DC Picogrids as Power Backups for Office Buildings

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***Abstract*—Office buildings in developing countries employ battery backups with inverters and/or diesel generators to power essential loads such as lighting, air conditioning and computing loads during power cuts. Since these backup solutions are expensive and inefficient, they form a significant proportion of the operating expenses. To address this problem, we propose using a personal comfort system (an illustrative configuration can comprise a LED light and a DC desk fan) that is powered by batteries in computing devices. With this approach, cost savings are realized through two mechanisms, (i) by reducing the dependence on high-power lighting and air conditioning during times of power outage, and (ii) by taking advantage of the variable cost of energy (due to time of use pricing as well as power outages) for charging the battery over the course of the day. Simulations show that the expected energy savings from this methodology are in the region of 26%, compared with the current system. In this paper, we present various architectures for the load-battery combination, a dynamic programming based framework that generates optimal charging/discharging schedules, and an experimental evaluation of the proposed approach.**

I. INTRODUCTION

Many developing countries suffer from intense electricity deficits. For instance, the Indian electricity sector, despite having the world's fifth largest installed capacity [1], suffers from severe energy and peak power shortages. In February 2013, these shortages were 8.4% (7.5 GWh) and 7.9% (12.3 GW) respectively [1]. To manage the deficits, many Indian electricity suppliers induce several hours of power cuts per day. Office buildings are particularly impacted by these power cuts as they consume significant amount of energy [2], [3]. Many of these buildings use a backup power source (such as a Diesel Generator (DG) and/or an inverter with a battery) to power their essential loads (such as lights and fans) during those power cuts [4]. Diesel generators require periodic fuel refills and can generate fumes. Moreover, due to local fuel prices, electricity generated by them could be expensive. In India, cost of diesel-based electricity can be three times as expensive as that from an electricity retailer [5]. This price difference could increase as the diesel subsidies are being gradually removed [6]. Compared to DGs, inverter backups can be simpler (no fuel) and cleaner (no fumes) to operate. However, they incur additional costs due to round-trip losses (from AC to DC and back to AC) [7] and due to limited lifetimes of inverters and batteries [4]. There is a significant price difference between a unit of electricity from the mains and the one from the power backups. It is important to note that office buildings are being exposed to differential electricity prices not only because of power cuts but also due to Time-of-Use (ToU) prices set by utilities and/or due to intermittent energy supplied by renewable sources. In essence, office buildings require an inexpensive solution for powering essential loads during high-tariff hours.

To address this need, we propose DC Picogrids that are based on local energy storage (laptop batteries) for powering personal DC appliances such as LED lights and DC fans as illustrated in Fig. 1. The intended application is to commercial buildings with many collocated laptops, a common occurrence in the IT sector in India. The DC appliances are powered by the laptop battery when there is a grid power outage and an expensive backup source is providing electricity. As a result, the power demand on the battery is equal to only the processor load when grid power is available, and is equal to the combined load of the processor and the devices when power is being provided by a higher-price energy source. Cost savings are realized through two mechanisms, (i) by reducing the dependence on high-power lighting and air conditioning during high-price hours, and (ii) by taking advantage of the variable cost of energy for charging the battery over the course of the day. The proliferation of inexpensive DC appliances in the market [8] makes the picogrid economically viable, while USB Power Delivery Specification 3.1 (which provides up to 100 W of power through USB ports) makes it technically feasible [9].

The key contributions of the paper are: (i) the picogrid architecture including both the energy flow and information flow aspects, (ii) a data-driven approach for modelling the battery charging and discharging characteristics, (iii) an optimization framework for determining battery charging and discharging schedules, and (iv) experimental evaluation of the proposed concepts. The rest of this paper is organized as follows. In Sec. II, we present the mathematical models for battery charge/discharge characteristics, with empirical validation. Sec. III describes the battery schedule optimization for the architecture shown in Fig. 1, as well as variations for other possible architectures. Sec. IV describes experimental and simulation results, while Sec. V provides an overview of related work in this field.

