Article:
Locatelli, G, Mancini, M and Lotti, G (2020) A simple-to-implement real options method for the energy sector. Energy, 197. 117226. ISSN: 0360-5442

https://doi.org/10.1016/j.energy.2020.117226

A simple-to-implement Real Options method for the energy sector

Giorgio Locatelli

University of Leeds - School of Civil Engineering

Woodhouse Lane - LS2 9JT

g.locatelli@leeds.ac.uk

CORRESPONDING AUTHOR

Mauro Mancini

Politecnico di Milano - Department of Management, Economics and Industrial Engineering

Via Lambruschini 4B, 20156 Milano – Italy

Mauro.mancini@polimi.it

Giovanni Lotti

Politecnico di Milano - Department of Management, Economics and Industrial Engineering

Via Lambruschini 4B, 20156 Milano – Italy

gvn.lotti@gmail.com

Please quote this paper as: G. Locatelli, M. Mancini, G.Lotti, 2020, "A simple-to-implement real options method for the energy sector", Energy, Vol 197, pp. 117226

A simple-to-implement Real Options method for the energy sector

Abstract

Investment appraisal methods based on real options are gaining popularity in academia, while the adoption by practitioners is still infrequent. Having in mind practitioners, the method is designed to be: conceptually easy to understand, based on realistic hypotheses and data available, able to provide quantitative indications and strategic guidelines. The method is based on a systematic simulation of several scenarios generated according to *exercise thresholds* of relevant investment parameters. An exercise threshold gives to the investors the exercise right of taking some decision, for instance building a power plant. An exercise threshold is therefore a rule to decide whether to exercise or not a certain option on the basis of the values of one or more state variables. Consequently, the probability distribution of the Net Present Value (or analogous indicator) of the investment is a function of the state variables and the exercise threshold. Systematically changing the exercise *thresholds* allow to (A) establishing the "real option value" and (B) calculate relevant indications about when and on which type of plant to invest. The method is presented in detail and applied to a case study assessing the investment appraisal of: coal plant, gas plant, large nuclear reactor and small modular reactor.

Keywords: Real Options; Decision-Making; Investment Appraisal; SMR; Large Reactors

1 Introduction

The deregulation of electricity and gas markets, which happened in many countries in the last decades, added uncertainties (e.g. the long term electricity price) for decision-makers in the energy sector [1,2]. Nowadays, the utilities have the ownership of the major risks [3] as they are thought to be the best stakeholders to manage them [4,5]. Consequently, utilities need to adopt adequate investment appraisal methods to select the type of power plant to build [6]. In the literature, there are two main approaches to deal with investment appraisals, as follows:

1. The Discounted Cash Flows (DCF). It is the largely the most used method for investment appraisal.
2. The Real Options (RO). It is a family of methods particularly valuable in uncertain contexts [7]. RO methods are considered as an expansion of the DCF.

Traditional methods for investment appraisal are based on the DCF, where cash flows are discounted to the current value, and the Net Present Value (NPV) is the sum of DCF over the investment life cycle [8]. The DCF analysis is mathematically easy to implement but has flaws presented in [9] and discussed here in section 2.1. These flaws are usually addressed by implementing different techniques, such as the sensitivity or scenario analysis. However, these techniques do not adequately consider the stochastic nature of the parameters that affect the analysis and implicitly assume a passive role of the investors once a certain decision is made. A RO method is an investment appraisal technique to take strategic decisions (e.g. investing or not and, if so, when) considering the evolution of specific variables (e.g. fuel and electricity price) in a given scenario. A RO method models the flexibility of the decision-making process, with the aim of dealing with risks to ultimately mitigate adverse projects outcomes, or exploit favourable outcomes [10].

RO have been widely accepted by academics as a tool for capital budgeting and investment appraisal [11]. However, specific challenges prevent the wide application of RO for practitioners and despite the relevance of RO in the energy sector the application is still scarce. [12] surveyed the 1500 largest companies from Denmark, Norway and Sweden discovering that only 6% of the chief financial officers use real options. The key reasons for not using RO was “Require too much sophistication” as reported by 58% of not users. Compared to the DCF analysis, RO appraisals are mathematically more complex, and often many of the academic hypotheses and assumptions (e.g. variable volatility constant over time, price (development cost) behaving stochastically, returns for assets normally distributed [13]) are not satisfied in reality. Nevertheless, utilities are very keen to work on this framework as long as the results provide valuable indications supporting the decision-making process [14,15].

A real options model can support energy utilities and stakeholders in the energy sectors in apprising a number of possible investment decisions. For instance real option can be used to decide:

- If building or not a power plant in a certain region,
- which type of power plant to build (e.g. coal, natural gas, nuclear etc.)
- if buying or not a larger plot of land to have space for future expansion
- If refurbish a plant to extend its life or close it down
- If it worth to build a more expensive plant but able to use more type of fuel or produce more types of outputs
- …

This paper aims to enable practitioners working in utilities and other relevant stakeholders to develop investment appraisal based on RO. The proposed RO method is:

1. Conceptually easy to understand;
2. Based on realistic hypotheses for the energy sector;
3. Based on data available to utilities, policymakers and investors; and
4. Able to provide quantitative indications and strategic guidelines to decide if, when and on which power plant to invest.

The rest of the paper is organised as follows: Section 2 reviews the literature presenting the most relevant limitations of the DCF model (2.1) and the merit of using RO in an investment appraisal (2.2). A novel method is detailed in Section 3, firstly presenting the key idea (3.1) and later the details necessary for implementation by practitioners (3.2). The method is applied to a case study in Section 4, while Section 5 brings together the main elements of this paper with the discussion and conclusions.

2 Literature review of investment appraisal in the energy sector

2.1 The DCF methods

In industrial practice, the most used project appraisal method is the DCF analysis [16]. Although the DCF analysis is mathematically simple and easy to implement, it has three substantial drawbacks, which fostered the development of the RO method. The drawbacks are described as follows:

1st - The weak consideration of the stochastic nature of the cash flows [13].

Future cash flows cannot be assumed as certain. Therefore, in DCF methods, uncertainties and risks analyses are based on forecasts, that are often erroneous [17] or biased for a number of reasons [18]. For example, when considering a power plant's life cycle of 30-60 years, the electricity price and fuel cost can vary considerably. The most popular techniques to cope with this issue are sensitivity analyses, scenarios analyses, and Monte Carlo simulations. Unfortunately, even the results of these techniques can be easily manipulated by arbitrary assumptions forced by contingent situations [19].

2nd - The choice of the discount rate to reflect the risks of the cash flows, which is unavoidably subject to estimation errors [20].

In the DCF method, the risks associated with the project are modelled through discounting risky investments with a higher discount rate than less risky ones following the rule: *Ceteris paribus* higher the risk, higher the discount rate [21]. This approach has several drawbacks: firstly, the definition of the discount rate is arbitrary and difficult to establish because it requires assumptions about the appropriate asset-pricing model and data on returns of financial instruments, which should have broadly-comparable risk profiles. Secondly, tuning the discount rate might not be the optimal approach since highly profitable projects associated with high uncertainties could be rejected [9].

3rd - The assumed passivity of the management, unable to improve the results after the resolution of specific uncertainties [22].

The DCF appraisal implicitly assumes that all future decisions are made today, while usually the investment decisions are continuously revised following market changes and/or the evolution of factors such as the regulatory system. Investments involve many contingent decisions, like expanding a project if it becomes very favourable or abandoning it in case of poor performance. There is an additional value associated with these decisions that is not considered by the DCF method. Indeed, using the DCF, assumptions are made on both the expected scenario of the operating cash flows and the commitment of the manager to a certain operating strategy [7].

2.2 The Real Options method

2.2.1 Introduction to Real Options

The RO analysis is an expansion of the DCF analysis [7] pricing the value of managerial flexibility. From a practical perspective, a RO creates value and reduces the risk [23] by giving the risk & investment holder the right, but not the obligation, to undertake some business decisions. RO can include the decision to make and/or to abandon and/or to expand and/or to contract a capital investment within or at a specific time. The most common RO include [24,25]:

- Option to invest, i.e. the decision if building or not a certain infrastructure and which type of infrastructure;
- Option to defer, i.e. the possibility to wait before taking irreversible decisions;
- Option to abandon, i.e. the possibility to abandon current projects permanently if market conditions became extremely unfavourable;
- Option to expand, contract, or extend the life of the facility, i.e., for example, the possibility to increase the capacity of a power plant, when profitable;
- Option to switch: the possibility to change products, processes or inputs [26].

RO are valuable when there is high uncertainty about the profitability of an investment, and the management can change the course of the project towards a more favourable direction. Conversely, when there are few uncertainties and no managerial flexibility, RO offers little value [9]. Figure 1 exemplifies the main differences between DCF and RO, and Table 1 highlights the key differences between DCF and RO in a context such as the energy sector.

In summary, using the RO to evaluate an investment, it is possible to recast the usual DCF discussion *whether* to invest or not, into the investigation on *when* it is more profitable to invest. In fact, [20] demonstrated that (1) waiting for new information to decide whether to invest or not in the future has a value and (2) investing is an irreversible decision killing this flexibility. When applying RO, the rule “invest if the investment’s NPV exceeds zero” becomes “invest if the investment’s NPV exceeds the value of the option to wait”. The method presented here focuses on the “option to invest”.

