Supply Scheduling and Usage-Based Pricing for Shared Storage in Adaptive Dynamic Islanding

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ABSTRACT

Customers are affected by power outages due to supply shortage, maintenance and other unexpected events. Utilities are evaluated by the authorities on metrics such as SAIDI and SAIFI that are based on the outages' duration and frequency. During outages, islanding is often used to supply backup power to a subset of the load by using local energy sources such as batteries or micro-generation. Due to the limited capacity of secondary supply, Adaptive Dynamic Islanding is used to dynamically allocate the energy among the customers during outages. Battery characteristics such as lifetime and available capacity depend on the usage patterns. Therefore, when battery is used as the secondary source for islanding, it is important to schedule the supply to satisfy the customer demand and improve reliability metrics while taking into account battery capacity and energy costs. Towards this, we propose a method for optimally scheduling supply from a shared battery among a set of customers during Adaptive Dynamic Islanding. Additionally, we also present a pricing mechanism to bill the customers for their consumption during islanding based on their usage patterns. This helps in avoiding penalizing customers for the usage behaviour of others in the community using the same shared battery. We show experimental results based on real consumption data and battery specifications.

Keywords

Energy Storage, Energy Scheduling, Storage Pricing

1. INTRODUCTION

Electricity is one of the primary necessities in the modern world. As countries extend the reach of electricity to provide access to all their citizens, the generation, transmission and distribution infrastructure is struggling to keep up. Despite the increase and upgradation of capacities, electricity outages are still frequent in various parts of the world. Outages occur due to several reasons such as systemic energy shortfall, device failures, faults in the network, scheduled maintenance and even natural events like storms or quakes among others. Outages could be scheduled or sudden; also outages can be of varying durations based on the underlying causes. Both the scheduled and sudden outages can last for several hours at a stretch until power is restored. In all cases, the loss in supply is undesired and affects customer productivity and comfort.

Electrical utilities are measured on several metrics by the regulators including reliability. Important reliability metrics are based on the duration and frequency of outages suffered by the customers. Moreover, utilities in many developed countries are moving towards performance based rate due to pressure from electricity regulators [7]. Hence the reliability metrics directly affect the revenues of utility companies.

Consequently, as utilities are under pressure to reduce interruptions to the supply, they undertake several measures such as *Adaptive Dynamic Islanding* during outages. Islanding is the method of isolating sections of the grid and supplying power to them using local sources in the event of an outage [3]. Especially for areas prone to outages, the ability to island is of great benefit for providing backup power in the event of loss. This helps in reducing the interruptions and improving the metrics. During an outage affecting a section of the service region of a utility, some areas within the outaged section turn into islands of power – the customers in those areas receive power through alternate sources such as micro-turbine, storage, renewable energy, etc. For that temporary duration, this can be considered equivalent to the off-grid settings where a community is not connected to the grid but is powered by its own local energy source.

As islanding uses local energy sources such as battery or renewables which are limited in capacity; thus supplying energy requirements of all the customers is often not possible. Adaptive Dynamic Islanding (ADI) is the advanced method of islanding wherein the utility differentiates between the loads of the customers and supplies the limited energy by cycling it over the customers [12]. ADI uses the advanced meter infrastructure at customer premises to turn-on and turn-off power for each customer independently during an

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outage. Consequently, a supply schedule is followed based on the limited energy resource such as a battery for supplying power to the customers. In this paper, we focus on such ADI scenarios *where a shared battery is used to supply power to customers during an outage*. In particular, we present a mechanism for scheduling the supply of energy among the set of customers in an optimal manner and also to price their energy consumption based on the battery characteristics and usage behaviour.

Scheduling and pricing the energy from a shared battery is challenging because of the special characteristics of the battery technology such Lead-Acid or Lithium-Ion. In short, batteries are expensive and come with a limited lifetime. Furthermore, the 'Rated Lifetime' and 'Rated Capacity' of a battery is specified by the manufacturers against a 'Rated Depth-of-Discharge (DoD)' and a 'Rated Discharge Rate'. However, since the DoD and discharge rates experienced by the battery depend on the actual usage (that is, the load being supplied), they vary significantly from the rated values. In fact, DoD and discharge rate vary from one discharge cycle to another based on the usage. The complexity lies in the fact that the effect of DoD and discharge rate on the battery lifetime and available capacity is non-linear.

When a battery is used as a shared energy source among a set of customers during an outage, it is necessary to schedule the supply to the customers in such a way as to satisfy each of their demands as much as possible while taking into account the affect of the discharge rate on the available capacity. Similarly, since DoD affects the deterioration in the lifetime of the battery, the customers have to be billed not just for their energy usage but also their contribution to the loss in battery life.

Alternatively, customers can install and use their own individual batteries instead of using the shared resource. One of the disadvantages of such an approach is that the customers will have to size the battery based on their peak demand although they might not always be using it at that capacity. In the shared setting, the battery will be sized based on aggregate peak which will be lower than sum of individual peaks due to complementary demand patterns. Moreover, the per kWh cost of a battery will be lower for batteries of larger size – thus, a community-wide shared battery will have a lower per kWh cost. Nevertheless, in the shared battery setting, it is important to have suitable pricing mechanism such that customers do not have carry the burden of the usage behaviour of others. At the same time, the pricing mechanism should also be such that, typically, it is more profitable to use the shared battery than purchase individual batteries.

Given the above necessities, in this paper, we propose a method for scheduling the supply of energy from a shared battery to the customers during ADI. The aim of the schedule is to achieve the following requirements – (i) satisfy a specified minimum percentage of demand of all customers, (ii) minimise the interruption duration or frequency at the utility level and, (iii) ensure feasibility of supply from the battery through control of the discharge rate and available capacity. We also propose a pricing mechanism for billing the customers for their battery usage based on their usage behaviour. The design of the scheme ensures that customers are not penalised for the inefficient usage patterns of others in the group. We demonstrate the effectiveness of our approaches through experimental evaluation based on real consumption data of a large set of customers and battery data from manufacturer's specifications. In summary, the contribution of this work is two-fold:

1. We are the first to propose a method for optimally scheduling the supply of energy from a shared battery resource to a set of customers based on historical consumption patterns.

2. We propose a novel pricing mechanism for billing customers using a shared battery resource that takes into account the effect of the usage behaviour of the customers on discharge rate and DoD in addition to the energy consumed.

While the motivation behind our work lies in the settings envisaged in ADI, the approaches we propose here are applicable to any scenario that involves a set of consumers seeking energy from a shared battery resource for a given duration. Thus, our work is equally applicable to both grid-tied and off-grid microgrids containing batteries.

In the next section, we study the literature relevant to this work. Following that, Section 3 provides a background on ADI and battery characteristics. Next, Section 4 describes our scheduling and pricing approach in detail. It is followed by experimental evaluation of the approaches in Section 5. Finally, Section 6 concludes the paper.

2. RELATED WORK

In this section, we provide a brief study of the literature related to islanding, shared storage systems and batteries.

