CZECH TECHNICAL UNIVERSITY IN PRAGUE
FACULTY OF MECHANICAL ENGINEERING
DEPARTMENT OF MANAGEMENT AND ECONOMICS

ADVANCED VALUATION OF GRID-SCALE BATTERIES BASED ON REAL OPTIONS THEORY

Doctoral dissertation

Ing. Adam Hurta

Prague, March 2024

Doctoral study programme: Mechanical Engineering

Field of study: Enterprise Management and Economics

Primary doctoral advisor: prof. Ing. František Freiberg, CSc.
Secondary doctoral advisor: Ing. Miroslav Žilka, Ph.D.

Declaration

I hereby declare that I have completed this doctoral dissertation solely by myself, and that I have cited all the literature used.

Prague, March 3rd, 2024 …………………………………………..

Ing. Adam Hurta

Acknowledgment

I would like to express my deepest appreciation to my primary doctoral advisor prof. Ing. František Freiberg, CSc. and my secondary doctoral advisor Ing. Miroslav Žilka, Ph.D. for their valuable advice and mentoring throughout the process of writing this dissertation.

I would like to extend my sincere thanks to my family; this endeavor would not have been possible without the endless support of Magdalena, Theodor and Karin.

Nomenclature

A_i	alternative *i*
B	amount of debt
C_j	criterion *j*
$CF(t)$	cashflow (EUR)
C_{MAX}	rated capacity (MWh)
$C(t)$	level of charge (MWh)
CL	cycle life (cycles)
COC	cost of the cycle (EUR/cycle)
d	rate of down movement
DOD	depth of discharge (%)
E	amount of equity
E_i	expert *i*
f	future value (in ROA method)
FV	future value (in DCF method)
$GM_{e,j}^{i}$	geometric mean of the *i*-th alternative in relation to the *j*-th criterion as valued by the *e*-th expert
GWM_j	geometric weighted mean of the criterion *j*
I	investment costs (EUR)
IRR	internal rate of return
K	strike price (EUR)
K_b	cost of debt
K_e	cost of debt and equity
$LCOS$	levelized cost of the storage (EUR/MWh)
m	length of the subproblem (time points)
n	number of time periods
NoC	number of theoretical cycles (cycles)
NPV	net present value
p	risk-neutral probability
$P_{IN}(t)$	power inflow (MWh)
$P_{OUT}(t)$	power outflow (MWh)
P_{MAX}	rated power (MW)
PV	present value
Q	amount of debt and equity
r	discount factor
r_a	expected return of security *a*
r_f	risk-free rate
r_m	expected market return
r_x	tax rate
RL	calendar life (years)

$S(t)$	power price (EUR/MWh) / price of underlying asset (EUR)
T	investment horizon / time-to-maturity (years)
u	rate of up movement
v_i	achieved score of criterion *j*
w_e	weight of expert *e*
w_j	normalized weight of criterion *j*
w_j^e	priority of criterion *j* from the point of view of the expert *e*
$WACC$	weighted average cost of capital
x_{ij}	data of the *j*-th criterion related to the *i*-th alternative
$x(t), y(t)$	binary variable
z_j^i	score of the *i*-th alternative in relation to the *j*-th criterion
$z_{e,j}^i$	score of the *i*-th alternative in relation to the *j*-th criterion as valued by the *e*-th expert
Z_i	total score of the *i*-th alternative
α	speed of reversion to mean
β_a	beta of security *a*
ε	round-trip efficiency
μ	mean / drift parameter
σ	volatility of price / project's returns
σ_A	annualized volatility
φ	rate of degradation
ω	length of overlapping window (time points)

(G)ARCH	(Generalized) Auto Regressive Conditional Heteroskedasticity model
BESS	battery energy storage system
BSM	Black-Scholes model
CAPM	capital asset pricing model
CRRM	Cox-Ross-Rubinstein binomial option pricing model
DP	dynamic programming
EES	electrical energy storage
EV	electric vehicles
EXAA	Energy Exchange of Austria
GBM	Geometric Brownian motion
$LiFePO_4$	lithium iron phosphate (battery)
LSMC	Least Squares Monte Carlo method
MCDA	multiple criteria decision analysis
MCS	Monte-Carlo simulation
MILP	mixed integer linear program
MRJM	mean-reverting jump-diffusion model
opt	option
OTC	over-the-counter (market)
OU	Ornstein-Uhlenbeck (process)
PDE	partial differential equation
PHES	pumped hydroelectric energy storage

PHV	photovoltaic
RES	renewable energy sources
ROA	real options analysis

Contents

List of figures

List of tables

Abstract

The liberalization of the energy sector and the continuous development of intermittent renewable energy sources (RES) has promoted advanced approaches to energy storage. Battery energy storage systems (BESS) offer satisfactory parameters of storage; however, high initial capital cost has been restricting more significant spread of the technology. The effect of high capital cost is worsened by the inadequate valuation processes used for this type of investment. BESS projects are implemented under high uncertainty, stemming mainly from high volatility of energy prices. At the same time, management typically possesses flexibility when it comes to the scope and timing of BESS projects. Traditional discounted cashflow (DCF) methods do not recognize these aspects properly, which can lead to undervaluation of the project. Real options analysis (ROA) recognizes both uncertainty and flexibility inherent in these types of projects, and offers an enhanced method of valuation. However, the ROA approach cannot be perceived as a complete substitute for the traditional DCF method, but rather as its extension.

This dissertation recognizes importance of both the DCF and ROA methods, and develops a valuation framework covering both approaches, designated specifically for BESS projects. The DCF method is based on a robust, mixed-integer linear programming (MILP) model, which maximizes net cashflow generated by deploying a BESS for arbitrage on the day-ahead market. The MILP model is solved without considering the degradation process of the BESS in the first Scenario, which leads to an extensive degradation of the BESS. As a result, the investment in a BESS under current market conditions cannot be justified, when valued with net present value (NPV). In the second step, the initial MILP model is extended with a degradation process, which ensures that the battery dispatch balances net cashflow with degradation cost. The improvement in the pattern of dispatch is reflected in a significant improvement in NPV, as demonstrated by the case study in Section 11 in Scenario 2.

In the third step, ROA is introduced to extend the NPV value from the preceding step with the value of uncertainty and flexibility inherent in a BESS project. A literature review of ROA in the field of BESS projects provides the grounds for deploying a multiple-criteria decision analysis (MCDA) in the next step. Eight decision criteria are proposed, based on extensive research in the field, in order to facilitate selection of the suitable ROA method. The created valuation framework enables practitioners to select the ROA method which best meets specific valuation requirements. The valuation framework is applied in a case study, where the Cox-Ross-Rubinstein binomial option pricing model (CRRM) received the highest score out of the three ROA methods considered. For calculating the volatility of a project, simulation of future project cashflow is demonstrated as a useful alternative to other methods, such as implied volatility determined on a derivatives market, or volatility predicted with (Generalized) Auto

Regressive Conditional Heteroskedasticity (G)ARCH family models. The case study shows the positive value of postponing the investment in a BESS project, and shows that even a BESS project with negative NPV can have a positive value, when being valued with ROA. Most importantly, it confirms the functionality and benefits of the proposed BESS valuation framework.

Introduction

The energy sector has undoubtedly been a volatile environment recently. Liberalization of the market and the development of intermittent sources of energy – or supply shocks – are some of the drivers of price volatility on the energy markets. With the commitment to deceasing the global volume of CO_2 emitted into the atmosphere, this trend in the energy sector cannot be expected to end any time soon. Instead, we can expect to see more photovoltaic (PHV) power plants and wind turbines, and more energy stored in different forms, such as chemical batteries, or H_2.

At the same time, technology develops rapidly, bringing new solutions to the market. These solutions offer new sources of energy, decrease production costs, and provide more environment friendly approach to extraction, transformation, and storage of energy. Storage solutions play an especially important role in supporting the spread of renewable sources of energy, including wind or PHV, which are referred to as intermittent sources, because energy supply from these sources cannot be easily matched with the demand. Grid-scale batteries are an efficient way of overcoming this problem, since they have a high round-trip efficiency [1], are easy to deploy, and their cost has continuously decreased [2], all of which have made their use economically viable.

The rapid evolution of the energy sector does not seem to be always reflected in the way investments in the sector are evaluated. Traditionally, DCF methods such as NPV, IRR or payback period are used. These methods discount the future cashflow using a factor which reflects the riskiness of the project, and assume that future cashflow is certain. However, in reality, actual cashflow can vary in volume and time, as events which were unexpected during the planning phase of the project can occur. For the investments in grid-scale batteries, revenues are a function of prices on the respective markets. Using NPV for valuation of such a project, and predicting cashflow with certainty, may lead to unrealistic assumptions, generating a significant valuation error. Instead, determination of a volatility of the future cashflow based on observation of the market may be a more realistic approach. Alternatively, the potential of the ever-growing power derivatives market can be leveraged to determine the future volatility of the cashflow as the best expectation of the market. In both cases, analyzing the investment with a clearly defined uncertainty over the future project cashflow provides decision makers with better information, and thus better starting position, than simply expecting clarity over the future cashflow, and then periodically updating the NPV.

A suitable investment valuation method for grid-scale batteries should also not ignore the decision power that management possesses during all the phases of the project. As new information emerges, management can approve changes to the project as it reacts to the information. For example, in a situation of low market volatility, the BESS project can be abandoned or moved to a more profitable market. On contrary, the scale of the project can be extended to benefit from positive market evolution. Such decisions are rational and thus expected, and their omission from the investment analysis can result in an unrealistic model. The real options analysis (ROA) addresses both the uncertainty and flexibility inherent in projects, and in the case of grid-scale batteries, these are undoubtedly attributes significantly influencing the quality of the investment appraisal process. Additionally, ROA can provide not only a more realistic valuation result, but can also serve as a contingency plan which enables the effective management of project risks (rather than ignoring them).

ROA does not replace DCF. Instead, ROA should be perceived as a method extending the traditional DCF method, whereby NPV is extended with an option value, to estimate the uncertainty and flexibility inherent in the project. Calculation of NPV for grid-scale batteries is specific to their technical properties and constitutes a separate topic, itself. Researching them in isolation, however, is not optimal, given the uncertainty and flexibility this type of project typically entails.

Motivation for this work arises from the necessity of an advanced valuation framework for investments in grid-scale batteries, one that integrates both NPV and ROA to harness the synergies between these methods. This need is a response to the ongoing changes in the energy sector.

The dissertation is divided into three parts. The first part provides the theoretical background and introduces the key components of the BESS valuation topic. Section 1 introduces the object of the capital investment valuation framework developed in this dissertation: BESS. The main characteristics of BESS are described, followed by its applications, with a focus on arbitrage. BESS is the object of the two key valuation methods—DCF and ROA. While the former (DCF) is described in Section 2, ROA process and its sub-processes are subject of the Sections 3-4. Types of real options are followed by popular valuation methods for financial options, namely BSM, CRRM, and MCS. These options are analyzed in relation to ROA. Once ROA has been introduced conceptually, a detailed review of ROA as applied to BESS projects is covered in Sub-section 4.1. Importance of the review lies in mapping of the current trends in ROA in the field of grid-scale batteries, which is subsequently used as an input for Part II. MCDA, used for selecting the suitable ROA method, is presented in Section 5. Section 6 sets the goals for the dissertation, presents the author's hypothesis, and describes study's research methods.

The second part proposes the advanced BESS valuation framework. The dissertation is concluded with the third part summarizing the findings of the dissertation.

PART I

Theoretical background

1. Storage of electrical energy

Near the end of 2021, new capacity of renewable power sources were on track to set another annual record, driven mainly by the improved policies and climate goals set at the 2021 UN Climate Change Conference, held in the United Kingdom. This trend is forecast to continue in the coming years, with up to 95% of the global power capacity covered by RES [3].

Renewable sources of energy, such as wind or solar power, are intermittent sources, in contrast to conventional energy sources that can be dispatched upon demand. Thus, the increasing supply of energy from non-dispatchable renewable energy sources exerts pressure on electrical grid operators, who must guarantee the balance between the supply and demand for electricity. To avoid losing the potential energy generated by intermittent sources, their electrical power can be transformed into a different form and stored.

Distinctions can be made between mechanical, electrical, thermochemical, chemical, thermal, and electrochemical electrical energy storage (EES) systems [4]. The latter group, more specifically the battery electricity storage systems (BESS), has been enjoying a substantial increase in popularity recently, due in part to their scalability [5].

1.1. BESS

Pumped hydroelectric energy storage (PHES) generated 8500 GWh in 2020, accounting for around 90% of the total global electricity storage capacity. Despite this fact, BESS is predicted to gain the highest share of future growth in electricity storage capacity. By the end 2021, BESS capacity accounted for around 16 GW, and 6 GW of this capacity was added in the very same year [5]. The strong trend is confirmed by plotting the grid-scale battery additions of the last years in Fig. 1, which also confirms the leading position of USA and China in new BESS installations, when measured by GW of capacity.

IEA predicts the grid-scale battery capacity to increase up to 680 GW by 2030, with yearly capacity additions of 80 GW in the years between 2022 and 2030. This trend will be predominantly driven by decarbonization of the electricity system, with BESS providing balancing services.

The European Commission expects BESS to play an important role in the "European Green Deal," a strategy paving the path towards carbon neutrality in the EU by enabling integration of RES [6].

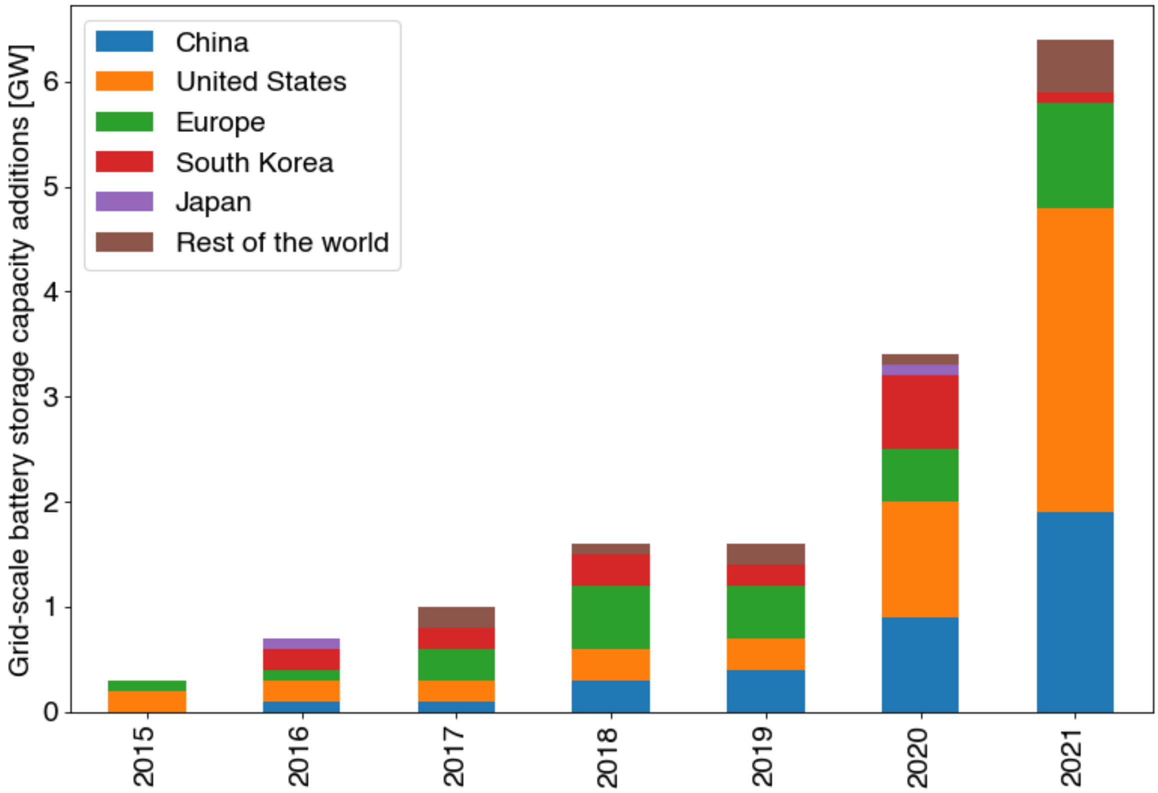

Fig. 1. Annual grid-scale battery storage additions [7].

To create a base for BESS in the EU, the energy union has introduced a comprehensive governance framework and the European Commission has issued a strategic action plan on batteries. Additionally, the European Commission, together with stakeholders in the battery industry, launched the European technology and innovation platform, which focuses on competitiveness in the global battery sector [8].

The market offers a wide range of battery types. Based on the material used for electrodes and electrolytes, rechargeable batteries can be divided into lead-acid, alkaline, metal-air, high temperature, and lithium-ion batteries [9]. Lithium-ion batteries can be further categorized in accordance to the material of a cathode into different battery types: e.g., $LiFePO_4$, $LiCoPO_4$, $LiCoO_2$, $LiNiO_2$, among others [10].

Lithium iron phosphate ($LiFePO_4$) BESS, a subset of lithium-ion batteries, is expected to represent the main battery chemistry in this trend [5]. The positive aspects of $LiFePO_4$ batteries are not only excellent electrochemical performance, long cycle life and good safety measures but also the fact the mineral resources required for their production are in abundance [11]. While the market share of $LiFePO_4$ batteries was 27% in 2020, it is predicted the market share will be 64% in 2025 [11].

When comparting battery types, the main characteristics or criteria to consider include:

- Energy storage capacity – the amount of energy (kWh) that can be stored in the battery.

- Energy density – the amount of energy per volume (Wh/L) or weight (Wh/kg) stored by a battery.
- Rated power capacity – the output of a battery (MW).
- Discharge time (C-rate) – a measure of the speed with which can a battery discharge/charge fully. 1C rate means that a battery can discharge/charge fully in one hour.
- Round-trip efficiency – the amount of energy discharged back to the grid, expressed as a percentage of the energy initially taken from the grid. A round-trip efficiency of 95% means that the loss from charging and discharging the battery was 5%, i.e., 1MWh was taken from the grid to charge the battery, but only 0.95 MWh out of this energy could be discharged back to the grid. The remaining 0.05 MWh accounted for a loss caused by the conversion.
- Self-discharge – batteries vary in their ability to store energy, long term. Continuous changes in the chemistry of a battery result in the inevitable loss of a certain percentage of energy stored.
- Cost – unit cost of a battery can relate to energy (EUR/MWh) or power (EUR/EUR/MW). It is necessary to distinguish the scope of the cost; as depicted in Fig. 2, BESS consists not only of battery cells but other components, such as a transformer or inverter. Further, deployment of BESS cannot be accomplished without a piece of land, which must be either bought or leased. Besides initial capital costs, a BESS requires regular maintenance.

The popularity of lithium-ion BESS stems from significant advantages of lithium-ion batteries, such as their high specific energy, specific power, and nominal voltage. They also provide round-trip efficiency of close to 100%, low self-discharge rate, no memory effect, and low maintenance costs [9]. This combination of properties makes lithium-ion batteries the most popular form of chemical EES by capacity in the world, showing exponential growth in popularity [12].

Besides facilitating integration of intermittent renewable sources of energy, EES can be used for other applications, such as [13]:

- Short term power supply – providing power back-up for critical customers or facilitating black-start [13].
- Price arbitrage on the spot market[1] – exploiting the price difference between peak and off-peak hours. By time shifting the energy on the grid, revenues are generated. This

[1] In this work, the term 'spot market' encompasses both the intraday market, facilitating real-time electricity trading, and the day-ahead market, which involves transactions for delivery on the following day.

application favors BESS with a high energy capacity [14]. The price arbitrage can be performed on the intraday market [15] as well as on the day-ahead market [16]. For example, the Energy Exchange of Austria (EXAA) provides auction trading on the day-ahead market, and both auction trading and continuous trading on the intraday market. The day-ahead auctions are divided into two blocks: independent classic auction (at 10:15) providing the first price signal for the given trading day, and European market coupling at 12:00. During the auction at 10:15 it is possible to trade 24 individual hours, 96 quarter hours and 15 different blocks. During the auction at 12:00 it is possible to trade the 24 individual hours and the 15 blocks. There is also a designated auction for green power certified with the European Energy Certificate System [17]. The market participants submit their orders in which they express their willingness to buy/sell the stated volume for all the price ticks between the minimum and maximum prices of the auction. Once the market participants send their orders and the order book is closed, the algorithm creates both a supply and demand curves, and determines the market clearing price (MCP) at the intersection of the curves which applies to both buyers and sellers. All buyers who submitted volumes at a price higher than the MCP are executed for these volumes and pay the MCP, and all sellers who submitted volumes priced lower than the MCP are executed for these volumes and receive the MCP. In this way, the volume with the delivery on the following day is traded. In contrast to it, there is also a continuous trading on the intraday market where the trade with the delivery on the very same day is executed once the buy- and sell-orders match [18]. The exact rules for auctions, and power trading on the exchange in general, can vary among exchanges and markets, and it is thus crucial to get familiar with the rules applied on the selected exchange.

- Power quality improvement – maintaining voltage levels within boundaries [19].
- Ancillary services – including load following, operational reserve, or frequency regulation [13]. The frequency regulation and the price arbitrage are considered the most popular applications of lithium-ion BESS [14]. In case of frequency imbalance, the BESS can be immediately charged for down-regulation or discharged for up-regulation. The exact requirements for frequency regulation depend on the specifics of countries and power regulators [20]. In contrast to the BESS used for the price arbitrage, the maximal capacity is not necessarily the main characteristics of interest, as changes in the state of charge of the battery are not typically significant because the aim is to remove fluctuations in the electrical grid, requiring changes in power direction and magnitude within seconds [14].

BESS does not have to provide one service only. It can combine several of the above applications to maximize its profitability, referred to as value-stacking [21].

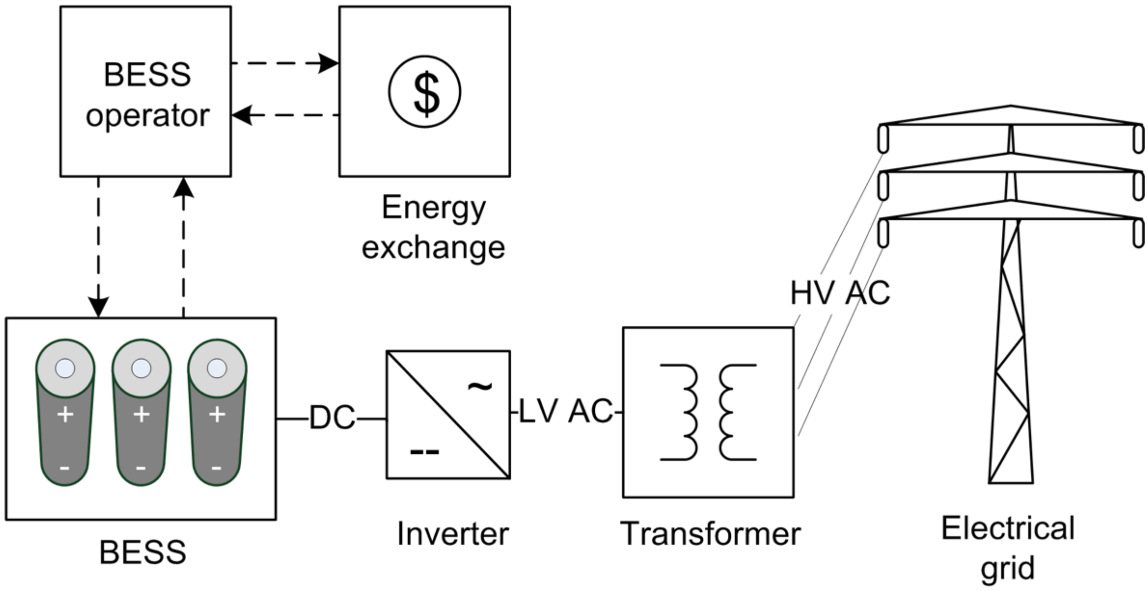

Fig. 2. Main components of BESS and its relation to an energy exchange, where *DC* is a direct current, *LV AC* is a low voltage alternating current and *HV AC* is a high voltage alternating current.

When solving the dispatch problem of BESS as an optimization problem, authors typically develop optimization models for either the price arbitrage [15, 16, 22, 23, 24], ancillary services [20, 25], or both price arbitrage and ancillary services simultaneously [26-27]. Recent literature suggests the frequency regulation yields higher revenues compared to price arbitrage, although price arbitrage remains necessary for balancing energy surplus or deficit [14]. Currently, BESS is not economically feasible for spot price arbitrage due to the high cost of lithium-ion batteries and/or the need for electricity prices to become more volatile to achieve a positive NPV, justifying investment in BESS [15, 22]. However, cashflow from the investment can be enhanced by participating in the reserve market, including frequency regulation, which offers higher profit potential [28].

With the spread of electric vehicles (EVs), the idea of using BESS for price arbitrage has been re-evaluated, especially as it relates to a vehicle-to-grid (V2G) system. This system enables an EV battery to discharge back to the grid and perform price arbitrage. Hand- in-hand with the proliferation of EVs, the V2G system shows promise for gaining importance.

The cost of four-hour lithium-ion BESS is predicted to decrease from 345 USD/kWh in 2020 to as little as 99 USD/kWh in 2046 [2]. Also, the spot price of electricity (or more precisely, its variance) is expected to evolve in a positive direction. Schöniger and Morawetz [29] investigated seven European electricity markets using a regression analysis, with the authors concluding that the relationship between the share of RES and price variance takes a U-shaped curve: for RES shares between 10% and 40%, the price variance is low, but it grows rapidly outside these boundaries. The highest price variance is achieved with a share of RES approaching 100%. However, there are tools such as PHES for exporting and importing electricity, which can mitigate the effect of high RES share. However, these do not necessarily work well in practice, as shown by the case of the German-Austrian bidding zone; bottlenecks in the transmission capacity in Central Europe limited the flow of electricity from the offshore wind power regions located in the North of Germany to the Austrian PHES [30].

Additionally, the ongoing penetration of RES into an energy mix is expected to lead to a higher frequency of negative prices in the day-ahead market [31], which imbodies more opportunity for price arbitrage.

Recent developments, such as the pandemic and the war in Ukraine, have introduced additional factors influencing prices on the European day-ahead market. In [32], the authors analyzed the profitability (measured by NPV) of a lithium-ion BESS focused solely on price arbitrage across 22 European day-ahead markets. Using a time series spanning from 2016 to 2022 for analysis, they found that while profits from dispatch were relatively consistent between 2016 and 2020, there was a notable market shift in 2021 and 2022. Profit doubled on the British day-ahead market and quadrupled on the Romanian day-ahead market. Although a positive NPV was not achieved, the study highlights a positive trend in BESS profitability across the European continent.

There are several reasons why price arbitrage may be considered more desirable than frequency regulation (or ancillary services in general). Ancillary services markets typically have smaller volumes compared to the spot market, leading to quicker saturation [33]. Additionally, the smaller size of these markets increases sensitivity to individual market participant actions, necessitating complex price prediction models [34]. While recent literature suggests higher profit potential in ancillary services markets compared to the spot market, this trend is expected to be short-lived due to increasing BESS installations, flexible loads, and improved forecast accuracy of renewable energy generation [34-36]. Some ancillary services markets, like the one operated by the Pennsylvania-Jersey-Maryland Interconnection, have already experienced saturation, resulting in significant drops in market clearing prices since 2014 [37-38].

Similar trends are observed in Europe, with an influx of new participants saturating the frequency regulation market and necessitating the stacking of multiple services provided by BESS to maintain profitability. This shift from initially more profitable but shallow markets, like ancillary services, to deeper but less profitable markets, such as the wholesale market, is already evident in the UK and is expected to occur in other European countries in the coming years [39-40].

Considering the potential growth in arbitrage opportunities in the future, this study focuses primarily on price arbitrage. Another reason for this focus is the higher complexity of determining prices in ancillary services markets compared to the spot market. Frequent and extreme price spikes in ancillary services markets make price prediction challenging [41], while the spot price has been more thoroughly studied and understood [42]. The solid empirical evidence on the behavior of the spot price can be then leveraged later in this work, when ROA is applied, to analyze the consistency between the characteristics of the spot price and the assumptions entering the ROA. This is perceived as an important step when utilizing ROA for pricing of an asset where the spot price of energy is a key determinant of the revenues.

BESS is considered as an emerging technology, which is riskier than the conventional energy asset projects. Lack of information and tools which would fully assess potential of BESS limits the flow of funds into these types of projects [21]. This doctoral dissertation seeks to improve the situation by providing a complex valuation tool recognizing the uncertainty bound to BESS projects, which can at the same time be translated into an opportunity for investors, when properly assessed.

2. DCF method

Because the DCF method is a vital part of the capital investment valuation process, and it can be also used as an input for the ROA methodology, it is necessary to describe the method in the first step.

2.1. Time value of money

The DCF method is based on the concept of the time value of money; 1000 EUR at time $t(0)$ and 1000 EUR at a future time $t(n)$ are not of the same value, due to the interest rate. If we assume a 10% per annum (p.a.) interest rate on the market, by investing the 1000 EUR, we can receive 1100 EUR at the end of the year. Alternatively, the 1000 EUR can be spent on new machinery, which results in lost interest. In other words, investing results in a lost opportunity of earning investment. The metrics based on the time value of money help determine the reward needed to compensate for the lost opportunity [43].

The relationship between the present value PV and future value FV is expressed in Eq. (1) [44]:

$$PV = \frac{FV}{(1+r)^n} \tag{1}$$

where, r is an interest rate, or in the case of a BESS project, a cost of capital which is used as a discount factor, and n is the number of time periods.

The time value of money is leveraged by two popular methods: NPV and Internal Rate of Return (IRR)

2.2. NPV

From the NPV perspective, a project can be considered worth undertaking when the sum of the discounted cashflows generated is higher than the amount of capital I required at the onset, as shown in the Eq. (2) [44].

$$NPV = \sum_{i=1}^{n} \left[\frac{FV(i)}{(1+r)^i} \right] - I \tag{2}$$

Three different results are possible [43]:

- $NPV>0$: accept the project.
- $NPV<0$: reject the project.
- $NPV=0$: the project is acceptable, but no discounted cashflow above project cost is provided.

2.3. IRR

The rationale behind the IRR method stems from the fact that decision makers may feel more comfortable measuring an investment project using relative, rather than absolute, metrics [43]. IRR can be understood as the discount rate at which NPV equals 0. This occurs in situations where the present value of all future cashflow matches the initial capital outlay *I*, as shown in Eq. (3).

$$\sum_{i=1}^{n}\left[\frac{FV(i)}{(1+IRR)^{i}}\right]-I=0 \tag{3}$$

Eq. (3) is solved by guessing at the discount rate in iterations until the equation is valid. If a computer cannot be used, the manual process based on discount tables can provide a reasonably close first guess [43].
The IRR method can provide three possible outcomes [43]:

- $IRR >$ cost of capital: accept the project.
- $IRR <$ cost of capital: reject the project.
- $IRR =$ cost of capital: the project is acceptable, but no surplus is provided.

2.4. Discount rate

The interest rate *r* used for discounting of future cashflows can be understood as the cost of capital outlay required for realization of the project. Depending on the source of the capital, various rates can be applied. In case all the funds are borrowed from a bank, the interest rate required from the bank is applied. If the funds are raised by issuing shares, the rate equals the dividend yield required by investors. If an organization's own funds before paying dividends are used, then the cost of capital is the opportunity cost reflected in the dividend yield [43].

In situations where the funds are sourced from both an issue of shares and a debt, the weighted average cost of capital (WACC) described in Eq. (4) can be used [45]:

$$WACC = [K_b \times (1 - r_x) \times (B/Q)] + [K_e \times (E/Q)] \tag{4}$$

where, K_b is the cost of debt, r_x is the tax rate, B is the amount of debt, Q is the amount of debt and equity, K_e is the cost of equity, and E is the amount of equity.

WACC in this form then equals the opportunity cost of capital: the rate of return a rational investor will require from an investment with a similar risk profile [45].

Kodukula [46] recommends to use WACC for discounting of cashflows which are subject to private risk. This approach is more adequate than a use of a risk-free rate which is only slightly increased.

When cashflows are affected by a market risk, the risk needs to be recognized by adding risk premium to the risk-free rate, to calculate the expected return of a security, which can then be used as a discount factor. One way of doing this is applying the capital asset pricing model (CAPM), which was originally developed for securities, and which is expressed in Eq. (5) [46]:

$$r_a = r_f + \beta_a (r_m - r_f) \tag{5}$$

where, r_a is an expected return of security a, r_f is risk-free rate, r_m is expected market return, and β_a is beta of security a.