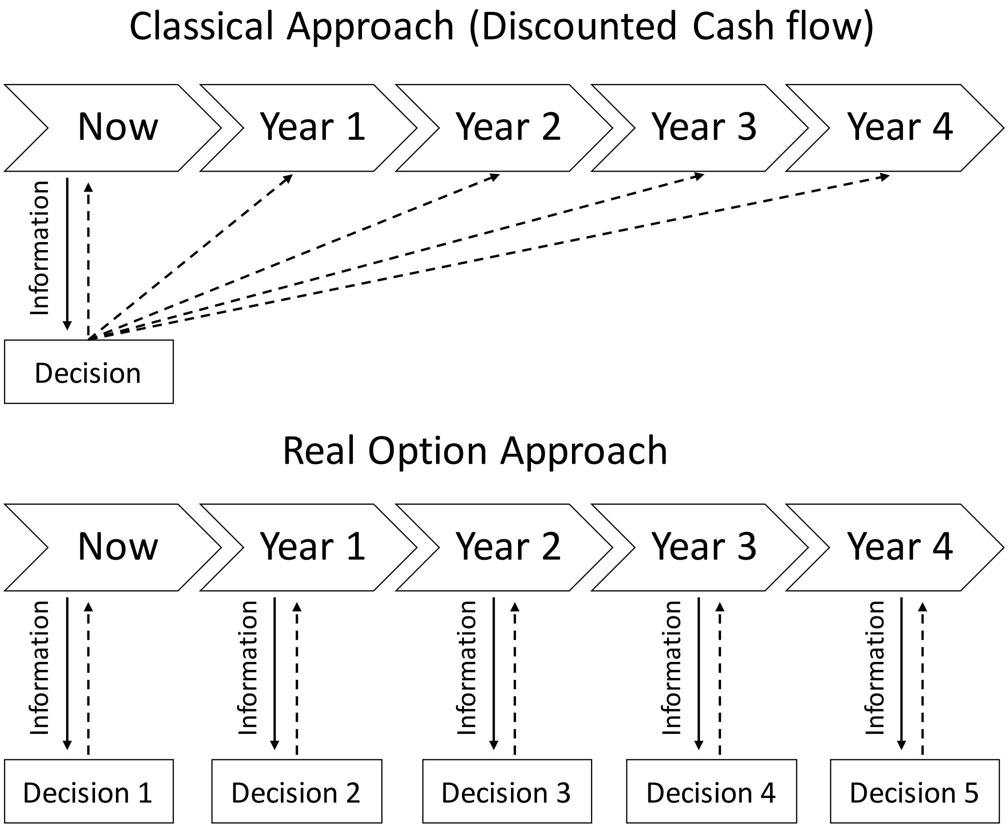


Figure 1: Classical approach (i.e. DCF) vs the RO approach

Discounted Cash Flow	Real Options
In the DCF analysis, uncertainties and risks are not adequately considered. Monte Carlo simulation, sensitivity analysis or changes in the discount rate are techniques to enhance the DCF analysis, by considering uncertainties and risks.	Uncertainty is the key factor that creates the option value.
All decisions are taken at the beginning of the development of the project.	Decisions can be made at different times.
All decisions are fixed and independent of future events. DCF does not capture the value of managerial flexibility during the project life cycle. DCF does not capture the dynamic nature of uncertainties.	Flexibility is implemented, as the management / decision-makers can do actions to alter the course of the project.
The expected payoff is discounted at a rate adjusted for the risk. The level of risk is expressed through the increment of a discount rate.	Risks are expressed through the probability distribution of the payoff.

Table 1: Comparison of DCF and RO method, elaborated from [9,27]

2.2.2 Choice of the Real Options appraisal method

Mathematical models originally developed to evaluate financial options are usually implemented for the RO appraisal. However, RO face more uncertainties than financial options [28] and there are more complicated interactions between options [29]. Gamba [30] argues that many methods have been proposed for assessing RO, but the majority of them are extensions of well-known algorithms used for financial options. RO models can be divided into analytical (based on exact equations – such as the Black–Scholes model) and numerical (based on approximation provided by computational simulations). Analytical methods are the best approach, when applicable [23], as they are extremely fast to compute and generate exact solutions. Analytical methods have been developed primarily for the financial world, consequently many of these methods are not suitable for the energy and utility sector, as they depend on very strict assumptions [31]. For example, unlike classical algorithms for the pricing of financial options, RO do not have a predetermined exercise date, the risk is not constant over time, returns for most real assets are not normally distributed, etc. In summary, these methods are applicable only to a few special cases, even if they are mathematically elegant [32].

When there is no analytical solution, numerical methods must be used [33]. Numerical methods approximate stochastic processes and divide the time horizon into a set of time-steps in which the options can be exercised. The most common numerical methods in the literature are: finite difference schemes to resolve partial differential equations, binomial (or multinomial) trees and lattices, Monte Carlo simulations.

The finite difference method discretises the state variable [34]. In practice, this method is hardly applicable because (1) options interact with each other, and (2) due to the phenomenon called "curse of dimensionality" [35].

Binomial (or multinomial) trees and lattices are methods based on the assumption that the stochastic variables can assume only a finite number of values (two in binomial case, three in the trinomial case, etc.) at each time step. For instance, in binomial trees, the value of the state variable could move up or down by a specific factor with a certain probability. This method, firstly proposed by [36] is relatively easy to implement with only one variable/risk, e.g. the electricity price [37], but it is hardly applicable for more than one state variable, as the number of nodes grows exponentially with the number of state variables [38].

The Monte Carlo simulation is usually implemented as "least-squares Monte Carlo", a method developed by [39], with the advantages of being able to cope with the complexity that remains fast and efficient. The inputs of this method are both deterministic (e.g. the size of the power plants) and stochastic (e.g. the electricity price) and the result of the method is the expanded NPV of the investment, which incorporates the value of the options [40]. An exemplary application of this methodology in the energy sector is presented in [41,42]. The main limitations of the least-squares Monte Carlo are:

- It requires advanced programming skills to create the model defining the mathematical relations between inputs and outputs;
- It does not provide guidelines to the managers about how to maximize the value of the

investment; and

- Implementing more than one option at a time escalates its complexity.

This method is, therefore, ideal for academics and scientists but it is hardly applicable by practitioners.

2.2.3 Real Options in the energy sector

The RO approach is not necessary for each investment appraisal. On the one hand, a RO approach is less approximated than the classical DCF method because it properly values uncertainties and degrees of freedom, but on the other hand, it requires more complex analyses and algorithms. The RO approach is particularly valuable when:

- The probability distribution of the NPV has a broad dispersion around zero, i.e. the profitability of the investment is uncertain. On the contrary, if it is "sure" that the investment's NPV will be positive or negative the investor will do or not the investment;
- The investor has flexibility (i.e. options) during the decision-making process. For example, RO enable to evaluate the "value of waiting" i.e. the flexibility of postponing investment to obtain more information. Keeping the option "alive", i.e. to maintain the feasibility to invest or not to invest, has a value that can be calculated [24].

[43] summarized that RO are more valuable in the energy sector as follows:

- When there is a contingent investment decision;
- When uncertainty is large enough that it is sensible to wait for more information;
- When the value seems to be captured in possibilities for future growth options rather than current cash flows;
- When uncertainty is large enough to make flexibility a relevant factor; and
- When there will be projects updates and mid-course strategy corrections.

More specifically, RO can support decision-makers in the energy sector in three important ways as follows:

1. To make strategic investment decisions and to choose from various designs that differ in terms of flexibility and the marginal cost of production.
2. During operation exercise rules resulting from RO models can be used to operate a power plant;
3. Profit and loss distributions can be used to integrate physical production assets with financial contracts considering enterprise-wide risk management [44].

Fernandez et al. [45] reviewed studies applying RO theory in the energy sector from 1987 to 2011. Locatelli et al. [46] update Fernandez' list by highlighting 15 selected studies of RO in the energy sector with the focus on energy storage systems, i.e. analysing [47–49] in more details. Zhang et al. [50]

present 20 studies on renewable energy investment using the RO method, highlighting that in the majority of the cases, the solution method was either partial differential equations or dynamic programming. Nevertheless, these two methods are unable to deal with more than two variables [50]. The literature also presents models to deal with compound options (i.e. considering more than one options), but these methods are mostly academic and too complex to be implemented by practitioners [9,51–53].

Similarly to [54,55], this paper considers the application of RO in the nuclear sector. Building on the framework introduced by [9], Table 2 compares this paper with [54,55].

	This paper	**[54]**	**[55]**
Aim of the paper	To present an algorithm to enable practitioners working in utilities and other relevant stakeholders to develop investment appraisal based on RO.	To assess the technical-economic feasibility of load following coupling Small Modular Reactors (SMR) with two cogeneration technologies: algae-biofuel and desalination.	To compare the investment in a single large nuclear reactor versus a series of SMRs built in the same site.
Type of algorithm	Exercise threshold	Monte Carlo simulation	Least Squares Method
Options considered	Option "to build" and option "to wait to build" one or more of the following four power plants: Large Nuclear Reactor, Combined Cycle Gas Turbines, SMR.	Assuming that the SMR plant is surely built, the paper considered the "option to wait" and "option to build" the desalination plant. The paper also considered the "option to switch" between alternative generation models.	With reference to the plan of building 4 SMRs in the same site the paper considered the "option to expand" and the option "to abandon".
Expiration time	20 years	10 years	Variable (9- 12- 15 years deployment)
Exercise price	The cost of building the power plant considered	The cost of building the desalination plant	The cost of building a further SMR unit
Option value	The option has a positive value for all the plants considered	The value depends mainly on the price of the plant, water and electricity	The value is positive (tested in different scenarios) unless the project is heavily de-risked with the support of the government

Table 2: Comparison of this paper with [54,55]

These and other numerous academic publications show that the RO method is suitable for the investment appraisal of different technologies (e.g., renewables [56,57], gas [58]), hydropower [59], but also to assess the effect of CO_2 prices [60], to model political uncertainties over greenhouse gasses [34,61], and market & policy uncertainties [62]. However, RO have been implemented by practitioners by just in a few cases, more notably [15,63]. In summary, the RO models proved to be useful for the utilities and energy sector, but the vast majority of applications has been done by academics for academic studies.

3 The new method: simulation with optimized exercise thresholds

3.1 Introduction – The key idea of thresholds

The methods presented in this work build on the contributions of [23,30,57,64,65]. The main differences with these methods presented in the literature are their enhancement and tailoring for the application of practitioners using modern computers and software not available at the time.

The key idea of the method proposed in this paper is to use an "**exercise threshold**". An exercise threshold gives the investors the "*exercise* right of doing something" e.g. to build a power plant. Before defining how to optimize an exercise threshold, it is helpful to understand what it does (Figure 2). An exercise threshold (part **(A)** in Figure 2) is a rule to decide whether to exercise or not a certain option on the basis of the values of one or more state variables **(B)**. For instance, an exercise threshold could be e.g. "to build the power plant if in the last year the average electricity price was above 50 $/MWh". Consequently, the probability distribution of the NPV **(C)** is a function of the specific inputs, e.g. the construction cost, and the exercise threshold.

