Lifetime Maximization of Lead-Acid Batteries in Small Scale UPS and Distributed Generation Systems

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***Abstract*—In this paper, we analyze lifetime maximization problem of lead-acid batteries commonly used in small scale Uninterrupted Power Supply (UPS) and distributed renewable energy systems. The aging process of batteries in these systems is a complex phenomenon and depends upon many factors. We consider the most comprehensive lead-acid battery model that is commonly known as the weighted Ah-throughput (Schiffer) model and identify three key factors affecting the lifetime of these batteries: 1) bad recharge, 2) time since last full recharge and 3) the lowest state of charge since last full recharge. Each factor depends on battery state of charge (SoC). An appropriate weighted sum of these three factors dictating the battery life is considered as optimization objective. The appropriate constrained optimization problems for the two common scenarios are solved and SoC-based charge/discharge algorithms are formulated. Simulation results show significant improvement in the lifetime of lead-acid battery (more than 85% in some cases) as compared to the traditional terminal voltage based charge control algorithms.**

Keywords*—Lead-acid batteries, UPS, intermittent grid, state of charge (SOC).

I. Introduction

The need of energy storage devices, such as batteries, pumped water storage, compressed air energy storage, super capacitors and flywheels in power grids is rapidly increasing. An economic report forecasts the global energy storage market, for grid use only, to reach over 10billion USD in 2017 [1]. The choice of an energy storage technology primarily depends on its suitability for a particular application, capital investment and lifetime.

In this paper, we consider the use of batteries as energy storage device in small scale Uninterrupted Power Supply (UPS) and distributed renewable energy systems. The power grids of several Asian and African countries such as India, Pakistan, South Africa, Nepal, etc., lack the capacity to meet load demand, which results in consistent power outages [2] [3]. In these countries, domestic consumers generally install a small UPS system (with an inverter and a lead-acid battery).The energy storage capacity of the battery in such UPS systems is sufficient to power up only few essential loads during the regular power outages [4]. Another small scale application of battery as a storage device is with the intermittent distributed renewable energy systems, e.g., solar photo-voltaic (PV) panels in homes. According to US Department of Energy, growth in solar PV capacity was around 64% between 2000-2013 [5]. In such systems, batteries can be used to smooth out PV power fluctuations and to store excess power for future use. Therefore, efficient utilization of batteries is required to ensure an optimal operation of these applications [6].

Different battery storage technologies are available in the market that can be used with small scale UPS and distributed generation systems. The two prominent battery technologies include lithium ion (Li-ion) and lead-acid batteries[1]. Lead-acid battery is a mature technology, while Li-ion is a relatively recent technology. Li-ion batteries, such as, Tesla Powerwall [7], are highly efficient, have high cycle life (maximum 10,000 cycles) but are extremely expensive $(500 - 1300\$/KWh)$. Lead-acid batteries are relatively cheap $(50 - 200\$/KWh)$ and their efficiency is comparable to Li-ion batteries. However, the cycle life of lead-acid batteries is relatively poor (maximum 1000-1200 cycles). Despite low cycle life, lead-acid battery generally remains the first choice in many domestic applications, mainly due to the low capital cost, wide availability and mature technology [8], [9], [10]. Lead-acid batteries are also predicted to remain cheaper than their alternatives for at least the next two decades [11]. A lead-acid battery typically accounts for 15% of the total capital cost of a small scale solar PV system [12], while it accounts for 50% of the total capital cost of a small scale UPS system [4]. The low cycle life of lead-acid battery can result in its periodic replacements, therefore, improvement in the lifetime of a lead-acid battery in these systems will ensure a better payback for the consumers.

A. Related work

The aging process in a lead-acid battery that results in capacity loss and its eventual replacement in UPS and distributed renewable energy systems is a complex process. The aging mainly occurs due to the following factors [13], [14]:

- Corrosion of positive grid: The thickness of corrosion layer around the positive grid increases with time, which

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[1]Nickel-metal hydride (NiMH) and Nickel-cadmium (NiCd) battery technologies are not popularly used in the applications discussed in this paper due to their poor efficiency.

results in decreased conductivity and reduced capacity.
- Active mass (AM) degradation: The conductivity of active mass (electrolyte) decreases over time and contributes towards the capacity loss.
- Sulphation: The formation of sulphate acid crystals during discharging contributes towards capacity loss.
- Active mass (AM) detachment: The active material may also detach over time and cause capacity loss.
- Acid stratification: The higher concentration of acid in specific areas of the electrolyte can also accelerate the damage.

