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Optimal Investment Strategy in Grid-Scale Energy Storage Systems

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Abstract

Grid-scale energy storage systems (ESS) have been widely recognized as a viable tool for integrating the growing renewable penetration in distribution networks. However, it is challenging to determine efficient and well-timed investment in the grid-scale ESS considering battery operational decisions and future uncertainties, such as varying electricity prices and the declining cost of the ESS technology. Within this context, in this paper, we present a methodology to incorporate the ESS operational decisions within the *real options valuation* (ROV), which quantifies the benefits from the ESS to the network and derive the optimal investment decisions upon future uncertainties. Specifically, a mixed integer quadratic model is developed to determine the optimal size of a grid-scale ESS. Then, the benefits to the network, including the reduction in the maximum energy delivered through the transformer and line loading reductions, are converted into cost savings compared with the costly network augmentation. The results are used as the inputs to the ROV for determining the economic performance of the investment, as well as the optimal investment strategy. The efficacy of the method is shown on two Australian low voltage test feeders, and the results from the ROV show that delaying the ESS investment to a later year mitigates the risk of financial losses in the presence of multiple future uncertainties.

1. Introduction

Rapidly growing PV penetration has become an indispensable energy supply resource in distribution networks. In Australia, the annual installed capacity of small-scale PV systems has increased from less than 200MW in 2009 to 1.1GW in 2017, and projections by the Australian Energy Market Operator (AEMO) see the total roof-top solar generation capacity to increase from 4.3GW in 2017 to 19GW in 2035 [1]. However, rising PV penetration has imposed numerous technical problems including over-voltages, reverse power flows with congestion problems, and phase unbalance in low voltage (LV) networks [2]. Network augmentation can be implemented to accommodate the increasing PV penetration, however, this method is too costly [3].

Alternatively, energy storage systems (ESS) are considered as a technically viable tool for mitigating these technical problems. Additionally, they can help manage the power flows in distribution networks, and relieve the burden from generators during peak periods [4], [5]. Meanwhile, the cost of the ESS technology is predicted to reduce in the future [1]. Although the technology is currently expensive to implement, it has already shown its potential to become an accessible alternative to the costly and time consuming network augmentation.

However, with increasing uncertainties in distribution network investment and operation in the electricity market environment, the distribution network service provider (DNSP) confronts a great challenge in determining efficient and well-timed investment in grid-scale ESS. The traditional *discounted cash flow* (DCF) either recommend abandoning the project if the *net present value* (NPV) is negative, or investing immediately if it is positive [6]. However, renewable generation investments, such as grid-scale ESS investment are not now or never, and the DNSP can make contingent decisions on the optimal investment timing and capacity based on the unfolding of future information. This leads to the concept of real options valuation (ROV), which highlights the importance of investment timing, taking into account the managerial flexibility of making contingent decisions upon the realizations of future uncertainties, including varying electricity price, and the declining cost of the ESS. These uncertainties are typically captured by the *geometric Brownian motion* coupled with *Monte Carlo* (MC) simulations before feeding into the ROV. Then, the ROV determines the optimal investment strategies for different realizations of future investment environment generated by the MC analysis, and thus provides more flexibility towards future uncertainty [7], [8].

1.1. Literature Review

In this subsection we review existing literature for: (i) ROV in transmission and distribution network investments, and (ii) the methods to calculate the value of real options.

ROV has been frequently applied for valuation of distribution and transmission network investments, including transmission network expansion [9], [10], distributed generation [11], hydro-power [12], wind generation [13], [14] and residential solar generation [15]. Specifically, the authors in [9], [10], [11] and [12] determined the value of deferring an investment in the presence of uncertain electricity market conditions or regulatory policies. The study in [15] evaluates the solar generation investment for a domestic residential customer, and calculates the value of the option to delay the investment via ROV. In [16], the authors used flexible AC transmission systems to add flexibility to the transmission expansion planning. Specifically, the study valuates the option to abandon and/or relocate the transmission network investment. None of these studies applies the ROV to ESS investments in distribution networks, because incorporating the operation of the ESS involves solving the battery scheduling optimization problem, which is time-consuming and impractical within the MC analysis that underpins ROV.