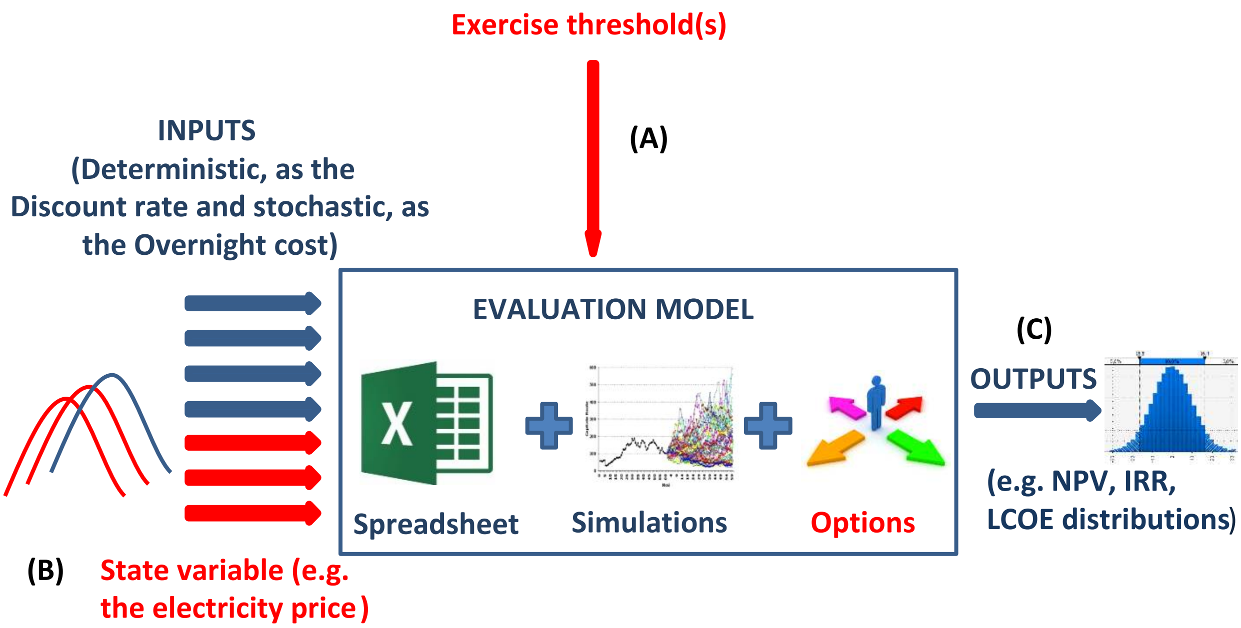


Figure 2: Graphical representation of the key idea. (NPV = Net Present Value, IRR = Internal Rate of Return, LCOE = Levelised Cost of Electricity. Adapted from [66]**)**

In general, exercise thresholds depend on the value(s) of stochastic processes, called "state variables" (e.g. the electricity price p_t). For instance, an exercise threshold can be the electricity price value p^* that, when reached by the state variable p_t, triggers the option to invest.

A high "electricity price" threshold will create a binomial like distribution with several iterations where the NPVs equal to zero and few iteration with high NPVs because the model will decide to invest only a few, very profitable iterations, when the electricity price reaches a very high value. Most times the model will decide not to invest, resulting in several iterations where the NPVs are equal to zero. The few times when the investment is triggered, there will be relevant profits for the utility since the electricity price is high and it enhances the NPV. Conversely, a low electricity price threshold generates a probability distribution similar to a DCF since the investment will always be triggered, and therefore the power plant will always be built.

Since the exercise threshold influences the output distribution, the method determines which threshold optimizes the output distribution, i.e. which threshold maximizes the mean NPV while reducing the risk. The aim is therefore to compare different exercise thresholds (e.g. different prices of $p^*$to reach) to find the optimal threshold, i.e. the exercise threshold that maximizes the mean NPV and/or minimizes its risk, i.e. standard deviation of the NPV probability distribution.

3.2 Implementation

This methodology can be implemented in a spreadsheet (like Microsoft Excel) in two simple ways:

1 - the discrete enumeration of all the possible thresholds (as in 3.2.1 and 3.2.2);

2 - the discrete enumeration of all possible states (as in 3.2.3 and 3.2.4).

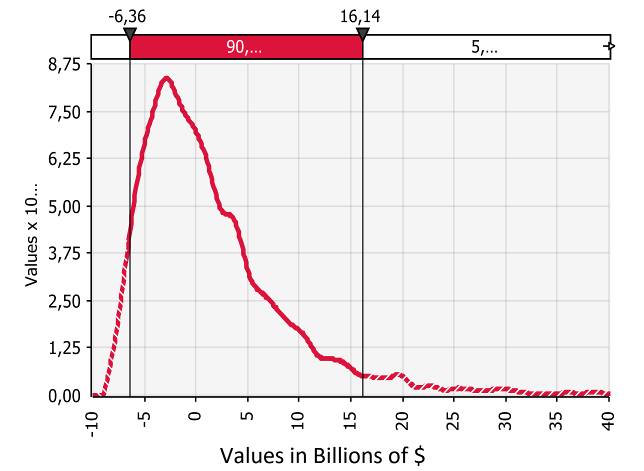
The assumptions about the inputs are provided in section 3.3[1].

3.2.1 Discrete enumeration of all the possible thresholds: Single variable

The key idea is to consider a set of different exercise thresholds and calculate, for each of them, the different effects on the NPV probability distributions. This method starts from an interval of exercise thresholds and with a Monte Carlo simulation calculates for each threshold the NPV probability distributions with its mean and standard deviation. From all these NPV probability distributions it is possible to select the threshold that provides the best distribution in terms of mean NPV, minimum standard deviation, etc.

As a case study let's consider a large nuclear reactor, and only one state variable: the electricity price (for the list of inputs see Table 3 in section 4.1). With the DCF approach, it is possible to calculate the NPV probability distribution assuming that the electricity price follows a Geometric Brownian Motion process with an initial value $P_0 = 90\ \$/\mathrm{MWh}$ and $\sigma = 20\%$. The DCF Monte Carlo generates the stochastic distribution of the NPV as in Figure 3 [66].

[1] Please remember that the primary goal of this paper is to present a novel methodology, not to discuss the economics of different types of power plants. Therefore, for the sake of simplicity and transparency, this paper uses, for the different technologies, generic publically available figures. Practitioners working utilities will use values specific for their scenario.



Mean [M$]	1758
Std. Dev [M$]	7901
25th Percentile [M$]	-3322
50th Percentile [M$]	-88
75th Percentile [M$]	4478
Probability (NPV<0)	51%
Profitability Index	1,33
Levelized cost of energy (LCOE) [M$]	73

Figure 3. NPV distribution with a DCF assessment

With the RO evaluated with the "exercise threshold" method, the option to invest will be exercised when the value of the electricity price will exceed a threshold P^* . The steps for this method are:

1. Define an interval of P^*, defined by a lower and an upper bound. The lower bound must be lower than the initial electricity price P_0 (so, for instance $P^* = 1$ [$/MWh]) the upper bound might be a value of P^* highly improbable to reach. (for instance, $P^* = 600$ [$/MWh])
2. Obtain the NPV probability distributions using a Monte Carlo simulation[2] starting from $P^* = 1$ [$/MWh] (construction starts with electricity price equal or superior to 1 [$/MWh]) then $P^* = 2$ [$/MWh] until $P^* = 600$ [$/MWh]. In this case 600 "exercise thresholds" are assessed with 600 Monte Carlo simulations.
3. For each of the 600 Monte Carlo simulations compute and record relevant indicators such as NPV mean and the standard deviation.

Figure 4 [66] shows the relationship between the $P^*$and mean value of the NPV probability distributions for the different thresholds (shortly "NPV mean") Figure 5 [66] shows the relation between the $P^*$and the standard deviation of the NPV probability distributions for the different thresholds (shortly "standard deviation"). Figure 6 combines the NPV mean and standard deviation in a single graph. Figure 4 shows that:

A. When $P^* < P_0 = 90$ [$/MWh] the option to invest is exercised at time 0, since P_0 already exceeds P^*. All the values of the NPV mean are the same, as the NPV_0 is the same than for the DCF (Area A).

B. When P^* is very high the NPV mean is almost zero (Area B), because of the probability of reaching

[2] Several commercial user-friendly Microsoft Excel add-ons can do this. Most of them even check the convergence with rigours statistical tests.

a very high value of $P^*$is very low, and not investing (that is most of the cases) equals to have a NPV mean for the probability distributions equal to zero.

C. Between these two extreme conditions, there is a value of P^* with the maximum NPV mean. This value is the "expanded NPV" (value C in Figure 4) and the difference between this value and the NPV_0 (the mean of the NPV probability distribution obtained from investing at time 0) is the value of the option to invest.

D. There is a gap after $P^* = P_0$. In fact, waiting for a value greater than P_0 implies not to invest at time zero, leading to a probability greater than 50% not to invest in the next time period, and to a probability of about 17.75% to never invest in the interval considered. The gap is originated by the time discretisation that, in this case, is one year. This is consistent with the unit of measure of the inputs and the practice of having DCF model based on annual cost and revenue; moreover all the discount factor are commonly presented with an annual unit of measure.