These factors cause internal damage and none of these can be directly controlled. It is important to note that the capacity loss of lead-acid batteries is largely irreversible but the rate of degradation can be substantially reduced. Battery models are developed in order to associate some or all of these aging factors to externally controllable parameters, such as, terminal voltage and state of charge (SoC). The most commonly used lead-acid battery models are the Kinetic Battery model (KiBaM), Trembley model, Ah-throughput model and Schiffer model (weighted Ah-throughput model). A comparison of these models based on their consideration of different aging factors is given in the Table I [15], [16], [17], [18], [19], [20].

Table I shows that the most comprehensive but complicated lead-acid battery model is the Schiffer model [21] which models all the aging factors, except AM detachment. This model defines the battery life by assuming the actual operating conditions that are typically more severe than those used by manufacturers for standard cycling and lifetime testing.

Table I: Comparison of different lead-acid battery models based on their consideration of different aging factors

Factors Considered	KiBaM Model	Trembley Model	Ah-throughput Model	Schiffer Model
Voltage and SOC	✓	✓	✓	✓
❶ Corrosion	✗	✗	✗	✓
❷ AM degradation	✗	✗	✓	✓
❸ Sulphation	✗	✗	✗	✓
❹ AM detachment	✗	✗	✗	✗
❺ Acid stratification	✗	✗	✗	✓

B. Contributions

In this paper, we consider the Schiffer model that is the most comprehensive but largely ignored (due to its complexity) lead-acid battery model. Our first contribution lies in identifying three important variables in the Schiffer model that have a huge impact on battery aging process. These variables include, i) number of bad recharges, ii) time since last full recharge, and iii) the lowest state of charge since last full recharge. Establishing the dependence of these factors on SoC and ultimately the externally controllable charge/discharge currents is our second significant contribution. SoC of a battery can be estimated from the battery terminal voltage [22]. The accuracy of SoC estimation can be further improved by using sophisticated techniques, e.g., coulomb counting and impedance spectroscopy [23]. It is important to note that for lead-acid batteries terminal voltage provides a simplified method to estimate SoC [22]. Our third contribution lies in the formulation of appropriate optimization problems. The objective of these optimization problems is the lifetime maximization of lead-acid battery based on the identified variables. Simulation results demonstrate that considering the load demand of small scale applications, the proposed approach considerably improves the lifetime of lead-acid batteries (up to 85%) in comparison to the simplified models based traditional SoC control.

The rest of the paper is structured as follows: In Section II we present the system setup and the Schiffer battery model. In Section III, we model the dependence of the important factors that affect battery lifetime and establish their dependence on SoC. In Section IV, we develop the constrained optimization problems for the two scenarios discussed in this paper and provide their solution. Simulation results and discussion is presented in Section V, while the paper is concluded in Section VI.

II. System Model and Schiffer Battery Model

In this section we describe our system model and discuss the Schiffer battery model.

A. System Setup

Fig. 1 presents a system setup for small scale residential system with battery storage. Primary source of energy is power grid while solar PV panels are also installed. A charge controller module is used to charge/discharge the lead-acid battery either from the main grid or the solar panels and also ties excess power to the grid. In the first scenario (scenario 1), we assume an intermittent and unreliable power grid without the consideration of solar PV panels in the system. In this case, inverter, charge controller and a small capacity lead-acid battery constitute a UPS system that provides power to few essential loads during the power outages. In the second scenario (scenario 2), we assume a reliable grid and solar PV panels. In this case, a battery is used to store the excess power produced by the solar panels and can be used for peak demand shaving or at times when the tariff is relatively higher, a common research problem in developed countries with stable grid.

Several other scenarios, e.g., intermittent grid with solar panels and battery or the two way flow of power between solar panels and grid, etc., are also possible but they are not considered with in the current scope of this paper.

