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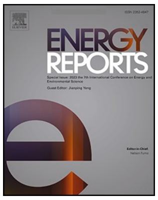

Research paper

# Optimal investment strategy based on a real options approach for energy storage systems in the Korean power market

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ABSTRACT

Energy storage systems (ESSs) are widely recognized as a possible solution for integrating the increasing renewable energy penetration in electrical grids. However, ESS investments have many uncertainties, such as curtailment effects, incentive value, cost overruns, and delays in construction levels. This study proposes an optimal investment strategy for the expanded net present value (ENPV) using the real options approach (ROA) that accounts for technical types and investment levels. The ROA is defined according to the sum of total values, including all uncertainties, in conjunction with the extended binomial tree based on economic theory. Simulations are performed to demonstrate the applicability of the ENPV with regard to evaluating the economic and technical viability of ESSs on the Korean power market. These results prove that lithium-ion ESSs are technologically suitable for RE but are economically risky. Thus, the current investment decision approach is not recommended. Although the ENPV improves the economic performance of ESSs with respect to uncertainties, investors can maximize future profits and reduce adverse risks based on the optimal ESS investment strategy. The investment of lithium-ion ESS under specific conditions requires incentives of at least 25$/MWh.

## 1. Introduction

### 1.1. Background

Global environmental and energy issues are major concerns nowadays. Particularly, a third of the global population continues to lack access to electricity, while certain nations are contemplating relying heavily on fossil fuels as their primary energy source. In order to comply with environmental regulations, a cost-effective and environmentally sustainable energy source is necessary. Presently, there exist obstacles pertaining to the viability of electricity generation through diverse sources, specifically with the integration of renewable energy (RE) into the power infrastructure. In particular, the management of electrical infrastructure is being significantly challenged by the increasing penetration of RE, as a high proportion of RE necessitates flexible power systems to compensate for the effects of variability (Lund, 2007). As a result, energy storage systems (ESSs) have the potential to mitigate the detrimental impacts of intermittent renewable energy sources on electricity storage (Krishnan and Das, 2015). In general, four categories of ESSs can be distinguished by the manner in which they are stored: 1) Mechanical energy storage (pumped hydro systems and compressed air), 2) chemical (batteries and fuel cells), 3) Capacitors and supercapacitors for electrical purposes, and 4) thermal storage at both low and high temperatures (Chen et al., 2009). Several parameters, including the amount of stored energy, absorption rate, efficiency, and applications, can affect an ESS (EPRI, 2010). However, it is difficult to measure the value of an ESS with respect to the uncertainty factors that affect profitability. Although several studies have explored this topic, uncertainties lead to issues in ESS investment strategies.

Nevertheless, numerous issues have emerged with the dissemination of ESS in Korea. One of the main challenges is the limited operational capacity, which restricts the ability to expand installations considerably. Although the Korean government has chosen ESS as a concentration of the RE and established several support policies with the REC weight exceeding 4.0–5.0 when sourced from solar and wind power interconnections, the amount of ESS installation is not high compared to other countries (Lee et al., 2021).

From an economic perspective, the profitability of ESS is influenced

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*Abbreviations:* DCF, discounted cash flow; ENPV, expanded net present value; ESS, energy storage system; IEA, International Energy Association; LNG, liquified natural gas; RE, renewable energy; ROA, real option approach; ROV, real option value; VOM, variable operating maintenance; WACC, weighted average capital cost.

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by both the electricity price and the renewable energy certificates (REC). The revenue of the power operator can be improved as the REC weight increases, which directly affects the operating income of the ESS investors. Based on the 2019 analysis conducted by the Korea Electric Power Corporation (KEPCO), the cost-benefit ratio for ESS with RE was only 0.05, which is below 1.0 (Lee Seong-in, 2014). The government establishes the weights for REC and RE operators engage in REC trading through the Korea Power Exchange (KPX). The KEPCO obtains electricity from power providers, which include RE, and compensates operators through settlement price in KPX (Kang et al., 2023). Hence, governmental intervention in market-based REC transactions is challenging, and it is feasible to indirectly undermine the RE supply scheme by controlling REC weight. The REC weight of 5.0 also indicates that ESS operations are not profitable, which implies that ESS business is very challenging and that expanding ESS installations in accordance with implementing government guidelines within the current policy scheme poses a significant challenge. Moreover, the policy environment, including alterations in the REC weight that transpire every three years, can influence investors' decisions regarding the expansion of their ESS capacity (Na and Jeon., 2023).

Furthermore, there is an issue of mitigating the dissemination of ESS as a result of many fire incidents. Since 2017, there have been ongoing fire accidents as the supply of ESS has increased (Na and Jeon., 2023). Following the government's announcement of fire safety measures, there was an increase in the occurrence of fires. As a result, battery maintenance procedures were intensified, which included deliberately reducing the battery's state of charge. Owing to the government's restricted battery charging rates as a fire prevention measure for ESS, Battery manufacturers contended that fires in ESS are not attributable to defective batteries but rather to improper ESS installation environments or operating procedures, given the absence of such incidents overseas. In summary, after the installation of ESS in 1,622 establishments in 2017, 28 of them have had fires; the estimated likelihood of fires in each establishment is 1.73%. Specific circumstances in Korea may give rise to ESS fires that are not documented elsewhere. Investors may opt to terminate the project, contingent upon its profitability, as a result of a decrease in ESS utilization and recurrent fire accidents. Furthermore, depending on the dependability or cost-effectiveness of the construction, investors can choose to proceed with the project's execution or abandon it entirely.

Finally, the proliferation of ESS is ultimately being criticized for potentially compromising the integrity of the power grid. The increased prevalence of ESS is going to contribute to the emergence of more intricate challenges in power grid management, which can be attributed to issues stemming from the charging and discharging patterns of ESS. While ESS increases the frequency when discharged acts as a decelerator when charged, but does not control the charging and discharge, and results in oscillation, which is similar to the effect of a generator dropping out of the power grid when the battery is completely discharged. Therefore, in order to use ESS economically and efficiently, a control system is needed to optimize charging and discharge at the power grid level. The government raised concerns that the ESS frequency adjustment issue could undermine the stability of the power grid and pointed out that the KEPCO would respond to ESS frequency adjustment. As a result of these diverse issues, investors are compelled to carefully assess the business viability of the ESS project from concept screening to construction level, which might result in project termination or the consideration of more investments. Therefore, it is necessary to develop an optimal investment strategy in ESS.

### 1.2. Literature Review

A critical issue is finding an optimal methodology for determining the uncertainties in various aspects of ESS projects. Accordingly, various methods have been proposed to identify an optimal feasibility methodology. From a technical perspective, an ESS involves three processes: a) discharging electrical power from the power grid; b) transforming energy into an appropriate way for storage, and c) converting and redirecting electricity to the grid (EPRI, 2010). Through these processes, energy is stored with reduced generation costs when electricity demand is low and with high market prices when electricity demand is high. Various studies have reviewed ESSs from a technical perspective (EPRI, 2010; Pearre and Swan, 2015; Denholm et al., 2010). The various uses of ESSs were enumerated in reference (Edmunds et al., 2014) in accordance with the discharge time, response time, and grid benefits. As stated by the authors in (Locatelli et al., 2015), price arbitrage is the most significant concern in the integration of substantial quantities of electricity. However, the large-scale deployment of RE may introduce balancing problems to grids. These balancing problems and the issue of price arbitrage can be addressed using lithium-ion and lead-acid storage as adequate ESSs.

Meanwhile, a few studies have also explored ESSs from an economic perspective. In particular, extensive investigations have focused on the measurement of the risks of ESSs, starting from the actual investment to their full operation. The authors categorized the internal and external hazards associated with ESS investments in (Radcliffe et al., 2014). Internal risks are technology-specific, in contrast to external risks which pertain to market and policy concerns. The authors also explained that high incentives or stable energy policies can greatly influence ESS investment strategies. Conversely, in (Newbery, 2018), the major risk for ESSs was found to be associated with the extreme volatility of electricity costs, which is primarily caused by an increase in RE. By making electricity prices more volatile during peak demand, a rise in intermittent RE may lower the relative value of power because of the higher price volatility (Zakeri and Syri, 2015; Hwang et al., 2019). Moreover, another major internal risk affecting ESS profitability is the delay in cost overrun at the construction level (Berrada et al., 2017). Delays in construction can also affect profitability because of negative cash flow. Therefore, additional studies on the uncertainties in electricity prices and capital costs are required to develop investment strategies for ESSs.

In addressing ESS investment problems, other recent studies have evaluated real options approach (ROA) as an optimal methodology for considering the uncertainties of ESSs. While the conventional methodology based on discounted cash flow (DCF) is inadequate for evaluating uncertainties and investor flexibility, ROA can assess investments in uncertain contexts (Kodukula and Papudesu, 2006). In (Kroniger and Madlener, 2014), the authors evaluated investments in ESSs for storing the surplus electricity generated by wind farms. Regarding the uncertainties attributed to Monte Carlo simulations, ROA addresses investor flexibility with optimal investment timing. In (Reuter et al., 2012), ROA was used because it considers the potential for incentives and the fluctuating cost of electricity. Herein, it has been demonstrated that the premium price of electricity can be used to initiate the investment, and then, the subsidy can compensate for the difference with fossil fuels. In (Muche, 2009), the authors presented DCF approach without considering the uncertainty and flexibility that are typically considered in the ROA, which can evaluate the fluctuating cost of electricity, future regulatory changes, prospective price hikes for fossil fuels, and unexpected increases in capital costs. However, previous studies could not evaluate the available ESS values at each investment level and only focused on the same technical type. Hence, extensive research must explore the methods that consider the effects of different technical types at each investment level as part of an ESS investment strategy.

### 1.3. Contributions and Paper Organization

This study presents a novel ROA that takes into account all the economic, technical, and other characteristics of each investment level. While numerous real option approaches exist in ESS, prior research designs reveal a number of characteristics: determining the sources of uncertainty, identifying the available real options, simulating the evolution of uncertain variables, and determining the value of the real options.

In Table 1, existing studies of most RE valuations recognize the commonly expected return on investment within the initial planning of a project. The most frequently recognized real option is the option to postpone an investment or the timing option. However, we investigate economic feasibilities regarding uncertainties from concept screening to construction level.

