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Priority Load Management for Improving Supply Reliability of Critical Loads in Healthcare Facilities Under Highly Unreliable Grids

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Abstract: Many developing countries suffer from unreliable grids and rolling blackouts on a daily basis. Losing electricity in healthcare facilities can be detrimental to human life and the required health services. Thus, it is often necessary to keep critical loads operational even if the grid experiences a blackout. Such support is usually provided using battery storage or diesel generators. In the system design phase, it is often unknown how the priority-based load management will impact the battery life, sizing of the optimal battery, or operational cost in the long run. This paper presents a comprehensive analysis of a priority load management strategy for healthcare facilities in areas of highly unreliable grids. A grid-connected battery backup system is used for the evaluation. To operate the system, a priority-based dispatch algorithm is developed, which classifies medical loads into three tiers based on their criticality. Synthetic medical facility load profiles and blackout patterns are constructed to test the algorithm. The battery model was enhanced with the introduction of aging calculations spanning multiple years. It was found that the priority-based algorithm improved the reliability served to the most critical loads at the expense of the least critical. The load priority strategy slowed the battery pack degradation over time and reduced the number of replacement cycles, which is financially favorable in the long run. Finally, some insights for designing such a backup system are provided.

Keywords: priority load management; demand response; energy storage; blackouts; battery aging; backup energy

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1. Introduction

Over the last century, electricity has transformed human civilization and the quality of life. The massive technological advances are made, in part, due to the accessibility and the reliability of the power system grid and constant access to electricity. Despite the massive growth and connectivity in the electricity supply in developed countries, the situation is not as auspicious in developing and underdeveloped parts of the world. It is estimated that roughly 1.5 billion people globally do not have a stable electricity supply [1]. Especially in the developing part of the world, energy shortage is a common problem, and blackouts occur quite frequently. This situation is particularly severe in developing countries in Africa, South Asia, and South America, where decades of under-investment combined with rapid population growth and urbanization have made multiple-hour blackouts a daily reality. As an example, in Nigeria, the total estimated demand of the country is around 8 times the current generation levels [2]. Thus, blackouts for multiple hours are a daily phenomenon. This fact has led individuals and businesses to rely on backup solutions, mostly petrol and diesel generators, to provide for their energy needs.

Besides the general lifestyle disruption, blackouts can cause significant damage to the operation of critical facilities such as hospitals, fire services, and communication facilities, which may lead to losses of human lives or monetary value. In general, the critical loads are supported by diesel generators, which are economically expensive and have a significant carbon footprint. To minimize the operational cost during a blackout, only critical loads are usually operated. Thus, priority-based load management plays a significant role in such cases.

Over the last decades, many priority-based load management techniques have been proposed in the literature. In Sonmez and Bagriyanik [3], a novel priority-based load management technique was proposed, which focused on using selected electrical loads to minimize energy usage while maintaining the same thermal comfort. Instead of fixed priority, the authors proposed a dynamic priority scheme following their thermal limit. Such dynamic changes are quite effective, given that the electricity grid is always present. However, it will be challenging to adopt such methods during blackouts.

Faxas-Guzman et al. [4] developed a control algorithm for an off-grid hybrid solar PV and battery system for optimal energy management of the connected system loads and the battery storage while guaranteeing a reliable energy supply for critical loads. The purpose of priority load control algorithms was to provide energy to the highest priority loads at the expense of the less critical loads. Using this priority load management technique increases the reliability of critical loads, protects the battery bank, and, in summation, minimizes the total life cycle cost of the system. Although the above claim was made, no analytical study on the battery life cycle, battery pack optimization, or levelized energy cost in the long run was presented in this work.

In Soudan and Darya [1], three intelligent energy dispatch algorithms were proposed based on an off-grid PV-battery-diesel system. The algorithms aimed to reduce the use of diesel generators and extend their lifespan by maximizing the usage of the PV and the battery. Despite being effective algorithms, the work did not take the impact on the battery life cycle into consideration or optimize the battery sizing.

Another priority-based load management algorithm is proposed in [5] based on a residential complex. The main objective of the strategy is to regulate PV, battery, and grid usage to minimize the electricity bill. A variable tariff system is taken into consideration, deploying different energy sources to support the load in different parts of the day and also aimed to minimize grid imports. The algorithm successfully reduced the bill and optimized the utilization of the PV and the batteries. However, the work did not consider the optimization of the battery sizing or the long-term impact on the battery life because of the proposed strategy. A similar approach was followed by Fernandes et al. [6] in which a priority-based strategy was proposed in a residential system. The output suggests that continuous adaptive load curtailment during a demand response event improved energy usage, ensured an adequate comfort level for the consumers, and reduced the total energy consumption. Further works on priority-based load management can be found in [7], where loads were operated based on peak schedule, off-peak schedule, customer priority, and blackout considerations. As a result, a smart home management system is developed to minimize energy consumption while keeping the home optimally operational. However, the impact on the loads during the blackout was not thoroughly investigated as a focused problem. A similar problem is being solved by [8] using Enhanced Differential Evolution (EDE) and the Genetic Algorithm (GA) to optimally schedule the residential loads while coordinating among renewable energy sources, battery storage, and grid availability. Similar to the previous work, battery charging and discharging were not taken into consideration, and the impact on the life cycle was unknown.

Alahmed and Muhaini [9] proposed smarter demand response actions that will ensure a minimized operational cost without shedding critical or essential loads for a grid-tied microgrid (PV, wind, and battery energy storage system) by using a neuro-fuzzy control algorithm. It determines the load category and corresponding amount that should be curtailed by intelligently and temporally ranking the loads in the system based on multiple factors, such as the load category nature, reliability indices, time, and generation availability. The work highlighted the significant benefits of using priority load management that optimizes energy utilization and serves the critical loads in moments of energy deficit. However, similar to other works, the authors did not consider optimizing the battery packs for the system and the impact of the strategy on the battery life cycle.

In Gelchu et al. [10], the authors implemented demand-side categorization to optimize PV-battery sizing in a rural microgrid. Since the system is islanded, the complexity was less. However, the authors clearly demonstrated that priority-based load categorization can reduce the PV and battery sizing significantly and reduce the levelized energy cost. Nevertheless, the authors omitted the long-term impact on the battery life due to load categorization and their replacement cost over the longer term. Basaran et al. [11] investigated hybrid renewable energy systems based on PV and wind with different storage backup systems to find out possible interactions with grid availability. The proposed energy management system offers a 10% increase in the system performance efficiency. However, no focus was given to the impact on the battery life cycle while implementing the process. Thornburgh and Krogh [12] have developed a software tool to assess the demand side management. Based on the smart meter data, they have suggested a rule-based strategy to operate the different loads smoothly. In another investigation by Azeem et al. [13], the authors designed a fuzzy logic-based load curtailment system based on human activity tracking. In this work, battery charging and discharging were thoroughly investigated and taken into consideration while designing the fuzzy rule table. Regardless, the long-term impact of frequent charging and discharging was not investigated, and battery performance was assumed constant. In Rajbhandari et al. [14], load priority is being used to minimize the blackouts in islanded microgrids integrated with PV and storage systems. It is demonstrated that priority loading reduces the blackout hours significantly while improving the users' satisfaction by 5%. However, the impact of priority loading on battery charging, discharging, and life cycle were not investigated. In Ogunjuyigbe et al. [15], a genetic algorithm-based load manager is proposed for a microgrid where loads are allocated for residential houses in a cost-effective manner. The strategy obtained high successful allocation loads, given that the supply of PV power is limited. However, the impact of such categorization on battery storage in the long-term operation was not analyzed.

It is evident from the literature survey that priority-based load management offers energy usage reduction, support to the critical load, and better operational conditions. However, the impact of the priority loading operation on the different loads, charging, and life cycle of the batteries, as well as the levelized energy cost for long periods of operation, is not investigated in depth. Thus, this work is conducted to do a thorough investigation and comparative assessment between priority- and non-priority-based load management and their impacts on the system operation, battery life cycle, and economic outlook in the long run. A hospital premise has been chosen for the case study since it is one of the facilities that requires priority load operations during blackouts. Three extensive studies have been performed. In Study 1, a fixed blackout pattern is considered as 12 h/day. Under that condition, the behavior of different loads, battery charging and discharging, and levelized energy cost (LEC) for 10 years has been studied, and a comparison has been made between priority and non-priority operation. In Study 2, to make the study robust, different blackout hours varying from 4 to 20 h were considered. Under each scenario, priority and non-priority operations are compared, load behavior is studied, and battery storage performance is observed. This study is further extended to study 3, where different charging rates of the battery packs are considered. The purpose of the study was to examine the impact of the battery charging rate on priority and non-priority operation, battery life cycle, and LEC. Under these three studies, recommendations are made on the effectiveness of priority load operation over non-priority strategies. Besides the impact on the battery life cycle, LEC is thoroughly investigated, and valuable insights are provided. In the above-mentioned three studies, a blackout pattern is considered as a rolling blackout. In many African countries, such as Nigeria, where the disparity between electricity demand and generation is significantly high, the blackout pattern resembles both rolling and stochastic behavior, depending on the region [16]. Thus, we extended our study to incorporate the stochastic blackout pattern and compared the results with the rolling blackouts. Furthermore, a brief comparative study has been done assuming diesel generators and PV are connected in the system. It can be seen clearly that the PV-battery combined system is better than the standalone battery system, while the diesel generator-based system would be economically the poorest choice compared to the other two. A sensitivity analysis of economic indicators is also provided to highlight the effect of different economic indicators on the cost of the system. It is envisaged that this paper will serve as a one-stop reference for engineers, researchers, and industry practitioners to take decisive action on adopting priority loading operations in critical facilities.

2. System Design and Study Parameters

2.1. Description of the System

The system considered in this study is a grid-connected battery system. The simplified structure of the system is presented in Figure 1. The grid and the battery are connected to the common AC bus, which is the distribution point for the loads. The load packs depict the various loads present in a healthcare facility. Some of these loads are highly critical for human life preservation, and some are required for regular operation purposes. In a highly unreliable grid, it is expected that the grid could be out of supply at any point of the day. Thus, the battery storage system is there to support the critical loads during that time. The load data is adopted from [17] and tabulated in Table 1. The list shows the equipment with their power and estimated daily energy needs for a health facility. In the prioritization column, "secured", "non-secured", and "non-critical" loads depict their priority. Thus, in this study, all secured loads are lumped into priority load 1, non-secured loads into priority load 2, and non-critical loads into priority load 3.

2.2. Grid Modelling

The grid is assumed to be a constant power source. When available, it is expected to supply the required energy for all the loads in the facility as well as charge the batteries. The voltage and frequency variability of the grid was not considered since this study does not concern the electrical operation of the system. When the grid experiences a blackout, battery packs are expected to fulfill the energy void. Such an operation could be on either a priority basis or a non-priority basis. Under the priority-based operation, battery packs are expected to supply critical priority loads P1 during the full blackout time. The lesser priority loads (P2 and P3) are supported by the battery, depending on the availability of the battery capacity (details in Section 2.4). On the other hand, the non-priority operation means the battery will support all the loads, regardless of the critical status, and continue to do that until it is fully drained.