The process of adaptive islanding and using distributed generation or local generation as backup source has been widely studied (see [9, 15, 16] and the references therein). In particular, authors in [9] describe a method for intentional islanding to improve frequency and voltage stability in distribution networks. Similar to our work, the focus of this paper is also on reducing customer interruptions and improving system reliability. However, they use local generators as backup source for islanded customers whereas our work focuses on using battery as the backup source.

There is a large body of work on optimizing use of energy storage systems in distribution networks with renewable energy sources. The authors in [10] focus on optimizing the the battery life and storage capacity by minimizing charge-discharge cycles. They use optimally-sized super capacitor to reduce perturbation of discharge current. In our work, we select loads to optimize the battery life. Bozchalui et al. propose a framework for scheduling energy storage systems in the distribution system containing renewable energy sources [4]. They focus on reducing imbalances at the substation level with various objectives. They do not schedule the demand or directly focus on reliability metrics. Similarly, [2] propose an optimal framework for scheduling energy from community storage systems to the grid to take advantage of fluctuating energy prices in the competitive markets.

Moving towards storage systems, [13] focus on optimising battery lifetime and cost of energy for consumers of a grid-tied microgrid. Here, the purpose of the schedule is to choose when to use energy from the grid directly and when to use the battery (which is charged using renewables). Thus, it is not applicable to outages or ADI.

Finally, [11] compares the benefits of using community-shared battery versus individually-owned storage systems. Their analysis reveals that there are considerable savings in storage requirements in the community-shared case. This arises mainly due to the diversity in consumption profiles of the members. Thus, this work provides us with an impetus to focus on the usage of shared storage systems during ADI.

3. BACKGROUND

In this section, we provide the background on electricity outages suffered by utilities and their customers and describe the relevant metrics used to measure them. This is followed by describing the approach taken to provide power to customers during such outages by using storage or other technologies. Next, we study the characteristics of the battery technologies that can be used by utilities to provide backup power to their customers during outages.

3.1 Electricity Outages

Electricity outages, both scheduled and unscheduled, occur for several reasons. In several developing countries, there is a severe energy and peak power shortage that leads utilities to induce power outages. For example, in India, the energy deficit was 8.4% (7.5 GWh) and peak power shortage was 7.9% (12.3 GW) in 2013 [6]. For the stable operation of the electricity network, utilities resort to planned outages during peak demand. Additionally, there are frequent unplanned outages due to unexpected events. Even in developed countries outages often occur due to maintenance issues and unexpected events. These lead to both scheduled and sudden outages.

To measure the utility's performance, there exist several measures of reliability. The two most often used reliability metrics are SAIDI and SAIFI.

- SAIDI: It stands for *System Average Interruption Duration Index* representing the average duration of outage per each customer served by the utility. It is calculated as:

$$\text{SAIDI} = \frac{\sum_i U_i N_i}{N_T} \tag{1}$$

  where N_i and U_i respectively denote the number of customers and the annual outage time for location i, and N_T is the total number of customers of the utility. SAIDI is usually measured in terms of minutes (or hours) per customer.

- SAIFI: Standing for *System Average Interruption Frequency Index*, SAIFI represents the average number of interruptions experienced by the customers of the utility. It is calculated as:

$$\text{SAIFI} = \frac{\sum_i \lambda_i N_i}{N_T} \tag{2}$$

  where λ_i and N_i respectively denote the failure rate and the number of customers for location i, and N_T is the total number of customers of the utility.

SAIDI and SAIFI are measured by regulatory authorities to keep track of the service performance of utilities. For example, for the year 2014, among the US based utilities, the highest SAIDI was recorded by *Coastal Electric Coop, Inc* at $7,266$ minutes per customer and the highest SAIFI was recorded by *Tallapoosa River Elec Coop Inc* at 118.2 interruptions per customer in the year [17].

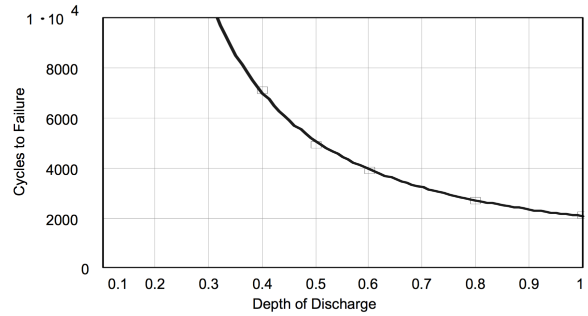

Figure 1: DoD versus battery lifetime

3.2 Adaptive Dynamic Islanding

During an outage, utilities have to supply power to critical demands such as hospitals, police stations etc. Restoration of power after an outage could take several hours since location of a fault and repair of a fault can be time-consuming. Typically utilities use backup power sources such as micro-generation or batteries to supply energy to few customers during an outage. *Islanding* is this process of supplying power to a subset of customers in a utility service region during an outage. An advanced method of islanding is known as *Adaptive Dynamic Islanding* (ADI) [12]. ADI uses the advanced meter infrastructure at customer premises to turn-on and turn-off power for each customer independently during an outage. Using ADI, utilities can differentiate critical loads such as hospitals, traffic controls and police stations from non-critical loads, and supply power to critical loads. Remaining energy is cycled for subset of non-critical loads. As mentioned in Section 1, in this work we develop the scheduling and pricing mechanisms for using battery storage towards providing power in such ADI settings.

3.3 Battery Cost

Batteries are electro-chemical devices which convert chemical energy to electrical energy or vice-versa by means of controlled set of chemical reactions between a set of active chemicals. Batteries are commonly used as a backup source of power during outages. Use of utility scale batteries is gaining prominence due to advances in battery technology and reduction in battery prices [5]. Lithium-Ion and Lead-Acid battery technologies are most widely used for applications of back-up power.

Due to high manufacturing costs, limited lifetime, and recycling costs, battery costs are still very high compared to the cost of energy generation. The life of battery is affected by ageing of the system and wear of the battery chemicals. Battery ageing refers to reduction in life of battery due to environmental exposure such as corrosion. Battery ageing can be minimised by having a proper enclosure as well as regular maintenance. In comparison, battery wear refers to reduction of ability to store and dispatch energy. Battery wear is a function of usage patterns of the battery. Two important characteristics that affect batteries are Depth of Discharge (DoD) and Discharge Rate [8]. In this paper, we model battery costs as a function of these two parameters.

Nominal Ah Capacity (5 Hour Rate)	DISCHARGE DURATION (seconds)										
	5	30	60	300	600	900	1800	3600	5400	10800	18000
58	399	326	298	219	171	140	88.7	49.9	34.8	18.6	11.6
67	453	370	338	249	194	160	102	57.6	40.2	21.4	13.4
85	564	462	422	314	248	203	129	73.1	51	27.2	17
93	615	504	460	343	272	223	142	80	55.8	29.8	18.6
102	665	546	498	372	295	243	154	87.7	61.2	32.6	20.4
111	714	587	535	401	318	263	167	95.5	66.6	35.5	22.2
128	814	671	612	460	366	306	194	110	76.8	41	25.6
137	860	710	647	487	389	326	207	118	82.2	43.8	27.4

Figure 2: Discharge rate versus available capacity

3.3.1 Effect of Depth of Discharge (DoD)

Depth of Discharge (DoD) is defined as the amount of battery capacity that has been discharged, expressed as a percentage of maximum capacity of the battery. For example, DoD of a fully charged battery is 0%. Batteries operated upto DoD 80% are called deep discharge batteries.