In our work, when confronted with a multitude of uncertainties, it is recommended to exercise caution until the uncertainty has been resolved. The decision to determine is represented by binomial trees, which facilitate the comparison of various timing alternatives. Additionally, the most prevalent option considered, whether to invest or not, embodies the concept of the entire investment enterprise as a tangible opportunity. Typically, it is represented as a singular choice. Hence, our work utilizes multiple layers, from concept screening to the construction level.

Furthermore, we can interchange inputs for ESS valuation that can be adjusted to accommodate fluctuating prices of electricity, raw materials, and asset prices of ESS. Monte Carlo simulation is frequently employed in our studies for revenue and cost, respectively. Those factors are simulated by beta-PERT (Project Evaluation and Review Technic) and Geometric Brownian Motion.

Therefore, no unified definition describes uncertainties in ESS investments based on the conventional DCF approach in prior studies. Our study can reflect these uncertainties by determining the expanded net present value (ENPV) for each investment level, incorporating the levels in which there are two options: delaying investment and construction. Consequently, our study demonstrates the extended binomial tree of the overall available value based on economic theory so that the ROA is constructed as the sum of the total values, including the total uncertainties. In summary, the main contributions of this study are as follows.

- The risk and options can be quantified in terms of investment using the ENPV.
- The proposed ROA can evaluate and compare the technical types of ESSs. The optimal storage type is suggested based on technical and economic perspectives.
- The proposed ROA is linked to the extended binomial tree, whereas the existing ROA is only based on the binomial tree. More importantly, the proposed ROA considers the estimation of risks and options in the investment strategy for ESSs.
- In implementing the proposed ROA at each investment level, the economic performance of ESSs can be determined through the ENPV.

The structure of this paper is as follows. The ENPV is conceptually defined and quantified through the utilization of a mathematical formulation in Section 2, and then compared with the conventional NPV. In Section 3, we present the proposed ROA using the ENPV. In Section 4, the optimal ESS investment strategy is demonstrated by applying the ROA to the Korean power market. In Section 5, the conclusions are summarized.

## 2. Economic evaluation method

### 2.1. ENPV

Financial project evaluation techniques typically rely on the tradi-

**Table 1**
Benchmarking table noting the literature concerning ROA and ESS.

| Research | Our work | (Kroniger and Madlener, 2014) | (Reuter et al., 2012) | (Muche, 2009) |
|---|---|---|---|---|
| Main topic | ESS's investment strategy is determined by the DCF and ROA. The DCF analysis incorporates storage optimization. | Assessment of the financial viability of energy storage for wind farms. | Comparison of the investment evaluation of energy storage with wind energy alone. | Assessment of financial analysis of energy storage. |
| Applications | Price arbitrage. | Electricity storing and sales. | Price arbitrage. | Electricity sales and reserve market. |
| Methodology | 1) Determine the optimal storage capacity using DCF and ROA.<br>2) Determine the incentives that ensure NPV equals zero.<br>3) Determining the capital cost threshold that ensures the highest NPV and the value of the actual alternative to defer investment.<br>4) Compiling the value of the actual alternative to construct and to postpone construction. | ROA to maximize the profit of ESS. | ROA to maximize the expected profit during the planning period. | Utilize ROA to quantify the planning unit commitment. |
| Stage of Real Options | Option to wait,<br>Option to build. | Option to switch,<br>Option to wait. | Option to wait. | Option to switch. |
| Results | Due to the economic risk and technological suitability of lithium-ion and lead-acid for renewable energy applications, investing in these substances is not advised at this time.<br>ROA can be utilized to assess the viability of hazardous investments by providing a more favorable evaluation of the investment's profitability.<br>Nonetheless, the progression of the scenario must be monitored, as the results indicate that an investment in ESS could be profitable under certain conditions. | Fuel cells are not economical in the first scenario.<br>The second scenario may provide a reserve, but if hydrogen prices exceed zero, avoiding the initial cost of fuel cells could generate a positive revenue flow.<br>ROA recommends this solution because the project value exceeds the investment cost of the ESS twofold. | The price premium is required to ensure a profitable investment in ESS, and the subsidy is required to achieve a more realistic price premium.<br>The specific premium price that incentivizes the implementation of an ESS is 70% in Germany and 75% in Norway. The subsidy intended to compensate for the discrepancy between this required premium and a more practical premium, which typically ranges from 10% to 30%, amounts to 35% in Germany and 50% in Norway. | A comparison between the Real Option values and the conventional NPV method reveals that the latter has reduced contribution margins, which would result in the investment being misvalued. |
| Limitation and further research | Simulating the indirect impact in relation to different types of technologies. | The cost is restricted. The cost of technological advancement is disregarded; only an increase in efficacy is considered. | Economies of scale, REC of Norway should be regarded. | The day-ahead market is only utilized for simulation. |

tional DCF (Damodaran, 2012), which is discounted to the current value. As a result, the NPV is the total of the project's DCF as follows:

$$NPV = \sum_{t=0}^{T} \frac{CF_t}{(1+WACC)^t} \tag{1}$$

where *NPV* is the net present value, *CF* is the cash flow, *WACC* is the weighted average capital cost rate, *T* expresses the maturity time, and *t* indicates the time interval.

The common investment rule is to proceed when the NPV is greater than zero. For two or more projects with comparable sizes, priority is assigned to the project with the higher NPV (Damodaran, 2012). However, this rule is limited because it cannot consider dynamic variables and is extremely sensitive to assumptions related to perpetual growth and discount rates. As a result, the NPV fluctuates, and the intrinsic value generated is inaccurate. Thus, DCF cannot precisely measure the value of ESSs (Trigeorgis, 1993). Project value can be significantly influenced by even a slight deviation in the assumptions concerning the final timing of an investment (Trigeorgis, 1993). Various methods have been proposed to overcome these disadvantages, and they include sensitivity and scenario analyses (Bowman and Moskowitz, 2001). However, these methodologies are only focused on linear effects and cannot evaluate nonlinear effects (Nissen and Harfst, 2019). Specifically, because power plant projects, including ESSs, are operated in extremely complicated environments, the evaluation of project value should consider volatility (e.g., volatility of electricity sales prices), fuel costs, and the indirect effects of managerial flexibility. The stochastic factor that affects an ESS project's value is unit revenue, which can be evaluated using electricity sales prices formulated through uncertain elements. If investors expect future value changes pertaining to a project, they obtain an additional return. Hence, the DCF should be modified to forecast project value by considering uncertainty and managerial flexibility. Therefore, more developed approaches are required to overcome the limitations of the DCF.

In our study, the investment value of a project can be expressed as the sum of the NPV and real option value (ROV) as follows:

$$ENPV = NPV + ROV \tag{2}$$

Eq. (2) defines the ENPV based on the NPV. Since the NPV does not account for uncertainties, it represents the value of a project without flexibility, but the ENPV is equal to the investment value of a project with flexibility. The ROV indicates the value of a project with regard to managerial flexibility and can be expressed as follows:

$$ROV = SN[d1] + Xe^{-r(T-t)}N[d2] \tag{3}$$

$$d1 = \frac{\ln\left(\frac{S}{X}\right) + \left(r + \frac{\sigma^2}{2}\right)\left(T - t\right)}{\sigma\sqrt{T-t}} \tag{4}$$

$$d2 = d1 - \sigma\sqrt{T-t} \tag{5}$$

where *N* denotes the normal distribution, *S* is the underlying asset value of the project, *X* denotes the execution price of the real options, *r* is the risk-free interest rate, and $\sigma$ represents the volatility associated with the rate of return for the underlying asset. The variability of underlying assets is directly estimated by applying the electricity sales price variability to project profits and the volatility of the capital costs of investment and maintenance costs. These main variables affect real options pricing.

### *2.2. ENPV evaluation process*

The ROA captures the value of managerial flexibility in adapting decisions to unexpected conditions in the power market. Thus, decision makers can leverage uncertainty with limited downside risks according to the ENPV. Project developers can also create shareholder value by identifying, managing, and implementing the ROA associated with their investment. The approach provides upside potential for leveraging project risk based on the argument that uncertainty can sometimes be a source of available value. The ROA is ideally suited to the values of ESSs and RE technologies as it determines the benefits of indirect effects (Zeng and Chen, 2020).

In the present study, the ROA is utilized to include all the economic and indirect benefits of ESS investments. ENPVs can be generated for all scenarios and then compared in terms of the variations in capacity and technical types. Consequently, the optimal capacity strategy for ESSs is implemented based on the ROA such that the ENPV is constructed as the sum of the NPV and ROV. The ENPV is mainly used to evaluate the DCF and ROA more efficiently. In this respect, the ENPV can be valuable in making investment-related decisions. The process of computing the ENPV in order to ascertain the most advantageous ESS investment for every scenario is illustrated in Fig. 1. The following describes the analytical procedure:

(i) **Initialize inputs and generate scenarios:** The procedure begins with the initialization of the inputs, including the capital cost, operating cost, and capacity factor. The scenario is then formulated based on the relevant parts of ESS capacity. The total cost changes according to each scenario depending on the investment level.

(ii) **Compute the ENPV for each scenario:** This step is based on the results obtained from scenario generation. Note that the investment can be checked if the overall cost of the power market is within the defined limits. Otherwise, because the NPV is below zero, another scenario must be generated, and the calculation process should be repeated.

(iii) **Compare the ENPVs:** Each scenario is solved to obtain the value that leads to the lowest total cost, including all investment levels. Subsequently, a sensitivity analysis based on the variation of *WACC* can be conducted, and the scenario results can be compared to obtain the optimal ESS investment strategy. This procedure is completed at this stage.