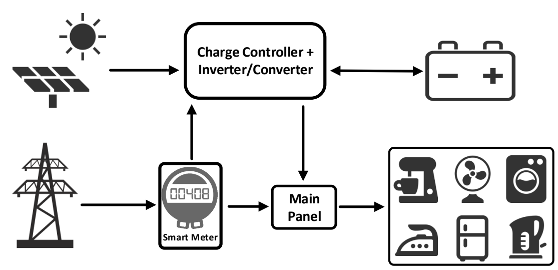


Figure 1: System Setup

B. Schiffer Battery Model

Schiffer model builds upon the basic Ah-throughput model. This model multiples the nominal Ah-throughput of battery by different factors in order to model the actual real life battery operating conditions. The high level working of Schiffer model is explained with the help of a flow diagram given in Fig. 2. $V_B(t)$ is the terminal voltage and $SOC(t)$ is the State of charge of the battery at time t. In the model (shown in Fig. 2), $V_B(t)$ is calculated by using a modified Shepherd equation, while $SOC(t)$ is determined by integrating the battery current denoted by $I(t)$, as given by Equation 1 & 7 in [21]. The values of $V_B(t)$ and $SOC(t)$ are then used to compute the capacity loss due to the active mass degradation and corrosion to update the battery parameters. At any time t, the normalized remaining battery capacity $C_{rem}(t)$ can be computed using the following equation,

$$C_{rem}(t) = C_d(0) - C_{corr}(t) - C_{deg}(t) \quad (1)$$

where, $C_d(0)$ is the initial normalized battery capacity, $C_{corr}(t)$ is the capacity loss due to corrosion and $C_{deg}(t)$ is the capacity loss due to degradation till time t [21].

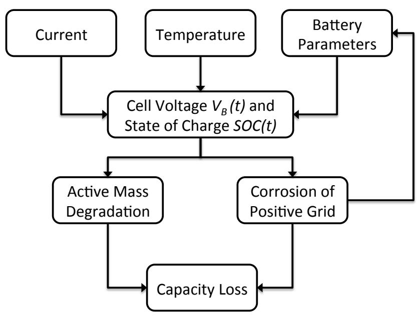


Figure 2: Flow Diagram of the Shiffer Battery Model

From Schiffer model, three significant factors that influence the values of $C_{corr}(t)$ and $C_{deg}(t)$ are identified. These are:

1) The number of bad recharges, denoted by $n_1(t)$.
2) Time since last full recharge, denoted by $n_2(t)$.
3) The lowest state of charge since the last full recharge, denoted by $n_3(t)$.

Active mass (electrolyte) degradation depends on the number of bad recharges. Thus, minimizing the number of bad recharges can significantly slow down the aging process. The size of sulfate crystals increases if the time since last full battery recharge increases. The bigger sized crystals increases the mechanical stress on the active mass and accelerates the battery aging process. As soon as battery is fully recharged the size of sulfate crystals returns to normal. Therefore, regular full battery recharges can increase the battery lifetime. Finally, if the lowest state of charge of a battery since its last full recharge is close to zero then the concentration of acid in specific areas of electrolyte (acid stratification) increases, which accelerates the electrolyte damage. Maintaining a high value of SoC can also improve battery lifetime. By considering these three factors in our algorithm design, we can significantly increase the lifetime of lead-acid battery in small scale UPS and DRES. Thus, we use the Schiffer model in reverse, i.e., from the capacity loss equations, we determine significant factors that effect battery lifetime. Using these factors, we determine appropriate $SOC(t)$ values to calculate the battery charging/discharging currents.

It is important to note that based on our approach, it no longer remains necessary to consider the complicated Schiffer equations. Moreover, the consideration of new variables does not significantly increase the complexity of the proposed approach over traditional controllers (because we are still controlling charging/discharging current)[2].

III. Modeling the Factors that Affect Battery Lifetime

In this section, we establish the dependence on $SOC(t)$ and derive a weighted sum of these three factors for battery lifetime maximization.

A recharge becomes bad if at the end of the charging interval the maximum value of $SOC(t)$ attained, lies anywhere between 0.9 and 1. After any recharge interval, t, the value of $n_1(t)$ can vary between $0 \leq \Delta n \leq 1$. The maximum value of $\Delta n = 1$ occurs, when the attained $SOC(t)$ is 0.95 at the end of the recharge interval. The variation of Δn with $SOC(t)$, attained at the end of the recharge interval is shown in Fig. 3 (it is defined by Equation 20 in [21].). Assuming, $n_1(0) = 0$, we can model $n_1(t)$ by the following equation,

$$n_1(t) = \begin{cases} \Delta n; & \text{only at end of charging period} \\ 0; & \text{otherwise} \end{cases}$$

Thus avoiding bad recharges and minimizing the total number of bad recharges can significantly boost battery lifetime. This can be achieved either by fully recharging the battery whenever possible or to avoid recharging or restrict recharging to certain limits if there is a chance that at the end of charging interval $SOC(t)$ could end up between 0.9 and 1.