In terms of calculating the value of real options, the *partial differential equations* (PDE) [17] based on the research of Black, Scholes and Merton, and binomial lattice [18] have been widely applied. However, the PDE approach can be used to incorporate only one uncertainty, or at most two correlated ones. This is not the case in the electricity market where multiple uncertainties exist. Meanwhile, the PDE is designed for European-type of option analysis in which the investment can only be taken on a specific future date[19]. Another alternative, binomial lattice, use backward induction, and the prior path of the underlying variable is unknown at the time computations are made, making it impossible to incorporate multiple interacting options [19]. Thus, these methods are not suitable for distribution network investments where there are multiple sources of uncertainty and interacting options.

In light of this, the *least square Monte Carlo* (LSMC) method is applied to determine the value of real options, and hence, deriving the optimal investment strategy [11], [10], [12], [13], [16] and [20]. This method allows us to incorporate many sources of uncertainty, and accurately capture the flexibility in delaying investments using MC simulations. For instance, the authors in [16] applied this method to value the flexible AC transmission systems (FACTS) devices in transmission networks by modeling both demand and fuel costs as stochastic processes, and providing the optimal timing for the option to install, locate and remove the asset. For these reasons, the LSMC method is used in our work.

1.2. Contributions

Given the above background, this work presents a ROV framework to evaluate the economic viability of replacing network augmentation with grid-scale ESS. Specifically, the framework assesses the benefits brought by the ESS using a battery optimization model, and quantitatively incorporates these benefits within the ROV to determine the optimal ESS investment strategy upon future uncertainties. In this work, we consider two sources of uncertainty: (i) the declining cost of the ESS technology, and (ii) varying wholesale electricity price. These prices are modelled using the *geometric Brownian motion* (GBM) and the GBM with mean reverting process, respectively.

In order to capture the value of managerial flexibility, and determine the optimal investment strategy within a pre-identified decision period, we need to feasibly include battery schedules within the ROV through the following steps:

- Solve the battery optimization problem to determine the benefits of the ESS to a LV feeder; and,
- Quantitatively incorporate the benefits within the MC paths of future uncertainties to calculate the payoff in each MC path; and,
- Use the payoffs as the input to the ROV to determine the optimal investment strategy.

The uncertainty in power demand growth is not considered in this work, because doing so requires running the battery optimization model within the MC analysis. Solving the battery optimization problem is timing-consuming, and therefore infeasible within the MC analysis.

By using the presented framework, we are able to evaluate the economic viability of the grid-scale ESS in distribution networks. Although ROV based on the LSMC method has already been used in the evaluation of network investments, it is the first time that the usefulness of these techniques has been shown for assessing the investment value of ESS projects in particular, and for distribution investments in general. The result shows that postponing the ESS investment to a later year maximizes the investment value, while this result changes as the size of the investment changes.

The rest of the paper is organized as follows. Section 2 explains the LSMC approach which is used for valuing the managerial flexibility. Section 3 presents the battery optimization model. Section 4 describes the costs and benefits analysis of the ESS investment, and the outcomes are evaluated and compared in Section 5. Finally, Section 6 draws conclusions.

2. Real Options Theory

The traditional DCF method fails to appraise an investment under uncertainties and in the presence of contingency. The problem can be solved by applying ROV, which allows the DNSP to make optimal investment decision in accordance with the unfolding of future information. In contrast to the NPV methods that consider managerial flexibility only as a passive factor and provide deterministic investment decisions, ROV recognizes the benefits of contingency and includes this as an active entity in its calculation, which potentially changes the investment strategy [21], [22].

The process of the ROV begins by computing the underlying investment value of the ESS investment with the traditional DCF method. It then calculates the option value of this investment using the LSMC method, which considers multiple uncertainties as well as the optimal timing of the decision over multiple time steps. Specifically, this method combines a forward-looking model for incorporating uncertainties, and a backward linear regression for determining the optimal investment timing [19]. The ROV is most valuable when the levels of uncertainties are high, and the management has the flexibility to change the direction of the course to a more favorable way. In our work, we assume that the ESS investment can be executed in each year from t_0 to the maturity time at T_{exp}. The investment value in year t is denoted as $F(t, X_t)$, where X_t is the state variable including varying electricity price and the declining cost of the ESS technology.

$$F(t, X_t) = \{E_t[\Pi(\tau, X_\tau)](1 + r)^{-(\tau-t)}\}. \tag{1}$$

where τ is the optimal stopping time, $\Pi(\tau, X_\tau)$ is the payoff of the investment at each time t, $E_t[\Pi(\tau, X_\tau)]$ is the expectation on the information available at t, and r is the risk-neutral discount rate.