As can be seen in Eq. (5), the product of a risk specific to the security β_a, and the difference between the market return and the risk-free rate is added to the risk-free rate r_f. Because β of the whole market equals 1, securities that are more volatile than the market have $\beta > 1$, and as a result, a higher return is required. On the contrary, securities less volatile than the market have $\beta < 1$, and as a result, require a lower return. Similarly, projects are believed to have β, which corresponds to their risk. To quantify project β, a publicly traded twin security, i.e., a security with a similar risk profile for future cashflows, can be used [46].

When compared to WACC, CAPM provides a project-specific rate, while the WACC rate is applied to all projects in a company. However, the cost for this approach is the complexity of determining the project β [47].

Another approach is to use a discount rate of benchmark projects with similar risk profiles. Projects from the same geographical area should be selected. It should be mentioned that the discount rate can vary across different stages of a project [48]. The benchmark discount rate is an expression of investor's expectations when it comes to return on the investment, and risk. It holds that the benchmark discount rate is equal WACC [49].

To apply the DCF method and calculate valuation metrics, such as NPV, it is necessary to first solve the dispatch problem of BESS, which determines the suitable BESS charge-and-discharge strategy, and thus its cashflow.

2.5. Review of BESS dispatch problem in the literature

The optimal dispatch of BESS combined with DCF method have been analyzed in multiple literature sources.

Metz and Saraiva [22] analyze an investment in BESS used for price arbitrage in the 15- and 60-minute German intraday market. The authors use NPV to assess the investment, and based on their sensitivity analysis, they conclude that a seven-fold (7x) increase in the probability and magnitude of price jumps would need to occur, in order to reach a positive NPV. Similarly, the authors in [15] used IRR to make an appraisal of BESS in seven (7) different US markets, coming to the conclusion that the capital cost of the analyzed lithium-ion BESS would need to decrease to between 5% and 20 % of the original costs to achieve 10% IRR. (Their conclusion was based on costs from 2008.)

Tarca et al. [26] analyzed the possibility to couple a wind farm with lithium-ion BESS to improve the penetration of intermittent RES into the Australian grid. For the dispatch problem, the authors used an incremental state-space model. The BESS supported time shifting, and provided an energy arbitrage and ancillary services. The model accounted for battery charge/discharge efficiency, but not for aging of the battery.

Komorowska et al. [16] compared economic justification of hydrogen storage with lithium-ion BESS. For the comparison, the authors selected the day-ahead Polish market, where both types of storage are used for price arbitrage. The authors found that BESS provides a higher NPV than the H_2 EES; while 1 MWh BESS generated NPV of -0.23 mil. EUR, H_2 EES generated only -4.85 mil. EUR. However, neither technology was able to reach a positive NPV. The decrease in capital cost was identified as the most probable future driver of profit for both technologies.

Mustafa et al. [27] considered BESS deployed in a health sector in the UK. Considering an arbitrage in a day-ahead market only, the BESS was not able to generate a positive NPV. Extending the scope of the BESS with ancillary services, the NPV generated by the BESS significantly improved, reaching over 5 mil. GBP.

Lamp and Samano [23] used a linear model to identify a profit-maximizing dispatch of a BESS. They included the technical constraints of the BESS, but did not include its aging, and the BESS investment did not generate a profit. The authors concluded that wholesale prices or/and initial capital costs would need to change to make the investment profitable. The analysis also confirmed the relationship between an increasing share of BESS on a given market and the decrease of an average, intra-day wholesale price spread.

McPherson et al. [24] claimed that the current literature on BESS dispatch in the day-ahead market does not often consider market rules in its analysis. This gap limits understanding of the process behind BESS revenues, and for that reason, should be subject to future studies. The same authors develop a MILP model, and compare storage bidding behavior in the day-ahead market with a storage bidding behavior in the real-time market. They concluded that it is impossible to make generic conclusions about which market provides a higher revenue, since net revenues of BESS depend significantly on jurisdiction-specific factors, such as the respective price profiles or the implementation of nodal (versus zonal) designs.

Gerini et al. [25] researched an optimization problem, including BESS providing multiple services to an electrical grid. They determined an optimal dispatch of the BESS in the day-ahead market by proposing a robust optimization problem.

Guo et al. [50] integrated BESS into a hydro-wind-PHV complementary system participating in a day-ahead market, to improve flexibility of the system. They concluded that the BESS significantly improves performance of the system: with 10% capacity configuration ratio, BESS improved system performance by 23.09%, and operational risks were reduced by 98.18%. Additionally, the peak shaving performance increased by 3.98%, and the daily average delivered power increased by 0.55%, which demonstrates the broad range of improvements a BESS can provide.

Alramlawi et al. [51] analyzed the role of BESS in a PHV-BESS-diesel microgrid. In their model, they considered BESS degradation, an active-reactive power generation cost, and a grid blackout problem. For the battery degradation, the authors used a simplified, weighted Ah battery-aging model. Including the battery degradation enabled the BESS to effectively minimize the total operation cost of the microgrid.

Zhao et al. [52] integrated BESS into a system supplying electricity, cold energy, and heat energy. Using an optimization model of day-ahead dispatch, the integration of BESS decreased the total operation cost by 9.2%.

Lai et al. [53] analyzed the integration of lithium-ion BESS into a system with PHV and a biogas power plant. Considering battery aging cost in the proposed dispatch problem, the authors concluded that, in order to generate a positive investment outcome, the BESS needs to participate in the short-term reserve market, while at the same time, its initial capital cost needs to drop to 200 USD/kWh.

When solving a dispatch problem in the day-ahead market using forecasted prices, accuracy of the forecast model plays a key role; Campos et al. [54] analyzed revenues from a project into a system consisting of PHV and BESS, evaluating 11 solar forecast accuracies.

3. ROA

Real options, which were introduced by Myers in 1977 [55], address the limitations of the DCF method and include uncertainty and flexibility into a project value. If decision makers have flexibility to adjust a project after new information is revealed, this freedom is of value. An option provides the right of its holder to make decisions, without being obliged to do so.

In contrast to traditional valuation methods, ROA is not a sheer valuation tool, but a complex framework, including strategic analysis by defining financial boundaries for decisions within the discovered options [56]. ROA should not be misinterpreted as a substitute for the traditional DCF method. It values the uncertainty and flexibility present in a project which can be added to the NPV. Thus, the DCF method still represents a starting point for analysis.

To understand the successful application of ROA, it is necessary to get familiar with financial options theory, from which ROA evolved. The option theory recognizes two basic types of financial options:

- *Call option,* which constitutes a right, but not an obligation, to buy an underlying asset at a predetermined price (premium) at a predetermined time.
- *Put option*, which constitutes a right, but not obligation, to sell an underlying asset at a predetermined price (premium) at a predetermined time.

European- and American-style options distinguish the exact time (or time frame) within which this right can be exercised. While the European option can be exercised (called) only *at* its termination date, the American option can be exercised (called) at any time *before* its expiration. Obviously, the latter option is more convenient, which is reflected in its higher price.

These basic types are referred to as plain vanilla options. With the development of option theory, the market has required more complex types of contracts. Because options are traded not only on standardized exchanges but also on non-standardized, OTC (over-the-counter) markets, there are literally no limitations when it comes to constructing options. More complex option structures are referred to as exotic options, and include (but are not limited to) the following option types:

- *Bermuda option*. An exotic option type falling between European and American options, since it can be exercised only on predetermined dates. This condition is also reflected in the option premium; this option is more expensive than a European one, but cheaper than an American one [57]. Jain et al. [58] use a Bermuda option to value a real option on sequential, modular small- and medium-sized reactors.

- *Barrier option*. The option value is conditional on a certain barrier that the underlying asset must reach. These barriers either activate or deactivate the option, and are referred to as knock-in and knock-out options, respectively [59]. Jain et al. [58] value a barrier option on a large-scale infrastructure project on hydrogen fuel stations, with the possibility of an immediate project failure included into the valuation process.

- *Compound option*. An option on another option. Such a structure has two strike prices and two exercise dates [60]. Ma et al. [61] construct a compound option, which is an option to delay on an option to expand, in order to evaluate subsidies for residential battery projects.

- *Spread option.* The payoff from this option type is determined by the difference (spread) between two variables [60]. For example, to value an ethanol plant, Kirby and Davison [62] presented spread between the price of corn and the price of gasoline as a spark option. Correlation among the assets is an important parameter determining a value of the option. If two assets evolve together in the same direction—i.e., correlation between them is high—then the value of the option is lower. On the contrary, assets evolving in different directions are of a higher value.

- *Asian option.* Payoff from this option type is dependent on the average of its underlying asset during the life of the option. Asian options can be distinguished as either arithmetic or geometric. The rationale for this option's construction is mainly to lower the dependence of the payoff on one-time market events; any outlier effect is minimized by taking an average. Premiums for Asian options are lower than European options' premiums, since the average of underlying asset prices has a lower volatility; thus, the option is worth less [63]. The use of Asian options in ROA was researched, for example, by [64].

- *Basket option.* As the name suggests, payoff for this option type is derived from a basket of underlying assets. Wörner and Grupp [59] used empirical evidence for 13 US bio-pharmaceutical companies, concluding that the value of a basket option on a company's R&D portfolio can be used to quantify their share price.

Table 1 lists the most important variables necessary for valuation of financial options with their counterparts for ROA. These variables are used in the valuation methods presented in Section 3.2. While shares, commodities, and interest rates can all be examples of underlying assets for financial options, *real* options have real, underlying assets, or more specifically, returns from those assets. The value of a real option is then derived from the difference between a project's returns and a project's costs (strike price), which is determined by a volatility of the returns (if we assume investment cost is a constant). Obviously, volatility plays a key role, and for that reason, volatility is analyzed in Section 9.4.

Table 1. Differences between financial and real options.

Variable	Financial option	Real option
S	Stock price	Project's returns
K	Strike price	Investment costs
T	Time-to-maturity	Investment horizon
r	Risk-free rate	Risk-free rate
σ	Standard deviation of stock returns	Standard deviation of project's returns

3.1. Types of real options

The various financial options described at the beginning of Section 3 are used to create different types of real options, which have evolved to meet different scenarios a business typically faces when implementing a project. Real options include (but are not limited to) the following types:

- *Option to defer*. If a project faces uncertainty, waiting for arrival of new information can be worthwhile, since it may resolve the uncertainty. The option to defer, also referred to as a time option, is by far the most popular option type in energy projects [65]. They can be constructed as call options, either of the European or American type, depending on whether early exercise is allowed for. Similarly, a Bermuda option could be used when considering an exercise on several dates.
- *Option to abandon.* Projects that were initially profitable can turn into non-profitable endeavors. The option to abandon recognizes such a scenario and values the possibility of selling the non-profitable asset with the aim of recovering its salvage value. This is a put option, with a strike price set to the salvage value. Good practice combines the option to abandon with another option (e.g., the option to expand) in a compound option, not omitting the salvage value of the asset from an investment appraisal.
- *Option to switch.* This option type values the flexibility of switching between inputs/outputs in an operation. For example, a nuclear power plant can switch between production of electricity and hydrogen. Similarly, switching between wind and photovoltaic power can be considered for optimal production of electricity. Option to switch can be constructed as a combination of a call option and put option [66].

- *Option to expand/contract*. The holder of this option may decide to expand or contract operations when market conditions are favorable or unfavorable, respectively. Similarly, as with a switch option, combination of a call and put option can be used for a construction of the option [66].
- *Option to stage*. This option type, also referred to as a compound option, can be especially meaningful in the industry such as energetics where projects are typically divided into many stages. The option to stage recognizes this project setup and assumes implementation of a project within a series of dependent steps; another stage can be initiated only after the previous one has been successfully completed. The payoff from the option requires completion of all the steps [56]. Li and Cao [67] value a stage option on a photovoltaic-energy storage system. The project is divided into an investment stage and an operation stage to account for different types of options; whilst the investment stage includes options to delay and options to abandon, the operational stage uses options to delay and options to expand.

3.2. Real options valuation methods

Literature distinguishes the following, four main valuation techniques [46], [68]:

- *Partial differential equations (PDEs).* PDEs with defined boundary conditions can be used to describe the change in an option value with respect to a given market variable [46]. However, many practitioners find PDEs and analytical methods in general too complex [56], [69]. The most famous exception is the Black-Scholes model (BSM), which solves Black-Scholes PDE for a closed-form solution that substantially simplifies option valuation. If a closed-form solution cannot be provided, computationally intensive and complex approximations and/or numerical methods, such as finite difference, must be used [46].
- *Lattices.* A lattice is a decision tree-like structure depicting evolution of an underlying asset that uses backward induction [56]. The structure of lattices can be of varying complexity, and lattices can be distinguished as binomial, trinomial, quadrinomial, or multinominal. The most popular example of a lattice model is the Cox-Ross-Rubinstein binomial option pricing model (CRRM).
- *Dynamic programming (DP).* DP is a recursive optimization method allowing for identification of the optimal timing of an investment. The value of multiple investment scenarios is compared with a continuation value, i.e., the value of waiting, which is calculated using backward induction. The value of the scenario is determined by

a separate, real options valuation method [65]. DP problems are often solved by using PDEs which can substantially increase complexity of the method [69].

- *Simulations.* A numerical approach based on a simulation of an underlying asset's price evolution. A large number of price paths must be simulated to arrive at the most probable values; the more time steps and paths are simulated, the more accurate result is calculated. Monte-Carlo simulation (MCS) is the most widely used simulation method [46]. For pricing of American options, the least squares Monte Carlo method (LSMC) can be used. The method recursively approximates the continuation value (a conditional expectation) by moving backward in time. This involves regressing the future optimal discounted cashflows against a set of basis functions of the underlying state variables at each time step [70]. Thus, LSMC can be considered more complex than MCS because of its additional step in the form of regression analysis. This also further increases its computational complexity.

BSM, CRRM and MCS are the ROA methods considered in this work. Not only because they are the most popular ROA methods in general [56], [71] but also because they are widely used in projects where a spot price of electricity is a source of uncertainty determining project's cashflow [68], [72].

3.2.1. BSM

Black and Scholes [73] provided a solution to pricing a European option in "The Pricing of Options and Corporate Liabilities," a major development in option pricing. The Black-Scholes PDE is based on a no-arbitrage concept, assuming a portfolio is set up, consisting of a derivative and a defined number of stocks. For example, a position in a call option can be hedged by a short position in a stock. If there are no arbitrage opportunities, the return from the portfolio must equal a risk-free interest rate r, thus risk preferences of investors have no effect on the option value: i.e., investors are risk-neutral. It may seem unrealistic to use a risk-free rate for discounting, especially for some practitioners who are accustomed to including a risk premium in the discounting factor. However, when moving from a risk-neutral world to a risk-averse world, the stock price growth rate and discount rates change in such a way that they offset each other [60]. The concept ensures that two different assets should have the same present price, if their future cashflow and risk profile are identical [74], which is an important assumption for pricing of derivatives. The introduction of a risk-free rate r significantly simplifies the option pricing. If we know the future value of an asset, we can discount it using the risk-free rate r to obtain its present value [60].

Hull [60] lists other assumptions used for deriving the Black-Scholes PDE:

- Returns from a stock are log-normally distributed.
- Short selling is allowed.
- No transaction costs are considered.
- No dividends during the life of the derivative are considered.
- Trading is continuous.
- The risk-free rate *r* is constant.

Variations of the BSM allow for dividend-paying stocks. Dividends can be included in the model by subtracting the present value of the dividends, which are due prior to an expiration date, from the stock price [75]. However, this approach represents a modification of the original BSM, and for that reason is not considered in the present study.

Eqs. (6)-(9) provide an interpretation of the BSM for calculating the value of call option *C* and the value of put option *P,* as provided in Hull [60]:

$$C = S(0)N(d_1) - Ke^{-rT}N(d_2) \tag{6}$$

$$P = Ke^{-rT}N(-d_2) - S(0)N(-d_1) \tag{7}$$

$$d_1 = \frac{ln\left(\frac{S(0)}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \tag{8}$$

$$d_2 = d_1 - \sigma\sqrt{T} \tag{9}$$

where, $N(d_1)$ and $N(d_2)$ represent the cumulative normal density functions of $d_1$and d_2, respectively, and *K* stands for a strike price.

The BSM assumes the underlying asset follows the Geometric Brownian Motion (GBM) [76], which is described in Section 9.1. The original form of the BSM is limited to the pricing of a European option on a non-dividend paying stock. The BSM can be used for valuation of early-exercise options only in the special case of an American call option bearing no dividends which is never optimal to be exercised prior to its expiration date [60]. Other American options cannot be standardly valued by the BSM. Approaches such as Black's approximation must be employed to overcome this BSM limitation. Here, the value of a European option is calculated for exercise time *T* and an earlier time t_n, to subsequently set the value of an American option to the greater of the two values [60]. In addition to this approach, numerical methods or numerical approximations in combination with analytical methods have been developed to value American options using the Black-Scholes framework. However, these are complex and have limited accuracy [77]. For this reason, the present work considers only the original BSM framework.

When applying the BSM to ROA, it is important to note that the model assumes that the revenues from an underlying asset are log-normally distributed. While the log-normal distribution is a widely accepted assumption in stocks and the financial markets in general [78], practitioners may have a hard time making the assumption that revenues of a real asset and all its drivers follow log-normal distribution.

Another questionable assumption when applying the BSM to ROA is the deterministic nature of the investment costs embodied by the strike price *K*. In reality, investment costs are stochastic. To determine an option value, it is then important to correlate volatility of project revenues with volatility of investment costs, since while there is a positive relationship between asset volatility and option value, the cost volatility has exactly the opposite effect, pushing the option value down. It is intuitive that highly uncertain project costs decrease the project's value [56]. Brach [56] mentions other pitfalls of the BSM model in relation to ROA:

- Constant project volatility can be an unrealistic assumption. Volatility of a real asset price can change over time, as the risk of the asset evolves.
- Real assets do not necessarily have clearly defined expiration dates. ROA is often used for valuation of projects when the time horizon of the project is an unknown variable in the project's initial stages.
- Values of real assets do not have to follow a symmetric random walk; jumps can occur in the evolution of an asset's price path. In such cases, the BSM underestimates the value of the asset.

3.2.2. CRRM

The Cox-Ross-Rubinstein pricing model option is a discrete binomial model, published by John Cox, Stephen Ross, and Mark Rubinstein [79]. Like the BSM, it is based on the no-arbitrage argument and risk-neutral valuation [60]. At each node of the lattice, the underlying asset price can go either up with probability *p*, or down with probability *1-p,* at a rate *u* and *d*, respectively. The Cox-Ross-Rubenstein value can be calculated using Eqs. (10)-(11) [60]. Fig. 3 shows evolution of a value of an asset using a binomial tree in four time steps.

$$u = e^{\sigma\sqrt{\Delta t}} \tag{10}$$

$$d = e^{-\sigma\sqrt{\Delta t}} \tag{11}$$

where, σ is the volatility of the underlying asset following GBM, and Δt is the length of time step. p is a risk-neutral probability, as expressed in Eq. (12) [60].

$$p = \frac{e^{r\Delta t} - d}{u - d} \tag{12}$$

where, r is a risk-free rate.

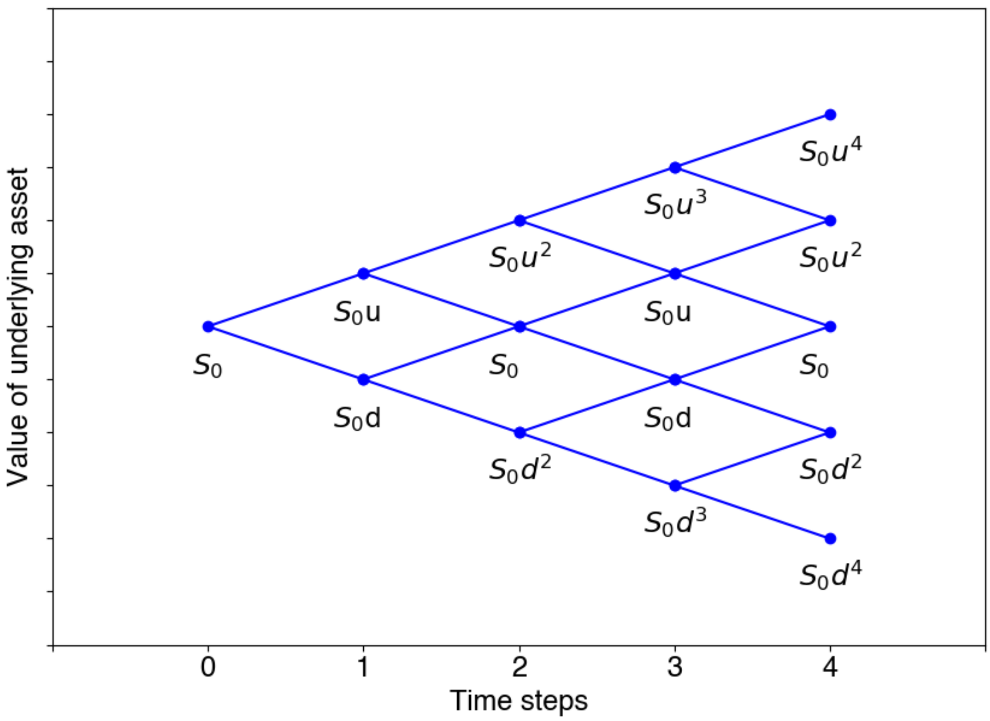

Fig. 3. Change of an asset value in a four-step recombining binomial tree.

When the lattice with the underlying asset's value has been constructed, the option value at terminal nodes can be calculated by comparing the value S_t of the underlying asset with a strike price K at that node, respecting whether the option is a call or a put option. If we assume a one-step binomial lattice with a payoff in the upper terminal node f_u and a payoff in the lower terminal node f_d, then the value f of the node preceding these two nodes (which equals an option value in this case) can be calculated by discounting the risk-adjusted sum of the future values f_u and f_d, as shown in Eq. (13) [60]. This method is referred to as backward induction. The process repeats itself, step-by-step, regardless of the number of steps used.

$$f = e^{-r\Delta t}[pf_u + (1-p)f_d] \tag{13}$$

When the option is American, at each node the value given by Eq. (13) must be additionally compared with the value which would be gained by an early exercise. The greater of these two defines the value at the given node [60].

As with the BSM, the model uses continuous GBM as the underlying process; for a sufficiently large number of steps and/or short time intervals, the discrete CRRM approximates GBM. Mean and variance of CRRM then equal the mean and variance of the underlying GBM's log-normal distribution [80]. While CRRM approximates an option value calculated by BSM [81], in contrast to BSM, CRRM offers more flexibility. While volatility is deterministic in BSM, it can be treated as a time-varying variable in CRRM [80].

Further, CRRM is capable of valuing both European and American options. By going backwards, it must be verified at each of the nodes, to determine if an early exercise can generate a value higher than the one calculated by Eq. (13). If the answer is yes, we replace the original value with the newly calculated payoff and continue backwards until we reach the initial node [60].

Boyle [82] also introduced a trinomial version of the lattice model. In addition to the two branches accounting for movements up and down, there is a third branch for situations in which the price is unchanged. This extra flexibility allows for a faster convergence on accurate values [83].

Another special type of a lattice is a quadrinomial lattice, which can be used to calculate the option value on a project which faces two sources of uncertainty. The main strength of the quadrinomial tree becomes apparent in situations where the two uncertainties are uncorrelated. The tree enables practitioners to translate the different evolutions of the two variables into the option value, and to separately evaluate the effects of the two variables over the option value. In contrast, MCS is typically used to provide an aggregated volatility as a product of the variables, which is then used as an input in an option-valuation model. As a result, the effect of the correlation over the option value cannot be assessed [46]. For cases with more underlying assets, exotic options such as a rainbow option are used [84].

The downside of the quadrinomial tree is its high complexity, which grows exponentially with the number of time steps used. Lattices with more than four branches are referred to as multinomial lattices. The author of the present study believes that the complexity of such a lattice outweighs its benefits, and for that reason, multinomial models are not further discussed in this work. As with the BSM, since the underlying binomial distribution converges to a log-normal distribution, using the model in ROA assumes a log-normal distribution of revenues from a real asset, which may be assuming far too much for some types of real assets. Employing a stochastic volatility brings clear improvement to the model's application to ROA, increasing the likelihood of it providing a more realistic valuation model. A new value of volatility can be used to update the u and d parameters, and the strike price K can be adjusted at each time step to reflect changes in investment costs (which rarely stay fixed).

Dividends are another aspect which are well covered by CRRM. Dividends can be understood as pay-outs, or forgone earnings, linked to the real asset, with an irreplaceable role in ROA [48]. In general, dividends reduce the value of the underlying asset, and as a result, decrease the value of a call option and increase a value of a put option. Dividends can be easily included in the CRRM by adjusting the risk-free rate r [85].

3.2.3. MCS

MCS is a numerical method that leverages computer power to determine the future value of an asset. The method does not require knowledge of the probability distribution of the asset value at the time of expiration, as long as we understand the process driving the value [56]. This method was published by Phelim Boyle [86] in 1977 and has since gained popularity as a simple but powerful tool for option pricing. The simplicity of the tool stems from the use of basic laws, such as the laws of large numbers and the central limit theorem [87]. The latter explains that, if we have a large number N of independent and identically distributed (i.i.d.) variables, then their sum will be approximately normally distributed, regardless of their underlying distribution [88]. Distribution of the Monte Carlo estimator can then be approximated as $\mathcal{N}(\mu, \sigma^2/N)$, which explains the need for a sufficiently large number of samples [89].

The laws of large numbers—expressed in Eq. (14)—state that the sample mean $\bar{x}_N$ approaches the population mean μ in the limit of N [90].

$$\lim_{N \to \infty} \bar{x}_N = \mu \tag{14}$$

One drawback of MCS is its inability to directly value American options, since it generates forwards paths and does not include the backward induction necessary for pricing of American-style options. The study [91] describes methods which can be used to overcome this limitation, including branching processes, a martingale optimization formula, the Least Squares Monte Carlo (LSMC) method, and quasi-random sequences in LSMC. LSMC integrates MCS with a least square regression [92], and provides the backward induction necessary for early-exercise types of options. Since these approaches are modification of the original MCS, their methods are not considered in the present work.

A strength of MCS in ROA is its significant versatility. Because an asset value is simulated for the whole life of an option, until the time of expiration, the method can be used for pricing of path-dependent options, such as Asian or barrier options. It can also be used in cases where an option value is dependent on more underlying assets.

While the BSM and CRRM assume GBM as the underlying process, MCS can be used to simulate any probability distribution, which can be especially desirable in ROA. MCS is used in ROA to not only value an option, but also as a supportive tool to quantify volatility of a project's revenues. Project revenues determined by multiple sources of uncertainty can be sampled using MCS to calculate an aggregated volatility for a project, which can subsequently be used as an input in the option-valuation method [46].

Due to the computational intensity of MCS, it is viewed as a last resort by some authors when it comes to option pricing [93]. With the rapidly increasing computational power, this should no longer be the case, and its versatility should make MCS a promising valuation method to consider in ROA.

4. ROA applied to BESS projects

4.1. Review of the literature on ROA applied to BESS projects

To better understand the current state of ROA applied to grid-scale batteries, the following literature was reviewed, employing the selection criteria below:

- The paper contains the keywords “real options” and “battery”.
- The paper was published by Elsevier, IEEE, or Springer.
- The paper was published since 2016.

4.1.1. Broad overview of the review

Table 2 contains an overview of the review, specifying the valuation method and types of real options explored in the reviewed studies, with DP identified as the most popular method.

Table 2. Overview of 9 studies that apply ROA to BESS.

Authors	Type of BESS	ROA method/model	Types of real options	Electricity spot price model
[49]	Lithium	BSM	Option to defer	GBM
[92]	Not defined	DP LSMC	Option to defer	GBM
[94]	Lithium-ion	DP	Degradation option	n/a
[95]	Not specified	DP	Option to defer	n/a
[96]	Not specified	DP	Option to defer	n/a
[97]	Lithium-ion	DP LSMC	Option to defer	Own construction
[61]	Not specified	DP LSMC	Compound option	n/a
[98]	Not specified	DP LSMC	Option to defer	n/a
[99]	Not specified	DP	Option to defer	ARMA model

Table 2 identifies the option to defer as the most popular real option in BESS-related studies.

In the ten reviewed BESS-related studies, the battery type is either a lithium battery or an unmentioned battery type.

Electricity spot price was one of the uncertainties analyzed in the reviewed studies, and GBM was used most frequently as the model explaining its behavior [49], [92], [99]. Additionally, historical prices were the only way of determining the volatility of electricity spot prices, when volatility was a necessary input for the selected real options valuation model.

4.1.2. Detailed overview of the review

In [49], the authors analyzed investment in a lithium battery with a capacity of 10 MWh and a power rate of 5 MW, which can be installed overnight in Jilin province. The authors used ROA to value a wind-integrated energy storage project, and to identify the optimal time window for realization of the investment. The authors assumed that electricity price follows GBM, and used BSM as the ROA method to extend the base value of the investment calculated as NPV. Volatility, as the input parameter for BSM, was calculated from historical prices. The proposed models also incorporated battery loss induced by the operation; 0.06 % battery loss was assumed with each charge and discharge, at 90% *DOD*.

Ma et al. [92] developed a mixed-integer quadratic program to determine the optimal sizing and dispatch of BESSs deployed in Australia. They extended the NPV calculation using the program with an option to defer, which is valued by combining a forward-looking MCS with a backward-looking least square regression. GBM is assumed for all the three random variables simulated in the study: power demand growth, electricity price, and BESS capital cost.

Kelly and Leahy [94] also used DP to determine optimal timing and sizing of a project using a lithium-ion 100 MW BESS, operating in a day-ahead market in Ireland. The approach consists of two models: an operational hourly model, and a yearly planning model, which is solved by applying dynamic decisions. While the operational model is used to determine the optimal BESS dispatch strategy generating daily revenue, the long-term planning model is deployed to optimize timing and sizing of the BESS. The authors concluded that the initial capital outlay has a minimal effect on project timing, but is crucial for sizing of the BESS.

Similarly, as the authors of the previous study, Bi and Lyu [95] decided to use DP to value an option to defer, which is modelled as an American call option. The study analyzes an investment into a BESS combined with PHV in a microgrid located in China. The model developed supports arbitrage, and it assumes electricity price subsidies. Initial capital cost, modelled as GBM, is identified as a major obstacle for the profitability of the project. Thus, the authors expect the incentives to become a key driver in promoting reviewable sources of energy.

Microgrids were also the object of research in [96], in which a BESS was combined with PHV, fuel-fired generator, and tank storage. The study proposed a dynamic methodology, including load growth and degradation of the model's assets. The approach enabled the authors to determine the optimal sizing of the BESS not only at the project outset, but also in later project phases.

Bakke et al. [97] applied ROA to a BESS project which was dispatched not only to perform time arbitrage in a spot market, but also to provide ancillary services. The study found that participation in the spot market with hourly contracts alone cannot justify the initial costs. The pivot point of the investment was reached only after simultaneous participation in the balancing market was considered. The case study presented was made more realistic by forecasting the spot price rather than using a historical time series. The model for a spot price consists of a deterministic, seasonal component combined with a residual, stochastic component. Capital costs were modelled using GBM with a negative drift. The proposed objective function maximizes the profit from participation in both the spot and balancing markets, while considering O&M costs. To value the flexibility inherent in the project, the authors considered an option to defer, which was modelled as a Bermudian call option, because only discrete time points were considered for exercising the option. The LSMC method was used to value the option; CF from operation of the BESS and initial capital cost were the two uncertainties simulated by the method. The authors concluded that operating the battery in both the UK and German markets generates a position option value. The results also show that the BESS participated most often in the balancing market, and only occasionally in the spot market. This was reflected in the structure of revenues, since 70% were generated in the former market.

Similarly, the LSMC method was applied by Ma et al. [61] to value a compound option on a BESS residential project. The compound option consists of an option to defer and an option to expand. According to the traditional capital investment appraisal, an investment should be realized in the fifth year, without any subsequent expansion, yet ROA suggests carrying out both the investment and the expansion in various years, depending on developments with the identified uncertainties.

