

# Maximising the investment returns of a grid-connected battery considering degradation cost

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**Abstract:** Energy storage systems (ESSs) are being deployed widely due to numerous benefits including operational flexibility, high ramping capability, and decreasing costs. This study investigates the economic benefits provided by battery ESSs when they are deployed for market-related applications, considering the battery degradation cost. A comprehensive investment planning framework is presented, which estimates the maximum revenue that the ESS can generate over its lifetime and provides the necessary tools to investors for aiding the decision making process regarding an ESS project. The applications chosen for this study are energy arbitrage and frequency regulation. Lithium-ion batteries are considered due to their wide popularity arising from high efficiency, high energy density, and declining costs. A new degradation cost model based on energy throughput and cycle count is developed for Lithium-ion batteries participating in electricity markets. The lifetime revenue of ESS is calculated considering battery degradation and a cost–benefit analysis is performed to provide investors with an estimate of the net present value, return on investment and payback period. The effect of considering the degradation cost on the estimated revenue is also studied. The proposed approach is demonstrated on the IEEE Reliability Test System and historical data from PJM Interconnection.

## 1 Introduction

Increasing uncertainty in the modern power grid due to the variability of renewable energy resources has led to the widespread deployment of energy storage systems (ESSs). ESSs are flexible devices with high ramp rates that can help in maintaining a balance between generation and demand in the face of such uncertainty. ESS can be deployed for various applications including frequency regulation, peak shaving, voltage support, energy arbitrage, and firming up of renewable resources. While a few of the applications are capable of generating direct monetary benefits, most are not. However, ESS projects are significantly expensive. Therefore, investment planning frameworks need to be devised for extracting maximum economic benefits from these projects which will aid in attracting more investors and utilities.

ESS traditionally participates in different electricity markets like energy and ancillary markets for generating revenue. In many countries, the power industry has gradually shifted from a centralised operation system to deregulated competitive markets in recent times [1]. In the United States, both regulated and deregulated systems exist today. For some wholesale markets, investor owned electric utilities own generation facilities as well transmission and distribution systems and are responsible for operating, managing, and providing power to retail consumers. In other regions, wholesale markets are operated by regional transmission organisations (RTOs) or Independent System Operators (ISOs). These ISOs and RTOs provide buyers and sellers the opportunity to bid for or offer generation for energy and ancillary services in their markets [2]. Some of the biggest electricity markets in the US are operated by PJM Interconnection, Midcontinent Independent System Operator (MISO), Electricity Reliability Council of Texas (ERCOT), California Independent System Operator (CAISO), and New York Independent System Operator (NYISO).

ESS can participate in a number of applications in these markets for generating revenue. A variety of applications of ESS have received widespread attention from researchers in the past.

Byrne *et al.* [3] present a summary of the leading applications of grid-connected storage systems. Among the applications of ESS prevalent today, energy arbitrage and frequency regulation have proved to be the most profitable ones according to multiple studies [4–6]. Walawalkar *et al.* [4] discuss the economic case for ESS in NYISO for the two previously mentioned applications. Tian *et al.* [5] present a method for determining the stacked benefits from ESS following the PJM market model while Nguyen *et al.* in [6] present an approach for maximising economic benefits from ESS in the MISO electricity market. Although these studies focus on maximising the economic benefits of ESS, none of them provides a detailed cost–benefit analysis or takes the degradation of batteries into consideration. On the other hand, the authors of [7–9] present various strategies for co-optimisation of ESS for participating in multiple services. However, a comprehensive investment planning methodology that focuses on the maximum economic benefits of ESS and provides a detailed cost–benefit analysis useful to the investors still needs to be developed.

A number of technologies exist today for grid-level ESS. The most popular among these are batteries, pumped-hydro storage (PHS), flywheels, and capacitors [10, 11]. The deployment of batteries has increased significantly in the US in recent years, with installation capacities growing almost two-folds annually since 2011 [12]. By the end of 2017, the installed battery capacity in PJM was 287.5 MW, and the total installed battery capacity in the US was 708 MW [13]. Among different grid-level battery technologies, lithium-ion batteries are the most popular, constituting more than 80% of large-scale battery storage in operation in the US by the end of 2016 [12]. Several characteristics of Li-ion batteries contribute to their popularity: high efficiency, high energy density, and fast response times.

While estimating the revenue generated from a battery ESS (BESS), degradation of batteries should be taken into account as it can affect the accuracy of results. Studies have shown that degradation of batteries is application specific. Peterson *et al.* [14] discuss the degradation of batteries for vehicle-to-grid applications,

the authors of [15–17] discuss various degradation cost models for economical operation of microgrids, while Xu *et al.* [18] propose a piece-wise linear cost function to model aging of batteries due to cycling from participation in electricity markets. The authors of [15–17] consider both the cycle life and the energy throughput while modelling the degradation cost of batteries for improved economic operation of microgrids. Although the degradation cost function has been used to minimise the life loss of the battery in [15–17], the cost of the battery packs was not considered. On the other hand, in [18], the authors consider the cost of the battery but not the lifetime energy throughput. The model proposed in [18] penalises the battery for every cycle of its operation and this requires the counting of cycles online. However, in practice, cycle counts are tracked using the rainflow counting algorithm (RCA) [19], which requires the entire time-series operation data of the battery and hence cannot be implemented online. As a result, the model proposed in [18] relies on certain approximations that can lead to inaccurate results. Hence, a degradation cost model considering both cycle life and energy throughput, along with the cost of batteries needs to be developed for ESS participating in electricity markets. This degradation cost model would enable the representation of the degradation cost in monetary units, thus providing the investors with a more realistic estimate of the ROI and payback period.