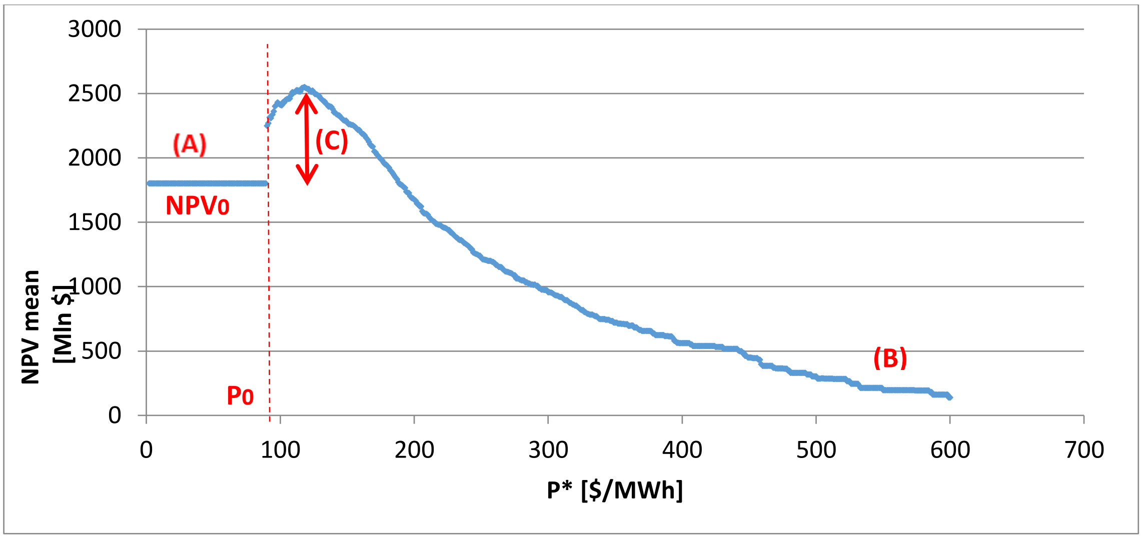


Figure 4: How the value of P* impacts on the mean of the NPV distribution

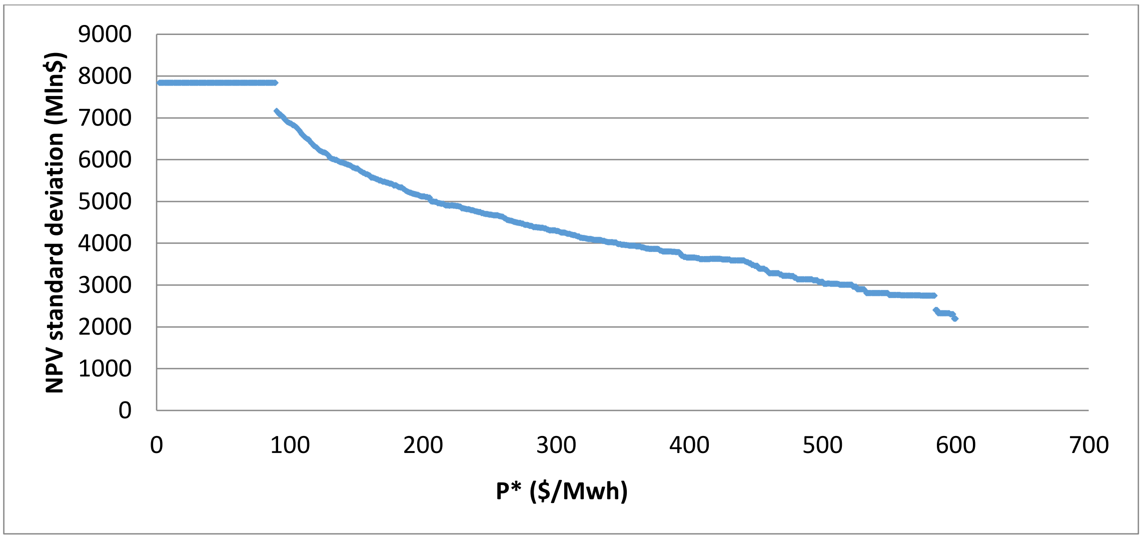


Figure 5: How the value of P* impacts on the standard deviation of the NPV distribution

Figure 6 presents the NPV standard deviation against the NPV mean by combining the value in Figure 4 and 5. In Figure 6 [66] each point is the NPV mean and the standard deviation of a probability distribution, obtained with a different value of P^*.

The left tail of this curve is an optimal frontier since the investor could decide to accept a lower NPV mean (i.e. the return of the investment), reducing the NPV standard deviation (i.e. the investment risk). Therefore all the points on the left tail of a curve in Figure 6 are reasonable choices. For each investor/utility the most appropriated point (i.e. investment strategy) can be selected following both quantitative and qualitative criteria. As an example of quantitative criterion, [67] described a parameter, called “Sharpe ratio”, that lets an investor compare the investment strategies in terms of their expected return for a unit of risk. Sharpe ratio is, therefore, a measure for calculating the risk-adjusted return, and this ratio is popular in the industry [66]. Qualitative considerations might involve the risk attitude of the investors. For example, some investors, e.g. pension funds, look for low risk/low return investments while other investors, e.g. venture capitals, are focused on high risk/high return. Moreover mixed qualitative and quantitative evaluations can be included using metrics such as the value of the project respect to the total value of the company investing and the effect of an investment default. Indeed, the failure of a USD 100 Million project can be an “unfortunate investment” for a USD 100 Billion utility, while could lead to a tragic bankruptcy a USD 150 Million utility. Therefore a large utility might have a higher risk appetite.

The right tail of the curve in Figure 6 is not efficient since, for the same value of NPV mean and standard deviation, a point on the left side of the curve has a lower standard deviation. Therefore:

1. Investing now (the isolated blue point on the right) is less profitable (the NPV mean is lower) and riskier (the standard deviation is greater) than waiting for a $P^* = 115$ [$/MWh] maximizing the NPV distribution.
2. The distribution obtained from waiting for $P^* = 115$ [$/MWh] has the highest NPV mean, but there are other distributions with lower NPV mean and lower standard deviation.

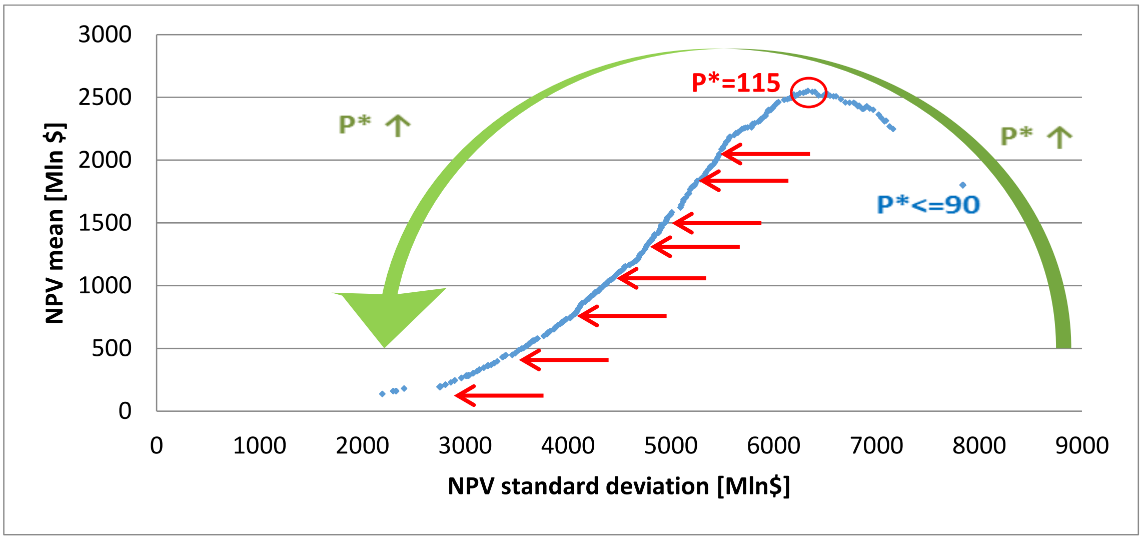


Figure 6: How different values of P* change the mean and the standard deviation

3.2.2 Discrete enumeration of all the possible thresholds: Extension to two or more state variables

The discrete enumeration of all possible thresholds can be easily expanded with multiple state variables. For example, assessing the investment of a gas power plant, two state variables can be included in the model. The state variables could be (i) the electricity price P_t and (ii) the cost of gas G_t. In this case, the exercise thresholds are a pair of state variables $(P^*; G^*)$ and the option to invest will be triggered when the two conditions are both satisfied at the same time (P_t exceeds P^* and G_t is minor than G^*). For every exercise threshold (P*; G*) there is a different NPV probability distribution. The steps to follow are:

1. Define the interval of the possible exercise thresholds $(\mathrm{P}^*, \mathrm{G}^*)$. For example, the possible combinations can be $0 < \mathrm{P}^* < 600$ [$/MWh] and $0 < \mathrm{G}^* < 60$ [$/MWh].
2. This interval is divided into the possible exercise thresholds, for example, the combinations $(\mathrm{P}^*, \mathrm{G}^*)$={(0;0),(0;4)…(2;0),(2;4)…(600,60)}.
3. For each exercise threshold, a Monte Carlo simulation generates a NPV probability distribution corresponding to waiting for that exercise threshold.
4. From each NPV probability distributions, the algorithm records the NPV mean and NPV standard deviation.

The conclusions obtained with one state variable can be extended to two state variables:

A. When $P^* < P_0 = 90$ [$/MWh] and $G^* > G_0 = 60$ [$/MWh] the option to invest is exercised at time 0 since P_0 already exceeds P^* (i.e. the actual electricity price is higher than the threshold value) and G_0 is already under G^* (i.e. the actual price of gas is lower than the threshold value). Mathematically they are the same results of a traditional DCF Monte Carlo simulations.

B. When P^* is very high and G^* is low, the NPV mean converges to zero. That is because there is a very low probability to reach a state where “P^* is very high” AND “G^* is very low”.

C. Between these two extreme conditions, there is a trade-off in which the NPV mean reaches a maximum.

It is possible to extend the method to 3 or more parameters. This will increase the computational cost, but the algorithm is exactly the same.

3.2.3 The discrete enumeration of all possible states – single variable

The second possible implementation of the method is the discrete enumeration of all possible states. It requires some programming literacy, but it provides more precise solutions with less computational effort (particularly relevant if the number state variables increase). A single variable example is described to illustrate the model in its simplest form. The method (illustrated in Figure 7) aims to simulate every possible “situation,” i.e. every possible combination of the state variables. Then, for every possible “situation”, this method answers to the question “in this situation, is it better to invest or to wait to invest?”