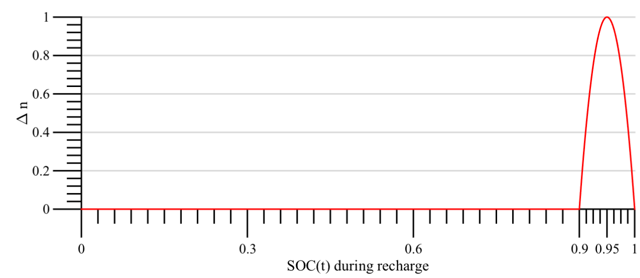


Figure 3: Bad Recharge: The variation of Δn with $SOC(t)$ attained at the end of the recharge interval [21]

Let, $t_o > 0$ denotes the last time when the lead-acid battery was fully charged. The fully charged battery can either discharge due to application demands or self-discharge. We can recharge battery but unless it is fully recharged, the size of sulfate crystals will not return to normal. Thus, at any time $t > t_o$, it becomes important to minimize the time since last full recharge. We model $n_2(t)$ as,

$$n_2(t) = \begin{cases} t - t_o, & \text{if: } SOC(t) < 1 \,\&\, t > t_o \\ 0 & \text{if: } SOC(t) = 1 \,\&\, t = t_o \end{cases}$$

It is also important to note that as soon as the value of $SOC(t)$ reaches 1, we reset the value of $t_o = t$.

The third significant factor that affects lead-acid battery lifetime is the minimum SoC value attained by the battery since last full battery recharge, denoted by $n_3(t)$. Initializing, $n_3(t_o) = 1 + \epsilon$, we model it as,

$$n_3(t) = \begin{cases} SOC(t) & \text{if: } SOC(t) < SOC(t-1) \,\&\, t > t_o \\ SOC(t-1) & \text{if: } SOC(t) > SOC(t-1) \,\&\, t > t_o \\ 1 + \epsilon & \text{if: } SOC(t) = 1 \,\&\, t = t_o \end{cases}$$

[2]The additional complexity could be in the measurement of SoC values and management of more variables.

The value of $n_3(t)$ is always equal to 1+ϵ, where, $\epsilon = 0.001$ represents a very small tolerance factor at times $t = t_o$, i.e., when the battery is fully charged. At other time slots, i.e., $t > t_o$, we compare the current $SOC(t)$ value with the previous $SOC(t-1)$ value. In this time slot, the value of $n_3(t)$ is equal to $SOC(t)$ if $SOC(t) < SOC(t-1)$, otherwise, $n_3(t)$ is equal to $SOC(t-1)$. Maximizing the value of $n_3(t)$ is therefore, important for battery lifetime maximization.

In order to simultaneously capture the impact of all the significant factors that affect battery lifetime, we define a weighted sum of $n_1(t)$, $n_2(t)$ and $n_3(t)$. Again the Schiffer model helps us derive the relative weights (derivation given in Appendix A.).

$$\mathcal{S}(t) = \frac{1}{10.8}n_1(t) + \ln(n_2(t)) + \ln(|1 - n_3(t)|) \qquad (2)$$

In order to have more control in adjusting the relative importance of these factors, we also introduce additional arbitrary constants $\alpha_1 > 0$, $\alpha_2 > 0$ and $\alpha_3 > 0$ and redefine (2) as,

$$\mathcal{L}(t) = \frac{\alpha_1}{10.8}n_1(t) + \alpha_2 \ln(n_2(t)) + \alpha_3 \ln(|1 - n_3(t)|) \quad (3)$$

The additional weights provide more flexibility as these can be adjusted independent of the Schiffer model. Minimizing (3) in every time slot will then maximize the battery lifetime.

In the next section, we discuss the load demand constraints of the two scenarios for which we want to maximize the battery lifetime and develop our optimization problems.

