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Development of a Real Options model to support utility investment strategy in power plant portfolio improvement

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Research Index

Index of Figures

Index of Tables

Abstract

This work is part of a research project between the Politecnico di Milano and the University of Lincoln (UK), which has led to the development of an innovative real options approach (The Simulation with Optimized Exercise Thresholds) to support a utility in its decision of investment in base – load power plants. The aim of this work is the further development of the model to make it as close to reality as possible with the objective of maintaining all the advantages it has if compared with the others real options evaluation methods and with the “discounted cash flow method”(DCF).

The steps of improvement we identify and develop in this work are:

The length and the cost of the pre – operational phase of a power plant is not determined only by the construction phase. The time elapsed from the moment the decision to invest is taken and the moment in which the plant starts effectively to produce electricity is really different between the base – load technologies. First aim of this work is to consider in the model different lead time between the decision of investment and the moment in which the PP starts to produce electricity.

To show how it is possible to use the intrinsic flexibility of the pre – operational phase of a nuclear PP modeling it as the succession of three sequential compound options and thus to show how the possibility to abandon or to delay the beginning of each phase at the end of the previous one add a great value to the overall investment.

From the utility’s point of view, an investment in a base – load PP is always an investment in a wider portfolio of already existing investments. Hence, this work aims to build an innovative framework that, thanks to the integration between the Simulation with Optimized Thresholds (SOET) Method and the most important method to perform portfolio analysis(The Mean Variance Portfolio Theory), consider the actual portfolio of a utility in its decision of investment

Through a literature review the advantages of this approach will be explained like for example how the main drawback that is limiting the use of the MVP Theory will be solved. With this method the most critical variables (including the price of electricity, the gas fuel cost, the coal fuel cost, the overnight cost, the study cost, the design cost and the cost of carbon emission) are modeled as stochastic processes. Furthermore several kind of real options has been implemented with the compound options to model the pre – operational phase of a nuclear PP. With this model four different technologies has been compared: the large nuclear reactor(LR), the small modular reactor(SMR), the gas plant(CCGT) and the coal plant. These technologies has been evaluated in different case – studies(in each of them the aim is to fulfill an additional request of 1,5 GWe) to show one at a time the three steps of improvement implemented.

The study – cases considered are:

The chosen of the “best” PP considering the whole length of the pre – operational phase of a PP modeling it both with and without the succession of three sequential compound options, without considering the actual portfolio of already existing investments.

The chosen of the “best” PP considering the whole length of the pre – operational phase of a PP modeling it both with and without the succession of three sequential compound options, and considering a dummy actual portfolio of already existing investments.

The chosen of the “best” PP considering the whole length of the pre – operational phase of a PP modeling it both with and without the succession of three sequential compound options, and considering the real actual portfolio of EDF’s already existing investments in UK.

Implementing this model each portfolio in the plane E(NPV) – σ(NPV) will not a single static point on it anymore but it will be function of the value of the exercise thresholds too that, by triggering the investment in different conditions, influence the value of the expected NPV and of the level of risk of the overall portfolio. Thus, each possible portfolio will have its own efficient frontier and it will be then possible to compare them building an Optimized Efficient Frontier. In this way the model user will be able to choose the best additional investment and the best condition to perform it in order to maximize a specific objective function. At the end of this work the model developed here will be applied to the real actual portfolio of EDF in UK when an additional request of 1,5 GW is implemented. The technology obtained as optimal to build is the SMR's one.

Sommario

Questo lavoro si inserisce in un percorso di ricerca già avviato presso il Politecnico di Milano con la collaborazione dell'Università di Lincoln (UK) che ha portato allo sviluppo di un modello di applicazione delle Opzioni Reali (la Simulazione Ottimizzata con Soglie d'Esercizio) che supporti una utility nella decisione di investimento in centrali elettriche di base load. Il presente lavoro ha come scopo lo sviluppo ulteriore di quel modello per renderlo il più aderente possibile alla realtà con l'obiettivo di mantenerne tutti i vantaggi che lo caratterizzano rispetto agli altri metodi di applicazione delle opzioni reali e al metodo "discounted cash flow" (DCF). Le direzioni di miglioramento identificate e sviluppate sono tre:

1. La durata e il costo della fase pre – operativa di una centrale elettrica non sono determinati solo dalla fase di costruzione. Il tempo trascorso dal momento in cui la decisione d'investimento è presa a quando l'impianto effettivamente diventa operativo si differenzia notevolmente tra le tecnologie di base load. Primo obiettivo di questo lavoro è considerare nel modello differenti lead time tra decisione di investimento e inizio delle operazioni.
2. Mostrare come sia possibile sfruttare la flessibilità intrinseca alla fase pre – operativa di un impianto nucleare modellandola come successione di tre "compound options sequenziali", modellando la possibilità di abbandonare o ritardare l'inizio di ogni fase al termine della precedente aggiunga valore all'investimento intero.
3. Un investimento in una centrale base load analizzato dal punto di vista di una utility è sempre un investimento in un portfolio di investimenti già esistente. Questo lavoro mira dunque a costruire un nuovo frame work che, integrando il metodo della Simulazione con Soglie d'Esercizio Ottimizzate (SOET) con il principale metodo per effettuare un'analisi di portfolio(la Mean Variance Portfolio Theory), tenga conto nella decisione di investimento del portfolio attualmente esistente.