## 3. Proposed ROA

The three common real option evaluation models are a) decision trees, b) the Black–Scholes model, and c) binomial models. The decision tree model focuses on investment value with multiple options to abandon; thus, it is appropriate for R&D projects (Herath and Park, 1999). The option value can be evaluated by considering current or potential future decisions; however, it can only be applied to future decisions that require the probabilities of uncertain outcomes. The Black–Scholes equation assumes that the asset value is log-normally distributed and that optimally diversified risk-neutral markets do not permit arbitrage transactions (Jackwerth, 2004). Hence, the Black–Scholes model is mainly based on European financial options. It only applies to the terminal date, and no dividends are paid during the option period. The binomial model permits the computation of assets and options for multiple periods, in addition to a range of potential outcomes for each period (Rubinstein, 1994), as opposed to the Black–Scholes model, which generates numerical outcomes based on inputs. By utilizing this model, users can assess option values in accordance with decisions made at various times and observe fluctuations in asset prices over time (Brandao and Dyer, 2005). Financial options can be exercised at any point prior to their expiration date, however depending on the option selected, the binomial model can be valuable. On the basis of these findings, we suggest a ROA calculated using a binomial model.

### *3.1. Binomial model*

The binomial model uses an iterative process that utilizes multiple

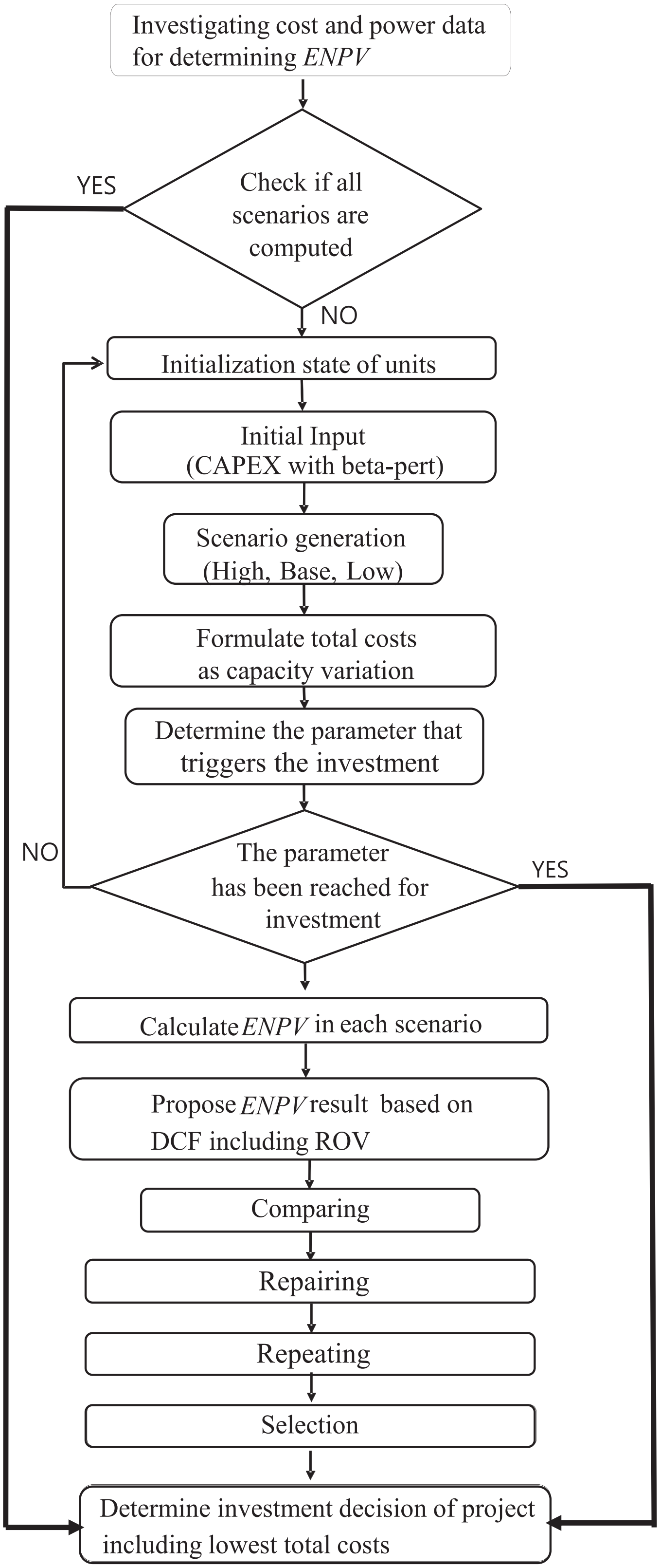


**Fig. 1.** Procedure describing the ENPV evaluation process. Note. ENPV: expanded net present value; DCF: discounted cash flow; ROV: real option value.

periods for option values. This model has two possible outcomes based on iterations, namely, upward and downward movements, which are based on the structure of the binomial tree. Although the binomial model is simple and can be used to denote mathematical expressions, it becomes increasingly complex at multiple levels. In contrast to the partial differential equation analysis, which can provide numerical results based on inputs, the binomial model allows intuitive calculations with a range of possible results for each level. Given its advantage of visualizing changes in asset prices from level to level, it can evaluate option values based on the decisions implemented at different nodes. The basic binomial model commonly uses the same probability of success or failure for each level prior to the expiration of the option. Nevertheless, a project developer may implement distinct probabilities for each level by applying additional information gathered over time. In general, two stages are executed for the ROA to evaluate the portfolio of ESSs as option pricing (Nazari and Keypour, 2019), and the investment valuation of the ESSs can then be modeled using a binomial model for simplicity. Utilizing scenario analysis and an n-step binomial tree, this discrete method for pricing numerical options is constructed. In this section, the process is presented as having two stages, and the option value in the ESS project is evaluated using a binomial model.

### *3.1.1. First stage: investment level evaluation*

The first evaluation stage involves analyzing the binomial lattice of the underlying asset value. Fig. 2 presents the model of a single-period binomial tree. Herein, $S$ is the value of the underlying asset represented by the first node of the single-period binomial tree, and $f$ is the equivalent option value. Concerning the price fluctuation of an underlying asset on the day of its expiration, as a characteristic of technical ESS types, the highest and lowest values can be expressed as $u$ and $d$, respectively, while the probability of these values occurring can be set as $p$ and $1$-$p$, respectively. The increases and decreases in the values of the underlying assets are $S_u$ and $S_d$, respectively, while the option values are $f_u$, and $f_d$, respectively.

The underlying asset value is represented by the binomial tree depicted in Fig. 2(a), which commences at the initial node located on the left side of the tree. The general binomial tree, illustrated by the solid lines, can be divided into several single-period binomial trees. Assuming that there are only two scenarios in which the value of the underlying asset fluctuates over the course of the time interval, $t$, is short enough (Liu and Yong, 2005). As shown in Fig. 2(b), the underlying asset value of the initial node $S$, illustrated by the dotted line in the new binomial model, can increase or decrease based on probabilities $q$ and $1$-$q$, respectively, as observed in the investment procedure, which involves concept screening, detailed design, construction, and operation level. When volatility $\sigma$ and time interval $t$ are known, $u$, $d$, $u'$, and $d'$ can respectively be given by

$$u = e^{\sigma\sqrt{t}} \tag{6}$$

$$u' = e^{\sigma'\sqrt{t}} \tag{7}$$

$$d = e^{-\sigma\sqrt{t}} = 1\Big/u \tag{8}$$

$$d' = e^{-\sigma'\sqrt{t}} = 1\Big/u' \tag{9}$$

Accordingly, $S_u$, $S_d$, $S_u$, and $S_{d'}$ can be determined as follows:

$$S_u = S\cdot u \tag{10}$$

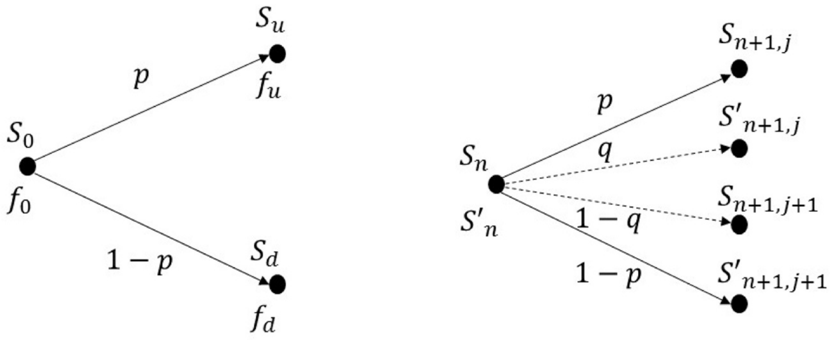
$$S_u = S\cdot u' \tag{11}$$

$$S_d = S\cdot d \tag{12}$$

$$S_{d'} = S\cdot d' \tag{13}$$

In Eqs. (10)–(13), because $S$ is known, the single-period binomial tree can be extended to a multistage binomial tree model, and the underlying asset value in each tree node $S_{nj}$ can then be computed in the ROA.

Fig. 2 shows the ROV of the proposed extended binomial model. At



(a) Basic binomial tree

(b) Extended binomial tree

**Fig. 2.** Single-period binomial tree.

the initial investment level, investors determine the optimal capacity of an ESS based on a DCF and have the option to wait for information on future expected returns before investing. At this level, $S$ varies according to probabilities $p$ and $q$. At the detailed design level, building or delaying construction is an alternative option for investors. The long-term economic implications of ESSs can be significantly influenced by various factors, including technological advancements, mass production, industrial learning, and currency fluctuations. Consequently, investors were able to not only delay their decision but also anticipate an additional decrease in capital expenditures resulting from external influences. Finally, at the construction and operation levels, investors can postpone the project and wait to sell their stake for exit value.

#### 3.1.2. *Second stage: technical type evaluation*

Recursive backward induction is then utilized to assess the actual option valuation lattice. The purpose of this phase is to construct a binomial tree for the ROV. ROV can be calculated at each final node of the binomial tree in accordance with the decision rule of value maximization and the potential values of the underlying asset. Assessing the potential outcomes throughout the option exercise period, the decision rule of the option model is centered on a maximization function.

In this procedure, the probabilities of the value increasing or decreasing, that is, $p$, 1-$p$, $q$, and 1-$q$, can be computed through a risk-neutral measure.

$$p = \frac{e^{rt} - d}{u - d} \tag{14}$$

$$q = \frac{e^{rt} - d'}{u' - d'} \tag{15}$$

After obtaining the value of $p$, the ROVs at all intermediate nodes located at each level can be determined using the option values of the latter two nodes.

$$f = e^{-rt}[pf_u + (1-p)f_d] \tag{16}$$

$$f' = e^{-rt}[qf_{u'} + (1-q)f_{d'}] \tag{17}$$

Using backward recursion from the final nodes at the operation level, the ROV at the initial node of the binomial tree can be obtained for the ESS project.