IV. Optimization problem formulation and solution

In this section, we develop optimization problems for our applications with the objective of battery lifetime maximization and constraints of load current, battery SoC and charging/discharging current. Let, $P_D(t)$ denotes the power demand of a consumer (without battery) at time t. In the charging mode, battery adds to overall load. Let, $P_L(t)$ denote the total power demand of a consumer including the battery during the charging mode. This load demand can be fulfilled by the combination of power drawn from the main grid, solar PV panels and battery. Power balance equation is given as,

$$P_{GL}(t) + P_{SL}(t) + P_{BL}(t) \geq P_L(t) \ ;\forall t \qquad (4)$$

In this equation, $P_{GL}(t) \geq 0$, $P_{SL}(t) \geq 0$, and $P_{BL}(t) \geq 0$ respectively denote the power drawn from the grid, solar PV panels and battery at time t. The power, $P_{GL}(t)$, drawn from the grid can be used for two purposes, i.e., to meet a portion of consumer demand $P_{GD}(t)$ and to charge the battery, $P_{GB}(t)$. Similarly, the power $P_{SL}(t)$ extracted from the solar panels can also be used to meet a portion of consumer demand $P_{SD}(t)$, and to charge the battery $P_{SB}(t)$. However, the power provided by the battery can only be used to meet a portion of consumer demand, denoted by $P_{BD}(t)$. Mathematically,

$$P_{GL}(t) = P_{GD}(t) + P_{GB}(t) \ ;\forall t \qquad (5)$$

$$P_{SL}(t) = P_{SD}(t) + P_{SB}(t) \ ;\forall t \qquad (6)$$

The constraint on fulfilling the consumer load demand from available sources can now be expressed as,

$$P_{GD}(t) + P_{SD}(t) + P_{BD}(t) \geq P_D(t) \ ;\forall t \qquad (7)$$

The usage of these equations for both the scenarios considered in the paper is straightforward. For example, in scenario 1, there are no solar PV panels, hence $P_{SL}(t) = 0$ and $P_{SD}(t) = 0$.

Let $I(t)$ denote the total battery current at time t. Maximum battery charging and discharging currents, denoted by $I_{bat}^{c,max}$ and $I_{bat}^{d,max}$ are always specified by the battery manufacturer, which results in the following two constraints,

$$I(t) \leq I_{bat}^{d,max}, \ ;\forall t \text{ when battery is discharging} \qquad (8)$$

$$I(t) \leq I_{bat}^{c,max}, \ ;\forall t \text{ when battery is charging} \qquad (9)$$

The charge controllers available in the market employ lower/upper voltage control limits in order protect battery. Since our approach is based on SoC, we define lower/upper limits on SoC i.e. $SOC_{min,limit} \geq 0$ and $SOC_{max,limit} = 1$.

$$SOC_{min,limit} \leq SOC(t) \leq 1, \ \forall t \qquad (10)$$

The final constraint that we discuss here is a consequence of limited battery capacity and (10). The battery capacity generally used in specified systems during power outage hours is just sufficient to provide power to few essential loads for limited time duration. Therefore, the value of load demand, i.e., $P_D(t)$, during the outage hours is always significantly less than the consumer load demand in the non-outage hours. However, due to intermittent nature of the grid, the energy stored in the battery might not be sufficient to even provide the limited load demand. To deal with such situations and to respect $SOC_{min,limit}$, we define,

$$P_{bat}^{avail}(t) = \left(\frac{SOC(t) - SOC_{min,limit}}{\Delta t}\right) \times C_N \times V_B(t) \quad (11)$$

where, C_N is the nominal battery capacity, $V_B(t)$ is the terminal voltage at time t and Δt is the outage duration. The load demand is given by the following equation,

$$P_D(t) = \begin{cases} P_D(t) & P_D(t) < P_{bat}^{avail}(t) \\ P_{bat}^{avail} & P_D(t) > P_{bat}^{avail}(t) \end{cases} \qquad (12)$$

Only when the load demand of the consumer during outage hours is greater than the power that can be provided by the battery we clip load demand to $P_{bat}^{avail}(t)$. Please note that this situation will never arise in scenario 2.

Over the complete lifetime of the battery we have to draw power from the main grid, solar PV panels and charge/discharge battery in such a way that (3) is minimized. Thus we can define the following objective function and the optimization problem,

$$\min_{P_{GD}(t), P_{SD}(t), P_{BD}(t)} \sum_t \mathcal{L}(t) \qquad (13)$$

subject to constraints (4) - (10)

The optimization problems can be easily solved using fmincon solver in Matlab (or some similar solver). Alternatively, appropriate algorithms can also be developed that could be implemented in practical battery charge controllers.