Attraverso l'analisi della letteratura verrà spiegato quali siano i vantaggi di questo approccio e come anche la principale debolezza che ha limitato l'uso della MVP Theory sia superata. Per utilizzare questo modello le variabili più critiche (prezzo dell'energia elettrica, costo del gas, costo del carbone, costo di costruzione, costo del design, costo dello studio e costo delle emissioni di CO_2) sono state modellate tramite processi stocastici. Allo stesso tempo sono state implementate diversi tipi di opzioni reali e le compound options per modellare la fase pre – operativa di un impianto nucleare. Quindi, usando questo modello, quattro diverse tecnologie sono state confrontate: i reattori nucleari di taglia grande (LR), di taglia piccola (SMR), le centrali a gas (CCGT) e le centrali a carbone. Queste tecnologie sono state valutate in differenti case – study(accomunati dal fatto che si va a soddisfare il bisogno energetico di 1,5 GW) per mostrare uno alla volta i tre step di miglioramento inseriti. I case – study considerati sono:

i. Scelta impianto più profittevole considerando l'intera durata della fase pre – operativa di una centrale e modellandola sia con che senza la successione di tre compound options, senza però considerare un portfolio attuale di investimenti già esistenti .
ii. Scelta impianto più profittevole considerando l'intera durata della fase pre – operativa di una centrale modellandola sia con che senza la successione di tre compound options e considerando un fittizio portfolio attuale di investimenti già esistenti .
iii. Scelta impianto più profittevole considerando l'intera durata della fase pre – operativa di una centrale modellandola sia con che senza la successione di tre compound options e considerando il portfolio attuale di investimenti già esistenti di EDF in UK.

Implementando tale modello ogni portfolio nel piano E(NPV) – σ(NPV) non sarà più un singolo punto statico su di esso ma diverrà anche funzione del valore delle soglie d'esercizio che, facendo scattare le opzioni in condizioni differenti, modificano il valore atteso e il livello di rischio dell'intero portfolio. Ogni portfolio avrà dunque una propria frontiera efficiente per cui sarà possibile confrontarne gli andamenti e costruire una Frontiera Efficiente Ottimizzata che garantisca all'investitore di scegliere l'investimento addizionale e la condizione in cui effettuarlo affinché una definita funzione obiettivo venga massimizzata. Nel caso di applicazione di tale modello al caso di portfolio attuale di EDF in UK la tecnologia ottimale su cui investire per colmare una richiesta di 1,5 GW sono gli SMR.

Executive Summary

1. Lo scenario elettrico attuale

Negli ultimi decenni, il consumo mondiale di elettricità è cresciuto ad un tasso di crescita superiore rispetto alla crescita complessiva nel livello di fornitura di energia primaria(EIA, 2012). In parallelo molti rapidi cambiamenti sono avvenuti. La liberalizzazione del mercato dell'elettricità e del gas ha permesso che la definizione di tali prezzi toccasse direttamente ai produttori e non più allo stato con la conseguenza di renderne molto meno prevedibili i rispettivi andamenti futuri(Möst & Keles, 2010). Altro effetto significativo è stato il crescente interesse statale nella limitazione delle emissioni di CO_2 tramite sovvenzioni quali la feed – in tariff per lo sviluppo di tecnologie rinnovabili e/o tramite la tassazione delle tecnologie ad alta emissione di inquinanti(UK Government, 2014).
La tabella seguente identifica i principali parametri caratterizzanti un investimento nel settore elettrico differenziandoli in base all'impatto che loro variazioni hanno sul risultato complessivo dell'investimento e alla probabilità che tali variazioni avvengano:

Fonte di incertezza	Impatto	Volatilità
Prezzo Elettricità	Alto	Alto
Costi di Costruzione	Alto	Alto
Costo del Gas Naturale	Alto	Alto
Costo del Carbone	Alto	Alto
Durata di Costruzione	Alto	Alto
Costo combustibile nucleare	Basso	Alto
Vita Impianto	Basso	Alto
Disponibilità	Alto	Basso
Tasso di attualizzazione	Alto	Basso
Costi O&M	Basso	Basso
Costo del fissile	Basso	Basso

Tabella 1. I fattori che incidono di più sulla rischiosità di investimenti energetici (adattata da (Roques et al., 2006))

La **Tabella 1** chiarifica quali siano i fattori di maggior influenza in un investimento nel settore energetico, e cioè quelli che posseggono grande impatto su di esso e grande volatilità durante la sua durata.
Obiettivo del lavoro è sviluppare il modello SOET[1] per l'analisi di tali investimenti, allo scopo di rendere tale modello il più aderente possibile alla realtà così da poter essere efficacemente sfruttato da una utility in una sua decisione di investimento. I passi seguiti sono riportati di seguito:

- Analizzasi delle metodologie presenti in letteratura per valutare investimenti nel settore elettrico
- Sviluppo di un nuovo modello che tenga superi i limiti dei modelli esistenti e migliori il modello di (Lotti, 2012) in tre direzioni:

[1] Simulazione Ottimizzata con Soglie d'Esercizio (Lotti, 2012)

- Considerando la fase pre – operativa di una centrale elettrica costituita non unicamente dalla fase di costruzione(Time to Market Effect)
  - Modellando con le opzioni reali la fase pre – operativa di una centrale nucleare come successione di tre fasi sequenziali[2] al termine delle quali, vista l'evoluzione dei parametri stocastici, l'investimento può essere abbandonato o ritardato
  - Considerando il portfolio attuale di investimenti già esistenti di una utility nella scelta della centrale aggiuntiva da costruire
- Utilizzo del modello sviluppato con i dati della (EIA, 2012)

Lo scopo di questo lavoro è rispondere alle seguenti domande di ricerca:

1. Che effetto ha considerare su un investimento in Base – Load PP l'intero tempo necessario per iniziare a produrre e non solo la fase di costruzione(TTM Effect)?
2. Come le RO possono modellare questa fase pre – operativa?
3. Come le RO possono aiutare una utility a scegliere un investimento in un PP addizionale rispetto ad un portfolio di investimenti già esistente?
4. Qual è la tecnologia più profittevole per colmare una richiesta di 1,5 GW tenendo conto del portfolio attuale di EDF in UK?