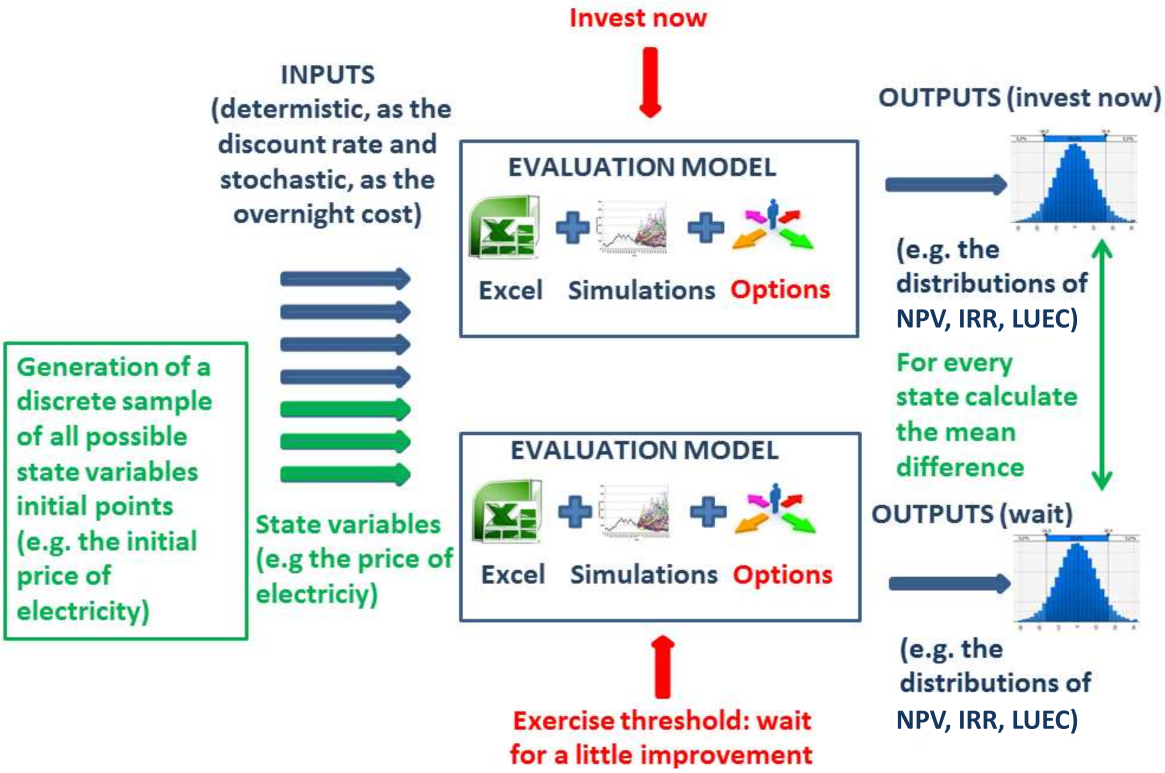


Figure 7: The scheme of the discrete enumeration of all possible state variable values

The method calculates for each possible value of the state variable(s) the difference between investing immediately and waiting. Continuing the example of paragraph 3.2.2: for values of P_0 lower than the $P^*_{\max(mean)}$ (the value of P^* maximizing the NPV mean), the difference ($P^*_{\max(mean)}$-P_0) will be positive (since it is better to wait). With P_0 values greater than the $P^*_{\max(mean)}$ the difference ($P^*_{\max(mean)}$-P_0) will be negative (since it is better to invest) and with $P_0 = P^*_{\max(mean)}$ it will be zero. Therefore, finding $P^*_{\max(mean)}$ is equivalent to testing all these possible values of P_0: when the difference between investing now and waiting for a "slightly" greater value is equal to zero, the value $P^*_{\max(mean)}$ is found. This occurs for two reasons:

1. Independently from the value of P_0, the value $P^*_{\max(mean)}$ remains the same;
2. There is a gap between investing now and waiting for a price slightly higher next year (Figure 4).

The steps of this method are:

1. Consider an interval of all possible discrete values of the state variable, defined by a lower and an upper bound. In this case, the lower bound is $P_l = 2$ [$/MWh] and the upper bound is $P_u = 600$ [$/MWh].
2. Then the interval is divided into *m/2* values. In the example, these values would be {2, 4…598,600}. Then, *m = 600* simulations are made, two for each possible value of the state variable considered. In other words, the first value $P_0 = 2$ [$/MWh] is considered, and it is computed using a MCS in which the initial electricity price is $P_0 = 2$ [$/MWh] and the investment is made immediately. A second simulation is then performed in which the value of P^* is incremented by a small amount, for instance to 2.01 [$/MWh]. This means that for each iteration, the investment is made at time *t* when $P_t > P^*$ and it is not made at time zero.
3. For each value {2; 4…598; 600}, there are two NPV probability distributions, and consequently two NPV means. If the first NPV mean is lower than the second, then it is better to wait.
4. Identify the two consecutive P_0 values where the difference of the NPV mean shifts from positive to negative.

This method validates the discrete enumeration of all possible thresholds because of the value of $P^*_{\max(mean)}$ is the same.

3.2.4 Extension with multiple state variables

This method is designed to be extended to multiple state variables (e.g. electricity and gas as in 3.2.2). Considering the case in section 3.2.2, the first step is to perform Monte Carlo simulation for the discrete combinations of P_0 and G_0 (P_0,G_0=({2,2};{2,4};{2,8}…{4,2};{4,4}…{60,600})). Each combination is valued calculating the NPV mean and comparing the scenarios "invest now" vs "wait to invest" for a more favourable situation (an increase of the electricity price or a decrease of the cost of gas) as illustrated in Figure 8. For example, if P_0, G_0= (2, 4), the NPV mean of investing immediately and the NPV mean of waiting to invest is calculated. An investment would only be made if, $P_t > 2.01$ [$/MWh] or $G_t < 3.99$[$/MWh]. The difference between the NPV means is calculated and when it is positive it is better to wait. When the difference becomes close to zero it is the optimal moment to invest. Figure 8 shows the logic of this extension. Also in this case the reader should not be misled by the rectangular shape in the second Cartesian graph. The rectangular shape only implies that the algorithm can move "up and down" all along the space represented by the point in the first Cartesian axes. Indeed the "frontier zone" can have any form, e.g. a straight line as in the third Cartesian graph.

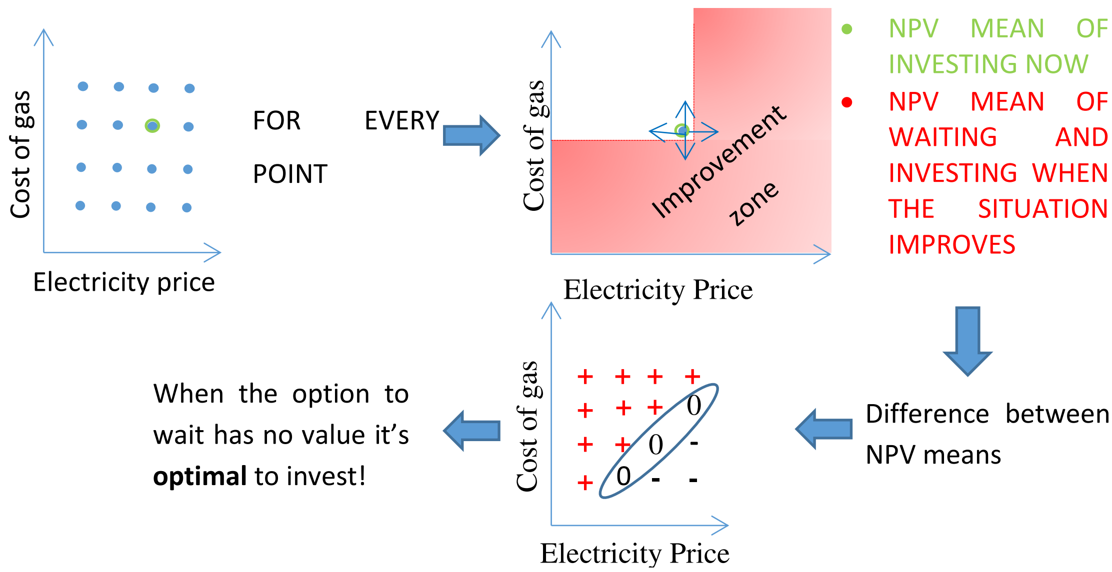


Figure 8: The steps of the discrete enumeration of all possible states with multiple state variables

4 Case study: application for the selection of baseload power plants

4.1 Definition of inputs and assumptions

The goal of this paper is to show a novel methodology, its application, and typical results, not to perform an actual investment appraisal. Therefore, even if the inputs for the case study presented in this section are from reliable organisations, this analysis mainly explains the implementation process. In RO investment appraisal, the modelling of stochastic processes is fundamental. The options analysed in this case study are the “option to build” and the “option to wait”. In this case, the utility can decide if building the power plant or not (so, there is an option to build) and this decision can be postponed for a certain number of years (so, there is an option to wait).

The first step is to divide the inputs into deterministic and stochastic, as below.

Electricity price

In most countries, the electricity price in the market has these characteristics:

- **High variance:** reflecting the variability of the electricity price;
- **Mean reversion:** the electricity price fluctuates around its average:
- **Seasonality:** changes that periodically occur every year (e.g. summer or winter price);
- **Jumps**: the combined effect of high price variance and quick mean reversion [11].

In the literature, there are different methods to simulate the electricity price; a complete survey is provided in [11]. The Geometric Brownian Motion process is the most common because:

1. it needs only three parameters to be modelled, or two if the drift is removed;
2. it is easy to model in a spreadsheet;
3. it is suitable to model long-term decisions, such as building a power plant, as the Geometric Brownian Motion is usually chosen to reflect longer-term uncertainty and is suitable for the energy sector [68].

Since the evaluation method is discrete-time based, this stochastic process is modelled as in equation (1):

$$P_{t+1} = P_t + \sigma P_t W_t \quad (1)$$

Where P_t is the electricity price at time t, σ is the standard deviation and W_t is a standard normal variable. While the initial value of the electricity price is country-specific, the standard deviation presents a pattern that is independent of the country. This work assumes $\sigma = 0{,}3$; the average between [69] and [70].

Capital investment costs

The Total Capital Investment Cost (TCIC) includes principally three components: the overnight cost, the interests during construction and the escalation cost.

The construction of power plants takes years, and the TCIC uncertainties can be divided into two types [71] :

- **Market uncertainties**, due to the fluctuation of prices for labour and materials. Numerous indexes deal with market uncertainty, like the CEPCI (Chemical Engineering Plant Cost Index), the M&S (Marshall & Swift index) and the PCCI (power Capital Costs Index) [72].
- **The project uncertainties**, including aspects such as scope/design changes that are difficult to quantify during the planning phase. Project uncertainties are addressed during construction; the actual cost unfolds as the project proceeds.

TCIC can be therefore modelled using the method described in [73] and the data from [72].

Fuel price

Fuel costs behave similarly to electricity prices (in terms of mean reversion, jumps, etc.), therefore can be modelled as a Geometric Brownian Motion. Gas and coal price are modelled with an annual standard deviation of ±7.75% and ±1.8% respectively [74]. The initial prices are 47.39 [$/MWh] for gas and 22.27 [$/MWh] for coal.