Table 1. Detailed load data [17]. Reproduced with permission.

Equipment	Power (W)	Hours Used Per Day (h)	Energy Per Day (Wh/day)	Prioritization
All healthcare facilities				
Lights (fluorescent)	11	6	66	Secured
Mobile phone charger	5–20	8	40–160	Non-critical
Ceiling fan (CD, AC)	30–100	10	300–1000	Non-secured
All healthcare facilities but health posts				
Water pump	100	6	600	Non-secured
Computer	15–200	4	60–800	Non-secured
Portable electrical heater	1000–1500	4	4000–7500	Non-critical
Radio	2–30	8	16–240	Non-secured
Only health centers and hospitals				
Printer (ink, laser)	65–1000	4	260–4000	Non-secured
Small waste autoclave	600–6000	1	600–6000	Non-critical
Medical equipment				
All healthcare facilities but health posts				
Sterilizer (steam)	500–1560	2	1000–3200	Non-secured
Suction	24	10	240	Non-secured
Pulse oximetry	24	2	48	Non-secured
Reverse-osmosis water purifier	260–570	8	2080–4560	Non-critical
Only health centers and hospitals				
X-ray machine (dental)	200	0.5	100	Secured
X-ray machine (portable and not)	3000–50,000	0.5	1500–25,000	Secured
Newborn incubator	420	24	10,080	Secured
Mechanical ventilator	200	10	2000	Non-secured
Ultrasound scanner	75	2–3	150–225	Non-secured
Electrocardiogram	50–80	0.5	25–40	Non-secured
(ECG) Nebulizer	180	3–5	540–900	Non-secured
Laboratory equipment				
All healthcare facilities				
Vaccine refrigerator (165 L)	40–500	4	160–2000	Non-secured
All healthcare facilities but health posts				
Microscopes	30	2	60	Non-secured
Only health centers and hospitals				
Centrifuge	600	2	1200	Non-secured
Spectrophotometer	63	1	63	Secured
Blood chemistry analyser	45	2	90	Secured
Haematology Analyser	230	2	460	Secured
Arterial blood gas (ABG) analyser	250	0.5	125	Secured

2.3. Battery Modelling

The battery model used in this study is a single node model that updates the value of the state of charge in each time increment based on the total charge balance over a specific time period. For a finite time step (Δt), the SOC can be computed numerically as follows:

$$SOC(t) = SOC(t - \Delta t) \times \frac{1}{Bat_{cap\_nom}} \left(I_{chrg}(t) - I_{dschrg}(t) \right) \eta_{\text{tot}} \Delta t \quad (1)$$

where Bat_{cap_nom} is the nominal capacity of the battery, Δt is the time step, I_{chrg}, I_{dschrg} are the charge/discharge currents during the same time period, and η_{tot} is the round-trip efficiency of the battery system. The self-discharge rate is neglected here due to the high utilization pattern of our intended study. According to the manufacturer's recommendations, the charging current is limited to 20 Amps/battery.

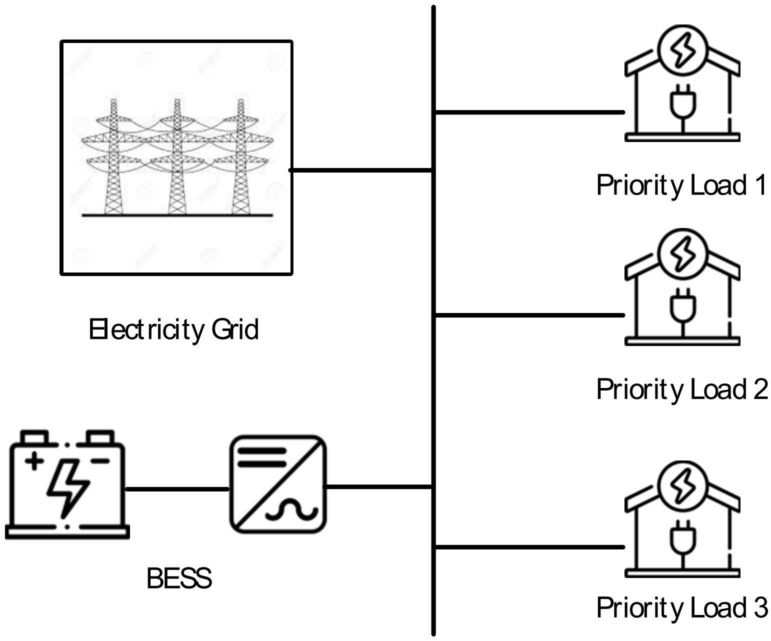

Figure 1. Schematic of the system under study.

Aging Calculations

For battery aging calculations, an empirical approach is adopted, in which the degradation of the battery capacity and open circuit voltage are functions of the number of cycles (n). Temperature effects are not considered in this study. A commercial lithium battery, Valence U1−12XP with 45 Ah at 12 V and 576 Wh, is used throughout the study. This capacity gives reasonable increments for better sizing. The aging information are shown in Figure 2. The end of life of the battery is drawn at around 40% reduction of capacity, equivalent to N = 4320 cycles.

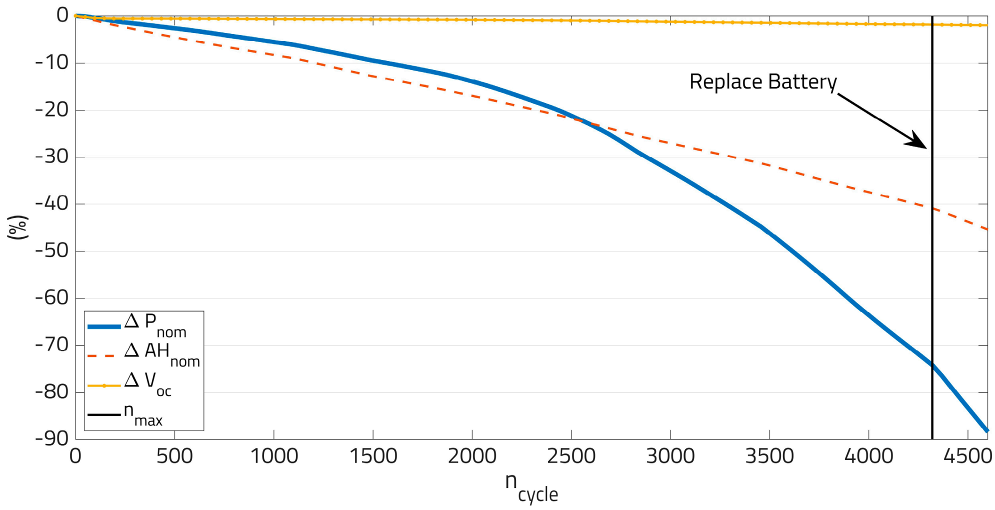

Figure 2. Aging characteristics for the Valence U1−12XP battery used in the model. Nominal capacity = 45 Ah at 12 V nominal with 576 Wh energy. The values are temperature-independent and correspond to room temperature conditions.

Battery aging calculations are shown in Algorithm 1 below. Aging is estimated at regular intervals (d) during time integration of the energy dispatch (see Section 2.4). Firstly, the number of discharge cycles is counted and adjusted to full equivalent cycles (n_{eq}). This, in turn, is used in lookup tables to find the revised values of $V_{oc}(n_{eq})$, $C_{bat}(n_{eq})$, $P_{bat}(n_{eq})$.

Finding the peaks and troughs is achieved through the local maxima search function available in MATLAB Version 9.14 (R2023a). The weights ω_i are computed by dividing the difference of each neighbouring peak and trough over the maximum allowable SOC range. The resulting n_{eq} is equal or less than the number of iterations i. If n_{eq} is larger than the maximum cycles of the battery (N), then the battery is replaced, and values of capacity and voltage are reset accordingly.

Algorithm 1: aging calculations

For i = 1:d:T do

- Find $SOC_{peak}(1 \to i)$
- Find $SOC_{trough}\ (1 \to i)$
- Compute weights $\omega_i(1 \to i)\ =\ \frac{\left|SOC_{peak}(1\to i)-SOC_{trough}(1\to i)\right|}{SOC_{max}-SOC_{min}}$
- $n_{eq}\ =\ \sum_i \omega_i$
- If $n_{eq} < N$,
  - Update $AH_{nom}\left(n_{eq}\right)$
  - Update $V_{oc}\left(n_{eq}\right)$
  - Update $P_{nom}(AH_{nom},\ V_{oc})$
- Else,
  - Reset $n_{eq},\ \ AH_{nom},\ V_{oc},\ P_{nom}$ (replace battery)
  - Update battery replacement counter
- End if

End for

To improve the accuracy of the aging calculations, multi-year simulations are used. Electrical loads are assumed to be constant and repeated from year to year. However, battery characteristics ($V_{oc},\ C_{bat},\ P_{bat}$) are carried over from year to year. This improves the accuracy of the calculations by accounting for the battery degradation effect on fulfilling loads in the subsequent years of battery life. Without this feature, there will be an overestimation of the battery throughput by assuming that the battery can fulfill the same number of loads in year 1 as in subsequent years of operation. This will become evident in the results section.

2.4. Energy Dispatch Strategy

The energy dispatch is governed by the availability of the grid. The flowchart for the energy dispatch is given in Figure 3. The dispatch algorithm gets the SOC of the battery at initialization as an input and calculates the available battery capacity (Bat_{cap}) as follows:

$$Bat_{cap}\ =\ (SOC_{bat} - SOC_{min}) \times Bat_{cap\_nom} \tag{2}$$

where SOC_{bat} is the present SOC of the battery pack, SOC_{min} is the minimum SOC up to which battery is allowed to be discharged (30%), and Bat_{cap_nom} is the nominal battery capacity. When the battery pack is new, Bat_{cap_nom} is equal to the value mentioned in the manufactured datasheet. However, Bat_{cap_nom} is a dynamic value that is updated within the algorithm considering the aging effect of the battery.