2. Analisi della Letteratura

2.1 Le Opzioni Reali: descrizione e stato dell'arte

Scopo della teoria che applica le opzioni reali è identificare e valutare le opzioni manageriali per correggere i progetti durante il loro svolgimento a seconda dell'evoluzione di certi fattori d'incertezza che li caratterizzano. Considera cioè l'abilità di chi gestisce i progetti di modificare questi ultimi per garantire il raggiungimento di determinate funzioni obiettivo. (Martínez Ceseña, Mutale, & Rivas-Dávalos, 2013) sintetizza chiaramente la ragione per cui l'applicazione delle opzioni reali nel settore energetico sia efficace: "*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".*
L'approccio RO nasce e si sviluppa dal considerare investimenti come delle opzioni finanziarie. Le opzioni finanziarie sono contratti che danno al possessore il diritto, ma non l'obbligo, di acquistare (opzione "call") o vendere (opzione "put")il sottostante (azioni, obbligazioni, valute etc...) ad un determinato prezzo di esercizio, in/entro una determinata data. Quando tale opzione viene esercitata il possessore ottiene un ritorno dato dalla differenza tra il valore del sottostante ed il prezzo di esercizio. Il valore di tali opzioni è dato dal fatto che nessun possessore razionale eserciterebbe tale opzione quando il ritorno è negativo, dando origine a ritorni asimmetrici (possono salire indefinitamente ma non possono scendere sotto zero). E' proprio per questa asimmetria che maggiore è la volatilità del valore del sottostante maggiore è il valore dell'opzione.
Le opzioni reali sono simili alle opzioni finanziarie poiché danno al possessore il diritto ma non l'obbligo di prendere determinate decisioni strategiche (ad esempio fare un certo investimento). Attraverso tale paragone è possibile implementare la flessibilità nella valutazione degli investimenti.

[2] Modellate tramite tre Compound Options sequenziali

Le opzioni reali implementate in questo lavoro sono (Kodukula & Papudescu, 2006)

- **L'opzione "to defer":** la possibilità di scegliere il momento più adatto entro un definito arco temporale per prendere una decisione di investimento.
- **L'opzione "to invest":** la possibilità di aspettare prima di prendere una decisione di investimento. Nel caso in cui lo scenario non sia profittevole questa opzione fornirà come decisione quella di non investire.
- **L'opzione "to abandon":** la possibilità di abbandonare una scelta presa precedentemente in funzione di nuove informazioni, come lo smettere di costruire una centrale elettrica od abbandonarla , dopo che una parte dell'investimento è stato fatto nel caso questo non appai più profittevole.
- **L'opzione "to choose":** la possibilità di scegliere tra diversi prodotti, processi o inputs.
- **Compound Options:** Progetto d'investimento costituito da fasi sequenziali in cui il management può decidere se continuare o meno il progetto tra una fase e la successiva dopo aver ottenuto nuove informazioni sull'evoluzione dei principali parametri stocastici caratterizzanti l'investimento.
  Esercitare un'opzione ne genera dunque una successiva. Una compound option dunque deriva il suo valore da un'altra opzione: il primo investimento crea infatti il diritto, ma non l'obbligo, di farne un secondo, che a sua volta permette di farne un terzo, e così via.

Dunque l'approccio con le opzioni reali rispetto all'approccio DCF permette di includere nell'analisi il fatto che le decisioni possano essere prese in funzione di informazioni non ancora disponibili. (Pindyck, 1992) definisce le opzioni reali come il diritto da parte del possessore, senza l'obbligo, di ritardare, abbandonare, o modificare un progetto seguendo l'evoluzione delle principali sorgenti di incertezza. Le opzioni reali dunque permettono di prendere decisioni in funzione di informazioni future, e non ciecamente al momento della valutazione d'investimento:

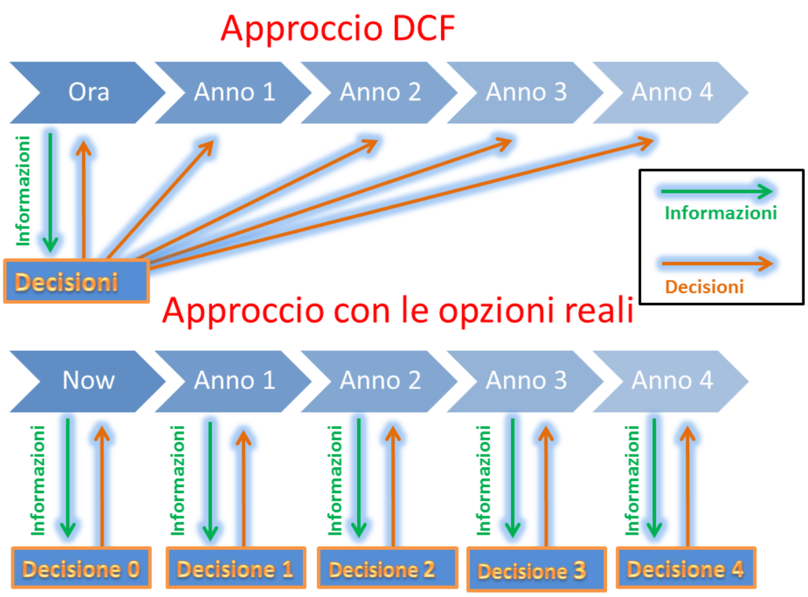

Figura 1. Differenza tra approccio DCF e con le Opzioni Reali (Cardin & Neufville, 2009)

Similmente alle opzioni finanziarie da cui traggono origine, le opzioni reali necessitano di un modello matematico per valutarne il valore. Il valore di un'opzione è il valore medio di questa in elevato numero di scenari[3]. Alcuni di essi garantiranno all'opzione di avere valore nullo in quanto non è esercitata ed altri invece le conferiranno valore positivo poiché l'opzione è esercitata in un determinato istante temporale. La complicazione matematica deriva dal fatto che questo istante temporale non è definito a priori ma è l'istante tale per cui l'opzione viene utilizzata al meglio, garantendo il ritorno massimo. Sono numerosi i metodi di valutazione delle opzioni reali e per la maggior parte sono metodi nati per la valutazione delle opzioni finanziarie.

Le opzioni reali sono però più complesse da trattare delle opzioni finanziarie: sono opzioni "americane" (possono essere esercitate in qualsiasi periodo temporale e non solo a scadenza), il prezzo di esercizio è aleatorio, e le opzioni interagiscono in maniera complicata (ad esempio il valore dell'avere le opzioni di investire nella costruzione di una centrale e nell'abbandonarla non è uguale ai valori delle singoli opzioni). La distinzione principale tra i modelli di applicazione delle opzioni strategiche esistenti risiede dunque nella loro capacità di risolvere problemi più o meno complessi.
Alcuni di questi modelli possono risolvere unicamente un problema semplice, ovvero con una sola opzione reale e con una o due variabili stocastiche. Altri invece possono risolvere problemi più complessi, con più opzioni reali e più variabili stocastiche. La scelta del modello di valutazione dipende quindi dalla complessità del problema e viceversa.