The LSMC integrates MC simulations with least square regression to accurately estimate the deferral option value. This method splits the investment time span, from the maturity time T_{exp} to the initial time t_0, into a number of discrete intervals, each interval is equivalent to one year. The dynamic feature of the state variables is simulated by generating Ω realization paths by means of geometric Brownian motion coupled with MC simulation. For each MC path, we estimate the *continuation value*, denoted Φ_{t,ω,X_t}, which represents the value of continuing to waiting for the unfolding of future uncertainty at each time via the LSMC method. Then, the Φ_{t,ω,X_t} is compared with the value of investing immediately ($\Pi(\tau, X_\tau)$), and the optimal stopping time is decided when $\Pi(\tau, X_\tau)$ is greater than Φ_{t,ω,X_t} for the first time along each MC path. The detailed formulations can be found in study [11].

The optimal stopping time of each MC path τ_ω forms a unique optimal stopping time matrix, which includes the earliest investment timing for all MC paths. Using this matrix, the option value at time t is determined by equation (2). The investment is only suggested to be executed when the payoff is greater than this option value.

$$F_{t,X_t} = \frac{1}{\Omega} \sum_{\omega=1}^{\Omega} (1 + r)^{-(\tau(\omega)-t)} \Pi(\tau(\omega), X_{\tau(\omega)}(\omega)). \tag{2}$$

3. Optimal Power Flow Model

This section introduces the optimization model that incorporates the battery operational model within a branch flow model. To include the battery schedules within the ROV to determine the optimal investment strategy, the ESS must be optimally operated to maximize the benefits to the network.

3.1. *Battery Operational Model*

The battery operational model is formulated as follows:

$$e_{t,i} = e_{t-1,i} + 3(\eta^+ p^+_{t,i} - \frac{1}{\eta^-} p^-_{t,i})\Delta t. \tag{3}$$

$$e_\Omega = e_0. \tag{4}$$

$$\sum_{t\in\mathcal{T}} \Big(\eta^+ p^+_{t,i} - \frac{1}{\eta^-} p^-_{t,i}\Big) = 0. \tag{5}$$

$$0 \le 3p^+_{t,i} \le \bar{p}^+. \tag{6}$$

$$0 \le 3p^-_{t,i} \le \bar{p}^-. \tag{7}$$

$$\underline{e} \le e_{t,i} \le \bar{e}. \tag{8}$$

Equation (3) shows the state of charge at time t of a battery ($e_{t,i}$), placed at bus i in the network, is a function of the state of charge at time $t-1$ and the charging ($p^+_{t,i}$) and discharging ($p^-_{t,i}$) rates for each phase during this time interval. In this study, the charging and discharging efficiency (η^+ and η^-) in the model are neglected. The initial state of charge after each cycle, typically one day, must be the same, as shown in equation (4). To ensure that the above constraint can be satisfied, several boundary conditions must be established: (i) the total charging and discharging power for one cycle must be the same, as shown in equation (5), (ii) the charging and discharging rates at each time interval Δt must be constrained the maximum charging and discharging rates given by the properties of the ESS (equation (6) and (7)), and (iii) the state of charge cannot exceed the minimum and maximum states of charge at all times, as described in equation (8).

3.2. *Branch Flow Model*

The optimization model aims to size the grid-scale ESS (e^{cap}) in an unbalanced LV network in order to minimize the maximum energy delivered through the distribution transformer ($\bar{S}$). Thus, the objective function can be formally stated as:

$$\underset{p^+_{t,j},p^-_{t,j},e^{\text{cap}}}{\text{minimize}}\ \bar{S} + c^{\text{ESS}}, \tag{9}$$

where c^{ESS} is the cost of the ESS, the decision variables are the battery charging (p^+_{b}) and discharging (p^-_{b}) rates, and the the size of the ESS. To determine the optimal size that minimizes $\bar{S}$, we set the weighting factor relatively small so that the cost component does not affect $\bar{S}$.