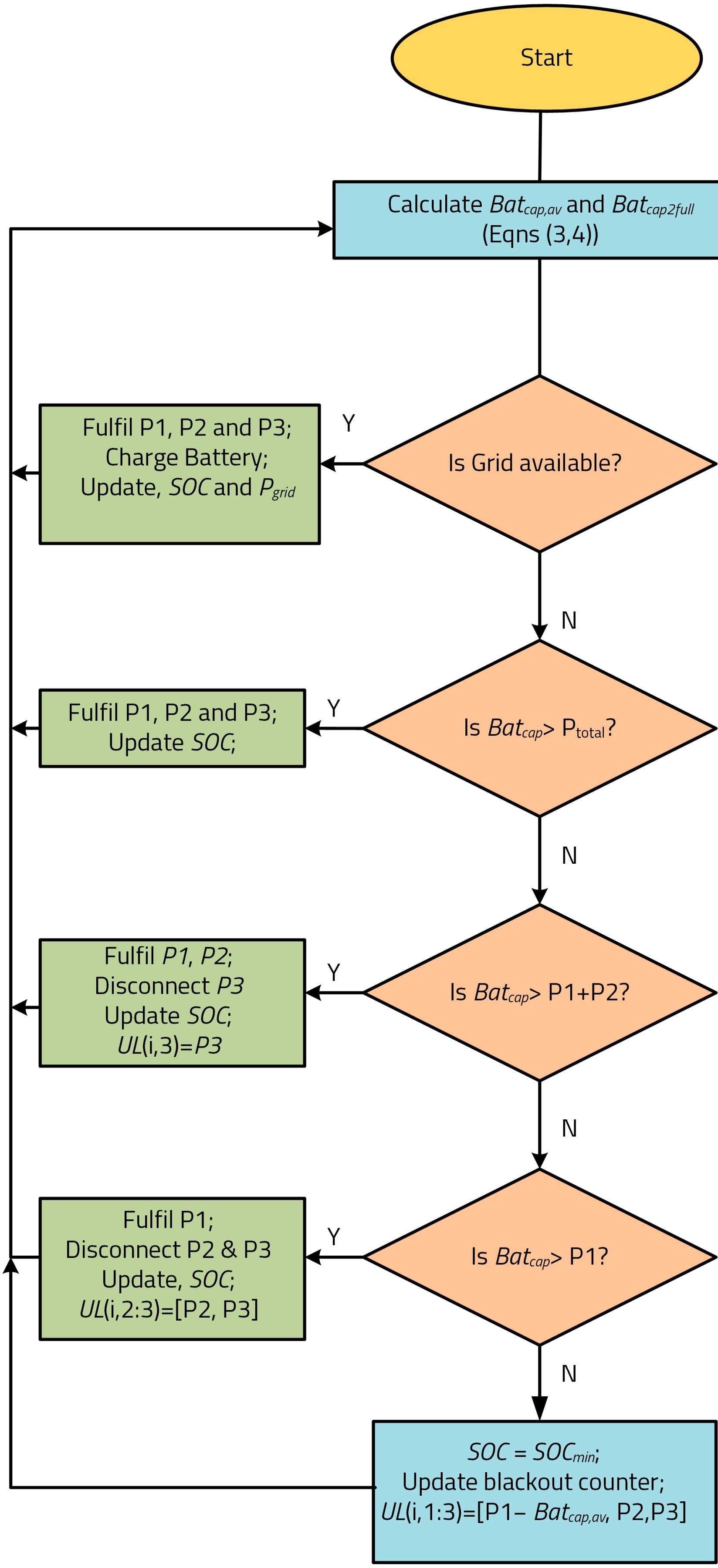

Figure 3. Energy dispatch strategy for three-tier load priority system with battery storage system.

At the beginning of time integration, the available capacity of the battery is updated based on the previous reading of the SoC as shown in Equation (3). Also, the capacity required to fully charge the battery is also calculated as per Equation (4). These two quantities are essential for an accurate energy management strategy.

$$Bat_{cap,av}(i) = (SOC(i-1) - SOC_{min})Bat_{cap\_nom}(n_{eq}) \tag{3}$$

$$Bat_{cap2full}(i) = (SOC_{max} - SOC(i-1))Bat_{cap\_nom}(n_{eq}) \tag{4}$$

Then, the algorithm will check the availability of the grid. If grid power is available, all the loads will be operated from the grid. Simultaneously, the battery pack will be charged with a maximum of $Bat_{cap2full}$, which is when charging is discontinued.

When the grid power is unavailable, Bat_{cap} will be compared with the total energy required (P_{total}) by loads P1, P2, and P3. If the Bat_{cap} is greater, it will fulfil all three loads simultaneously. SOC_{bat} and Bat_{cap} is updated continuously, and it is expected that both will fall gradually. When Bat_{cap} goes below P_{total}, it will be compared with the energy required for P1 and P2. When it is greater than (P1 + P2), P3 will be disconnected and account for the unmet load. After some time, SOC_{bat} and Bat_{cap} will be decreased further and go below the energy levels of P1 and P2 but remain above the required energy for only P1. In that case, P2 will be discontinued and both P2 and P3 will account for the unmet load. Eventually, Bat_{cap} will be lower than the energy required for P1. In such a case, the battery pack will be allowed to discharge until SOC_{min} (30%) and through this transition the unmet load is calculated as ($P_{total} - Bat_{cap}$). When the battery pack hits SOC_{min} P1 will be disconnected. It will be considered the complete blackout and P1, P2, and P3 will contribute to the unmet load. The unmet load for all cases is updated in each time step:

$$UL_j = \sum_{j}^{3} P_j > Bat_{cap,av} \tag{5}$$

2.5. System Reliability

The system reliability measures chosen in this study are the unmet load, normalized unmet load, and the number of blackouts (not grid blackouts but blackouts of the battery backup system).

In the case of a non-priority system, the system reliability is computed as follows:

$$Re_{sys} = \sum^{year} \sum_{j=1}^{3} \sum_{i}^{N} \frac{UL_j(i)}{P_j(i)} \tag{6}$$

where the summation over the years of simulation and over all loads (j) and all timesteps (i). $UL_j(i)$ is computed from Equation (5). In the case of a priority system, the reliability of the system is computed as follows:

$$Re_{sys} = \sum^{year} \sum_{i}^{N} \frac{UL_1(i)}{P_1(i)} \tag{7}$$

Here, only P1 priority loads are included in the system reliability as, by definition, P2 and P3 are not critical loads. In situations of highly unreliable grids, this is a reasonable principle of operation. One of the benefits of such "reliablility" definition is that the desired level of reliability can be set.

To calculate the blackout hours, the dispatch strategy contains a dedicated counter for each priority load, which is then added throughout the years of the project and compared with grid availability hours.

2.6. Cost Modelling

Calculating the cost of the system over the lifespan of the project is done using the Levelized Cost of Energy (LCE) measure, which can be calculated as follows:

$$LCE = \frac{C_{ann}}{L_{el} - UL} \tag{8}$$

where C_{ann} is the annualised total cost of the installed system, L_{el} is the served electrical load, and UL is the unmet load. The annualized total cost can be calculated as follows:

$$C_{ann} = CRF \times NPC \tag{9}$$

where NPC is the net present value of all costs incurred by the project during its lifetime (Y). It is calculated as follows:

$$NPC = \sum_{i}^{Y} \frac{C_i}{(1 + d)^i} \tag{10}$$

where C_i is the total cost incurred in year (i). It is calculated as follows:

$$C = C_{capital} + C_{om,fixed} + C_{om,var} \tag{11}$$

where CRF is the capital recovery factor, calculated as follows:

$$CRF = \frac{d(1 + d)^Y}{(1 + d)^Y - 1} \tag{12}$$

where d is the discount rate.

A flat inflation rate ($in = 2\%$) is assumed for the duration of the project. This will cause the nominal discount rate to change as per the following equation:

$$d_{real} = \frac{(d - in)}{(1 + in)} \tag{13}$$

The parameters used in the cost modeling are shown in Table 2 below.

Table 2. Cost modeling parameters used in simulations.

	Capital Cost (CC)	Fixed O&M Cost	Variable O&M Cost	Nominal Life
Battery System	350$/kWh	0.01 × CC	0	10 years
Grid	0	0	0.25$/kWh	-

2.7. Case Study

To illustrate the developed dispatch strategy, a case study of a hospital is conducted. The electrical loads are based on hospital loads reported by [17] and categorized as P1, P2, or P3 based on their criticality, with P1 being the most critical. Figure 4 shows a sample day of loads in the hospital. The demand is highest between 8 am and 8 pm, with increased non-essential loads during the daytime. The large spike in the middle of the day happens when the X-ray machines are turned on. The ratio of P1, P2, and P3 are 44%, 10%, and 46%, respectively, and the total annual load is around 30 MWh.

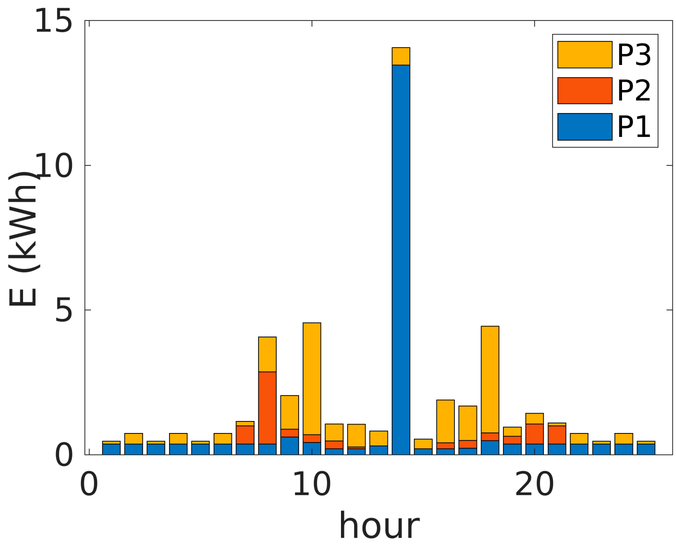

Figure 4. Hourly energy consumption of the studied hospital on a typical day showing the magnitude of the different priority loading. The large jump in the early afternoon coincides with using the X-ray machines, which have a capacity of 12 kW.

The motivation of this study was the power cuts in developing and underdeveloped countries. Thus, as a study, the Nigerian grid situation has been chosen as it is a particularly acute case of grid unreliability. To illustrate this, Figure 5 shows the discrepancy between supply and demand on six days in the past half-year. The data is collected from the Nigerian Electricity System Operator [18]. Similar levels of generation exist on other days.

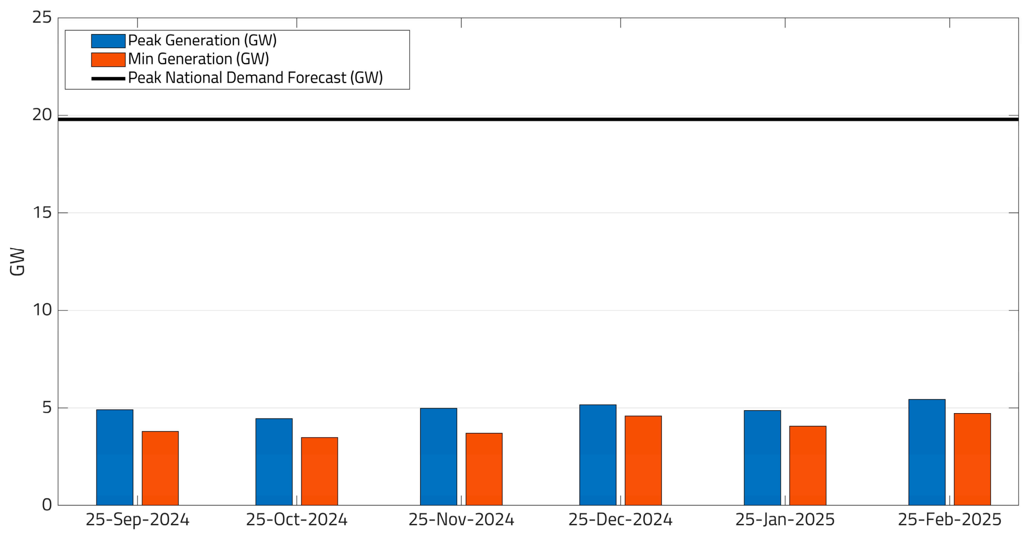

Figure 5. Peak and average national generation in Nigeria for selected days. The maximum daily load forecast is shown in the solid line at the top of the graph. The data are collected from the Nigerian Electricity System Operator [18].