II. BATTERY MODELLING

In this section, we explain the data driven framework for modelling battery characteristics. The models obtained are used in Sec. III to define the state dynamics for the optimization algorithm. The modelling procedure described here is based on a data collection effort from batteries on laptops being used in a commercial building. While the parameters estimated during this study are for the specific set of batteries

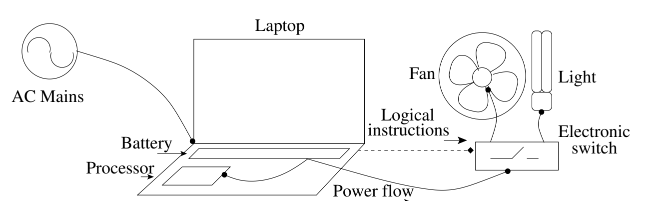

Fig. 1: An exemplary Picogrid.

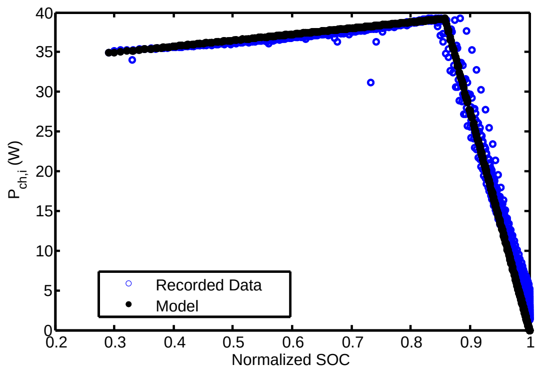

Fig. 2: Experimentally obtained charging rate as a function of the normalized SOC for one laptop battery. Similar characteristics were observed for other batteries in the experiment.

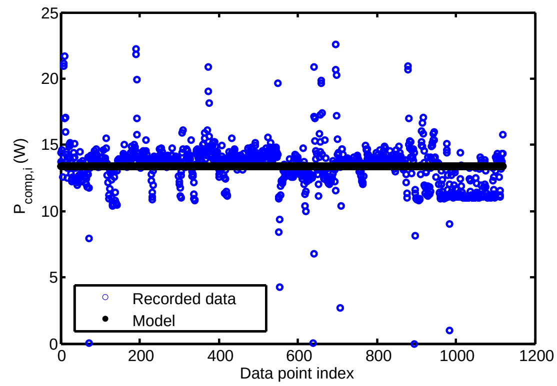

Fig. 3: Experimentally observed discharge rate for one laptop battery, recorded over an extended period of time. Similar characteristics were observed for other batteries in the experiment.

under investigation, the modelling procedure can be applied to any Lithium-ion laptop battery.

A. Charge characteristics

It has been reported previously [10], [11] that the charging rate of a Lithium-ion battery is a function of its state of charge (SOC) at any given instant. To quantify this dependency, we plot the experimentally obtained charging rate against the normalized SOC (the ratio of the actual state of charge to the battery capacity) of the battery. Fig. 2 shows the charging rate characteristics for data obtained over a period of one week for one of the batteries used in the data collection effort. Regression analysis was then used to develop a piecewise linear model of the charging rate as a function of the normalized SOC. Here, $P_{\text{ch},n}$ denotes the charging rate of the n^{th} laptop battery and x_n denotes its normalized SOC. The constants $a_{1,n}$, $a_{2,n}$, $a_{3,n}$ and c_n are obtained from regression analysis.

$$P_{\text{ch},n} = \begin{cases} a_{1,n} \cdot x_n + a_{2,n} & 0 \leq x_n < c_n \\ a_{3,n} \cdot (1 - x_n) & c_n \leq x_n < 1. \end{cases} \tag{1}$$

Note that in the above model, $P_{ch,n} = 0$ when $x_n = 1$. This is consistent with the fact that when the battery is charged to its maximum capacity, no power is drawn for charging the battery even when the laptop is plugged in.