In recent times, the prices of Li-ion batteries have decreased significantly. While the price of these batteries in 2010 was more than \$1000/kWh, in 2020 it has decreased to around \$200/kWh [20]. However, utilities are still struggling to make BESS projects profitable due to high capital and daily operating costs. Also, there are only a handful of applications in the electricity markets that reward the storage units monetarily, e.g. energy arbitrage, frequency regulation, spinning reserve, and black start among others. In such a scenario, new methodologies need to be developed for extracting the maximum economic benefits for BESS projects. This paper presents a new approach by developing a comprehensive planning framework that enables the BESS to maximise economic benefits while also incorporating the degradation cost of batteries. The lifetime revenue of the BESS is calculated considering battery degradation and a cost–benefit analysis is also performed to provide investors with appropriate tools for making decisions. The applications of the BESS selected for this study are energy arbitrage and frequency regulation. The proposed framework also provides a methodology to determine the optimal location which maximises the economic benefits. The widespread popularity of Li-ion batteries due to the characteristics mentioned earlier makes it the choice of the BESS for this study. The battery degradation cost is incorporated as a component of the objective function. The degradation cost function in this work is developed specifically for BESS participating in the electricity markets considering both the cycle life and the energy throughput of the battery. Calculating the degradation cost with respect to the energy throughput is advantageous to calculating the cost per cycle since the former can be easily determined for every time period while the latter can only be determined after the entire time-series data for the operation of the BESS is available, which may lead to inaccurate results.

The economic benefits from the BESS are maximised by developing an optimisation framework. The objective function of this optimisation framework includes the revenue from the applications, and the degradation cost of the battery modelled as a penalty function. It also provides the option of optimally locating the BESS when such an opportunity exists. The constraints include the capacity and operational limitations of the BESS and the characteristics of the power system network it is connected to. The proposed optimisation framework is a linear. Previously, in [21], the authors have proposed a mixed-integer non-linear programming (MINLP) problem for maximising the economic benefits of ESS. However, MINLP problems are computationally complex and the scalability of such problems for big systems might be challenging. Hence, a linear framework is proposed here, which can be scaled irrespective of the system size. The proposed framework estimates the lifetime revenue of a BESS and provides a comprehensive cost–benefit analysis for the BESS project. The revenue is

estimated both with and without considering the degradation cost. The results show the significant difference between the two values and underlines the importance of considering the degradation cost within the framework. The main contributions of this paper can be summarised as follows:

- i. This paper presents a new framework for a comprehensive investment planning study of grid-connected storage systems with the objective of maximising economic benefits. This framework is capable of including multiple products (such as energy arbitrage and frequency regulation) as well the battery degradation cost, along with a comprehensive set of operating constraints.
- ii. This paper also adds to prior art by proposing an improved degradation cost model for Li-ion batteries participating in the electricity markets and incorporating it within the optimisation framework as an operational expense. This new degradation cost model considers both the lifetime energy throughput and the cycle count of the batteries. It also considers the cost of the battery packs which reflects the cost of degradation in monetary units. All these aspects have not been considered together in the prior literature while modelling the degradation cost of BESS participating in the electricity markets.
- iii. The framework developed in this paper includes the methodology for an exhaustive cost–benefit analysis of BESS projects that can aid in the decision making process of investors and utilities in the planning phase based on the net present value, return on investment, and the payback period.

The remaining of the paper is organised as follows. The participation of the storage system in the electricity market is discussed in Section 2. The degradation process of the battery and the development of the degradation cost model is described in Section 3. An optimisation framework for maximising the economic is presented in Section 4. A comprehensive cost–benefit analysis is presented in Section 5. Section 6 presents the results of the study while Section 7 provides some concluding remarks.

## 2 Participation in the electricity market

Only a few applications in the US electricity markets provide economic opportunities for storage systems. These include energy arbitrage, frequency regulation, spinning reserve, and black start among others. A general framework is first developed to quantify the revenue generated by a BESS by participating in any of the market services. For this study, energy arbitrage and frequency regulation are then chosen to demonstrate the efficacy of the proposed framework.

### 2.1 Revenue model of BESS

A BESS can participate in multiple market services to generate revenue. A general framework is developed in this section to quantify this revenue from any service that the BESS participates in. Let the BESS participate in  $n$  market services. Then, the revenue from the  $i$ th service,  $J_i$ , can be expressed as follows:

$$J_i = f_i(t, q_i(t), m_i(t)) \quad (1)$$

where  $f_i$  is a function of time  $t$ ,  $q_i(t)$  is the energy exchanged through the BESS and  $m_i(t)$  is the value of the market parameters at time  $t$ . Hence, the total revenue generated by the BESS from  $n$  services,  $J$ , for a given time horizon  $T$  can be expressed as follows:

$$J = \sum_{t=1}^T \sum_{i=1}^n f_i(t, q_i(t), m_i(t)) \quad (2)$$

Energy arbitrage and frequency regulation are the services selected for this study. However, this framework can be easily extended to include other applications as well.

## 2.2 Energy arbitrage

Energy arbitrage is one of the oldest and most common applications of storage systems. The revenue from this application depends on the temporal variability in the price of electricity. The price of electricity at a bus in the network is indicated by the locational marginal price (LMP) and depends on the geographic location, variation in load, and connectivity of the bus with the rest of the network. The uncertainties in the load also give rise to uncertainties in the LMPs. For this reason, the LMPs are modelled as random variables in this work. Historical LMP data is used to estimate the distribution of LMPs, and the LMP for each hour is represented by a random variable. The weekly LMP cycle is preserved while fitting the distribution. The random variable representing the LMP for a particular hour is found to be following a normal distribution. The mean and variance of the normal distribution are determined from historical data. The hourly LMPs for the system are generated using the estimated normal distributions.