It can be seen that the peak generation is 25% of the peak demand forecast. Such disparity forces the country to experience severe blackouts throughout the year. In this study, the range of daily blackout hours is representative of the Nigerian grid conditions. Both rolling and stochastic blackouts can be observed in Nigeria. Some areas of Nigeria primarily experience stochastic blackouts, which are unplanned and occur randomly due to various factors affecting the power supply. These blackouts result from unexpected system failures, infrastructure issues, or supply-demand imbalances. In contrast, other areas experience rolling blackouts, which are deliberate, scheduled outages implemented to manage electricity demand and prevent system overloads. These are systematically planned by the operators in advance. In this study, power cuts are primarily simulated as rolling blackouts. Recently, Jacal et al. [19] reported on the usage of backup generators in Nigerian households and found that the daily usage ranges from 2–16 h. This is confirmed by Farquharson et al. [20], who found that Nigerians suffer from an average of 33 outages per month, each lasting on average 11.6 h per day and totaling around 4600 blackout hours per year. To account for the spread of the blackout distribution and based on the previous insights from literature, we will assume four blocks of blackouts distributed throughout the day with varying numbers of hours, starting with 4–20 h and with four-hour increments, as shown in Figure 6 below. Furthermore, we will consider stochastic patterns to account for unscheduled blackouts in Section 3.6. In Section 3.7, we will consider a block of 12 h of continuous blackout. We believe the three studies cover all the different blackout scenarios that might occur in a healthcare facility in Nigeria, including the worst-case scenarios.

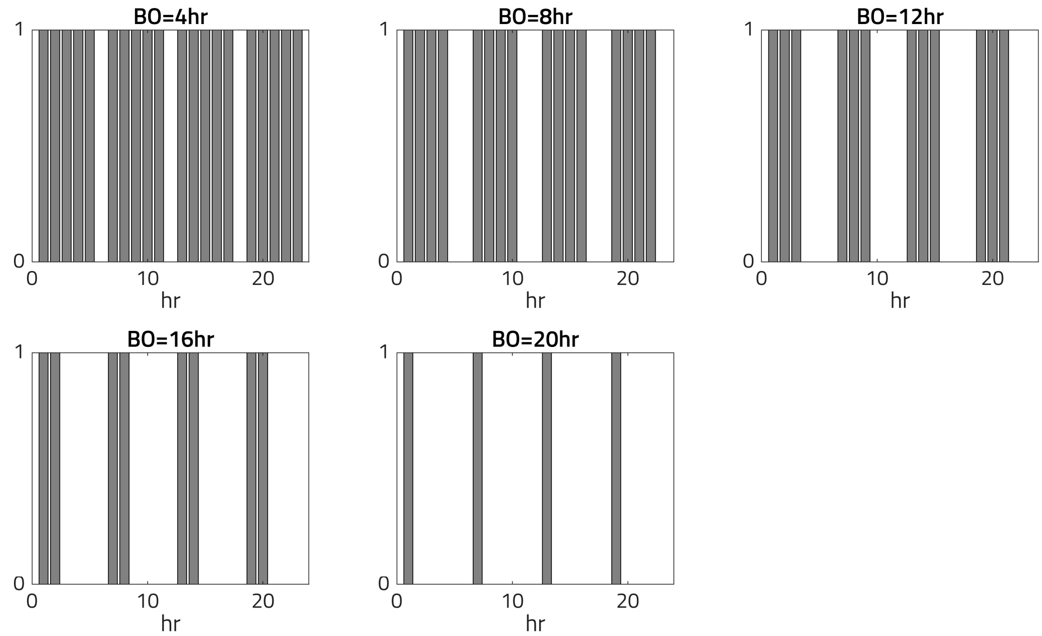

Figure 6. Typical blackout patterns with varying number of hours per day. A value of 1 means a grid is available, while a value of 0 means a blackout. Each day has four periods of blackouts.

The simulations were carried out using an exhaustive search and full factorial design of experiments. This was possible due to the small search space, which facilitates simulating every possible combination of the studied parameters' range.

3. Results and Discussion

3.1. Study 1: Fixed Blackout and Fixed Charging Rate Condition

The first study aimed to evaluate the behavior of the system under a fixed blackout pattern and fixed charging rate for the batteries. Assuming a grid with poor reliability, the grid blackout hour was fixed as 12 h/per day. The charging rate for the batteries was adopted from the recommended value from the datasheet, which is 0.5 C. Based on these two fixed criteria, the study was conducted for a stretch of 10 years for both non-priority and priority-based load operation. Since the objective of the priority load management is to maximize the support for load P1, the first comparison was made based on the amount of normalized unmet load for P1. The normalized unmet load for P1 is illustrated in Figure 7, and is based on the different number of battery packs available in the system. It can be seen that with a low number of battery packs (less than 5), both priority and non-priority are unable to support load P1 and normalized unmet load in 10~20% for the 10-year period. With the increase in the number of battery packs, load P1 receives better support, as expected, and the normalized unmet load decreases. It can be seen that for a pack of 25 batteries, priority-based load management successfully reduces the normalized unmet load to below 1% and fulfills the objective of priority-based load management. On the other hand, non-priority load management requires more than 50 packs of batteries to fully support load P1. That is not a feasible solution due to the large initial investment it would require.

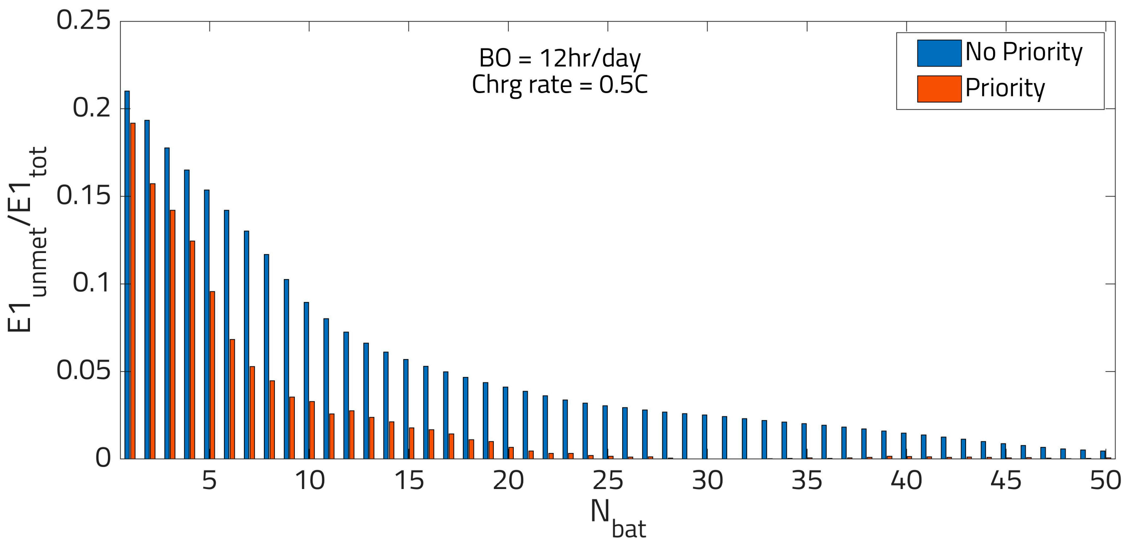

Figure 7. Normalized unmet energy for P1 load (E1) as a function of the dispatch strategy and number of batteries in the system. In the non-priority case, the P1 unmet ratio is assumed to be the same as the ratio of the total unmet load to the total load in each timestep.

Figure 8 presents an overview of all three loads under a fixed blackout pattern and charging rate. In the figure, the normalized total unmet load is plotted across the number of battery packs available. It can be observed that for a 25-battery pack, both loads P1 and P2 can be fully supported all the time. To fulfill all three loads would require about 60 battery packs to reduce the normalized unmet load to less than 1%. From a system designer's point of view, using a 25-battery pack would be a good design point for this system since both P1 and P2 could be supported fully. Under the same battery pack number, non-priority load operation would experience 10% blackout over the 10 years of operational time.

Figure 9 breaks down the instances of complete shutdown for the individual loads under both priority and non-priority-based load management. Under the non-priority scheme, the occurrence of a complete shutdown for the three loads is the same and is reduced uniformly with the increase of the number of battery packs. Since there was no priority involved, whenever the battery packs were fully dissipated, all loads were disconnected instantly. On the other hand, the blackout occurrence for P1, P2, and P3 reduced significantly with the increase of battery packs. As expected from our previous observations of around 25 battery packs, blackout for P1 and P2 approach 0. Interestingly, at around N = 40, P2 blackout occurrence goes slightly up under the priority load management. The reason for this is related to battery aging and their replacement schedule. With a higher number of battery packs, they will be drained out less frequently, which slows down their aging process and shifts the replacement schedule to a later date. Thus, for a number of battery packs over 40, P3 seems to have experienced some blackouts before the replacement schedule has taken place.

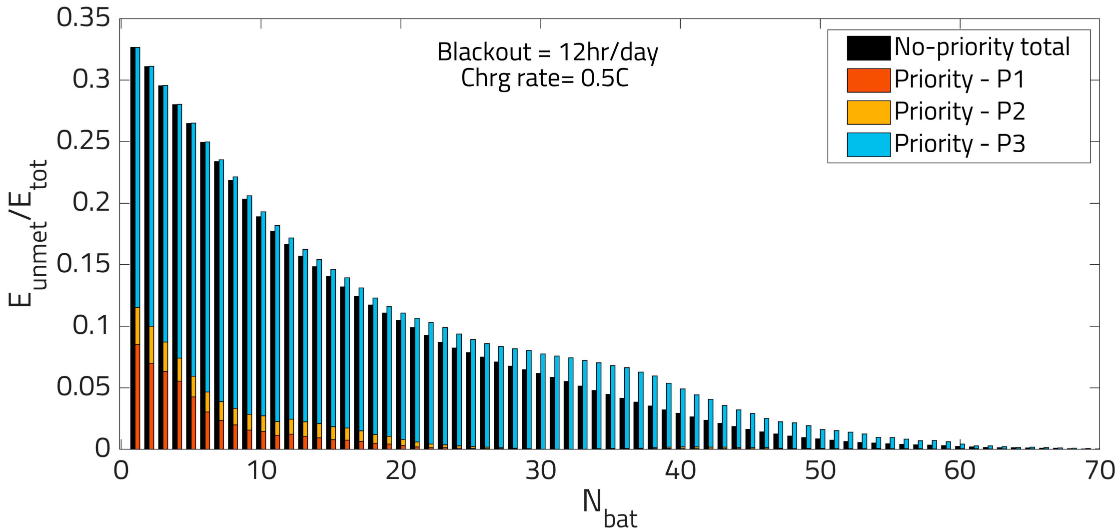

Figure 8. Ratio of unmet to total load as a function of the number of batteries in no-priority and priority loading.