Greenhouse gases cost

Greenhouse gases cost (either carbon tax or carbon sequestration) are uncertain and impact on profitability. Different technologies emit different amounts of greenhouse gases per unit of electricity generated and therefore this cost must be included in the analysis. Similar to the electricity and fuel prices, Greenhouse gases costs can be modelled as Geometric Brownian Motion process. The long-term average carbon cost is 30 [$/t] and the standard deviation is 10% [75].

Deterministic inputs

Representative discount rates can be found in [75,76]; the model considers 5% for all the technologies. The option is modelled to expire in 20 years, and decisions to invest can be taken once a year. The utility can decide to never invest. The 20 years constraint implies that the utility can start the construction in any of these 20 years. Regardless of the start date of the project, the duration of construction will be the number of years named “Construction time” in Table 3, and also operational life will be the number of “Operating years” in Table 3. These are realistic hypotheses because power plants (especially nuclear) have an operating life that is predetermined by their licences. Such licences are issued for a specified number of years which start from the successful commissioning of the plant. The “operation Table 3 summarizes the most relevant inputs.

	Large Nuclear Reactor	Gas - Combined Cycle Gas Turbines (CCGT)	Coal	Small Modular Nuclear Reactor (SMR)
Capacity [MW]	1500	500	750	335
Capacity factor [%]	85%	85%	85%	95%
Overnight cost [$/KW]	5335	1003	3220	6362
O&M [$/MWh]	13.96	15,03	13,43	21.28
Fuel [$/MWh]	8.26	47.4	22.27	8.26
Carbon Intensity [t/MWh]	0	0.35	0,8	0
Greenhouse gases cost [$/MWh]	0	10.54	23.96	0
Construction time [Years]	6	3	4	5
Operating years [Years]	60	30	40	60

Table 3: The deterministic inputs used in this work. For Nuclear Reactors the fuel cost includes front-end and back-end. Values from [3,75,77,78]

4.2 Results

The goal of this section is to show representative results produced by this novel RO approach. The first result is the NPV probability distribution using a DCF method. Figure 9 illustrates the NPV mean and NPV standard deviation (per MW installed) of the four different power plants. Gas power plants seem the best choice since gas power plants have the highest NPV mean and lowest standard deviation. Large nuclear is also an attractive investment because of high returns. Investments in Small Modular Nuclear Reactors (SMR) and coal present a risk comparable or higher than gas and large nuclear, but the return is lower making these investments less attractive.

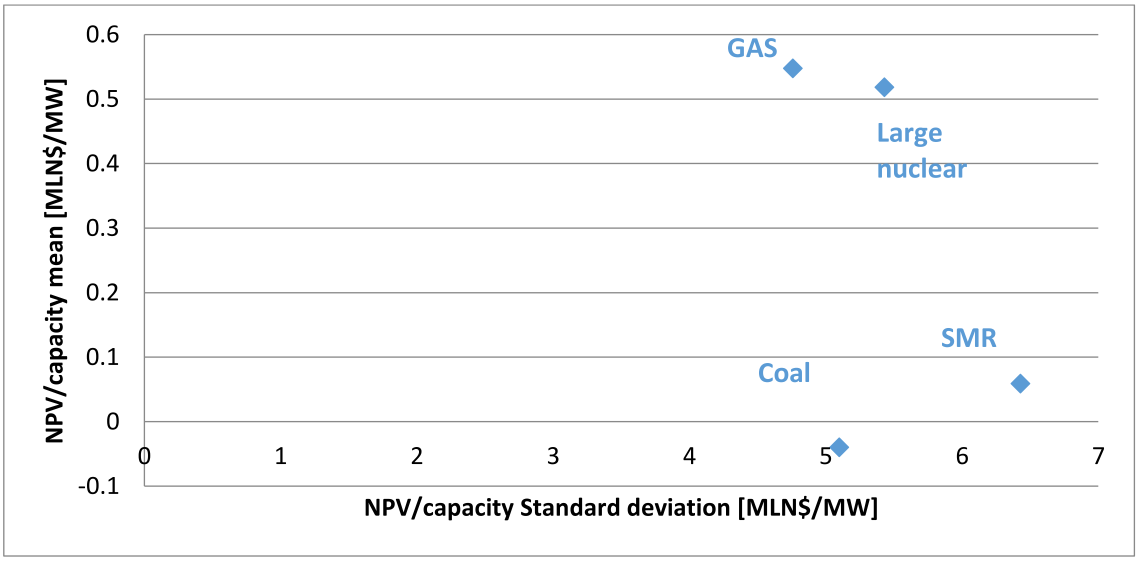


Figure 9: The NPV and standard deviation of different power plants

Figure 10 shows how a utility can improve its investment performance by using an electricity price P^* as a decision variable. For all the four power plants the option to weight has a value. All the NPV means increase and the standard deviation decreases, confirming that the exercise thresholds have a relevant positive effect on the NPV probability distributions.

The method also provides information about the investment strategy. The P^*_{max} and the expected investment time are outputs available for the decision-makers, along with the probability to reach these electricity prices. The P^*_{max} of different technologies are (not surprisingly) different and, other variables being equal, the rational investor will always wait for at least the first P^*_{max} to invest. These results are summarized in Table 4 and are relevant both for investors and policymakers. For instance P^* can be used to calculate the fair value of a power purchase agreement, which is a very relevant topic in the energy market [79,80]. Using this criterion, the gas plant, having a P* of $110/MWh, results to be the first to build. Quite remarkably the value of investing in coal plants increases shifting from negative NPV mean to positive NPV mean. The value to wait for favourable scenarios unveil a value for this technology. Remarkably the investment is recommended only for 48% of the times but in such cases the investment will be very likely profitable since the probability of having a negative NPV mean will only be 11%

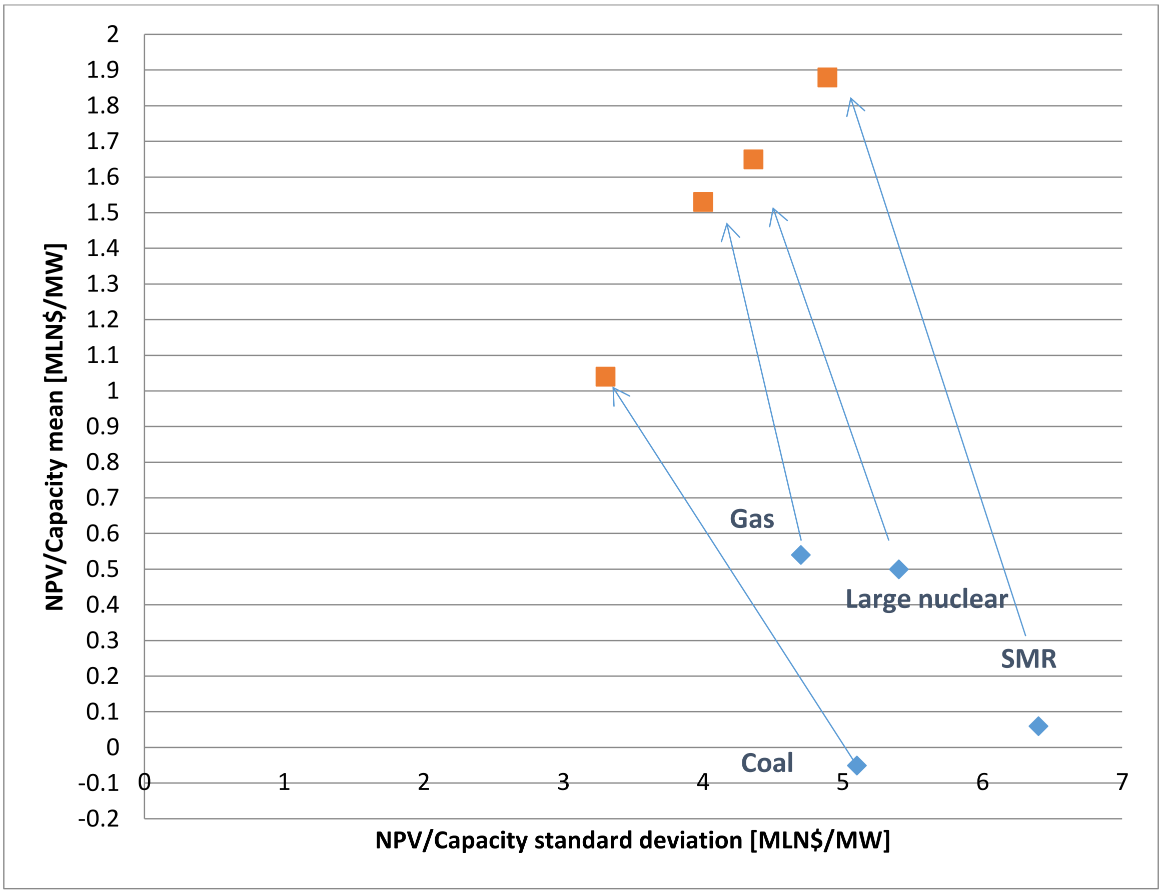


Figure 10: Effects on the NPV/capacity of the option to wait to invest.

The blue diamonds are the results of the DCF; the orange squares are the optimised results

	Discounted cash flow					Real options							
PP	NPV mean (M$)	NPV St. dev(M$)	IRR (%)	Profitability Index	Probability of NPV mean <0 (%)	NPV mean (M$)	NPV St. dev(M$)	IRR (%)	% invest (%)	Profitability Index	Probability of NPV mean <0 (%)	P*($/MWh)	Average year of investment
LR	705	7967	7%	1.1	58%	2128	6174	12%	49%	2	14%	125	5
SMR	2.9	2357	5%	1	60%	601	1853	11%	49%	2.1	17%	120	4
Gas	251	2318	9%	1,3	49%	689	1928	20.5%	27%	6.1	18%	110	3
Coal	-69	3754	4%	0.9	59%	961	2773	15%	48%	3.2	11%	135	8

Table 4: The overall results of the option to invest in one state variable. "% invest (%)" is how many times the algorithm decided that it was worth to invest in the project

5 Discussion and Conclusions

There is relevant merit for using RO in the appraisal of investments in the energy sector. RO can be applied to decisions of investing in power plants (like in this case) or for the construction of other energy infrastructure such as pipelines or Oil & Gas facilities. RO can also be used as criteria for investment decisions on infrastructure using relevant amount of energy. RO can be used during the appraisal stage of novel technologies that might need substantial investment to be brought to the market [9].