The BESS takes advantage of the temporal difference in the LMPs to generate profits. It should be noted that the sizes of the BESS considered in this study are significantly smaller than the peak load of the system. Hence, the BESS follows the price taker model, not the price maker model. In other words, the size of the BESS is too small to influence the LMPs of the system [5, 18]. Therefore,  $J_{arb}$ , the revenue generated from the energy market, is expressed as follows:

$$J_{arb} = \sum_{t=1}^T \lambda_{imp}(t) [q_d(t) - q_r(t)] \quad (3)$$

where  $\lambda_{imp}(t)$  is the LMP at the time  $t$ ,  $q_d(t)$  and  $q_r(t)$  are the quantities of energy sold to and purchased from the market by the BESS at the time  $t$ .

## 2.3 Frequency regulation

The Real Power Balancing Control Performance (BAL001) and Disturbance Control Performance (BAL002) Standards of the North American Electric Reliability Council [22] mandate that the grid frequency should be maintained within certain predefined limits to guarantee grid stability. Frequency regulation helps to serve this purpose. The fast ramping capability of BESS makes them ideal candidates for providing frequency regulation. Federal Energy Regulatory Committee (FERC) order 755 [23] makes it mandatory for independent system operators (ISOs) and utilities to consider the speed and accuracy while buying frequency regulation provides the recommendations for pay-for-performance. A variety of models are employed by different ISOs to comply with this FERC order. The model developed and implemented by PJM interconnection has been used in this paper.

PJM employs a two-part payment model for resources committed to providing frequency regulation. These are regulation market capability clearing price (RMCCP) and regulation market performance clearing price (RMPCP). The former rewards the resource based on the capacity committed to regulation while the latter depends on the actual performance of the resource. These two payments make up the total revenue generated by the resource (which translates to the BESS in this study) from the regulation market. The RMCCP credit for a given hour can be calculated as follows [24]:

$$\text{RMCCP Credit} = q_{reg}(t) \times \eta_t \times \lambda_c(t) \quad (4)$$

where  $q_{reg}(t)$  is the BESS dispatch based on the hourly integrated regulation signal,  $\eta_t$  is the actual performance score, and  $\lambda_c(t)$  is the RMCCP, at the time  $t$ . On the other hand, the RMPCP is determined as follows:

$$\text{RMPCP Credit} = q_{reg}(t) \times \eta_t \times \beta_t^M \times \lambda_p(t) \quad (5)$$

where  $\beta_t^M$  is the mileage ratio at the time  $t$ .

The calculation of the mileage ratio is explained as follows. Two distinct regulation signals are offered by the PJM for different types of resources. The *RegA* signal is designed for traditional resources and is a low-pass filtered area control error (ACE) signal. On the other hand, *RegD* is designed for faster responding resources like BESS and is a high-pass filtered ACE signal. Then, the mileage ratio,  $\beta_t^M$ , is defined as

$$\beta_t^M = \frac{\text{RegD Mileage}}{\text{RegA Mileage}} \quad (6)$$

where mileage can be defined as the movement requested by the regulation control signal.

Therefore, the total income of the BESS from the frequency regulation market,  $J_{reg}$ , can be expressed as follows:

$$J_{reg} = \sum_{t=1}^T [\eta_t q_{reg}(t) (\lambda_c(t) + \beta_t^M \lambda_p(t))] \quad (7)$$

## 2.4 Optimal location

The proposed framework provides the flexibility of locating an optimal site that can maximise the economic benefits of the BESS. The revenue from the energy arbitrage application depends on the temporal price difference in the electricity, which is indicated by the LMPs. The LMPs at each node of a system are influenced by several factors including the geographic location, variability of load, connectivity with the rest of the network and the uncertainty associated with renewable energy generation. Hence, it would be more profitable to locate the BESS at a node with a high variability in LMPs. It should be noted that most of the revenue is generated by the frequency regulation application, for which the signals remain unchanged across all nodes in the network as these are dictated by the ISOs and do not vary locally. However, performing regulation alone is not sustainable as the regulation signal in most control areas does not display zero average power [25]. This implies that the storage device needs to participate in other application(s) to preserve the charge–discharge dynamics of the battery subject to its total capacity. In summary, the BESS can be located at nodes with a high variability in LMPs if such provision is allowed for and if the effort leads to tangible benefits. The focus of this study is not on the siting aspect although it offers the flexibility of choosing an optimal location if the need arises.

## 3 Battery degradation cost

As batteries undergo charging and discharging repeatedly, they degrade by losing their active material. The degradation process reduces the life of the battery and hence the degradation cost should be considered as an operational cost while determining the revenue of a BESS for a more accurate estimate. Hence, a degradation cost model is developed in this study and incorporated within the optimisation framework and is described in this section.

### 3.1 DOD stress model

The lifetime of batteries depends on two components: its cycle life and its calendar life [26]. Cycle life quantifies the loss of battery life due to cycling, while calendar life quantifies the life loss due to ageing. The development of a degradation cost model is accomplished in this study with the help of cycle life only. Calendar life is not considered as it has a little effect on the day-to-day operation of the battery.