### 3.2. *Option value in ESS project*

As a project is evaluated by managing risk and flexibility in the ROA, it can have upside potential by leveraging risk based on uncertainty, which contains available value. In other words, the value of a project can vary based on uncertainties, such as electricity sales prices, fuel costs, and indirect effects. Therefore, investors can use the proposed ENPV to evaluate the available value of the project. The ROV indicates the potential benefits from the cost difference associated with the ESS. When investors choose to delay option, the ROV is determined by the volatility of the cost savings value. Investors can anticipate the ESS deployment option to have exceptional value because to the existing uncertainty around future costs and the availability of fossil fuels. Specifically, in the binomial model, the ESS can be assessed based on uncertainties depending on the options created and valued. If investors have the option to meet the incremental energy demand at each moment in the integration of the ESS and RE, the expected payoff is the present value of any cost savings from the installation of the ESS. The aforementioned savings reflect the value of the underlying asset in a financial option, an investment that entails switching costs and irreversible infrastructure investments.

The option with the ESS has the benefit of the cost differences between the ESS schemes integrated with RE and non-RE generation schemes. These differences can be affected by ongoing ESS investments, including holding costs before exercising the option. In financial options, this uncertainty corresponds to the volatility of the underlying assets. Fig. 3 illustrates the option's payoff with respect to the difference between the underlying asset value and the present value of the exercise price. Whether the exercise price is reduced to a level below the asset value will result in a positive return on investment or option exercise. Conversely, the return is negative when the exercise price exceeds the value of the asset. When considering option pricing, the former option is more cost-effective, whereas the latter is non-economical, indicating high future uncertainty and potential ROV by leveraging risk. As shown in Fig. 3, the possibility of an advantageous outcome increases with the option's holding costs, while the adverse risk is constrained to those expenses. In other words, even if the future value of an asset is expected to be considerably low, a financial option can still have value because of the possibility of an increased future value of the underlying asset. In particular, hedging the downside risk of ESSs can allow continued capital investment expenditure while the option is being held. Meanwhile, the upside potential is the value generated by ESSs in an environment where fossil fuel prices are high. From a financial perspective, the option to wait and the volatility of cost savings contribute hold value to the ENPV. It is noteworthy that delaying deployment in an unpredictable future environment carries a hidden value that is not quantified by the DCF. Certainly, a more negative NPV is documented in a volatile environment; in such cases, the option to wait for the ENPV is more valuable. Investors can anticipate the ESS deployment option to have significant value given the existing uncertainty surrounding the costs and availability of fossil fuels in the future (Barbour et al., 2016).

### 3.3. *ESS investment strategy*

In our study, a multilevel process is developed to evaluate the ROA

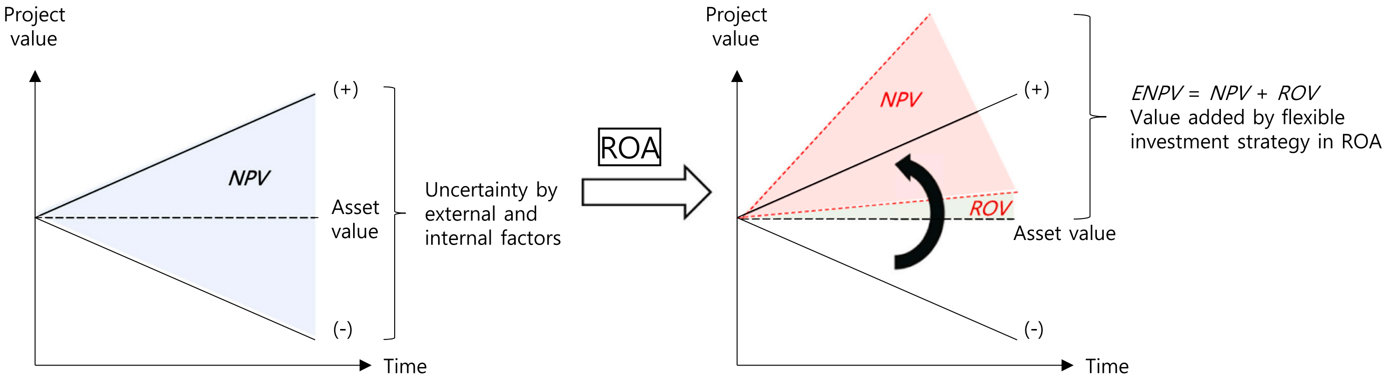


**Fig. 3.** Option value of ESS based on the ROA. Note. NPV: net present value; ROV: real option value; ENPV: expanded net present value.

method. The option values can be obtained to achieve the optimal economics in each scenario. In the ROA, the ENPV distributions of the project can characterize the stochastic state of the main ESS risks using the expected mean value, standard deviation, and other parameters, such as kurtosis and skewness, to support investors' decisions. From this perspective, the valuation of dependent variable probability distributions can be approximated through the use of Monte Carlo simulations, wherein the values of independent variables are extracted from their stochastic processes. As the proposed ROA can consider investors' options to invest at each level based on uncertainties, scenarios are generated for each simulation, with the stochastic variables influencing the probability distribution of the ENPV.

The general procedure of ESS project development has the following characteristics: 1) To begin a process, all previous processes must be completed; 2) the process cannot return to the previous step; 3) it cannot be repeated within the process network; and 4) the entire process has one starting point and one ending point. The overall design of ESSs must be completed before other activities, such as site selection, purchaser

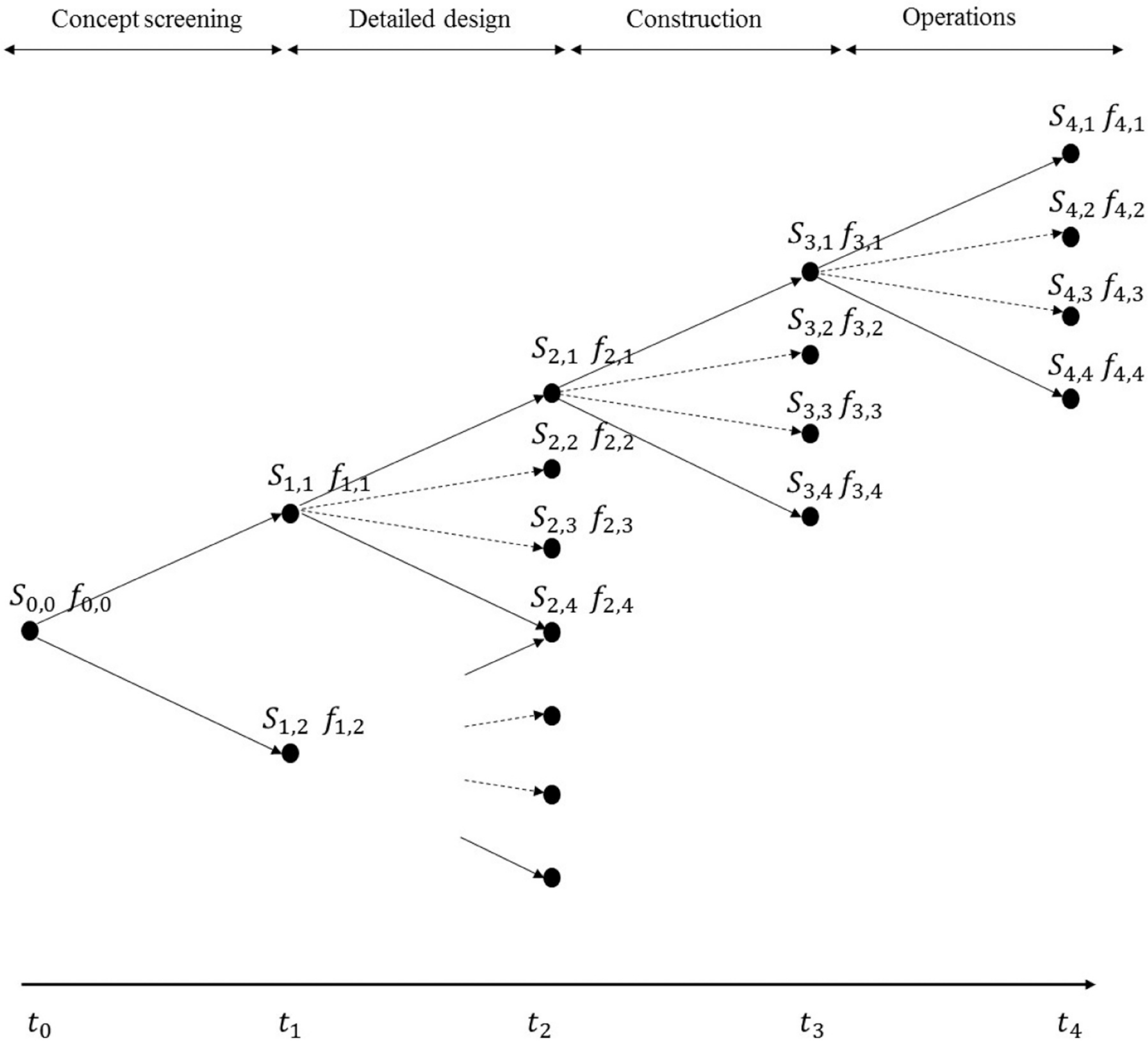


**Fig. 4.** Multi-binomial tree.

finding, or hiring operators. Additionally, battery installation is possible only after site selection and battery production. No actual activity is carried out between these stages, though, some cases require the sequence of events to be indicated. For example, site selection activities cannot be completed until a buyer is announced. Hence, buyer selection must be completed before location selection. This relationship can be shown in the process as a hypothetical activity represented by a dotted line in Fig. 4.

Fig. 4 illustrates the process followed by the multi-binomial model. At each level, such as the initial investment and detailed design levels, investors can have another option (i.e., to build or wait to build) because of the capital cost variation caused by external factors. At each stage of the investment process, investors can select a new ESS type or decide to terminate the investment. Additionally, investment may be delayed if investment costs increase owing to high battery prices and construction costs, which depend on global macroeconomic conditions. At the operation level, the project can be carried out when global gas and electricity prices are expected to rise owing to geopolitical issues, such as the war in Russia and Ukraine. Thus, at the construction and operations levels, investors can postpone the project and wait to maximize its value.