B. Discharge characteristics

During discharge, the battery provides power to laptop components such as the processors, display, cooling fans and GPU (for simplicity, we refer to this as *processor load* in the rest of the paper), as well as any external devices connected to the laptop. Since the external devices draw a constant amount of power, the modelling effort was carried out for the processor load only. It was observed that the discharge rate for each laptop battery was nearly uniform over time, as shown in Fig. 3. Therefore, the power consumption $P_{\text{comp},n}$ by the processor load is modelled to be constant and nominally equal to the mean discharge rate. More conservative estimates may be acquired, if desired, by choosing a high percentile value of the empirical discharge rates.

III. Optimization Methodology

In this section, we describe an optimization algorithm for one type of picogrid architecture. This algorithm uses a combination of the model presented in Sec. II and a schedule of the power tariffs from Fig. 4 over the course of the day, in order to compute charge/discharge decisions for the battery. Several variations and extensions of the basic architecture as well as the optimization methodology are also presented. This optimization framework is important for realising the greatest benefits from the picogrid, because (i) it automatically handles variations in the power tariff, including those caused by power outages, (ii) it requires no user intervention, and (iii) it is robust to vastly different price regimes.

Fig. 1 depicts the setup for laptops with high-power USB ports as defined by USB standards 3.1 [12], connected directly to a fan and a light. The switch to change the on-off status of the devices can be implemented in the form of software. In the following sections, it is assumed that the devices are activated when there is grid power outage and power is being supplied by a diesel generator. As a result, the power demand on the battery is equal to only the processor load when grid power is available, and is equal to the combined load of the processor and the devices when power is being provided by diesel generators.

A. Formulation

From Sec. II, we note that the battery charging rate is given by Eq. (1). Whenever the picogrid devices are activated, let the combined power drawn by the devices be equal to P_{dev}. We discretize the time period of optimization into N intervals, and use the subscript i to index all quantities by time period. The binary variable $w_{\text{dev},i}$ is defined to be equal to 1 when the picogrid devices are active, and 0 otherwise. Then the battery discharge rate $P_{\text{dch},i}$ is given by Eq. (2), with the computational load of the processor being $P_{\text{comp},i}$

$$P_{\text{dch},i} = P_{\text{comp},i} + w_{\text{dev},i} \cdot P_{\text{dev}}. \tag{2}$$

Let us define the decision variable for drawing power from the plug in time period t_i to be $u_{\text{plug},i}$. If the maximum energy capacity of the battery is given by E_{max} and each time interval is of length ΔT, the total power drawn from the plug in period t_i is given by Eq. (3) and the state (normalized SOC) update for the next time step is given by Eq. (4).

$$P_{\text{plug},i} = u_{\text{plug},i} \cdot \left[P_{\text{ch},i} + P_{\text{dch},i}\right]. \tag{3}$$

$$x_{i+1} = x_i + \frac{u_{\text{plug},i} \cdot P_{\text{ch},i} - (1 - u_{\text{plug},i}) \cdot P_{\text{dch},i}}{E_{\max}} \Delta T. \quad (4)$$

The total cost over the optimization time window is the sum of the energy consumed during each time interval of length ΔT, scaled by the corresponding power tariff η_i. This is formulated in Eq. (5), with the total number of time periods in the optimization window being N.

$$J = \sum_{i=1}^{N} \eta_i \cdot u_{\text{plug},i} \cdot [P_{\text{ch},i} + P_{\text{comp},i} + w_{\text{dev},i} \cdot P_{\text{dev}}] \cdot \Delta T. \quad (5)$$

An optimum charge/discharge policy is one that minimizes J over the decision variable space defined by $u_{\text{plug},i}$ with $i \in \{1, 2, \ldots, N\}$, subject to the dynamics defined by Eq. (4) and the constraints,

$$u_{\text{plug},i} \in \{0, 1\} \qquad \text{Binary decision variable,}$$

$$x_i \geq \frac{T_{\text{res}} \cdot (P_{\text{comp},i} + P_{\text{dev}})}{E_{\max}} \qquad \text{Minimum charge level.}$$

The minimum charge constraint is based on a user-defined threshold for the minimum battery reserve time that must be maintained by the algorithm, T_{res}. The scaling factor for T_{res} is calculated assuming that this reserve time must be maintained even with the devices running. We will now apply this formulation to the specific problem at hand.