In the literature, there are several methods for the appraisal of RO but are generally cumbersome to implement by practitioners, use unrealistic assumptions and most importantly are suitable (or applicable by practitioners) only for problems with one state variable. Often the most used analytical methods are Closed-form models. These are the best approaches when they are available [23] since they are extremely fast to compute and generate precise solutions, but although mathematically elegant, are applicable in a few cases [32]. The most famous example of these methods is the Black & Scholes equation [81] that derives the price of a European option written on a single underlying asset. This specific formula cannot be used in most of the practical cases because [13]:

- The options are not European with a determinate exercise date, on the contrary; usually there is not a definite expiration date;
- Project volatility is not constant over time;
- Strike price (development cost) behaves stochastically;
- Returns for real assets are not normally distributed.

The method introduced in this paper leverages the computational power of modern business computers and software to develop an algorithm easy to implement by practitioners. Moreover, the method is able to cope with several options and state variables described by stochastic processes.

The advantages of this method respect to other RO methods available in the literature are:

- It is simple to implement and can be applied by practicioners in the energy sector.
- It is fast, and with one option and one state variable, it needs less than one minute to find the exercise thresholds that maximizes the objective function.
- It allows the practitioners to model each variable stochastically without increasing the complexity of the problem but only the computational effort.
- It produces several valuable outputs, including the exercise thresholds used to maximize this value, the optimal frontier maximizing the NPV mean and minimising the NPV standard deviation.
- It gives information about the pattern of the problems showing what a utility should do to improve their investments.

- It gives the possibility to compare different solutions (expressed by the exercise thresholds), allowing utilities to choose between alternatives to achieve their strategic objectives.
- It is possible to customize the objective function, making considerations about the risk profile of the investments.

Indeed, other methods described in the literature can provide one or more of the results or have these characteristics (e.g. [82] presents an approach to compare different solutions). However, the key novelty of this RO method is to provide all these outputs together with a single simple algorithm.

Remarkably, if the computational time is a matter of minutes the time to implement the model is surely longer. As order of magnitude, the time required to build the RO model presented in this paper is comparable to the time to create a DCF model. For a DCF model, the time to build the excel spreadsheet is only a fraction of the total time required. In general, most of the time is spent on:

- Establishing which are the inputs and outputs to model and their level of details
- Collecting information about the inputs. For example, to calculate the "construction cost" (and its probability distribution) of a power plant is a process that can take days if not months.

Remarkably, while academics are usually concerned with "presenting an algorithm" and test it using generic data from the literature (like in this case), this is not the case for practitioners and investors that use real money in the investment. Consequently, for practitioners and investors, the data collection is the most crucial and time-consuming activity that might involve the co-operation with subcontractor and payments to consultants. In summary, the computational time to execute the model is "much shorter" than the time to build a model (DCF model or this RO model), that is itself "much shorter" than the time to collect the real data about the inputs.

More specifically, for the aim of this paper, the time to build the RO model depends on the experience of the practitioners, the number of plants and scenarios that they intend to analyse etc. However, given all the time required to work on inputs and outputs the actual time to build this RO model is just a fraction of this time. For the sake of the reader, the construction of a RO model like the one presented in this paper is, for someone if a good literacy in excel, a matter of 1-2 days.

By increasing the number of state variables the computational cost increases exponentially, however the computational cost is also a function of many other aspects such as the size of the intervals and the discretisation of the interval. For instance, section 3.2.1 considered for the price of electricity an interval 1- 600 [$/MWh] with incremental steps of 1 [$/MWh] leading to 600 Monte Carlo simulations. If the interval is reduced to 1- 300 [$/MWh] with incremental steps of 2 [$/MWh] the number of Monte Carlo simulations drops to 150. In this situation, the common practice is to proceed with a trial-error process assessing the trade-off between the influence of different state variables, intervals and precision. This allows identifying the key elements of the investment, along with the most reasonable scenarios and precision required. Also, in this case, it is impossible to provide a precise number since data availability, number of variables, accuracy required, literacy with spreadsheet (e.g. MS Excel), number of outputs investigated (NPV, IRR, LCOE etc.) affect the time required to build and execute the model in the different scenarios. In conclusion, the only relative disadvantage of this method is the computational cost, but nowadays ordinary business laptops with a commercial Monte Carlo simulation software can apply the method described in this paper in real scenarios within a computational time of minutes.

This paper paves the way to the opportunity to further develop the model presented here. Further modelling work will have to be conducted to assess more complex and realistic scenarios. In particular, the authors recommend the following two research streams

- The combination of simulations and thresholds still imposes relevant simplification of the uncertainties encountered when decisions are contingent on changing and interacting variables. In particular the "risk orthogonality issue" (i.e. that all risk are assumed independent) needs to be properly modelled. Aspects like inflations and contextual factors, stakeholder's skills and competence etc. Underpin several risks that therefore cannot be assumed independent. Further research is required to investigate and model cases where risk orthogonality is not a valid hypothesis.
- The modern portfolio theory states that one investment dominates another if the return is equal or larger and the risk is equal or smaller (as in the case of gas). In other situations, it will depend upon the utility of the investor, as to how much additional reward they require for undertaking additional risk. The interaction between the investments, including the impact on the electricity price, is an area that needs further research. Further research is required to model and optimise the balance of risk/return at the portfolio level.

Acknowledgements

The authors are very grateful to the colleagues, whose suggestions substantially contributed to increasing the quality of this paper. The authors are particularly grateful to Diletta Colette Invernizzi, Chun Sing Lai and Ata Babaei for their precious and thoughtful review. The authors remain the only persons accountable for any omissions or mistakes.

References

[1] Lai LL. Power system restructuring and deregulation : trading, performance and information technology. John Wiley; 2001.

[2] Sainati T, Locatelli G, Smith N. Project financing in nuclear new build, why not? The legal and regulatory barriers. Energy Policy 2019;129:111–9.

[3] Roques FA, Nuttall WJ, Newbery DM. Using Probabilistic Analysis to Value Power Generation Investments under Uncertainty. 2006.

[4] Rogge KS, Hoffmann VH. The impact of the EU ETS on the sectoral innovation system for power generation technologies – Findings for Germany. Energy Policy 2010;38:7639–52. https://doi.org/10.1016/j.enpol.2010.07.047.

[5] Mastropietro P, Barroso LA, Batlle C. Power transmission regulation in a liberalised context: An analysis of innovative solutions in South American markets. Util Policy 2015;33:1–9. https://doi.org/10.1016/j.jup.2015.01.006.

[6] Mukaida K, Katoh A, Shiotani H, Hayafune H, Ono K. Benchmarking of economic evaluation models for an advanced loop-type sodium cooled fast reactor. Nucl Eng Des 2017;324:35–44.

[7] Trigeorgis L. Real options: managerial flexibility and strategy in resource allocation. MIT Press; 1996.

[8] Moore M, Korinny A, Shropshire D, Sadhankar R. Benchmarking of nuclear economics tools. Ann Nucl Energy 2017;103:122–9. https://doi.org/10.1016/J.ANUCENE.2017.01.020.

[9] Kodukula P, Papudesu C. Project Valuation Using Real Options: A Practitioner's Guide. Fort Lauderdale, Florida: J. Ross Publishing; 2006.

[10] Henao A, Sauma E, Gonzalez A. Impact of introducing flexibility in the Colombian transmission expansion planning. Energy 2018;157:131–40.

[11] He Y. Real options in the energy markets. University of Twente, 2007.

[12] Horn A, Kjærland F, Molnár P, Steen BW. The use of real option theory in Scandinavia's largest companies. Int Rev Financ Anal 2015;41:74–81.

[13] Brach MA. Real Options in practice. 2003.

[14] Arthur D. Little. Real Options for the Future Energy Mix. 2008.

[15] Ofgem. Real Options and Investment Decision Making - https://www.ofgem.gov.uk/publications-and-updates/real-options-and-investment-decision-making. 2012.

[16] Graham JR, Harvey CR. The theory and practice of corporate finance: evidence from the field. J Financ Econ 2001;60:187–243.

[17] Neufville R De, Weck O De, Lin J, Scholtes S. Identifying Real Options to Improve the Design of Engineering Systems. In: Nembhard HB, Aktan M, editors. Real Options Eng. Des. Oper. Manag., vol. 02138. CRC Press, 2008, p. 75–98.

[18] Morgan M, Small M. Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press; 1992.

[19] Locatelli G. Why are Megaprojects, Including Nuclear Power Plants, Delivered Overbudget and Late? Reasons and Remedies. 2018.

[20] Dixit A, Pindyck R. Investment under uncertainty. Princeton University Press; 1994.

[21] Markowitz HM. The early history of portfolio theory: 1600-1960. Financ Anal J 1999;55:5–16.

[22] Neufville R De, Scholtes S. Flexibility in Engineering Design. The MIT Press; 2011.

[23] Gamba A, Sick G. Some important issues involving real options: an overview. Finance 2001;14:73–123.

[24] Madlener R, Stoverink S. Power plant investments in the Turkish electricity sector: A real options approach taking into account market liberalization. Appl Energy 2012;97:124–34. https://doi.org/10.1016/j.apenergy.2011.11.050.

[25] Yao X, Fan Y, Xu Y, Zhang X, Zhu L, Feng L. Is it worth to invest? -An evaluation of CTL-CCS project in China based on real options. Energy 2019;182:920–31.

[26] Locatelli G, Boarin S, Fiordaliso A, Ricotti ME. Load following of Small Modular Reactors (SMR) by cogeneration of hydrogen: A techno-economic analysis. Energy 2018;148:494–505. https://doi.org/10.1016/j.energy.2018.01.041.

[27] Kozlova M, Fleten SE, Hagspiel V. Investment timing and capacity choice under rate-of-return regulation for renewable energy support. Energy 2019;174:591–601.

[28] Alvarez L. Adoption of uncertain multi-stage technology projects: a real options approach. J Math Econ 2001;35:71–97. https://doi.org/10.1016/S0304-4068(00)00050-1.

[29] Gamba A, Tesser M. Structural estimation of real options models. J Econ Dyn Control 2009;33:798–816. https://doi.org/10.1016/j.jedc.2008.10.001.