Fig. 5 presents the investment strategy for ESSs based on the proposed ROA. Herein, investors' options can be executed at four levels: concept screening, detailed design, construction, and operation. The concept screening level comprises three steps: ESS sizing, DCF analysis, and the option to wait to invest. If any level is insufficient to satisfy the initial investment standard, investors can delay the project and modify its detailed specifications. The final step can be performed at the detailed design level. Moreover, at each level, the investors' options can be illustrated such that the first option considers the postponement of the investment immediately after the concept screening level, but the investor can wait until the relevant cost parameters decrease. The second option considers investors' options when deciding whether to build. In summary, investors have four options when deciding to invest at the concept screening and detailed design levels. The fifth option allows investors to postpone the decision to build the ESS by waiting for further capital cost reductions at the construction level. The last option is to operate the ESS or wait at the operation level. In other words, investors can postpone a project and wait to sell their stake for the exit value. Thus, the ENPV determines the optimal ESS investment at each level.

The detailed procedure is as follows:

- Level 1: Concept screening

(1) Optimal ESS capacity

In the first step, we calculate the optimal investment capacity of the ESS operating price arbitrage. At this level, the optimal ESS size can be determined with respect to the market environment, including the electricity demand and power reserve.

(2) DCF analysis

In the second step, the DCF of the plant's life cycle cost is evaluated. The DCF analysis reveals the following:

- NPV, internal rate of return, and payback time
- Ratios between capital and operating expenses when the entire life cycle cost is considered. For the ESS to evaluate how the price of coal and natural gas affects life cycle costs, these ratios are especially pertinent.
- Incentives to guarantee the NPV for the ROVs of the ESS operating price arbitrage

(3) Option to wait to invest

The ENPV can be used at this level as an input as follows:

- Expected values of capital costs [\$/MW]
- Current values of fuel cost [\$/MWh]
- Current values of sales price [\$/MWh]

Capital cost overruns are the most relevant risk factors for ESS investments; therefore, their economic feasibility must be assessed.

- Level 2: Detailed design

  The detailed design level determines the capital expenditures anticipated to initiate the ESS investment. Optimal capital expenditure can guarantee the maximum ENPV given the probability of reaching the target internal rate of return. Accordingly, this study determines the cost reduction effect in combination with the probability of cost variation.

  Batteries in ESSs are composed of four major materials: cathode, anode, separator, and electrolyte. The cathode material accounts for 40% of the total capital cost. In general, it is prepared by mixing lithium with a precursor, which is a mixture of metals such as nickel, cobalt, and manganese. The price of metals, which are the main raw materials, greatly influences the prices of cathode materials and batteries. If metal prices continue to increase, investment costs will inevitably increase. Meanwhile, the electricity sales price is determined by the marginal price of power plants in power grids; therefore, it is generally linked to gas prices. If metal prices rise without increasing gas prices, the profitability of the ESS worsens.
- Level 3: Construction

  This level evaluates the possibility of the cost being higher than the expected capital cost. It is strongly influenced by the procurement schedule and proficiency. Large-scale ESS projects have high uncertainty owing to large cost fluctuations that depend on the geology and ground conditions when conducting underground construction. Given these uncertainties, the optimal capital expenditure can be generated for the maximum ENPV through further capital cost reduction. Thus, investors can hold an option to invest in an ESS.
- Level 4: Operation

  At this level, if profitability cannot reach the expected value formulated at the concept screening level, investors can choose to sell their stake in the project or operate it throughout its life cycle. Inputs such as capital costs, fuel costs, and sales prices are determined at the concept screening level and can be used to examine the economic feasibility of the ESS.

## 4. Case study

To evaluate investor opportunities, we analyze the optimal ESS investment strategies with the proposed ROA subject to multiple uncertainties that can affect the profitability of ESS investments as technical types vary at multiple levels. The Korean power market, which

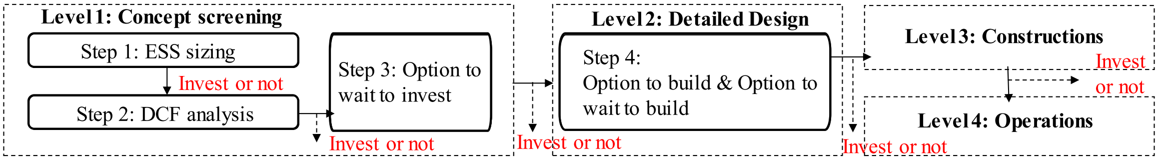


**Fig. 5.** Multilevel process with the ROA. Note. ESS: energy storage system; DCF: discounted cash flow.

operates as a cost-based pool, is affected by diverse RE capacities, which have very low marginal costs. RE reduces the demand for energy sources, thus, a lower electricity price results in uncertain profits for ESSs. In the present study, the Korean power market is chosen to reflect the uncertainty factors associated with the simulation results. Different from derivation of the optimal time and project values, our study determines the ENPV through the proposed ROA, which considers the available value of uncertain profit, to establish an optimal investment strategy.

The details of the data analyzed in this study are provided in Table 2 to investigate the Korean power market. The evaluation period for this study was established at 10 years, commencing in 2020, in consideration of the availability of data. In addition to historical market data and technical reports published by KEPCO, additional variables are estimated through publicly accessible information obtained from KPX. The following section describes the methods and assumptions utilized in the parameter estimation process.

The annual revenue is calculated by multiplying the volume of electricity sales by the REC weight of ESS with the electricity price. While the historical electricity price is obtained from KPX, the REC weight is set to 5.0. Future electricity prices are calculated using IEA energy price projections. Specifically, the anticipated rate of increase in electricity sales price that is associated with ESS sales.

Additionally, ESS costs are based on NREL data, and beta-PERT distribution is utilized to estimate future prices that account for the cost of anode, cathode, and electrolyte materials according to technical types of ESS. This enables the calculation of NPV by discounted future revenue by *WACC* and establishing the relationship between revenue and costs. BNEF suggests an average *WACC* of 7.5% for renewable energy, and then *WACC* is utilized as a reference to BNEF data.

Finally, it is represented in the option value calculation, which takes project development level and technology into account. The investor's available value is then computed by comparing it with the current DCF.

### 4.1. Cost data

In this section, we summarize the total annualized costs of the ROV. Table 3 lists the cost parameters of the ESS project according to the National Renewable Energy Laboratory (NREL) (Hale et al., 2016). The fixed expenses and additional factors utilized in the calculation of annualized expenses are detailed in this table. Variable costs are computed using cost estimates of operational and maintenance expenses rather than initial investment expenses with fixed maintenance and operation levels. As initial investment costs primarily refer to the construction costs of ESS projects, they drive the construction state of the project. When this step is completed and the arbitrage transaction is executed, the initial cost is not required. Thus, a one-off cost is incurred from the onset of construction to the end of the life cycle, even though its proportion with respect to the total cost is higher than that of other items. This cost is largely divided into equipment, labor, overhead, and interest costs for construction. Equipment, construction, and indirect costs typically account for 62%, 25%, and 9% of total costs, respectively (Kapila et al., 2017). Among these operating costs, the fixed cost includes the cost of the regular replacement and maintenance activities of power plants, which occur every year in the case of part replacements. The variable cost includes the cost of irregular maintenance for unexpected incidents.

**Table 2**
Parameters of the model.

| Category | Parameter | Value |
|---|---|---|
| Project | Operating periods (year) | 10.0 |
| | Risk-free rate (%) | 5.0 |
| | Simulated paths (Number) | 1,000 |
| | Initial load growth rate (%) | 0.6 |
| Electricity price | Drift rate (%) | 1.1 |
| | Volatility (%) | 23.6 |
| Battery Price | Drift rate (%) | -0.5 |
| | Volatility (%) | 43.1 |

**Table 3**
Initial investment and operating costs for energy storage systems.

| Storage subclass | Description | Energy capacity (h) | Capital cost ($/kW) | FOM ($/MW per year) | VOM ($/MWh) |
|---|---|---|---|---|---|
| c0 | Lithium ion for regulation | 0 | 1,038 | 6,403 | 1.0 |
| c1 | Lead acid for reserves | 1 | 1,633 | 5,917 | 0.5 |
| c2 | Lithium ion | 1 | 1,426 | 6,984 | 3.7 |

Note. VOM: variable operating maintenance

The Korea Power Exchange predicts the electricity demand in the day-ahead market. Accordingly, power supply is requested based on the available capacity as fuel costs are calculated according to annual power generation. The marginal cost of a power plant (Min and Kim, 2017), which is linked to international crude oil prices, determines the market price. Contracts for liquefied natural gas (LNG), which are typically sourced from the Middle East, are predominately determined by the price of crude oil (Ason, 2019). Fuel costs are established in the present investigation using projections from the International Energy Association (IEA). The crude oil and gas price projections for the IEA's (International Energy Agency IEA, 2018) global energy outlook are detailed in Table 4. The prices of crude oil and LNG are projected to increase by as much as $11.9/mmBTU and $111/bbl, respectively, by 2030, according to these calculations. We compute the minimal market price and maximum market profit in the Korean power industry according to the time of day in order to approximate the profit volatility caused by fuel costs. Volatilities can also be estimated for a given scenario based on the capacity of ESSs. The project charges electricity to the capacity level for the time period associated with the minimum prices, whereas it discharges electricity at a rate of loss for the time period associated with the maximum prices. Finally, the differences between the two time periods can be evaluated, and the averages of the differences can be calculated on an annual basis.

In this study, the electricity storage guide of the NREL is used to select different technologies for utility-scale energy capacity in the Korean power market. These technologies are chosen by sorting the lithium-ion battery and lead-acid storage systems, which are listed according to their energy capacities, and through the selection of one to two technical categories according to their relative costs and efficiencies at each energy capacity level. In order to assess the feasibility of deploying ESSs, these storage technologies are maintained; nevertheless, the capital expenditure is increased by a fraction equal to or less than 1.0 (Hale et al., 2016). Therefore, our study attempts to model realistic learning curves and time-varying cost reductions for any technology. Table 5 displays the fractional costs ranging from 1.0 to 0.1 of the total capital cost in order to examine the impact of varying cost magnitudes on the deployment of storage. The applicability of these multipliers to lead-acid technologies may be limited due to their relatively advanced stage of development and reliance on specific sites. Thus, we impose an additional minimum cost reduction of $100 /kWh.

