Energy
Volume 170 Issue EN2
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ice | proceedings

Proceedings of the Institution of Civil Engineers
Energy 170 May 2017 Issue EN2
Pages 51–66 http://dx.doi.org/10.1680/jener.16.00004
Paper 1600004
Received 29/01/2016 Accepted 20/12/2016
Published online 15/02/2017
Keywords: economics & finance/energy/management

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Institution of Civil Engineers
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Appraisal of small modular nuclear reactors with 'real options' valuation

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Small modular nuclear reactors have the advantage of flexibility in deployment and shorter construction time compared with large reactors. Investment appraisals in the energy sector are traditionally based on discounted cash flow, but this tends to underestimate the value of management flexibility during the decision-making process. The 'real options' valuation method can better support an investment appraisal. This paper, leveraging the real options approach, gives an account of two key strategic aspects to support the decision-making process in building small modular reactors: the time to market with the relative stage-gate process and the effect of a new plant on the existing portfolio. This paper assesses small modular reactors against other base-load power plants and, once applied to the UK scenario, it shows the superior performance of small modular reactors.

Notation

$a_{[\,]}$	'differential coefficient' of a linear exercise threshold
$\mathrm{d}p$	differential price
$\mathrm{d}z$	differential Wiener process
e	Euler's number
E	expected
ECTC_t	expected cost to complete the construction at time t
$\mathrm{ECTC}_{\mathrm{threshold}}$	expected cost to complete the construction threshold
ECTD_t	expected cost to complete the design at time t
$\mathrm{ECTD}_{\mathrm{threshold}}$	expected cost to complete the design threshold
G^*	gas price triggering the investment
G_0	gas price at the time now
G_t	gas price at time t
I	is the investment rate
K	remaining cost,
$m_{[\,]}$	'multiplication factor' of a linear exercise threshold
P^*	price triggering the investment
P_0	price at the time now
P_{LB}	lower bound price
P_{lim}	price limit
P_{SR}	sharpe ratio price
P_t	price at time t
P_{t+n}	price at time $t+n$
$P_{\mathrm{threshold}}$	price threshold
P_{UB}	upper bound price
R	mean value of the net present value distribution
W	Wiener process
$w1 + w2$	respective percentage of each technologies 1 and 2 in the portfolio
W_t	standard normal variable (time t)
$\alpha p\mathrm{d}t$	drift component (α) for the price (p) with respect to the differential time ($\mathrm{d}t$)
μ	mean value
ρ_{12}	correlation coefficient between technologies 1 and 2 in the portfolio
σ	standard deviation
$\sigma p\mathrm{d}z$	drift component (σ) for the price (p) with respect to the differential Wiener process (z)

1. Introduction

1.1 The case for small modular reactors

The International Atomic Energy Agency (IAEA, 2016: p. 1) defines small modular reactors (SMRs) as 'newer generation reactors designed to generate electric power up to 300 MW, whose components and systems can be shop fabricated and then transported as modules to the sites for installation as demand arises'. Several SMR designs, detailed by IAEA (2014, 2016) and Locatelli *et al.* (2013), are currently at different stages of development. Ingersoll (2009: p. 589) provides a good summary of the innovative feature of SMRs: 'reactor designs that are deliberately small, i.e. designs that do not scale to large sizes but rather capitalize on their smallness to achieve specific performance characteristics'.

Several papers have discussed the competiveness of SMRs against large reactors (LRs) and how SMRs might balance the 'diseconomy of scale' with the 'economy of multiples' (Boarin *et al.*, 2012, 2015; Carelli *et al.*, 2008; Locatelli and Mancini, 2012a; Locatelli *et al.*, 2014). Carelli *et al.* (2007, 2010) analyse specific factors, such as grid characteristics, construction time, financial exposition, modularisation and learning, which distinguish SMRs from LRs in the evaluation of capital cost. Once these factors are considered, the capital cost is comparable between the two technologies (Boarin *et al.*, 2012; Carelli *et al.*, 2008). Locatelli and Mancini (2011b) discuss the effects of 'non-financial parameters', such as electric grid vulnerability, public acceptance, risk associated with the project and others, on the evaluation of the best reactor size for an investment in the nuclear sector. For many of these parameters, they explain how SMRs show an advantage with respect to LRs.

One of the key SMR advantages is the possibility to split a large investment into smaller ones. The construction of a single LR is a risky investment (Brookes and Locatelli, 2015). The construction of *n* SMRs is an investment decision with *n* degrees of freedom that allows investment risks to be hedged. The economic merit of flexibility can be calculated using the 'real options' (ROs) valuation approach. This paper presents a novel investment appraisal based on ROs with two key innovations.

- The modelling of the time to market (TTM) effect.
- The investment in a certain power plant (PP) considering the utility portfolio.

The TTM is the time from a product concept definition to its availability for sale (Cohen *et al.*, 1996). In this paper, the TTM is the time between the decision to build a PP and the beginning of commercial operations. In the energy sector, reducing the TTM means reducing the risk (e.g. from electricity price fluctuation) and collecting early revenues increasing the net present value (NPV). SMRs can be built faster than LRs, which is a relevant aspect to consider. The utility portfolio is relevant since PPs might not be considered as a 'single asset' investment, but must fit into a broader strategy of a utility owning a portfolio of PPs.

1.2 ROs in the energy sector

The construction of large projects, and PPs in particular, is jeopardised by overbudget and delay (Brookes and Locatelli, 2015; Flyvbjerg, 2006; Locatelli and Mancini, 2010, 2012b, 2014; Locatelli *et al.*, 2016a; Ruuska *et al.*, 2011). Since ROs assess the decision-maker's options (i.e. degrees of freedom) to hedge the investment risks, they increase the expected returns and, at the same time, minimise the volatility of the investment considered. The 'RO theory postulates that projects under uncertainty might possess RO; the projects become flexible if the RO can be identified and timely executed; flexibility adds value to the projects' (Martinez-Cesena *et al.*, 2013: p. 574).

In the last decade, much research focused on the application of the ROs theory in the power and energy sector. Myers (1977) first presented the term 'real option', observing that corporate investment opportunities can be viewed as call options on real assets. Pindyck (1993) explained that an RO is the right, without obligations, to defer, abandon or adjust a project in response to the evolution of uncertainty. Thus, RO offers flexibility, resources and the capability to benefit from the uncertainty surrounding a business (Driouchi and Bennett, 2012). With the RO approach, a project is considered an option of the underlying cash flows and the optimal investment strategies are just the optimal exercise rules of the option (He, 2007).

In the energy sector, the RO model evaluates opportunities such as waiting for the most advantageous moment to invest, abandon an unprofitable investment, switching from a technology to a more profitable one, producing outputs for more than one market (Locatelli *et al.*, 2015) and so on. The most relevant ROs described in the literature are as follows (Kodukula and Papudesu, 2007).

- The option 'to invest'. The possibility to decide whether to invest or not (e.g. building a further unit)
- The option 'to defer'. The possibility to postpone the investment decision (e.g. until the electricity price is at least a certain value X)
- The option 'to abandon'. The possibility to abandon a course of action (project) previously decided due to new information (e.g. the abandonment of an already triggered investment in a new PP if the scenario is not profitable anymore).