[30] Gamba A. Real Options : a Monte Carlo approach Real Options : a Monte Carlo approach. University of Verona, 2003.

[31] Moreno M, Navas JF. On the Robustness of Least-Squares Monte Carlo (LSM) for Pricing American Derivatives. Rev Deriv Res 2003;6:107–28. https://doi.org/10.1023/A:1027340210935.

[32] Mun J. Real options analysis: Tools and techniques for valuing strategic investments and decisions. 2nd Editio. Wiley; 2005.

[33] Cortazar G. Simulation and Numerical Methods in Real Options Valuation. In: Schwartz ES, Trigeorgis L, editors. Real Options Invest. under Uncertain. Class. Readings Recent Contrib., 2001, p. 601–20.

[34] Shahnazari M, McHugh A, Maybee B, Whale J. Overlapping carbon pricing and renewable support schemes under political uncertainty: Global lessons from an Australian case study. Appl Energy 2017;200:237–48.

[35] Bellman RE, Corporation R. Dynamic programming. Princeton University Press; 1957.

[36] Cox JC, Ross SA, Rubinstein M. Option pricing: A simplified approach. J Financ Econ 1979;7:229–63. https://doi.org/10.1016/0304-405X(79)90015-1.

[37] Wang X, Cai Y, Dai C. Evaluating China's biomass power production investment based on a policy benefit real options model. Energy 2014;73:751–61. https://doi.org/10.1016/j.energy.2014.06.080.

[38] Stentoft L. Convergence of the Least Squares Monte Carlo Approach to American Option Valuation. Manage Sci 2004;50:1193–203. https://doi.org/10.1287/mnsc.1030.0155.

[39] Longstaff F a., Schwartz ES. Valuing American options by simulation: a simple least-squares approach. Rev Financ Stud 2001;14:113–47. https://doi.org/10.1093/rfs/14.1.113.

[40] Zhu L, Fan Y. Modelling the investment in carbon capture retrofits of pulverized coal-fired plants. Energy 2013;57:66–75. https://doi.org/10.1016/j.energy.2013.03.072.

[41] Pringles R, Olsina F, Garcés F. Designing regulatory frameworks for merchant transmission investments by real options analysis. Energy Policy 2014;67:272–80.

https://doi.org/10.1016/j.enpol.2013.12.034.

[42] Pringles R, Olsina F, Garcés F. Real option valuation of power transmission investments by stochastic simulation. Energy Econ 2015;47:215–26. https://doi.org/10.1016/j.eneco.2014.11.011.

[43] Kulatilaka N, Amram M. Real options: managing strategic investment in an uncertain world. vol. 36. 1999. https://doi.org/10.5860/CHOICE.36-5767.

[44] Hlouskova J, Kossmeier S, Obersteiner M, Schnabl A. Real options and the value of generation capacity in the German electricity market. Rev Financ Econ 2005;14:297–310. https://doi.org/10.1016/j.rfe.2004.12.001.

[45] Fernandez P, McCarthy IP, Rakotobe-Joel T. An evolutionary approach to benchmarking. Benchmarking An Int J 2001;8:281–305.

[46] Locatelli G, Invernizzi DC, Mancini M. Investment and risk appraisal in energy storage systems: A real options approach. Energy 2016;104:114–31. https://doi.org/10.1016/j.energy.2016.03.098.

[47] Kroniger D, Madlener R. Hydrogen storage for wind parks: A real options evaluation for an optimal investment in more flexibility. Appl Energy 2014;136:931–46. https://doi.org/10.1016/j.apenergy.2014.04.041.

[48] Reuter WH, Fuss S, Szolgayová J, Obersteiner M. Investment in wind power and pumped storage in a real options model. Renew Sustain Energy Rev 2012;16:2242–8. https://doi.org/10.1016/j.rser.2012.01.025.

[49] Muche T. A real option-based simulation model to evaluate investments in pump storage plants. Energy Policy 2009;37:4851–62. https://doi.org/10.1016/j.enpol.2009.06.041.

[50] Zhang MM, Zhou P, Zhou DQ. A real options model for renewable energy investment with application to solar photovoltaic power generation in China. Energy Econ 2016;59:213–26.

[51] Siddiqui AS, Marnay C, Wiser RH. Real options valuation of US federal renewable energy research, development, demonstration, and deployment. Energy Policy 2006;35:265–79. https://doi.org/10.1016/j.enpol.2005.11.019.

[52] Loncar D, Milovanovic I, Rakic B, Radjenovic T. Compound real options valuation of renewable energy projects: The case of a wind farm in Serbia. Renew Sustain Energy Rev 2017;75:354–67.

[53] Cui H, Zhao T, Wu R, Cui H, Zhao T, Wu R. An Investment Feasibility Analysis of CCS Retrofit Based on a Two-Stage Compound Real Options Model. Energies 2018;11:1711. https://doi.org/10.3.

[54] Locatelli G, Boarin S, Pellegrino F, Ricotti ME. Load following with Small Modular Reactors (SMR): A real options analysis. Energy 2015;80:41–54.

[55] Locatelli G, Mancini M, Ruiz F, Solana P. Using real options to evaluate the flexibility in the deployment of SMR. Int. Congr. Adv. Nucl. Power Plants 2012, ICAPP 2012, vol. 4, 2012.

[56] Zambujal-Oliveira J. Investments in combined cycle natural gas-fired systems: A real options analysis. Int J Electr Power Energy Syst 2013;49:1–7. https://doi.org/10.1016/j.ijepes.2012.11.015.

[57] Detert N, Kotani K. Real options approach to renewable energy investments in Mongolia. Energy Policy 2013;56:136–50. https://doi.org/10.1016/j.enpol.2012.12.003.

[58] Santos L, Soares I, Mendes C, Ferreira P. Real Options versus Traditional Methods to assess Renewable Energy Projects. Renew Energy 2014;68:588–94. https://doi.org/10.1016/j.renene.2014.01.038.

[59] Fleten SE, Linnerud K, Molnár P, Tandberg Nygaard M. Green electricity investment timing in

practice: Real options or net present value? Energy 2016;116:498–506.

[60] Fuss S, Szolgayova J, Obersteiner M. Assessing the effects of CO2 price caps on electricity investments-A real options analysis. Energy Policy 2008;36:3974–81. https://doi.org/10.1016/j.enpol.2008.07.006.

[61] ShahNazari M, McHugh A, Maybee B, Whale J. The effect of political cycles on power investment decisions: Expectations over the repeal and reinstatement of carbon policy mechanisms in Australia. Appl Energy 2014;130:157–65.

[62] Fuss S, Szolgayova J, Obersteiner M, Gusti M. Investment under market and climate policy uncertainty. Appl Energy 2008;85:708–21.

[63] Samis M. An Extended Evaluation Framework for Nuclear Power Plants – A Dynamic DCF and Real Options Approach - Ernst and Young LLP. Int WPNE Work Role Electr Price Stab Long-Term Financ Nucl New Build 2013.

[64] Fishburn PC. Mean-Risk Analysis with Risk Associated with Below-Target Returns. Am Econ Rev 1977;67:116–26.

[65] Broadie M, Detemple J. American Option Valuation: New Bounds, Approximations, and a Comparison of Existing Methods. Rev Financ Stud 1996;9:1211–50.

[66] Locatelli G, Pecoraro M, Meroni G, Mancini M. Appraisal of small modular nuclear reactors with 'real options' valuation. Proc Inst Civ Eng - Energy 2017;170:51–66.

[67] Sharpe WF. The Sharpe Ratio. J Portf Manag 1994;21:49–58. https://doi.org/10.3905/jpm.1994.409501.

[68] Zhou W, Zhu B, Chen D, Zhao F, Fei W. How policy choice affects investment in low-carbon technology: The case of CO2 capture in indirect coal liquefaction in China. Energy 2014;73:670–9. https://doi.org/10.1016/j.energy.2014.06.068.

[69] Roques F. Technology choices for new entrants in liberalized markets: The value of operating flexibility and contractual arrangements. Util Policy 2008;16:245–53. https://doi.org/10.1016/j.jup.2008.04.004.

[70] Madlener R, Glensk B, Raymond P. Applying Mean-Variance Portfolio Analysis to E . ON ' s Power Generation Portfolio in the UK and Sweden. Int. Energiewirtschaftstagung an der TU Wien, Vienna: 2009, p. 1–15.

[71] Espinoza, Luccioni. Simplified Investment Valuation Model for Projects with Technical Uncertainty and Time to Build. Real Options 9th Annu. Int. Conf., 2005, p. 1–14.

[72] Locatelli G, Mancini M. Large and small baseload power plants: Drivers to define the optimal portfolios. Energy Policy 2011;39:7762–75. https://doi.org/10.1016/j.enpol.2011.09.022.

[73] Schwartz ES. Patents and R&D as Real Options. Econ Notes 2004;33:23–54. https://doi.org/10.1111/j.0391-5026.2004.00124.x.

[74] Blyth W, Yang M, Bradley R. Climate policy uncertainty and investment risk. OECD Publishing; 2007.

[75] IEA, NEA. Projected Costs of Generating Electricity. OECD Publication, Paris. 2010.

[76] Locatelli G, Mancini M. Small–medium sized nuclear coal and gas power plant: A probabilistic analysis of their financial performances and influence of CO2 cost. Energy Policy 2010;38:6360–74. https://doi.org/10.1016/j.enpol.2010.06.027.

[77] EIA-DOE, EIA. Assumptions to the Annual Energy Outlook 2012. 2012.

[78] Boarin S, Locatelli G, Mancini M, Ricotti ME. Financial case studies on small- and medium-size modular reactors. Nucl Technol 2012;178.

[79] Harris G, Heptonstall P, Gross R, Handley D. Cost estimates for nuclear power in the UK. Energy Policy 2013;62:431–42. https://doi.org/10.1016/j.enpol.2013.07.116.

[80] Serra P. Contract market power and its impact on the efficiency of the electricity sector. Energy Policy 2013;61:653–62. https://doi.org/10.1016/j.enpol.2013.06.058.

[81] Black F, Scholes M. The Pricing of Options and Corporate Liabilities 1973;81:637–54.

[82] Maybee B, Lowen S, Dunn P. Risk-based decision making within strategic mine planning. Int J Min Miner Eng 2010;2:44.