The cycle life of a battery depends on its DOD among other things. The degradation of a battery per cycle depends on the DOD stress factor and can be expressed as follows [27]:

$$\Delta_c = (k_{D1} \text{DOD}^{k_{D2}} + k_{D3})^{-1} \quad (8)$$

where  $\Delta_c$  is the degradation per cycle, and  $k_{D1}$ ,  $k_{D2}$  and  $k_{D3}$  are constants whose values depend on the battery technology. The use of a Lithium Nickel Manganese Cobalt Oxide (Li(NiMnCo)O<sub>2</sub>) or

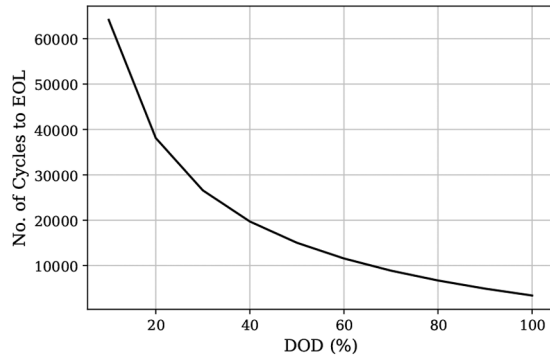


**Fig. 1** No. of cycles to EOL versus DOD

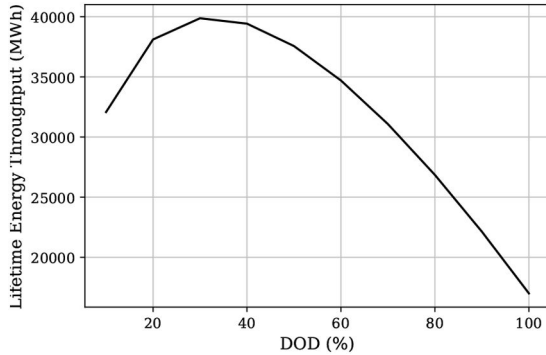


**Fig. 2** Lifetime energy throughput versus DOD

LMO battery is assumed in this paper. The stress model for DOD may be different for different battery technologies. The relationship between DOD and the number of cycles until its end of life (EOL) is illustrated in Fig. 1.

In this study, it is assumed that the battery reaches its EOL when its maximum capacity reduces to 80% of its original capacity. It is widely accepted in the automotive industry for the batteries to be discarded when they have depleted 20% of their original capacity. However, some researchers have proposed the use of these second-life batteries to be used for stationary power applications [28–31]. While second-life batteries can be suitable candidates for some applications like transmission support and load following, they are not suited to provide services like spinning reserve and frequency regulation [28]. This study considers the participation of the BESS in providing frequency regulation service, and hence the assumption that the battery reaches its EOL after depleting 20% of its original capacity is justified.

### 3.2 Degradation cost function

The degradation cost function of a BESS can be derived from its lifetime energy throughput [32], number of cycles and the cost of the battery packs. First, a degradation cost coefficient,  $c_{\text{deg}}$  (\$/MWh), is defined as follows.

$$c_{\text{deg}} = \frac{c_{\text{bat}}}{E_{\text{ltp}}} \quad (9)$$

where  $c_{\text{bat}}$  is the battery cost and  $E_{\text{ltp}}$  is the lifetime energy throughput of the BESS.  $E_{\text{ltp}}$  can be defined as follows:

$$E_{\text{ltp}} = N_c \times \bar{S} \times \overline{\text{DOD}} \quad (10)$$

where  $N_c$  is the number of cycles the battery undergoes until its EOL,  $\bar{S}$  the energy capacity, and  $\overline{\text{DOD}}$  the average DOD of the battery.  $N_c$  is calculated for a particular  $\overline{\text{DOD}}$  and varies, as shown

in Fig. 1. The relationship between the lifetime energy throughput and DOD is shown in Fig. 2. In this work, DOD has been assumed to be 80% to accommodate for the worst-case scenario since the state of charge (SOC) of the BESS is also restricted to 80% of the total capacity. In practice, not all cycles will have DOD as high as 80%. Hence, the results obtained by using this model will be conservative estimates of the actual values.

The degradation cost function,  $C_d(t)$ , is then derived from  $c_{\text{deg}}$  and the energy throughput of the battery for the time period  $t$  as follows:

$$C_d(t) = c_{\text{deg}} \times q(t) \quad (11)$$

where  $q(t)$  is the total energy throughput from the BESS at the time  $t$ . Since the BESS participates in the energy arbitrage and frequency regulation markets, the energy exchanged from these markets is the energy throughput from the BESS at any time  $t$ , and thus  $q(t)$  can be expressed as

$$q(t) = \eta_c q_r(t) + q_d(t) + (\eta_c \gamma_{\text{rd}}(t) + \gamma_{\text{ru}}(t)) q_{\text{reg}}(t) \quad (12)$$

Here  $\eta_c$  is the round trip efficiency of the battery,  $\gamma_{\text{ru}}$  is the fraction of the regulation up reserve capacity actually employed at the time  $t$ , and  $\gamma_{\text{rd}}$  is the fraction of the regulation down reserve capacity actually employed at the time  $t$ .

## 4 Optimisation framework

This section describes the optimisation framework for extracting the maximum economic benefits of the BESS. This framework includes the objective function, the network constraints, and the capacity and operational constraints for the energy storage.

### 4.1 Objective function

The objective of this framework is to maximise the BESS revenue by performing energy arbitrage and frequency regulation, and also to optimally locate the BESS. The revenue function,  $J$  can thus be expressed with the help of (2) as follows:

$$J = J_{\text{arb}} + J_{\text{reg}} - C_d \quad (13)$$

Therefore, the objective function can be expressed as (see (14)), where  $\lambda_{\text{imp}}(t, n)$  is the LMP at bus  $n$  for the time period  $t$ . The optimisation framework is designed in a manner so as to calculate the revenue at each bus and automatically chooses the bus with the maximum economic benefits by comparing their individual revenues.