Depth of discharge affects the cycle-life of a battery. Cycle-life of battery is defined as number of charge-discharge cycles that battery can experience before it stops operating at rated specifications. Figure 1 shows a sample graph of dependency of cycle-life on DoD [8]. Typically battery specifications give rated cycle life for 80% DoD[1]. The battery manufacturers provide cycle-life vs DoD curves such as given in Figure 1 in the product technical specifications.

3.3.2 Effect of Discharge Rate

The discharge rate of a battery affects the effective energy derived from the battery. Typically the battery specifications determine the effective capacity of a battery as a function of C-Rate. C-Rate is defined as the rate at which battery is discharged relative to its maximum capacity. For example, 1C rate means the discharge current will exhaust the entire battery capacity in one hour. Figure 2 is a sample table derived from a battery specification giving the dependency between discharge rate and effective capacity [8].

The relationship between discharge rate and available capacity is given by Peukart's law [14] in the form of the equation given below:

$$C_p = I^k.t \tag{3}$$

where C_p is the amp-hour capacity at 1A discharge rate, I is the discharge rate in Amperes, t is the discharge time in hours and k is the Peukert coefficient.

Battery lifetime, costs and columbic efficiency depends on usage patterns of the battery; thus it is important to consider these factors for optimal usage of battery during outages and ADI. Since each customer's usage patterns are different, the contribution of each customer to battery wear costs and energy costs also differ. It is important to price the energy consumed from the battery in ADI fairly, without penalizing a customer who uses the battery optimally (within rated specifications) as compared to a customer who uses the battery beyond the rated specifications, contributing more to the wear of the battery and wastage of energy.

4. SHARED STORAGE MECHANISM

[1]http://www.hoppecke.com/content/download/brochures/rp/TechnicalDocumentation/Montagehandbuch_verschl_en.pdf

In this section, we describe our mechanism of using shared battery storage to supply to a set of customers that are either affected by an outage or islanded for some other reasons. Based on the background, we identify the following value propositions that we seek to satisfy.

1. *Performance Based Rating* uses grid reliability metrics as one of the key parameters determining energy prices. Hence these metrics directly affect utility revenues. Our method focuses on improving grid reliability metrics such as SAIDI and SAIFI during ADI using batteries. Even in the case of ADI being adopted by a community independently, minimising SAIDI and SAIFI would constitute as the ambition for efficient operation of the storage.

2. *Fairness* is an important criterion when sharing a limited resource. Utilities are legally obliged to serve their customers fairly. A schedule can be considered fair if all customers at least get a designated minimum percentage of their power requirements (such that no one is drastically deprived compared to others). Our approach ensures fairness during schedule optimization by using bounds derived from historical consumption patterns.

3. *Battery cost* of large-scale lead-acid or lithium-ion batteries are significant. Effective usage of stored energy is of utmost importance. Our method ensures that battery is operated with a discharge profile that brings about effective usage of the battery.

4. *Pricing* the use of the shared battery needs to be fair given that the pattern of usage has a strong effect on the battery lifetime. We propose a pricing mechanism that ensures that individuals are not penalised by the actions of others, at the same time, they pay the share for their contribution to the energy cost and loss in battery life.

The setting is formalised as follows: A given set of customers (such as a community) are sharing a battery resource for backup power for a given outage period. The outage period consists of a known number of contiguous time slots. The battery is assumed to be fully charged prior to the outage. At every time slot, the battery can either be steady or discharging. A subset of customers (could be none) are chosen for using the battery power for each time slot based on the derived schedule.

4.1 Shared Storage Scheduling

We use linear optimisation formulation to obtain the customer allocation schedule for ADI with the objective of minimizing system reliability indices such as SAIDI and SAIFI.

Let N be the set of customers and T be the set of contiguous time slots (say hours) of outage duration. Let C be the set of possible discharge profiles (schedule configurations) of the battery. Each $c \in C$ essentially denotes a battery configuration, that is, the subset of time slots of T for which the battery is kept on. Also, let $\mathcal{E}(c)$ be the effective energy available in the battery for configuration c. $\mathcal{E}(c)$ is derived based on the battery specifications data (as explained in Section 3.3). For example, suppose $T = \{1, 2\}$, then C can be $\{\{1\}, \{2\}, \{1, 2\}\}$; also suppose the battery offers an effective capacity of 60 units when discharged at 1 time unit, and a capacity of 100 units when discharged for 2 time units. Then $\mathcal{E}(\{1\}) = \mathcal{E}(\{2\}) = 60$ and $\mathcal{E}(\{1,2\}) = 100$.

The estimations of the demand requirements of each of the customers for each of the time slots are available. These estimates can be derived based on the historical consumption data of the customers. Then, $e_{i,t}$ denotes the estimated energy demand of customer $i \in N$ at time slot $t \in T$. Finally, γ represents the minimum percentage of any customer's total demand during the outage period that the utility should seek to satisfy during ADI. This can be set by the grid or by utilities themselves (or even the community of customers in case of self-installation). γ essentially acts as the fairness metric.

We use two sets of indicator variables x and y in formulating the linear program for minimization of SAIDI and SAIFI. The first set of indicator variables x is defined for every customer and every time slot: $x_{i,t} = 1$ if consumer i is served at time slot t, otherwise $x_{i,t} = 0$. The indicator variable y is defined for every configuration: $y_c = 1$ if the battery discharge profile $c \in C$ is selected, otherwise $y_c = 0$. Since SAIDI and SAIFI are both important as metrics, we provide optimisation formulation for minimising each of them separately. Of course, a utility can seek to obtain a balance by optimising over a weighted combination of the two.

4.1.1 *Minimising* SAIDI

SAIDI can be minimised during an outage by maximising the total duration of backup power being provided to the customers under ADI. The following formulation seeks to obtain the schedule that maximises the duration of supply to the customers under the feasibility and fairness constraints.

$$\begin{aligned}
\underset{x,y}{\text{maximise}} \quad & \sum_{i\in N,\ t\in T} x_{i,t} \\
\text{subject to} \quad & \sum_{c\in C} y_c = 1 \\
& x_{i,t} \le \sum_{c:t\in c} y_c, \quad \forall i, \forall t \\
& \sum_{i\in N} x_{i,t} e_{i,t} \le \sum_{c\in C} y_c \frac{\mathcal{E}(c)}{|c|}, \quad \forall t \\
& \sum_{t\in T} x_{i,t} e_{i,t} \ge \frac{\gamma}{100} \cdot \sum_{t\in T} e_{i,t}, \quad \forall i
\end{aligned} \tag{4}$$

The first constraint ensures that only one configuration is selected by the optimisation, thus providing the battery schedule. The second constraint guarantees that a customer can receive energy in a time slot only if the battery is on in that time slot for the chosen configuration. The third constraint states the requirement that the total energy consumed in time slot cannot exceed the energy available for that time slot from the battery. Here, it is important to note that we are stating the available energy as the total energy available in the configuration divided by the number of time slots contained in the configuration. Although, this assumes a uniform rate of discharge across the time slots for the optimisation purpose, the actual rate of discharge will depend on the actual demand. This assumption is necessary to obtain the value $\mathcal{E}(c)$, because available capacity is dependent on the discharge rate (as studied in Section 3.3). While the above constraints are designed to ensure feasibility of the obtained schedule, the last constraint is important because it ensures fairness of the schedule. It states that every customer should receive at least γ percentage of their total energy requirements during the outage period.