Table 1 summarises relevant examples of articles applying the RO theory in the power and energy sector and benchmarks them against this paper.

To model the decision-making process realistically, two ROs can be merged to create 'compound options'. For instance, the option to wait and build is a compound option since it merges

Table 1. Recent applications of ROs in the energy field

	This work	Shi and Song (2013)	Jain *et al.* (2013)	Zambujal-Oliveira (2013)	Detert and Kotani (2013)	Santos *et al.* (2014)
Scope of work	Building a realistic investment model in the energy sector by considering the TTM effect and the actual portfolio of a utility	Evaluate how all risks and uncertainties impact the development of new nuclear PP in China	Help a utility determine the value of sequential SMR	Analyse different RO model types to assess the best for making investment in the energy sector	Examine energy switching from non-renewable to renewable technologies in Mongolia	Apply an RO to a mini-hydro PP case comparing its results with the results obtainable through the classical DCF approach
Real option evaluation method	SOET (Appendix)	Partial differential equation	Dynamic programming method	Binomial tree	Simulation method	Binomial tree
Options considered	Compound option; option to invest/abandon/defer/choose	Compound option; option to invest/abandon	Option to invest; option to abandon	Option to defer; option to invest	Option to switch	Option to invest
Outputs	*E*(NPV); *σ*(NPV); exercise thresholds; efficient frontier two-dimension (2D) for each technology; efficient frontier three-dimension (3D) for each portfolio	Value of the option	*E*(NPV); classical NPV	Value of the options	Decision to switch; option value	*E*(NPV); classical NPV; option value

DCF, discounted cash flow; NPV, net present value; ROs, real options; SMR, small modular reactor; SOET, simulation with optimised exercise threshold; TTM, time to market; *E*, expected; *σ*, standard deviation

the option to build, where the investor can make the investment or not, and to wait, where there is a time window available for the investor to make this decision. It is not easy to find applications of these kind of options in the literature due to their intrinsic complexity. Geske (1977) applies the technique for valuing compound options to the risky coupon bond problem. He presents a theory for pricing option on option, which means to evaluate a compound option. Siddiqui *et al.* (2006) describe an approach to determine the option value of research, development, demonstration and deployment programmes on renewable energy technology. Cheng *et al.* (2011) present a modified binomial lattice model to apply compound options to create a flexible management approach to decide clean energy strategies that are embedded with a lead time. Locatelli *et al.* (2016b) apply compound options to energy storage plants. This work uses 'compound options' to simulate and assess the 'stage-gate process' typical of the power and energy sector.

2. Literature review

2.1 Portfolio analysis

The boundary conditions of electricity markets encourage utilities to diversify their portfolios. The importance of considering the portfolio in the investment appraisal for a further unit is explained by Hlouskova *et al.* (2005: p. 300) 'The risk position of the company is determined by the entire portfolio and the interaction of various positions. Therefore, the decision to enter into new contracts cannot be taken independently from the current portfolio'. Portfolio theories were developed first for financial uses and then adapted to the energy sector. Locatelli and Mancini (2011a) summarise the most relevant methods used to perform a portfolio analysis. The model proposed in this paper is a development of the mean–variance portfolio theory (MVP) because

- it is the most used method in the literature since it is relatively straightforward to implement and provides meaningful information to the decision makers
- it can be used to find the optimal solution based on different objective functions (e.g. maximisation of the NPV mean; minimisation of risk)
- it allows a portfolio of investment to be treated as an investment in a single technology, allowing the integration of MVP with the RO method
- each single portfolio can be directly compared with the others in terms of expected NPV (*E*(NPV)) and risk (*σ*(NPV)).

Most of the research about MVP is a development of a seminal paper (Markowitz, 1952). According to the MVP theory, each portfolio has two attributes: its mean value (μ) and its standard deviation (σ). The mean value is the mean value of the controlled variables (e.g. the NPV), while σ

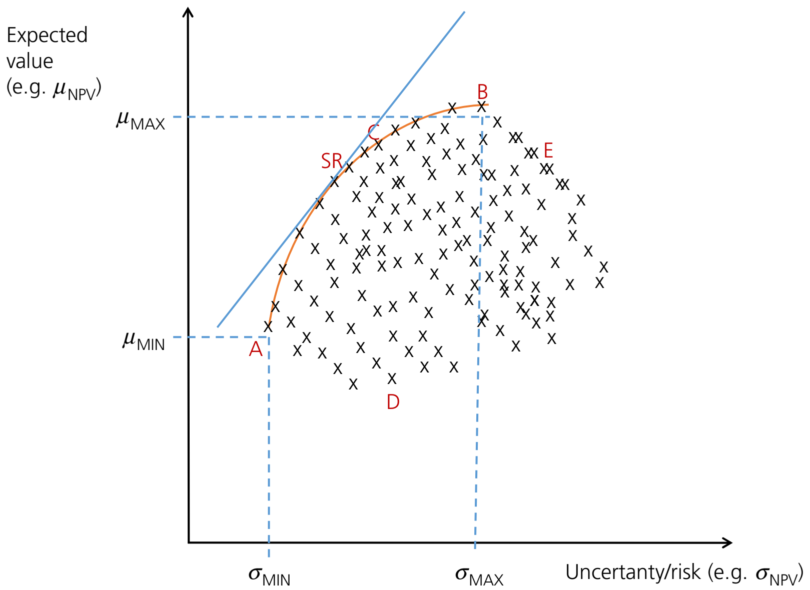


Figure 1. Efficient frontier: the classical mean–variance portfolio theory

represents the risk on the investment. Combining the different percentages of PPs, it is possible to obtain thousands of portfolios, each of them characterised by its own μ and σ. However, only few of them represent a rational choice because, given a certain μ, it is reasonable to choose only the portfolio with the lowest σ – that is, the lowest risk. Alternatively, from the opposite point of view, given a certain σ, a reasonable investor implements only the portfolio with the highest μ; therefore, there is a one-to-one link among μ and σ. Given a certain level of μ, the only σ is automatically linked (and vice versa). With reference to Figure 1, the optimum portfolios are the so-called 'efficient frontier' – that is, the continuous line from 'A' to 'B'. 'A' is the portfolio with the lowest return and risk, while 'B' has the highest return and risk. 'C' is another optimal portfolio because, given a certain level of risk, it maximises the return or, given a certain level of return, it minimises the risk. 'D' is not a rational portfolio since, for the same risk, the 'C' portfolio provides a higher return. 'E' is not a rational portfolio since, for the same expected return, the C portfolio has the lowest risk.

According to MVP theory, all the portfolios lying on the efficient frontier are optimal. Sharpe (1994) described a parameter that let an investor compare them in terms of their expected return for a unit of risk, the Sharpe ratio (SR). According to Investopedia (2016) the SR is a measure for calculating risk-adjusted return, and this ratio has become the industry standard for such calculations. It was developed by the Nobel laureate William F. Sharpe (1994). The SR is the average return earned in excess of the risk-free rate per unit of volatility or total risk. Subtracting the risk-free rate from the mean return (the expected value of all the likely returns of investments comprising a portfolio), the performance associated with risk-taking activities can be isolated. One intuition of this calculation is that a portfolio engaging in 'zero risk' investment, such as the purchase of US Treasury bills (for which the expected return is the risk-free rate), has an SR equal to zero. Generally, the greater the value of the SR, the more attractive the risk-adjusted return. The investor is likely to prefer the portfolio on the efficient frontier with the highest expected return for unit of risk (i.e. the highest SR). Geometrically, the point of the efficient frontier that corresponds to the solution of this problem is tangent to the efficient frontier: the optimal portfolio received is called the 'tangent portfolio'.