Modello di valutazione	Risoluzione problema semplice	Risoluzione problema complesso
Soluzioni in Forma Chiusa	No. Non permettono la soluzioni di opzioni americane standard	No
Soluzioni alle derivate parziali (Black & Scholes, 1973)	Sì.	Problema "curse of dimensionality": avere tante variabili stocastiche rende troppo grande e complessa la dimensione del problema in analisi
Modelli Binomiali(alberi o reticoli) ; (Cox, Ross, & Rubinstein, 1979)	Sì.	Oltre al problema "curse of dimensionality" non sono applicabili perché i cammini sono dipendenti: le decisioni del passato incidono sul futuro
Metodo Least Square Monte Carlo (LSMC)	Sì	Metodo più usato in letteratura per problemi complessi. Alto sforzo computazionale richiesto
Simulazione con Soglie d'Esercizio Ottimizzate(SOET)	Sì	Sì

Tabella 2. I modelli di valutazione delle opzioni reali

I metodi esistenti possono dunque essere divisi tra quelli in grado di risolvere solo problemi semplici ma che forniscono molte informazioni circa il problema, e quelli (e.g., LSMC) che permettono la soluzione di problemi complessi senza però dare informazioni circa il problema, dove con"informazioni"circa il problema si intende il fornire informazioni all'utilizzatore circa quando e come sia più conveniente esercitare le opzioni.
Esempi di recenti applicazioni delle opzioni reali nel settore energetico sono riportate di seguito:

[3] Che in questo lavoro saranno simulati tramite la simulazione Monte Carlo

	Questo lavoro	(Yu & Tao, 2013)	(Jain et al., 2013)	(Zambujal-Oliveira, 2013)	(Detert & Kotani, 2013)	(Santos et al., 2014)
Scope of Work	Costruzione realistico modello di investimenti nel settore elettrico che consideri il TTM Effect e il portfolio attuale di una utility	Valutazione di impatto che rischi e incertezze hanno sulla costruzione di nuovi impianti nucleari in Cina	Aiutare una utility a determinare il valore di investimenti in SMR sequenziali	Analizzare diversi modelli RO per scegliere il miglior investimento nel settore energetico	Valutare l'opzione di switchare da tecnologie non rinnovabili a rinnovabili in Mongolia	Applicare un ROA al caso di investimenti in impianto idroelettrico paragonandone risultati con quelli ottenuti con approccio DCF
Real Option Evaluation Method	Metodo SOET	Equazioni alle derivate parziali (PDE)	Metodo Programmazione Dinamica	Albero Binomiale	Simulazione	Albero Binomiale
Options Considered	Compound Options, Opzione to invest/abandon / defer/choose	Compound Option; Opzione to Invest; to Abandon	Opzione to Invest; to Abandon	Opzione to defer; to invest	Opzione to Switch	Opzione to invest
Outputs	E(NPV); σ(NPV); Soglie d'esercizio; Frontiera Efficiente 2D per ogni tecnologia; Frontiera Efficiente 3D per ogni Portfolio	Valore dell'opzione	E(NPV); Classical NPV	Valore dell'opzione	Decisione se switchare o no; Valore dell'opzione	E(NPV); Classical NPV; Valore dell'opzione

Tabella 3. Esempi di applicazione delle Opzioni Reali nel settore energetico

2.2 La Simulazione Ottimizzata con Soglie d'Esercizio

Il metodo della Simulazione Ottimizzata con Soglie d'Esercizio ha il vantaggio di risolvere problemi complessi fornendo anche informazioni all'utilizzatore del modello differentemente dalle metodologie più diffuse in letteratura (e.g. Metodo LSMC).
Il metodo SOET, sviluppato in un precedente lavoro di tesi, usa infatti una logica profondamente diversa dai metodi classici di applicazione delle opzioni reali perché non si chiede più ad ogni istante temporale se sia meglio esercitare le opzioni od aspettare, ma si chiede sin dall'inizio in quali condizioni future sarebbe "meglio" investire. Con il termine "meglio" si intende che è possibile implementare nel modello differenti funzioni obiettivo: non si limita cioè a massimizzare la profittabilità ma punta a valutare diverse possibilità considerando la rischiosità degli investimenti. Questo rende il metodo SOET il più adatto ad essere migliorato ed integrato con un metodo per effettuare un'analisi di portfolio dato che uno degli obiettivi di questo lavoro è costruire un modello che tenga conto del portfolio attuale di una utility nella decisione d'investimento. L'idea è di esternalizzare il meccanismo con cui viene scelto quando esercitare le opzioni o meno, rappresentato tramite le cosiddette "soglie di esercizio".