4.1.2 *Minimising* SAIFI

Just like in the case of SAIDI, SAIFI can be minimised during an outage by reducing the number of interruptions to the customers under ADI. Here we use another set of indicator variables z: $z_{i,t} = 1$ if customer i experiences an interruption at time t. Interruption is defined as the power switching to the off state from an on state. Thus,

$$z_{i,t} = \begin{cases} 1 & \text{if } x_{i,t-1} = 1 \text{ AND } x_{i,t} = 0 \\ 0 & \text{otherwise;} \end{cases} \quad \forall t = 2, 3 \ldots; i \in N \tag{5}$$

The following formulation seeks to obtain the schedule that minimises the number of interruptions of supply while satisfying the feasibility and fairness constraints.

$$\begin{aligned}
\underset{x,y}{\text{minimise}} \quad & \sum_{i\in N,\ t\in T} z_{i,t} \\
\text{subject to} \quad & \sum_{c\in C} y_c = 1 \\
& x_{i,t} \le \sum_{c:t\in c} y_c, \quad \forall i, \forall t \\
& \sum_{i\in N} x_{i,t} e_{i,t} \le \sum_{c\in C} y_c \frac{\mathcal{E}(c)}{|c|}, \quad \forall t \\
& \sum_{t\in T} x_{i,t} e_{i,t} \ge \frac{\gamma}{100} \cdot \sum_{t\in T} e_{i,t}, \quad \forall i \\
& z_{i,t} \ge x_{i,(t-1)} - x_{i,t}, \quad \forall i, \forall t \ge 1 \\
& z_{i,1} \ge 1 - x_{i,1}, \quad \forall i
\end{aligned} \tag{6}$$

The objective function captures the requirement to minimise the total number of interruptions across the customers over the whole outage period. The rest of the formulation is similar to Eq. 4 except for two additional constraints. The fifth constraint provides the definition of an interruption, that is, customer i suffers an interruption if served with power for time slot $t-1$ but not served for time slot t. The last constraint represents the same but for the special case of $t = 1$, the beginning of the outage period.

With the above formulation for SAIDI or SAIFI a schedule is obtained prior to the outage period for the customer consumptions and battery supply. The schedule is represented by the values (0 or 1) of all the $x_{i,t}$s and y_cs. Based on the derived schedule, energy is provided from the battery to the selected set of customers at every time slot.

However, as the schedule is derived based on the typical demand pattern of the customers, the actual consumption realised during the outage might vary. This can result in slightly different levels of energy available in the battery and different levels of demands of the customers being satisfied from what was assumed for the schedule. This difference is a result of the demand forecast error of the customers which is beyond the scope of this paper. Nevertheless, when the error is low, the minor differences tend to get ironed out themselves. In cases when the forecast error is high, the above optimisation can be re-computed at the end of every time slot to obtain a revised schedule for the rest of the outage period. This re-optimisation is based on the latest availability of energy in the battery and the updated demand requirements. Therefore, revising the schedule at every time step will ensure that the best possible performance metrics are maintained even in the face of uncertain demand of the customers.

Next, we present our method for pricing the energy supply based on the usage behaviour of the customers.

4.2 Usage-Based Pricing

Our pricing method calculates the total wear cost of the battery and the cost of the energy depleted in the battery for the discharge cycle (which corresponds to the outage period). We calculate these using the data given in the product specifications of the battery and the physical model of the battery. This cost amount is then apportioned to the customers based on their individual consumption behaviour in that cycle using the consumption data.

The challenge in designing a pricing scheme lies in the fact that while the total cost at the community level will depend on the overall consumption pattern such as the DoD reached and discharge rate of the shared battery, a customer should be charged only as per her consumption pattern. At the same time, the cost of energy supplied to the customer using shared battery should be less than or equal to having her own battery. Otherwise, a customer will not be motivated to use the shared battery; she may install her own battery. We devise a pricing mechanism which essentially provides incentive to the customer to use the shared battery and also bills the customer for only her contribution to battery wear and energy consumption.

The intuition behind our method is as follows. We calculate every customer's incurred cost of energy consumption as if she had her own battery with specification similar to that of shared battery, but sized with a capacity to supply her peak historical consumption. Then, we apportion the total cost of energy among all the supplied customers in proportion to what would have been the incurred cost if customer had her own battery. As the per kWh capex cost of a shared battery tends to be lower than an individual smaller battery, the cost for each customer will also end up being lower compared to having her own battery.

Let K_R, D_R and L_R be the rated capacity, rated DoD and rated life cycles of the shared battery respectively. If B is the cost of the battery, then the rated *wear cost* per cycle $W_R = \frac{B}{L_R}$. As the battery is used for the total outage period of T time slots, that can be considered as one discharge cycle for the battery. If the actual DoD reached at the end of the cycle is D^T, $\mathcal{P}_d(D^T)$ is defined as the DoD cost factor, which adjusts the total wear cost of the battery for the deviation from rated DoD. $\mathcal{P}_d$ is obtained from the battery specifications such as given in Figure 1. Similarly, if I^T is the actual rate of discharge for the cycle, $\mathcal{P}_r(I^T)$ gives the discharge rate cost factor, which adjusts the total energy cost from the battery for the deviation of operation from rated discharge rate. $\mathcal{P}_r$ is a function derived from Peukert's law and battery specifications as seen in Figure 2 (see Section 3.3). Hence, the actual wear cost for the cycle T is:

$$W^b = \mathcal{P}_d(D^T) W_R \tag{7}$$

Thus, W^b constitutes the actual battery cost for the discharge cycle. Let S be the cost per kWh of the energy used to charge the battery, then the total energy cost for the cycle is:

$$W^s = D^T K_R S \tag{8}$$

W^b and W^s together constitute the total battery usage cost for the discharge cycle. As discussed above, to calculate the battery wear cost and energy cost of a given customer, we assume that the customer has used her own battery.

We begin with the effective energy cost computation. For a given customer $i \in N$, let $q_{i,t}$ be the actual energy consumed and I_i^t be the measured discharge rate of customer i during time slot t. Then the total effective energy consumed over the outage period T is:

$$w_i^s = \sum_{t \in T} \mathcal{P}_r(I_i^t) q_{i,t} \tag{9}$$

Normalising with the overall energy consumption, we obtain the effective energy cost for customer i as:

$$\tilde{w}_i^s = \frac{w_i^s}{\sum_{j \in N} w_j^s} W^s \tag{10}$$

Now, moving onto the battery wear cost computation, let the capacity and cost of the battery of customer i, sized based on her historical peak consumption, be k_i and b_i respectively. Since L_R is the rated number of life cycles, the rated wear cost for customer i is $w_i = \frac{b_i}{L_R}$.