The power tariff schedule, the power outage times, and the corresponding cost of providing power through diesel generators at the chosen location for the pilot study, are depicted in Fig. 4. The tariff levels and outage times are based on empirical data from the pilot location. The time slots 12:00-1:00 pm and 4:00-5:00 pm are commonly observed power outage times. The per-kWh cost of electricity supplied by diesel generators is calculated using a procedure similar to that found in prior literature [13]. Based on the September 2013 diesel price of INR 56.1 per litre, the per-kWh cost of electricity from diesel generators is INR 18.54.

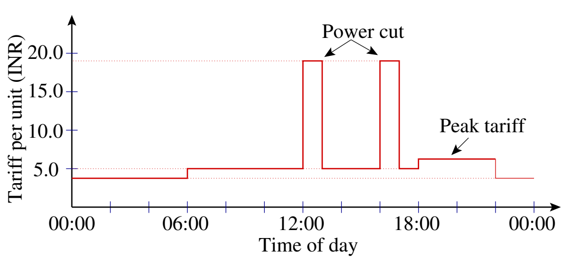

Fig. 4: Variation of power tariff over the course of a day. Declared power cut times are assumed to be from 12pm-1pm and 4pm-5pm, which is when a diesel generator is in use.

B. Computation of Dynamic Schedules

The goal of the optimization algorithm is to compute the decisions for controlling the state of the battery over the length of the look-ahead window. Therefore, there are two natural state variables in the problem: x (the normalized SOC) and t (time). In order to keep the computation simple, both variables are discretized to some desired level of granularity. The minimum time to discharge T_{res} can be easily converted to a minimum SOC constraint using the discharge rate $(P_{\text{comp},i} + P_{\text{dev}})$. Assuming that the SOC at the start of

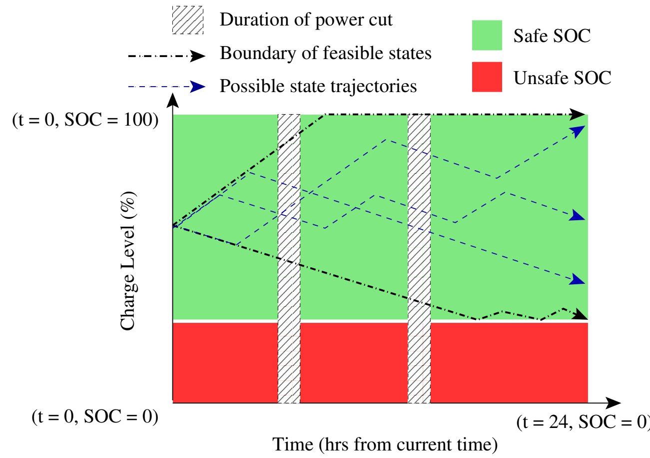

Fig. 5: Representation of battery state dynamics over time. The cost associated with each trajectory should be scaled according to the power tariff applicable at any time.

optimization window $x(t_1)$ is known, the state dynamics can be propagated forward. The state space and the constraints are illustrated in Fig. 5. The reachable portion of the state space is defined by the initial state and the battery dynamics. The uppermost arrow defines one boundary of the reachable state space, which can be realized by assigning $u_{\text{plug},i} = 1 \; \forall i$. The lowermost arrow depicts the other boundary, which can be realized by discharging the battery to its minimum acceptable SOC and keeping it close to this value using short charge/discharge cycles. All other SOC trajectories must remain within the two boundaries defined above.