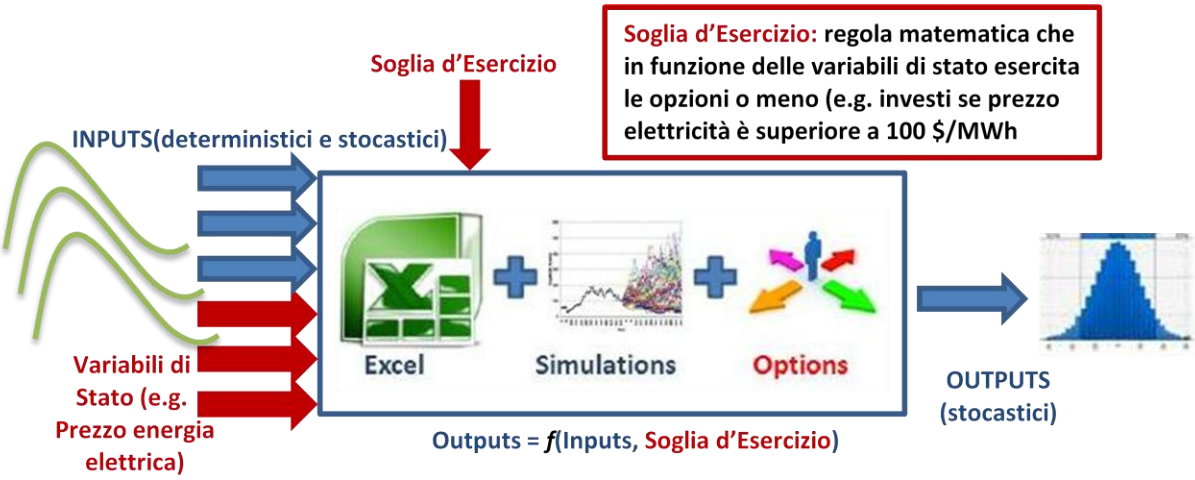

Figura 2. Schema a Blocchi Modello Simulazione con Soglie d'Esercizio Ottimizzate

Le soglie di esercizio sono regole matematiche che indicano al modello quali opzioni esercitare e quando. Per fare ciò ricevono in input i valori di alcune variabili stocastiche (dette di stato), come il prezzo dell'energia elettrica o il costo atteso di costruzione, ed in funzione di questi valori prendono le decisioni. Si potrebbe ad esempio implementare nel modello che l'investimento scatti unicamente quando il prezzo dell'energia elettrica supera i 100 $/MWh, oppure quando il costo atteso di costruzione è inferiore ai 5000 $/kW. Volutamente sono stati presi ad esempio due differenti tipologie di soglie d'esercizio poiché per una corretta applicazione del metodo è necessario che l'utilizzatore comprenda che non esiste una soglia univocamente corretta da utilizzare ma che a seconda del problema in analisi e dell'influenza dei diversi parametri stocastici, la scelta della/e variabile/i di stato debba mutare.
L'idea chiave del metodo è che diverse soglie di esercizio originano scenari diversi (e.g. estremi come investire subito o non investire mai) e quindi a profittabilità diverse. Lo scopo del metodo SOET è trovare la/le soglia/e di esercizio migliore per l'utilizzatore del modello.
Tali scenari sono simulati utilizzando la simulazione Monte Carlo che, effettuando migliaia di iterazioni, fornisce i valori delle distribuzioni stocastiche in input ed usa le soglie d'esercizio per prendere decisioni in ogni iterazione. Per esempio, se si usa come unica variabile di stato il prezzo dell'energia elettrica e come soglia di esercizio un valore che, se superato, fa scattare l'investimento (e.g. in una centrale per la produzione di energia elettrica), in alcuni scenari si investirà, in altri no ed in generale i momenti di esercizio nei vari scenari saranno diversi.

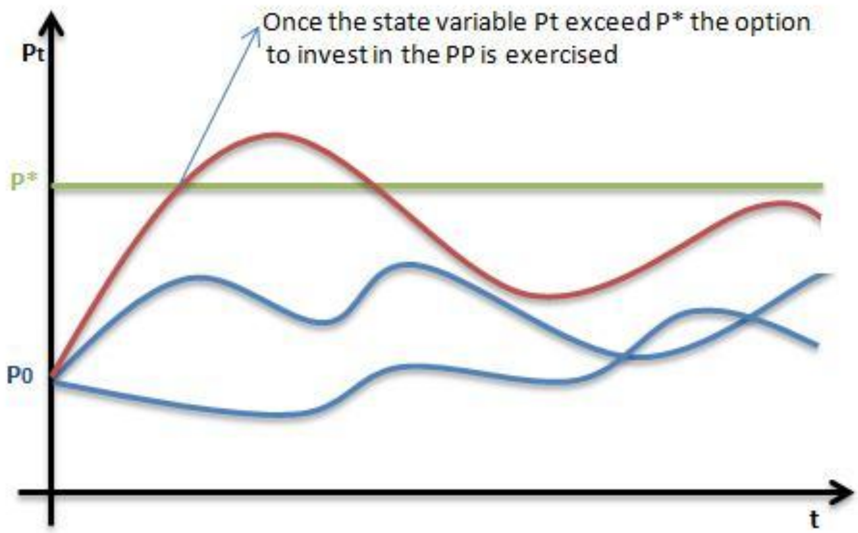

Figura 3. Come il metodo SOET sfrutta in ogni iterazione la soglia di esercizio P* per far scattare l'investimento

L'idea base del metodo SOET è una ma le modalità per implementarla sono tre e sono sintetizzate nella seguente tabella:

	Enumerazione Discreta di tutte le possibili Soglie	Enumerazione Discreta di tutti i possibili stati	Algoritmo di Ricerca
Idea del Metodo	Richiede enumerazione di un campione discreto di tutte le possibili soglie. Per ognuna genera, grazie a una MCS, la distribuzione di NPV. Da essa estrae indicatori come media e deviazione standard aiutando cosi l'utilizzatore del modello a selezionare la soglia d'esercizio che più si avvicina alla funzione obiettivo implementata	Ha l'obiettivo di simulare ogni possibile "situazione" vista come ogni possibile combinazione delle variabili di stato. Poi, per ogni possibile situazione, la domanda è "in questa situazione è meglio investire o attendere?" e non più "quale valore della variabile di stato è l'ottimo da attendere?"	Dato un valore iniziale della variabile di stato, genera automaticamente molti valori della soglie d'esercizio e per ognuno di essi calcola, attraverso una MCS, la distribuzione di NPV da cui estrae i valori di media e deviazione standard. Ha il vantaggio di non enumerare tutti i possibili valori assunti da una soglia d'esercizio ma cerca la "migliore" attraverso un algoritmo
Vantaggi	Permette di paragonare direttamente tutti i valori soglia, capendo lo schema del problema. Metodo migliore per problemi a una variabile di stato.	E' il metodo più preciso. Unica funzione obiettivo implementabile è la massimizzazione dell'NPV	E' il metodo più generale e più veloce a trovare soluzione. Può risolvere teoricamente ogni tipo di problema. Metodo più adatto a problemi con molte variabili di stato; unico metodo in grado di risolvere problemi con molte opzioni interagenti tra loro
Svantaggi	Con più di una variabile di stato è difficile capire lo schema del problema. Non applicabile a problemi con molte opzioni interagenti tra loro.	Può massimizzare solo il valore atteso dell'NPV e non tiene conto della componente di rischio. Necessita algoritmo nel caso di molte variabili di stato. Non applicabile al caso di molte opzioni interagenti tra loro.	Può offrire solo una soluzione che è poi considerata anche l'ottima.
Soluzioni	Multiple. Produce una frontiera efficiente in output	Una. Massimizza solo il valore atteso dell'NPV	Allo sviluppo attuale una. Quella che massimizza la funzione obiettivo implementata