Load flows in LV networks with numerous branches can be difficult to solve, especially when the network is unbalanced and each phase must be taken care of individually. In this case, the branch flow model introduced in [23] is employed, which has been shown to be accurate in modelling power flows in radial distributed networks [24]. Specifically, the branch flow model governs the power flows in the distribution system by formulating the active power flow $p_{t,ij}$ on each phase from bus i to bus j as a function of power flow ($p_{t,jk}$) and power loss ($p^{\text{loss}}_{t,ij}$) entering bus j, and the generation ($p^{\text{pv}}_{t,j}$) and consumption ($p^{\text{load}}_{t,j}$) at bus j. Same goes with the reactive power flow formulation. The battery operational model from (3) to (8) are incorporated into the branch flow models to formulate a mixed integer quadratic programming model for determining the optimal capacity and the operational decisions of the grid-scale ESS.

4. Costs and benefits of the ESS Investment

As described by the ROV model in Section 2, the key part for calculating the option value is the payoff, $\Pi_{t,\omega}$, from equation (1), in other words, the profit from investing in ESS. Specifically, $\Pi_{t,\omega}$ is the cost difference between investing in ESS ($c^{\text{ESS}}_{t,\omega}$) and network augmentation (c^{Aug}_t) from each year of the decision period. In this work, the DNSP is responsible for the ESS procurement, installation and operation. Meanwhile, we assume that the DNSP has

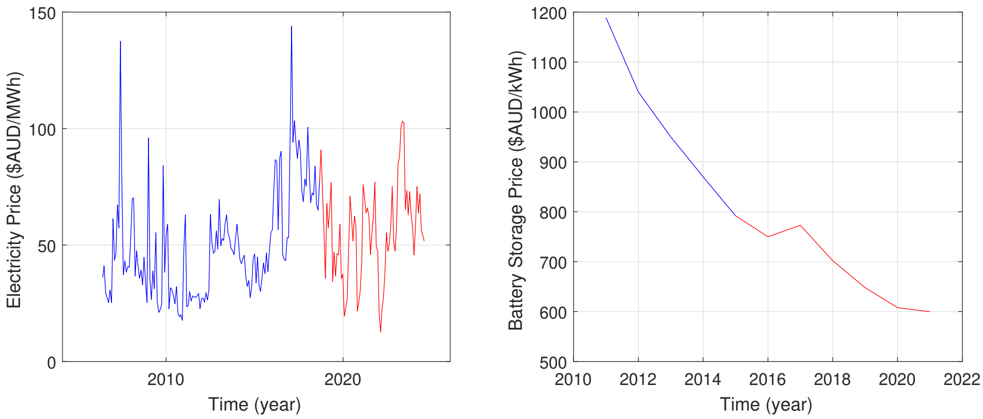


Figure 1: Historical (blue) and simulated (red) electricity prices of the 65th MC path

the obligation to pay for the power delivered through the substation transformer that is above the transformer thermal limit, at the wholesale electricity price, c_t^e. Given this, the annual reduction in the additional generation delivered through the transformer, ΔE_t^{Add} is included in the payoff calculation. Thus, the profit equation for the ω^{th} MC path is shown as follows:

$$\Pi_{t,\omega} = c_{t,\omega}^{\text{ESS}} - c_t^{\text{Aug}} + c_t^{\text{s}}, \tag{10}$$

where c_t^{s} is determined by c_t^e and ΔE_t^{Add}, and c_t^{Aug} is given by:

$$c_t^{\text{Aug}} = c^{\text{T}} \Delta p_t^{\text{Max}} + \sum_{n \in \mathcal{N}} c^{\text{Line}} \Delta l_{t,n}. \tag{11}$$

where c^{T} and c^{Line} are the costs for upgrading the transformer and lines, respectively. Δp_t^{Max} and $\Delta l_{t,n}$ are the reduction in the maximum generation delivered through the transformer and the reduction in the loading of each line, $n \in \mathcal{N}$.