Dynamic programming is well suited to the mathematical structure of the problem formulation [14], since it allows easy inclusion of time-varying and non-linear objective functions and constraints. The computational complexity of the algorithm scales linearly with the length of the time window and the level of discretization, which is a further recommendation for this approach. The minimum cost trajectory within the feasible set described above, can be obtained by framing the problem as a shortest-path problem, and solving it using Djikstra's algorithm [14]. Let us assume that x (the normalized SOC) belongs to a discrete set of size K, and that the optimization time window is discretized into N time periods. Then we define the following matrices of size $K \times (N+1)$, with the $(N+1)^{\text{th}}$ column representing the end of the final time period: $\mathcal{C}$, each element being the minimum cost to reach state $(x(t_i), t_i)$ where i is an integer, $1 \leq i \leq (N+1)$; $\mathcal{P}$, each element being the SOC at time step t_{i-1} on the optimal path from $(x(t_1), t_1)$ to $(x(t_i), t_i)$; and $\mathcal{D}$, the decision taken at time step t_{i-1} on the optimal path from $(x(t_1), t_1)$ to $(x(t_i), t_i)$.

The initial value of all entries in $\mathcal{C}$ is ∞, except for the initial state $(x(t_1), t_1)$. The algorithm begins by enumerating all the decisions that can be taken at this initial state. With one decision variable $u_{\text{plug},1}$ that can take two values, the number of available decisions is two. This leads to two potential destination states at the time stage t_2. The cost to reach these states is a function of $u_{\text{plug},1}$, and is given by the corresponding term in Eq. (5). The elements of $\mathcal{C}$, $\mathcal{P}$ and $\mathcal{D}$ corresponding to the two potential destination states are updated appropriately. Proceeding similarly, the algorithm enumerates the decisions that can be taken at all the reachable states at time t_i. If a given state is reachable through more than one combination of decisions, only the least-cost path is saved.

Since the maximum number of reachable states is upper bounded by the total number of states KN, and the maximum number of feasible decisions at any state is two, the maximum number of cost evaluations required is $2KN$. The computational complexity thus scales linearly with K and N. The optimum solution can be found simply by selecting the minimum entry in the $(N+1)^{\text{th}}$ column of $\mathcal{C}$ and following the path and decision matrices backwards starting from this entry. Note that the optimal decisions calculated for the optimization time window of 24 hrs are only implemented for the first 2 hrs, following which a new set is computed.

C. Variations of the formulation

1) Additional state constraints: The final state of charge may be constrained to be equal to the initial state of charge, in order to maintain day-to-day continuity. This can be handled by only looking for the shortest path from $(x(t_1), t_1)$ to $(x(t_1), t_{N+1})$. Other state constraints may be similarly imposed, either as a range of acceptable final SOC or as fixed values for the decision variables $u_{\text{plug},i}$ for some t_i.

2) Effect of charging cycles on battery life: The number of charging cycles is known to affect the life of Lithium-ion batteries. However, it is difficult to estimate the number of cycles when the depth of discharge is variable. To simplify this analysis, we assume that each switch from charging to discharging, or vice versa, reduces the life of the battery by a fraction α. Switches are penalized by increasing the stage cost from time t_{i-1} to t_i by the fraction α of the replacement cost of the battery. Assuming $u_{\text{plug},0} = 1$, the objective function in Eq. (5) now has an additional term, $[(1 - u_{\text{plug},i})\, u_{\text{plug},i-1} + u_{\text{plug},i}\,(1 - u_{\text{plug},i-1})]\alpha\, \Delta T$. Everything else remains unchanged. In a similar fashion, the effect of discharging rate can be included as long as the effect can be quantified.