### 4.2. Scenario framework

ESS investment strategies have been demonstrated in the Korean

**Table 4**
Energy price forecasts by the IEA.

| Energy name | 2020 | 2022 | 2026 | 2030 |
|---|---|---|---|---|
| Crude oil price ($/bbl) | 79.0 | 82.2 | 85.8 | 111.0 |
| LNG price in Asia ($/mmBTU) | 9.6 | 9.8 | 9.8 | 11.9 |

Note. LNG: liquified natural gas

**Table 5**
Capital cost multipliers for different time periods.

| Duration | Capital cost multiplier |
|---|---|
| 2020–2023 | 1.0 |
| 2024–2026 | 0.5 |
| 2027–2030 | 0.1 |

power market by modeling the high and low ESS assumptions for each technical scenario. In the current study, the proposed strategy primarily focuses on the costs of flexible technologies until 2030 that can be included to the allocated type, such as the annual energy constraints with highly uncertain characteristics. Table 6 lists the capacity scenarios for renewable ESSs according to the Korean power policy. These capacity scenarios can affect electricity generation. As the utilization rate of fossil fuels can vary in accordance with the decline in power consumption owing to RE application with ESSs, differences in RE penetration are analyzed repeatedly, with each technical type serving as scenarios across three baseline assumptions.

In the proposed ROA, the ROV of ESS penetration can be distinguished by modeling the high and low RE assumptions with ESS capacity in the Korean power market based on a process that compares these scenarios. The base assumptions result in a 20% penetration of renewable energy sources by 2030 (Park and Kim, 2019), while the high RE assumptions lead to a 40% penetration using exactly the same metric. Scenario 1 is the base case used to distinguish the ROV of ESS capacity. According to Korea's RE 3020 plans, RE penetration is assumed to increase by 20% in terms of total consumption. Scenario 2 is the low case and includes zero additional capacity for ESSs until 2030, thereby resulting in a low share in total consumption. By comparing Scenarios 1 and 2, the ROV of ESS penetration in Korea can be computed at a low level. Scenario 3 pertains to the case with a high level, where the ESS portion is equal to 40% of the total consumption, as per the Green New Deal policy (Stangarone, 2020). As the cost of each scenario is different, the scenarios are used to obtain the price points for deploying ESSs at each investment level. Ultimately, the price associated with investors' willingness to pay changes and the price points for ESS deployment are determined by the reduction in capital costs for each scenario.

### 4.3. Results of ENPV based on technical type

According to the technical ESS types for evaluating the ROA, our investment strategy considers options to invest at each level based on uncertainties. Accordingly, option values can be obtained to achieve the optimal economics for each scenario. As capital cost overrun can be a risky parameter in an ESS project, the major risks affecting ESS investments can be modeled as stochastic inputs and applied to the investment. In this study, the beta-PERT distribution, which can provide historical data-driven probability estimation of the optimal minimum and maximum cost distribution ranges (Clark, 1962), is utilized to assess the uncertainties associated with capital expenditures for each technical type. It closely approximates a realistic probability distribution, which is also comparable to normal distributions, and is capable of determining the most probable value. The beta-PERT can also introduces the concept of uncertainty by using three types of estimates for each stage. In the best case, everything goes as expected. The normal case is the time that is most likely taken. The worst case is when nothing is going well. Assuming that the case required for each activity with different technology types is an independent beta analysis random variable, the main process follows a normal distribution. Therefore, the average value is calculated as the sum of the expected average values of the activities constituting the main process. For example, assigning a minimum value of 0.5 and a maximum value of 2.0 to the distribution pertaining to the concept screening level serves to underscore the substantial uncertainty associated with capital costs (Generation et al., 2007). In the detailed design, the beta-PERT distribution has with a minimum value of 0.9 and a maximum value of 1.6. In this manner, the distribution is equal to the expected capital costs between the lower and upper limits to consider the variation in capital costs owing to the technical types based on the investment level.

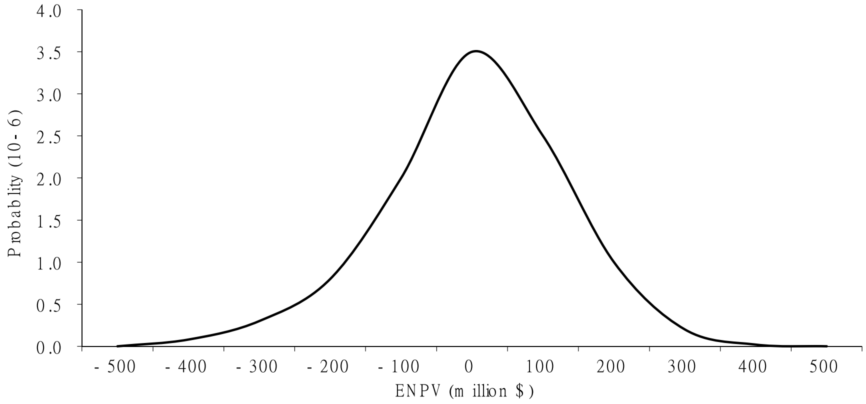
Fig. 6 shows the simulation results for the ENPV of the ESS. As shown in Fig. 6(a), the stochastic probability distribution of the ENPV with very low capital costs is close to zero because of its negligible probability. Conversely, the ENPV associated with exceptionally high capital costs is equal to a value that disregards the investment's entirely triggered threshold. Between these two cases, the ENPV has a maximum value that corresponds to the capital costs. Fig. 6(b) shows the ENPV variation of capital costs that affect ESS feasibility. At point P, the NPV is equal to the ENPV when the threshold is not considered. The ENPV is lower than that obtained at the concept screening level when the capital costs are lower than P. Additionally, even if capital costs are reduced, the NPV can decrease. Notably, investing entails greater risk and lower profitability than deferring one's ENPV distribution mean until capital cost thresholds are optimized. The distribution that results from awaiting the threshold therefore produces the greatest ENPV. Due to the reduced standard deviations observed in ENPV distributions characterized by capital costs below the threshold, the deficient leverage effect-ascertained ENPV is diminished. As shown in Fig. 6(c), it is challenging to reduce capital costs due to their already substantial impact on the ENPV. Additionally, it is challenging to minimize capital costs when the ENPV is too low, which results in a positive ENPV. For instance, a lithium-ion ESS with a rated power of 2.1 MW and a discount rate of 7.5% has an ENPV at the concept screening level equal to 3.0 MW. Here, there is no need to delay the project till capital expenses are decreased and the investment profit rises. There is a negative impact on the ENPV when the possibility of reducing capital costs is low. In contrast, an ESS powered by lead acid and rated at 1.2 MW may be deemed ineffective. As a result, the ENPV is equivalent to 3.0 MW if the capital costs remain at zero and have decreased significantly. It is possible for operational expenses to surpass revenue, resulting in a net profit loss, even in the absence of capital expenditures.

To evaluate the ENPV variation according to the technical types, our main assumption is that uncertainties decrease with regard to available values during the evolution of the project. In the project's life cycle, the ROA can assess the option value to build or not. In the detailed design stage, the ROA assigns the distribution of the capital costs with an established reduction in uncertainty. As an ENPV distribution with low

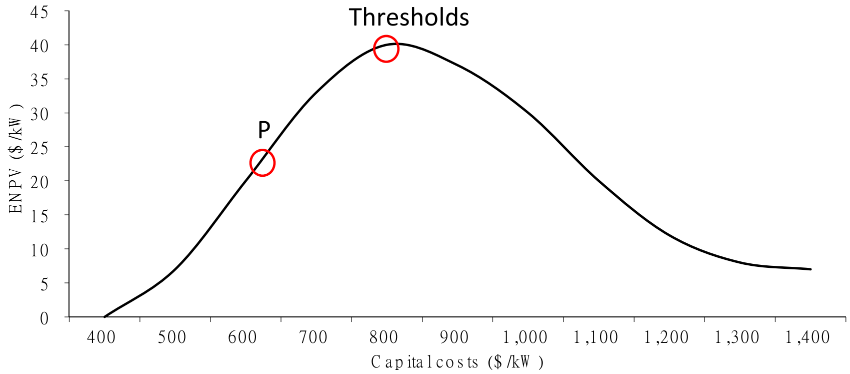
**Table 6**
Scenario framework.

| Year | Scenario 1 | | | Scenario 2 | | | Scenario 3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Electricity generation (TWh) | RE capacity (GW) | ESS capacity (GW) | Electricity generation (TWh) | RE capacity (GW) | ESS capacity (GW) | Electricity generation (TWh) | RE capacity (GW) | ESS capacity (GW) |
| 2020 | 34.4 | 11.3 | 1.1 | 34.4 | 11.3 | 1.1 | 34.4 | 11.3 | 1.1 |
| 2022 | 116.6 | 23.3 | 2.3 | 86.6 | 17.3 | 1.7 | 176.7 | 35.3 | 3.5 |
| 2026 | 179.4 | 38.8 | 3.8 | 115.6 | 25.1 | 2.5 | 305.9 | 66.3 | 6.6 |
| 2030 | 251.6 | 58.5 | 5.8 | 150.1 | 34.9 | 3.5 | 454.6 | 105.7 | 10.5 |

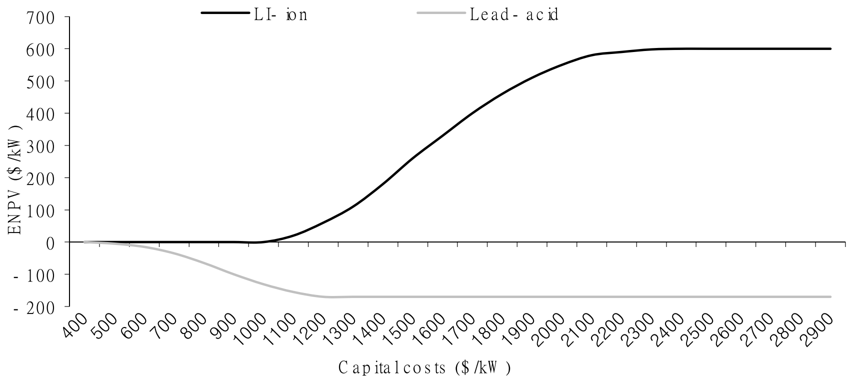
Note. RE: Renewable energy; ESS: Energy storage systems