Given the energy consumption w_i^s, the equivalent DoD of customer i is given as:

$$D_i^T = \frac{w_i^s}{k_i} \tag{11}$$

With this DoD, the wear cost of customer i's battery for the cycle T is:

$$w_i^b = \mathcal{P}_d(D_i^T) w_i \tag{12}$$

The actual battery wear cost attributed to i for the cycle will be an equivalent proportion of the shared wear cost obtained in Eq. 7 as follows:

$$\tilde{w}_i^b = \frac{w_i^b}{\sum_{j \in N} w_j^b} W^b \tag{13}$$

Finally, the total cost of battery usage for customer i for outage period T is obtained by adding up the contributing energy cost and wear cost.

$$w_i^T = \tilde{w}_i^s + \tilde{w}_i^b \tag{14}$$

In the next section, we conduct experiments to understand the performance of the scheduling and pricing approaches.

Algorithm 1: Greedy algorithm for minimizing SAIDI

1: Suppose battery with capacity $\mathcal{E}$ is discharged at uniform rate for the entire set T of the outage time slots.
2: Energy available for any time slot $t \in T$ is $\mathcal{E}_t = \frac{\mathcal{E}}{|T|}$.
3: **for** every time slot $t \in T$ **do**
4: Sort the customers in ascending order based on their energy requirements $e_{i,t}$ for time slot t.
5: Satisfy the demand request of the maximal set $\mathcal{A}$ of customers ($\mathcal{A} \subseteq N$) selected in above order such that $\sum_{i \in \mathcal{A}} e_{i,t} \leq \mathcal{E}_t$.
6: **end for**

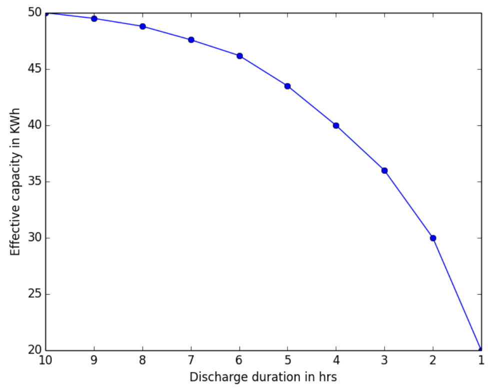

Figure 3: Discharge Rate vs Effective Capacity for Sample Battery

Algorithm 2: Greedy with Fairness algorithm for minimizing SAIDI

1: Suppose battery with capacity $\mathcal{E}$ is discharged at uniform rate for the entire set T of the outage time slots.
2: Energy available for any time slot $t \in T$ is $\mathcal{E}_t = \frac{\mathcal{E}}{|T|}$.
3: Set unsatisfied customer set $\tilde{N} = N$.
4: **for** every time slot $t \in T$ **do**
5: Sort the customers in ascending order based on their energy requirements $e_{i,t}$ for time slot t.
6: **if** $\tilde{N} = \emptyset$ **then**
7: set $\mathcal{X} = N$
8: **else**
9: set $\mathcal{X} = \tilde{N}$.
10: **end if**
11: Satisfy the demand request of the maximal set $\mathcal{A}$ of customers ($\mathcal{A} \subseteq \mathcal{X}$) selected in above order such that $\sum_{i \in \mathcal{A}} e_{i,t} \leq \mathcal{E}_t$.
12: If any customer $i \in \tilde{N}$ has $\gamma\%$ of its total energy requirement satisfied already, then remove i from $\tilde{N}$.
13: **end for**

5. EXPERIMENTAL EVALUATION

In this section, we present simulation results to evaluate the optimisation approach and to demonstrate the working of our pricing scheme. We use Irish CER dataset, which contains energy consumption measurements of around 5,000 consumers over 1.5 years[2]. The measurements started in July 2009 and ended in December 2010, and recorded energy consumption in kWh every 30 minutes. We choose residential consumers that belong to the control group and have no missing values. This results in the selection of 782 consumers; we use this data at hourly resolution.

For every simulation run, we randomly chose a set of 30 customers from among the total 782 customers. To estimate the demand requirements, we assume availability of past 30 days data. This period of 30 days is also chosen from among the 18 months for each selected customer.

We use the average consumption of a customer in the time slots pertaining to the outage period for the 30 historical days as a forecast of the energy consumption pattern of that customer during the outage period. This demand pattern later forms the basis for generating the supply schedule using optimisation or greedy (described below) approaches.

[2]Electricity customer behaviour trial. The Commission for Energy Regulation (CER), 2012

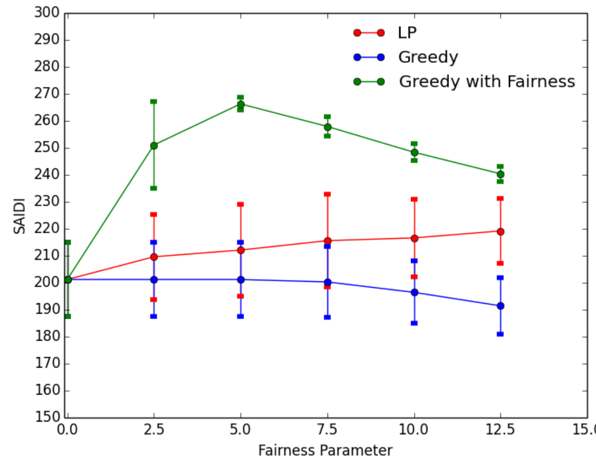

Figure 4: SAIDI minimisation

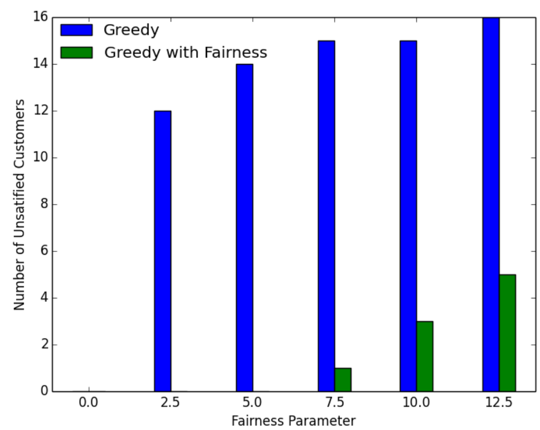

Figure 5: SAIDI minimisation: Number of customers not receiving minimum share of energy (LP method is not plotted because all customers receive minimum share by design).

For the simulations, we assume a shared battery with capacity of 50 kWh at the discharge rate of 10 hours. The cycle life of battery is 2000 when operated at DoD of 80%. The capacities at various discharge rates are obtained from curve shown in Fig 3.

For each simulation run, the selected 30 customers (with demand patterns given from 30 days of data) are assumed to suffer an outage of 10 hours duration. The shared battery is used to supply power to them based on some schedule (obtained via optimisation or naive approaches such as greedy as described below). The actual demand of the customers during that 10 hours is given by the actual consumption of each customer from a randomly selected day. Thus, the simulation method does not make any assumptions about the type of customers, demand patterns, customer requirements or actual consumption of customers. Instead, it derives all these values by sampling from a real dataset. Next, we first describe our experiments for the scheduling mechanism before moving onto the pricing mechanism.