3) Handling unexpected unplug events: Such events invalidate $u_{\text{plug},i} = 1$ decisions for the relevant periods t_i. The optimizer can plan for such events using stochastic modelling of state transitions. Since stochasticity has the effect of introducing greater uncertainty in the forecast, we intuitively expect the effect to be an increase in the threshold for the minimum acceptable SOC. The precise changes will depend on the probability model for the unplug events.

IV. Testing and Simulation

This section describes an experimental study as well as simulations carried out in order to validate the hypotheses presented in this paper. The experimental study implemented the battery management algorithm as a software service on a set of five laptops with processor loads only, and is described in Sec. IV-A. These laptops were taken through the full cycle of battery modelling, software installation, and one week of normal usage with the software service running in the background. In Sec. IV-B we predict the total savings that would be observed on a larger scale, if the combination of battery management and picogrid devices were to be applied to a commercial setting.

A. Testing of battery management software

A software service for charge management was developed and installed on five laptops, as part of a pilot study. The focus of the study was on validation of the battery model and on testing the software under various operating conditions. Therefore, the only load on the battery was that of the laptop's processor. The charging and discharging characteristics for each battery were calculated based on two weeks of usage data. The parameters as described in Sec. II and pertaining to the five batteries, are tabulated in Table I. The software was installed and run on each laptop for one week, after which data logs were processed. The participants were asked to use their laptops as usual throughout the duration of the study.

For the savings estimates presented in this section, the effective power tariffs are assumed to be the same as those shown in Fig. 4. The pattern of behaviour shown by the battery management software during the course of the pilot study, can be inferred from Fig. 6. The solid lines in the upper plot show the actual battery level for one of the five laptops used in the pilot study. Two representative days are depicted, based on the initial level of charge. The dashed lines in the upper plot show the simulated battery levels, had the user not been using the charge management software. It can be seen that these lines rise to 100% and remain there for the rest of the day, since the user was plugged in throughout the day. By contrast, the actual observed battery levels rise and fall depending on the optimal schedule calculated by the software. The lower plot in Fig. 6 denotes the corresponding cumulative energy cost over the course of the two days. It can be seen that the cost saving

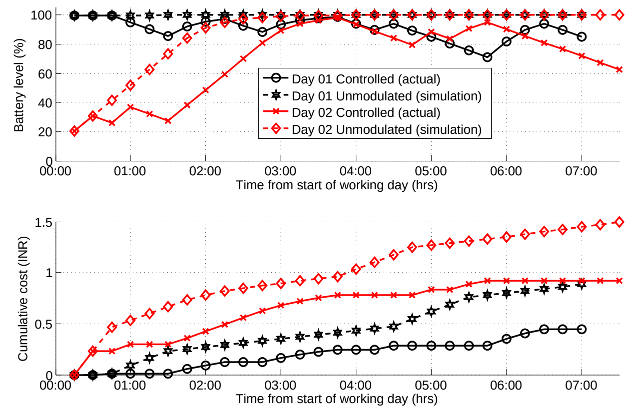

Fig. 6: A comparison of battery level and cumulative energy cost for one of the five laptops in the pilot study. Two representative days are shown, based on the state of initial charge.

User	$a_{1,n}$ (W)	$a_{2,n}$ (W)	$a_{3,n}$ (W)	c_n	$P_{\text{comp},n}$ (W)
A	-1.56	39.32	152.59	0.75	11.75
H	1.95	13.95	77.57	0.80	19.03
M	0.54	37.04	149.77	0.75	17.98
V	4.58	37.99	279.24	0.85	13.65
Z	1.76	35.29	146.46	0.75	15.54

TABLE I: Battery characteristics for the five laptops involved in the pilot study.