Specifically, the capacity to be upgraded in the transformer is equal to the reduction in the maximum power delivered through the transformer (Δp_t^{Max}) with the ESS, while for each cable this is decided by the corresponding loading reduction, Δl_t, as shown in equation (11). In this work, the MC analysis captures the future uncertainty in varying electricity price, c_t^e, and the declining cost of ESS. These stochastic variables are governed by the GBM. This method is chosen ahead of other techniques due to its ability to adequately describe the stochasticity and drift of a variable. In addition, the increments of process in the GBM show Markov property which assumes that any future change is independent from the previous values, while the variable remains positive throughout the process [25]. The GBM for the declining cost of the ESS technology can be described mathematically as follows:

$$dc_t^{\text{E}} = \mu c_t^{\text{E}} dt + \sigma c_t^{\text{E}} dW_t, \tag{12}$$

where c_t^{E} is the sought stochastic value of the cost of ESS, μ is the percentage drift, σ is the percentage volatility of the data, and W_t is the Wiener process that describes the stochastic component. Therefore, the discretization recursion formula is given by:

$$c_{t+\Delta t}^{\text{E}} = c_t^{\text{E}} e^{(\mu - \frac{\sigma^2}{2})\Delta t + \sigma dW_t}. \tag{13}$$

Using this method, the future ESS price is simulated for 10,000 MC paths with the percentage drift and volatility being -0.26% and 0.13%, respectively. A possible scenario of the future ESS price (red) is extracted along with the historical price (blue) from a random MC path, as shown in Fig. 1, right. This figure shows that the price continues to decrease in the near future, while the speed of decreasing has slowed down. The historical ESS price data are obtained from [26].

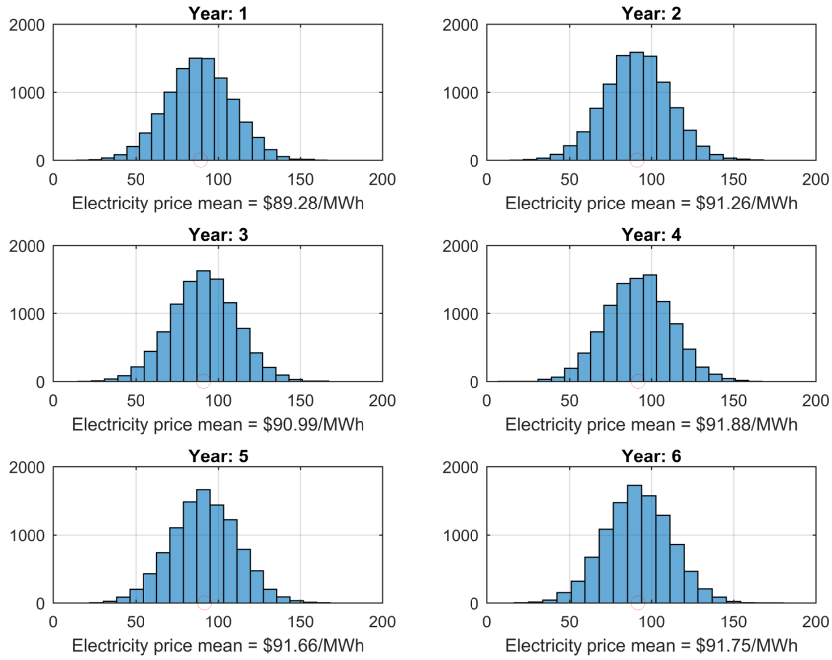


Figure 2: Prediction of future wholesale electricity price

In the wholesale electricity market, the long-term uncertainty of electricity price, c^{e}_t is simulated by the geometric Brownian mean reverting process, considering that the electricity market prices tend to conform to a long-term mean.

$$dc^{\mathrm{e}}_t = \alpha_{\mathrm{e}}(\bar{c}^{\mathrm{e}} - c^{\mathrm{e}}_t)dt + \beta_{\mathrm{e}} dW_t, \tag{14}$$

where α_{e} is the speed of reversion to the mean, β_{e} is the volatility of the electricity price, and $\bar{c}^{\mathrm{e}}$ is the reversion level. Therefore, the corresponding discretization recursion formula is given by:.

$$c^{\mathrm{e}}_{t+\Delta t} = e^{-\alpha_{\mathrm{e}}\delta t}(c^{\mathrm{e}}_t - \bar{c}^{\mathrm{e}}) + \bar{c}^{\mathrm{e}} + \beta_{\mathrm{e}} \sqrt{\frac{1 - e^{-2\alpha_{\mathrm{e}}\delta t}}{2\alpha_{\mathrm{e}}}}. \tag{15}$$