V. Simulation Setup and Results

The lifetime of a lead-acid battery used in UPS system and DRES is evaluated based on the developed optimization problem. We will compare our approach with a simple voltage based control that is widely used in practical systems. Battery lifetime is defined as the total number of days after which the remaining battery capacity reaches 80% of its nominal capacity [13].

A. Simulation Setup

Scenario 1 considers a small scale UPS system without solar PV panels with an intermittent power grid all year long. The daily power outage pattern used in our simulations was recorded by the authors in Lahore Pakistan and is shown in Fig. 4. The power outage pattern has seasonal or sometimes monthly variations but in our simulation setup we consider it fixed.

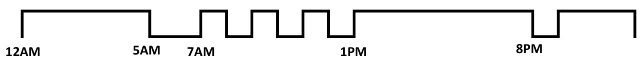


Figure 4: Power outage pattern

In scenario 1, we consider a middle income urban home in India or Pakistan. The total power demand during the non-outage hours (depending on the season) varies between 1-5KW. It is a common practice in these countries to deploy a small scale UPS system in homes to power up few essential appliances, such as, lights, fans and mobile chargers. Thus, in our setup, we assume an inverter with a power rating of 1000VA and a 12V lead-acid battery with 220Ah nominal capacity to meet the critical load requirements during outage. Datasets of power consumption values are not available,therefore, we model the power demand during outage hours as a random value between 200-800W (using MATLAB random function). The maximum charge current for the battery is assumed to be 22A, while the maximum discharge current is limited to 66A. The value of discharge current is sufficient to provide the maximum load demand of 800W during the power outage hours without causing damage to the battery. The parameters required for the Schiffer model are based on the values presented in [13], [21]. The value of $SOC_{min,limit}$ is assumed to be 0.3. The values of weights, i.e., α_1, α_2 and α_3 are all set equal to 1.

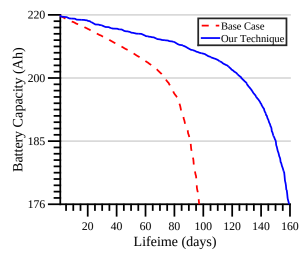
Scenario 2 considers solar PV panels with battery and a reliable power grid. Load demand is fulfilled by a combination of power drawn from the grid, solar PV panels and battery. The home power demand is modeled using the household power consumption dataset provided by the UCI machine learning repository [24]. The hourly solar power data was obtained form PVWatt that is made available by National Renewable Energy Laboratory (NREL) [25]. We used the dataset for a New-York based solar PV system with 2KW rating. All other parameters including battery specifications and Schiffer model parameters are assumed to be the same as considered in scenario 1.

It is important to note that in scenario 2, for battery lifetime improvement, some extra energy produced by the solar PV panels would be discarded (e.g., to avoid bad recharges, etc.). In the results and discussion section, we will compare the cost of the wasted energy with the gains provided by the enhancements in the battery lifetime. It is also important to note that in case of two way power transactions between the power grid and solar panel, the consumer can maximize his/her advantage by selling the extra energy (that is not useful for battery lifetime maximization and otherwise wasted) back to the grid. However, this scenario is not considered in this paper.

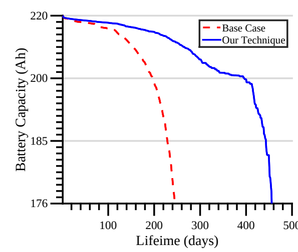
B. Results and Discussion

For comparison, we consider as our base case, a simple charge controller that works on terminal voltage control limits. For the 12V lead-acid battery considered in our simulation setup, the base case control algorithm sets an upper and lower voltage thresholds respectively as 13.5V and 10.8V. This is a widely used control algorithm in many practical charge controllers [26].