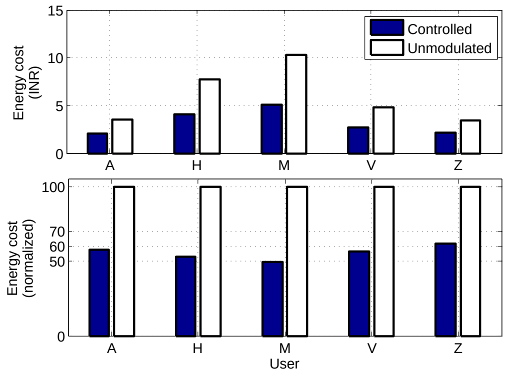

Fig. 7: Energy cost comparison for the five laptops involved in the study. Cost units are in INR, or Indian Rupees.

User	A	H	M	V	Z
Active hours	20.5	39.0	44.5	28.0	19.0

TABLE II: Number of hours for which each laptop was plugged in, during the course of the pilot study.

is close to 50% on Day 01, when the initial battery charge was almost full, and that the cost saving is approximately 35% on Day 02, when the initial charge was quite low. This behaviour can be intuitively explained by the fact that the optimization algorithm has greater freedom to plan the charge / discharge cycles when the initial charge level is far above the minimum threshold, thus resulting in greater savings.

The cumulative savings over one week for the five laptops involved in the pilot study are shown in Fig. 7, while Table II tabulates the number of hours for which each laptop was plugged in. The simulations of the default strategy assume that the laptops are charging whenever they have access to an external power supply. The percentage savings are seen to vary between 35% and 50%, and will potentially increase further if the machines are plugged in for longer periods. It is shown in Sec. IV-B that the delivered benefits will be even higher for the picogrid architecture.

B. Prediction of cost savings

The laptops involved in the study described in Sec. IV-A were used as seeds for generating the battery characteristics for a larger set of laptops. The operations of these laptops were then simulated in the default (always charging), and picogrid modes over a period of 24 hours. The results are presented here. The feasibility of replacing HVAC systems by personal DC devices was tested through an experimental user study. We cannot describe the study in detail in this paper due to a lack of space. However, it was noted that the thermal inertia within the building was sufficient to maintain air quality levels within the bounds set by ANSI/ASHRAE Standard 55-2010 [15] for at least one hour at a time.

Fig. 8 shows the projected savings for a set of 667 simulated laptops. The relative cost savings over a period of 24 hours are shown, with the power outage and tariff characteristics being the same as those depicted in Fig. 4. This implies that the personal DC devices (in this simulation, a fan and LED light totalling to a 10W load) are turned on when there is a power outage, and the central lighting and HVAC are turned off. Based on Table I, this additional load is between 60% and 100% of the computational load. If a typical

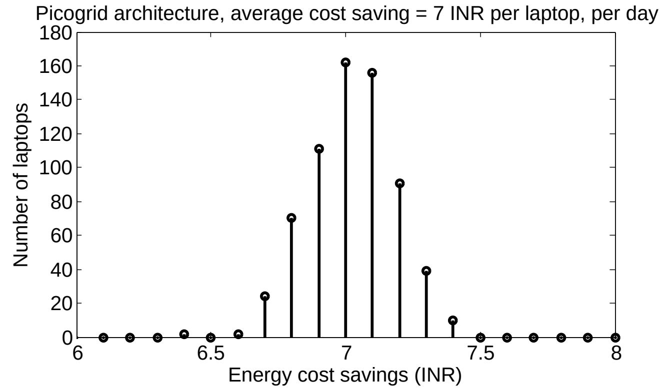

Fig. 8: Projected energy cost savings compared to the default case, for the picogrid architecture. The average fractional cost saving per laptop is 26%.

laptop battery lasts for 4 hours before needing to be plugged in, the same battery will last for at least 2 hours in the picogrid mode. This value is sufficient for handling the type of power cuts assumed in this work. Should there be an unusually long power cut, the battery can be charged using the more expensive backup power source.