(a) Stochastic probability distribution of ENPV



(b) Relationship between ENPV and capital costs

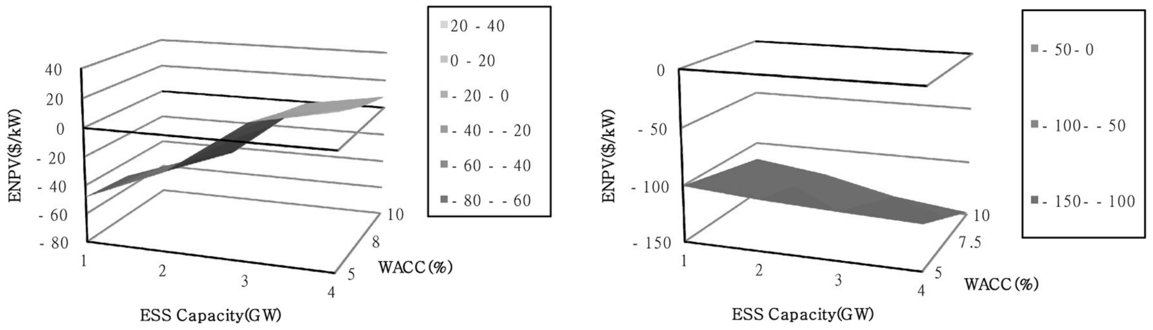


(c) Impact of capital costs by technology type

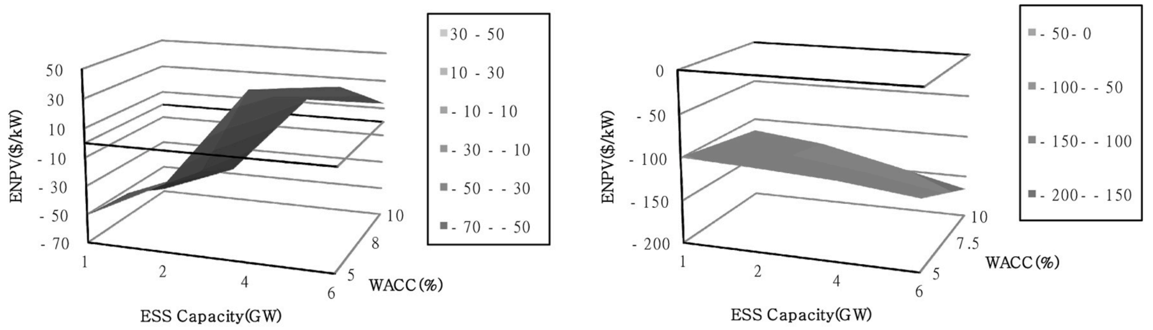
**Fig. 6.** Simulation results for ENPV.

uncertainty has not been executed, the project may be abandoned after concept screening. At this level, the ENPV can be increased when the project is canceled owing to cost savings before the detailed design stage. Ultimately, the ROA can measure the available value from the reduction in capital costs and delay in the decision to build or not. The canceled option yields a high ENPV, which can change from negative to positive. Although investors can decide to build or not, they may postpone the decision for further savings in capital costs caused by external exogenous factors.

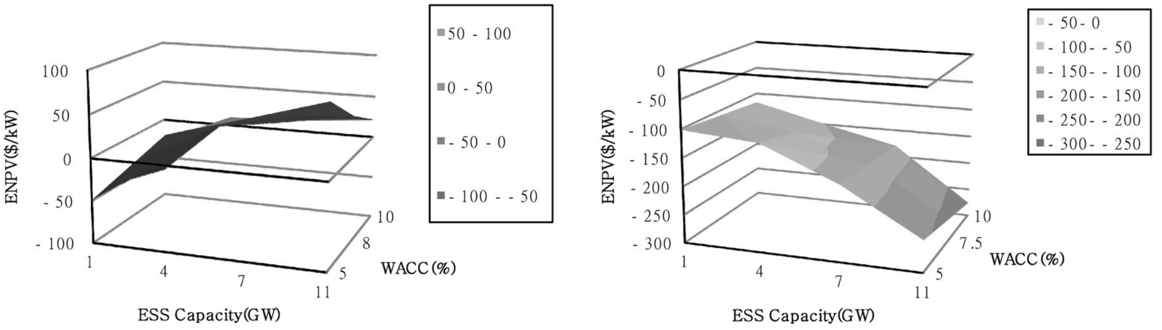
Fig. 7 shows the ENPV results for the lithium-ion and lead-acid types in each scenario. The variation is indicated to be very high or low when the capacity of the ESS is volatile, that is between 1.1 and 10.5 GW. As shown in Fig. 7(a), when the ROA generates available value in Scenario 1, it can change the investment decision because the ENPV varies for lithium-ion batteries. Conversely, Fig. 7(b) shows a limitation of the lead-acid types such that the ENPV decreases during capacity investments. Fig. 7(c) illustrates that a small variation in *WACC* causes remarkable ENPV changes. As the capital costs of lithium-ion ESSs are more than 85% of the life cycle costs, the ENPV is significantly affected. An available value cannot be provided when the *WACC* is equal to 5% or



(a) Scenario 1 (Li-ion) (b) Scenario 1 (Lead-acid)



(c) Scenario 2 (Li-ion) (d) Scenario 2 (Lead-acid)



(e) Scenario 3 (Li-ion) (f) Scenario 3 (Lead-acid)

**Fig. 7.** Variations of ENPVs for different battery types.

10% because the ENPV is either very high or very low. However, Fig. 7(d) shows that the high capacities of lead-acid batteries yield low ENPVs at high capital costs. Figs. 7(e) and 7(f) also indicate that the ENPV for lead-acid batteries is lower than that for lithium-ion batteries. Thus, better incentives for the use of lead-acid batteries are required. Finally, a larger storage capacity can be determined from the capital cost, which can be higher than the revenues provided by a higher capacity in lead-acid technology.

The ESS revenue in our study can be generated using different incentives when the marginal price of the system does not vary. If the incentive is unclear, then the ENPV can be lower than the capital costs. Eventually, the investment will have no optimal capital cost threshold. Hence, the capital cost overrun can be a risk factor for the ESS project. As the probability distribution is addressed according to the ROA as uncertainties are related to capital costs, the revenue is equal to the expected capital costs based on the technical type and investment level. Table 7 lists the capital cost thresholds with distributions at the concept screening level. They are particularly relevant relative to the construction level because more careful decisions to implement the option with investment can be formulated. It can be exercised only in a few cases where the capital costs are lower than the thresholds. Without capital cost thresholds, the ENPV cannot be used for comparisons at the operational level. An important note is that a comparison between capital cost thresholds and current anticipated capital expenditures are pertinent. The distributions of capital costs have negative skewness when preceding the thresholds, the anticipated capital expenditures are nominal. When the investment at the detailed design level is applied, since the ENPV is less than zero, the project is unable to continue beyond the detailed design phase. If the ENPV is higher than zero, the project progresses with low uncertainty after the endorsement of the option to build.

Table 8 presents a comparison of the ENPVs between the principal

**Table 7**
Capital cost thresholds for evaluating the ENPV.

| Incentives | *WACC* | Technical type | | | | | |
|---|---|---|---|---|---|---|---|
| ($/MWh) | (%) | Lithium ion (GW) | | | | Lead-acid (GW) | |
| | | 1.1 | 2.3 | 3.8 | 5.8 | 1.1 | 5.8 |
| 0.0 | 5.0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | 1,440 | 1,211 |
| | 7.5 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 |
| | 10.0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 |
| 10.0 | 5.0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV>>0 | ENPV>>0 |
| | 7.5 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | 1,550 | 1,309 |
| | 10.0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 |
| 25.0 | 5.0 | 643 | 536 | 548 | 478 | ENPV>>0 | ENPV>>0 |
| | 7.5 | ENPV<<0 | ENPV<<0 | 369 | 334 | ENPV>>0 | ENPV>>0 |
| | 10.0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | ENPV<<0 | 1,737 | 1,427 |
| 40.0 | 5.0 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 |
| | 7.5 | 818 | 699 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 |
| | 10.0 | 612 | 514 | 526 | 452 | ENPV>>0 | ENPV>>0 |
| 55.0 | 5.0 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 |
| | 7.5 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 |
| | 10 | 920 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 | ENPV>>0 |

Note. ENPV: expanded net present value; WACC: weighted average capital cost

**Table 8**
Summary of ENPV evaluation results at each level.

| Technology type | Capacity (GW) | Incentives ($/MWh) | *WACC* (%) | Concept screening level | | NPV distribution corresponding to the capital cost thresholds | | Detailed design level: | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Option to build | | Option to wait to build | |
| | | | | ENPV | NPV << 0 | ENPV | NPV << 0 | ENPV | NPV << 0 | ENPV | NPV << 0 |
| | | $/MWh | % | $/MW | % | $/MW | % | $/MW | % | $/MW | % |
| Lithium-ion | 1.1 | 25.0 | 5.0 | -96,685 | 72.8 | -54 | 3.8 | 252 | 8.1 | 1,586 | 7.6 |
| | 2.3 | 25.0 | 5.0 | -66,890 | 65.5 | 3,226 | 8.1 | 4,705 | 9.4 | 4,811 | 7.6 |
| | 3.8 | 25.0 | 5.0 | 13,182 | 42.2 | 29,126 | 20.4 | 32,257 | 19.5 | 34,887 | 18.6 |
| | 5.8 | 25.0 | 5.0 | 28,863 | 37.3 | 37,170 | 22.8 | 40,635 | 22.4 | 42,650 | 21.3 |
| | 1.1 | 40.0 | 10.0 | -86,436 | 79.0 | 108 | 5.3 | 1,280 | 4.9 | 1,973 | 4.1 |
| | 2.3 | 40.0 | 10.0 | -63,337 | 74.1 | 1,386 | 5.8 | 2,528 | 5.7 | 3,067 | 4.7 |
| | 3.8 | 40.0 | 10.0 | 9,368 | 40.3 | 24,548 | 10.4 | 27,588 | 11.6 | 30,521 | 9.1 |
| | 5.8 | 40.0 | 10.0 | 17,773 | 34.4 | 26,890 | 13.6 | 29,795 | 11.6 | 19,019 | 1.6 |
| Lead-acid | 1.1 | 0.0 | 5.0 | -134,954 | 74.9 | 7,645 | 6.0 | 10,032 | 4.9 | 12,599 | 4.5 |
| | 5.8 | 0.0 | 5.0 | -152,889 | 77.6 | 3,135 | 5.9 | 6,379 | 4.8 | 6,124 | 4.9 |
| | 1.1 | 10.0 | 7.5 | -120,055 | 70.4 | 36,910 | 6.5 | 42,042 | 5.6 | 45,721 | 3.3 |
| | 5.8 | 10.0 | 7.5 | -137,447 | 73.9 | 37,455 | 6.6 | 36,142 | 5.0 | 37,362 | 4.1 |
| | 1.1 | 25.0 | 10.0 | -33,599 | 51.1 | 27,548 | 8.5 | 35,501 | 7.1 | 47,046 | 1.1 |
| | 5.8 | 25.0 | 10.0 | -59,008 | 57.4 | 15,178 | 4.3 | 20,942 | 5.3 | 25,574 | 1.2 |