This work overcomes one of the principal drawbacks in the literature about the MVP that limits its use: 'MVP is a static methodology, heavily relying on past data. As a result, a portfolio that is thought of as optimal today might already be way off the efficient frontier tomorrow, depending on how the environment has changed. It is therefore a method that should only be considered within a very limited time frame' (Madlener and Wenk, 2008: p. 8). The application of RO to the portfolio analysis tackles this limitation.

2.2 Application of ROs to perform portfolio analysis

In the literature, there are only few examples of application of RO to perform a portfolio analysis. Table 2 benchmarks this work with respect to the literature.

Table 2. Examples of ROs application to perform portfolio analysis

	This work	Jain *et al.* (2013)	Liu (2012)	Fuss *et al.* (2012)
RO evaluation method	SOET	Stochastic grid bundling method	Partial differential equations	Dynamic programming method
Options considered	Compound options; option to invest; option to choose; option to abandon	Option to invest; option to abandon	Respectively option to invest and to abandon	Option to invest
TTM effect	Modelled	Not considered	Not considered	Not considered
Pre-operating phases	Modelled as the succession of three compound options	Only the construction phase is considered	Only the construction phase is considered	Only the construction phase is considered
Actual portfolio	Influence results	Results not influenced	Influence results	Results not influenced
Method used to perform the portfolio analysis	MVP theory	MVP theory	Stochastic dominance	Conditional value-at-risk method
Output indicators	E(NPV); σ(NPV); exercise thresholds; efficient frontier 2D for each technology; efficient frontier 3D for portfolio	Efficient frontier 2D for portfolio in which every technology is a single static point on it; value of the option	Value of the option. The efficient frontier is not built: the partial differential equation do not find out the level of risk of the investment	Expected cost; level of risk; a single technology is a single static point on the plane E(cost) – level of risk

SOET, simulation with optimised exercise threshold

According to Table 2, the steps followed by classical approaches to perform a portfolio analysis are as follows.

- Apply a backward approach using the Monte Carlo simulation (MCS) to find the best policy of investment for each technology in the portfolio.
- Calculate the E(NPV) and σ(NPV) of the overall portfolio.
- Build the efficient frontier to compare all the possible portfolios to identify the one maximising the profit for a specific level of risk.

The key idea is to consider a set of different exercise thresholds (see the Appendix for a discussion on exercise thresholds) and calculates the different effects on the output distribution of the overall portfolio. Each portfolio in the Cartesian graph E(NPV)–σ(NPV) is no longer a single point, but a function of the values of the exercise thresholds that, triggering the options in different conditions, modify the NPV distribution of the overall portfolio – that is, the output is the efficient frontier for each portfolio. The main drawback of classical approaches which apply RO to perform a portfolio analysis in the energy field is that they are too complex to be applied to realistic cases. The method developed in this work overcomes this problem because it guarantees the model user can analyse cases of investment in real portfolios with roughly the same effort of investments in simple portfolios.

3. Results

3.1 Appraisal of a single plant

This section presents the results obtained by applying the RO method (refer to the Appendix) to a hypothetical portfolio presented in Table 3. The assumption is that the utility needs to build a new PP to guarantee an additional demand of 1·5 GW in 20 years. The RO method builds an efficient frontier for each portfolio in function of the value of the exercise threshold triggering the additional investment. Figure 2 and Table 4 shows the following results.

Table 3. Composition of the hypothetical existing portfolio

Technology	Capacity installed: MW	Percentage in the overall actual portfolio
Nuclear	1500	46·15
Coal	750	23·08
CCGT	1000	30·77

CCGT, combined cycle gas turbine

- The solution found by applying the standard discounted cash flow (DCF) method with the MVP theory is inefficient in this case because the 'base case – that is, 90 – DCF' (the 'static traditional solution' calculated with a DCF, see Appendix) is dominated by other portfolios (i.e. more profit for the same risk or less risk for the same profit) generated by the RO analysis.
- The points on the efficient frontier have these properties
  - the option has to be exercised when $P_{\text{threshold}} > P_0$ (i.e. is it worth waiting)
  - after a specific value P_{lim} the points do not belong on the efficient frontier anymore (i.e. the decision has to be taken in a finite time).

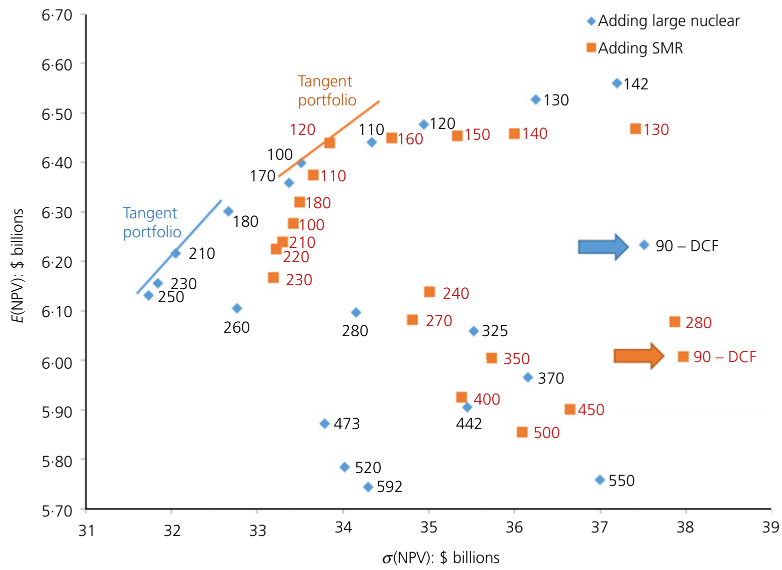


Figure 2. Efficient frontier of the portfolio with an additional LR or equivalent power in SMR

Table 4. Results obtained with the hypothetical portfolio

Additional PP	Lower bound efficient frontier: \$/MWh	Upper bound efficient frontier: \$/MWh	Tangent portfolio condition: \$/MWh
Large nuclear	$P^*_{LB} = 100$	$P^*_{UB} = 250$	$P^*_{SR} = 210$
SMR	$P^*_{LB} = 100$	$P^*_{UB} = 230$	$P^*_{SR} = 120$

- All the points on the efficient frontier have these characteristics
  - the condition to find them is to exercise the option only when $P_0 < P_{threshold} \leq P_{lim}$
  - the portfolio on the efficient frontier can be compared in terms of SR. This is a value of the exercise threshold P_{SR} that corresponds to the tangent portfolio of the efficient frontier.

With a traditional DCF model, the efficient frontier is the investment appraisal comparing the present and future hypothetical portfolios. The RO model provides a completely new form of outputs – that is, the optimised efficient frontier. Analysing Figure 2, the decision maker can find the best investment and the condition of the exercise threshold that optimises every possible objective function (defined as the profit maximisation for a specific level of risk). Table 5 shows how the decision to invest varies according to different specific objective functions. The decision maker can choose the most suitable PP depending on his/her risk appetite.