Ma et al. [98] applied LSMC to value a compound option on an investment in a residential PHV-battery project. The analysis considered multiple, interacting options, including an option to defer and an option to expand. The option to expand could be exercised only after the option to defer had been exercised. The authors' model projected uncertainties, such as power demand, diesel price, and the declining cost of PHV-BESS technology. The investment generated a negative NPV, and only after adding the option value could the investment be considered justifiable. The ROA results suggest that waiting for one year instead of an immediate investment is a better investment strategy, since uncertainties evolve in favor of the project at that time.

The objective in [99] was a study combining PHV with BESS, where the ARIMA model was applied to the project's uncertainties, specifically, to electricity spot prices and renewable energy generation. The proposed ARIMA-based model considers important characteristics of the spot price for electricity, such as non-stationarity and heteroscedasticity. The BESS was dispatched in both the spot- and reserve-electricity markets in Germany. The authors chose a one-year time window for the optimization problem, to cover all seasonal-related dynamics of the electricity spot price. The authors applied DP to value an option to defer the dispatch. The postponement is made with the goal to delay the discharge until a time with more favorable prices. The authors concluded that operating a BESS in the electricity spot market and minute reserve electricity market cannot be economically justified, unless major increases in electricity price volatility take place, or unless the BESS also participates in the primary and secondary reserve markets.

5. Multiple criteria decision analysis (MCDA)

There are multiple methods by which ROA can be used to value a real option, so it can be difficult for a practitioner to get oriented in the field and select the suitable method, especially if ROA is a completely new topic to the organization. In these instances, MCDA can be used to facilitate and standardize the ROA method selection process, ensuring a suitable approach to valuation of a BESS project.

MCDA is likewise an effective tool in an environment with multiple options and multiple criteria. According to Fotr and Švecová [100], the decision process should be constituted by the following elements: the goal of the decision process, assessment criteria, the subject and object of the decision process, and finally, the generation of alternatives and scenarios. For the purposes of the present work, these elements are combined with the decision-making process steps defined by Ren [101] to form the following steps:

- Determination of a goal for the decision process.
- Determination of assessment criteria.
- Determination of the subject and object of the decision process.
- Generation of alternatives.
- Criteria weighting.
- Creation of a decision-making matrix.
- Scoring and ranking.

5.1. Determination of a goal of a decision process

Decision processes can have a single or multiple goals, and these goals can be either complementary of conflicting. The time frames for such goals can likewise be short- or long-term [102]. For the purposes of further work, it is important to distinguish between qualitative and quantitative goals. The existing literature recommends that proposed goals be SMART: Specific, Measurable, Achievable, Relevant, and Time-bound [100]. When defining goals, it is necessary to identify all key stakeholders who will be impacted by the goals, and to consider their expectations in the definition process. More details on the rules for goals determination can be found in [102].

5.2. Determination of assessment criteria

The next step is determining the criteria by which the defined alternatives may be assessed. Since criteria are derived from the defined goals, like those goals, the criteria can similarly be either quantitative or qualitative [100], [102]. When selecting the criteria, practitioners should keep in mind the expectations for fulfilling that criteria, in order to satisfy the subject of the decision process. In general, criteria creation is a complex task, with no clearly defined output, since any set of suitable criteria can vary, depending on timing or the organization's current situation [102]. Multiple attributes may be used to categorize criteria [102]:

- *Number of criteria*. A criteria set may consist of one criterion only. Such a set is referred to as monocriterial. On contrary, multiple criteria can constitute a set, which is then referred to as multicriterial.
- *Type of criteria.* Criteria can be either cost- or revenues-related. Depending on whether only one type or both types are included in a set, the set can be referred to as homogenous or combined, respectively.
- *Character of criteria*. Criteria can either substitute for or complement each other.
- *Significance to a subject of the decision process.* From the subject's perspective, the decision process criteria may be either different or indifferent, depending on the importance the subject places on them.

Grasseová et al. [102] recommend the following four requirements when defining an appropriate set of criteria:

- *Complexity.* The proposed set of criteria must provide a complex assessment of the defined alternatives.
- *Intelligibility.* The criteria need to be clear and measurable.
- *Non-redundancy*. The criteria should not overlap each other.
- *Minimalist approach.* The number of criteria in a set should be kept as few as possible, in order not to complicate the assessment process beyond the number of alternatives necessary.

5.3. Determination of the subject and object of the decision process

A subject is defined as a person or a group of persons who selects the winning alternative for realization. When the subject is a collective of people (the latter case), it is more complex, due to the necessary definition procedures for processing the votes of the deciding body as it selects the winning alternative [100]. The decision process must proceed through areas of the organization that will be impacted by the decision.

5.4. Generation of alternatives

Alternatives represent groups of activities leading to a decision. The subject of the decision process must first collect criteria data on the determined alternatives. A literature review, a simulation or the judgment of experts can all be used as information sources [101]. Grasseová et al. [102] list the most frequent mistakes practitioners make when defining alternatives:

- Practitioners focus on one alternative.
- The alternatives generation process is too simplified; only the usual alternatives are considered.
- The alternatives generation process takes too much time, and the best alternatives are no longer available.
- The alternatives generation process already includes a partial assessment of the alternatives, which can reject some alternatives at early stages, without proper assessment.
- The alternatives generation process is ended abruptly, once an alternative that seems to satisfy the subject(s) of the decision process is found.

5.5. Criteria weighting

The collected data, in combination with weighting criteria, then form the basis of the decision-making process. The numerically expressed weight of a criterion reflects its importance for the subject(s) of the decision process. To simplify working with weights, it is recommended that the weights be normalized to result in a sum of 1 or 100.

The extant literature on MCDA provides multiple criteria weighting methods, which may be categorized as either subjective or objective. While the former methods rely on the opinion of the decision makers, the latter methods use statistical techniques [101].

In [102] the following methods are introduced:

- A scoring method.
- A pairwise comparison (Fuller's triangle).
- Saaty's method.

There are other, popular MCDA methods, such as the Technique for Order of Preference, by Similarity to Ideal Solution (TOPSIS), and the Analytic Network Process (ANP), which are described in [103].

5.5.1. Scoring method

The scoring method is a type of weighting method in which the decision maker assigns a certain score to each of the determined criteria. The maximum score available depends on the scale being used. The starting point for scale definition should be the difference between the criteria with highest and lowest priority. One variation of the scoring method assumes that the scale consists of 100 points, which must be allocated among the criteria. The weight with the highest score then has the highest priority [100]. The normalized weights w_j can be calculated from the score v_j assigned to n criteria by using Eq. (15) [102].

$$w_j = \frac{v_j}{\sum_{j=1}^{n} v_j} \tag{15}$$

5.5.2. Pairwise comparison (Fuller's triangle)

Pairs of criteria are compared to quantify preferences. In Fuller's triangle, the number of preferences for each criterion is quantified, in relation to all other criteria. Fotr and Švecová [100] recommended using a matrix in which each criterion in a row is compared with a criterion in a column. If the criterion in the row is believed to have a higher priority than the criterion in the column, the decision maker adds the number one (1) into the cell intersecting the given row and column; otherwise, the decision maker enters a zero (0). If two criteria are indifferent, a value of 0.5 is entered. The number of cells containing a one (1) in each row is then summed and entered in the cell at the end of the row, to arrive at the number of preferences f_j for each of the criteria. Normalized weights w_j can be calculated with the use of Eq. (16), where the number of preferences of each criterion is increased by one (1), to overcome situations where one of the criteria has zero preferences. In such a situation, the weight would equal zero, unless each criterion is increased by one [100].

$$w_j = \frac{f_j + 1}{n + \sum_{j=1}^{n} f_j} \tag{16}$$

where, n is the number of criteria, and the number of realized comparisons is expressed in Eq. (17).

$$\sum_{j=1}^{n} f_j = \frac{n(n-1)}{2} \tag{17}$$

In situations where two criteria achieve the same number of preferences, the preference selected for this pair decides which criterion scores a higher preference [100].

Fotr and Švecová [100] also note some drawbacks to the method, the most important of which is (likely) the fact that the method of the pairwise comparison only defines which criterion in a pair has a higher priority, but it does not express the size of the preference. This limitation is removed by the Saaty's method, described in Section 5.5.3. However, the Fuller's triangle method is still popular for its reliability and simplicity.

5.5.3. Analytic Hierarchy Process (Saaty's method)

The first portion of Saaty's method is similar to that of Fuller's triangle, described in the previous section; preferences for each pair-wise combination of the criteria are determined in a Saaty matrix. In contrast to Fuller's triangle, however, the comparison includes the size of preferences respecting the defined scoring scale. The authors in [100] propose to proceed in the three following steps when creating the scoring scale:

1. Order the criteria in accordance to priority in a descending order.
2. Define the range of the scale by defining how many times is the most preferable criterion is preferable to the least preferable criterion.
3. The scale's end points, determined in the preceding step, then define an interval which does not need to be an integer.

Approximation can subsequently be used to determine the values of the weights w_i; The authors in [100] distinguish between two approaches, based on their accuracy:

- The less accurate method involves division of the sum of values in a given row by the sum of all values in the matrix.

- The more accurate method is based on a geometric mean GM of the rows in the Saaty matrix. The resulting geometric means are not normalized; thus, normalization needs to occur before using the weights.

When the subject of the decision process is a group of people and not just one individual, the aggregated weight w_j of a criterion j can be calculated as the geometric weighted mean GWM_j of the individual weights w_j^e, as shown in Eq. (18) [104]:

$$w_j = GWM_j = \prod_{e=1}^{n} \left(w_j^e\right)^{w_e} \tag{18}$$

where, w_e is a weight of expert e, and w_j^e is priority of criterion j from the point of view of the expert e. Here, it is assumed that the experts are not equally important; thus, the weights w_e of all n experts must be determined in the first step. It must hold that $\sum_{e=1}^{n} w_e$. Either the weights can be assumed to be equal, or they can be estimated by a supra decision-maker [104].

5.6. Creation of a decision-making matrix

If m alternatives A_i, and n criteria C_j have been defined, it is possible to build the decision-making matrix shown in the Eq. (19) [101]:

$$\begin{array}{c c} & \begin{array}{ccc} C_1 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \\ & \begin{array}{ccc} w_1 & \dots & w_n \end{array} \end{array} \tag{19}$$

where, x_{ij} is the data of the j-th criterion C_j, related to the i-th alternative A_i, and w_j is the criteria weights of the j-th criterion C_j.

5.7. Scoring and ranking

Fotr and Švecová [100] introduce several simple scoring and ranking methods that differ in the extent to which they are suitable for quantitative and qualitative criteria.

Among the simple methods applicable to qualitative criteria, the following two methods can be applied:

- Weighted order method (Section 5.7.1)
- Direct assessment method (Section 5.7.2)

Another group of scoring and ranking methods that can be used for qualitative criteria is a group of methods based on pair-wise comparison of alternatives. This group includes the Saaty's method, which is analogous to the Saaty's method used for criteria weighting described in Section 5.5.3. This method will be described further in Section 5.7.3.

The three mentioned methods calculate ranking of an alternative as a weighted sum of individual rankings of the alternative for all criteria, as expressed in Eq. (20) [100]:

$$Z_i = \sum_{j=1}^{n} w_j \times z_j^i \tag{20}$$

where, Z_i is a total score of the i-th alternative, n is the number of criteria, w_j is the weight of j-th criterion, and z_j^i is the score of the i-th alternative, in relation to the j-th criterion. The i-th alternative scoring the highest number of points Z_i is determined as the optimal alternative to pursue.

If multiple experts are considered, the geometric weighted mean can be used to aggregate the individual scores [104], as expressed in Eq. (21):

$$z_j^i = GWM_j^i = \prod_{e=1}^{n} \left(z_{e,j}^i\right)^{w_e} \tag{21}$$

where, $z_{e,j}^i$ is the score of the i-th alternative, in relation to the j-th criterion, as valued by the e-th expert. The scores z_j^i must be subsequently normalized, so that $\sum_{e=1}^{n} z_j^i = 1$.

5.7.1. Weighted order method

In this method, preference of an alternative in relation to a single criterion is expressed to identify the most preferable alternative in relation to all criteria. The score z_i^j of the i-th alternative in relation to the j-th criterion is determined, as expressed in Eq. (22) [100]:

$$z_i^j = m + 1 - p_j^i \tag{22}$$

where, p_i^j is the order of the i-th alternative in relation to the j-th criterion.

This method can be inaccurate, because it assesses only the order of alternatives in respect to a single criterion, and it does not consider the exact values of the criteria. For this reason, the method is recommended for MCDA with qualitative criteria [100].

5.7.2. Direct assessment method

The direct assessment method places high demands on the person assessing the proposed alternatives, since this individual assigns scores directly to the alternatives. For this purpose, a scoring scale is established—a scale which can range, for example, from 1 to 10 points, or from 1 to 100 points—where the higher, the score the better the result. The decision maker proceeds through all the alternatives one by one, and assigns a score to the alternatives in respect to each criterion. An appropriately determined scale enables assessment of the respective alternatives' priorities in a more accurate way than the previous, weighted order method, which considers only the order of the alternatives [100].

5.7.3. Analytic Hierarchy Process (Saaty's method)

Saaty's method for ranking of alternatives is analogous to Saaty's method for criteria weighting, as described in Section 5.5.3. The only difference is the object of comparison. Saaty's matrix is created for each of the defined criteria to carry out pair-wise comparison. All available combinations of alternatives are created, covering all pairs of alternatives, and subsequently, the alternatives are compared in the pairs in an effort to define which of the alternatives have higher priority in relation to a given criterion [100].

A scoring scale can be determined for Saaty's method, similar to the scale used for criteria weighting, by applying the three-step procedure. Thus, Saaty's method can be used effectively for both criteria weighting and ranking of alternatives.

6. Goals

6.1. Research questions

This project asks the following research questions:

Q1: "Can ROA be recommended as an extension of the traditional DCF method for valuation of investments in BESS projects?"

Q2: "What is the impact of initial capital cost on dispatch of the battery, and on the resulting value of the investment?"

Q3: "What assessment criteria can be used for selection of ROA method used for capital investment valuation of BESS project out of the existing ROA methods?"

6.2. Goals of the dissertation

The main goal of this dissertation is the **creation of an ROA-based framework for advanced capital investment valuation of BESS projects.**
To meet this goal, the following sub-goals are considered:

- Create an optimization program for a dispatch of BESS to maximize the NPV of the investment, which can then be used as one of the inputs for ROA.
- Consider popular ROA methods in the proposed valuation framework and provide a method for selecting the suitable method for valuation of a BESS project, based on specific valuation requirements.
- Verify functionality of the created framework through its application to a real-world business case.

6.3. Author’s Hypotheses

The author defined the three hypotheses below to be accepted or rejected, based on the study’s findings:

H1: The traditional DCF method undervalues investments in BESS projects, but results can be improved by applying ROA to value the uncertainty and flexibility inherent in these types of projects.

The uncertainty stems from the characteristics of day-ahead prices for electricity, which make it difficult to predict future project cashflow. Similarly, the cost of a battery can be considered a stochastic variable. Flexibility is provided by the decision-maker’s ability to make changes to a project, in various phases of the project’s life.

To evaluate the hypothesis H1, a comprehensive literature review is conducted to examine existing research on the valuation of BESS projects. Secondly, a case study analysis is undertaken to assess the practical implications of the hypothesis.

H2: Including the battery cost in the optimization program will significantly improve quality of the battery dispatch, which results in an improved NPV of the investment.

DCF is still considered an important part of the capital investment valuation process, which affects the final value calculated by ROA. Thus, the quality of calculation of NPV is an important factor in this dissertation.

To evaluate the hypothesis H2, sensitivity of the developed dispatch model to battery cost is assessed in the case study. The model's sensitivity to cost variations is assessed by analyzing changes in the optimized dispatch decisions and the resulting NPV of the investment. By evaluating how the MILP model performs under different cost scenarios, the study aims to provide empirical evidence regarding the impact of battery costs on the quality of dispatch optimization and investment profitability.

H3: Selection of a ROA method for a BESS project is a complex process that should be based on clear decision criteria, maximizing the probability that decision makers will accept the method’s results.

There are multiple ROA methods available for valuation of real options. Selecting a ROA method suitable for BESS valuation is not a straightforward task, and it impacts the quality of a project’s valuation.

To evaluate the hypothesis H3, a comprehensive literature review is conducted. This helps to gather knowledge and insights on the current ROA methods and specifics of BESS projects. Assumptions on which the existing ROA methods are based should be compared with the identified specifics, to define a set of assessment criteria, which would help facilitate the selection process, and provide decent valuation of the project. Acceptance of the proposed assessment criteria is tested during MCDA in which the criteria are shared with subject-matter experts.

6.4. Methods of Research

This dissertation employs both qualitative and quantitative data. The qualitative secondary data was collected in the form of literature review. Quantitative primary data came from EXAA, which is used as the source for day-ahead prices of electricity [17]. The main research methods of the present study are a literature review, experiment, and case study.

In the experiment, causation between project value as a dependent variable and independent variables, such as battery parameters or electricity prices, are examined. An important part of the experiment is an optimal dispatch of the battery, an optimization problem which is defined as an MILP model. The model is solved with the use of PuLP library in Python, a programming language (which is also used for all simulations in the Section 11).

The literature review provides an overview of the existing methods and gaps in the research field, analyzing and synthesizing the collected scholarship in the context of the present study.

Case study methodology is used not only to demonstrate the functionality of the proposed valuation framework with real-world data, but also to help answer the defined research questions. Case study methods provide in-depth understanding of the implications that initial battery costs have for project value.

This dissertation uses the following research methods:

- Analysis.
- Synthesis.
- Induction.
- Deduction.
- Comparison.
- Analogy.

6.5. Structure of Part II

The DCF method is perceived as the cornerstone of the valuation framework, and as a key input of ROA. A robust MILP model-solving dispatch problem for BESS is described in Section 8. The MILP model is developed within two scenarios: the first maximized net cashflow generated by BESS without considering the degradation process of the battery; the second MILP model improved on this scenario by incorporating the degradation process into the model. The dispatch model becomes more selective, which is expected to be reflected positively in the resulting NPV.

Components critical for ROA applied to BESS projects, such as important models explaining behavior of spot price of electricity, are analyzed in Section 9.

The key component of MCDA in this thesis is my proposed list of assessment criteria in Section 10, which has been designed specifically for BESS projects. ROA practitioners are encouraged to use these criteria when valuing a BESS project in order to apply the most appropriate ROA model.

To verify functionality of the developed valuation framework, Section 11 defines the case concept. Applying the model to real-world business requires considering an investment in grid-scale lithium iron phosphate ($LiFePO_4$) batteries, which enable not only testing of all processes and sub-processes of the valuation framework, but also help answer my research questions, and determine the acceptance or rejection of the defined hypotheses.

PART II

BESS Valuation Framework

7. Introduction of the BESS Valuation Framework

As described in the Section 1, BESS can be used for multiple purposes, and depending on the exact purpose, the required characteristics of BESS can vary. Regardless of the purpose, revenues generated by BESS typically depend on the price of electricity, which can be classified by the market on which the electricity is traded.

Accordingly, the investment in BESS faces high uncertainty: i.e., the revenues generated by the BESS can fluctuate significantly, depending on price variance. Similarly, the cost of the battery can be considered as a stochastic variable. Still, BESS projects can offer high flexibility; not only can management adjust the BESS project as new information arrives, its modular design adds extra flexibility.

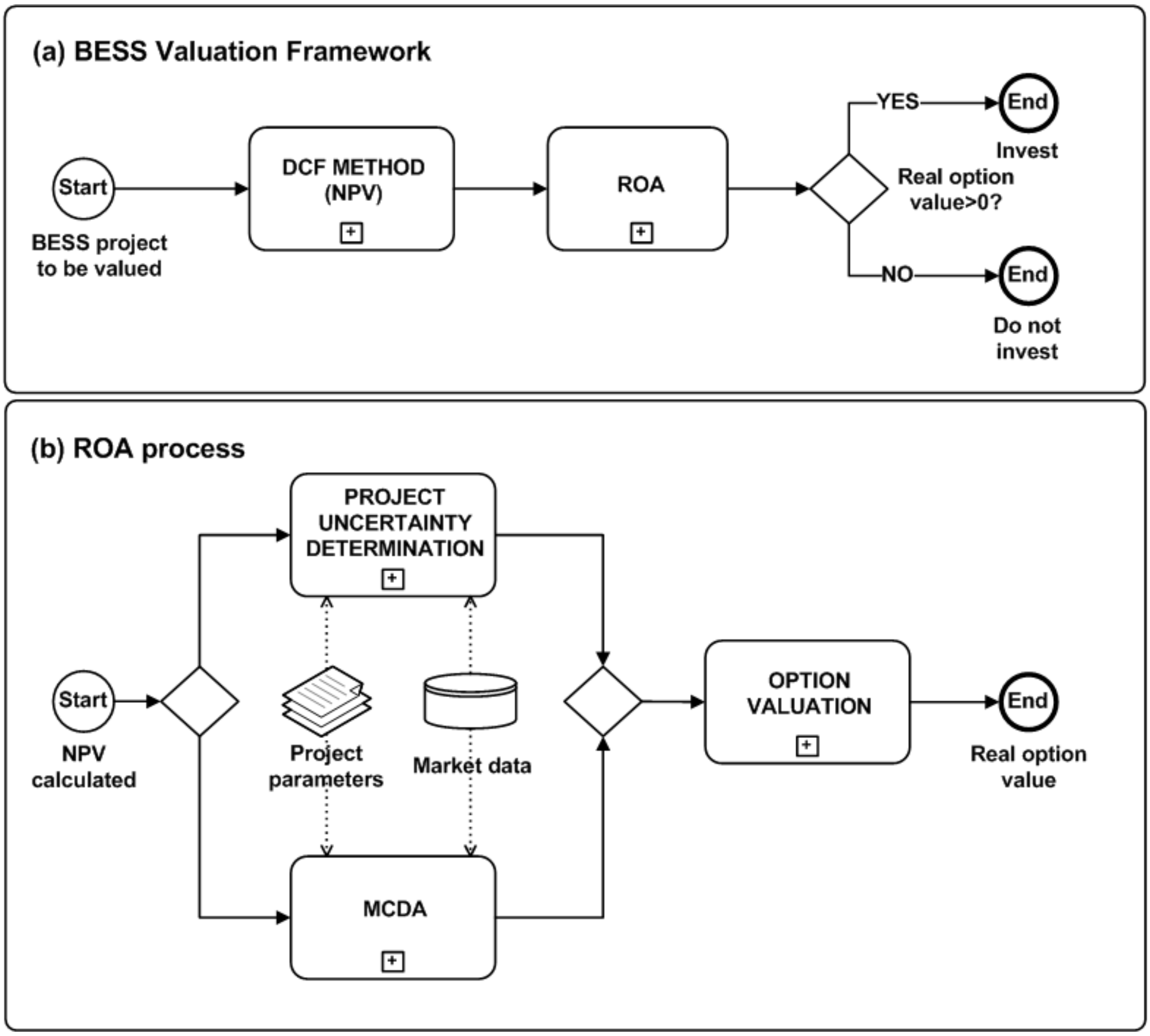

Fig. 4. BESS Valuation Framework: **(a)** High-level view of the valuation framework; **(b)** ROA process in detail.

Traditionally, energy assets have been valued with the use of the DCF method, which is popular for its simplicity and transparency. The expected future cashflow is discounted with the interest rate to receive a present value, and compared with a capital outlay.

Traditional capital investment appraisal methods, including the DCF (and the above-mentioned NPV and IRR), do not properly recognize uncertainty and flexibility properties. ROA addresses both uncertainty and flexibility, and values a project accordingly. Because ROA can be perceived as an extension of the DCF method, both the DCF and ROA methods are analyzed for the use of valuation of BESS projects, and both are integrated in the proposed valuation framework depicted in Fig. 4a. The valuation framework consists of two processes, DCF and ROA. The DCF process based on MILP model is described in Section 8. The ROA process depicted in Fig. 4b consists of the sub-process Option Valuation (described in Section 3), the sub-process Project Uncertainty Determination (described in the Section 9), and the sub-process MCDA (described in Section 5) leaning on the assessment criteria proposed in Section 10.

8. BESS dispatch problem – MILP model

The BESS dispatch problem is solved with the MILP model developed by Hurta et al. [105]. The novelty of the model lies in the way it balances the maximization of net cashflow from arbitrage with battery degradation. It considers both cycle and calendar degradation induced by the operation. The construction of the model allows for an analysis of the relationship between *DOD* and NPV to identify the optimal *DOD* that results in the maximization of NPV for the BESS dispatch.
The MILP model is based on the following assumptions:

- No O&M costs.
- No taxation.
- No costs related to the land used for the BESS.
- No transaction costs.
- No external limits on the exchange between BESS and the electrical grid.
- Zero BESS salvage value.
- No temperature control system required.

Hurta et al. [105] developed the MILP model in two scenarios; in the first scenario, the MILP does not include a battery degradation process, which is reflected negatively in the resulting NPV. The incorporation of the battery degradation process in the second scenario enabled the authors to find a balance between net cashflow and battery loss, which significantly improved the investment valuation result.

8.1. Scenario 1 – BESS dispatch not constrained with battery degradation cost

The first part of the model to maximize net cashflow from the operation of a BESS, described by Hurta et al. [105], is expressed in Eqs. (23)-(33).

Eq. (23) maximizes the differences between cash inflow and cash outflow; cash inflow is provided by injecting the amount of energy $P_{OUT}(t)$ at the price $S(t)$ into the grid. On the other hand, cash outflow equals the amount of energy taken from the grid, multiplied by the spot price $S(t)$.

$$MAX \sum_{t=1}^{T} \left(S(t) \times \left(P_{OUT}(t) - P_{IN}(t) \right) \right) \tag{23}$$

The power inflow $P_{IN}(t)$ and power outflow $P_{OUT}(t)$ cannot exceed the rated power of battery P_{MAX}, as ensured by the conditions in Eqs. (24)-(25). The binary variables $x(t)$ and $y(t)$ are introduced in Eq. (26) to avoid situations when the battery would be charged and discharged at the same time, which is not considered as feasible given the current technology available on the market [105].

$$0 \leq P_{IN}(t) \leq P_{MAX} \times \; x(t) \tag{24}$$

$$0 \leq P_{OUT}(t) \leq P_{MAX} \times y(t) \tag{25}$$

$$x(t) + y(t) \leq 1 \begin{cases} charging: x(t) = 1, y(t) = 0 \\ discharging: x(t) = 0, y(t) = 1 \end{cases} \tag{26}$$

Eq. (27) ensures that the battery's level of charge $\mathrm{C(t)}$ is neither negative nor exceeds its rated capacity, $\mathrm{C_{MAX}}$.

$$0 \leq C(t) \leq C_{MAX} \tag{27}$$

The level of charge $C(t)$ of the battery is brought into relation with the power inflow $P_{IN}(t)$ and power outflow $P_{OUT}(t)$ in Eq. (28):

$$C(t) - C(t-1) = \left(P_{IN}(t) \times \sqrt{\varepsilon} \right) + \left(P_{OUT}(t) \times \left(\sqrt{\varepsilon} \right)^{-1} \right), \qquad where, t \in [2, T] \tag{28}$$

where, ε stands for the round-trip efficiency of the battery.

Eq. (29) ensures that the BESS's level of charge $C(t)$ is 0 at the beginning of the operation; thus, the first operation of the battery is charging.

$$C(1) = 0 \tag{29}$$

In the next step, the DCF method is applied to calculate the NPV of the investment, as expressed in Eq. (30):

$$NPV = -CF(0) + \sum_{t=1}^{T} \frac{CF(t)}{(1+r)^t} \tag{30}$$

where, *r* is the discount factor.

The method takes the net cashflow $CF(t)$ described in Eq. (31) as an input.

$$CF(t) = \sum_{t=1}^{T} \left(S(t) \times \left(P_{OUT}(t) - P_{IN}(t) \right) \right) \tag{31}$$

The calculation of the initial capital outlay $CF(0)$ is expressed in Eqs. (32)-(33). To calculate the number of theoretical cycles $NoC(T)$ performed within ΔT, there are well established methods such as the average equivalent full cycles method or the rainflow method [106]. The approach in Eq. (33) calculates the number of theoretical cycles as the sum of energy charged and discharged, normalized by the available maximal battery capacity. Compared to the two above mentioned methods, this approach does not convert the theoretical cycles to equivalent full cycles, neither it counts explicitly the charge/discharge cycles. It is characterized by simplicity, at the same time enabling analysis for a selected *DOD*.

$$CF(0) = I \times MAX\left(\frac{T}{RL}, \frac{NoC(T)}{CL}\right) \tag{32}$$

$$NoC(T) = \frac{\sum_{t=1}^{T} \left[\left(P_{IN}(t) \times \sqrt{\varepsilon} \right) + \left(P_{OUT}(t) \times \left(\sqrt{\varepsilon} \right)^{-1} \right) \right]}{2 \times C_{MAX} \times DOD} \tag{33}$$

where, *I* is the investment cost, *RL* is the battery calendar life, *CL* is the battery cycle life, and *DOD* is the depth of discharge of the battery.

8.2. Scenario 2 – BESS dispatch constrained with battery degradation cost

Battery degradation is an inevitable process. Once battery capacity drops to 80% of the nominal value, the battery is considered at the end of its life [107]. Without considering battery aging, they would be deployed in an excessive manner, exploiting small price differences, which would not justify the battery life loss caused by the arbitrage [105]. Battery life can be expressed either in years or cycles. A lithium-ion battery has typically a lifetime of between 10 and 15 years [19], a term not conditional on battery use, and thus corresponding to fixed costs.

BESS management is not the only determinant of a battery life. There are other factors, such as ambient temperature and cumulative usage time, which are difficult to control [108]. Among the influenceable factors, the battery's depth of discharge (*DOD*) is a critical parameter of the deployment strategy, as *DOD* is a determinant of battery life.

Omar et al. [109] used a least-square fitting method on empirical data to capture the relationship between *DOD* and cycle life of a $LiFePO_4$ battery. As can be seen in Fig. 5, the relationship between battery life and *DOD* is exponential. While a deployment strategy based on 100% *DOD* enables completion of only 2600 cycles, flat cycles provided by 20%

DOD increase the number of cycles to as many as 34957. Given that the function is exponential, one could assume that a deployment strategy using 20% *DOD* would provide operation with the highest NPV. However, there are two reasons why this does not necessarily apply. First, there is still the burden of fixed costs stemming from battery calendar life, costs weighing down the BESS operation. Put simply, the BESS should complete all the cycles within its calendar life, otherwise each unused cycle embodies lost opportunity, decreasing NPV generated by the BESS. The second reason may be less intuitive; price arbitrage uses a simple algorithm: energy is purchased at a time of low price, to be subsequently sold at a time of high price. If one theoretical cycle consists of one charging sequence and one discharging sequence, then we require that the number of charging/discharging sequences equals roughly one cycle life [105]. When we put these figures together, then: assuming a 20% *DOD*, 34957 cycles should be completed within 15 years. If we assume that with each charging/discharging sequence, the capacity of battery is charged/discharged fully, in order to maximize the profit, this process requires 34957 peak periods and 34957 off-peak periods within 15 years.

According to Kovacevic et al. [110], there are typically between one and two peaks in the spot prices of electricity every day, depending on the season. This is in line with findings of Hurta et al. [105], who identified two peaks per day in day-ahead prices. If we return to our example and assume two peaks per day in day-ahead market prices, then within the calendar life of 15 years, there will be 10950 periods of high prices which can be used for discharging the battery. Given that the battery requires more than three (3) times that many discharging modes, the battery must also be discharged between peaks. However, this means that the profit realized from the additional cycle must exceed the lost caused by not completing the previous cycle during the daily maximum. Hurta et al. [105] concluded that the highest NPV was generated by a dispatch pattern with *DOD* set to 60%, since, out of the all *DOD* rates considered, the projected battery life of 10019 cycles is closest to the target number of 10950: specifically, 20%, 40%, 60%, 80% and 100%.

In order to better analyze the effects of changing *DOD* over variable costs of the battery, it is possible to use the cost of the cycle *COC* and the levelized cost of the storage *LCOS,* as defined in Eqs. (34) and (35), respectively [111]:

$$COC = \frac{CF(0)}{CL} \tag{34}$$

where, $CF(0)$ is the initial capital cost and *CL* is the cycle life of the battery.

$$LCOS = \frac{CF(0)}{CL \times C_{MAX} \times DOD \times \varepsilon} \tag{35}$$

where, C_{MAX} is the rated storage capacity and ε is a round-trip efficiency of the battery.