The average lighting and HVAC load per person was calculated based on numbers obtained for an office building located in India. The building accommodates an average of 4,132 occupants working in three shifts, and consumes a total of 22.14 MWh per day. Lighting and HVAC loads are observed to account for 75% of this consumption, thus giving average load per person of 167.5 W. Fig. 8 shows that the savings for all the laptop-device picogrid units are between INR 6.5 and 7.5 per day, with an average cost reduction of INR 7 per day (26% in relative terms). This implies that the expected savings for a set of 667 picogrid units over a period of one year (260 working days) would be INR 1,213,940 or USD 20,232. The cost savings delivered by the picogrid are the result of two mechanisms: (i) direct energy savings delivered by replacing the 167.5 W prorated load by the 10 W device load, and (ii) cost savings delivered by the charge schedule optimization algorithm, which reduces the load on the diesel generator. This simulation does not include the effect of reduced load on generator efficiency, but it is expected that consistent load reduction will allow installation of smaller, more efficient generators on the premises.

C. Implementation challenges

Practical application of the picogrid architecture needs to overcome some logistical and technical challenges. Notifications of power cuts need to be conveyed to all laptops seamlessly. This can be implemented through a web service that is polled by each laptop at the beginning of each time period. A second challenge is to prove the validity of the user comfort hypothesis in Sec. IV-B for a larger set of users. Finally, the prediction of power cuts and user schedules needs to be accurate enough to deliver significant cost savings. This can only be evaluated using empirical data. Consequently, a large-scale pilot study is currently being carried out by the authors to evaluate the scalability of the picogrid methodology.

V. Related Work

Charge management of re-chargeable batteries has been investigated previously, in a residential context. Prior studies [16] have described algorithms for reduction of residential energy cost by switching between the grid and a battery in the presence of a real-time electricity pricing regime. However, the battery models are theoretical in nature and the optimal schedules are calculated *a priori*. On the other hand, this work estimates parameters for each battery based on empirical data, and also features re-optimization based on certain trigger events. In addition, it is better suited to commercial locations. Studies have also highlighted the importance of providing batteries with appliances and have described ways for automated identification of power sources [17]. These methods can enable the application described in this paper, to detect power outages and to react to them accordingly.

Commercial charge management solutions for laptop batteries such as Samsung's *Easy Battery Manager* [18], Lenovo's *Power Manager* [19], and FatBatt [20] require active user participation to prescribe appropriate settings. They also primarily focus on augmenting backup power availability, and do not consider the price of energy in their charge management decisions. In contrast, our proposed methodology seeks to perform automated charge management by making use of temporal variations in energy tariffs to drive cost savings. It requires minimal user intervention and is implementable as a software service running silently in the background.

Prior studies have attempted to leverage distributed battery banks available in laptops to reduce peak load through demand response (DR) [10]. However, such solutions cannot be applied in developing countries as they currently lack the infrastructure for DR systems. Our proposed methodology requires minimal infrastructure and can be implemented on each laptop separately because of its decentralized architecture. Dynamic programming algorithms for charge scheduling of battery storage systems have been proposed earlier [21], but they are not efficient enough to guarantee global optimality. In addition, they do not handle load stochasticity or re-optimize in the case of unexpected events.

VI. Conclusion

In this paper, we presented a solution to the increasingly important problem of energy costs for commercial entities in developing countries. The primary problem that we addressed was that of reducing the reliance on expensive power backups during times of power outage. It was noted that commercial buildings contained a large pre-existing capability for energy storage in the form of laptop batteries. We used this fact to present a concept that relies on optimal charge management for batteries on laptops and takes advantage of upgraded incipient hardware capabilities (USB 3.1). The concept was experimentally tested by developing a software service and installing it on a set of five laptops. It was shown that a significant fractional reduction in energy cost was attainable through this concept. Additional simulations for the full picogrid architecture showed that the energy reduction could be as much as 26% of the energy supplied per building occupant. We believe that judicious application of the picogrid concept on a wide scale has the potential to significantly reduce the energy consumption and operating costs of commercial entities. It can also enable a reduction in the reliance on carbon-intensive and expensive fossil fuels for backup power during power outages in developing countries.

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