Tabella 4. Differenze tra i diversi metodi SOET (adattata da (Lotti, 2012))

Questo lavoro mostra l'applicazione di una versione estesa e migliorata di tutti e tre i metodi per validare i risultati ottenuti in tutti i tre steps di miglioramento che verranno affrontati e cioè nella:

i. Scelta dell'impianto più profittevole considerando l'intera durata della fase pre – operativa di una centrale, modellandola però senza la successione di tre compound options e senza considerare un portfolio attuale di investimenti già esistenti .

ii. Scelta dell'impianto più profittevole modellando l'intera durata della fase pre – operativa di una centrale come successione di tre compound options, ma senza considerare un portfolio attuale di investimenti già esistenti .

iii. Scelta dell'impianto più profittevole modellando l'intera durata della fase pre – operativa sia con che senza la successione di tre compound options e considerando la presenza di un portfolio attuale di investimenti già esistente.

2.3 L'Analisi di Portfolio nel settore energetico: l'MVP Theory

"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". (Hlouskova et al., 2005) sottolinea l'importanza del considerare il portfolio attuale di una utility nella sua decisione di investimento.
Essendo uno degli scopi principali di questo lavoro dunque migliorare il metodo SOET per costruire un modello di investimenti che tenga conto del portfolio attualmente esistente di una utility, questa sezione sintetizza le principali metodologie presenti in letteratura con cui effettuare un'analisi di portafoglio nel settore energetico.

Metodo	Vantaggi	Svantaggi	Note	Riferimenti
Mean-Variance Portfolio theory (MVP)	Semplice. Chiarezza nei risultati. Direzioni miglioramento identificabili. Espandibile e adattabile per considerare output addizionali	Richiede in input deviazioni standard e correlazioni tra le diverse tecnologie nel portfolio in analisi	Tecnica più usata in letteratura. Permette di trattare un portfolio come una singola tecnologia	(Markowitz, 1952); (Bar-lev & Katz, 1976); (Madlener & Wenk, 2008); (Awerbuch, Shimon, Yang, & Spencer, 2007);(Kienzle et al. 2007); (Roques et al. 2007); (Paz et al. 2012); (Abadie, Neufville, & Chamorro, 2014)
Maximization of the geometric mean returns	Identifica il portfolio con la più alta probabilità di ottenere il massimo profitto	Non è possibile implementare funzioni obiettivo diverse da massimizzazione NPV. Non tiene conto del rischio.	Portfolio trovato appartiene a frontiera efficiente che si troverebbe applicando MVP.	(Latanè, 1959), (Young & Trent, 1969); (Weide et al., 1977); (Jean, 1980); (Estrada, 2010); (De Santiago & Estrada, 2011)
Value at Risk (VaR)	Molto flessibile, considera varianza, covarianza e correlazione tra I fattori	La diversificazione non permette di ridurre il rischio. Soggettivo, non permette di trovare soluzioni generali		(Deng et al. 2013); (Fortin, Ines et al., 2007); (de Oliveira et al.2011); (Spangardt et al., 2006);(Unger & Luthi, 2002);(Doege et al., 2005)

Safety First (SF)	Molto semplice. La scelta è fatta basandosi sulla probabilità di avere ricavi sotto una certa soglia	Non considera covarianze e interazioni tra I fattori. Semplifica troppo il problema non permettendo di trovare soluzioni generali e risolvere problemi complessi	I suoi risultati appartengono alla frontiera efficiente garantita in output dall'MVP	(Bawa, 1978); (Roy, 1952); (Dorfleitner & Utz, 2011); (Norkin & Boyko, 2012)
Stochastic dominance(SD)	Classifica e paragona le diverse possibili alternative di portfolio identificando l'ottimo in un range di soluzioni già definito	Non considera l'investitore e il suo livello di avversione al rischio; richiede grande ammontare di dati e identifica una sola soluzione	Non adatto alla soluzione di problemi complessi	(Fishburn, 1964), (Bawa, 1982);(Levy, 1992); (Ogryczak & Ruszczyński, 1999)

Tabella 5. Analisi di Portfolio: descrizione di tutti i possibili metodi (adattato da (Locatelli & Mancini, 2011))

In questo lavoro applicheremo l'MVP Theory per tener conto del portfolio attuale di una utility nella sua decisione d'investimento. Le ragioni di questa scelta sono di seguito sintetizzate:

1. E'il metodo più diffuso in letteratura(e.g. (Abadie et al., 2014); (Jain et al., 2013)) perché è quello che fornisce in output al suo utilizzatore il maggior numero di informazioni sul problema grazie alla costruzione di una frontiera efficiente
2. Garantisce di tenere conto di differenti funzioni obiettivo(e.g. Massimizzazione NPV; Minimizzazione Rischio; Massimizzazione Sharpe Ratio)
3. Permette di trattare un intero portfolio di investimenti come una singola tecnologia. Questa proprietà ci permetterà di integrarlo efficacemente al metodo SOET(capitolo 3)
4. Ogni singolo portfolio può essere paragonato agli altri in termini di Expected NPV e livello di rischio garantendoci così la possibilità di modellare differenti funzioni obiettivo.
5. Questo metodo è espandibile e adattabile per considerare input addizionali
6. Può essere implementato in un foglio di calcolo Excel e garantisce grande chiarezza di risultati.