### 4.2 Energy storage constraints

The operation of the energy storage is constrained by its physical capabilities, charging and discharging power limits, and cycle and self-discharge efficiencies. As the BESS charges and discharges every hour due to its participation in different applications, its remaining capacity changes every hour. The remaining capacity of a BESS is indicated by a metric known as the state of charge (SOC), which can be mathematically formulated as follows:

$$s(t+1) = \eta_s s(t) + \eta_c q_r(t) - q_d(t) + (\eta_c \gamma_{\text{rd}}(t) - \gamma_{\text{ru}}(t)) q_{\text{reg}}(t) \quad (15)$$

where  $s(t+1)$  is the SOC at the time  $(t+1)$ .  $\eta_s$  is the self-discharge efficiency of the battery,  $\gamma_{\text{ru}}$  and  $\gamma_{\text{rd}}$  are calculated using historical data for PJM regulation signals [33, 34].  $\gamma_{\text{ru}}$  and  $\gamma_{\text{rd}}$  are illustrated in Fig. 3 for a sample week.

The BESS operation is constrained by the following equations:

$$\max J = \sum_{n=1}^{N_{\text{bus}}} \left[ \sum_{t=1}^T \lambda_{\text{imp}}(t, n) [q_d(t) - q_r(t)] + \sum_{t=1}^T [\eta_c (\lambda_c(t) + \beta_t^M \lambda_p(t)) q_{\text{reg}}(t)] - \sum_{t=1}^T C_d(t) \right] \quad (14)$$

$$\gamma_{\text{reg}}^{\min} q_{\text{reg}}(t) + \gamma_s^{\min} \bar{S} \leq s(t+1) \quad (16)$$

$$s(t+1) \leq (1 - \gamma_s^{\max}) \bar{S} - \eta_c \gamma_{\text{reg}}^{\max} q_{\text{reg}}(t) \quad (17)$$

$$q_r(t) + q_d(t) + q_{\text{reg}}(t) \leq \bar{Q} \quad (18)$$

$$s(T) = s_0 \quad (19)$$

where  $\bar{S}$  is the BESS energy capacity in MWh;  $\bar{Q}$  is the energy charge/discharge rating in MWh and is derived from the power limit of the BESS;  $\gamma_s^{\min}$  and  $\gamma_s^{\max}$  are the fractions of energy capacity to be reserved for discharging and charging, respectively;  $\gamma_{\text{reg}}^{\min}$  and  $\gamma_{\text{reg}}^{\max}$  are the fractions of regulation bid reserved for discharging and charging, respectively. The  $\gamma_{\text{reg}}$  parameters ensure that the BESS meets all the regulation obligations and does not incur a penalty.

The minimum and maximum SOC limits are indicated by (16) and (17), respectively. Constraint (18) restricts the throughput based on the power rating while allowing charging and discharging during the same time step. The SOC level is maintained at the same level at the beginning of each day with the help of (19).

#### 4.3 Generation and transmission constraints

The network power flow is governed by generator limits, power balance, and transmission line constraints. A DC network model is applied in this research; as a result, the reactive power is neglected. The power flow in the network is constrained by the following equations.

• **Power balance:** The quantity of real power injected at any bus  $m$  must balance out the difference between the generation and demand at that particular bus at any given point of the time  $t$ . The contribution of the BESS in the power exchange at each bus  $m$  is represented by the variables  $q_d(t)$  and  $q_r(t)$ . It should be noted that the regulation variable  $q_{\text{reg}}$  is ignored as the regulation signal does not have any significant local effect. This constrained is modelled as follows:

$$P(t, n) = P_G(t, n) - P_L(t, n) + q_d(t) - q_r(t) \quad (20)$$

where

$$P(n) = \sum_{k=1}^{N_{\text{bus}}} B_{nk} \delta_k$$

$P(t, n)$ ,  $P_G(t, n)$  and  $P_L(t, n)$  are the real power injection, generation and demand at bus  $n$  at time  $t$ , respectively;  $B$  is the imaginary part of the admittance matrix, and  $\delta_k$  is the voltage angle of bus  $k$ .

• **Generator constraints:** The operation of each conventional generator is limited by its capability limit

$$P_{\min}(g) \leq P(g) \leq P_{\max}(g) \quad (21)$$

where  $P(g)$  is the power generated by the  $g$ th generator, and  $P_{\min}(g)$  and  $P_{\max}(g)$  denote its minimum and maximum capacities, respectively.  $g$  is an index for the generators that ranges from 1 to  $N_g$ , the total number of generators in the system.

• **Transmission line constraints:** The transmission lines of the network are constrained by the amount of real power that can be transmitted

$$P_{kn} = \frac{(\delta_k - \delta_n)}{x_{kn}} \leq P_{kn}^{\max} \quad (22)$$

Here  $P_{kn}$  and  $x_{kn}$  are the real power transfer and the reactance between buses  $k$  and  $n$ , respectively,  $\delta_k$  and  $\delta_n$  are the voltage angles for buses  $k$  and  $n$ .