Fig. 1, left illustrate the historical electricity price (blue) and the simulated price for the next 6 years (red) for a random MC path. Fig. 2 shows the distribution of the simulated MC paths of future electricity price. Both figures indicate that the predicted electricity price tends to revert to the reversion level, $\bar{c}^{\mathrm{e}}$, at 0.37. The historical wholesale electricity price data are extracted from [27]. The presented methodology now can be described as a four-step process as listed as follows:

- Run power flow optimization and quantify the benefits brought by the ESS, including the reduction in the maximum power going through the transformer ($\Delta p^{\mathrm{Max}}_t$) and the line loading reduction ($\Delta l_{t,n}$).
- Use the GBM to generate 10,000 MC paths of varying electricity price (c^{e}_t) and the declining cost of ESS (c^{E}_t).
- Calculate the payoff, $\Pi_{t,\omega}$, for each MC path using the results from Steps 1 and 2.
- Use $\Pi_{t,\omega}$ and c^{E}_t in the LSMC method described in Section 2 to determine the optimal investment strategy for each MC path, and the deferral option value.

Table 1: LV Test Networks

	No. of consumers			Feeder	Transformer	Optimal ESS
	Phase A	Phase B	Phase C	length (km)	capacity (kW)	size (kWh)
Feeder 1	41	60	49	4.3	1200	174
Feeder 2	98	109	93	10.2	1800	445

5. Case Studies

To demonstrate the efficacy of the methodology, we adopted two LV test circuits from Electricity North West Limited (ENWL), a British network operator [28]. The basic feeder information is summarized in Table 1. To match the larger air-conditioning loads on typical Australian feeders, these UK test networks are transformed into Australian-type LV networks by tripling the transformer and line capacity[1]. The demand and solar data are from the Ausgrid Smart-Grid Smart-City (SGSC) project. Each consumer, which follows a specific demand profile, adopts a single phase PV system. Feeder 2 is about twice as large as Feeder 1, and both feeders are reasonably loaded, presenting great potential for over-loading problems. In addition, the transformer thermal limits are 800 kVA and 1500 kVA, respectively, meaning that any energy delivered through the transformer that has a greater value than these limits is paid by the DNSP. Our work assumes to execute the ESS investment within a 5-year decision period, with a 7.5 % annual risk-neutral discount rate. The presented methodology helps the DNSP decide the optimal investment strategy to invest in the ESS on both Feeder 1 and Feeder 2, considering the value of managerial flexibility and future uncertainty, and the results are evaluated in this section.