La maggior parte delle ricerche che applicano l'MVP prendono sviluppo dal lavoro di (Markowitz, 1952) che per primo considerò la diversificazione degli investimenti come necessaria per la costruzione di portfoli efficienti e diede una formalizzazione matematica di questa idea. Identificò un range di soluzioni ottime che seguivano la seguente proprietà: "*Massimizzano il ritorno atteso per un definito livello di rischio*". I portfoli ottimi giacciono cioè su una Frontiera Efficiente e ognuno di essi è considerato una soluzione ottima.

Considerando ad esempio un portfolio composto da due sole tecnologie l'MVP calcola le performance dell'intero portfolio come segue:

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

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

Dove:

- $w1 + w2 = 1$, percentuale di ogni tecnologia all'interno del portfolio complessivo
- ρ_{12} , coefficiente di correlazione tra le due tecnologie nel portfolio
- $R1; R2$, valore medio della distribuzione di NPV di ciascuna delle due tecnologie nel portfolio

- σ_1; σ_2 , deviazione standard della distribuzione di NPV di ciascuna delle due tecnologie nel portfolio

In sintesi dunque il principio sul quale si base un'analisi di portfolio effettuata con l'MVP Theory è riassumibile in due maniere equivalenti:

a. Tra tutti i portfoli ottenibili, dato un limite superiore di livello di rischio σ_p accettato, trova il portfolio con il massimo valore atteso di ricavi μ_p
b. Tra tutti i portfoli ottenibili, dato un limite inferiore di profittabilità minima μ_p richiesta, trova il portfolio con il minimo livello di rischioσ_p

In ogni caso i portfoli sulla frontiera efficiente sono tutti equivalenti tra loro. Come può dunque un investitore scegliere quale composizione tra essi raggiungere? Per rispondere a questo quesito (Sharpe, 1966) introduce un parametro che permette di comparare i portfoli sulla frontiera efficiente in termine di profitto garantito per unità di rischio: lo Sharpe Ratio:

$$SR(w) = \frac{\mu_p}{\sigma_p}$$

Una possibilità, che sarà considerata anche in questo lavoro, è dunque identificare il portfolio sulla frontiera efficiente con il più alto profitto atteso per unità di rischio. Geometricamente il punto sulla frontiera efficiente cui corrisponde la soluzione di questo problema è tangente alla frontiera efficiente: il portfolio ottimo calcolato massimizzando lo Sharpe ratio è quindi definito Portfolio Tangente.

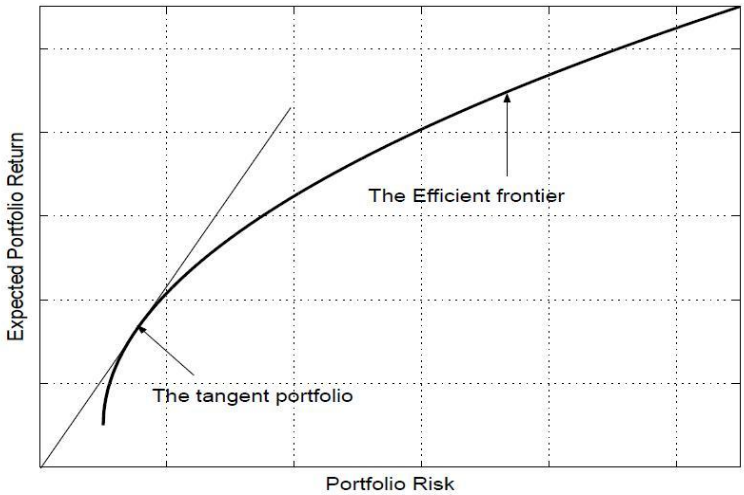

Figura 4. La Frontiera Efficiente e il Portfolio Tangente (Stoyanov et al., 2005)

Più recentemente, (Awerbuch et al., 2007) fornisce una sintesi delle più diffuse funzioni obiettivo implementabili quando una analisi di portfolio viene effettuata:

- Ricerca del portfolio che garantisce il massimo profitto ottenibile
- Ricerca del portfolio che garantisce il minimo livello di rischio possibile
- Ricerca del portfolio che garantisce il massimo profitto possibile dato un fissato livello di rischio
- Ricerca del portfolio che garantisce il minimo livello di rischio dato un fissato profitto obiettivo
- Ricerca del portfolio che massimizza il valore dello Sharpe Ratio

Da un lato dunque questo lavoro mira a costruire un modello che permetta l'implementazione di ognuna delle funzioni obiettivo citate sopra oltre che di qualunque altra che leghi la massimizzazione dei ricavi a un valore determinato di rischio, o viceversa che minimizzi il livello di rischio dato un profitto obiettivo fissato.

D'altro lato però, l'integrazione del metodo SOET di applicazione delle Real Options, ha come obiettivo anche superare il principale limite presente in letteratura dell'MVP che ne ha limitato l'uso:
"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 & Wenk, 2008).
Diventa come detto perciò necessario per il superamento di questo limite l'integrazione di un metodo che considera le opzioni strategiche all'MVP Theory per effettuare un'analisi di portfolio.

2.4 Applicazione delle Opzioni Reali per effettuare Analisi di Portfolio

In letteratura sono pochi gli esempi di applicazioni delle opzioni reali per effettuare analisi di portfolio. Tra gli esempi più rilevanti segnaliamo (Fuss et al., 2012) e (Jain et al., 2013). La ragione di questo risiede nella complessità intrinseca ai principali metodi di applicazione delle opzioni reali presenti in letteratura oltre che alla complessità richiesta nell'effettuazione di un'analisi di portfolio. Tra i metodi principali infatti solo il LSMC sarebbe utilizzabile per risolvere compiutamente problemi complessi ma fornisce poche informazioni all'utilizzatore su come e quando implementare le opzioni. Gli altri invece sono applicabili solo in casi a una variabile di stato o in cui è implementata una sola opzione e dunque il modello creato risulta eccessivamente semplificato.
La tabella seguente mostra i principali casi di applicazione delle opzioni reali ad analisi di portfolio evidenziando le differenze e i miglioramenti garantiti dall'applicazione del nuovo frame work sviluppato in questo lavoro che integra il metodo SOET e l'MVP. E' anche effettuato un confronto con il lavoro di (Lotti, 2012) per sottolineare gli sviluppi fatti da esso.