3.2 Application to a UK utility portfolio

The inputs data used in this work are both deterministic (Table 6) and stochastic. The stochastic variables have been modelled as geometric Brownian motion (GBM). Consistent with EIA-DOE (2012), the initial values of the variables modelled with the GBM model are: gas cost 47·39 \$/MWh, coal cost 22·27 \$/MWh and for the electricity price a value of 90 \$/MWh.

Table 5. Improvement of results guaranteed by this method

Objective function	Large reactor's results	SMR's results	PP chosen	Condition of investment: \$/MWh
Maximisation of NPV mean	E(NPV) = 6560 million \$	E(NPV) = 37 193 million \$	Large reactor	$P^* = 142$
Minimisation of σ NPV	E(NPV) = 6131 million \$	σ(NPV) = 31 786 million \$	Large reactor	$P^* = 250$
Maximisation of the SR value	SR = 0·191	SR = 0·197	SMR	$P^* = 120$

Table 6. The deterministic inputs used in this work (EIA-DOE, 2012)

	Nuclear	Coal	CCGT	SMR
Capacity: MW	1500	750	500	335
Capacity factor: %	85	85	85	95
Overnight cost: $/KW	5335	3220	1003	6362
Operations and maintenance cost: $/MWh	13·96	13·4	15·03	21·28
Fuel cost: $/MWh	8·26	22·27	47·4	8·26
Carbon cost: $/MWh	0	23·96	10·54	0
Construction time: years	6	4	3	5
Study time: years	1	/	/	1
Design time: years	2	/	/	2
Life: years	60	40	30	60

The GBM functional form applied in this work on the electricity price is

$$\mathrm{d}p = \alpha p\mathrm{d}t + \sigma p\mathrm{d}z$$

where α is the drift; σ is the volatility of the process in a time period; t is the time and z is a Wiener process, where Wiener process is a continuous-time Gaussian process with independent increments used for modelling the Brownian motion. This model does not consider the mean reversion, spike jumps and price proportional volatility.

The reasons for using this model are as follows.

- The mathematical simplification of the model. The process has no memory and future expectations depend only on the volatility and on the value at time zero of the electricity price. In addition, modelling this variable with a GBM process has the following properties

$$E(P_{t+n}) = P_t$$

$$\mathrm{Var}(P_{t+n}) = P_t^2\left(\mathrm{e}^{\sigma^2}n - 1\right)$$

  GBM is particularly suitable for reflecting long-term uncertainty.
- The model is relatively simple and can be implemented in a Microsoft Excel spreadsheet.
- Even if the removal of the mean reversion and jumps simplifies the model, this is not a major concern for base-load PPs, since the weight of these two parameters in a base-load scenario is negligible.

The following equation models the electricity price

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

where P_t is the electricity price at time t; W_t is a standard normal variable; σ is the volatility of the process in a time period and $\sigma = 0, 3$ as in Locatelli and Mancini (2011a).

The same description can be considered for the gas cost and for the coal cost too.

The total capital investment cost (TCIC) follows the method developed by Pindyck (1993) and Schwartz (2004) as

$$\mathrm{d}K = -I\mathrm{d}t + \sigma(IK)^{1/2}\mathrm{d}z$$

As in the paper by Schwartz (2004) the mean and the variance of the TCIC are described by the following relationships

$$E(\mathrm{TCIC}) = K$$

$$\mathrm{Var}(\mathrm{TCIC}) = \frac{\sigma^2K^2}{2-\sigma}$$

Since the evaluation model is discrete-time based, this stochastic process is modelled with

$$K_{t+1} = K_t - I + \sigma(IK)^{1/2}W_t$$

where W_t is a standard normal variable that gives the variability to these data.

The utility's actual portfolio is: renewables 116 MWe, nuclear 8741 MWe, coal 3987 MWe, gas 1306 MWe.

Figure 3 summaries the results using the model in the Appendix.

- If the pre-operational phase of a PP is not modelled with compound options, all the possible solutions of investment belong to the efficient frontier. The investments in SMR or in an LR guarantee only a slightly greater profit than a combined cycle gas turbine (CCGT) or in coal PPs. However, SMR and LR have a remarkably higher level of risk. SMR and LR have a poor SR and thus they are not an ideal investment.
- Modelling the flexibility in the pre-operational phase of a nuclear PP with compound options, the investments in this technology become more appealing. Indeed, at the end of each of the pre-operational phases, the model allows one to abandon or to delay investment if the scenario is not profitable anymore. In this way, the SR of investment in SMR or in large

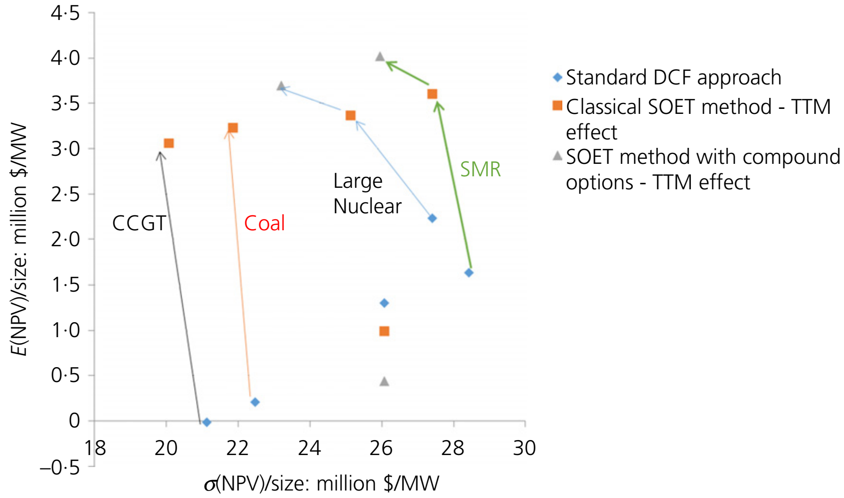


Figure 3. Comparison between the results considering the TTM effect

nuclear reactors improves and the investment becomes more attractive.

Figure 4 shows three further results

- the classical DCF approach with the MVP theory for each of the possible additional PPs
- the value of the compound options with the option to defer for each of the possible additional PPs
- the value of the pre-operational phase of additional PPs as the succession of three sequential compound options with the option to defer.

Figure 4 shows how compound options increase further the value of investment in SMR or in LR than investment in CCGT or in coal PPs.