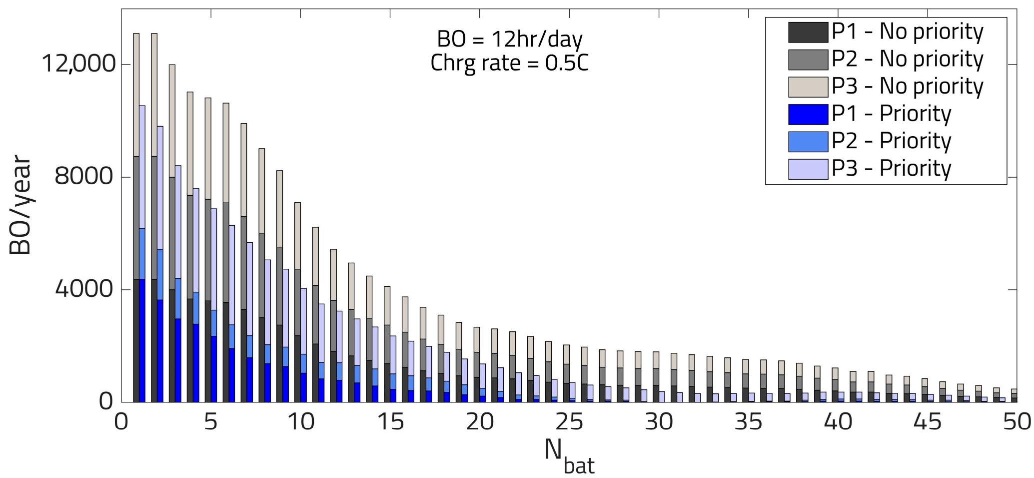

Figure 9. Comparison of blackout instances per year of priority and no-priority loading conditions as a function of the number of batteries in the system. In the no-priority scenario, every time a blackout occurs, all three loads are disconnected. With priority loading, P1 is prioritized.

Figure 10 illustrates the levelized cost of energy (LCE) for the 10 years of operation. LCE was calculated based on Equations (8)–(12). It is interesting to note that LCE for priority and non-priority dispatch follow the same trend when the battery pack numbers are low. The first drop in LCE is observable at 14 battery packs. This is due to the fact that a higher number of battery packs resulted in fewer replacement cycles. There is another major drop in LCE, which is noticeable at 30 battery packs, coinciding with one fewer replacement. It is also important to note that non-priority-based load management achieves the same LCE at 32 battery packs, which is marginally inferior to the priority-based load management. Based on the observations from Figure 10, it can be concluded that 30 battery packs would be an optimized choice for priority-based load management based on the observation of normalized unmet load and the levelized cost of energy.

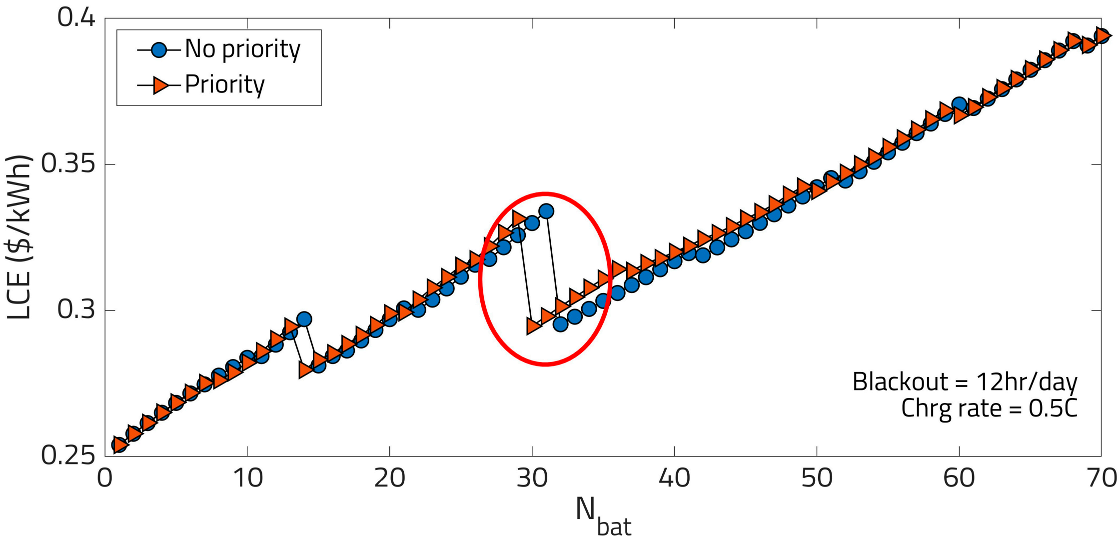

Figure 10. Levelized cost of energy as a function of the number of batteries in the system. The priority load management causes the battery replacements to reduce around N = 14 and N = 30 (indicated with the red circle). This causes drop in LCE.

The explicit simulation of multiyear duration improves the confidence in simulations. As the battery degrades, more loads will be unmet, especially when the battery is used to the high number of cycles we set in this study. The total number of blackouts over the 10-year period is depicted for priority and non-priority dispatch in Figure 11 below. For the same number of batteries, the priority dispatch has roughly cut the number of blackouts in half throughout the project's life. The spikes in the lines represent the effect of aging, which is most pronounced around year 4 and year 8, when most of the battery replacement happens. It is also worth noting that the spike is more visible at the 1500 isolines in both sub-figures. This indicates that a larger number of batteries will be able to utilize batteries for longer before replacement.

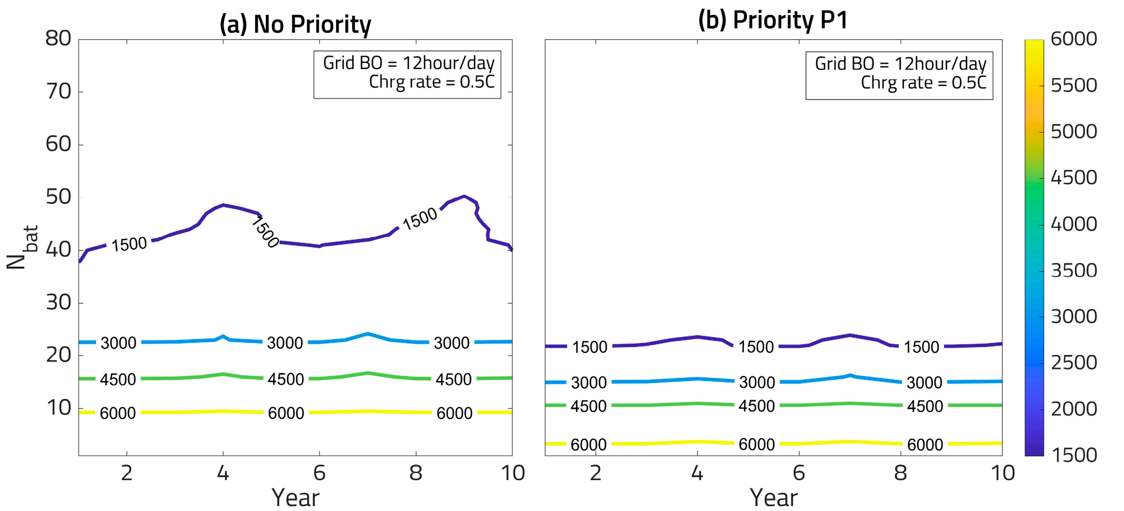

Figure 11. Contour plot of annual blackout instances progression with years due to the aging of the batteries: (**a**) no-priority dispatch for total loads and (**b**) priority dispatch for P1 loads. Priority dispatch is reducing the fluctuations of blackout instances along with battery aging. This is achieved at the expense of P2 and P3 loads The reduction in the number of blackout instances is achieved due to battery replacement. The priority dispatch allows for a battery use up to 80% reduction while maintaining a minimum increase in P1 blackout instances due to aging.

3.2. Study 2: Variable Grid Blackouts and Fixed Charging Rate

In Study 2, the optimized battery pack number of 30 is adopted as the design point, and the grid blackout is varied as 4, 8, 12, 16, and 20 h a day. Under all the cases, the charging rate is kept constant as 0.5 C. The objective of this study is to find out the performance of priority and non-priority dispatch under different blackout patterns that were shown in Figure 6 earlier. The normalized unmet load for P1, P2, and P3 is illustrated in Figure 12. Under a four-hour blackout, there would be no unmet load. If the facility experiences eight hours of blackout, the loads start to experience a blackout. For high-priority load P1, non-priority load operation causes 2% blackout over the 10 years. On the contrary, the priority loading operation is less than 1%, which suggests that load P1 is always supported by the battery packs. A similar observation can be made for load P1 under 12 h of blackout. This was the part of Study 1 where the blackout time was kept constant at 12 h. Under such a scenario, non-priority loading caused a 4% blackout of P1. Meanwhile, the priority loading operation kept the blackout for P1 close to 0 for the 10-year study period. For the grid blackout period of 16 h and 20 h, P1 started having blackouts under both priority and non-priority loading operations. Under non-priority loading, the load blackout is 7% and 9% for 16 h and 20 h grid blackout, respectively, while priority loading causes load P1 blackout 3% and 4%. Such performance is significantly better compared to the non-priority operation.