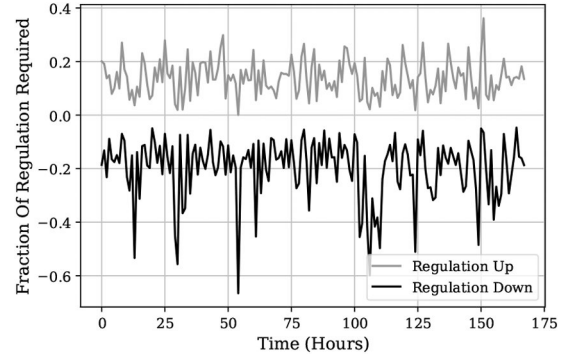


Fig. 3 PJM regulation data for an example week

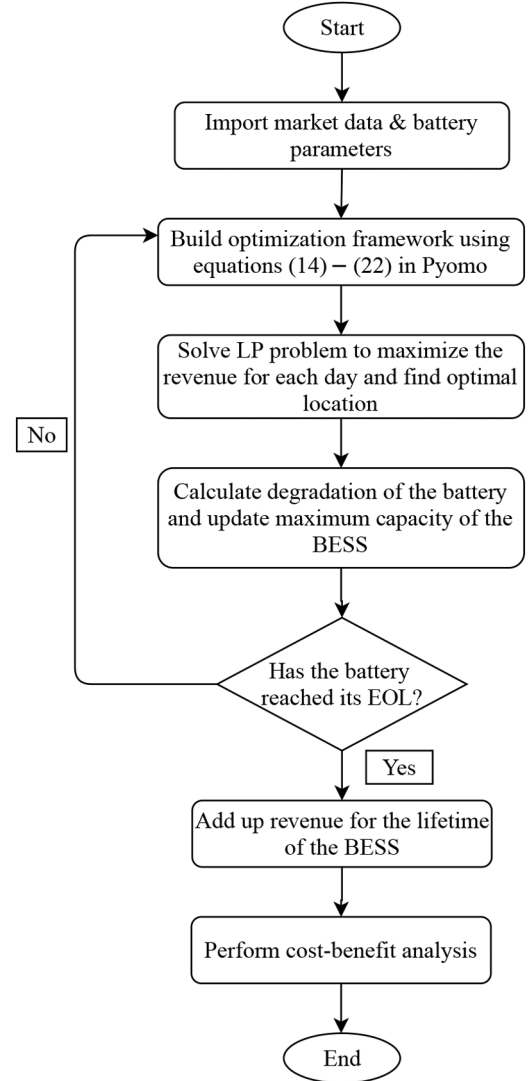


Fig. 4 Flowchart summarising the methodology used in this paper

The decision variables in the proposed optimisation framework are  $q_d(t)$ ,  $q_r(t)$ ,  $q_{\text{reg}}(t)$ ,  $P(g)$ ,  $\delta_k$ , and  $s(t)$ .

The methodology used in this paper has been summarised using a flowchart, as shown in Fig. 4.

#### 4.4 Calculation of lifetime revenue

The lifetime revenue offered by the BESS is calculated by using the optimisation framework described in the previous subsections. As the battery operates over time, it loses active material due to repeated charging and discharging. Hence, the maximum capacity of the battery decreases gradually.

In this work, the lifetime revenue is calculated using the method proposed in [35]. A semi-empirical degradation model is used to

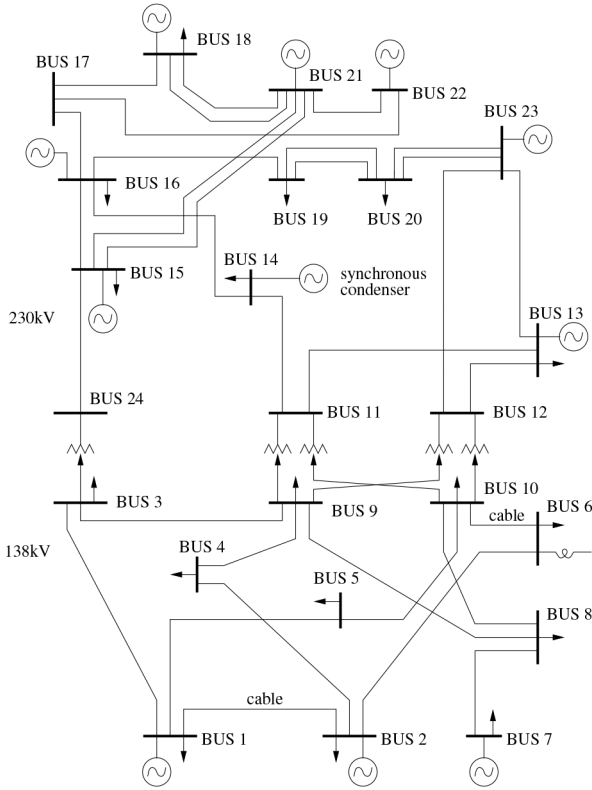


**Fig. 5** Single-line diagram of the IEEE Reliability Test System

**Table 1** BESS Parameters

| Parameter                    | Value    |
|------------------------------|----------|
| power capacity               | 10 MW    |
| energy capacity              | 5–20 MWh |
| $\gamma_s^{\min}$            | 15%      |
| $\gamma_s^{\max}$            | 5%       |
| $\gamma_{\text{reg}}^{\min}$ | 5%       |
| $\gamma_{\text{reg}}^{\max}$ | 5%       |
| $\eta_c$                     | 95%      |
| $\eta_s$                     | 95%      |

track the degradation of the battery and the maximum capacity of the battery is updated at regular intervals. The revenue is calculated and accumulated until the battery reaches its EOL.