Fig. 5 presents the lifetime of lead-acid battery achieved by our approach and the base case for the two scenarios. The lifetime is defined as the total number of days after which the nominal battery capacity of 220Ah to reach 176Ah (i.e., 80% of 220Ah). In scenario 1, we are considering a consistent pattern of 7hour power outages per day, which is extremely harsh. The base case is only able to provide a lifetime of 109 days. On the other hand, using our approach battery lifetime can be extended up to 157 days. This indicates more than 44% increase in battery lifetime[3]. Similarly, in scenario 2, which is less harsh on battery than scenario 1, the base case provides a battery lifetime of 243 days as compared to 454 days for our approach (more than 85% improvement). These improvements in the battery lifetime results from avoiding bad recharges, minimizing the time between full recharges and maintaining a high value of SoC between full recharges.



(a) Scenario 1



(b) Scenario 2

Figure 5: Battery Lifetime Results

In Table II, we present the total number of bad recharges for both the scenarios. We can observe that in scenario 1 (the harsh scenario), the number of bad recharges for the base case are 13.4, while for our approach there are only 1.2 bad recharges. Similarly, for scenario 2, the total number of bad recharges for the base case are 12.3, while there are 0 bad recharges for our approach. It is interesting to note that our strategy can completely avoid bad recharges in scenario 2 because we track SoC and always discard excess energy produced by the solar panels if there is a chance of $SOC(t)$ ending up anywhere between $0.9 < SOC(t) < 1$. The other two factors, i.e., $n_2(t)$ and $n_3(t)$ also play a significant role in improving the lifetime of lead-acid battery in both the scenarios.

Table II: Total number of bad recharges

	Scenario 1		Scenario 2	
	Base Case	**Our Approach**	**Base Case**	**Our Approach**
Total # of bad recharges	13.4	1.2	12.3	0

Finally, we discuss and compare the cost of excess energy produced by solar panels in scenario 2 that is discarded in our strategy to avoid bad recharges. The total energy stored in the

[3]It is important to note that in developing countries with power outages, in order to avoid replacements, a typical consumer keeps on using the battery even after its capacity drops below 80% of the nominal capacity, albeit with reduced performance.

battery by the base case charge controller is 15816KWh over its lifetime of 243 days. On the other hand, the total energy stored in the battery by proposed technique in same number of days is 15230kWh. This energy is wasted to avoid bad recharges. Assuming an average electricity price of \$0.1215/KWh in USA [27], the total cost of wasted energy is equal to $(15816 - 15230) * 0.1215 = \$71.2$. The cost of 220Ah battery is \$305 [28]. Our algorithm provides a lifetime improvement of 86.8% over the base case that translates to $305 * .868 = \$264.8$ as savings. The net benefit of our strategy is therefore, $264 - 71.2 = \$192.8$. Alternatively, to avoid energy wastage, elastic home loads such as heaters/water pumps could be added.

VI. CONCLUSIONS

In this paper we maximize the lifetime of lead-acid batteries commonly used in small scale UPS and distributed renewable energy systems. We revisited the most comprehensive lead-acid battery model (known as the Schiffer model) and identified three important factors, i.e., the number of bad recharges, time since last full recharge and the lowest state of charge since last full recharge. These factors are entirely dependent on battery SoC. We then developed a weighted sum of these factors as our objective function and developed appropriate constrained optimization problems for the two scenarios considered in this work. These optimization problems can be readily solved to obtain SoC-based charge/discharge algorithms. Results showed a significant improvement in the lifetime of lead-acid battery (more than 85% in some cases) as compared to the traditional terminal voltage based charge control algorithms.

APPENDIX

We start with equation (15) in [21] and re-write it in terms of the variables defined in our paper,

$$f_{SOC}(t) = 1+(A + B \times (|1 - n_3(t)|)) \times f_I(I, n_1(t)) \times n_2(t) \tag{14}$$

where, A and B are constants and the value of $A << B$. Dropping A, simplifies (14),

$$f_{SOC}(t) \approx 1+B \times (|1-n_3(t)|) \times f_I(I, n_1(t)) \times n_2(t) \tag{15}$$

Next we substitute the value of $f_I(I, n_1(t))$ (equation (19) in [21]) into (15) to obtain,

$$f_{SOC}(t) \approx 1 + B \times (|1 - n_3(t)|) \times \exp^{\frac{n_1(t)}{10.8}} \times n_2(t) \tag{16}$$

To obtain a weighted sum of the three factors $n_1(t)$, $n_2(t)$ and $n_3(t)$ for use as an objective function for our optimization problems, we drop the constant 1 and the scaling factor B and then take the natural logarithm of the resulting expression, which leads us to our desired equation (2).

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