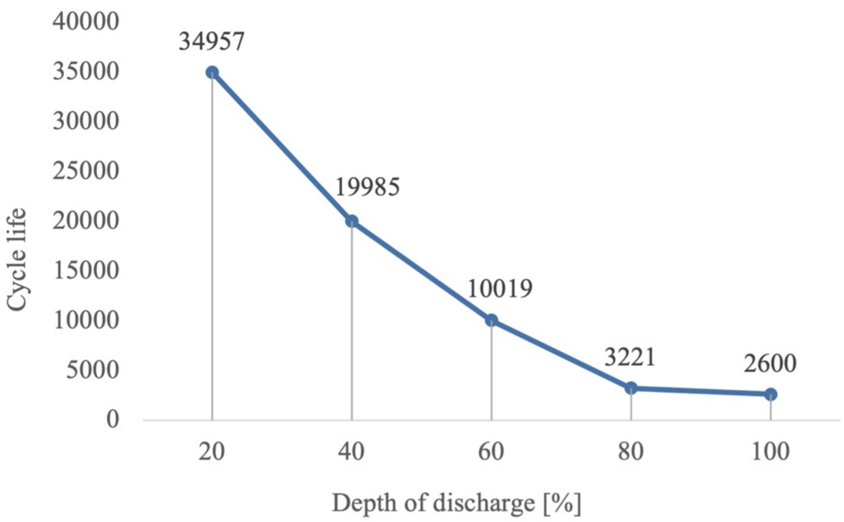

Fig. 5. Exponential relationship between the *DOD* and *CL* of the LiFePO4 battery [109].

Table 3 shows values of *COC* and *LCOS* for different *DOD*, assuming a 1MWh $LiFePO_4$ battery, where $CF(0)$ is 100000 USD, ε is 0.9604, and the EUR/USD exchange rate is set to 0.86.

Table 3. *CL* and *COC* of 1 MWh $LiFePO_4$ battery. Source: [105].

DOD [%]	CL [cycles]	COC [EUR/cycle]	LCOS [EUR/MWh]
100	2600	35.66	43.17
80	3221	28.78	43.56
60	10019	9.25	18.67
40	19985	4.64	14.04
20	34957	2.65	16.05

The difference between *COC* and *LCOS* is striking, for a battery with *DOD* set to 100% and 20%. Also, we can see that the cost of storage of 1 MWh varies minimally for *DOD,* in the range between 60% and 20%. This means that the highest NPV is generated using a dispatch strategy with a *DOD* set to 60%, as Hurta et al. [105] concluded.

To include the degradation process of the battery in the MILP model, the objective function from the Scenario 1 shown in Eq. (23) is extended with the initial capital cost $CF(0)$ and the rate of degradation φ, as shown in Eq. (36) [105].

$$MAX \sum_{t=1}^{T} \left(S(t) \times \left(P_{OUT}(t) - P_{IN}(t)\right)\right) - CF(0) \times \varphi \tag{36}$$

Battery life loss must reflect both the fixed costs arising from continuous, calendar aging, as well as variable-cycle aging, conditional on the intensity of operation; both are incorporated with the variable φ, expressed in Eq. (37). While the former depends on the total time of operation ΔT and the calendar battery life RL, cycle aging tracks the number of theoretical cycles NoC completed within the operation time ΔT, out of the cycles *CL,* which constitute the total life of the battery [105].

$$\varphi \geq MAX\left(\frac{T}{RL}, \frac{NoC(T)}{CL}\right) \tag{37}$$

DOD sets the lower boundary of the battery's permissible level of charge $C(t)$, as defined by Eq. (38) [105].

$$(1 - DOD)C_{MAX} \leq C(t) \leq C_{MAX} \tag{38}$$

The remaining constraints from Scenario 1 are unchanged.

Applying the defined MILP problem to longer periods ΔT can require long computation times. One option for overcoming this problem, and for shortening the computation time, is dividing the MILP problem into a series of MILP sub-problems, as described by Metz and Saraiva [22], and applied by Hurta et al. [105]. The sub-problems overlap each other, and the overlapping window ω provides the necessary outlook into prices for the next sub-problem. Hurta et al. [105] recommend deriving the length of the window from a combination of market properties and battery properties. By performing a test run on a shorted MILP problem, the optimal window length can be determined within acceptable error boundaries.

The MILP problem is divided into ΔT/m MILP sub-problems of the length $\Delta t = m + \omega$, where m stands for the number of time points used for the subproblem [105]. The resulting MILP sub-problems cannot be solved completely in isolation; the level of charge $C(t)$ at the end of each sub-problem needs to be provided as an input for the next sub-problem, as follows: $C(m) = C(m + 1)$, $C(2m) = C(2m + 1)$, ... [105].

Ignoring the stored energy at the end of each sub-problem would otherwise lead to underestimation of the project value.

9. Components critical for ROA applied to BESS projects

In Hurta's [112] review, GBM and MRM were identified as the most popular models to explain the behavior of a spot price of electricity, when ROA is applied. Price and volatility of asset were found to be critical for ROA, when applied to BESS projects. These will be analyzed as follows:

- Price of asset
  - GBM
  - MRM
  - Spot price of electricity – empirical evidence
- Volatility
  - Historical
  - (G)ARCH
  - Volatility proxy
  - Implied volatility
  - Educated guess

9.1. GBM

Geometric Browning Motion (GBM) is popularly used to explain movements on stock markets, but the motion also laid the groundwork for options theory, which used the concept to construct major valuation models. In fact, GBM is the most frequently used stochastic process in ROA [113]. As discussed in Section 3.2.1, BSM assumes the underlying asset follows GBM. CRRM uses a binomial distribution, but as the number of time steps grows, it approximates GBM as well. Thus, understanding GBM is a prerequisite for a successful application of ROA.

GBM $G(t)$, followed by a spot price $S(t)$, is expressed in Eq. (39). It describes the return that an asset with the price S provides in a very short time. The right side of the equation consist of two terms: the is the expected value of the return, and the second is a stochastic component [60].

The exponential relationship between the GBM $G(t)$ and Brownian motion $W(t)$ is shown in Eq. (40) [114], [115]:

$$\frac{dS(t)}{S(t)} = \mu dt + \sigma dW(t) \tag{39}$$

$$G(t) = e^{W(t)} \tag{40}$$

where, μ is a drift parameter and W is the Brownian motion.

GBM is an exponential lognormal process, growing at the rate $\mu + \sigma/2$ [115]. Because GBM is an exponential function, it can take positive numbers only, unlike the standard Brownian motion [115]. This is especially desirable in a stock market that does not allow for negative values, but can be less desirable in ROA.

The model is a Markov process; the next step depends on the current step only, so the history of the process has no relevance to its future development [113].

As can be seen in Eq. (39), volatility is assumed to be constant. As mentioned above, this can be limiting in ROA, because volatility of project's revenues can vary.

To demonstrate some of the above-mentioned properties of GBM, MCS is used to simulate 10000 random paths following GBM. The result is plotted in the Figs. 6-7. Both simulations start at the value of 20. The first example uses a higher volatility of 29.26 to show that the model can simulate positive values only. This is obvious, especially in Fig. 6b, with the distinctive cut-off at 0. The simulation in Fig. 7, on the other hand, has volatility set to 5.39, which ensures that the histogram in Fig. 7b already resembles a lognormal probability density function, with its distinctive right tail. The exponential growth can be observed in both Fig. 6a and Fig. 7a.

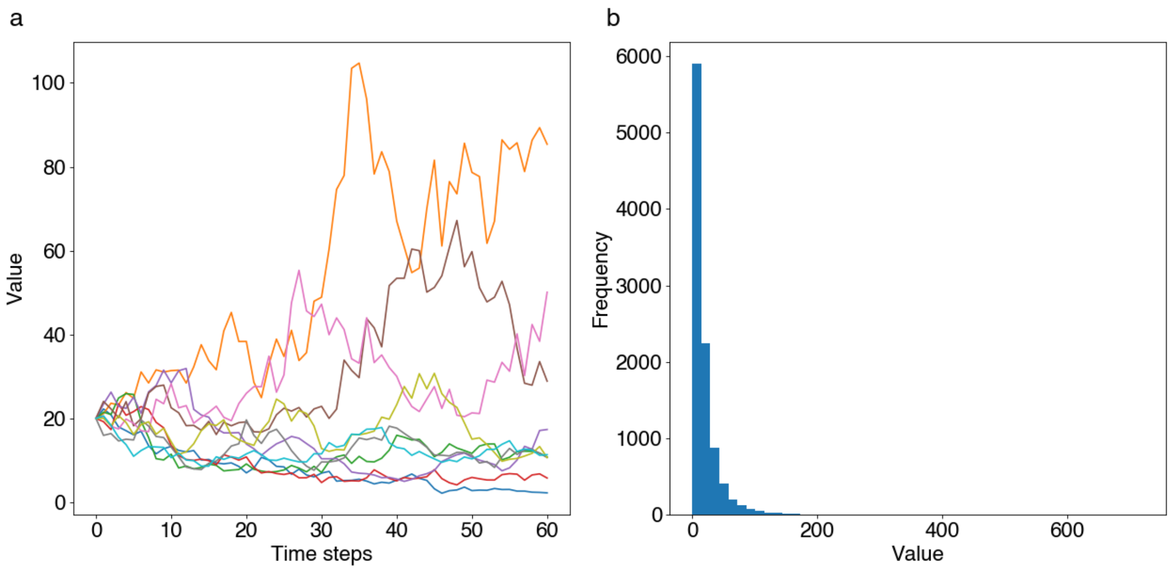

Fig. 6. 10000 paths generated by MCS, assuming GBM expressed in Eq. (39) as the underlying process, where σ is 29.26: (a) Plot of 10 samples; (b) Histogram of the distribution of 10000 paths with a distinctive cut-off at 0, caused by the log-normal property.

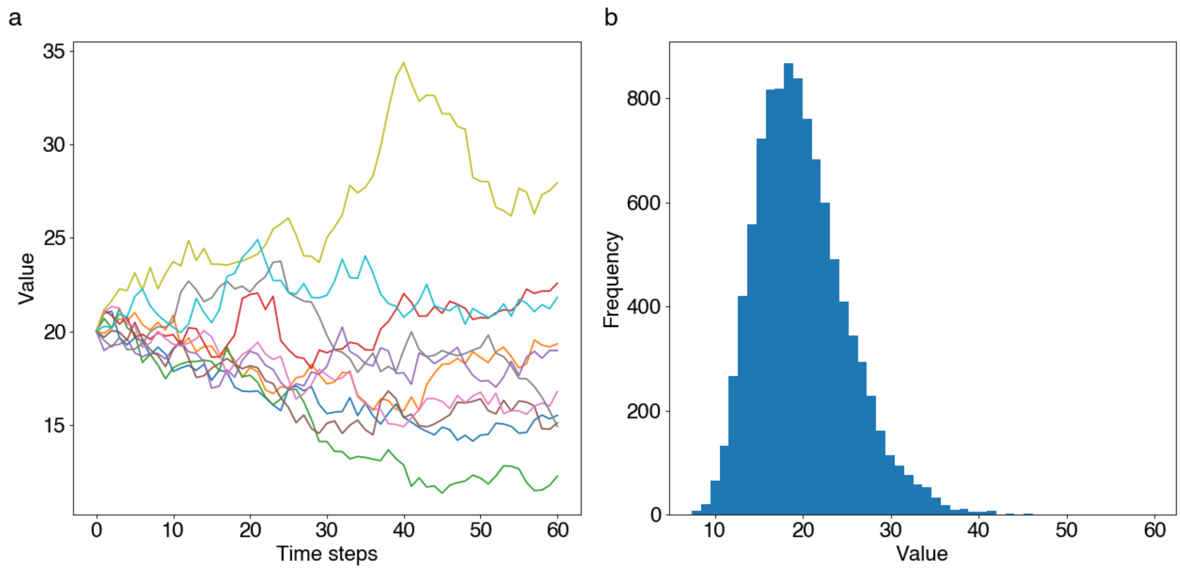

Fig. 7. 10,000 paths generated by MCS assuming GBM expressed in Eq. (39) as the underlying process, where σ is 5.39: **(a)** Plot of 10 samples; (**b)** Histogram of the distribution of 10,000 paths, with the distinctive right tail.

GBM is not only used as an assumption in major real options valuation methods, but also as an explanation of the movement of the spot price of electricity, as reviewed by Hurta [112].

9.2. MRM

MRM is one of the most popular models used for electricity prices [112], [116]. Popular MRM is the Ornstein-Uhlenbeck (OU) process described by Ornstein and Uhlenbeck [117] and Vasicek [118]. It describes a situation when a stochastic price fluctuates around its mean.

OU process can be expressed in the form of the stochastic differential equation in Eq. (41) [119]:

$$dS(t) = \alpha\big(\mu - S(t)\big)dt + \sigma dW(t) \qquad (41)$$

where, α>0 is the speed of reversion at which price $S(t)$ converges to its long-term value μ, σ is a constant volatility, $\big(\mu - S(t)\big)$ is a drift component, and $dW(t)$ is the Brownian motion.

As shown in Fig. 8, the numbers generated by the OU process can be both positive and negative, standing in contrast to GBM, which allows for non-negative numbers only.

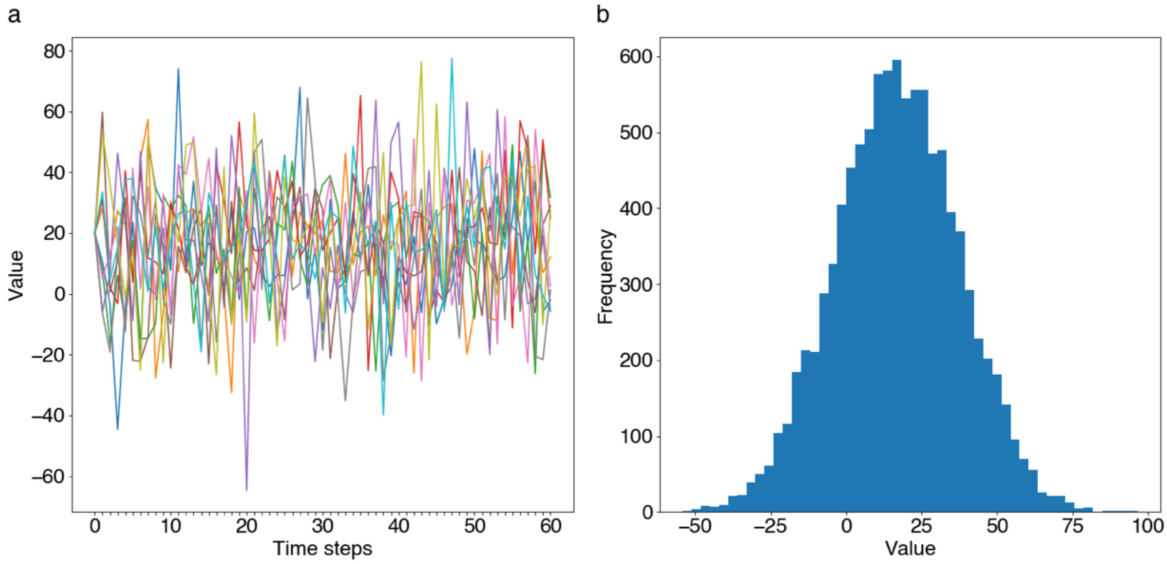

Fig. 8. 10000 paths generated by MCS assuming OU process expressed in Eq. (33) as the underlying process, where σ is 20.14: **(a)** Plot of 10 samples; **(b)** Histogram of the distribution of 10000 paths.

Either the maximum likelihood estimation or the least-square estimation can be used for estimating the parameters of the OU process. Time series can be tested for stationarity and for presence of the mean-reversion effect by using the unit root test.

Another possibility is to use the property of MRM, which says that the variance of returns grows as a function of time. While this property holds for MRM, it does not for a random walk, a fact which is used in the construction of the variance ratio test. Variances of two time periods are compared. A variance equaling one means reject the random walk hypothesis [120].

Some authors believe the mean-reverting jump-diffusion model (MRJM)—a combination of MRM and jumps—captures the empirical properties of energy prices even better. As a result of demand shocks, energy commodities prices often experience rapid price changes, followed by mean reversion, which can be better modelled with MRJM than MRM [60]. However, as the review carried out by Hurta [112] shows, MRM has a strong place in ROA. The present work follows the findings of the review and uses the standard MRM.

A majority of researchers model fuel prices as MRM. However, this model cannot be used as a rule; the process describing the same type of fuel prices can change from MRM to GBM—and vice versa—as time passes [121]. A low speed of mean reversion and constant implied volatility can be seen as indicators that a random walk (rather than an MRM) will not lead to considerable errors in the valuation process. This holds, even if unit root tests and variance ratio tests confirm a mean-reversion effect in the prices [122].

It is also important to consider the different treatment of negative prices in the models. While it is desirable in stock markets not to allow for negative prices, the same conditions can be less realistic in energy markets [123].

9.3. Spot price of electricity – empirical evidence

The profitability of investments in a BESS used for price arbitrage is strongly determined by the properties of the input prices. It is necessary to understand empirical properties of electricity price, to compare these with the assumptions made in real options valuation methods, and to evaluate the expected accuracy of the methods.

Electricity is part of the commodities asset class, which has properties distinctive from equities (including stocks), an important fact to highlight, since stocks are the asset type used to create the major real options valuation methods, such as the BSM. Thus, applying the methods of real assets to the electricity price can risk a serious departure from the original assumptions, and impact the credibility of the entire valuation method.

Spot prices of commodities have the following empirical properties [119]:

- Mean reversion with a seasonal central tendency.
- Heteroscedasticity.
- Jumps.
- Seasonality—not only in spot prices, but also in volatility of the prices.

Electricity stands out among other commodities because of its non-storability. While crude oil or natural gas can be kept in storage facilities, electricity cannot be stored directly. As a result, electricity cannot be held as an investment. Instead, it must be consumed immediately, so the spot price of electricity is considered a consumption good, instead. This classifies electricity as a non-asset, rather than an asset. The spot price of electricity is determined not only by an immediate demand, but also by location [119].

When it comes to an electricity price, it can be distinguished between a spot price, a forward price, and a futures price. Spot price can be defined as a $t+1$ price, determined in a day-ahead market. Market participants ask for available trading products (15-min blocks, 60-min blocks, multiple-hour blocks, etc.) for the following day(s), and send their bids to an auction, where these are matched using the merit order to set the price. The differences between the settled volume and the actual supply and demand are covered by the intraday market, on which trading takes place immediately after the closing of the day-ahead auction [17]. The intraday market acts as a correction market, removing imbalance from the market, caused by inaccurate forecasts. To set the price, the intraday market does not use a clearing price but the first-come, first-serve principle [124].

A special type of electricity-regulating market is the balancing market. The market's objective is to process imbalances from the previous 24 hours. The transmission system operator is the only participant on the supply side who participates in the market, with the goal to reach a balance in the electricity grid [125]. The intraday market is smaller than the day-ahead (spot) market, but it can provide higher revenues from the arbitrage. Some authors recommend participation in the balancing market to improve on a negative economic result from arbitrage performed in the spot market [22, 28].

In addition to a spot price, settled on a day-ahead market, there are forward and futures prices, settled on derivative markets. These are long-term contracts used by speculators or hedgers. Both forwards and futures electricity price contracts are fixed at current time t for delivery at a future time T. While forwards are settled at OTC markets, futures are standardized contracts traded on specialized energy exchanges. In essence, both types of contracts are similar, but the non-standardization of forwards enables it to meet the specific requirements of a counterparty by customizing the trade.

Prices of derivatives such as forwards and futures are derived from their underlying asset. Compared to spot prices, they have distinctive properties and dynamics, which are beyond the scope of the present work.

The spot price of electricity can vary not only in accordance with the location and time of delivery, but also in accordance with the origin of the electricity. In addition to the electricity generated by non-specified energy sources, the energy exchanges also trade electricity generated by RIS, which is referred to as green electricity. On the contrary, electricity from conventional energy sources is labelled as gray [17]. In 2012, EXAA became the first European energy exchange which offered trading of green energy, which is certified with the European Energy Certificate System (EECS), guaranteeing its origin [126]. Fig. 9 captures the substantial differences in price between green and gray energy.

It is clear from Fig. 9 that the price of gray electricity traded negatively many times within the time period analyzed. In September 2008, the European Energy Exchange (EEX) was the first European energy exchange allowing negative prices [123]. Negative prices occur in situations where supply is higher than demand, and a supplier prefers to pay the price rather than shut down the generation unit. The supplier can do so for the following reasons [127]:

- Technical constraints prohibiting the supplier from decreasing output.
- Anticipation of higher prices in a short future, in a combination with a long process for changing output.
- Bilateral purchase contracts are not impacted by the wholesale price of electricity.
- Regulation of utilities.
- Production incentives.

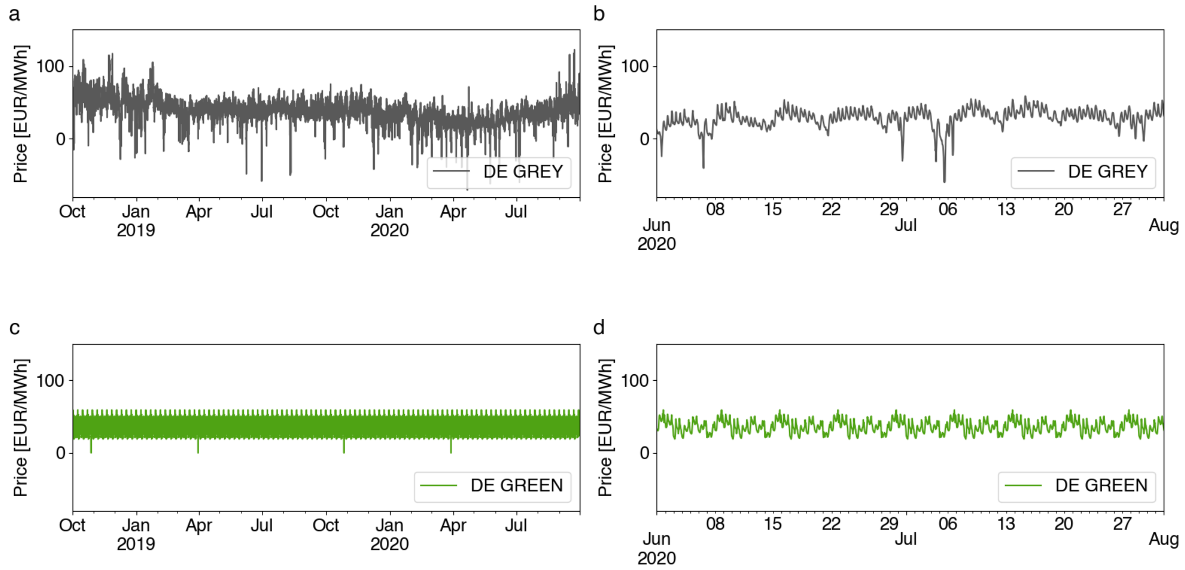

Fig. 9. Spot price of electricity generated by conventional and renewable energy sources: **(a)** Hourly contracts on gray electricity for the German (DE) market in the long term (1 October 2019–30 September 2020); **(b)** Hourly contracts on gray electricity for the German (DE) market in the short term (1 June 2020–31 August 2020); **(c)** Hourly contracts on green electricity for the German (DE) market in the long term (1 October 2019–30 September 2020); **(d)** Hourly contracts on green electricity for the German (DE) market in the short term (1 June 2020–31 August 2020) [112].

9.4. Volatility

Volatility σ is a key parameter determining the value of a real option. The higher the volatility, measured as a standard deviation of underlying real asset's revenues, the higher the option value.

Volatility of commodity returns present some specific behavior, such as [128]:

- Changes in time
- Conditionality on previous returns
- Clustering
- Mean reversion

If we assume the price of a commodity such as electricity as a key determinant of the project's revenues, we can expect these properties to be translated into the project's volatility.

The above properties are not always recognized in option-valuation models, which are built on simplified assumptions. In BSM, volatility σ is necessary to quantify the parameters d_1 and d_2 in Eqs (8)-(9). Here it is assumed that volatility is constant. In CRRM, knowledge of volatility is required to calculate the rate of up and down movements, as expressed in Eqs. (10) and (11), respectively. The rate of the movements can be adjusted within any time step, to account for changes in volatility. Nor can volatility be avoided in MCS, when GBM or MRM are used for modelling of the stochastic process, as can be seen in Eqs. (39) and (41).

While other input parameters in the option models are, in general, easy to acquire, this is not the case with volatility. With its significant impact on an option value, incorrect determination of volatility can result in undermining the whole valuation framework, which can jeopardize the acquisition of buy-in from decision makers.

In order to quantify the future volatility, the following approaches can be used:

- Historical volatility (Sub-section 9.4.1)
- (G)ARCH (Sub-section 9.4.2 and Sub-section 9.4.3)
- Volatility proxy (Sub-section 9.4.4)
- Implied volatility (Sub-section 9.4.5)
- Educated guess (Sub-section 9.4.6)

9.4.1. Historical volatility

A time series of historical volatility is used, with the expectation that historical changes in prices can also explain future volatility. Simple models and metrics can be used, including a random walk, the historical average, the moving average, or the exponential weighted moving average.

This work employs a logarithmic returns approach to determine volatility from historical prices; standard deviation of the natural logarithm of returns $r(t)$ is calculated as expressed in Eqs. (42)-(43):

$$\sigma = \sqrt{\frac{\sum_{t=1}^{T}(r(t) - \mu)^2}{T}} \tag{42}$$

$$r(t) = \ln\frac{S(t)}{S(t-1)} \tag{43}$$

where, μ is a mean and $S(t)$ is a price at time *t*.

The calculated volatility is linked to the frequency of data, which was used for its calculation, and the value must be annualized before applying it as an input in the option valuations model. Annualized volatility σ_A can be calculated from the non-annualized volatility σ, with the use of the relationship in Eq. (44), where *N* equals the number of periods used for σ fittings in one year. If σ is a daily volatility and we assume a year has 252 business days, then N equals 252; if σ is a weekly volatility, then N equals 52; if σ is a monthly volatility, then N equals 12, and so on.

$$\sigma_A = \sigma * \sqrt{N} \tag{44}$$

9.4.2. ARCH

An autoregressive conditionally heteroscedastic (ARCH) model was introduced by Engle [129], with the main improvement being a move from constant volatility to time-dependent volatility in returns. Volatility is now modelled as a stochastic process that is prone to clustering. The ARCH(m) model uses *m* preceding time steps (lags) to explain future volatility. In the single-lag ARCH(1) model, the return $r(t)$ and variance $\sigma(t)^2$ can be expressed as in Eqs. (45) and (46), respectively:

$$r(t) = \sigma(t)\epsilon(t) \tag{45}$$

$$\sigma(t)^2 = \alpha(0) + \alpha(1)r(t-1)^2 \tag{46}$$

where, $\epsilon(t)$ ~ i.i.d. N(0,1) is the standard Gaussian white noise and $\alpha(0)$ and $\alpha(1)$ are parameters that can be estimated by a conditional maximum likelihood estimation [130].

Obviously, in the ARCH(1) model, the variance $\sigma(t)^2$ at *t* is conditional on the previous return $r(t-1)$, and there is a positive relationship between the size of the variance $\sigma(t)^2$ and the absolute value of previous return r_{t-1}. This results in clustering, of a length determined by the order *m*; a large swing in $r(t-1)$ is followed by large swing in $r(t)$ [131].

The general ARCH(m) model can be used for order *m*>1, and expresses the return just as the ARCH(1) model, but the variance $\sigma(t)^2$ is conditional on *m* previous returns, as shown in Eq. (47) [131]:

$$\sigma(t)^2 = \alpha(0) + \alpha(1)r(t-1)^2 + \cdots + \alpha(m)r(t-m)^2 \tag{47}$$

9.4.3. GARCH

The generalized ARCH (GARCH) model was published by Bollerslev [132].
The basic GARCH(1,1) model has a return $r(t)$ modelled in the same way as the ARCH model expressed in Eq. (45), but the relationship for the variance $\sigma(t)^2$ has been extended into the form of Eq. (48) [130].

$$\sigma(t)^2 = \alpha(0) + \alpha(1)r(t-1)^2 + \beta(1)\sigma(t-1)^2 \tag{48}$$

Here, variance $\sigma(t)^2$ is conditional not only on the previous return $r(t-1)$, which is the ARCH term, but also on the variance itself.

Similarly, GARCH(m,n) extends Eq.(48) into Eq. (49) [130].

$$\sigma(t)^2 = \alpha(0) + \sum_{j=1}^{m} \alpha(j)r(t-j)^2 + \sum_{j=1}^{n} \beta(j)\sigma(t-j)^2 \tag{49}$$

While the $\alpha(j)$ parameter expresses the sensitivity of volatility to market shocks, $\beta(j)$ is used to define the persistence of the shocks [133].

Several authors have modified the G(ARCH) model to accommodate more empirical properties of volatility, such as non-linearity, asymmetry, or long memory. These modifications are referred to as EGARCH, GJR-GARCH, AGARCH, and TGARCH models [134].

9.4.4. Volatility proxy

Stock volatility among companies that operate a similar business can be used as a proxy for a project's volatility [56]. Another possibility is using the volatility of revenues from already implemented projects.

9.4.5. Implied volatility

When we know prices of exchange-traded options, we can use those prices to solve for volatility in the BSM defined in Eqs. (6)-(9). Such a volatility is referred to as implied volatility. Whereas volatility calculated from historical returns is backward-looking, implied volatility is forward looking, embodying the expectations of the market.

In this way, the risk that market participants can expect is determined. In contrast to historical volatility, implied volatility typically includes a premium required by option traders [135]. Electricity options traders assume a higher probability of significant price increases, and this expectation is reflected in a higher option price [136]. It is unclear whether an implied volatility forecasts a volatility with a higher accuracy than the time series models such as GARCH [135].

9.4.6. Educated guess

As a last resort, decision makers can provide an estimate of a project's volatility according to previous experience from projects with similar risk profiles. Due to fact, ROA is often used for novel projects, this method can be of limited use.

10. Assessment criteria for selection of suitable ROA method used for capital investment valuation of BESS project

Hurta [112] proposed seven assessment criteria to select the suitable ROA valuation method for a project in the energy sector, where a spot price of electricity is a key determinant of the project's cashflow. The present study extends the list of proposed decision criteria, adding volatility as the eighth criterion, and analyzes the decision criteria for use in valuation of BESS projects, in order to accommodate the specifics of these types of projects. The following decision criteria were set and analyzed:

- Expected acceptance by management.
- Early exercise.
- Negative prices.
- Time horizon.
- Volatility.
- Ability to value popular types of real options.
- Number of sources of uncertainty.
- Speed of option value calculation.

As explained in Section 3.2, this work considers the three most popular ROA methods: BSM, CRRM, and MCS. Neither the DP method nor the LSMC method is analyzed due to their potential complexity, which could pose an obstacle for practitioners adopting them. Given that complexity is one of the primary reasons why ROA has not been more widely adopted in practice [137], this work aims to limit the calculus requirements associated with the methods analyzed. Only the three above methods are thus reflected in the subsequent analysis of the assessment criteria.

10.1. Time horizon

Due to the complexity of large energy projects, the time horizon of an investment project is undoubtedly a parameter that must be considered, and for that reason, time horizon should be one the proposed decision criteria. An energy project typically consists of several phases, such as engineering, procurement, transport, construction, precommissioning, commissioning, and performance tests [138]. Since the BESS can be contained in easy-to-deploy containers, a project's implementation time can be significantly reduced; however, BESS projects are often combined with other energy assets, such as wind or PHV plants, which can prolong a project's implementation time. Thus, time plays an important role in BESS projects. During the time required for completion of a project, uncertainties can evolve significantly, and the assumptions which were used for valuation of the project at its onset may no longer be valid. When selecting an ROA method, it is necessary to understand the assumptions of the model, which must be accepted for project revenues upon the model's adoption.

Hurta [112] concluded that the spot price of electricity was the most recognized project uncertainty. As explained in Section 9.3, spot prices of commodities are, in general, considered mean-reverting and seasonal, which is reflected by the majority of researchers who model fuel prices as MRM [121]. In a BESS project, daily seasonality of a spot price of electricity is of great importance, because it is the main driver of revenues. Just how the pattern of spot price movement is reflected in the revenues of the BESS project depends on the optimization model used for the dispatch problem. Depending on the strength of the mean-reversion of a spot price of electricity—and especially on how strongly the mean reversion effect is transferred into the project revenues as a result—different ROA methods have been proposed.