## 5 Cost–benefit analysis

A life cycle cost-benefit analysis of BESS projects is performed in this study after obtaining the lifetime revenue as described in the previous sections. This analysis will enable investors in their decision making process by providing them with an estimate of the net present value (NPV), the return on investment (ROI), and the payback period for the BESS projects.

### 5.1 Capital cost

The total capital cost,  $C_0$ , includes the cost of battery, power conversion system, balance of plant, and other investment costs. The annualised capital cost  $C_{\text{acc}}$  is calculated by multiplying the capital cost with the capital recovery factor (CRF). These quantities are determined as follows [36, 37]:

$$C_0 = C_{\text{bat}} + C_{\text{inv}} + C_{\text{bos}} + C_{\text{oth}} \quad (23)$$

$$C_{\text{acc}} = C_0 \times \eta \quad (24)$$

$$\eta = \frac{i(i+1)^{T_p}}{(1+i)^{T_p} - 1} \quad (25)$$

where  $C_{\text{bat}}$ ,  $C_{\text{inv}}$ ,  $C_{\text{bos}}$ , and  $C_{\text{oth}}$  represent costs of battery, battery central inverter, electrical and structural balance of system, and other investments including labour and tax, etc., respectively.  $\eta$  represents the CRF, which is related to the interest rate  $i$  and the system lifetime  $T_p$ .

### 5.2 Replacement cost

To accommodate the replacement costs for replaceable systems, e.g. batteries, the future cost of replacement and replacement period in years should be known. Annualised replacement costs can be calculated, given the number of replacements during the application lifetime [37]. The annualised replacement cost,  $C_{\text{arc}}$ , is calculated as follows:

$$C_{\text{arc}} = C_{\text{rc}} \times [(1+i)^{-t} + (1+i)^{-2t} + \dots + (1+i)^{-n_r t}] \times \eta \quad (26)$$

$$t = \min [T_{\text{cal}}, T_{\text{cyc}}] \quad (27)$$

where  $C_{\text{rc}}$  is the replacement cost of battery,  $t$  is the replacement period, which is estimated with the degradation model in this study.  $t$  should be the calendar or the cycle life of the battery, whichever comes first.  $n_r$  is the number of replacements during a certain period  $T_p$ .

### 5.3 Net present value

The NPV for a BESS project is determined using the following equation:

$$\text{NPV} = -C_0 + \frac{C_1}{1+r_1} + \frac{C_2}{(1+r_2)^2} + \dots + \frac{C_t}{(1+r_t)^t} \quad (28)$$

Here  $C_t$  represents the net cash flow and  $r_t$  the discount rate for year  $t$ . The net cash flow is calculated as the revenue obtained from the market less the O&M costs.

### 5.4 Payback period and ROI

The payback period represents the time required to recover the cost of an investment, while the ROI indicates the profitability of an investment over the lifetime of the battery. Unlike the NPV, when evaluating the ROI and payback period, the time value of money is not considered.

## 6 Results and discussion

The proposed approach is validated using the IEEE Reliability Test System (IEEE RTS). The original system consists of 24 buses, 33 transmission lines, 5 transformers, and 32 generating units [38]. The single-line diagram of this test system is shown in Fig. 5.

Historical data from PJM interconnection has been utilised for this study. PJM's Data Miner [39] has been utilised to obtain the RMCCP, RMPCP, mileage ratio, and the actual performance score for each hour. Data for one year starting from 1 January 2018 has been used.

The parameters of the BESS utilised are shown in Table 1. The cost of a Li-ion battery has been assumed to be \$209,000 per MWh [40].

### 6.1 Revenue

The optimisation framework presented in Section 4 has been solved to obtain the annual revenue from the BESS. The BESS is optimised for the day-ahead market. Hence, the time horizon for the optimisation problem is 24 hours, i.e.,  $T = 24$ . The revenue has been evaluated for three different sizes of BESS. The power

**Table 2** Lifetime revenue from BESS considering degradation cost

| Battery size  | Lifetime, years | Revenue, \$ | Mean cycles per year |
|---------------|-----------------|-------------|----------------------|
| 10 MW, 5 MWh  | 6               | 8,116,541   | 1829                 |
| 10 MW, 10 MWh | 8               | 11,062,330  | 1731                 |
| 10 MW, 20 MWh | 10              | 13,139,466  | 1526                 |

**Table 3** Lifetime revenue from BESS without considering degradation cost

| Battery size  | Lifetime, years | Revenue, \$ | Mean cycles per year |
|---------------|-----------------|-------------|----------------------|
| 10 MW, 5 MWh  | 5               | 10,492,202  | 2028                 |
| 10 MW, 10 MWh | 6               | 13,865,585  | 2072                 |
| 10 MW, 20 MWh | 8               | 17,629,318  | 1752                 |

**Table 4** Results of the annualised cost analysis

| Battery size  | Capital cost, \$/kWh [40] | Battery cost, \$/kWh [40] | Annualised capital cost, \$ | Annualised replacement, cost, \$ |
|---------------|---------------------------|---------------------------|-----------------------------|----------------------------------|
| 10 MW, 5 MWh  | 895                       | 209                       | 593,688                     | 100,546                          |
| 10 MW, 10 MWh | 601                       | 209                       | 797,333                     | 180,672                          |
| 10 MW, 20 MWh | 454                       | 209                       | 1,204,623                   | 0                                |

**Table 5** Results of the life cycle cost–benefit analysis

| Battery size  | Payback period, y | NPV, \$   | ROI, % |
|---------------|-------------------|-----------|--------|
| 10 MW, 5 MWh  | 3.5               | 2,041,521 | 80.6   |
| 10 MW, 10 MWh | 4.5               | 2,441,298 | 83.4   |
| 10 MW, 20 MWh | 6.5               | 510,846   | 44.0   |

**Table 6** Variation in annual revenue and location for all sample paths

| Sample path | Revenue, \$ | Location (bus no.) |
|-------------|-------------|--------------------|
| 1           | 1,448,518   | 1                  |
| 2           | 1,448,507   | 1                  |
| 3           | 1,448,514   | 1                  |
| 4           | 1,448,428   | 1                  |
| 5           | 1,448,509   | 1                  |

capacity is maintained at 10 MW, while the energy capacity is varied from 5 to 20 MWh. Results are presented in Tables 2 and 3.