Algorithm 3: Greedy algorithm for minimizing SAIFI

Suppose battery with capacity $\mathcal{E}$ is discharged at uniform rate for the entire set T of the outage time slots.
Total energy available for any time slot $t \in T$ is $\mathcal{E}_t = \frac{\mathcal{E}}{|T|}$.
Sort the customers in ascending order based on their total energy requirements $\sum_{t \in T} e_{i,t}$.
Let $\tilde{\mathcal{E}}_t$ denote the available capacity in time slot t; initialize $\tilde{\mathcal{E}}_t = \mathcal{E}_t$.
for every customer i chosen in the above order **do**
    Find the first time slot t where $\tilde{\mathcal{E}}_t - e_{i,t} \geq 0$ (where i's demand can be satisfied based on available battery capacity).
    while $\tilde{\mathcal{E}}_t - e_{i,t} \geq 0$ AND $t \in T$ **do**
        Satisfy the demand request of customer i at t.
        Reduce available capacity: $\tilde{\mathcal{E}}_t = \tilde{\mathcal{E}}_t - e_{i,t}$.
        $t = t + 1$.
    end while
end for

Algorithm 4: Greedy with Fairness algorithm for minimizing SAIFI

Suppose battery with capacity $\mathcal{E}$ is discharged at uniform rate for the entire set T of the outage time slots.
Total energy available for any time slot $t \in T$ is $\mathcal{E}_t = \frac{\mathcal{E}}{|T|}$.
Sort the customers in ascending order based on their total energy requirements $\sum_{t \in T} e_{i,t}$.
Let $\tilde{\mathcal{E}}_t$ denote the available capacity in time slot t; initialize $\tilde{\mathcal{E}}_t = \mathcal{E}_t$.
Set unsatisfied customer set $\tilde{N} = N$.
for every customer $i \in \tilde{N}$ chosen in the above order **do**
    t=1.
    repeat
        if $\tilde{\mathcal{E}}_t - e_{i,t} \geq 0$ **then**
            Satisfy the demand request of customer i at time slot t.
            Reduce available capacity: $\tilde{\mathcal{E}}_t = \tilde{\mathcal{E}}_t - e_{i,t}$.
        end if
        $t = t + 1$.
    until customer i has at least γ% of its total energy requirement satisfied
    Remove i from $\tilde{N}$.
end for

5.1 Scheduling

In order to compare the performance of our optimisation approach, we designed two other scheduling methods – (i) **Greedy** and (ii) **Greedy with Fairness**. Broadly, Greedy refers to the approach that blindly attempts to minimise the metric (either SAIDI or SAIFI) based on battery capacity with no regard for allocating a minimum share of energy to all customers. In contrast, Greedy with Fairness refers to the approach that gives priority to fairness (that is, every customer should receive at least γ percentage of their required demand during the outage period) and then generates the schedule in a greedy fashion. Therefore, for the sake of comparison, one can consider the Greedy and Greedy with Fairness approaches as the upper and lower bounds on performance respectively. The pseudocodes of Greedy and Greedy with Fairness algorithms are presented in Algorithm 1, Algorithm 2 respectively for SAIDI minimisation. Similarly, Algorithm 3 and Algorithm 4 provide the pseudocodes for SAIFI minimisation. For ease, we call our optimisation based approach as the **LP** scheduling method. IBM ILOG CPLEX Optimizer [1] was used to solve the integer linear programs. Cplex uses either primal or dual variants of the simplex method or the barrier interior point method to solve integer/linear programming problems.

Moving onto the results, Figure 4 shows the performance of the three approaches for minimising SAIDI. We conducted experiments by varying the fairness parameter γ from 0 to 12.5%. The results shown here are the average over 50 simulation runs for each data point (have plotted the mean and standard deviation). Since there are 30 customers undergoing an outage of 10 hours in each run, the maximum SAIDI possible is 300 hours. The x-axis denotes the fairness parameter γ from 0 (no minimum requirement) to 12.5% of energy requirement while y-axis gives the resultant SAIDI values (lower is better). We see that when $\gamma = 0$, all three methods converge at around 200. But with increasing γ, while Greedy remains around 200, Greedy with Fairness shoots upto 260. For $\gamma \geq 7.5\%$, Greedy with Fairness begins to fall slowly, but that coincides with it being unable to satisfy the minimum requirement of all customers (as seen later). In contrast, our method LP rises in a much more gradual fashion to around 215. The error bars of LP and

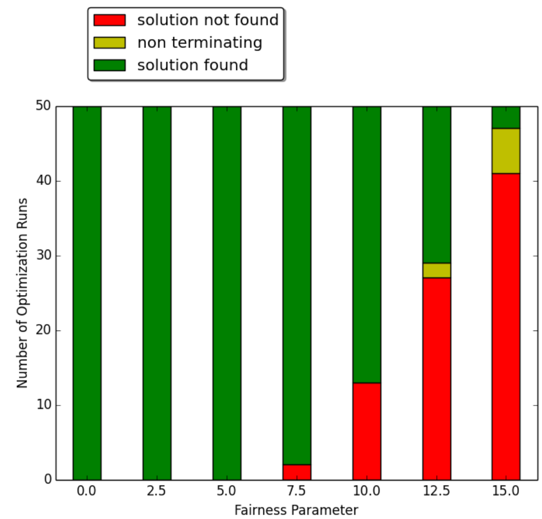

Figure 6: SAIDI minimisation: Number of LP runs with feasible solutions

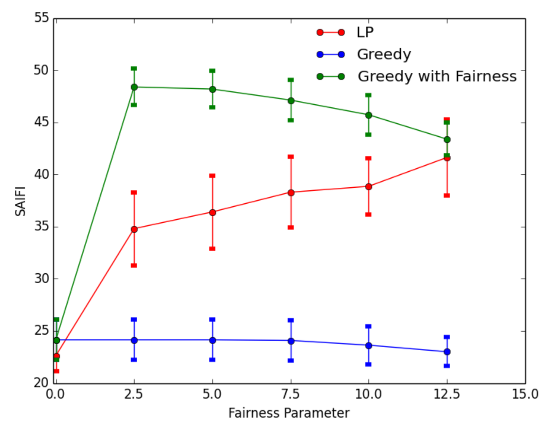

Figure 7: SAIFI minimisation

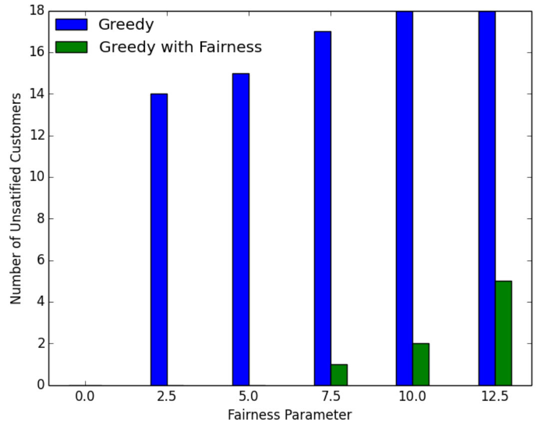

Figure 8: SAIFI minimisation: Number of customers not receiving minimum share of energy (LP method is not plotted because all customers receive minimum share by design).