Fig. 10 depicts the effect of the speed of mean reversion and investment horizon on the selection of an ROA method. When the mean-reversion effect present in the project revenues is high, MCS is recommended as the suitable ROA method, regardless of the investment horizon. This enables practitioners to essentially use any model (including MRM) for modelling project revenues. If BSM or CRRM were used instead, it would be assumed project revenues follow GBM; thus, the revenues would not tend toward their long-term optimum, and the variance of the relative revenue changes would grow exponentially. The latter effect is why MCS is also recommended in the long investment horizon, even when the rate of mean reversion is low. Use of BSM or CRRM under such market conditions would result in an increase in the model's deviation, due to empirical behavior, which would inevitably decrease the accuracy of the option value provided.

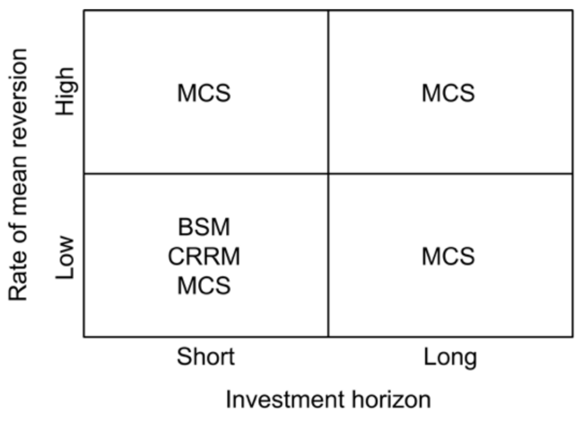

Fig. 10. Selection of an ROA method according to the rate of mean reversion and investment horizon [112].

10.2. Volatility

Volatility is a key determinant of an option value, and for that reason, it should be one of the decision criteria in an ROA method selection process. In ROA, it is important to distinguish between the volatility of a project and the volatility of the uncertainties driving project value. While the former can be expressed as the volatility of project revenues, the latter measures the standard deviation of various variables, such as commodity price or initial capital cost. As described in Section 9.4, the volatility of commodity returns exhibits stochastic, time-varying behavior. Depending also on volatility behavior of other project uncertainties, and on the correlations between them, the stochastic behavior is then (to varying extents) transformed into the volatility of the project.

As identified in Section 4.1, the spot price of electricity and battery cost are the two most recognized uncertainties considered in BESS projects. Battery costs are popularly modelled with GBM (again, as in Section 4.1). In such a case, the volatility of battery cost is treated as a constant. On the other hand, the volatility of a spot price of electricity can hardly be considered as constant, as explained in Section 9.4.

When deciding which model to use for option valuation, it is important to understand how the model treats volatility. While the BSM assumes deterministic volatility, volatility can be time-varying in CRRM and MCS, which provides more flexibility—especially in situations where there is an overlap between project duration and distinctive changes in market volatility. Otherwise, the project value can be significantly undervalued—or, conversely, overvalued. Implied volatility can be used as a valuable indicator when evaluating future market volatility. Calculation of implied volatility from derivatives with different tenors (to get a volatility surface) can help practitioners understand the evolution of volatility that the market expects, and thus support their decision in model selection.

10.3. Number of sources of uncertainty

There are two important uncertainties to consider in a BESS project: spot price of electricity and capital cost. Additional sources of uncertainty can be considered, depending not only on the project's external factors, but also on its configuration. As an example of external factors, subsidies in the form of cash payments or tax reduction can be considered. Regarding project configuration, a BESS is often projected in combination with other energy assets, such as renewable sources of energy, P2G systems, or heat generation. Such complex systems require consideration of a broader list of uncertainties, including, for example: solar radiation, wind power, or the price of hydrogen and the price of heat. It is not necessary that the model capture all uncertainties, especially if the complexity of the model outweighs its benefits. It is always necessary to consider the *purpose* and *audience* of the model, when determining its accuracy and its number of uncertainties.

It is important to identify the sources of uncertainty at the beginning of the capital investment appraisal process, since the number of project uncertainties impacts the choice of a suitable ROA model, as shown in Fig. 11.

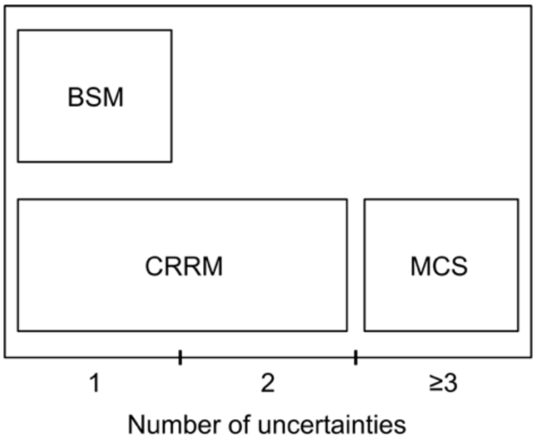

Fig. 11. Relationship between the number of uncertainties and the suitable ROA model [112].

Focusing on the number of project uncertainties, Hurta [112] only recommended using the BSM for energy projects with one uncertainty, unless the uncertainties are correlated. When the BSM is used for valuation of projects with multiple, uncorrelated uncertainties, there is no link between option value and the multiple uncertainty sources; thus, only the aggregated effect of all the uncertainties over the option value can be analyzed.

For projects with one or two sources of uncertainty, Hurta [112] recommended using a binomial or quadrinomial tree model, respectively. With the latter option, the tree provides a pair of branches for each of the two uncertainties, which enables practitioners to clearly track both uncertainties over time—and at the same time, to track the effect uncertainties have over option value.

If there are more than two uncertainties in the BESS project, MCS offers an effective way of simulating all the uncertainties. Since MCS is forward-looking, employing it may require combining the method with a backward-looking one, in situations where it is allowed, for an early exercise of the option.

10.4. Negative prices

As can be seen in Figs. 6-7, the spot price of electricity simulated with GBM cannot be negative. This is evidenced by the histograms, plotted with the distinctive cut-off at 0 EUR/MWh. On the other hand, simulations based on MRM, as can be seen in Fig. 8, allow for negative values. Hurta [112] emphasized the role of negative electricity prices in BESS projects; revenues from BESS projects depend on peak-valley spreads, and curbing the lower extremes by not allowing for negative prices can result in significant undervaluation of the project.

It is important to start the project evaluation with an analysis of market uncertainties. If the spot price of electricity (as one of the uncertainties considered in the BESS project) settles frequently in negative territory, and this behavior is reflected similarly in revenues, then GBM cannot be considered an accurate model for the price. In such cases, MRM can offer a more accurate alternative to GBM. MRM can be further extended with jumps, if necessary, to capture the rich dynamics of the spot price.

As explained in Section 9.1, both BSM and CRRM assume the underlying asset follows GBM. On the contrary, MCS is flexible enough to accommodate other models, including MRM.

At this point, we need to distinguish between: 1) modelling of the spot price of electricity as one of the project uncertainties, and 2) modelling of project revenues as a result of project uncertainties. The latter is decisive when selecting an ROA method. When the spot price of electricity trades frequently in the negative, and at the same time effects the project revenues to such an extent that the revenues can also evolve negatively, then neither BSM nor CRRM can be recommended as an accurate ROA method to value an option on such a project. Instead, MCS in combination with a model other than GBM can be recommended as the most suitable valuation method.

10.5. Expected acceptance by management

In a business environment where discounting cashflow is still the main valuation method for capital investments, it can be difficult to get buy-in from management for a project valued using ROA. Hurta [112] proposed three criteria for consideration, in order to increase the likelihood of acceptable results using ROA-based valuation: treatment of time, graphical representation, and complexity of calculus.

Treatment of time. As one of the constraints of the project management triangle, time plays a key role in projects. Projects involving a BESS, especially those in combination with other energy assets, can span over several years, which places specific demands on the way time is measured in the project.

Based on whether we measure time in a discrete or continuous manner, we distinguish between CRRM and the remaining two methods, respectively [112]. The CRRM approach, where the project horizon is divided into discrete time points, can be deemed more realistic by management, since the CRRM time points can correspond to milestones in the project.

Management may also be accustomed to using discrete-time-based capital valuation, from methods such as NPV. In such cases, a transition from discrete time to continuous time may decrease the probability of management buy-in. Thus, the discrete/continuous time evaluation should include an assessment of the maturity of the current capital appraisal method, with respect to the time framework.

Graphical representation. The manner in which information is conveyed plays an important role in the acceptance of valuation method results. Similar to the case with time, evaluation of the representation criterion should include assessment of the maturity of the current capital valuation process. If an organization currently employs graphical communication approaches to conveying information, then CRRM is the most suitable method for project valuation [112]. CRRM clearly depicts the evolution of the value of both the underlying asset and the option in time, making it is easier for management to comprehend value of the option (i.e., the project), based on the graphical representation of the lattice.

BSM can be defined as the exact opposite: the model provides *no* graphical representation, and as a result, management can find the closed-form solution of BSM difficult to comprehend. In this respect, MCS represents a transition between the two preceding methods: that is, a simulation of the sources of uncertainty still provides a graphical explanation of the logic behind the option value. The method can be subsequently combined with another ROA method to further enhance the graphical representation of the results [112].

Complexity. When a capital valuation method is too complex, managerial decision makers may be reluctant to adopt the method, and may reject the results provided.

Of the three methods considered here, CRRM is considered the least complex ROA approach [112]. As can be seen in Eqs. (10)-(13), the method requires only basic mathematics, and can easily be explained to management.

Since BSM offers a closed-form solution, the process of option valuation is considerably simplified. The BSM formulas are expressed in Eqs. (6)-(9). Hurta [112] concluded that the closed-form formulas are not intuitive, and to understand them, the practitioner should derive the formulas themselves—a process requiring knowledge of PDEs, which some practitioners can find too complex. For this reason, BSM cannot be regarded as less complex than CRRM. The derivation step can be also avoided by applying MCS, which is (as explained in Section 3.2.3) based on more intuitive laws, such as the laws of large numbers, and the central limit theorem.

10.6. Speed of option value calculation

As technology and computation power evolve, the speed of calculation criterion may seem less important; however, there are still distinct differences among the ROA methods when it comes to the time required to value an option.

Clearly, the closed-form solution of BSM enables valuation of options very quickly. CRRM may be considered the more time-intensive valuation method, depending on how many nodes and branches are modelled, but the lattice can be plotted by computer, which significantly simplifies the work. Computational time requirements for MCS depend on the number of uncertainties being modelled, but also on the time range, and on the model being used as an input for the simulation. In general, MCS is considered the most computationally intensive method of the three, and for that reason is usually considered as a last resort [119].

10.7. Early exercise

The possibility of exercising an option early significantly impacts the ROA method selection process, but its impact depends on whether an option bears any dividends. As explained in Section 3.2, dividends can be incorporated into the ROA model to include pay-outs or foregone earnings linked to the real asset. While practitioners often omit dividends from ROA models [112], the inclusion of dividends can undoubtedly provide a more realistic model, and clarification on whether dividends will be included is necessary at this point in the process. When dividends are not considered, the BSM can value both European-and American-style call options on a stock, which are never optimal to exercise early when they bear no dividends [60]. It should be stressed here, however, that the same holds true for stocks.

When early exercise may be desirable, BSM in its basic form cannot be applied for valuation of American options on complex real assets. On the other hand, CRRM can provide a reasonable alternative to BSM, since the backward induction used in CRRM is well-suited to valuation of American options.

MCS in its basic form, as explained in Section 3.2.3, is forward looking, and cannot value early-exercise options. Therefore, MCS should be combined with other methods—for example within LSMC—but such extensions are not considered in the present work.

10.8. Ability to value popular types of real options

Table 2 shows that the option to defer has been the most frequently applied real option type in BESS projects. Similarly, Hurta [112] identified the option to defer as the most popular option in the field of energetics, as can be seen in Table 4. Since the option to defer can be constructed as a call option, all three analyzed models can be used for valuation of the option.

Table 4. Overview of 20 studies that: 1) employ ROA in the energy sector, and 2) identify a spot price of electricity as one of the project uncertainties [112].

	Type of asset	ROA method/model	Types of real options	Electricity spot price model
1	PHES	Simulation	Option to defer	Customized ARIMA model with jumps
2	Wind	DP CRRM	Option to abandon	MRM with jumps
3	Photovoltaic	DP	Option to defer	ARMA model
4	Photovoltaic	MCS	Option to defer	Other GARCH
5	PHES	DP	Option to defer	GBM
6	Coal Gas	DP MCS	Spark spread option	AR model with jumps
7	Nuclear	DP MCS	Option to defer	GBM
8	Biogas	CRRM	Other (regulatory)	MRM with jumps
9	Photovoltaic	DP PDE	Option to defer	GBM
10	Coal Gas	DP MCS	Option to defer	MRM
11	Nuclear hydrogen	DP MCS	Option to switch	GBM
12	Coal	CRRM MCS	Option to stage	GBM
13	Wind Photovoltaic	CRRM MCS	Option to switch Option to defer	MRM with jumps
14	Photovoltaic	MCS	Option to defer	GBM
15	Compressed air	CRRM	Option to defer	MRM
16	PHES	CRRM MCS	Option to defer	GBM
17	PHES	MCS	Option to defer	Other
18	Wind	BSM	Option to defer	GBM
19	Lithium battery	BSM	Option to defer	GBM
20	Hydropower	DP MCS	Option to defer	GBM

Still, application of BSM and MCS for valuation of a deferral option may be seen as far too restrictive by some practitioners, because they do not allow for early exercise. Early exercise is also a reasonable requirement in the case of other types of real options, such as the option to switch or the option to abandon [112]. As described in Section 10.7, CRRM is the preferred method for valuation of such options.

MCS is a meaningful method for valuation of path-dependent exotic options, such as the Asian or barrier options that may be considered marginal in ROA applied to the energy sector [112]. MCS is still valuable, in combination with other ROA methods, to simulate the possible paths an underlying asset can take, where it plays an irreplaceable role.

11. Case study

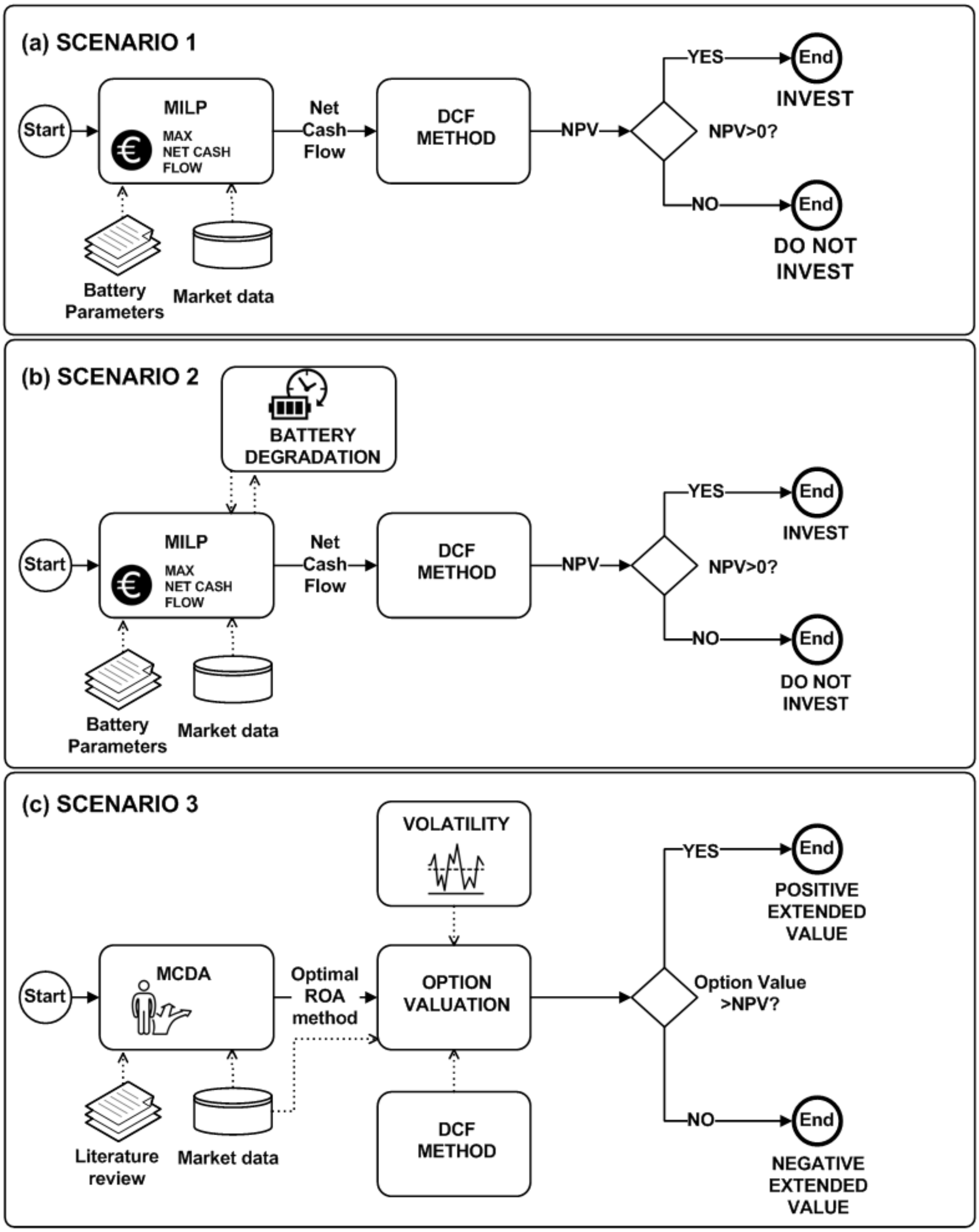

Fig. 12. Structure of the Case study: **(a)** Scenario 1 – MILP model without battery degradation process; **(b)** Scenario 2 – MILP model with battery degradation process; **(c)** Scenario 3 – ROA process.

A real-world case study was formulated to verify the proposed valuation framework depicted in Fig. 4. The study tests the functionality of the methodology, helps answer the research questions raised at the beginning of the study, and ultimately leads to either accepting or rejecting the defined hypotheses.

The proposed real-world Case study assumes the company 'Energy4' is considering an investment in the $LiFePO_4$ BESS, used for price arbitrage in the day-ahead market for electricity at the end of the year 2020. Lithium iron phosphate batteries are still the preferred choice for grid-scale storage, due to their favorable ratio between cost and energy density [5]. The exponential relationship between the DOD and cycle life (shown in Fig. 5) was used for the purposes of this study. While the $LiFePO_4$ BESS was selected specifically for this study, the key conclusions should be applicable to other battery types as well.

Based on findings of Hurta et al. [105], Germany was selected as the location for the $LiFePO_4$ BESS in the case study; in their study, the investment deploying the BESS in the German day-ahead market with gray electricity was able to provide a positive NPV. The positive outcome was facilitated by setting the capital cost to the forecasted value of 100 USD/kWh, but this setting does not overvalue the potential of the German day-ahead market; the ongoing increase of wind energy in the German energy mix is expected to be reflected in the continued increase in volatility of the electricity spot price, which creates potential for the investment.

This case study considers a 1 MWh containerized $LiFePO_4$ BESS from the company GreensunSolar [139], with parameters defined in Table 5.

To determine the size of the discount factor r, various methods such as WACC, CAPM or benchmark projects can be utilized, as explained in Section 2.4. However, applying WACC assumes knowledge of the company's financing, which may be a complex task beyond the scope of this work. Similar complexity can be encountered when trying to find a twin security for the BESS project. For these reasons, the benchmark projects are analyzed to determine a realistic discount rate for the project. In the Energy Storage Benefit-Cost Analysis prepared by the Applied Economics Clinic in December 2022, the discount rate for BESS reported in recent years ranges from 8 to 10% [140]. The International Renewable Energy Agency, in its analysis on the cost of financing for renewables [141], provides the cost of capital based on surveys carried out in 45 countries in 2020/2021. The cost of capital ranges from 1.1% to 12%, depending not only on the exact type of project but especially on the country. Although BESS was not subject of the survey, the wide range demonstrates the variability of the discount rate applied to energy projects, where the country of installation plays a major role. For this study, the discount rate r is set to 9% p.a. / 0.75% p.m., which falls within the ranges of both the cited analyses. The monthly cashflows are discounted with the monthly discount rate to determine the present value of the cashflows.

Table 5. Parameters of the $LiFePO_4$ BESS used in the Case study.

Parameter	Value	Reference
C_{MAX}	1.0 MWh	[139]
P_{MAX}	1.0 MW	[139]
ε	0.96	[1]
CL	2600 - 34957 cycles	[109]
Calendar life	15 years	[109]
I	345 USD/kWh	[2]
r	9% p.a.	[140-141]

The initial capital outlay is set to 345 USD/kWh, which was a valid cost level for the year 2020 [2]. The exchange rate as of September 11, 2022 was 1 EUR/USD [142], a figure used to convert the values to EUR-denominated costs.

No energy storage grid fees are considered. The rationale behind this assumption is the fragmented treatment of the energy storage across the EU when it comes to grid fees. The European Union Agency for the Cooperation of Energy Regulators (ACER) issued a report on electricity tariff methodologies across Europe in 2021 [143] in which it states that there is no common understanding of the term "distribution tariffs". Given there is a significant number of different tariffs in place, they conclude that any comparison would be difficult and potentially misleading [144]. The fragmentation can be better explained on the example of Germany which is the only assessed country applying a "negative injection charge". By this instrument, a distribution system operator can avoid the amount of electricity from the upstream grids that is injected into their grid by decentralized generators. The decentralized generators then receive "avoided network charges" [143]. BESS that went into operation before January 1st 2023 belong currently among the energy assets being remunerated [145]. Including such charges in the analysis would complicate a potential use of the model and its results on different markets. In none of the 13 studies reviewed in Section 2.5, grid fees were considered.

Similarly, any fees related to trading on the exchange such as transaction fees, annual fees or technical fees are not considered, as these are specific to the selected exchange. See for example the price list applied by EXAA [146].

Zero taxation is assumed to avoid added complexity introduced by varying tax regimes across different countries. O&M costs are also assumed to be zero because these can be significantly varying depending on the country or the size of a company. Additionally, no maintenance downtime is considered, and inflation rate is assumed to be zero. These assumptions aim to enhance focus on the dispatch problem.

To calculate NPV, the prices of gray energy on the DE day-ahead market operated by EXAA [17] are used. As the consideration is made at the end of the year 2020, prices from the period 2020-01-01 to 2020-12-31 are selected. The selection of the one-year time series should provide representative behavior of the market while respecting constraints such as data availability and computational complexity.

As shown in Fig. 12, the Case study is divided into three Scenarios. While Scenarios 1 and 2 verify functionality of the DCF process, Scenario 3 is dedicated to the ROA process. Scenario 1 solves the defined Case study as a BESS dispatch problem unconstrained by the battery degradation costs described in Section 8.1, while Scenario 2 solves it as a problem constrained by the battery degradation costs described in Section 8.2. Scenario 3 uses the results of the more mature model from Scenario 2 as an input for ROA.

In Scenario 3, the company 'Energy4' is aware of the uncertainty in the day-ahead market shown in Fig. 13, and wants to quantify the value of deferring the investment until a later time. The company can reserve the necessary resources until the year 2025, and it possesses the flexibility to provide those resources to invest in any year until 2025. There is flexibility to carry out project changes related to scope, cost, and time in all phases of the project. The company perceives the future day-ahead price of electricity as the main driver of the project's cashflow, and thus as the only important uncertainty of the project. It is not required to consider pay-outs or foregone earnings, so dividends do not need to be included in the analyses. The ROA method is required to provide decently accurate results; however, high accuracy at simplicity's expense is not desirable, as the company currently uses the DCF method as its valuation method for capital investments.

Management of the company demands an update presentation as soon as possible, with results of the capital investment appraisal from Scenario 2 with ROA. Thus, there is time pressure to deliver the results, and to support the investment decision process.

The project can be perceived as an option to wait. Given the flexibility possessed by management, an American call option should be used to value the option, and MCDA is used to select a suitable valuation model for this option. Of the three methods described in Section 5.5, Saaty's method is selected for criteria weighting. In contrast to the Scoring method, it makes comparisons between all the criteria. Because it also enables expressing the size of the preference, Saaty's is preferred to Fuller's triangle, and was also selected as the preferred method for ranking of alternatives and for determining the weights of the experts. This choice is in line with the high popularity of the Saaty's method as an MCDA technique [147-148].

The case study is segmented into 3 Sections. Section 11.1 presents results of the DCF method process, which is followed by the ROA process; Section 11.2 is dedicated to the MCDA sub-process, and Section 11.3 (specifically Sections 11.3.1 and 11.3.2) to two sub-processes: project uncertainty determination and sub-process option valuation, respectively.

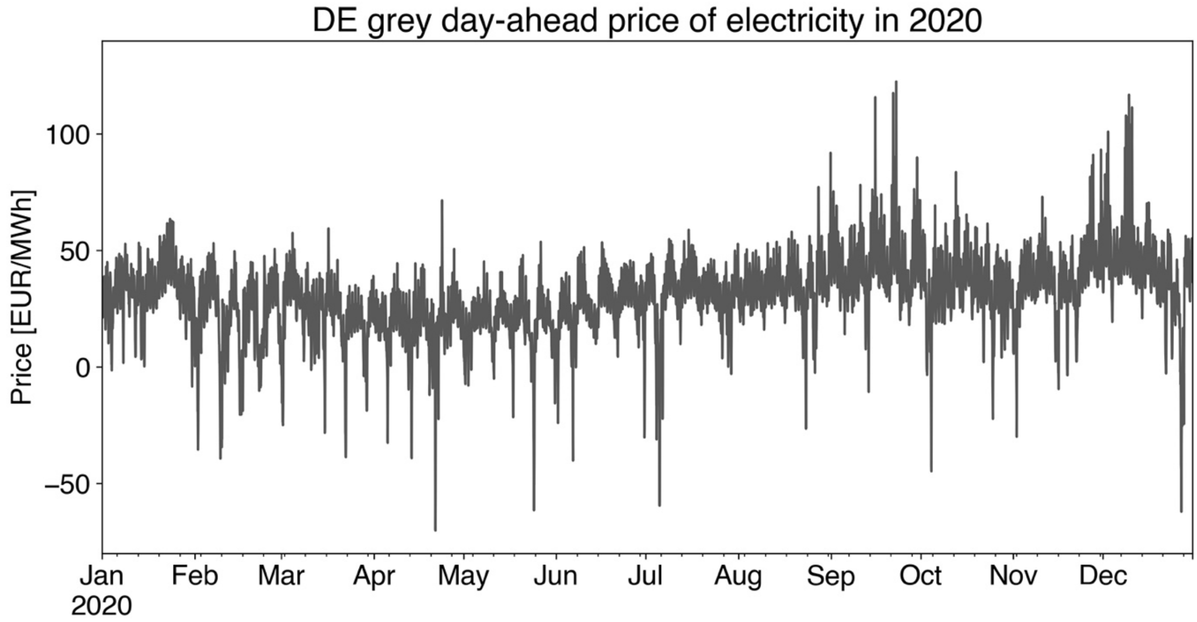

Fig. 13. Evaluation of the DE gray day-ahead price of electricity in the year 2020 [17].

11.1. DCF

The results of the DCF method process are divided into Scenario 1 (in 9.1.1), and Scenario 2 (9.1.2). As shown in Fig. 12, Scenario 1 does not consider aging of the BESS, a factor improved in Scenario 2 by incorporating the battery degradation process into the MILP model.

11.1.1. Scenario 1

The discounted net cashflow and NPV of the BESS project in Scenario 1 are presented in Fig. 14 and Table 6. The sum of the discounted net cashflow generated in 2020 equals 12794 EUR. To generate the cashflow, as much as 28.8% of the cycle life was used up just during the one year, which can be translated into 99360 EUR as the initial capital outlay. This inevitably leads to a negative NPV of -86566. The result does not justify investment in the BESS project.

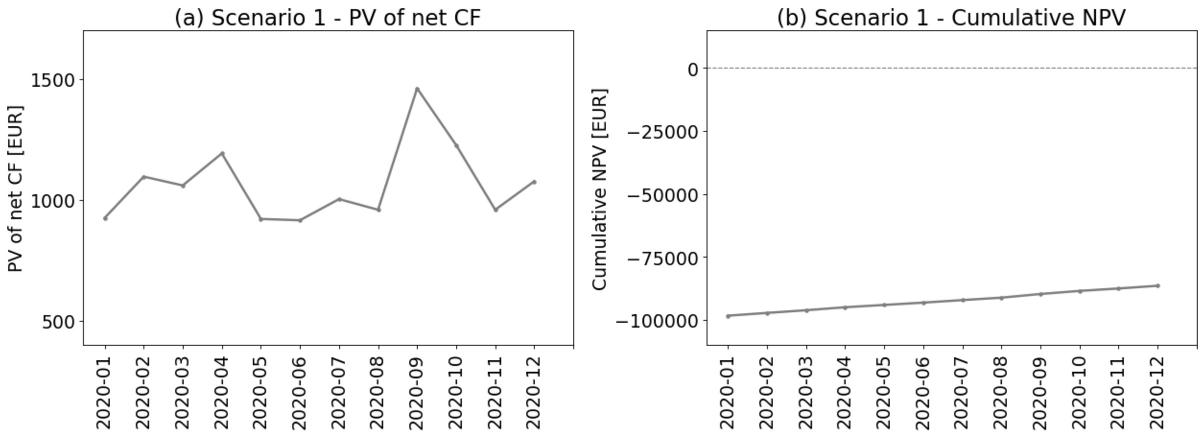

Fig. 14. Scenario 1 – Discounted net cashflow and cumulative NPV from a BESS dispatch ignoring the battery degradation process in the dispatch model.

Table 6. Scenario 1 – Results of the BESS dispatch.

Parameter	Value
Accumulation [MWh]	806
Generation [MWh]	774
Sum of PV net CF [EUR]	12794
NoC(T)	748
NoC(T)/CL	0.288
T/RL	0.067
NPV [EUR]	-86566

11.1.2. Scenario 2

In comparison to the previous Scenario, in Scenario 2 the dispatch model has been extended to consider the degradation process of the battery. As can be seen in the objective function described in Eq. (36), the degradation factor φ guarantees that the operation of the BESS does not only pursue maximization of net cashflow, but also considers both cycle and calendar degradation, with the goal of finding an optimum between the two variables. The key driver of cycle degradation is *DOD*, thus sensitivity of the model to this variable is evaluated. The results are presented in Fig. 15 and in Table 7.

When comparing Fig. 14a with Fig. 15a, it is clear that discounted net cashflow has decreased significantly, peaking at 841 EUR in September in Scenario 2, instead of 1460 EUR in Scenario 1. However, the more selective dispatch has been positively rewarded by the increase of NPV, as can be seen by comparing Figs. 14b and 15b. While NPV totaled at -86414 in Scenario 1, NPV significantly improved in Scenario 2, reaching the value of - 15635 EUR (for 60% *DOD)*.

When evaluating sensitivity of the model to *DOD*, the highest NPV has been generated when dispatching the battery at 60% *DOD*. This finding is in line with the conclusions of Hurta et al. [105], and it stems from the typical pattern in the selected day-ahead prices with two peaks a day. When the battery is constrained with the calendar life of 15 years, and the cycle life equals 10019 cycles, then the battery should perform 1.83 cycles a day to fully utilize its cycle life within the calendar life. Out of all the *DOD* considered, in case of 60% *DOD* is this minimal utilization coefficient closest to the 2 peaks a day, which balances best cycle aging with calendar aging. More shallow cycling (40% *DOD* or even 20% *DOD*) requires performing on average more than two cycles a day, which cannot be justified on the current price level with only two peaks a day.