4. Conclusions

There are several discussions about the economic and strategic aspects of SMR. Surely, the diseconomy of scale is a key factor; however, SMR has several advantages. Among others, they can be built quickly with respect to LR and their smaller size allows better diversification of investment with the 'portfolio effect'. These two factors can potentially contribute to

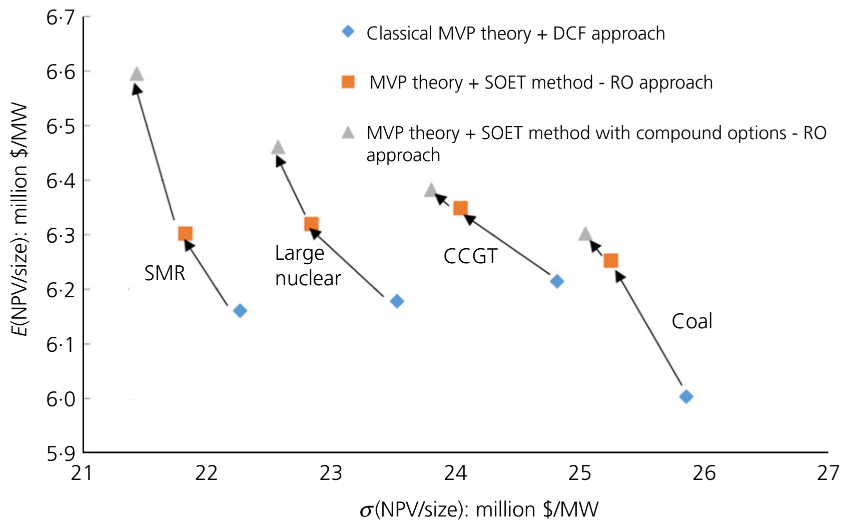


Figure 4. Results obtained considering the utility portfolio in UK

reducing the investment risk and improving its attractiveness. Even if these advantages are intuitive, a rigorous quantitative analysis is needed. This paper accomplishes this task, presenting a model based on the RO approach useful for investment appraisals in the power and energy sector. The key improvements with respect to the literature are first the inclusion of the TTM (and the related stage-gate process) and second the 'portfolio effect'.

Considering the TTM has two opposite effects: on the one hand, it reduces the value of investments in nuclear plants because their TTM is much longer than for coal-fired plants and combined cycle plants. On the other hand, it is possible to have a better assessment of the project risk since the model evaluates the opinions to abandon the plan if, during the TTM, the market conditions are not favourable to the investment.

The integration between the method and the MVP theory overcomes the key limitation of the portfolio analysis in the power and energy sector, since the MVP is traditionally a static methodology (heavily related to past data). Consequently, a portfolio that is considered optimal now might already be far from the efficient frontier in the future. The RO approach assesses the intrinsic degrees of freedom for the portfolio. Modelling the pre-operational time of nuclear PPs with compound options and considering a hypothetical utility portfolio in the UK show that, if the objective function is the maximisation of the NPV mean and σ and the maximisation of the SR value, SMRs are the most valuable option. Nerveless, the choice of the technology will ultimately depend on the investor risk appetite.

Appendix: methods

The simulation with optimised exercise threshold (SOET) model

The key idea of thresholds

The key idea of this RO method is to use an 'exercise threshold'. Before defining how an exercise threshold works, it is helpful to focus on what it does (Figure 5). An exercise threshold (part (a) in Figure 5) is a rule to decide whether or not to exercise the option, considering the values of one or more state variables (b). For instance, an exercise threshold can 'build the PP if the electricity price is above 50 \$/MWh'. Consequently, the output distributions (c) (e.g. the NPV distribution) are not only functions of the inputs, but also of these exercise thresholds.

Some exercise thresholds trigger the investment only with extremely profitable scenarios – for example, when the price of the electricity is very high; others also trigger the investment in less profitable scenarios and others consider the scenario at time zero sufficient to invest immediately.

Thresholds are therefore mathematical rules that, depending on the value(s) of the stochastic processes, defined as 'state variables' (in the previous case the electricity price P_t), trigger or not the options. 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 creates a binomial distribution with several NPVs equal to zero and few high NPVs since

- the model invests few times as the probability to reach that high value of electricity price is very low;

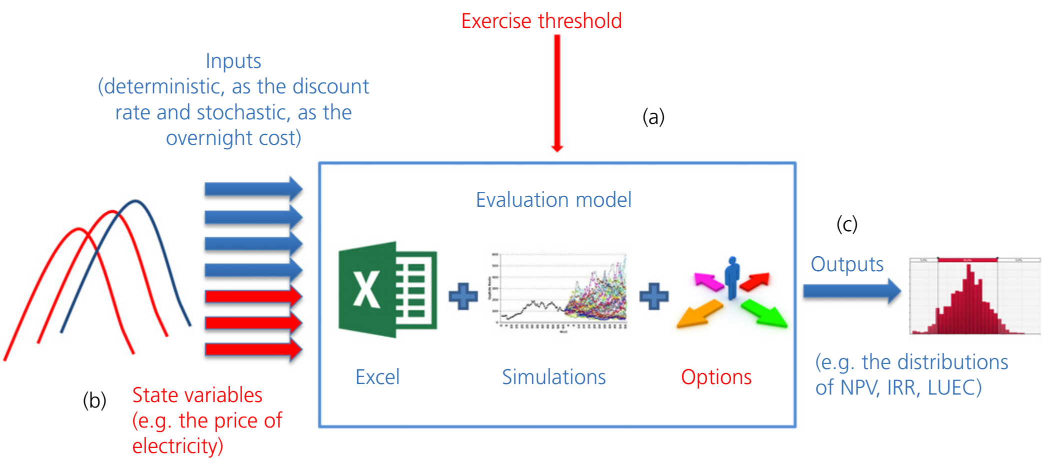


Figure 5. The exercise threshold triggers the options in the evaluation method, in function of the value of the state variables

most of the times the algorithm decides to not invest
- the few times in which the investment is triggered, the NPV is high because the price of electricity is high.

Conversely, a low 'electricity price' threshold generates a normal distribution similar to a DCF since the investment is always triggered and therefore the PP is always built.

Since the exercise threshold influences the output distribution, the method determines which one optimises the output distribution – that is, maximise the NPV reducing the volatility. The method compares different exercise thresholds (different price of P^* to reach) to find the optimum one – for example, the exercise threshold maximising the expected value of the NPV and/or reducing its variability.

Implementation and indicators

SINGLE VARIABLE

The key idea is to consider a set of different exercise thresholds and calculate the different effects on the output distributions (e.g. the NPV distributions). This method generates a discrete sample of all possible thresholds, and then for each one it generates, through a MCS, an NPV distribution. From each NPV distribution are then calculated relevant indicators (e.g. mean and σ), so that it is possible to select the threshold that provides the preferred distribution (maximum NPV, minimum variance etc.).

For instance, it is possible to evaluate the profitability of an investment in an LR, considering only one state variable, the electricity price, and it is possible to solve this problem both with the DCF approach and with the RO through the present method (called SOET). With the DCF approach, it is possible to evaluate the profitability of the investment at time zero with an MCS. Assuming that the electricity price follows a GBM with initial value $P_0 = 90$ \$/MWh and volatility $\sigma = 20\%$, it is possible to generate the stochastic distribution of the NPV of the investment as represented in Figure 6. The mean of the distribution is positive (\$1758 million); therefore, the classical DCF approach would suggest to invest.

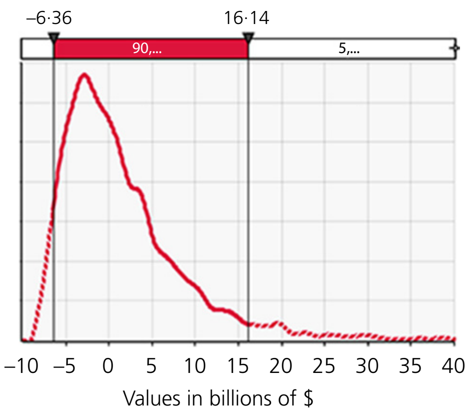
With the new method, the option to build is exercised when the value of the price of electricity exceeds a threshold P^*. The steps are as follows.