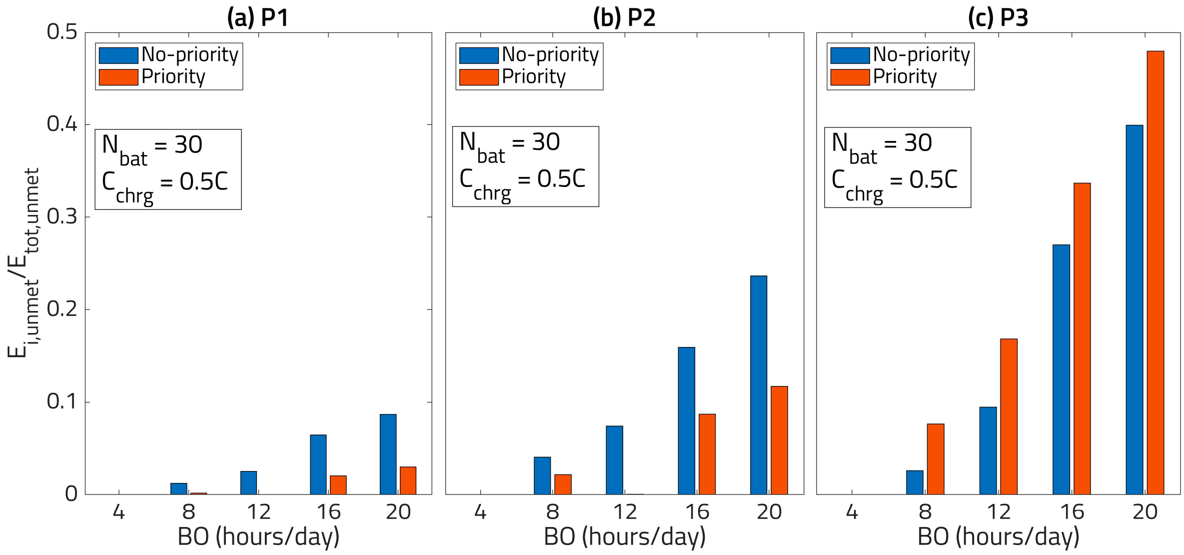

Figure 12. Energy ratio of different loads as a percentage of the total unmet load. The design point is taken at N_{bat} = 30 and C_{chrg} = 0.5 C. The priority dispatch strategy will reduce the ratio of P1 and P2 unmet loads at the expense of P3 unmet loads.

For load P2, which has the second priority in load classification, a similar trend to that of load P1 can be observed. Under four hours of grid blackout, the load P2 is always supported by the battery pack. From 8 h to 20 h grid blackout, non-priority loading causes P2 to experience blackouts 5%, 9%, 16%, and 25%, respectively. On the other hand, priority-based loading provides better support for the P2. It results in 3%, 0%, 9%, and 10% normalized unmet load. The dropping of the unmet load while the grid blackout is increasing from 8 h to 12 h is an interesting observation and is counterintuitive. The expected pattern would be an unmet load increasing along with the grid blackout, which does not happen for the P2. Such an occurrence is related to the battery life cycle and the replacement schedule. Under eight hours of grid blackout, batteries are expected to charge and discharge less frequently compared to the 12-h blackout. Thus, their aging will be slower, and they will be operating with a lower capacity for some time until they reach the replacement threshold. Such operation at a lower capacity causes the unmet load for P2. On the contrary, under a 12-h blackout, charging and discharging frequency will be higher, and the aging will be faster. Thus, the battery pack will reach the replacement threshold quickly and will spend less time in operation with a lower capacity. Besides, 30 battery packs were optimized based on the observation under 12 h blackout and, thus, the better output in unmet load is observed for P2. Nevertheless, the priority-based load operation performs significantly better in supporting P2 compared to the non-priority load operation.

In the case of load P3, the opposite trend can be observed. The unmet load is higher under priority load operation compared to the non-priority loading under all the blackout durations. That is expected due to the operational difference between priority and non-priority operations. Under priority load management, the battery is dedicated to supporting P1 all the time. Whenever battery capacity is dropped below the threshold, P3 is disconnected first, followed by P2 for further battery drainage. Thus, P3 is expected to experience a significant unmet load that is clearly visible in Figure 12c. On the other hand, non-priority loading operation handles the load indifferently and shuts them off whenever the battery is fully drained. Thus, the unmet load is distributed over P1, P2, and P3 proportionately, and non-priority supports load P3 better than the priority operation.

3.3. Study 3: Variable Blackout Hours and Variable Charging Rates

The variable blackout pattern in Study 2 is further extended to observe the impact of different battery packs' performance on the loads. When the priority is taken into consideration, Figure 13 depicts the improvement done by priority load management under different blackout patterns, and the charging rate is fixed at 0.5 C while battery pack numbers are varied. As can be seen, unmet load P1 is significantly lower under priority operation compared to the non-priority-based load management. Under a four-hour blackout period, only three battery packs are needed to support P1 for priority load operation, while seven battery packs are needed when non-priority loading is performed. If the daily occurrence of blackouts increases to 8 h, the required number of battery packs also increases. For non-priority loading operations, it will take more than 35 battery packs to support load P1. On the other hand, the priority loading operation will get the job done with just 8 battery packs. Thus, if supporting the top priority pack P1 is the concern, the priority load operation is significantly beneficial from an economic point of view. The 12-h blackout pattern was not shown in Figure 13 since it was presented and analyzed in Study 1. A similar observation can be made for 16-h and 20-h blackout patterns. To support load P1, the priority operation needs 38 battery packs and 49 battery packs, respectively. In contrast, non-priority-based load operation requires 67 battery packs and 78 battery packs to provide full support to P1.

The study is further extended to observe the impact of charging rate on the optimal battery pack design. Three different charging rates are chosen as 0.2 C, 0.5 C, and 0.8 C for comparison, and the results are summarized in Table 3. Under four-hour and eight-hour daily blackouts, the charging rate has no impact on the battery pack sizing. The battery packs have enough time to get fully charged during the grid availability hours. However, priority loading requires a smaller number of battery packs compared to the non-priority loading operation. These numbers further increase under 12 h of daily blackout. The non-priority battery pack requirement increases to 49, while the priority load operation requires 19 or 20. Here, the impact of a slow charging rate is slightly noticeable. Such impact is more prominent in 16 h and 20 h of daily blackout. Under 16 h, if priority loading is considered, the battery pack requirement is 47 for a 0.2 C charging rate, while 38 battery packs are required for a 0.5 C and 0.8 C charging rate. Such discrepancy is even higher in 20 h of blackout. A charging rate of 0.2 C pushes the required number to 80 under priority loading, while 0.5 C and 0.8 C require only 49 and 44 battery packs, respectively. On the other hand, it is interesting to observe that the charging rate has a less significant impact on non-priority loading even under 16 h and 20 h of daily blackout. Since non-priority loading simultaneously feeds all the loads regardless of their priority, it will drain out faster under 16 h or 20 h of blackout. Thus, the battery pack numbers are pushed to nearly 80, even though charging rates are varied.

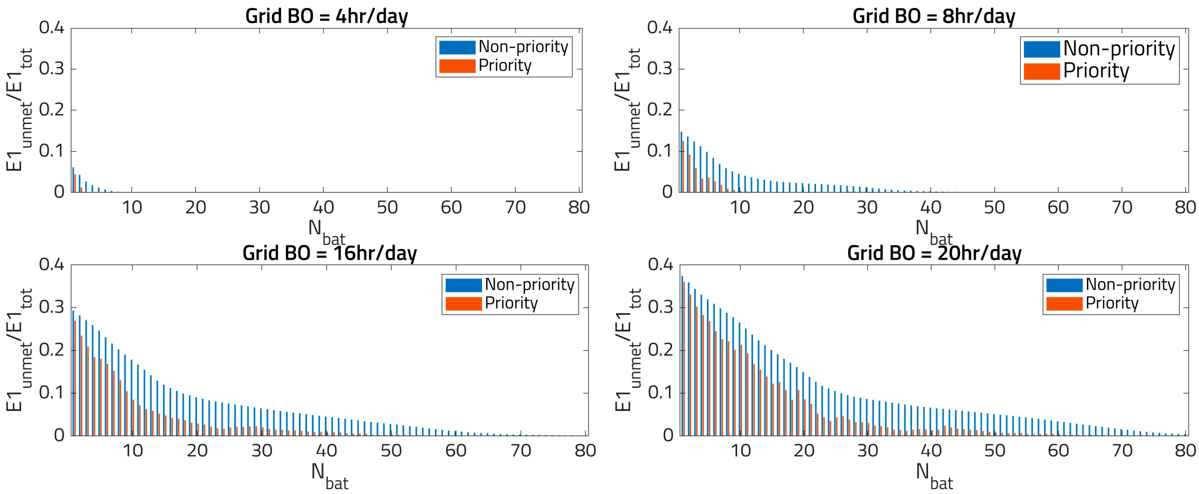

Figure 13. Ratio of unmet load P1 as a percentage of the total P1 load. All results are at C_{chrg} = 0.5 C. The priority dispatch strategy will reduce the ratio of P1 loads at the expense of P3 unmet loads.

Table 3. The minimum number of batteries that would achieve 1% unmet load or better as a function of the blackout duration and charging rate. (NPr) is the no-priority algorithm, and (Pr) is the priority algorithm. The unmet load is defined as P_{tot} for NPr and P1 for Pr.

Chrg. Rate	4 h BO		8 h BO		12 h BO		16 h BO		20 h BO	
	NPr	Pr	NPr	Pr	NPr	Pr	NPr	Pr	NPr	Pr
0.2 C	7	3	35	8	49	20	72	47	80	80
0.5 C	7	3	35	8	49	19	67	38	78	49
0.8 C	7	3	35	8	49	19	67	38	77	44

The effect of the blackout duration on battery life is shown in Figure 14, under both priority and non-priority dispatch operations. The nominal battery life is set to 10 years, after which the battery pack is replaced regardless of the cycling. Whenever the priority line is above the non-priority line, this indicates the advantage of priority dispatch in extending the battery life; where the two lines meet indicates no advantage. This is evident between 3–8 batteries at 4-h blackout regime; the priority loading has increased the life of the battery by one year on average. This can be explained by throughput due to switching P2 and P3 loads off. This will have the effect of reducing the equivalent number of cycles and, therefore, aging. A similar improvement can be noticed at 12-h blackouts between 20–60 batteries. At 20-h blackout, there is hardly any advantage to priority in terms of battery life. This can be explained by the lack of time to charge and the high frequency at which deep discharge happens. As seen before in Figure 13, the advantage of priority in a 20-h grid blackout is the reduction of the unmet load.