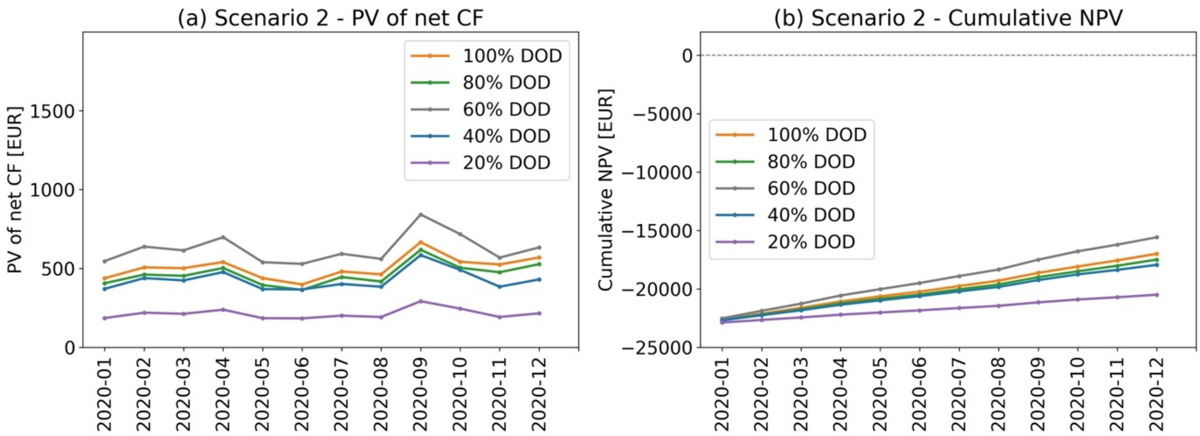

Fig. 15. Scenario 2 – Discounted net cashflow and cumulative NPV from a BESS dispatch respecting the battery degradation process in the dispatch model. Sensitivity of the dispatch model to *DOD*.

Table 7. Scenario 2 – Sensitivity of the dispatch model to *DOD*.

	DOD=20%	DOD=40%	DOD=60%	DOD=80%	DOD=100%
Accumulation [MWh]	162	322	402	160	159
Generation [MWh]	155	310	387	153	152
Sum of PV net CF [EUR]	2561	5121	7480	5569	6069
NoC(T)	761	754	626	188	149
NoC(T)/CL	0.022	0.038	0.062	0.058	0.057
T/RL	0.067	0.067	0.067	0.067	0.067
NPV [EUR]	-20554	-17994	-15635	-17546	-17046

Obviously, when battery degradation process was not part of the defined MILP, the BESS was dispatched at high frequency, which is reflected in (among other factors) the relatively higher accumulation and generation in Scenario 1; the cycle degradation (*NoC(T)/CL*) exceeded the calendar degradation (*T/RL*), which proved to be economically unjustifiable, looking at the negative NPV.

After the introduction of the battery degradation process in Scenario 2, the MILP model has substantially improved financial expectations from the investment.

In the next step, sensitivity of the model to the size of investment costs is analyzed. Five different investment costs are considered. The highest investment costs, the baseline scenario, are 345 USD/kWh. In the following sensitivity scenarios, the investments costs are reduced up to 10 EUR/kWh. For the sensitivity analysis, 100% *DOD* is selected to enable comparison of the results also with Scenario 1. The results are presented in Fig. 16 and Table 8. As the investment costs decrease, the frequency of dispatch goes up, which results in the increase of accumulation, generation, sum of cashflow, number of cycles and cycle degradation. In the last sensitivity scenario (10 USD/kWh), the value of cycle degradation exceeds the calendar degradation, and it approaches the value from Scenario 1, but in contrast to Scenario 1, the increase in the degradation is justified by the positive NPV.

The last two sensitivity scenarios (50 USD/kWh and 10 USD/kWh) resulted in a positive NPV, unlike the third sensitivity scenario (100 USD/kWh) with NPV close to the NPV breakeven point. To determine the breakeven point, the input investment costs are stepwise changed by the unit of 1 USD/kWh in the model to identify the first occurrence of investment costs generating a positive NPV. By this procedure the breakeven point is identified at 98 USD/kWh.

The sensitivity analysis of the model to investment costs confirmed the model is sensitive to the size of investment costs. Reduction of the initial capital outlay led *ceteris paribus* to a more frequent dispatch of the BESS, and to an increase of NPV. While the increase of the dispatch frequency was rather subtle until the NPV breakeven point, the sensitivity to investment costs has significantly increased when there was an incentive in the form of a positive NPV, i.e., beyond the NPV breakeven point.

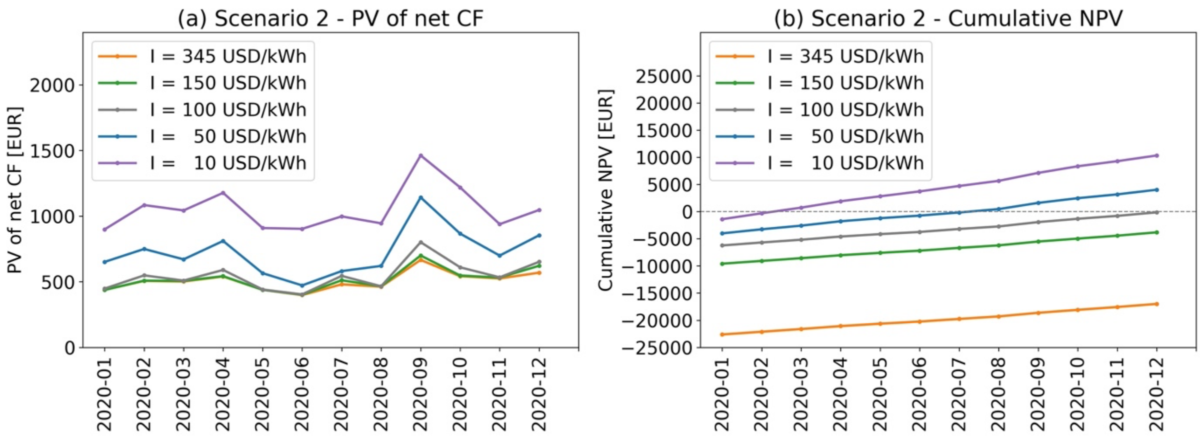

Fig. 16. Scenario 2 – Discounted net cashflow and cumulative NPV from a BESS dispatch respecting the battery degradation process in the dispatch model. Sensitivity of the dispatch model to investment costs.

Table 8. Scenario 2 – Sensitivity of the dispatch model to investment costs.

	345 USD/kWh	150 USD/kWh	100 USD/kWh	50 USD/kWh	10 USD/kWh
Accumulation [MWh]	159	161	168	259	642
Generation [MWh]	152	153	161	248	617
Sum of PV net CF [EUR]	6069	6212	6546	8684	12625
NoC(T)	149	151	158	242	597
NoC(T)/CL	0.057	0.058	0.061	0.093	0.230
T/RL	0.067	0.067	0.067	0.067	0.067
NPV [EUR]	-17046	-3838	-154	4034	10325

11.2. ROA: MCDA

The following Sub-sections correspond to the flow of MCDA sub-process, as described in Section 5.

11.2.1. Determination of a goal of a decision process

MCDA should help to identify the suitable ROA method, of the three methods considered, and fulfil the following qualitative goals:

- Extend the NPV value quantified in Section 11.1 with a positive project value, stemming from the uncertainty of the project, and the fact the decision makers have the flexibility to make changes to the project in all of its phases.
- Represent in graphical form the evolution of the extended project value, which can be easier to comprehend by the broad audience with different backgrounds.
- Identify the optimal time point for the investment.
- Provide a valuation method possessing a reasonable level of accuracy, keeping in mind that high accuracy at the expense of comprehensibility is not desirable.

11.2.2. Determination of assessment criteria

The assessment criteria defined in Section 10, which are recommended for use in selecting the suitable ROA method for valuation of a BESS project, are applied to fulfil the goals set in Section 6.2. These eight assessment criteria include:

- Expected acceptance by management.

- Early exercise.
- Negative prices.
- Time horizon.
- Volatility.
- Ability to value popular types of real options.
- Number of sources of uncertainty.
- Speed of option value calculation.

11.2.3. Determination of subject and object of the decision process

For the purposes of this study, five experts were selected to act on behalf of the model company, to carry out MCDA. To select the suitable decision makers, three attributes have been considered: education, years of experience, and number of publications. All three attributes were evaluated in relation to the fields of financial derivatives, energetics and project management.

Profile of *Expert 1* (E1) – after graduating from the Prague University of Economics and Business in Finance, E1 started his career in one of the biggest Czech banks in 2009, working as a market risk specialist/manager. He has since gained knowledge across a variety of asset classes and trade types, including financial options. He has not published any publications so far.

Profile of *Expert 2* (E2) – received his master's degree in finance from the Masaryk University in Brno in 2012. Since 2019 the expert has been working in the bank industry, where he is focusing on derivatives including option contracts. The expert has published three (3) publications, which include coverage of option theory.

Profile of *Expert 3* (E3) – graduated from the Faculty of Information Technology and has completed several business and finance related courses. Since 2019, the expert has been working in an international bank, being responsible for the development of applications used for monitoring credit risk. An expert with a strong IT background, E3 was selected to complement the group of experts with distinct IT skills, which can be beneficial when evaluating some of the defined assessment criteria, including expected acceptance by management and speed of option value calculation.

Profile of *Expert 4* (E4) – graduated from the Faculty of Electrical Engineering and Communication. For 5 years, the expert has been an analyst in one of the leading Czech energy companies, where he values diverse energy assets including battery storage projects.

Profile of *Expert 5* (E5) – received his master's degree in economics from the Charles University. Since 2013 the expert has been working as a project manager in a strategy and business development department of one of the leading Czech energy companies, where he is focusing on valuation of energy projects.

In the first step, the weights of the respective expert opinions must be determined. The role of the supra decision-maker, who performs the Saaty's method to analyze the experts, was performed by the author of the present study. Table 9 summarizes the criteria used as an input for Saaty's method. The weights of criteria $\boldsymbol{w_j}$ are set to 0.333, as they are believed to have the same priority. Results of the pair-wise comparison of the experts in respect to the three criteria, based on Eq. (18), are shown in Tables 15-17 of the Appendix A, and a summary is provided in Table 10. The expert E_2 earned the highest score and, consequently, has the highest priority. In contrast, expert E_3 achieved the lowest score and, therefore, holds the lowest priority.

Table 9. Criteria used for determination of priority of the experts.

	Education	**Years of experience**	**Number of publications**
E_1	3	14	0
E_2	3	4	3
E_3	1	4	0
E_4	3	5	0
E_5	3	10	0
w_j	0.333	0.333	0.333

Table 10. Scores of the experts with respect to the three criteria, including the resulting weights.

	E_1	**E_2**	**E_3**	**E_4**	**E_5**	$\boldsymbol{w_j}$
z_1^i	0.231	0.231	0.077	0.231	0.231	0.333
z_2^i	0.378	0.095	0.095	0.145	0.286	0.333
z_3^i	0.143	0.429	0.143	0.143	0.143	0.333
$Z_i = w_e$	0.250	0.252	0.105	0.173	0.220	

A capital investment appraisal process, which is under supervision of the investment controlling department, is defined as the object of the decision process.

11.2.4. Generation of alternatives

The following three alternatives were analyzed:

- BSM (A_1)
- CRRM (A_2)
- MCS (A_3)

These three ROA methods are considered the most popular valuation methods in energy projects, where a spot price of electricity is an important determinant of project's cashflow [68], [72], [112]. The review conducted in Section 4.1 confirmed the popularity of both DP and LSMC, a finding that contradicted the conclusion of the above authors. For this reason, neither DP nor LSMC is analyzed in this work. Another reason for their omission is the generally higher complexity of these two methods compared to the three defined methods, as explained in Section 3.2. This work should provide a bridge between DCF and more quantitative approaches to valuation of capital investments; thus, only the three simpler methods were considered.

The literature review carried out in Section 4.1 was used to compile criteria data for the defined alternatives.

11.2.5. Criteria weighting

In the first step, the criteria are ordered according to their assumed priority in a descending order, and they are assigned an ordinal number respecting this order, as can be seen in Table 11. The supra decision-maker (i.e., the author of the present study) believes that the expected acceptance by management is the most important criterion because it covers several sub-criteria which the existing literature considered especially important for business environments in which DCF is the preferred way of valuing capital investments. On the other hand, the speed of option value calculation was assessed as the least important criterion. The order can be changed, depending on the specific requirements and preferences of the organization carrying out this assessment.

The ordered list of criteria in the Table 11 enables determination of the scoring scale in the next step. By assuming that the most preferable criterion C_1 is eight times more preferable than the least preferable, criterion C_8, the scoring scale is set to range from 1 to 8 points, where 8 points is the maximum number of points available.

Table 11. Decision criteria order by priority, in descending order.

Criterion	Description
C_1	Expected acceptance by management
C_2	Early exercise
C_3	Negative prices
C_4	Time horizon
C_5	Volatility
C_6	Ability to value popular types of real options
C_7	Number of sources of uncertainty
C_8	Speed of option value calculation

All pairs of criteria are compared in Saaty's matrix, and one matrix was constructed for each expert. The resulting matrices, with expert scores, are found in Tables 18-22 of the Appendix B. A summary of the tables with normalized criteria weights is shown in Table 12, including the priority (weight) w_j^i of each criterion *j* from the view of each expert *i*. The resulting, prioritized criteria matches the order determined at the beginning of the analysis; Criterion C_1 was viewed as the most important, while criterion C_8 was seen as the least important.

Table 12. Criteria weights from the perspective of the three experts.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
w_j^1	0.330	0.200	0.160	0.130	0.070	0.050	0.030	0.030
w_j^2	0.275	0.161	0.157	0.137	0.077	0.102	0.055	0.037
w_j^3	0.319	0.251	0.095	0.090	0.086	0.057	0.053	0.050
w_j^4	0.314	0.240	0.100	0.095	0.085	0.058	0.054	0.054
w_j^5	0.305	0.233	0.104	0.099	0.082	0.062	0.057	0.058

11.2.6. Creation of a decision-making matrix

For each of the experts, a decision-making matrix such as the one in Eq. (50) can be constructed. Each of the metrices is a result of:

- three alternatives A_m, defined in Section 11.2.4,
- eight criteria C_n, defined in Section 11.2.2 or more specifically in the Section 10,
- eight weights w_n, calculated in Section 11.2.5.

$$\begin{array}{cc} & \begin{array}{ccc} C_1 & \cdots & C_8 \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ A_3 \end{array} & \begin{bmatrix} x_{11} & \cdots & x_{18} \\ \vdots & \ddots & \vdots \\ x_{31} & \cdots & x_{38} \end{bmatrix} \\ & \begin{array}{ccc} w_1 & \dots & w_8 \end{array} \end{array} \tag{50}$$

The variables $x_{11} - x_{38}$ represent the data for all alternatives combined, including all criteria. In other words, *each* alternative must be analyzed from the perspective of *each* of the eight defined criteria. This data has been compiled as part of the analysis carried out in Section 10.

11.2.7. Scoring and ranking

Because Saaty's method was used for criteria weighting, it was also used for scoring and ranking of the defined alternatives. For all criteria, the scoring scale was set to range from one to three points, which means that the most preferable alternative may be three times more preferable to the least preferable alternative, in relation to any of the criteria.

All alternatives must be compared with each other, with respect to all criteria. Given the number of experts (in this case, five), a total of 40 metrices were required to perform the full comparison. The resulting metrices with expert scores, are provided in Tables 23-62 of the Appendix C.

In the tables' last columns, the normalized scores $z_{e,j}^{i}$ are calculated by normalizing $GM_{e,j}^{i}$ for the *i*-th alternative, *j*-th criterion, and *e*-th expert.

Eq. (21) is applied to the normalized scores $z_{e,j}^{i}$ to aggregate the individual weights into the aggregated scores z_j^i, shown in Table 13.

Table 13. Scores Z_i of the alternatives, and the resulting ranking.

	A_1	A_2	A_3
z_1^i	0.173	0.534	0.293
z_2^i	0.204	0.578	0.218
z_3^i	0.288	0.430	0.282
z_4^i	0.293	0.399	0.308
z_5^i	0.239	0.409	0.352
z_6^i	0.258	0.365	0.377
z_7^i	0.320	0.447	0.233
z_8^i	0.539	0.284	0.177
Z_i	0.250	0.471	0.279
Ranking	3	1	2

In the same table, Eq. (20) is applied to calculate normalized scores Z_i of the three alternatives. Based on the achieved scores, CRRM (A_2) is the most preferred method, followed by MCS (A_3) and BSM (A_1).

11.3. ROA: CRRM

The results from Scenario 2 were used as inputs for Scenario 3, to calculate the value of waiting, and to determine the optimal timing of the investment. The assumptions defined at the beginning of Section 11, which were used for the previous Scenarios, remain unchanged. Before constructing the CRRM for valuation of the American call option in Section 11.3.2, project uncertainty must be determined, as shown in Fig. 4b.

11.3.1. Volatility of project's cashflow

To calculate the u and d rates defined in Eqs. (10) and (11), respectively, and to subsequently calculate the risk-neutral probability p defined in Eq. (12), it was necessary to determine the volatility σ of the project's cashflow. MCS was deployed to simulate the cashflow, and the process of the simulation is as follows:

1. The future day-ahead spot price of gray electricity in the German market is the only source of uncertainty in the project. The MRM defined in Eq. (41) was selected as the model for the price, since it enables to model both negative prices and daily seasonality. To calibrate the model, the historical volatility approach described in Eqs. (42)-(43) was selected over the other methods explained in Section 9.4. because of its transparency, and because of the availability of the historical data. This approach is conservative and assumes the future volatility is derived from past movements. A total of 1000 simulations were performed to generate the expected future realizations of the price. More simulations were not performed, due to high computational time.
2. For Scenario 3, the project's cashflow for all the 1000 different sets of prices was calculated based on the defined MILP model, i.e. the MILP model was executed 1000 times. The sensitivity analysis carried out in Section 11.1.2 identified 60% *DOD* as *DOD* generating the highest NPV, and, therefore, it is used in Scenario 3. The investment costs are set to 345 USD/kWh, which is the value from the baseline scenario (cost level of the year 2020). Similarly, as in the previous point, the logarithmic returns approach was applied to calculate volatility of the simulated weekly returns in Scenario 3. Weekly returns were preferred to hourly/daily returns, because they better reflect the changes driven by the behavior of the day-ahead prices. Hourly/daily returns were driven by the algorithm defined in the MILP program, which allowed some hours

of negative revenues, in order to generate positive revenues in the following hours. The volatility calculated from the hourly/daily revenues would then produce an overestimated value of project's volatility. Weekly returns smooth these short-term negative revenues, i.e. they remove the noise, and better reflect the revenues profile as a result. The annualized volatility σ is calculated from the weekly volatility σ_W by annualization: $\sigma = \sigma_W\sqrt{52}$.

Ad 1

The initial price P_0 of the process was set at 47.36 EUR, which was the price of the last hourly contract on gray power in the DE market in the year 2020 (2020-12-31 23:00). The prices of the same market in the year 2020 were used to calibrate the model, as follows:

- $\sigma = 16.86$
- $\mu = 30.35$
- $\alpha = 9.71$

Prices of 8760 hourly contracts, which equals the length of one year, are simulated. Ten (10) out of the 1000 simulations performed are plotted in Fig. 17.

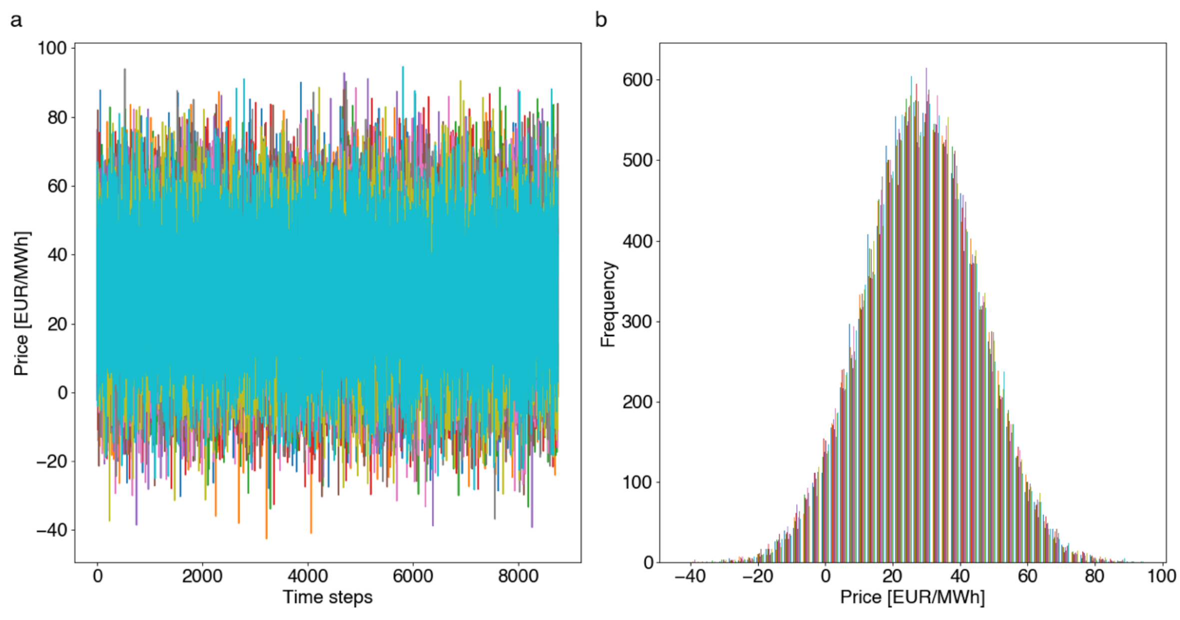

Fig. 17. Simulations (totaling 1000) of the day-ahead price based on MRM: **(a)** Price plot of 10 simulations; **(b)** Histogram of 10 simulations.

Ad 2

The prices simulated in the preceding step were used for calculating the net cashflow in the next step. Ten (10) plots out of the 1000 simulations for Scenario 3 are plotted in Fig. 18.

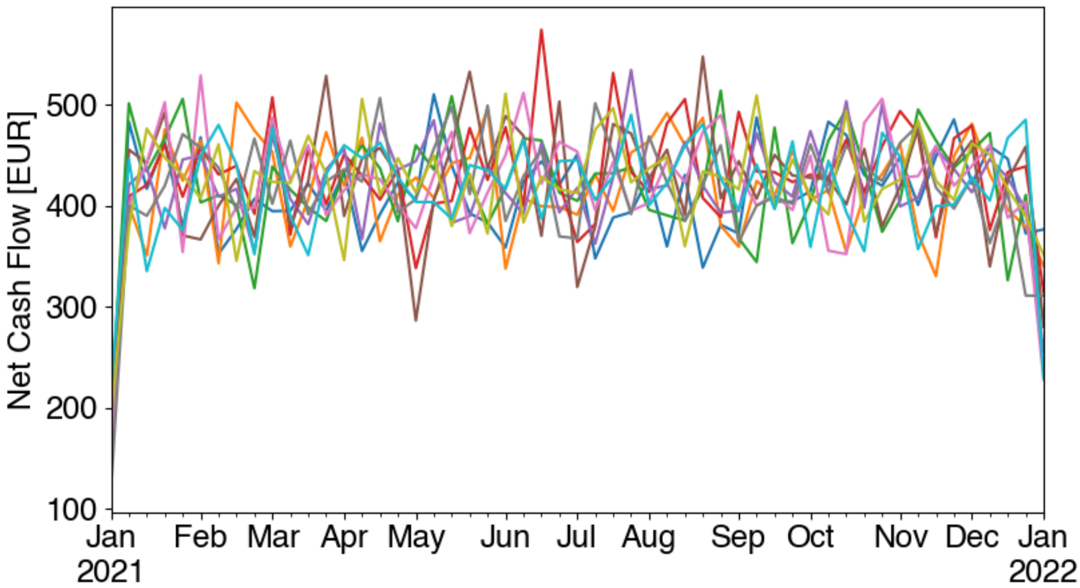

Fig. 18. Scenario 3 – Net Cash Flow of 10 out of the 1000 simulations.

In Scenario 3, σ_W calculated from the resulting weekly data equals 0.2050, so the annualized value σ equals 1.4783.

11.3.2. Construction of CRRM

The volatility of project cashflow calculated in the preceding step is used for construction of the CRRM. The parameters necessary for its construction are summarized in Table 14.

The sum of discounted net cashflow generated in the year 2020 in Scenario 2 is used as the initial value of the underlying asset S_0. The strike price K corresponds to the battery degradation accrued in the year 2020—i.e., the initial capital costs (345000 EUR) are multiplied by the rate of degradation (0.067). By this adjustment both the discounted net cashflow and the capital costs relate to the same period. The rate of up movement u and down movement d are calculated according to Eqs. (10) and (11), respectively. Similarly, the risk-neutral probability p is calculated with Eq. (12). Just as in Scenario 2, the discount rate r is assumed to be 9% p.a.

The resulting lattice for the underlying asset, i.e., the net cashflow, is shown in Fig. 19. In the best scenario, when the underlying asset value evolves only upwards, the net cashflow equals 2766761.53 EUR in 2025. In the opposite situation, i.e., when the underlying asset value evolves only downwards, the net cashflow equals 20.22 EUR.

Table 14. Scenario 3 - values of the parameters used for the construction of CRRM.

Variable	Value
$S(0)$	7480.00 EUR
K	23115.00 EUR
σ	1.4783
u	4.3855
d	0.2280
p	0.2083
r	9% p.a.

The lattice for the determination of the option value is presented in Fig. 20. The value in the first node corresponding to the option value equals 6018.33 EUR. In none of the nodes leading to the terminal nodes, the option value in the given node is greater than the intrinsic value in this node. This means it is not optimal to exercise the option before its maturity. Instead, it is optimal to continue holding the option until 2025. The investment recommendation for the lattice is plotted in Fig. 21 recommending investing only in two terminal nodes. In the remaining three terminal nodes, the same as in their three preceding nodes, the recommendation is to let the option expire as the option value is zero. Thus, given the market situation, the company should use its flexibility to postpone the investment until the end of the four-year period. As can be seen in Fig. 21, the company can abandon the investment plans prior to the year 2025, when the market evolves in an unfavorable direction, and direct the resources into different, more profitable, projects.

The value of waiting can be determined by subtracting the NPV (-15635 EUR) calculated in Scenario 2 from the option value (6018.33 EUR). The positive value of waiting of 21653.33 EUR quantifies the benefit of delaying the investment and provides an alternative to investing immediately quantified by NPV. It shows that counting solely on the traditional methods such as NPV would undervalue the investment by not including the value of waiting in the value of the investment.

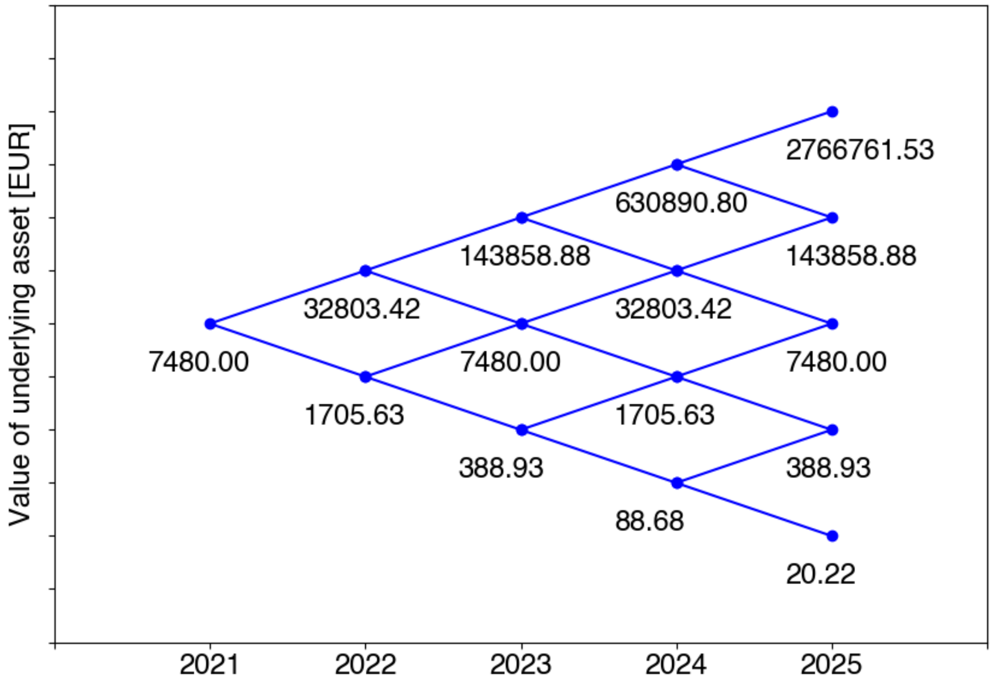

Fig. 19. Scenario 3 – Value of the underlying asset.

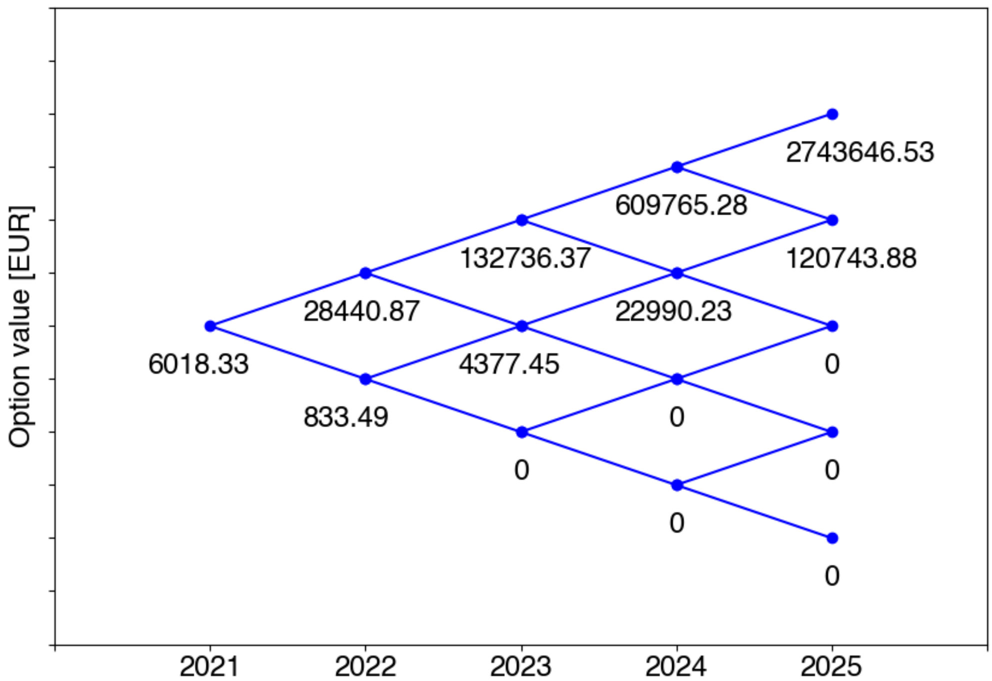

Fig. 20. Scenario 3 – Value of the American call option.

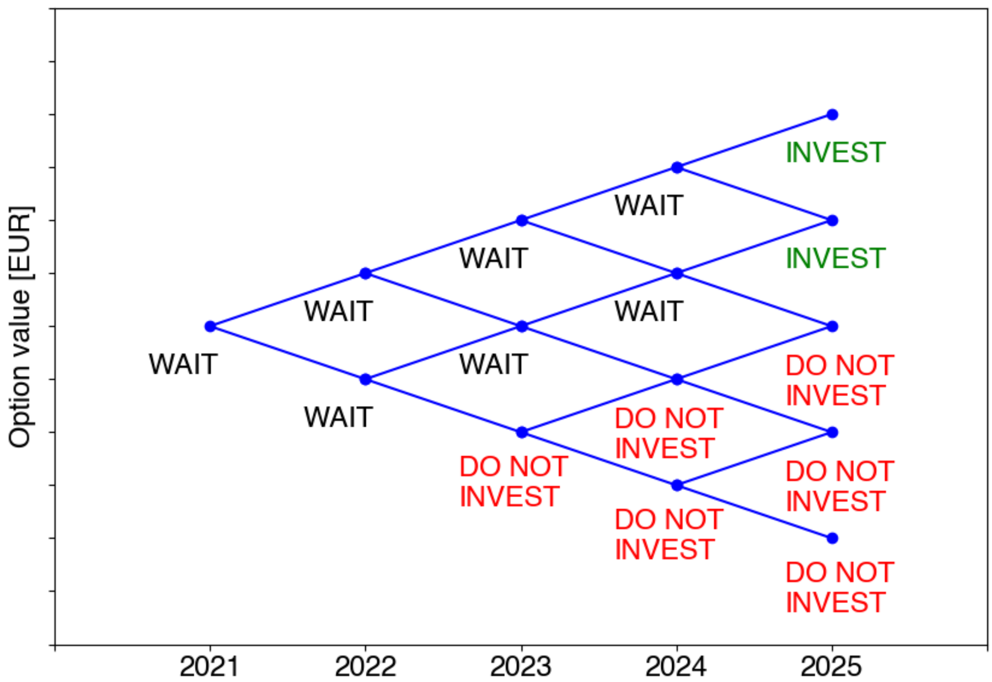

Fig. 21. Scenario 3 – Decision on the investment.