These particular BESS sizes were selected as these are the most commonly used utility-size BESS in the US and also represent short, medium, and long duration BESSs [40].

Upon observing the results presented in Tables 2 and 3, it can be seen that neglecting the degradation cost of batteries leads to overestimation of the lifetime revenue of the BESS. The average number of cycles undergone by the BESS per year is reduced when the degradation cost is considered, thus prolonging its lifetime. This observation holds true for all sizes of BESS used in the case studies and underlines the importance of considering the degradation cost while estimating the revenue of a BESS. Also, it can be observed that the lifetime revenue of longer duration BESS is higher than the shorter duration BESS due to the higher energy capacity of longer duration BESS.

The revenues generated by the individual applications were calculated to analyse the contribution of each application to the total revenue. It is found that most of the revenue is generated by the frequency regulation application. For example, for the 10 MW, 10 MWh BESS, frequency regulation contributes \$2,348,109 for

the first year, while the cumulative revenue from arbitrage was actually negative (−\$2,942). However, it should be noted that performing regulation alone is not sustainable as the regulation signal in most control areas does not generate zero average power [25]. This implies that the storage device needs to participate in other application(s) to preserve the charge–discharge dynamics of the battery subject to its total capacity. Also, to participate in the more rewarding regulation market, the battery might sometimes need to be charged during periods of high LMPs which can lead to negative revenues from arbitrage. In summary, participating in the regulation market is extremely valuable for the BESS, but is not sufficient for technical reasons as explained.

## 6.2 Cost–benefit analysis

The results of cost–benefit analysis are provided in this subsection. For the purpose of this analysis, only the case considering the degradation cost is included since the case without the degradation cost overestimates the revenue. Table 4 lists the annualised capital cost and annualised replacement cost. The project life is assumed to be 10 years in these calculations based on the calendar life of the battery [27]. The number of replacements is calculated based on the result of degradation analysis. There is no annualised replacement cost for the 10 MW, 20 MWh battery since its remaining capacity is larger than 80% at year 10, and thus no replacement is needed during the BESS project life.

The payback period, NPV and ROI for different battery sizes are compared in Table 5. The fixed O&M cost is assumed to be 6 \$/kW per year [41] while the discount rate  $r$  is assumed to be 5.5% [42]. The payback period represents the time required to recover the cost of an investment, while the ROI indicates the profitability of an investment over the lifetime of the battery. It should be noted that the time value of money is not considered while calculating the payback period and the ROI but is considered while calculating the NPV.

From the results of Table 5, it can be observed that for larger BESS sizes, the payback period is longer and the NPV and the ROI are smaller. This can be attributed to the higher investment cost for larger BESS. Also, most of the revenue is generated by the frequency regulation application and BESS with smaller energy capacity and moderate power capacity is preferred for this purpose [25]. Hence, it can be concluded that the 10 MW, 5 MWh and the 10 MW, 10 MWh BESS are better choices for investors due to their shorter payback period and higher NPV and ROI.

## 6.3 Effect of uncertainty in LMPs on revenue and siting

Five sample paths of annual LMPs are generated to demonstrate the variation in revenue and optimal location. The results are presented in Table 6. The degradation cost is considered while calculating the annual revenue.

From the results, it can be observed that the variation in revenue due to uncertainty is very low. This is due to the fact that the revenue from energy arbitrage constitutes a very small portion of the total revenue. Also, the location remains unchanged due to the variability introduced in the LMPs.

## 6.4 Modelling language & solver

Pyomo [43], a Python-based, open-source optimisation modelling language is employed for modelling the problem. The objective function and the constraints in the proposed optimisation framework are linear. Hence, the problem can be solved using any linear programming solver. *GLPK* has been used in this paper.

## 7 Conclusion

This paper proposes a new framework to maximise the economic benefits of a grid-connected BESS, by optimising the annual dispatch strategy and location while also considering the degradation of batteries within the proposed framework. A general model is presented for the quantification of BESS revenue obtained from the electricity markets. Energy arbitrage and frequency regulation are chosen to be the applications in which the BESS

participates due to their high profitability. A lithium-ion battery is the choice of the BESS for this study. The degradation cost of the BESS is taken into consideration for a more realistic estimate of the ROI. A new model for quantifying the degradation cost of batteries based on their lifetime energy throughput and number of cycles is developed for batteries participating in the electricity markets and incorporated within the objective function. Results indicate that inclusion of the degradation cost contributes in making the revenue estimate more realistic and accurate. Ignoring the degradation cost leads to the overestimation of the revenue. A comprehensive cost-benefit analysis is presented to provide an estimate of the ROI and the payback period. Results indicate that shorter duration BESS are better suited for market-related applications due to better ROI and shorter payback period when compared to longer duration BESS. The findings obtained by employing the proposed methodology can be utilised by investors and utilities during the planning phase of a BESS project and aid in the decision making process based on the ROI and payback period.

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