5.1. Real Options Valuation

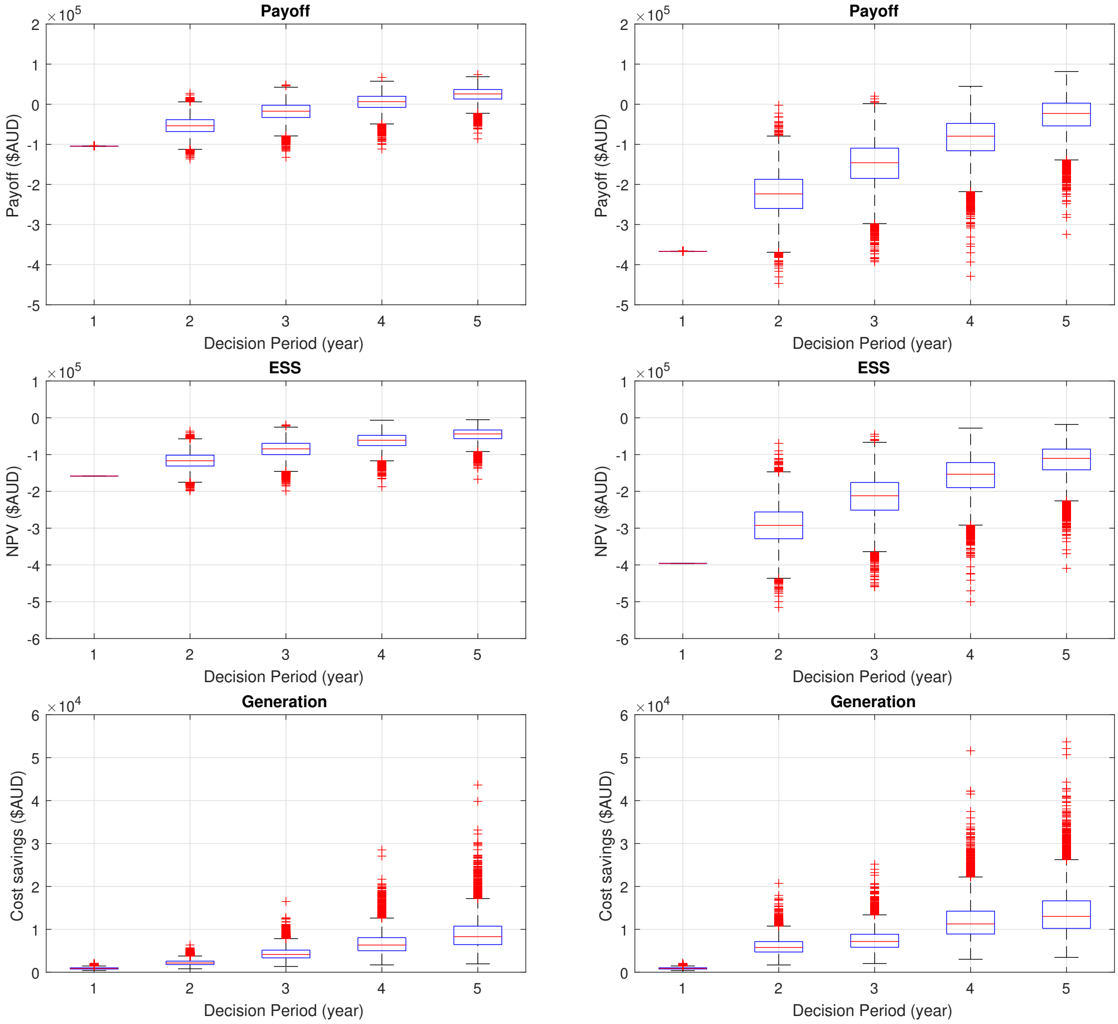
The ROV framework captures the value of managerial flexibility, and therefore determines the optimal timing for the ESS investment. The process follows the LSMC method described in Section 2: (i) use the payoff $\Pi_{t,\omega}$ to calculate the continuation value, Φ_{t,ω,X_t}, using least square regression, (ii) compare Φ_{t,ω,X_t} with $\Pi_{t,\omega}$ for each year during the decision period, and decide whether to execute the investment immediately, and (iii) calculate the value of deferring the investment using equation (2).

The payoff ($\Pi_{t,\omega}$), NPV (c_t^{ESS}), and cost savings from generation reduction (c_t^{s}) of the ESS investment for both Feeder 1 and Feeder 2 are shown in Fig. 3. The average payoff for Feeder 1 increases from -\$1 million in year 1 to \$0.3 million in year 5, while this value peaks in year 4 at -\$0.1 million for Feeder 2. Base on the traditional DCF, the investment is not profitable on either feeder as the average payoffs are both negative, and therefore, this investment is abandoned. However, this decision is changed after taking into account the managerial flexibility and future uncertainties via the ROV framework. Using the LSMC method, the option to invest is abandoned in the case of a negative payoff to reduce the computation time. Along each of the remaining paths, the optimal timing, τ_ω, to execute the ESS investment is when the payoff, $\Pi_{t,\omega}$, is greater than the continuation value, Φ_{t,ω,X_t}, for the first time.

The ROV evaluates the future uncertainties and draws different decisions for the two test feeders. Specifically, the frequency distribution of τ_ω is extracted from the LSMC method, as shown in Fig. 4. From the Feeder 1 distribution, 41% of the MC paths have a greater $\Pi_{t,\omega}$ than Φ_{t,ω,X_t}, in year 4, followed by 30% in year 5 and 15% in year 3. The proportion for not to execute this investment is therefore only 14%. Thus, it is likely that the ESS investment on Feeder 1 will be delayed to year 4. For Feeder 2, on the other hand, the largest frequency is only 25% in the final decision year, followed by 2.5% in year 4, and the chances of abandoning the ESS investment on this feeder is increased to 72.5%. Therefore, it is highly unlikely that the ESS investment will be executed within the decision period for Feeder 2. These results are confirmed by the deferral option values, F_{t,X_t} calculated using equation 2. Specifically, the option values for the ESS investment are 628 and 165 for Feeder 1 and Feeder 2, respectively. The investment should only be executed when the average payoff exceeds this value, which is in year 4 for Feeder 1 and none for Feeder 2.