PART III

Conclusions

12. Evaluation and suggestions for future research

12.1. Evaluation of research questions

The concluding chapter of this dissertation provides answers to the three defined research questions.

Q1: "Can ROA be recommended as an extension of the traditional DCF method for valuation of investments in BESS projects?"

ROA proved to be a capable tool for evaluating the uncertainty and flexibility inherent in BESS projects in both the literature review and the case study. Because the traditional DCF method excludes these two factors, it can undervalue a BESS project. The effect was striking, especially in the case study when comparing Scenario 2 with Scenario 3. When counting solely on NPV, the investment would be unlikely to earn management approval, given the negative NPV value. Valuation of the very same investment using ROA showed potential for the investment, given the high volatility on the day-ahead market. The chance that the market will evolve in a favorable direction is of value, especially when management has the power to reject the investment when the opposite situation arises. For the above reasons, BESS projects should be always valued with *both* the DCF method and ROA.

Q2: "What is the impact of initial capital cost on dispatch of the battery, and on the resulting value of the investment?"

As confirmed by the preceding case study (Section 11), lower initial costs lead, *ceteris paribus,* to a higher frequency of dispatch for BESS, reflected in the higher NPV value as shown in Scenario 2. The sensitivity to investment costs has significantly increased beyond the NPV breakeven point.

Q3: "What assessment criteria can be used for selection of ROA method used for capital investment valuation of BESS project out of the existing ROA methods?

Eight assessment criteria have been proposed: expected acceptance by management, early exercise, negative prices, time horizon, volatility, ability to value popular types of real options, number of sources of uncertainty, and speed of option value calculation. These assessment criteria help facilitate the process of selecting a ROA model for valuation of a BESS project.

12.2. Evaluation of goals of the dissertation

The main goal of this dissertation, namely **creation of an ROA-based framework for advanced capital investment valuation of BESS projects,** has been achieved in Sections 7-10. Functionality of the framework has been verified by performing the case study in Section 11.

The sub-goals supporting the main goal have been achieved as follows:

- Create an optimization program for a dispatch of BESS to maximize the NPV of the investment, which can then be used as one of the inputs for ROA.

  The program for dispatch of a BESS was defined with two versions of the MILP model, where the initial MILP maximizing net cashflow of a project was extended with a battery-degradation process in the second, more advanced, MILP. The extended version of the model was subsequently used as an input for ROA in the case study in Section 11.
- Consider popular ROA methods in the proposed valuation framework and provide a method for selecting the suitable method for valuation of a BESS project, based on specific valuation requirements.

  MCDA was proposed as a suitable selection method. Eight assessment criteria were determined, based on the in-depth literature review, and defined as follows: expected acceptance by management, early exercise, negative prices, time horizon, volatility, ability to value popular types of real options, number of sources of uncertainty, and speed of option value calculation. These eight assessment criteria have been combined with three alternatives, representing the most popular ROA models: BSM, CRRM and MCS. This combination was used to create a decision matrix which can easily be re-used and applied to any specific conditions and requirements to value a BESS project.
- Verify functionality of the created framework through its application to a real-world business case.

  The case study in Section 11 confirmed that the proposed valuation framework is functional and that it can be used to:

  - Calculate NPV value of BESS project considering the battery degradation process.

- Select an ROA method for a BESS project which best meets the specific conditions and requirements of the valuation process.
- Calculate the value of uncertainty and flexibility inherent in a BESS project.

12.3. Evaluation of author's hypotheses

H1: The traditional DCF method undervalues investments in BESS projects, but results can be improved by applying ROA to value the uncertainty and flexibility inherent in these types of projects.

The review of the literature on ROA applied to BESS projects in Section 4.1 showed that ROA can really improve the value of the investment, and that counting solely on the traditional methods such NPV could have otherwise led to rejecting the investment.

The case study in Section 11 demonstrated that valuation of a BESS project relying solely on the DCF method undervalues the project and confirms the findings from the literature review. In Scenario 1, the project was unable to reach a positive NPV, generating NPV of only -86566 EUR. In Scenario 2, incorporation of the degradation process improved the project value significantly, resulting in the NPV of -15635 EUR for 60% *DOD*, and identified the NPV breakeven point for 100% *DOD* at 98 USD/kWh. By deploying ROA in Scenario 3, the project value increased even more, showing the positive value of waiting. Given that management possess flexibility to defer the project, the value of waiting in Scenario 3 equals 21653.33 EUR. By postponing the investment until 2025, management can profit from the high uncertainty on the market and realize a positive value for the company.

These findings enable the acceptance of the H1 hypothesis and confirm the significant role of ROA in the valuation of BESS projects. By extending the NPV method with ROA, practitioners can avoid situations where BESS projects are undervalued, and thus rejected.

H2: Including the battery cost in the optimization program will significantly improve quality of the battery dispatch, which results in an improved NPV of the investment.

Hypothesis H2 can be accepted based on the findings of Scenarios 1 and 2 in the case study; in the MILP model, failing to consider the impact of the dispatch on the degradation of the BESS led to high net cashflow. However, after assessment of the battery life loss as a direct impact of the arbitrage, the BESS investment resulted in a significantly negative NPV. In Scenario 2, net cashflow was balanced with the degradation effect of the BESS, to determine the optimal dispatch strategy. This approach provided a positive effect on NPV, which generated an improved NPV in Scenario 2, and provided a firm ground for valuation in Scenario 3. The sensitivity analysis of the model to investment costs confirmed the model is sensitive to the size of investment costs. Reduction of the initial capital outlay led *ceteris paribus* to a more frequent dispatch of the BESS, and to an increase of NPV. While the increase of the dispatch frequency was rather subtle until the NPV breakeven point, the sensitivity to investment costs has significantly increased when there was an incentive in the form of a positive NPV, i.e., beyond the NPV breakeven point.

H3: Selection of a ROA method for a BESS project is a complex process that should be based on clear decision criteria, maximizing the probability that decision makers will accept the method's results.

Comprehensive literature review on both ROA and BESS has been conducted. Compared to other projects, the BESS projects have some specifics which have been addressed in the review. The output of the literature review enabled to propose the set of eight assessment criteria which help to facilitate the selection process. Acceptance of the proposed assessment criteria has been positively tested in the MCDA.

Without clear assessment criteria, a less-suitable ROA method could be chosen for valuation of a BESS, which would inevitably lead to a less accurate estimate and a lower probability of getting a buy-in from the decision makers. All of these findings support accepting H3.

12.4. Suggestions for future research

BESS is currently a trending topic with high potential for further research. While the case study in the present research assumed $LiFePO_4$ BESS, new types of batteries are being developed. These may have better properties, and at the same time may become cheaper. Inclusion of new battery types into the present model should provide improved results.

Another area of research that may result in the promotion of BESS as a profitable investment entails analyzing BESS not in *isolation*, but as a part of a complex energy *system.* Grid-scale BESS can be combined with assets generating electricity, such as wind turbines or PHV.

Additionally, other types of energy storage, such as H_2, can be considered. The MILP model, enriched with these assets, may point to new investment opportunities. These assets should not be analyzed solely with the DCF method, but—most importantly—also with ROA method, due to the significantly fluctuating prices of technologies and outputs (e.g. H_2) over time. Further research should consider not only the option to wait, but also other option types, such as the option to switch.

There are other, quality-determining aspects for future researchers to consider, including the models used for simulation of the uncertainties considered. Richer and more realistic models may provide more accurate valuation results. Similarly, the identified real options can be valued with customized models, based on partial PDEs, which are (in general) more difficult to solve, but can provide more accurate results.

While this research focused solely on the use of BESS for arbitrage on the day-ahead market in one country, future work might analyze more markets in parallel. In situations where cross-border electricity exchange is possible, the analysis of the interconnected European electricity market can point toward new market opportunities, further improving the value of a given BESS project. Similarly, other types of electricity markets (not just the day-ahead market), such as the reserve market, may be the subject of fruitful, future analysis.

References

[1] Amirante, R., Cassone, E., Distaso, E., & Tamburrano, P. Overview on recent developments in energy storage: Mechanical, electrochemical and hydrogen technologies. *Energy Conversion and Management*. 2017, 132, pp. 372-387. doi: 10.1016/j.enconman.2016.11.046.

[2] Cole, W., Frazier, A. W., & Augustine, C. Cost Projections for Utility-Scale Battery Storage: 2021 Update. *National Renewable Energy Laboratory*, pp. 1-21. Available at: https://www.nrel.gov/docs/fy21osti/79236.pdf.

[3] *Renewables 2021: Analysis and forecasts to 2026*. (2021). IEA. Retrieved October 22, 2022, from https://www.iea.org/reports/renewables-2021.

[4] Luo, X., Wang, J., Dooner, M., & Clarke, J. Overview of current development in electrical energy storage technologies and the application potential in power system operation. *Applied Energy*. 2015, 137, pp. 511-536. doi: 10.1016/j.apenergy.2014.09.081.

[5] *Grid-Scale Storage*. (c2021). IEA. Retrieved December 2, 2022, from https://www.iea.org/reports/grid-scale-storage.

[6] Commission, E., Energy, D. -G. for, Andrey, C., Barberi, P., Nuffel, L., Gérard, F., Gorenstein Dedecca, J., Rademaekers, K., El Idrissi, Y., Crenes, M., & Lacombe, L. (2020). *Study on energy storage: contribution to the security of the electricity supply in Europe: contribution to the security of the electricity supply in Europe*. Publications Office, pp. 7-13. doi: 10.2833/077257.

[7] IEA, *Annual grid-scale battery storage additions, 2016-2021*, IEA, Paris. Retrieved December 2, 2022, from https://www.iea.org/data-and-statistics/charts/annual-grid-scale-battery-storage-additions-2016-2021. Licence: CC BY 4.0.

[8] *Energy storage*. (2022). European Commission. Retrieved December 2, 2022, from https://energy.ec.europa.eu/topics/research-and-technology/energy-storage_en.

[9] Nikolaidis, P., & Poullikkas, A. A comparative review of electrical energy storage systems for better sustainability. *JOURNAL OF POWER TECHNOLOGIES*. 2017, 97(3), pp. 220-245. Available at: http://papers.itc.pw.edu.pl/index.php/JPT/article/view/1096.

[10] Armand, M., Axmann, P., Bresser, D., Copley, M., Edström, K., Ekberg, C., Guyomard, D., Lestriez, B., Novák, P., Petranikova, M., Porcher, W., Trabesinger, S., Wohlfahrt-Mehrens, M., & Zhang, H. Lithium-ion batteries – Current state of the art and anticipated developments. *Journal of Power Sources*. 2020, 479, pp. 1-26. doi: 10.1016/j.jpowsour.2020.228708.

[11] Ding, Y., Fu, J., Zhang, S., He, X., Zhao, B., Ren, J., Zhong, J., & Liu, Z. Advances in recycling LiFePO4 from spent lithium batteries: A critical review. *Separation and Purification Technology*, 2024, *338*, pp. 1-12. doi: 10.1016/j.seppur.2024.126551.

[12] IRENA. (2017). *Electricity Storage and Renewables: Costs and Markets to 2030*. International Renewable Energy Agency, ISBN 978-92-9260-038-9, pp. 32-33. Available at: https://www.irena.org/publications/2017/Oct/Electricity-storage-and-renewables-costs-and-markets.

[13] Tan, X., Li, Q., & Wang, H. Advances and trends of energy storage technology in Microgrid. *International Journal of Electrical Power & Energy Systems*. 2013, 44(1), pp. 179-191. doi: 10.1016/j.ijepes.2012.07.015.

[14] Ellis, B., White, C., & Swan, L. Degradation of lithium-ion batteries that are simultaneously servicing energy arbitrage and frequency regulation markets. *Journal of Energy Storage*, 2023, *66*, pp. 1-10. doi: 10.1016/j.est.2023.107409.

[15] Bradbury, K., Pratson, L., & Patiño-Echeverri, D. Economic viability of energy storage systems based on price arbitrage potential in real-time U.S. electricity markets. *Applied Energy*. 2014, 114, pp. 512-519. doi: 10.1016/j.apenergy.2013.10.010.

[16] Komorowska, A., Olczak, P., Hanc, E., & Kamiński, J. An analysis of the competitiveness of hydrogen storage and Li-ion batteries based on price arbitrage in the day-ahead market. *International Journal of Hydrogen Energy*. 2022, 47(66), pp. 28556-28572. doi: 10.1016/j.ijhydene.2022.06.160.

[17] *EXAA*. (c2021). Retrieved December 14, 2021, from https://www.exaa.at/.

[18] *Basics of the Power Market*. (c2024). Epexspot. Retrieved February 15, 2024, from https://www.epexspot.com/en/basicspowermarket.

[19] Castillo, A., & Gayme, D. F. Grid-scale energy storage applications in renewable energy integration: A survey. *Energy Conversion and Management*. 2014, 87, pp. 885-894. doi: 10.1016/j.enconman.2014.07.063.

[20] Hameed, Z., Træholt, C., & Hashemi, S. Investigating the participation of battery energy storage systems in the Nordic ancillary services markets from a business perspective. *Journal of Energy Storage*, 2023, *58*, pp. 1-14. doi: 10.1016/j.est.2022.106464.

[21] Bowen, T., Chernyakhovskiy, I., & Denholm, P. *Grid-Scale Battery Storage: Frequently Asked Questions*. NREL, 2022, pp. 1-8. Retrieved October 27, 2022, from https://www.nrel.gov/docs/fy19osti/74426.pdf.

[22] Metz, D., & Saraiva, J. T. Use of battery storage systems for price arbitrage operations in the 15- and 60-min German intraday markets. *Electric Power Systems Research*. 2018, 160, pp. 27-36. doi: 10.1016/j.epsr.2018.01.020.

[23] Lamp, S., & Samano, M. Large-scale battery storage, short-term market outcomes, and arbitrage. *Energy Economics*. 2022, 107, pp. 1-16. doi: 10.1016/j.eneco.2021.105786.

[24] McPherson, M., McBennett, B., Sigler, D., & Denholm, P. Impacts of storage dispatch on revenue in electricity markets. *Journal of Energy Storage*, 2020, 31, pp. 1-16. doi: 10.1016/j.est.2020.101573.

[25] Gerini, F., Zuo, Y., Gupta, R., Zecchino, A., Yuan, Z., Vagnoni, E., Cherkaoui, R., & Paolone, M. Optimal grid-forming control of battery energy storage systems providing multiple services: Modeling and experimental validation. *Electric Power Systems Research*, 2022, 212, pp. 1-10. doi: 10.1016/j.epsr.2022.108567.

[26] Tarca, S., Roughan, M., Ertugrul, N., & Bean, N. Dispatchability of Wind Power with Battery Energy Storage in South Australia. *Energy Procedia*. 2017, 110, pp. 223-228. doi: 10.1016/j.egypro.2017.03.131.

[27] Mustafa, M. B., Keatley, P., Huang, Y., Agbonaye, O., Ademulegun, O. O., & Hewitt, N. Evaluation of a battery energy storage system in hospitals for arbitrage and ancillary services. *Journal of Energy Storage*. 2021, 43, pp. 1-12. doi: 10.1016/j.est.2021.103183.

[28] Bakke, I., Fleten, S. -E., Hagfors, L. I., Hagspiel, V., Norheim, B., & Wogrin, S. Investment in electric energy storage under uncertainty: a real options approach. *Computational Management Science*. 2016, 13(3), pp. 483-500. doi: 10.1007/s10287-016-0256-3.

[29] Schöniger, F., & Morawetz, U. B. What comes down must go up: Why fluctuating renewable energy does not necessarily increase electricity spot price variance in Europe. *Energy Economics*. 2022, 111, pp. 1-22. doi: 10.1016/j.eneco.2022.106069.

[30] Janda, K., Málek, J., & Rečka, L. Influence of renewable energy sources on transmission networks in Central Europe. *Energy Policy*. 2017, 108, pp. 524-537. doi: 10.1016/j.enpol.2017.06.021.

[31] Prokhorov, O., & Dreisbach, D. The impact of renewables on the incidents of negative prices in the energy spot markets. *Energy Policy*, 2022, 167, pp. 1-13. doi: 10.1016/j.enpol.2022.113073.

[32] Komorowska, A., & Olczak, P. Economic viability of Li-ion batteries based on the price arbitrage in the European day-ahead markets. *Energy*, 2024, 290, pp. 1-25. doi: 10.1016/j.energy.2023.130009.

[33] Fares, R. L., & Webber, M. E. What are the tradeoffs between battery energy storage cycle life and calendar life in the energy arbitrage application? *Journal of Energy Storage*, 2018, *16*, pp. 37-45. doi: 10.1016/j.est.2018.01.002.

[34] Naemi, M., Davis, D., & Brear, M. J. Optimisation and analysis of battery storage integrated into a wind power plant participating in a wholesale electricity market with energy and ancillary services. *Journal of Cleaner Production*, 2022, *373*, pp. 1-18. doi: 10.1016/j.jclepro.2022.133909.

[35] Apt, J., & Jaramillo, P. *Variable Renewable Energy and the Electricity Grid*. Taylor & Francis, 2014. pp. 198. ISBN 9781317907671.

[36] Kim, J. H., Kahrl, F., Mills, A., Wiser, R., Montañés, C. C., & Gorman, W. Economic evaluation of variable renewable energy participation in U.S. ancillary services markets. *Utilities Policy*, 2023, *82*, pp. 1-16. doi: https://doi.org/https://doi.org/10.1016/j.jup.2023.101578.

[37] Xu, B., Shi, Y., Kirschen, D. S., & Zhang, B. Optimal Battery Participation in Frequency Regulation Markets. *IEEE Transactions on Power Systems*, 2018, *33*(6), pp. 6715-6725. doi: https://doi.org/10.1109/TPWRS.2018.2846774.

[38] *PJM State of the Market - 2016*. (c2024). Monitoring Analytics. Retrieved February 15, 2024, from https://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2016.shtml.

[39] Forsyth, O. *As frequency regulation markets across Europe saturate, new installations will be driven by new market opportunities and battery energy storage systems adding new sources of revenue*. (c2024). S&P Global. Retrieved February 17, 2024, from https://www.spglobal.com/commodityinsights/en/ci/research-analysis/as-frequency-regulation-markets-across-europe-saturate-new-ins.html.

[40] Colthorpe, A. *Batteries earn big in European ancillary services, but investors warned of high expectations*. (c2024). Energy Storage News. Retrieved March 2, 2024, from https://www.energy-storage.news/batteries-earn-big-in-european-ancillary-services-but-investors-warned-of-high-expectations/.

[41] Weron, R. Electricity price forecasting: A review of the state-of-the-art with a look into the future. *International Journal of Forecasting*, 2014, *30*(4), pp. 1030-1081. doi: 10.1016/j.ijforecast.2014.08.008.

[42] Buchsbaum, J. F., Hausman, C., Mathieu, J. L., & Peng, J. Spillovers from Ancillary Services to Wholesale Energy Markets. *National Bureau of Economic Research Working Paper Series*, *No. 28027*, 2020. doi: 10.3386/w28027.

[43] Weetman, P. *Financial and Management Accounting: An Introduction* (4 ed.). Financial Times Prentice Hall, 2006. pp. 652-673, ISBN 9780273703693.

[44] Svozilová, A. *Projektový management: systémový přístup k řízení projektů* (3., aktualizované a rozšířené vydání). Grada Publishing, 2016. pp. 93-98, ISBN 9788027100750.

[45] Geddes, R. *IPOs and Equity Offerings: Securities Institute Global Capital Markets*. Elsevier Science, 2003. pp. 90-94, ISBN 9780080478784.

[46] Kodukula, P., & Papudesu, C. *Project Valuation Using Real Options - A Practitioner's Guide*. J. Ross Publishing, 2006. pp. 1-189, ISBN 9781523100996.

[47] Hill, R. A. *The Capital Asset Pricing Model*. Bookboon, 2010. pp. 32-37, ISBN 9788776817121.

[48] Trigeorgis, L. *Real Options in Capital Investment: Models, Strategies, and Applications* (1st ed.). Greenwood Publishing Group, 1995. pp. 33-41, ISBN 9780275946166.

[49] Liu, Y., Zheng, R., Chen, S., & Yuan, J. The economy of wind-integrated-energy-storage projects in China's upcoming power market: A real options approach. *Resources Policy*, 2019, 63, pp. 1-10. doi: 10.1016/j.resourpol.2019.101434.

[50] Guo, Y., Ming, B., Huang, Q., Liu, P., Wang, Y., Fang, W., & Zhang, W. Evaluating effects of battery storage on day-ahead generation scheduling of large hydro–wind–photovoltaic complementary systems. *Applied Energy*, 2022, 324, pp. 1-20. doi: 10.1016/j.apenergy.2022.119781.

[51] Alramlawi, M., Mohagheghi, E., & Li, P. Predictive active-reactive optimal power dispatch in PV-battery-diesel microgrid considering reactive power and battery lifetime costs. *Solar Energy*, 2019, 193, pp. 529-544. doi: 10.1016/j.solener.2019.09.034.

[52] Zhao, X., Yang, Y., & Xu, Q. Day-ahead robust optimal dispatch of integrated energy station considering battery exchange service. *Journal of Energy Storage*, 2022, 50, pp. 1-13. doi: 10.1016/j.est.2022.104228.

[53] Lai, C. S., Locatelli, G., Pimm, A., Tao, Y., Li, X., & Lai, L. L. A financial model for lithium-ion storage in a photovoltaic and biogas energy system. *Applied Energy*, 2019, 251, pp. 1-16. doi: 10.1016/j.apenergy.2019.04.175.

[54] Campos, R. A., Martins, G. L., & Rüther, R. Assessing the influence of solar forecast accuracy on the revenue optimization of photovoltaic + battery power plants in day-ahead energy markets. *Journal of Energy Storage*, 2022, *48*, pp. 1-6. doi: doi.org/10.1016/j.est.2022.104093.

[55] Stewart C. Myers. Determinants of corporate borrowing. *Journal of Financial Economics*, 1977, pp. 147-175.

[56] Brach, M. A. *Real Options in Practice*. John Wiley, 2003. pp.1-144, ISBN 0471263087.

[57] Xu, J. *Practical C# and WPF For Financial Markets*. UniCAD Publishing, 2016. pp. 438-443, ISBN 0979372550.

[58] Jain, S., Roelofs, F., & Oosterlee, C. W. Valuing modular nuclear power plants in finite time decision horizon. *Energy Economics*, 2013, 36, pp. 625-636. doi: 10.1016/j.eneco.2012.11.012.

[59] Wörner, S. D., & Grupp, H. The derivation of R&D return indicators within a real options framework. *R&D Management*, 2003, 33(3), pp. 313-325. doi: 10.1111/1467-9310.00300.

[60] Hull, J. C. *Options, futures, and other derivatives* (9th ed). Pearson Education, 2015. pp. 213-321, 598-624 and 775-792, ISBN 978-0-13-345631-8.

[61] Ma, Y., Chapman, A. C., & Verbič, G. Valuation of compound real options for co-investment in residential battery systems. *Applied Energy*, 2022, 318, pp. 1-10. doi: 10.1016/j.apenergy.2022.119111.

[62] Kirby, N., & Davison, M. Using a spark-spread valuation to investigate the impact of corn-gasoline correlation on ethanol plant valuation. *Energy Economics*, 2010, 32(6), pp. 1221-1227. doi: 10.1016/j.eneco.2010.02.004.

[63] Brugnano, L., & Iavernaro, F. *Advanced Numerical Methods in Applied Sciences*. MDPI, 2019. pp. 153-155, ISBN 3038976660.

[64] Zahra, S., & Reza, R. Asian real option: New approach to project economic valuation. In *2012 International Conference on Information Management, Innovation Management and Industrial Engineering,* 2012, pp. 475-479. doi: 10.1109/ICIII.2012.6339881.

[65] Kozlova, M. Real option valuation in renewable energy literature: Research focus, trends and design: Research focus, trends and design. *Renewable and Sustainable Energy Reviews*, 2017, 80(Supplement C), pp. 180-196. doi: 10.1016/j.rser.2017.05.166.

[66] Zajicek, M. *Mergers & Acquisitions - a Real Option valuation approach of investment decision under uncertainty* (1st ed.). Diplomica Verlag, 2004. pp. 36-42, ISBN 9783832475758.

[67] Li, L., & Cao, X. Comprehensive effectiveness assessment of energy storage incentive mechanisms for PV-ESS projects based on compound real options. *Energy*, 2022, 239, pp. 1-14. doi: 10.1016/j.energy.2021.121902.

[68] Martínez Ceseña, E. A., Mutale, J., & Rivas-Dávalos, F. Real options theory applied to electricity generation projects: A review. *Renewable and Sustainable Energy Reviews*, 2013, 19, pp. 573-581. doi: 10.1016/j.rser.2012.11.059.

[69] Peters, L. *Real Options Illustrated*. Springer International Publishing, 2016. pp. 11-14, ISBN 9783319283104.

[70] Jain, S., Leitao, Á., & Oosterlee, C. W. Rolling Adjoints: Fast Greeks along Monte Carlo scenarios for early-exercise options: *Journal of Computational Science*, 2019, *33*, pp. 95-112. doi: 10.1016/j.jocs.2019.03.001.

[71] Katz, J. O., & McCormick, D. *Advanced Option Pricing Models*. McGraw Hill, 2005. pp. 7-9. ISBN 9780071454704.

[72] Balibrea-Iniesta, J., Rodríguez-Monroy, C., & Núñez-Guerrero, Y. M. Economic analysis of the German regulation for electrical generation projects from biogas applying the theory of real options. *Energy*, 2021, 231, pp. 1-10. doi: 10.1016/j.energy.2021.120976.

[73] Black, Fischer, and Myron Scholes. "The Pricing of Options and Corporate Liabilities". *Journal of Political Economy,* 1973, 81(3), pp. 637-654.

[74] Mody, A. *Infrastructure Delivery: Private Initiative and the Public Good* (1st ed.). World Bank Publications, 1996. p. 190, ISBN 0821335200.

[75] Redhead, K. *Personal Finance and Investments: A Behavioural Finance Perspective* (1st ed.). Routledge, 2008. pp. 680-711, ISBN 1134088388.

[76] Seydel, R. *Tools for Computational Finance* (5 ed.). Springer, 2012. pp. 7-31, ISBN 1447129946

[77] Alghalith, M. Pricing the American options using the Black–Scholes pricing formula. *Physica A: Statistical Mechanics and its Applications*, 2018, 507, pp. 443-445. doi: 10.1016/j.physa.2018.05.087.

[78] Ho, T. S. Y., & Lee, S. B. *The Oxford Guide to Financial Modeling: Applications for Capital Markets, Corporate Finance, Risk Management and Financial Institutions* (1st ed.). Oxford University Press, 2004. pp. 25-29, ISBN 0199727708.

[79] Cox, J. C., Ross, S. A., & Rubinstein, M. Option pricing: A simplified approach: A simplified approach. *Journal of Financial Economics*, 1979, 7(3), pp. 229-263. doi: 10.1016/0304-405X(79)90015-1.

[80] London, J. *Modeling Derivatives in C++* (1st ed.). John Wiley, 2005. pp. 123-132, ISBN 047168189X.

[81] Pachamanova, D. A., & Fabozzi, F. J. *Simulation and Optimization in Finance: Modeling with MATLAB, @Risk, or VBA* (1st ed.). John Wiley, 2010. pp. 510-511, ISBN 0470882123.

[82] Boyle, Phelim P. Option Valuation Using a Three-Jump Process. *International Options Journal*, 1986, (Vol. 3), pp. 7–12.

[83] Mack, I. M. *Energy Trading and Risk Management: A Practical Approach to Hedging, Trading and Portfolio Diversification* (1st ed.). John Wiley, 2014. pp. 50-52, ISBN 9781118339336.

[84] Carmichael, D. G. *Future-proofing—Valuing Adaptability, Flexibility, Convertibility and Options: A Cross-Disciplinary Approach* (1st ed.). Springer Nature, 2019. pp. 49-50, ISBN 9811507236.

[85] Quail, R. *Understanding Options* (1st ed.). John Wiley, 1995. pp. 171-176, ISBN 0471085545.

[86] Boyle, P. P. Options: A Monte Carlo approach: A Monte Carlo approach. *Journal of Financial Economics*, 1977, 4(3), pp. 323-338. doi: 10.1016/0304-405X(77)90005-8.

[87] Duffy, D. J., & Kienitz, J. *Monte Carlo Frameworks: Building Customisable High-performance C++ Applications: The Wiley Finance Series*. Wiley, 2011. pp. 190-198, ISBN 9780470684061.

[88] Benhamou, E. *Global Derivatives: Products, Theory And Practice* (1st ed.). World Scientific Publishing Company, 2007. pp. 337-338, ISBN 9813106670.

[89] Korn, R., Korn, E., & Kroisandt, G. *Monte Carlo Methods and Models in Finance and Insurance* (1st ed.). CRC Press, 2010. pp. 57-60, ISBN 1420076191.

[90] Dunn, W. L., & Shultis, J. K. *Exploring Monte Carlo Methods* (2nd ed.). Elsevier, 2022. pp. 42-43, ISBN 0128197455

[91] Czamanski, D., Keller, J. B., Givoli, D., Grote, M. J., Papanicolaou, G. C., & Papanicolaou, G. *A Celebration of Mathematical Modeling: The Joseph B. Keller

Anniversary Volume: The Joseph B. Keller Anniversary Volume. Springer Netherlands, 2004. pp. 1-12, ISBN 9781402018428.

[92] Ma, Y., Verbič, G., & Chapman, A. C. Estimating the Option Value of Grid-Scale Battery Systems to Distribution Network Service Providers. In *2019 IEEE Milan PowerTech*, 2019, pp. 1-6. doi: 10.1109/PTC.2019.8810600.

[93] van Leeuwen, J., Watanabe, O., Hagiya, M., Mosses, P., & Ito, T. (Eds.). (2003). *Theoretical Computer Science: Exploring New Frontiers of Theoretical Informatics: International Conference IFIP TCS 2000 Sendai, Japan, August 17-19, 2000 Proceedings* (1st ed.). Springer, 2013. pp. 243-244, ISBN 3540449299.

[94] Kelly, J. J., & Leahy, P. G. Optimal investment timing and sizing for battery energy storage systems. *Journal of Energy Storage*, 2020, 28, pp. 1-12. doi: 10.1016/j.est.2020.101272.

[95] Bi, Y., & Lyu, S. How to promote the widespread commercial adoption of photovoltaic microgrids under investment uncertainty? A real options analysis in China. *Sustainable Production and Consumption*, 2022, 32, pp. 344-356. doi: 10.1016/j.spc.2022.04.022.

[96] Fioriti, D., Poli, D., Duenas-Martinez, P., & Perez-Arriaga, I. Multi-year stochastic planning of off-grid microgrids subject to significant load growth uncertainty: overcoming single-year methodologies: overcoming single-year methodologies. *Electric Power Systems Research*, 2021, 194, pp. 1-11. doi: 10.1016/j.epsr.2021.107053.

[97] Bakke, I., Fleten, S. -E., Hagfors, L. I., Hagspiel, V., Norheim, B., & Wogrin, S. Investment in electric energy storage under uncertainty: a real options approach: a real options approach. *Computational Management Science,* 2016, 13(3), pp. 483-500. doi: 10.1007/s10287-016-0256-3.

[98] Ma, Y., Swandi, K., Chapman, A. C., & Verbič, G. Multi-stage compound real options valuation in residential PV-Battery investment. *Energy*, 2020, 191, pp. 1-10. doi: 10.1016/j.energy.2019.116537.

[99] Keles, D., & Dehler-Holland, J. Evaluation of photovoltaic storage systems on energy markets under uncertainty using stochastic dynamic programming. *Energy Economics*, 2022, 106, pp. 1-17. doi: 10.1016/j.eneco.2021.105800.

[100] Fotr, J., & Švecová, L. *Manažerské rozhodování: postupy, metody a nástroje* (2., přeprac. vyd). Ekopress, 2010. pp. 25-213, ISBN 9788086929590.