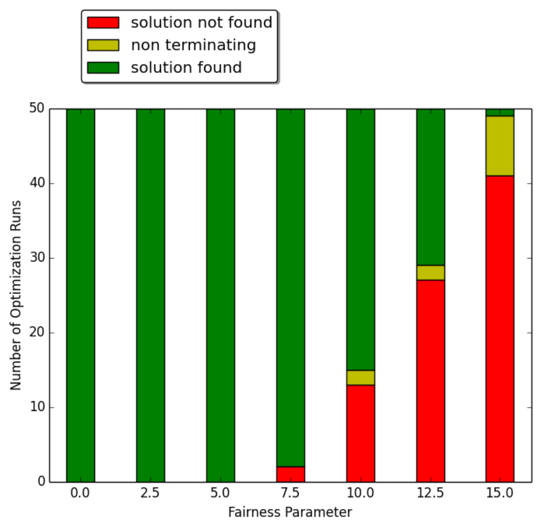

Figure 9: SAIFI minimisation: Number of LP runs with feasible solutions

Greedy overlap until $\gamma = 10\%$ which shows that in some cases, the performance of LP is equivalent to Greedy. This is especially notable because LP follows the fairness requirements while Greedy doesn't. This difference is further highlighted in Figure 5. Here, for each γ value, we plot the number of customers out of the total 30 who did not even receive the minimum percentage of energy as specified by γ. The values shown here are the mean over 50 runs. $\gamma = 0$ is the trivial case. But for higher values of γ, we find that 13 to 16 customers do not receive the minimum energy requirement; thus approximately 30-50% of the customers receive less than the minimum energy requirement in Greedy. We also note that for $\gamma \geq 7.5\%$, even Greedy with Fairness method is unable to satisfy all customers. This shows that a greedy-based scheduling approach does not have the look ahead to determine which is the best time slot to serve a customer. Hence, a customer might be put off for a later time slot, but satisfying her requirement in the later time

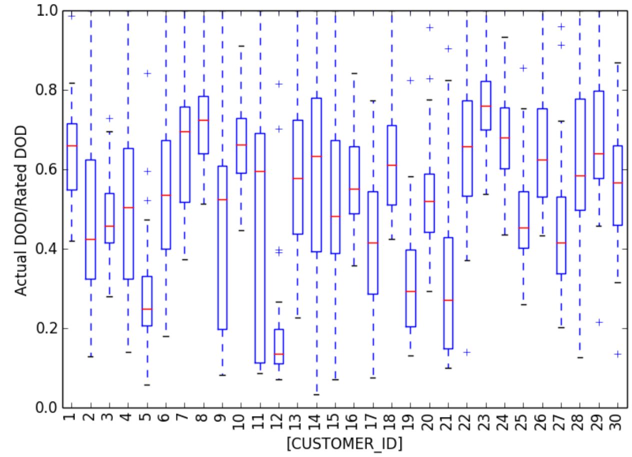

Figure 10: Deviation from rated DoD of individual customer batteries

slot might not be enough to provide enough energy over the outage period. LP by definition satisfies all customers. However, in some cases, LP fails to find a feasible solution. Figure 6 shows the ratio of runs that had a feasible solution through LP for different values of γ. For lower values, all runs result in a feasible solution, but for higher values, the number of runs with no solution keep rising. For $\gamma = 15\%$ and beyond, feasible solutions become hard to find. Therefore, we limited our experiments to $\gamma = 12.5\%$ and all the results presented earlier were averaged only for feasible runs.

We conducted the same set of experiments for SAIFI minimisation. Figure 7 shows the obtained SAIFI values for the three methods. The lower the SAIFI values, the better it is in terms of reliability. Here, the maximum possible value is 150. For all values of γ, the Greedy method remains stable between 20–25 because it ignores the fairness constraint. However, we see that Greedy with Fairness rises as high as 50 for $\gamma = 2.5\%$ to 5%, while LP rises gradually with increasing γ. LP and Greedy with Fairness converge to similar values of 40–42 for $\gamma = 12.5\%$. This is because Greedy with Fairness improves SAIFI for $\gamma \geq 7.5\%$ as it correspondingly begins to fail in satisfying the fairness requirement of all customers. This can be seen in Figure 8. Greedy with Fairness left 1 customer unsatisfied at $\gamma = 7.5\%$ and 5 customers unsatisfied at $\gamma = 12.5\%$. The Greedy method has left around half or more of all customers unsatisfied for all values of γ. LP, however, ensures minimum energy supply to all the customers. Finally, Figure 9 shows the ratio of runs that result in a feasible solution for LP with increasing values of γ. The trend seen here is similar to that of SAIDI.

5.2 Pricing

We conducted a set of experiments to examine our pricing mechanism. We use the same instances of dataset selected for the scheduling experiments above. For every simulation run, 30 customers are randomly selected from the dataset, and a 30 day period is also randomly chosen to act as their historical consumption data. Particularly, for the pricing experiments, we also use this historical consumption data of each customer to derive the size of the hypothetical individual batteries of each customer. For these experiments, we set the battery price at USD 330 per kWh. The rated DoD

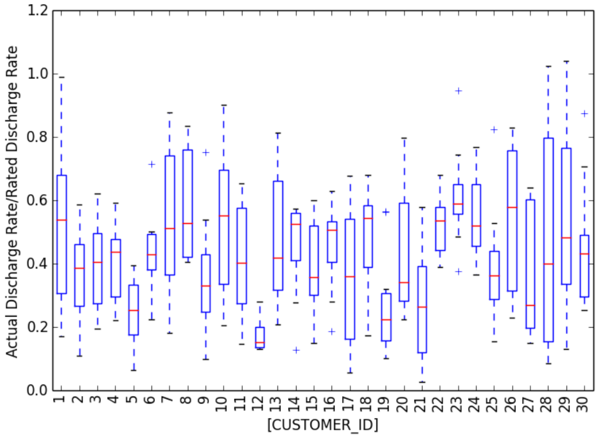

Figure 11: Deviation from rated discharge rates of individual batteries for each customer

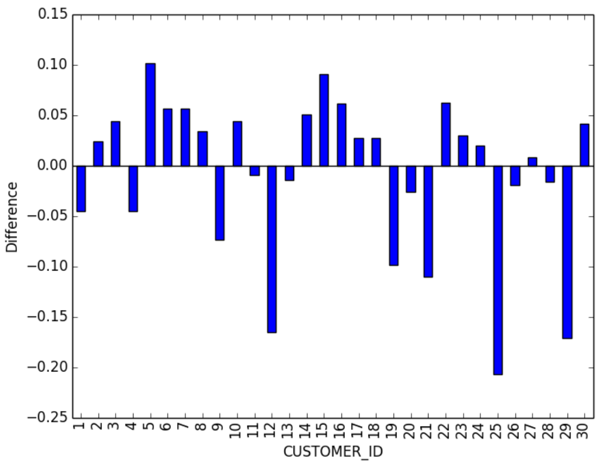

Figure 12: % Difference in cost of energy between usage-based pricing and conventional pricing

was taken as 80%, and rated discharge rate set to 10 hours (equivalent to the outage period). Energy cost for battery charging is based on solar power source and set at 12.5 cents per kWh. All these values are taken from the latest U.S. Energy Information Administration's annual report [18].