- Consider an interval of P^*, defined by a lower and an upper bound. The lower bound has to be lower than the initial price of electricity P_0 – for example, $P^* = 1$ (\$/MWh); the upper bound has to represent a value of P^* highly improbable to reach – for example, $P^* = 600$ (\$/MWh).
- Simulate the NPV distributions using an MSC simulation starting from $P^* = 1$ (\$/MWh), which means that the investment is made when the price of electricity is equal or superior to 1 (\$/MWh), then $P^* = 2$ (\$/MWh) until $P^* = 600$ (\$/MWh). In this case, 600 possible thresholds are evaluated.
- Compute for each of the 600 NPV distributions relevant indicators such as the mean and the σ of the NPV.

Typical results are presented in Figure 7 representing the relationship between the P^* and NPV mean. Figure 8 shows the relation between the P^* and the σ. Figure 9 summarises the mean and σ of the NPV in a single graph.

Remarkable results are shown in Figure 7.

- 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: NPV_0 as in the standard DCF.



Mean: million \$	\$1758
Std dev.: million \$	7901
25th percentile: million \$	–3322
50th percentile: million \$	–88
75th percentile: million \$	4478
Prob. (NPV < 0)	51%
Profitability index	1·33
LUEC: million \$	73

Figure 6. NPV distribution of an investment in a nuclear PP

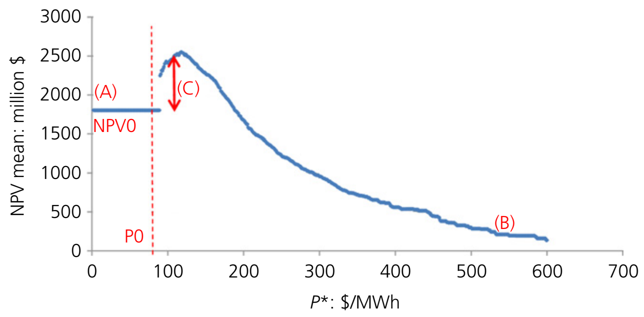


Figure 7. How the value of P^* impacts the mean of the NPV distribution

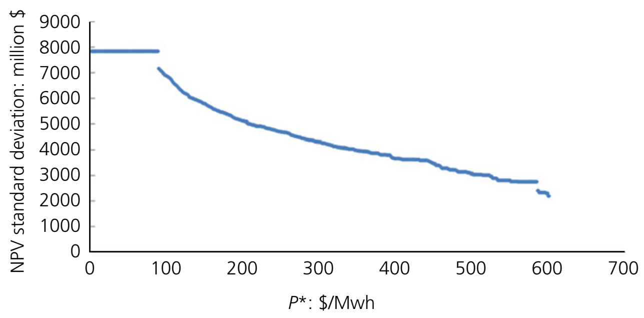


Figure 8. How the P^* impacts on the standard deviation of the NPV distribution

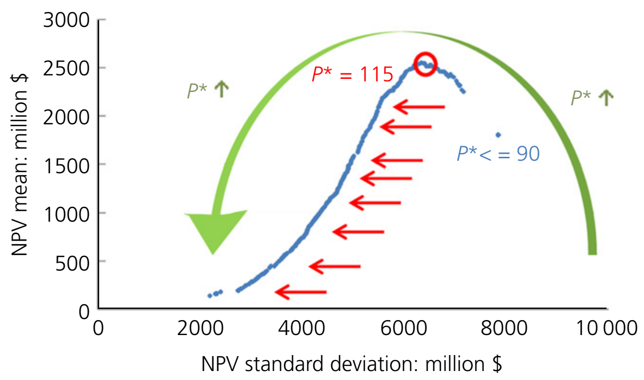


Figure 9. How different values of P^* change the mean and the variance

- When P^* is very high the NPV is zero. Since the probability not to invest is very high and not investing equals having an NPV equal to zero.
- Between these two extreme conditions exists a P^* with the maximum NPV. Such a value is called 'expanded NPV' and the difference between this value and the NPV_0 (the NPV obtained from investing at time 0) is the value of the option to invest.
- There is a discontinuity after $P^* = P_0$. In fact, waiting for a value greater than P_0 means not investing at time zero and leads to a probability greater than 50% of not investing the next time and to a probability greater than 17·75% of never investing in the interval considered.

Several commercial user-friendly Microsoft Excel add-ins can check the convergence with rigorous statistical tests. The add-in used in this work is @Risk. The computer used in this work uses an Intel Core 2 Duo T9500/2·6 GHz processor with two cores with a speed 0·8 GHz and the software used were Microsoft Excel 2007 and Palisade @Risk5·5.

The amount of time needed ranged from 5 min for the search algorithm with one option used for the appraisal of a single plant without modelling the TTM effect to 30 min for the search algorithm with compound options for the evaluation of an additional investment considering the actual portfolio of a utility modelling the TTM effect as well.

Figure 9 joins the functions of Figures 7 and 8 (eliminating the axis of P^*) to create a Pareto frontier. The left tail of this curve is a Pareto frontier since the investor could decide to reduce the NPV mean, reducing the NPV σ. The right tail of the curve is not efficient since for the same level of return (NPV mean) a point on the left side is less risky. Moreover

- investing now is less profitable and riskier than waiting for a certain value (in this case $P^* = 115$ (\$/MWh)) that maximises the NPV distribution
- the distribution obtained from waiting for this value ($P^* = 115$ (\$/MWh)) has the highest mean but there are other distributions with lower NPV and lower variance. All these distributions correspond to a Pareto frontier.

Extension to two or more state variables

The discrete enumeration of all possible thresholds can be easily expanded with multiple state variables. Without loss of generality, it is possible to demonstrate an example with two state variables: investment in a gas PP. The state variables are the price of electricity P_t and the cost of gas G_t. Instead of assuming the exercise threshold to be defined as P^*, that if exceeded by P_t triggers the option to invest, it is possible to define the exercise threshold as a pair (P^*;G^*). For each exercise threshold, the option to invest is triggered when the two conditions are satisfied at the same time: P_t exceeds P^* and G_t is less than G^*, as in Figure 10. The steps are as follows.

- Define the interval of the possible exercise thresholds (P^*;G^*). For example, the possible combinations can be $0 < P^* < 600$ (\$/MWh) and $0 < G^* < 60$ (\$/MWh).

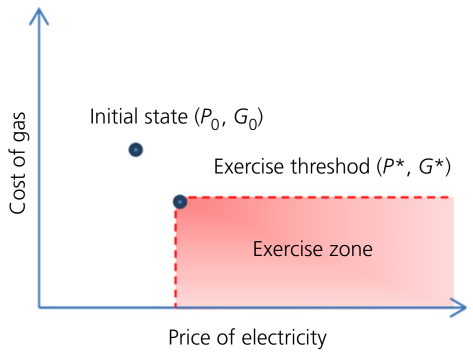


Figure 10. The discrete exercise threshold used in the discrete enumeration of all possible exercise thresholds

- This interval is divided into the possible exercise thresholds, for example, the combinations (P*;G*) = {(0;0), (0;4)…(2;0),(2;4)…(600,60)} for a total of $m = 9331$ simulations (with a number n of 1000 iterations each).
- For each exercise threshold, an MCS is performed and this generates an NPV distribution that is the result of waiting for that exercise threshold.
- From each one of these NPV distributions (i.e. each one obtained from an MCS), the algorithm records the results.