Note: NPV: Net present value; ENPV: expanded net present value; WACC: weighted average capital cost

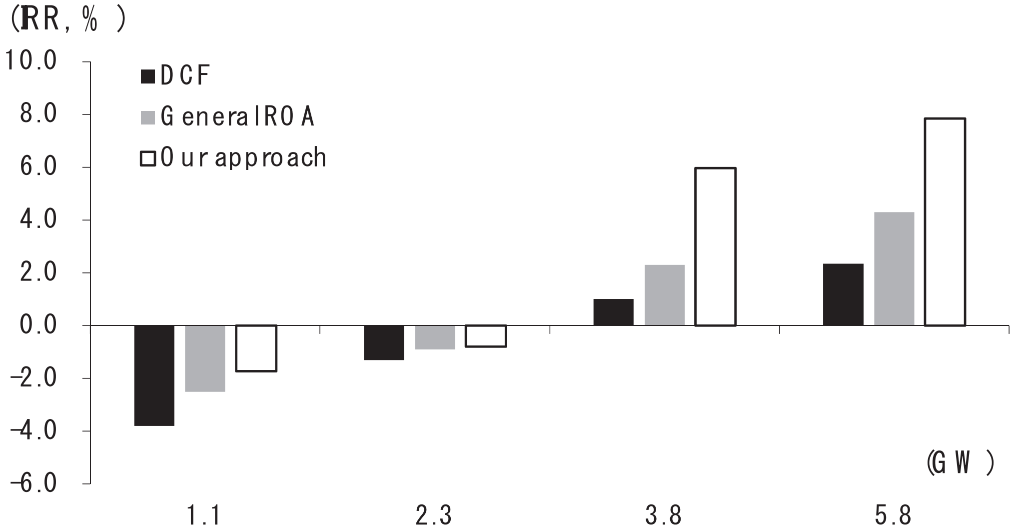


**Fig. 8.** Comparison simulation results between conventional methodologies with our work. Note. IRR: internal rate of return.

parameters of the distribution at various thresholds at the level of concept screening. Here, each level used is implemented to apply the option of the decision to wait to build after the detailed design stage. Specifically, when the ESS capacity varies according to the scenario assumption, the ENPV variation is analyzed based on two parameters: incentives and *WACC*. As shown in Table 8, the ENPV variation due to the parameter combination follows similar characteristics when the ENPV decreases abruptly at the concept screening level. Investors hold the option to cancel the ESS project when the ENPV is below zero to maximize profits. Conversely, the increased proportion of lead-acid battery types yields a low ENPV as capital costs increase. Additionally, a high lithium-ion penetration represents a high ENPV case. As indicated by these results, investors can utilize the ROA for investment decisions by selecting the technical type at each level.

This study utilized real option analysis to incorporate the specific technology type of ESS and uncertainties at each level of the project. A procedure of validation was carried out by comparing the approach with an existing model. The appropriateness of using ENPV, as presented in this study, was assessed by comparing it to two other methods: 1) DCF, which is commonly employed in evaluating ESS projects, and 2) real option that only take into account the fluctuation of electricity prices. Upon examining Fig. 8, it can be observed that the ESS project, which appeared unprofitable when assessed using the DCF approach, was found to be profitable when considering real options. Furthermore, it is evident that the advantages from the investor's point of view are amplified when both electricity pricing and technological uncertainty are taken into consideration. Under the existing energy policy, investing in ESS is highly unpredictable. However, it is apparent that the proposed methodology may contribute to mitigate risks associated with such investments. From a policymaker's perspective, our approach can be used to provide tax benefits, hedge risks for investors through public-private joint investment, and secure standard regulations to prevent unexpected accidents such as fires and cost overrun.

## 5. Conclusion and discussion

Increased RE generation is becoming a key issue in the electricity market given its promising operation. Enabling future smart grids to store electricity and react to demand fluctuations, ESSs may represent one of the most effective means of enhancing flexibility. However, uncertainties in economic feasibility for ESSs investment are acting as a major reason for limiting technology diffusion. Considering the inherently precarious circumstances surrounding investments in these technologies, the primary determinants of profitability impact reduction in electricity prices, incentive values, cost overruns, and construction level delays. Cost overruns are also a major challenge because the capital costs of lithium-ion and lead-acid batteries contribute to 89% and 43% of the life cycle cost, respectively. The detailed conclusions regarding uncertainties at each level are as follows:

- **Level 1: Concept Screening**

  The current state of the Korean power market would be unfavorable to ESS, as the expenses associated with construction would surpass the income generated by a larger capacity. Comparable results have been obtained using analyses pertaining to various types of ESS in order to ascertain the outcomes of our work concerning the optimization of the ESS's capacity.

  Table 8 lists the ESS's NPV for each of the scenarios under review. When the intrinsic value of the option fails to increase, it identifies scenarios with extremely high or very low NPV. Whether an investment is successful or unprofitable is independent of the uncertainties modeled. Scenarios in which the option creates significant additional value are emphasized, and the evaluation of uncertainty value might alter an investor's decision to invest or not.
- **Level 2: Detailed Design**

  Due to different incentives, the lithium-ion ESS's ENPV varies from an extremely high value to an extremely low value. Tabulated results indicate that even a minimal shift in the *WACC* can result in significant variations in the ENPV.

  Lithium-ion ESSs have larger capital costs than the life cycle costs and even a minor fluctuation in the *WACC* significantly affects their ENPV. The fact that just a 2.5% variance can cause a substantial shift in the evaluation of the investment and the suitability of the real option emphasizes the significance of the *WACC*. When *WACC* is equal to 5% or 10%, real options do not offer any additional value because the corresponding NPV is already either extremely high or extremely low. The incentive requirements for lead-acid ESSs that were analyzed range from 10 to 25$/MWh for large capacity. In contrast, the incentive requirements for lithium-ion ESSs are between 25$/MWh and 50$/MWh. It has been pragmatic to examine five scenarios wherein the incentive levels for each megawatt-hour of electricity sales volume.
- **Level 3: Construction**

  The NPV distributions of the option to build are especially pertinent compared to the NPV distributions of the option to delay. Therefore, in order to compare the outcomes of the option to build, the ENPV and the likelihood that the aforementioned distributions would have a negative NPV.

  Table 7 enumerates the scenarios' capital cost thresholds where the net present value is neither extremely high nor too low. In the absence of a capital cost threshold, scenarios in which NPV is less than zero or greater than zero are excluded from further analysis. The values of Table 7 and the present estimated capital costs can be compared because (1) Under specific conditions, the anticipated capital expenditures approach the capital expenditure thresholds; (2) Under other conditions, the expected capital expenditures have already fallen below the threshold due to the adverse variance in the capital cost distributions.
- **Level 4: Operation**

  The project can be abandoned in a situation where the number of times the investment in detailed design, the capital cost is less than the threshold, and the NPV is less than zero. On the other hand, the number of times the NPV was greater than zero implies that the simulation was realized with minimal uncertainty. Thus, the distribution of ENPV follows the execution of the construction and operation options. Simulation results are shown in Table 8, where the ENPV is compared with the concept screening level. The scenario where capital costs are equal to the threshold implies that the option to delay investment is implemented. Furthermore, the option to build after the detailed design and the option to wait for construction after the detailed design can also be utilized.

This study proposes an optimal investment strategy based on the ROA to evaluate the profitability of ESS investments and determine the available value. This study's primary contribution is the quantification of risks encountered when implementing choices during the decision-making process. The option before the detailed design level appraises the value of waiting to reduce capital costs. The option at the detailed design level calculates the available value when the ESS is postponed. The last option assesses the value of the decision to wait to build after the detailed design stage. The proposed ROA can assess additional profitability values relative to existing methods of measuring investment uncertainty. The simulation results indicate that the probability of incurring a negative NPV is significantly reduced and the ENPV is significantly increased with the implementation of the first option. In all scenarios with a negative ENPV, the option to wait for a reduction in capital costs can change the negative ENPV into a positive one. Similarly, Additionally, the option of the second alternative raises the ENPV and diminishes the likelihood of a negative outcome. The third option indicates that the decision to delay construction beyond the detailed design stage does not yield any accessible value in the form of reduced capital costs. Therefore, the proposed ESS investment strategy can guide investors in making efficient decisions with low risk in the electricity market.

In our future work, we aim to focus on the changes in the ENPV in response to the interaction of various hidden effects, such as environment and safety, owing to the expansion of ESSs. We also plan to extend the study design to include different technical types and available values from a societal perspective.

## CRediT authorship contribution statement

**Sunghyun Hwang:** Formal analysis, Investigation, Methodology, Writing – original draft. **Mun-Kyeom Kim:** Conceptualization, Funding acquisition, Validation, Writing – review & editing.

## Declaration of Competing Interest

There are no conflicts of interest to declare.

## Data availability

The data that has been used is confidential.

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