The first set of results highlight the need for a usage-based pricing. For a selected set of 30 customers, Figure 10 shows a boxplot of the deviation of the DoD from the rated DoD of the batteries assuming that customers consumed energy from their own individual hypothetical batteries. The y-axis denotes the ratio of the actual DoD versus rated DoD. The boxplot is generated over the consumption pattern during the outage from the period of 30 days and shows distribution across the four quartiles. Essentially, the figure shows the variation of the effect on DoD of the individual batteries across the customers. We see that not only does the median vary significantly across the customers, even the ranges of their 2nd and 3rd quartiles show significant differences. While for around half of the customers, the 3rd quartile ends around 0.5, for the rest it reaches upto 0.8. Similarly, Figure 11 shows the boxplot for discharge rate. Here again, the same trend is seen – there is a lot of variation across the customers in terms of their discharge rates. These two plots together underline the need for usage-based pricing. Different customers withdraw energy from battery in different distributions of DoD and discharge rates if they had their own individual batteries. Thus, when sharing a battery, the customers need to be priced based on their usage-pattern.

Conventional pricing schemes bill the customers solely based on their proportion of the total energy consumption. As a result, they assume the same price for all customers; this doesn't truly reflect the effect each customer has on the battery capacity and lifetime. In contrast, our usage-based pricing scheme denotes a customised price for each customer based on their usage patterns. Figure 12 demonstrates an instance showing the percentage difference between the costs paid by customers using our usage-based pricing and conventional pricing. Here, conventional pricing is based on calculating total shared battery cost (both battery wear and energy cost) for the outage period and dividing it in proportion of energy consumed (simply as measured by the smart meter) by each customer. The plot shows that the difference in costs using the two pricing schemes ranges from +10% to -15%. Therefore, the cost charged per customer using usage-based pricing varies significantly from the conventional pricing method. However, the variation is still reasonable and hence understandable to customers.

6. CONCLUSIONS

The adverse effects of power outages can be reduced by utilities by employing ADI, wherein isolated areas receive backup power through local energy sources such as a storage or micro-generation. In this paper, we provide support for the functioning of ADI based on battery resources. Particularly, given the demand patterns of the customers and battery capacity, we devise a method for optimally scheduling energy supply from the battery during an outage. The optimal schedule ensures that all customers receive a defined minimum percentage of their energy requirement while also attempting to minimise the reliability metrics SAIDI or SAIFI. We have also presented a usage-based pricing mechanism to enable billing the customers for their battery usage during the outage. The pricing mechanism ensures that customers pay for their effect on the battery lifetime and capacity in addition to their actual energy consumption.

We conducted experiments based on the consumption data from Irish CER dataset and actual battery characteristics. Our simulations showed that the linear optimisation based schedule is able to improve SAIDI or SAIFI compared to the equivalent greedy schedule (with fairness constraint). The simulations also showed that our usage-based pricing mechanism is necessary and is able to capture the varying effects of customers on the lifetime and capacity of the shared battery.

For future work, we would like to focus on ADI scenarios that involve renewable generation in addition to batteries. Particularly, we would like to develop techniques for optimising battery life when multiple customers with renewable energy sources are charging the shared battery. Another stream of work will focus on modelling and optimizing schedule for more complex battery technologies such as redox flow batteries. On the pricing front, we would like to develop suitable battery-state based payment schemes for these customers supplying energy. Finally, we would like to bring in game-theoretic guarantees for the pricing mechanisms.

7. REFERENCES

[1] Ibm ilog cplex optimization studio. http://www-03.ibm.com/software/products/en/ibmilogcpleoptistud.

[2] R. Arghandeh, J. Woyak, A. Onen, J. Jung, and R. P. Broadwater. Economic optimal operation of community energy storage systems in competitive energy markets. *Applied Energy*, 135:71–80, 2014.

[3] I. J. Balaguer, Q. Lei, S. Yang, U. Supatti, and F. Z. Peng. Control for grid-connected and intentional islanding operations of distributed power generation. *Industrial Electronics, IEEE Transactions on*, 58(1):147–157, 2011.

[4] M. C. Bozchalui and R. Sharma. Optimal operation of energy storage in distribution systems with renewable energy resources. In *Power Systems Conference (PSC), 2014 Clemson University*, pages 1–6. IEEE, 2014.

[5] R. Carnegie, D. Gotham, D. Nderitu, and P. V. Preckel. Utility scale energy storage systems. *State Utility Forecasting Group. Purdue University*, 1, 2013.

[6] Central Electricity Authority, Ministry of Power, Government of India. Monthly power supply position. http://www.cea.nic.in/monthly_power_sup.html, Feb 2013.

[7] G. Comnes, S. Stoft, N. Greene, and L. Hill. Performance-based ratemaking for electric utilities: review of plans and analysis of economic and resource planning issues, volume i. *Oak Ridge, Ten. Oak Ridge National Laboratory and University of California, Berkeley*, 1995.

[8] S. Drouilhet, B. L. Johnson, et al. A battery life prediction method for hybrid power applications. In *AIAA Aerospace Sciences Meeting and Exhibit*, 1997.

[9] S. Hirodontis and H. Li. An adaptive load shedding method for intentional islanding. In *Clean Electrical Power, 2009 International Conference on*, pages 300–303. IEEE, 2009.

[10] X. Hu, K. Tseng, and M. Srinivasan. Optimization of battery energy storage system with super-capacitor for renewable energy applications. In *Power Electronics and ECCE Asia (ICPE & ECCE), 2011 IEEE 8th International Conference on*, pages 1552–1557. IEEE, 2011.

[11] M. Lee, G. C. Shaw, and V. Modi. Battery storage: Comparing shared to individually owned storage given rural demand profiles of a cluster of customers. In *Global Humanitarian Technology Conference (GHTC), 2014 IEEE*, pages 200–206. IEEE, 2014.

[12] A. Nourai and D. Kearns. Batteries included. *IEEE Power and Energy Magazine*, 8(2):49, 2010.

[13] S. A. Pourmousavi, R. K. Sharma, and B. Asghari. A framework for real-time power management of a grid-tied microgrid to extend battery lifetime and reduce cost of energy. In *Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES*, pages 1–8. IEEE, 2012.

[14] T. Reddy. *Linden's Handbook of Batteries, 4th Edition*. Mcgraw-hill, 2010.

[15] R. T. Roberto Caldon, Andrea Stocco. Adaptive islanded configuration for quality improvement in power delivery systems with distributed generation. *Power Tech*, 2005.

[16] R. T. Roberto Caldon, Andrea Stocco. Feasibility of adaptive intentional islanding operation of electric utility systems with distributed generation. *Electric Power Systems Research*, 78:2017–2023, 2008.

[17] U.S. Energy Information Administration. Annual electric power industry report. https://www.eia.gov/electricity/data/eia861/, 2014.

[18] U.S. Energy Information Administration. Annual electric power industry report. http://www.eia.gov/forecasts/aeo/pdf/0383(2015).pdf, 2015.