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

- 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 price of electricity 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). All the values of the NPV mean are the same: NPV_0 is the same as that in the standard DCF.
- When P* is very high and G* is low the function converges to zero. That is because the probability that P* is very high and G* is low is negligible.
- Between these two extreme conditions exists a trade-off in which the mean of the NPV distribution is higher.

Figure 11 summarises the results, showing the mean and σ of all exercise thresholds together.

Modelling TTM and compound options

Considering the TTM means modelling the stage-gate process from the decision to invest to the beginning of commercial operation. This time is longer than the construction phase. Table 7 gives an account for the US and European scenario. For instance, in the case of nuclear PPs in the USA, the review

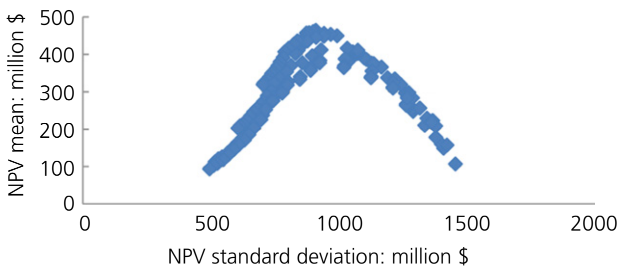


Figure 11. The effects, on the NPV mean and on the NPV standard deviation, of the different exercise thresholds

of each combined license application (WNA, 2012) lasts about 3 years or more (Sainati *et al.*, 2015).

In general, in the planning and delivery of a PP there are three main phases.

- 'Study phase' also called 'feasibility study' in IAEA (2012).
- 'Design phase' also called 'the detailed site survey' in IAEA (2012).
- 'Construction phase' also called 'site preparation; excavation; construction' in IAEA (2012).

'Construction schedules of nuclear power plants, from the first placement of structural concrete to grid connections, have ranged from less than five years to more than twelve years. Achieving short and accurately predicted construction durations is critical to the financial success of any new PP project' (IAEA, 2012: p. 1). A detailed statistical study of the construction phase duration of a nuclear PP can be found in the paper by Thurner *et al.* (2014).

In the TTM period, the financial, economic and social conditions could significantly change, making the investment not convenient anymore. ROs are relevant because an investment in a PP can be considered as the succession of the three aforementioned sequential phases. Hence, this work models this pre-operational phase as the succession of three options – that is, as a compound option. The investor/decision maker, gaining information about cost and time performance and following the evolution of the most uncertain variables, can decide to defer or to abandon the investment if the scenario is not profitable anymore.

The three underlying and options exercise thresholds implemented in this work are as follows.

- The electricity price '$P_{threshold}$' for the study phase.
- The expected cost to complete the design '$ECTD_{threshold}$' for the design phase.

Table 7. TTM of different base-load PPs (based on data from Graber and Rothwell (2006), TIACT (2005))

Technology	Study phase (site specific): years	Design phase (site specific): years	Construction phase (site specific): years	TTM: years
Large nuclear	1	2	6	9
SMR	1	2	5	8
Coal	1		4	5
CCGT	1		3	4

- The expected cost to complete the construction '$\mathrm{ECTC}_{\mathrm{threshold}}$' for the construction phase.

Table 8 summarises the cost breakdown.

Assuming

- P_t = electricity price at time t
- $m_{[\,]}$ = 'multiplication factor' of a linear exercise threshold
- $a_{[\,]}$ = 'differential coefficient' of a linear exercise threshold

The model considers the expected cost to completion of the design and of the construction ones and thus, if in a specific decisional moment 't'

- $P_t > P_{\mathrm{threshold}}$ ➔ the study phase is triggered
- $\mathrm{ECTD}_t < \mathrm{ECTD}_{\mathrm{threshold}}$ ➔ the design phase is triggered
- $\mathrm{ECTC}_t < \mathrm{ECTC}_{\mathrm{threshold}}$ ➔ the construction phase is triggered

The electricity price is the most influential variable on the overall investment (Roques *et al.*, 2008) and therefore is the first underlying one. The thresholds of the design and of the construction phase are the second and third underlying and can be modelled as

$$\mathrm{ECTD}_{\mathrm{threshold}} = m_{\mathrm{design}} + \left(P_t - a_{\mathrm{design}}\right)$$

$$\mathrm{ECTC}_{\mathrm{threshold}} = m_{\mathrm{construction}} + \left(P_t - a_{\mathrm{construction}}\right)$$

Table 8. Correlation between pre-operational phases of an nuclear PP (adapted from Graber and Rothwell (2006), TIACT (2005))

Parameter	Study phase	Design phase	Construction phase
Cost	1%*K	5%*K	K
Time	1 year	2 years	6 years

The key idea is to link the thresholds of the expected cost to complete the design and the construction phases with the electricity price: the higher the electricity price, the higher the incentive for the utility to start or continue construction. The scope of the model is to find the optimal values of the exercise thresholds that trigger each of the three pre-operational phases. This means finding the optimal value of five different parameters

- the value of $P_{\mathrm{threshold}}$
- the multiplication factor of the $\mathrm{ECTD}_{\mathrm{threshold}}$: '$m_{\mathrm{design}}$'
- the differential coefficient of the $\mathrm{ECTD}_{\mathrm{threshold}}$: '$a_{\mathrm{design}}$'
- the multiplication factor of the $\mathrm{ECTC}_{\mathrm{threshold}}$: '$m_{\mathrm{construction}}$'
- the differential coefficient of the $\mathrm{ECTC}_{\mathrm{threshold}}$: '$a_{\mathrm{construction}}$'.

The upper and the lower bound of the multiplication factor and of the differential coefficient must have the following properties.

- The lower bound of (m_{des};a_{des}) has to guarantee a value of $\mathrm{ECTD}_{\mathrm{threshold}}$ remarkably lower than the expected total capital design cost – for example, (m_{des};a_{des}) = (1;100).
- The lower bound of (m_{cos}; a_{cos}) has to guarantee a value of $\mathrm{ECTC}_{\mathrm{threshold}}$ remarkably lower than the expected total capital investment cost – for example, (m_{cos};a_{cos}) = (1;100).
- The higher bound of (m_{des}; a_{des}) has to guarantee a value of $\mathrm{ECTD}_{\mathrm{threshold}}$ remarkably higher than the expected total capital design cost – for example, (m_{des};a_{des}) = (20;1).
- The higher bound of (m_{cos}; a_{cos}) has to guarantee a value of $\mathrm{ECTC}_{\mathrm{threshold}}$ remarkably higher than the expected total capital investment cost – for example, (m_{cos};a_{cos}) = (120;1).