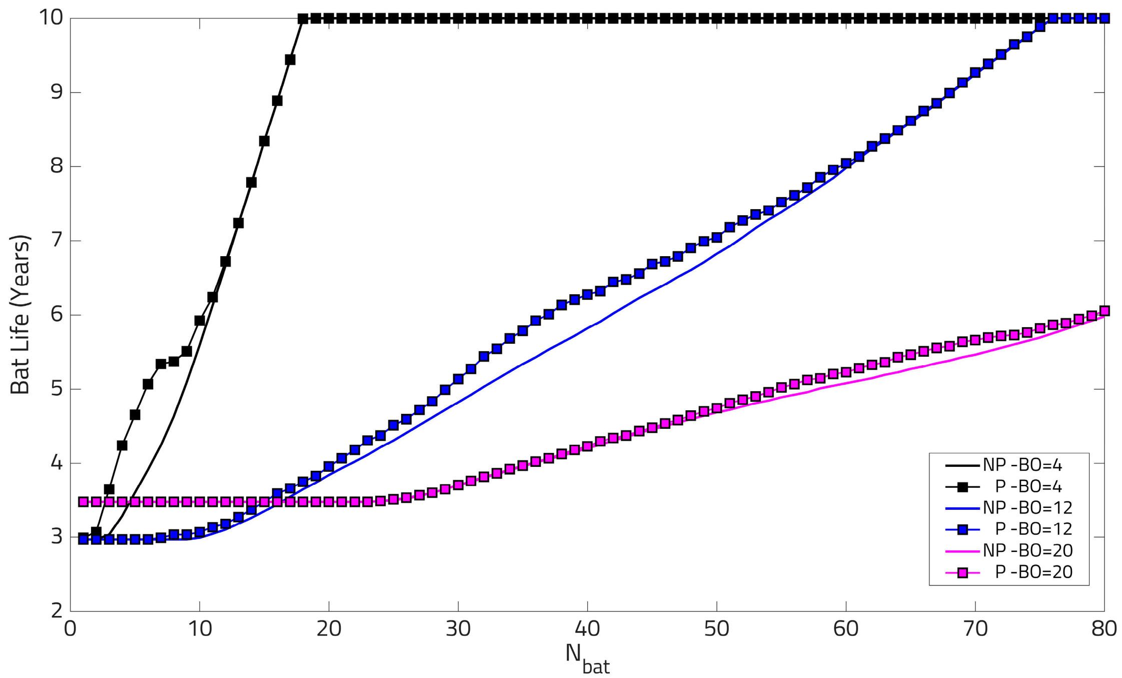

Figure 14. Effect of dispatch strategy on battery life at different blackout rates. NP = No-priority dispatch, P = Priority dispatch. Nominal battery life is assumed to be 10 years, regardless of cycling.

3.4. Cost Comparison with Diesel Generator Backup System

In order to quantify the economic benefit of using a battery backup system, an economic comparison is carried out against a DG-only backup system. It is acknowledged here that the reliability of a well-maintained diesel generator is high, which means that blackouts are less likely to occur; however, the aim of this section is to establish the cost of maintaining such a system for hospital operators. The power and cost modeling of the DG system follow the procedure shown in [21], along with the main parameters used in the cost calculations shown in Table 4.

Table 4. Parameters used in the economic calculation of the DG backup system.

Parameter	Unit	Value	Comments
Capital cost (CC)	$\$/W_{nom}$	0.375	[21]
Installation cost	$\times$ CC	0.6	[21] cabling, fuel delivery, exhaust, etc.
Fixed O&M	$/h	0.02	[21] Hour of operation
DG life	h	20,000	Hour of operation
Diesel fuel cost	$/L	0.966	[22]

It is worth noting in Table 4 that the high price of diesel reflects recent developments in Nigeria. The fuel subsidy was lifted in May 2023 [23], which drove the prices up to the level mentioned in the table. However, we ran similar calculations with fuel prices half of the current cost, and running the DG was more expensive than the proposed battery system.

Figure 15 shows the comparison between the DG-only system and the battery-only system. For comparison, we used a battery system with priority load management, $N_{bat} = 30$, and $C_{chrg} = 0.5C$. This configuration is highly reliable (refer to Figure 12). It can be seen from Figure 15 that DG-based operation costs are higher under every blackout scenario. Depending on the cases, cost was generally higher by 17–25% for DG, assuming a fixed nominal fuel price over 10 years.

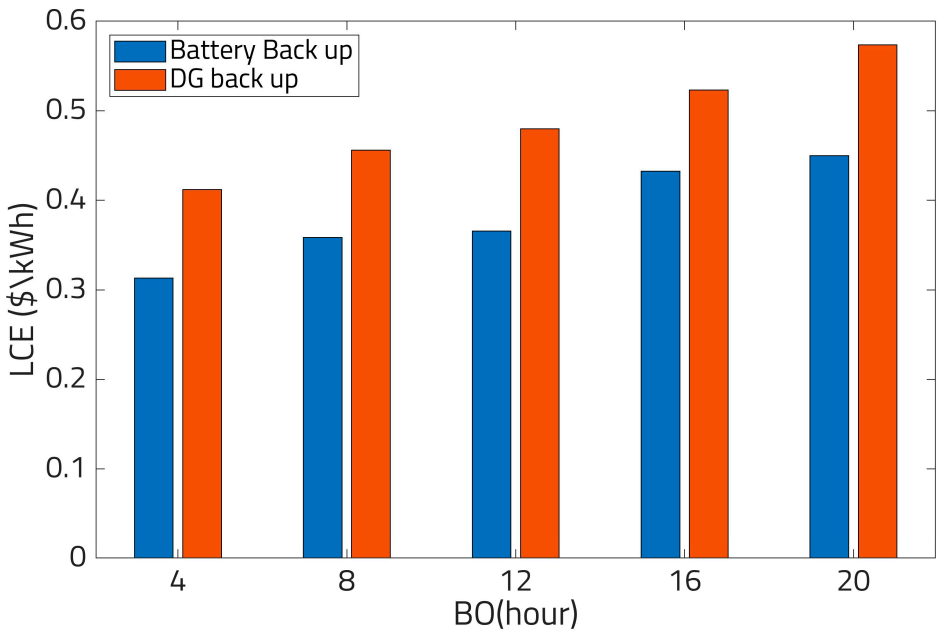

Figure 15. Comparison of levelized cost of energy of the battery backup system and the DG backup system. The chosen battery system is with priority dispatch, $N_{bat} = 30$, and $C_{chrg} = 0.5$ C. The DG system is sized based on the maximum load in the hospital, around 30 kW.

3.5. Long-Term Solution—Battery with PV

While the priority load management proposed in this paper effectively reduces the critical blackouts, the full functionality of the hospital is severely impaired in times of prolonged blackouts. Given the strong solar irradiance in Nigeria, installing PV panels on the roof of the hospital is a convenient solution to improve reliability and reduction in emissions.

To illustrate this, the model was rerun with a 16 kW solar PV array. This could be installed on the roof of the hospital. A typical meteorological year (TMY) data for Lagos, Nigeria was used in obtaining the power output. The data was imported from PVGIS online platform [24] with hourly resolution. The PV was coupled with the priority load management. Figure 16 below shows the results. For ease of reference, Figure 7 is replicated and the results from the new system configuration with solar is added to the plot. It is clear that the unmet E1 load is approximately halved and reaches zero with $N_{bat} = 7$ compared with $N_{bat} = 25$ in the absence of the solar system. Although the PV system size did not change, increasing the size of the battery helped mitigate the blackouts of P1 by storing more of the energy to be used during blackouts. The integration of solar and battery is a vast topic. A more detailed analysis of this topic will be addressed in future work.

3.6. Stochastic Blackout Pattern

In order to study the effect of the stochastic nature of blackouts, a simplified stochastic blackout distribution is used instead of the rolling blackout pattern studied earlier. A normal distribution of blackouts is proposed for this case. The mean was set at 4 pm, and the standard deviation was varied between 4–9 h. Parameters are tuned to produce a maximum likelihood of blackouts in the afternoon period (12 pm–6 pm) and into the evening. This distribution is assumed because it was hard to find detailed data on grid failures in Nigeria. The distribution is created so that it can be controlled by the number of expected blackouts per day. Figure 17 shows the distribution of blackouts for 1 year during the day and according to the expected number of blackouts per day.

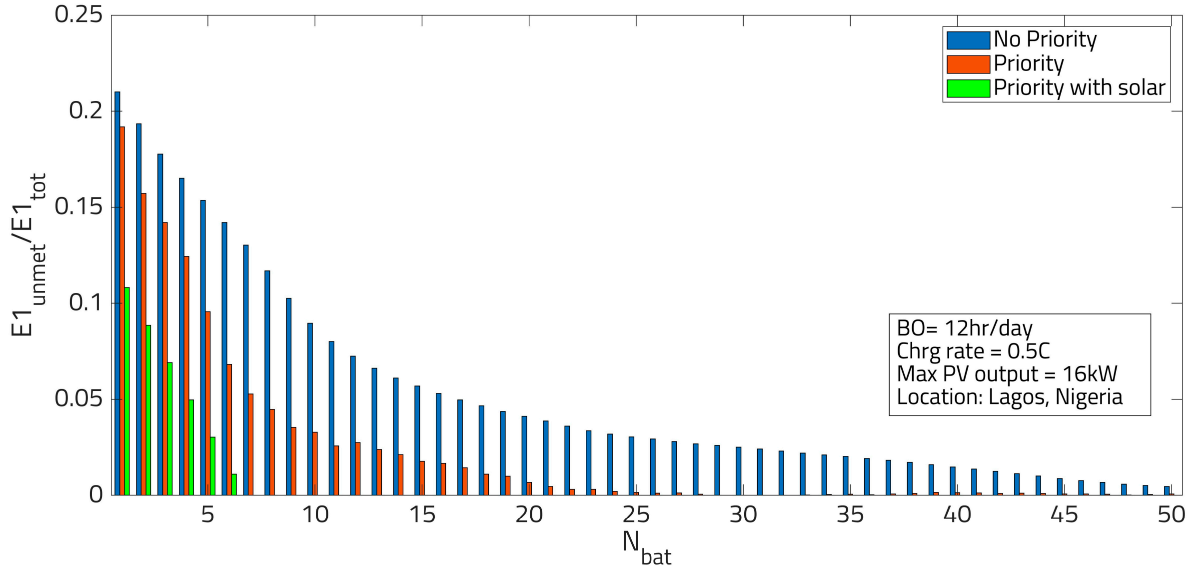

Figure 16. Normalized unmet energy for P1 load (E1) as a function of the system configuration and number of batteries in the system. This Figure is based on Figure 7 with the addition of the solar system to the priority load dispatch.

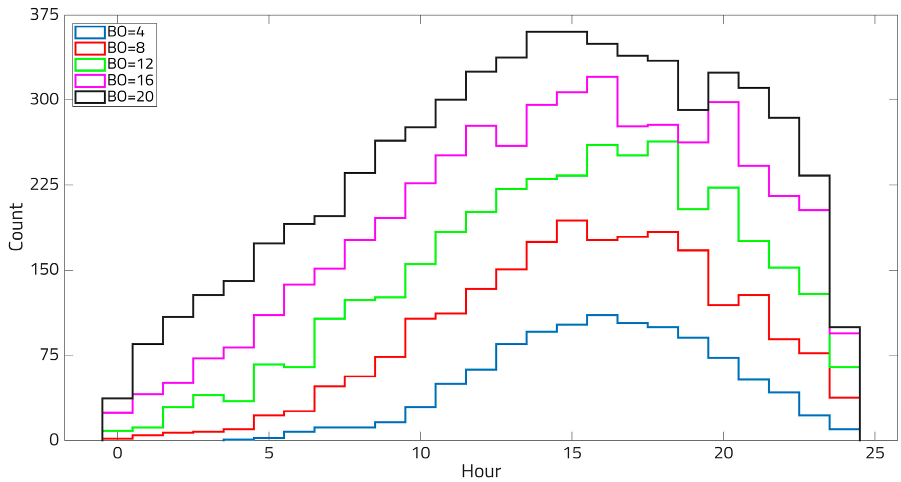

Figure 17. Histograms of the blackout distributions against the time of the day for different blackout durations for one year. The highest likelihood of blackout coincides with 4 pm and lowest is at midnight. Normal distribution is followed with standard deviation values between 4 and 9.