The difference in the final decisions made to the test cases is caused by the increasing size of the ESS. From the battery optimization, the optimal size for Feeder 1 is 174kWh, which is increased significantly to 445kWh for Feeder

[1]For transformers, we reduced the impedance, while for transmission lines we only reduced the resistance. The reactance mainly depends on the distance between the conductors, so we left it unchanged.



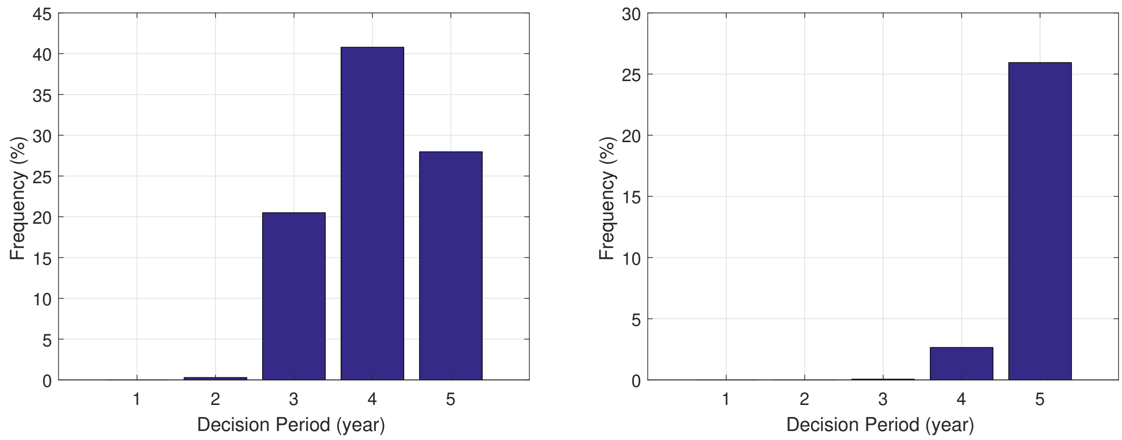
(a) FEEDER 1 (b) FEEDER 2

Figure 3: Payoff, costs of the energy storage system, and the cost savings from the reduction of the additional generation

2. Consequently, the NPV of the ESS for Feeder 2 becomes much greater than that for Feeder 1, which translates into a much smaller payoff, as shown in Fig. 3, payoff plots. In addition, there are more outliers below the average than above, especially for Feeder 2, as indicated in Fig. 3, ESS plots. This raises the amplitude of the outliers below the average in the payoffs, increasing the risk for the investment to become less profitable. The results derived from the methodology shows that the ROV accounts for the opportunity values from future uncertainties, and thus draws different conclusions from the NPV analysis.

6. Conclusion

This work presents a framework that can (i) explicitly incorporate battery operational decisions within the ROV, and (ii), determines the optimal timing of the grid-scale ESS investment considering the values of future uncertainty and managerial flexibility. The framework models the future stochastic variables, including varying electricity price and the declining cost of ESS using the GBM, and then generates a large pool of MC paths characterized by these variables. Then, the benefits brought by the grid-scale ESS to the network determined by battery optimization are quantified and used as a measure to evaluate the economic performance of the investment via ROV. The year with the



(a) FEEDER 1

(b) FEEDER 2

Figure 4: Frequency distribution of optimal investment timing

greatest investment value is considered as the optimal investment timing. The efficacy of the methodology is shown on two Australian LV test feeders. The results show that the optimal investment timing is year 4 for Feeder 1, while the investment is abandoned for Feeder 2. Moreover, by doing so, we have demonstrated how to incorporate battery operational decisions and evaluate the ESS investments in distribution networks considering future uncertainties. Further, the method shows that grid-scale ESS can sufficiently decrease the ampacity of the cables, and therefore improve the hosting capacity of renewable generation in distribution networks.

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