Modelling the portfolio

Table 2 shows that the classical approaches are too simplistic and they do not leverage the advantages guaranteed by an RO evaluation method. Indeed, each possible portfolio is a single static point in the plane E(NPV)–σ(NPV), represented with crosses in Figure 1 that vary only in function of the scenario hypothesised. With the new algorithm, each portfolio in the plane E(NPV)–σ(NPV) is a function of the values of the exercise thresholds that, triggering the options in different conditions, modify the NPV distribution of the overall portfolio. It is possible to obtain in output an efficient frontier for each portfolio and the decision maker can know the conditions that make reasonable this additional investment and compare the trend of the efficient frontiers of all the possible portfolios building the 'optimised efficient frontier'. This innovative form of output shows the best additional investment and the best condition in which it should be triggered.

By extending the conceptual model presented in Section 2.1, the steps to integrate MVP theory and the SOET method are as follows.

1. Enumeration of all the technologies in the actual utility portfolio.
2. Run an MCS to evaluate the NPV distribution of these PPs.
3. Enumeration of all the possible additional investments.
4. Enumeration of all the possible values of the exercise thresholds considered.
5. Run an MCS in correspondence to each of these and obtain in output the NPV distribution of one of the additional investments defined in point 3.
6. For each MCS, apply the MVP theory to obtain in output the NPV mean and σ of the overall portfolio in which the additional investment is made.
7. Select another of the possible additional investments and perform points 5 and 6 again.

As an example, considering a portfolio of two technologies, MVP calculates the portfolio's performances as follows

$$E\left(\mu_p\right) = w1 * R1 + w2 * R2$$

$$\sigma_p^2 = w1 * \sigma_1^2 + w2 * \sigma_2^2 + 2 * (w1 * w2 * \rho_{12} * \sigma_1 * \sigma_2)$$

where $w1 + w2 = 1$ are the respective percentage of each technology in the portfolio; ρ_{12} is the correlation coefficient between the two technologies in the portfolio; σ_1 and σ_2 are the standard deviation of the NPV distribution of each technology in the portfolio; $R1$ and $R2$ are mean value of the NPV distribution of each technology in the portfolio.

The MVP gives in output the E(NPV) of the overall portfolio as the weighted average between the profitability of each PP in the portfolio. Therefore, the E(NPV) of an already existing PP is greater than that of a new PP because it does not include the sunk costs of the existing plants. If the option to invest is implemented, a portfolio with only already built PPs is compared with a portfolio with a PP whose construction cost has

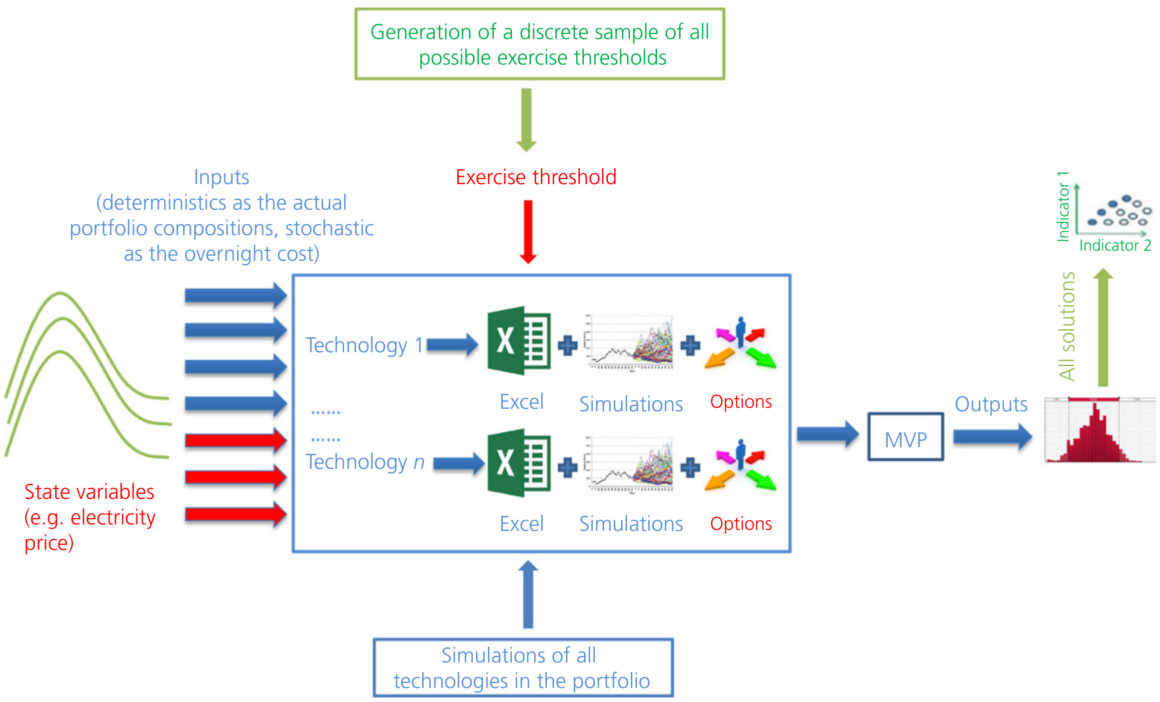


Figure 12. Conceptual model applied to the portfolio analysis

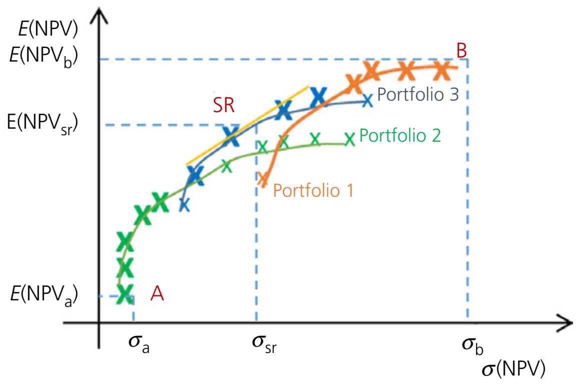


Figure 13. The optimised efficient frontier

not been incurred yet. Consequently, the E(NPV) of the actual portfolio is higher than the one with additional investment. The search for the optimal value of the exercise threshold model would suggest never to invest because the E(NPV) of the actual portfolio is the highest obtainable, even when the additional investment guarantees a positive E(NPV). Therefore, the algorithm must be applied only to evaluate the additional investment and, after the optimal value of the threshold that triggers this investment is found, the decision maker can apply the MVP theory to find out the E(NPV) and the σ(NPV) of the overall portfolio. The steps to apply this method are as follows (see also Figure 12).

- Perform an MCS to evaluate the NPV distribution of each PP in the actual portfolio.
- Consider the possibility of an additional investment
  - select the range of possible variation of the state variable P^* considered
  - select the number of iterations to be performed in each MCS.
- Run an MCS in correspondence to each value of P^* in the range defined in the previous step.
- For each MCS, implement the MVP theory to find the performance of the overall portfolio.

Figure 13 compares three different portfolios and each cross represents the efficient performance obtained by the single portfolio in function to different values of the exercise threshold. However, the point of this method is that only the large crosses represent effectively efficient solutions for the utility because they belong to the optimised efficient frontier obtained by comparing the efficient frontier of each single portfolio. Therefore, this model gives in output not only the composition of the portfolio that maximises a specific objective function, but even the conditions in which the additional investment should be performed.

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