Simulations of the priority load system with $N_{bat} = 30$, $C_{chrg} = 0.5\,\mathrm{C}$ are conducted for five levels of blackouts (4, 8, 12, 16, 20) h. They are compared with the same system and regular pattern in Figure 18. It is clear from Figure 18a that highly stochastic and severe blackouts negatively impact the cost and especially the unmet load under every scenario depicted in Figure 18b. This is a consequence of having a higher number of consecutive blackout hours in the stochastic pattern than the regular one. As a result, the battery pack would not be able to support the P1 load for the full duration. As can be seen in Figure 18b, the P1 load remains unmet for a significant amount of time if stochastic blackouts occur. This will also negatively affect the aging of the battery and, therefore, the replacement rate.

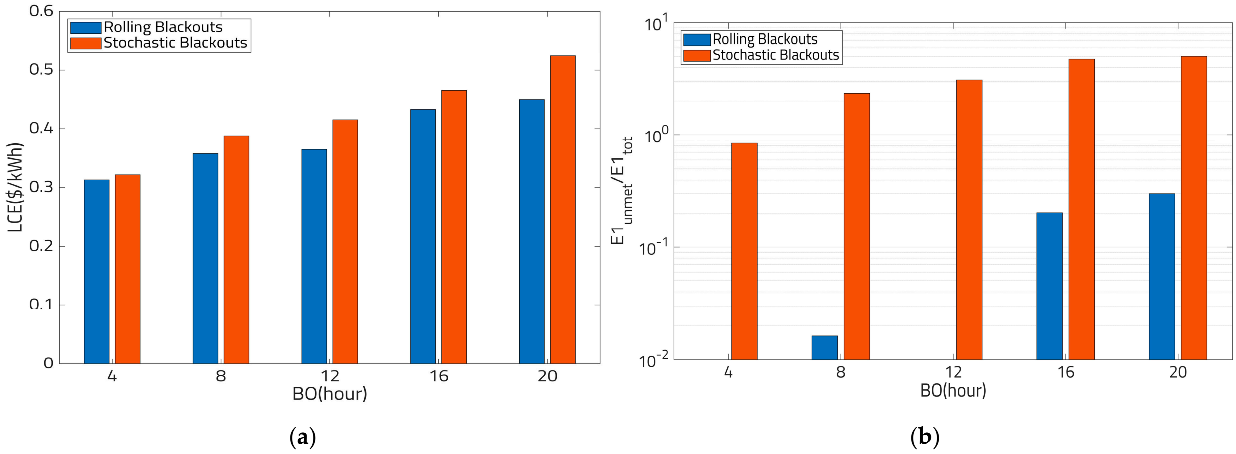

Figure 18. Comparison of the same system but with different blackout patterns: rolling (regular) blackouts (in blue) or stochastic blackouts with normal probability distribution function. (**a**) LCE and (**b**) normalized unmet critical load. The studied system has priority management, $N_{bat} = 30$, and $C_{chrg} = 0.5$ C. Note the logarithmic scale on subfigure (**b**).

3.7. Extreme Case Scenario—One-Block Blackouts

In this section, the effect of the block blackout assumption on the reliability of the power supply is examined. The distribution of blackouts throughout the day will generally reduce the burden on the battery backup system and result in a smaller sizing. Following from the discussion in Section 2.7, it was shown in the literature that in the case of Nigeria, 12-h block blackouts happen often and warrant further consideration. In Figure 19, a comparison has been made among the ratio of unmet critical load for priority and no-priority algorithms in the case of rolling 12-h blackouts (3-on, 3-off) and in the case of 12-h block blackouts that coincide from 8 am to 8 pm. The system under study is similar to the one shown in Section 3.2, i.e., ($N_{bat} = 30$, $C_{chrg} = 0.5$ C). As can be seen, the block loading significantly reduces the reliability of the system. In this case, the number of batteries will have to be drastically increased; otherwise, the battery system alone will not be enough to meet the critical demand, especially since most of the P1 demand happens in the time of the block blackout. However, the priority algorithm reduces the critical blackouts (compare bars 2 and 4) by around 54% for the same number of batteries.

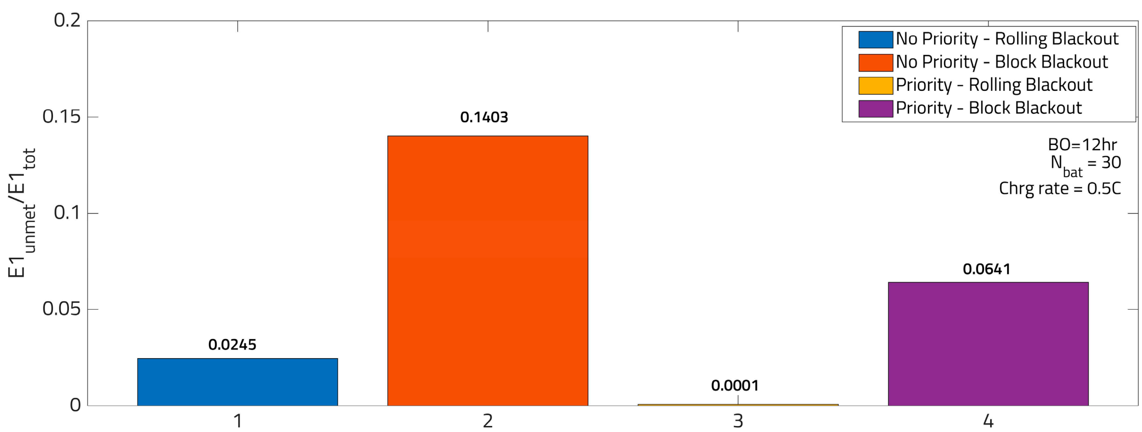

Figure 19. Comparison between priority and non-priority algorithms in the case of rolling blackout vs. block blackouts.

3.8. Sensitivity Analysis of Economic Indicators

In order to estimate the effect of the economic factors on the results, a sensitivity analysis is carried out. The battery cost, discount rate, inflation, and blackout hours are varied in the full factorial design of the experiment, according to Table 5. In the case of the capital cost of the battery and the discount rate, the original value used is multiplied by a factor ranging from 0.6 to 1.4. Inflation is kept below the discount rate to avoid negative real discount values. The number of batteries is kept constant at $N_{bat} = 30$, the charge rate is kept at $C_{chrg} = 0.5$ C, and the priority load management algorithm is used. The total simulations is 375 and the studied output is the LCE.

Table 5. Factors and their levels for economic sensitivity analysis.

Variable	Levels	Unit
CC_{bat}	350 × [0.6, 0.8, 1, 1.2, 1.4]	$/kWh
d_{nom}	0.08 × [0.6, 0.8, 1, 1.2, 1.4]	[-]
inflation	[0, 0.02, 0.04]	[-]
BO	[4, 8, 12, 16, 20]	[hour]

Figure 20 shows the main effects of the economic factors on the cost of the system. The total mean value was 0.387$/kWh. Increasing the discount rate caused the LCE to increase, as it tends to increase the cash outflow across the project life. Inflation has the opposite effect since it causes the cash outflow to decrease in real terms, thereby causing the project to become more affordable. Finally, the largest effect is the capital cost of the battery, which is expected as it is the major component of the studied backup system. Given the recent global trends, battery prices are expected to fall in the coming years due to technological maturation and economies of scale. As such, installing a battery backup system will become more attractive, especially in places with high diesel price volatility.

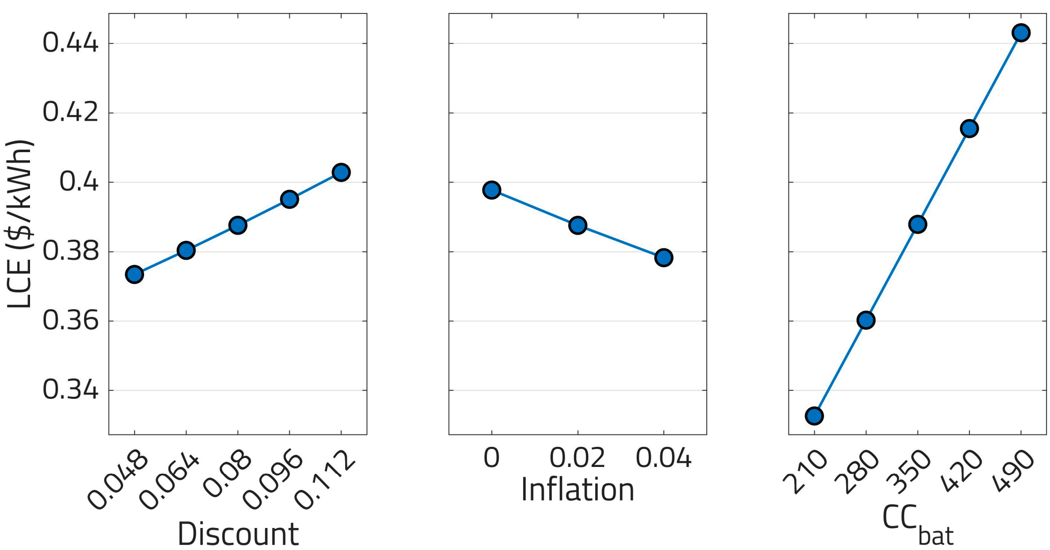

Figure 20. Main effects plot for the economic parameters effect on the levelized cost of energy of the battery backup system. Priority load management, $N_{bat} = 30$, $C_{chrg} = 0.5$ C, and blackouts between 4–20 h are used to obtain the results.

4. Concluding Remarks

In this work, we presented a priority-based energy dispatch strategy for battery backup systems operating in a healthcare facility. The algorithm included battery aging calculations and multi-year time series integration for the duration of the nominal battery life (10 years).

Improvements to the reliability of supply for the most critical load were observed with a significantly lower number of batteries, albeit at the expense of the least critical loads. Furthermore, the algorithm reduces the increase in blackouts near the end of the life of the batteries, therefore making the system cheaper. The effect of the charging rate was observed only with a high number of blackout hours per day.

Some of the limitations of the study can be summarized as follows: the effect of temperature on aging was not included. In a country such as Nigeria, this is expected to be a somewhat significant factor and future work by the authors will include the effects of temperature and different battery chemistry. Inverter design considerations are not modelled in this work, as the main focus here was the overall energy balance. In most existing health facilities, there is a standby diesel generator. Our study did not consider this since it will make priority-based loading less urgent. We aimed to see how much a healthcare facility can realistically run without having a backup generator. As is evident from the results, as long as the blackouts are less than 12 h a day, a highly reliable system can be achieved with a relatively small number of batteries, as long as the management of the facility is willing to sacrifice some non-essential loads.

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