[101] Ren, J. *Energy Systems Evaluation (Volume 2): Multi-Criteria Decision Analysis: Green Energy and Technology*. Springer International Publishing, 2021. pp. 5-11, ISBN 9783030673765.

[102] Grasseová, M., Mašlej, M., & Brechta, B. *Manažerské rozhodování: teoretická východiska a praktické příklady*. Univerzita obrany, 2010. pp. 11-53 and 78-115, ISBN 9788072317301.

[103] Behl, A. *Multi-Criteria Decision Analysis in Management: Advances in Logistics, Operations, and Management Science.* IGI Global, 2020. pp. 139-168, ISBN 9781799822189.

[104] Forman, E., & Peniwati, K. Aggregating individual judgments and priorities with the analytic hierarchy process. *European Journal of Operational Research*, 1998, 108(1), pp. 165-169. doi: 10.1016/S0377-2217(97)00244-0.

[105] Hurta, A., Žilka, M., & Freiberg, F. Impact of the splitting of the German–Austrian electricity bidding zone on investment in a grid-scale battery energy storage system deployed for price arbitrage with gray and green power in Austrian and German day-ahead power markets. *Energy Reports*, 2022, 8, pp. 12045-12062. doi: 10.1016/j.egyr.2022.09.045.

[106] Dufo-López, R., Bernal-Agustín, J. L., & Domínguez-Navarro, J. A. Generation management using batteries in wind farms: Economical and technical analysis for Spain. *Energy Policy*, 2009, *37*(1), pp. 126-139. doi: 10.1016/j.enpol.2008.08.012.

[107] Shahjalal, M., Roy, P. K., Shams, T., Fly, A., Chowdhury, J. I., Ahmed, M. R., & Liu, K. A review on second-life of Li-ion batteries: prospects, challenges, and issues: prospects, challenges, and issues. *Energy*, 2022, 241, pp. 1-19. doi: 10.1016/j.energy.2021.122881.

[108] Zhang, Z., Wang, J., & Wang, X. An improved charging/discharging strategy of lithium batteries considering depreciation cost in day-ahead microgrid scheduling. *Energy Conversion and Management*, 2015, 105, pp. 675-684. doi: 10.1016/j.enconman.2015.07.079.

[109] Omar, N., Monem, M. A., Firouz, Y., Salminen, J., Smekens, J., Hegazy, O., Gaulous, H., Mulder, G., Van den Bossche, P., Coosemans, T., & Van Mierlo, J. Lithium iron phosphate based battery – Assessment of the aging parameters and development of cycle life model. *Applied Energy*, 2014, 113, pp. 1575-1585. doi: 10.1016/j.apenergy.2013.09.003.

[110] Kovacevic, R. M., Pflug, G. C., & Vespucci, M. T. *Handbook of Risk Management in Energy Production and Trading: International Series in Operations Research & Management Science*. Springer US, 2013. pp. 9-14, ISBN 9781461490357.

[111] Javadi, M. S., Anvari-Moghaddam, A., & Guerrero, J. M. Optimal scheduling of a multi-carrier energy hub supplemented by battery energy storage systems. In *2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*. pp. 1-6. doi: doi.org/10.1109/EEEIC.2017.7977520.

[112] Hurta, A. Real Options Analysis in The Energy Sector with A Focus on The Spot Price of Electricity: Decision Criteria for Selecting the Optimal Method. *International Journal of Advanced Research in Engineering and Technology*, 2023, 14(1), pp. 1-32. doi: 10.17605/OSF.IO/7VPDY.

[113] Schiel, C. *Real Option Based Appraisal of Environmental Investments – An Assessment of NO_x Emission Control Techniques in Large Combustion Plants* (1st ed.). KIT Scientific Publishing, 2019. pp. 95-117, ISBN 9783731509257.

[114] Samuelson, Paul A. Rational Theory of Warrant Pricing. *Industrial Management Review,* 1965, 6(2), pp. 41-50.

[115] Glasserman, P. *Monte Carlo methods in financial engineering*. Springer, 2004. pp. 93-97, ISBN 0387004513.

[116] Keles, D. *Uncertainties in energy markets and their consideration in energy storage evaluation: Produktion und Energie*. KIT Scientific Publishing, 2014. pp. 80-81, ISBN 9783731500469.

[117] Uhlenbeck, G. E., & Ornstein, L. S. On the Theory of the Brownian Motion. *Physical Review*, 1930, 36. doi: 10.1103/PhysRev.36.823.

[118] Vasicek, O. An equilibrium characterization of the term structure. *Journal of Financial Economics*, 1977, 5(2), pp. 177-188. doi: 10.1016/0304-405X(77)90016-2.

[119] Ronn, E. I. *Real Options and Energy Management* (ed.). Risk Books, 2002. pp. 1-113, ISBN 1899332987.

[120] Shaik, M., & S, M. A new method based on range to detect mean reversion. *IIMB Management Review*, 2020, 32(2), pp. 208-216. doi: 10.1016/j.iimb.2020.08.001.

[121] Geiger, A. *Strategic power plant investment planning under fuel and carbon price uncertainty* (1st ed.). KIT Scientific Publishing, 2011. pp. 25-28 and 245-251, ISBN 9783866446335.

[122] Pindyck, R. S., & Research, M. I. of T. C. for E. and E. P. *The Long-run Evolution of Energy Prices: MIT-CEEPR*. Center for Energy and Environmental Policy Research, Massachusetts Institute of Technology, 1999. pp. 1-17. Available at: http://hdl.handle.net/1721.1/45087.

[123] Keles, D., Genoese, M., Möst, D., & Fichtner, W. Comparison of extended mean-reversion and time series models for electricity spot price simulation considering negative prices. *Energy Economics*, 2012, 34(4), pp. 1012-1032. doi: 10.1016/j.eneco.2011.08.012.

[124] Mikalef, P., & Parmiggiani, E. *Digital Transformation in Norwegian Enterprises*. Springer International Publishing, 2022. pp. 70-78, ISBN 9783031052767.

[125] Schavemaker, P., & van der Sluis, L. *Electrical Power System Essentials*. Wiley, 2017. pp. 264-268, ISBN 9781118803479.

[126] *EXAA - ENERGY EXCHANGE AUSTRIA*. Europex: Association of European Energy Exchanges. Europex, 2022. Retrieved October 27, 2022. Available at: https://www.europex.org/members/exaa/.

[127] Seel, J., Millstein, D., Mills, A., Bolinger, M., & Wiser, R. Plentiful electricity turns wholesale prices negative. *Advances in Applied Energy*, 2021, 4, pp. 1-4. doi: 10.1016/j.adapen.2021.100073.

[128] Halkos, G. E., & Tsirivis, A. S. Effective energy commodity risk management: Econometric modeling of price volatility: Econometric modeling of price volatility. *Economic Analysis and Policy*, 2019, 63, pp. 234-250. doi: 10.1016/j.eap.2019.06.001.

[129] Engle, R. F. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 1982, 50(4), pp. 987-1007.

[130] Shumway, R. H., & Stoffer, D. S. *Time Series Analysis and Its Applications: With R Examples* (2nd ed.). Springer Science+Business Media, 2006. pp. 253-262, ISBN 9780387362762.

[131] Sabbatini, M., & Linton, O. A GARCH model of the implied volatility of the Swiss market index from option prices. *International Journal of Forecasting*, 1998, 14(2), pp. 199-213. doi: 10.1016/S0169-2070(98)00027-2.

[132] Bollerslev, T. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 1986, 31(3), pp. 307-327. doi: 10.1016/0304-4076(86)90063-1.

[133] Mhd Ruslan, S. M., & Mokhtar, K. Stock market volatility on shipping stock prices: GARCH models approach. *The Journal of Economic Asymmetries*, 2021, 24, pp. 1-16. doi: 10.1016/j.jeca.2021.e00232.

[134] Stengos, T. *Nonparametric Econometric Methods and Application: Online access: OAPEN DOAB Directory of Open Access Books*. MDPI, 2019. pp. 124-136, ISBN 9783038979647.

[135] Birkelund, O. H., Haugom, E., Molnár, P., Opdal, M., & Westgaard, S. A comparison of implied and realized volatility in the Nordic power forward market. *Energy Economics*, 2015, 48, pp. 288-294. doi: 10.1016/j.eneco.2014.12.021.

[136] Algieri, B., Leccadito, A., & Tunaru, D. Risk premia in electricity derivatives markets. *Energy Economics,* 2021, 100, pp. 1-15. doi: 10.1016/j.eneco.2021.105300.

[137] Simkins, B., & Simkins, R. *Energy Finance and Economics: Analysis and Valuation, Risk Management, and the Future of Energy: Robert W. Kolb Series*. Wiley, 2013. pp. 264. ISBN 9781118017128.

[138] Anthreas, S. *Project Execution of Mega-Projects for the Oil and Gas Industries* (1st ed.). CRC Press, 2021. pp. 5-69, ISBN 9781000361636.

[139] *BESS lithium-ion-lifepo4-battery containerized*. GreensunSolar, 2022. Retrieved December 16, 2022. Available at: https://www.greensunpv.com/ess-bess-lithium-ion-lifepo4-battery-containerized-300kwh-500kwh-800kwh-1mwh-1-5mwh-energy-storage-system_p200.html.

[140] *Energy Storage Benefit-Cost Analysis: A Framework for State Energy Programs*. (c2024). Clean Energy States Alliance. Retrieved February 15, 2024, from https://www.cesa.org/wp-content/uploads/Energy-Storage-Benefit-Cost-Analysis.pdf.

[141] *The cost of financing for renewable power*. (c2024). IRENA. Retrieved February 22, 2024, from https://www.irena.org/Publications/2023/May/The-cost-of-financing-for-renewable-power.

[142] *US dollar (USD)*. European Central Bank: Eurosystem, 2022. Retrieved September 10, 2022. Available at: https://www.ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/html/eurofxref-graph-usd.en.html.

[143] *Report on Distribution Tariff Methodologies in Europe*. (c2023). European Union Agency for the Cooperation of Energy Regulators. Retrieved March 2, 2024, from https://acer.europa.eu/sites/default/files/documents/Publications/ACER%20Report%20on%20D-Tariff%20Methodologies.pdf.

[144] *The Way Forward for Energy Storage Grid Fees: General Overview and Best Practices Across Member States*. (c2024). European Association for Storage of Energy. Retrieved February 22, 2024, from https://ease-storage.eu/wp-content/uploads/2022/07/2022.07.07_The-Way-Forward-for-Energy-Storage-Grid-Fees_EASE.pdf.

[145] *Avoided network fees*. (c2024). Bundesnetzagentur. Retrieved March 2, 2024, from https://www.bundesnetzagentur.de/EN/RulingChambers/Chamber8/RC8_06_Network%20charges/67%20Avoided%20network%20fees/RC8_Avoided%20network%20fees.html.

[146] *Price List*. (c2024). EEX. Retrieved March 2, 2024, from https://www.eex.com/en/markets/trading-ressources/price-list.

[147] Gul, M., Yucesan, M., & Erdogan, M. *Multi-Criteria Decision Analysis: Case Studies in Disaster Management* (1st ed.). CRC Press, 2022. pp. 80-82, ISBN 9781000804447.

[148] Badiru, A. B. *Handbook of Industrial and Systems Engineering: Systems Innovation Book Series* (1st ed.). CRC Press, 2005. pp. 763-768. ISBN 9781420038347.

List of author's publications cited in this dissertation

List of author's publications in journals with impact factor

[105] Hurta, A., Žilka, M., & Freiberg, F. Impact of the splitting of the German–Austrian electricity bidding zone on investment in a grid-scale battery energy storage system deployed for price arbitrage with gray and green power in Austrian and German day-ahead power markets. *Energy Reports*, 2022, 8, pp. 12045-12062. doi: 10.1016/j.egyr.2022.09.045.

WoS Journal Impact Factor 2021: 4.937; Scopus CiteScore 2021: 4.5

List of other author's publications

[112] Hurta, A. Real Options Analysis in The Energy Sector with A Focus on The Spot Price of Electricity: Decision Criteria for Selecting the Optimal Method. *International Journal of Advanced Research in Engineering and Technology*, 2023, 14(1), pp. 1-32. doi: 10.17605/OSF.IO/7VPDY.

List of author's publications not cited in this dissertation

Hurta, A. Potential of data science in mechanical engineering – current trends impacting demand for mechanical engineering graduates. In *Recenzovaný sborník příspěvků z 20. odborné konference z cyklu Integrované inženýrství v řízení průmyslových podniků na téma Aplikace a využití moderních nástrojů, metod a technologií v praxi*. Czech Technical University in Prague, 2020, pp. 43-52. ISBN 9788001067758.

Hurta, A. Vývoj hodnoty flexibility v české energetice. In *Albín Bráf International Scientific Conference Year IV*. České vysoké učení technické v Praze, Masarykův ústav vyšších studií, 2019, pp. 69-75. ISBN 9788001065846.

Hurta, A. Real Options Valuation Methods in Energetics. In *Konference STČ*. České vysoké učení technické v Praze, Fakulta strojní, 2021, pp. 1-6.

Hurta, A. (2021). *Studie* [Studie]. České vysoké učení technické v Praze, Fakulta strojní, 2021, pp. 1-25.

Hurta, A. Stochastic Variables in Battery Energy Storage System Valuation: A Literature Review. In *Konference STČ*. České vysoké učení technické v Praze, Fakulta strojní, 2023, pp. 1-5.

Appendix A: weighting of experts

Table 15. Pair-wise comparison of the experts with respect to criterion C1 using Saaty's matrix.

E_i	E_1	E_2	E_3	E_4	E_5	GM_1^i	z_1^i
E_1	1	1	3	1	1	1.246	0.231
E_2	1	1	3	1	1	1.246	0.231
E_3	1/3	1/3	1	1/3	1/3	0.415	0.077
E_4	1	1	3	1	1	1.246	0.231
E_5	1	1	3	1	1	1.246	0.231

Table 16. Pair-wise comparison of the experts with respect to criterion C2 using Saaty's matrix.

E_i	E_1	E_2	E_3	E_4	E_5	GM_2^i	z_2^i
E_1	1	3	3	3	2	2.221	0.378
E_2	1/3	1	1	1/2	1/3	0.561	0.095
E_3	1/3	1	1	1/2	1/3	0.561	0.095
E_4	1/3	2	2	1	1/3	0.850	1.145
E_5	1/2	3	3	3	1	1.683	0.286

Table 17. Pair-wise comparison of the experts with respect to criterion C3 using Saaty's matrix.

E_i	E_1	E_2	E_3	E_4	E_5	GM_3^i	z_3^i
E_1	1	1/3	1	1	1	0.803	0.143
E_2	3	1	3	3	3	2.408	0.429
E_3	1	1/3	1	1	1	0.803	0.143
E_4	1	1/3	1	1	1	0.803	0.143
E_5	1	1/3	1	1	1	0.803	0.143

Appendix B: criteria weighting

Table 18. Saaty's matrix used for criteria weighting from the perspective of expert E_1.

C_j	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	GM_j^1	w_j^1
C_1	1	3	3	4	4	4	7	8	3.660	0.330
C_2	1/3	1	1	2	4	5	6	6	2.160	0.200
C_3	1/3	1	1	1	3	3	5	5	1.720	0.160
C_4	1/4	1/2	1	1	2	3	4	5	1.400	0.130
C_5	1/4	1/4	1/3	1/2	1	2	3	3	0.810	0.070
C_6	1/4	1/5	1/3	1/3	1/2	1	2	2	0.570	0.050
C_7	1/7	1/6	1/5	1/4	1/3	1/2	1	2	0.380	0.030
C_8	1/8	1/6	1/5	1/5	1/3	1/2	1/2	1	0.300	0.030

Table 19. Saaty's matrix used for criteria weighting from the perspective of expert E_2**.**

C_j	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	GM_j^2	w_j^2
C_1	1	2	3	3	3	2	4	5	2.611	0.275
C_2	1/2	1	1	1	2	3	2	5	1.530	0.161
C_3	1/3	1	1	1	3	2	4	3	1.488	0.157
C_4	1/3	1	1	1	2	1	4	3	1.297	0.137
C_5	1/3	1/2	1/3	1/2	1	1	1	3	0.733	0.077
C_6	1/2	1/3	1/2	1	1	1	3	3	0.965	0.102
C_7	1/4	1/2	1/4	1/4	1	1/3	1	2	0.518	0.055
C_8	1/5	1/5	1/3	1/3	1/3	1/3	1/2	1	0.354	0.037

Table 20. Saaty's matrix used for criteria weighting from the perspective of expert E_3**.**

C_j	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	GM_j^3	w_j^3
C_1	1	4	4	3	4	4	4	4	3.245	0.319
C_2	1/4	1	4	4	3	5	6	5	2.552	0.251
C_3	1/4	1/4	1	1	1	2	2	3	0.965	0.095
C_4	1/3	1/4	1	1	1	2	3	1	0.917	0.090
C_5	1/4	1/3	1	1	1	2	2	1	0.872	0.086
C_6	1/4	1/5	1/2	1/2	1/2	1	1	2	0.578	0.057
C_7	1/4	1/6	1/2	1/3	1/2	1	1	2	0.537	0.053
C_8	1/4	1/5	1/3	1	1	1/2	1/2	1	0.504	0.050

Table 21. Saaty's matrix used for criteria weighting from the perspective of expert E_4**.**

C_j	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	GM_j^4	w_j^4
C_1	1	4	3	4	4	4	3	4	3.130	0.314
C_2	1/4	1	4	3	4	5	6	3	2.394	0.240
C_3	1/4	1/4	1	1	1	2	2	3	1.000	0.100
C_4	1/4	1/3	1	1	1	2	4	1	0.951	0.095
C_5	1/4	1/4	1	1	1	2	2	1	0.841	0.085
C_6	1/4	1/5	1/2	1/2	1/2	1	1	2	0.578	0.058
C_7	1/3	1/6	1/2	1/4	1/2	1	1	2	0.537	0.054
C_8	1/4	1/3	1/3	1	1	1/2	1/2	1	0.537	0.054

Table 22. Saaty's matrix used for criteria weighting from the perspective of expert E_5.

C_j	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	GM_j^5	w_j^5
C_1	1	4	4	4	4	3	4	2	2.975	0.305
C_2	1/4	1	4	4	3	5	6	2	2.276	0.233
C_3	1/4	1/4	1	1	1	2	3	3	1.015	0.104
C_4	1/4	1/4	1	1	1	2	3	2	0.965	0.099
C_5	1/4	1/3	1	1	1	2	1	1	0.799	0.082
C_6	1/3	1/5	1/2	1/2	1/2	1	1	2	0.599	0.062
C_7	1/4	1/6	1/3	1/3	1	1	1	2	0.557	0.057
C_8	1/2	1/2	1/3	1/2	1	1/2	1/2	1	0.565	0.058

Appendix C: scoring of alternatives

Table 23. Scoring of alternatives with respect to criterion C_1 using Saaty's matrix from the perspective of expert E_1.

A_i	A_1	A_2	A_3	GM_{11}^{i}	z_{11}^{i}
A_1	1	1/3	1/2	0.550	0.163
A_2	3	1	2	1.817	0.540
A_3	2	1/2	1	1.000	0.297

Table 24. Scoring of alternatives with respect to criterion C_2 using Saaty's matrix from the perspective of expert E_1.

A_i	A_1	A_2	A_3	GM_{12}^{i}	z_{12}^{i}
A_1	1	1/3	1	0.693	0.200
A_2	3	1	3	2.080	0.600
A_3	1	1/3	1	0.693	0.200

Table 25. Scoring of alternatives with respect to criterion C_3 using Saaty's matrix from the perspective of expert E_1.

A_i	A_1	A_2	A_3	GM_{13}^{i}	z_{13}^{i}
A_1	1	1	1	1.000	0.333
A_2	1	1	1	1.000	0.333
A_3	1	1	1	1.000	0.333

Table 26. Scoring of alternatives with respect to criterion C_4 using Saaty's matrix from the perspective of expert E_1.

A_i	A_1	A_2	A_3	GM_{14}^{i}	z_{14}^{i}
A_1	1	1	1	1.000	0.333
A_2	1	1	1	1.000	0.333
A_3	1	1	1	1.000	0.333

Table 27. Scoring of alternatives with respect to criterion C_5 using Saaty's matrix from the perspective of expert E_1.

A_i	A_1	A_2	A_3	GM_{15}^{i}	z_{15}^{i}
A_1	1	1/2	1/2	0.630	0.200
A_2	2	1	1	1.260	0.400
A_3	2	1	1	1.260	0.400

Table 28. Scoring of alternatives with respect to criterion C_6 using Saaty's matrix from the perspective of expert E_1.

A_i	A_1	A_2	A_3	GM_{16}^{i}	z_{16}^{i}
A_1	1	1/2	1	0.794	0.250
A_2	2	1	2	1.587	0.500
A_3	1	1/2	1	0.794	0.250

Table 29. Scoring of alternatives with respect to criterion C_7 using Saaty's matrix from the perspective of expert E_1.

A_i	A_1	A_2	A_3	GM_{17}^{i}	z_{17}^{i}
A_1	1	1	2	1.260	0.400
A_2	1	1	2	1.260	0.400
A_3	1/2	1/2	1	0.630	0.200

Table 30. Scoring of alternatives with respect to criterion C_8 using Saaty's matrix from the perspective of expert E_1.

A_i	A_1	A_2	A_3	GM_{18}^{i}	z_{18}^{i}
A_1	1	2	3	1.817	0.540
A_2	1/2	1	2	1.000	0.297
A_3	1/3	1/2	1	0.550	0.163

Table 31. Scoring of alternatives with respect to criterion C_1 using Saaty's matrix from the perspective of expert E_2.

A_i	A_1	A_2	A_3	GM_{21}^{i}	z_{21}^{i}
A_1	1	1/3	1	0.693	0.221
A_2	3	1	1	1.442	0.460
A_3	1	1	1	1.000	0.319

Table 32. Scoring of alternatives with respect to criterion C_2 using Saaty's matrix from the perspective of expert E_2.

A_i	A_1	A_2	A_3	GM_{22}^{i}	z_{22}^{i}
A_1	1	1/3	1	0.693	0.210
A_2	3	1	2	1.817	0.550
A_3	1	1/2	1	0.794	0.240

Table 33. Scoring of alternatives with respect to criterion C_3 using Saaty's matrix from the perspective of expert E_2.

A_i	A_1	A_2	A_3	GM_{23}^{i}	z_{23}^{i}
A_1	1	1	1	1.000	0.327
A_2	1	1	2	1.260	0.413
A_3	1	1/2	1	0.794	0.260

Table 34. Scoring of alternatives with respect to criterion C_4 using Saaty's matrix from the perspective of expert E_2.

A_i	A_1	A_2	A_3	GM_{24}^{i}	z_{24}^{i}
A_1	1	1/2	1	0.794	0.260
A_2	2	1	1	1.260	0.413
A_3	1	1	1	1.000	0.327

Table 35. Scoring of alternatives with respect to criterion C_5 using Saaty's matrix from the perspective of expert E_2.

A_i	A_1	A_2	A_3	GM_{25}^{i}	z_{25}^{i}
A_1	1	1/2	1/2	0.630	0.196
A_2	2	1	2	1.587	0.493
A_3	2	1/2	1	1.000	0.311

Table 36. Scoring of alternatives with respect to criterion C_6 using Saaty's matrix from the perspective of expert E_2.

A_i	A_1	A_2	A_3	GM_{26}^{i}	z_{26}^{i}
A_1	1	1/2	1	0.794	0.250
A_2	2	1	2	1.587	0.500
A_3	1	1/2	1	0.794	0.250

Table 37. Scoring of alternatives with respect to criterion C_7 using Saaty's matrix from the perspective of expert E_2.

A_i	A_1	A_2	A_3	GM_{27}^{i}	z_{27}^{i}
A_1	1	1/2	2	1.000	0.311
A_2	2	1	2	1.587	0.493
A_3	1/2	1/2	1	0.630	0.196

Table 38. Scoring of alternatives with respect to criterion C_8 using Saaty's matrix from the perspective of expert E_2.

A_i	A_1	A_2	A_3	GM_{28}^{i}	z_{28}^{i}
A_1	1	3	3	2.080	0.594
A_2	1/3	1	2	0.873	0.249
A_3	1/3	1/2	1	0.550	0.157

Table 39. Scoring of alternatives with respect to criterion C_1 using Saaty's matrix from the perspective of expert E_3.

A_i	A_1	A_2	A_3	GM_{31}^{i}	z_{31}^{i}
A_1	1	1/3	1/2	0.550	0.157
A_2	3	1	3	2.080	0.594
A_3	2	1/3	1	0.873	0.249

Table 40. Scoring of alternatives with respect to criterion C_2 using Saaty's matrix from the perspective of expert E_3.

A_i	A_1	A_2	A_3	GM_{32}^{i}	z_{32}^{i}
A_1	1	1/3	1	0.693	0.200
A_2	3	1	3	2.080	0.600
A_3	1	1/3	1	0.693	0.200

Table 41. Scoring of alternatives with respect to criterion C_3 using Saaty's matrix from the perspective of expert E_3.

A_i	A_1	A_2	A_3	GM_{33}^{i}	z_{33}^{i}
A_1	1	1/2	1	0.794	0.250
A_2	2	1	2	1.587	0.500
A_3	1	1/2	1	0.794	0.250

Table 42. Scoring of alternatives with respect to criterion C_4 using Saaty's matrix from the perspective of expert E_3.

A_i	A_1	A_2	A_3	GM_{34}^{i}	z_{34}^{i}
A_1	1	1	1	1.000	0.333
A_2	1	1	1	1.000	0.333
A_3	1	1	1	1.000	0.333

Table 43. Scoring of alternatives with respect to criterion C_5 using Saaty's matrix from the perspective of expert E_3.

A_i	A_1	A_2	A_3	GM_{35}^{i}	z_{35}^{i}
A_1	1	1/2	1	0.794	0.260
A_2	2	1	1	1.260	0.413
A_3	1	1	1	1.000	0.327

Table 44. Scoring of alternatives with respect to criterion C_6 using Saaty's matrix from the perspective of expert E_3.

A_i	A_1	A_2	A_3	GM_{36}^{i}	z_{36}^{i}
A_1	1	1	1	1.000	0.333
A_2	1	1	1	1.000	0.333
A_3	1	1	1	1.000	0.333

Table 45. Scoring of alternatives with respect to criterion C_7 using Saaty's matrix from the perspective of expert E_3.

A_i	A_1	A_2	A_3	GM_{37}^{i}	z_{37}^{i}
A_1	1	1	1	1.000	0.327
A_2	1	1	2	1.260	0.413
A_3	1	1/2	1	0.794	0.260

Table 46. Scoring of alternatives with respect to criterion C_8 using Saaty's matrix from the perspective of expert E_3.

A_i	A_1	A_2	A_3	GM_{38}^{i}	z_{38}^{i}
A_1	1	3	3	2.080	0.594
A_2	1/3	1	2	0.873	0.249
A_3	1/3	1/2	1	0.550	0.157

Table 47. Scoring of alternatives with respect to criterion C_1 using Saaty's matrix from the perspective of expert E_4.

A_i	A_1	A_2	A_3	GM_{41}^i	z_{41}^i
A_1	1	1/2	1/2	0.630	0.190
A_2	2	1	3	1.817	0.547
A_3	2	1/3	1	0.873	0.263

Table 48. Scoring of alternatives with respect to criterion C_2 using Saaty's matrix from the perspective of expert E_4.

A_i	A_1	A_2	A_3	GM_{42}^i	z_{42}^i
A_1	1	1/3	1	0.693	0.210
A_2	3	1	2	1.817	0.550
A_3	1	1/2	1	0.794	0.240

Table 49. Scoring of alternatives with respect to criterion C_3 using Saaty's matrix from the perspective of expert E_4.

A_i	A_1	A_2	A_3	GM_{43}^i	z_{43}^i
A_1	1	1/2	1	0.794	0.250
A_2	2	1	2	1.587	0.500
A_3	1	1/2	1	0.794	0.250

Table 50. Scoring of alternatives with respect to criterion C_4 using Saaty's matrix from the perspective of expert E_4.

A_i	A_1	A_2	A_3	GM_{44}^i	z_{44}^i
A_1	1	1	1	1.000	0.327
A_2	1	1	2	1.260	0.413
A_3	1	1/2	1	0.794	0.260

Table 51. Scoring of alternatives with respect to criterion C_5 using Saaty's matrix from the perspective of expert E_4.

A_i	A_1	A_2	A_3	GM_{45}^i	z_{45}^i
A_1	1	1/2	1	0.794	0.260
A_2	2	1	1	1.260	0.413
A_3	1	1	1	1.000	0.327

Table 52. Scoring of alternatives with respect to criterion C_6 using Saaty's matrix from the perspective of expert E_4.

A_i	A_1	A_2	A_3	GM_{46}^{i}	z_{46}^{i}
A_1	1	1	1	1.000	0.333
A_2	1	1	1	1.000	0.333
A_3	1	1	1	1.000	0.333

Table 53. Scoring of alternatives with respect to criterion C_7 using Saaty's matrix from the perspective of expert E_4.

A_i	A_1	A_2	A_3	GM_{47}^{i}	z_{47}^{i}
A_1	1	1	1	1.000	0.327
A_2	1	1	2	1.260	0.413
A_3	1	1/2	1	0.794	0.260

Table 54. Scoring of alternatives with respect to criterion C_8 using Saaty's matrix from the perspective of expert E_4.

A_i	A_1	A_2	A_3	GM_{48}^{i}	z_{48}^{i}
A_1	1	2	2	1.587	0.493
A_2	1/2	1	2	1.000	0.311
A_3	1/2	1/2	1	0.630	0.196

Table 55. Scoring of alternatives with respect to criterion C_1 using Saaty's matrix from the perspective of expert E_5.

A_i	A_1	A_2	A_3	GM_{51}^{i}	z_{51}^{i}
A_1	1	1/3	1/3	0.481	0.135
A_2	3	1	3	2.080	0.584
A_3	3	1/3	1	1.000	0.281

Table 56. Scoring of alternatives with respect to criterion C_2 using Saaty's matrix from the perspective of expert E_5.

A_i	A_1	A_2	A_3	GM_{52}^{i}	z_{52}^{i}
A_1	1	1/3	1	0.693	0.200
A_2	3	1	3	2.080	0.600
A_3	1	1/3	1	0.693	0.200

Table 57. Scoring of alternatives with respect to criterion C_3 using Saaty's matrix from the perspective of expert E_5.

A_i	A_1	A_2	A_3	GM_{53}^{i}	z_{53}^{i}
A_1	1	1/2	1	0.794	0.250
A_2	2	1	2	1.587	0.500
A_3	1	1/2	1	0.794	0.250

Table 58. Scoring of alternatives with respect to criterion C_4 using Saaty's matrix from the perspective of expert E_5.

A_i	A_1	A_2	A_3	GM_{54}^{i}	z_{54}^{i}
A_1	1	1/2	1	0.794	0.250
A_2	2	1	2	1.587	0.500
A_3	1	1/2	1	0.794	0.250

Table 59. Scoring of alternatives with respect to criterion C_5 using Saaty's matrix from the perspective of expert E_5.

A_i	A_1	A_2	A_3	GM_{55}^{i}	z_{55}^{i}
A_1	1	1	1	1.000	0.333
A_2	1	1	1	1.000	0.333
A_3	1	1	1	1.000	0.333

Table 60. Scoring of alternatives with respect to criterion C_6 using Saaty's matrix from the perspective of expert E_5.

A_i	A_1	A_2	A_3	GM_{56}^{i}	z_{56}^{i}
A_1	1	1	1/3	0.693	0.200
A_2	1	1	1/3	0.693	0.200
A_3	3	3	1	2.080	0.600

Table 61. Scoring of alternatives with respect to criterion C_7 using Saaty's matrix from the perspective of expert E_5.

A_i	A_1	A_2	A_3	GM_{57}^{i}	z_{57}^{i}
A_1	1	1/2	1	0.794	0.250
A_2	2	1	2	1.587	0.500
A_3	1	1/2	1	0.794	0.250

Table 62. Scoring of alternatives with respect to criterion C_8 using Saaty's matrix from the perspective of expert E_5.

A_i	A_1	A_2	A_3	GM_{58}^{i}	z_{58}^{i}
A_1	1	2	2	1.587	0.493
A_2	1/2	1	2	1.000	0.311
A_3	1/2	1/2	1	0.630	0.196