoff. It is assumed that DEMS delivers electric supply homogeneously to a certain group of smart power consumers with their appliances operated in the consumers queue. It is also assumed that the central grid can provide 500 units of energy to a single consumer at any time t. Now the concept of residuals is introduced retrieving from day-ahead energy forecasting errors. These residuals are then differentiated into users excess energy and users demands based on residual characteristics as shown in Fig. 2b. It is retrieved from the data that the maximum demands from any consumer which was experienced is about 290 units and 310 units of excess energy, which are of low power and small durations. Smart meters from the users end and the DEMS from the aggregator side are interlinked with each other exchanging relevant data. In the first two cases, DEMS in conjunction with smart meter make the scheduling decision, observing users load demands and scanning excess energy of all users in the time slot t and it can be said that this is a hybrid demand response. In the last case DEMS alone makes decisions for scheduling load demands of all consumers which we can call direct load control.

The proposed optimization policy is executed in 5-minute time slot and has demonstrated with different type of comparisons . For the following figures, it is assumed that the average load demand $\hat{\lambda}_u^C(k)$ is 50 units per user and the average excess energy is 70 units per user. Both are exponentially distributed over the whole day. It is further assumes that the control parameter V = 100000 and the virtual queue arrival rate $\epsilon = 10$. Real time MCP graph for electricity price for a full day is used.

Fig. 3a illustrates the total accumulated electricity cost incurred to the DEMS over each time slot. It compares the total electricity cost for the three cases (LSET), (LSUE) and (LSGE). It is clearly seen that the proposed LSET policy reduces the cost of the electricity by approximately a factor of 3.63 from LSGE policy and 2 from LSUE policy in the tested one-day window. The slopes of these three lines are nearly different, suggesting unbounded savings with increase in time. The reason why the LSET policy shows optimum cost solution is the intelligent usage of consumers own excess energy by deferring the load demands on upcoming time slots. Whereas, LSUE is not fully intelligent because it cannot provide a user with free excess energy. Moreover, LSGE provides energy only from the grid which is more costly. Fig. 3b shows the development of queue backlogs for the three cases. The queue length reveals the number of load demands in the queue. The higher the queue length the maximum is the delay. It is clear from the figure that the algorithm LSET has on average an optimum delay as compared to LSUE which exhibits much higher delays to their load. In Fig. 3c the performance of the algorithm for different values of ϵ is considered. The simulation for $\epsilon = \{35, 30, 25\}$ is run. The total cost decreases as ϵ decreases whereas, the maximum observed waiting times increases.

VI. Conclusion

This work demonstrates a Lyapunov optimization technique to deal with the problem of efficient use of users excess energy by using deferrable loads. A flexible framework that



(a) (b) (c)

Fig. 3: (a) Total electricity cost incurred to users for a whole day, (b) Time evolution of average queue lengths, (c) Cost of electricity for energy purchased at electricity market for different values of ϵ.

allows DEMS to minimize cost associated with using users own excess energy within certain delay bound is presented. The load demands are placed in users queue and wait for the users own excess energy to be available or wait for low price energy from DEMS. The load demands are being tolerated to operate, to investigate the problem of cost minimization while allowing bidirectional energy transactions. The proposed solution is simple and operate efficiently without knowing the statistical properties of the supply, demand, and energy requests. The results ensure that the worst case delay of demands is bounded by introducing a virtual queue along with the contribution of Lyapunov optimization theory. The solution includes a decision variable 'V' as a control parameter and can be modified as desired to affect a cost-delay trade-off. The proposed solution provides a general framework of scheduling problems and can be a relevant substitute to the dynamic programming. Simulation shows that the optimum policy LSET achieves a lower cost than both LSUE and LSGE.

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