	Questo Lavoro	**(Jain et al., 2013)**	**(Liu, 2012a); (Liu, 2012b)**	**(Fuss et al., 2012)**	**(Lotti, 2012)**
MODEL					
RO Evaluation Method	Metodo SOET	Metodo SGBM	PDE	Metodo Programmazione Dinamica	Metodo SOET
Options considered	Compound options; Opzione to invest; Opzione to Defer; Opzione to choose;Opzione to abandon	Opzione to invest; opzione to abandon	Rispettivamente opzione to invest e to abandon	Opzione to invest	Opzione to invest; opzione to abandon; opzione to switch
TTM Effect	Modellato	Non considerato	Non considerato	Non considerato	Non considerato
Pre – Operating Phases	Modellata come succession di tre compound options sequenziali	Solo la fase di costruzione è considerata	Solo la fase di costruzione è considerata	Solo la fase di costruzione è considerata	Solo la fase di costruzione è considerata
Actual Portfolio	Influenza i risultati	Risultati non influenzati	Influenza i risultati	Risultati non influenzati	Risultati non influenzati

Method used to perform the portfolio analysis	MVP Theory	MVP Theory	Stochastic Dominance	CVar Method	Non effettuata
OUTPUT Indicators	E(NPV); σ(NPV); Soglie d'esercizio; Frontiera Efficiente 2D per ogni tecnologia; Frontiera Efficiente 3D per ogni Portfolio	Frontiera Efficiente 2D per ogni portfolio in cui ogni tecnologia è un singolo punto statico su di essa; Valore dell'opzione	Valore dell'opzione. La frontiera efficiente non è costruita: PDE non ricava il livello di rischio connesso a investimento	Costo atteso; Rischio; ogni portfolio è un punto singolo e statico nel piano E(NPV) – σ(NPV)	E(NPV); σ(NPV); Soglie d'esercizio singolo investimento

Tabella 6. Esempi di Applicazione Opzioni Reali ad Analisi Portfolio

L'approccio classico presente in letteratura e nei lavori citati in tabella prevede di ricavare la distribuzione di NPV di ogni tecnologia nel portfolio tramite un approccio backward che applica la simulazione Monte Carlo con lo scopo cosi di ricavare la politica ottima di investimento per ognuna delle possibili tecnologie aggiuntive rispetto al portfolio attuale di una utility. Dopo questo passo si ricavano E(NPV) e σ(NPV) del portfolio intero caratterizzato da questo investimento addizionale e si costruisce la frontiera efficiente che, come evidenziato nella figura sottostante confronta tutti i portfoli generati da ogni possibilità di investimento addizionale e tra essi identifica come possibili soluzioni quelli che garantiscono il massimo ritorno atteso in corrispondenza di un certo livello di rischio. Punti significativi di tale frontiera si hanno in corrispondenza delle composizioni di portfolio che:

i. Massimizzano il ritorno atteso(portfolio B)
j. Minimizzano il rischio(portfolio A)
k. Massimizzano lo Sharpe Ratio (portfolio SR)

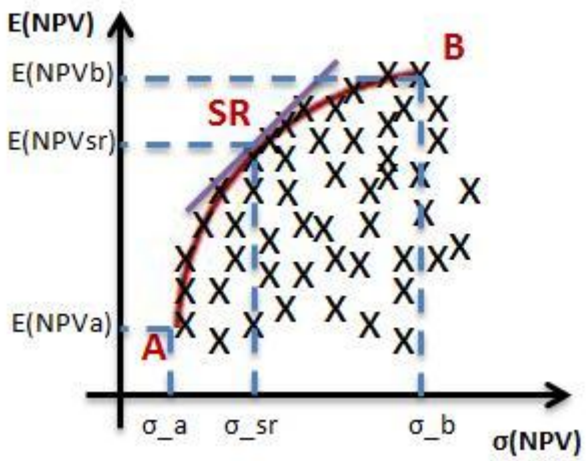

Figura 5. Frontiera Efficiente Standard

Si intuisce come questi approcci, oltre che limitati a casi semplificati, non sfruttino tutti i vantaggi garantiti da un metodo di valutazione che applica le opzioni reali invece che il classico metodo del Discounted Cash Flow. Ogni possibile portfolio resta infatti un singolo e statico punto nel piano E(NPV) – σ(NPV), rappresentato tramite croci nella figura soprastante, che varierebbe solo al variare dello scenario ipotizzato prima di effettuare l'analisi. Come conseguenza dunque, nessuno di questi metodi risolve la principale limitazione dell'MVP citata in precedenza.

Applicando il metodo SOET con l'MVP Theory questo lavoro ambisce invece a risolvere questo problema costruendo un frame work dinamico che fornisca alla utility la migliore decisione di investimento in funzione dell'istantanea variazione del contesto(misurata come istantanea variazione delle variabili di stato). L'idea è, quando possibile, considerare un set di diverse soglie d'esercizio e calcolarne i diversi effetti sulla distribuzione dell'intero portfolio in output.
Ogni portfolio nel piano E(NPV) – σ(NPV) non sarà più un singolo punto statico su di esso funzione unicamente della composizione del portfolio stesso ma diventerà anche funzione del valore delle soglie d'esercizio che, facendo scattare le opzioni in condizioni differenti, modificano il valore atteso e il livello di rischio dell'intero portfolio. Sarà quindi possibile avere in output una frontiera efficiente anche per un singolo portfolio di forma analoga a quella mostrata in Figura 5 per ricavare così le condizioni che lo rendono efficiente e dunque in cui è ragionevole far scattare l'investimento aggiuntivo. Avendo però ogni portfolio una propria frontiera efficiente funzione delle diverse soglie d'esercizio è possibile confrontarne gli andamenti costruendo una Frontiera Efficiente Ottimizzata che garantisca all'utilizzatore del modello di capire quale sia l'investimento addizionale e in quale condizione vada effettuato affinché una qualsiasi funzione obiettivo venga massimizzata.

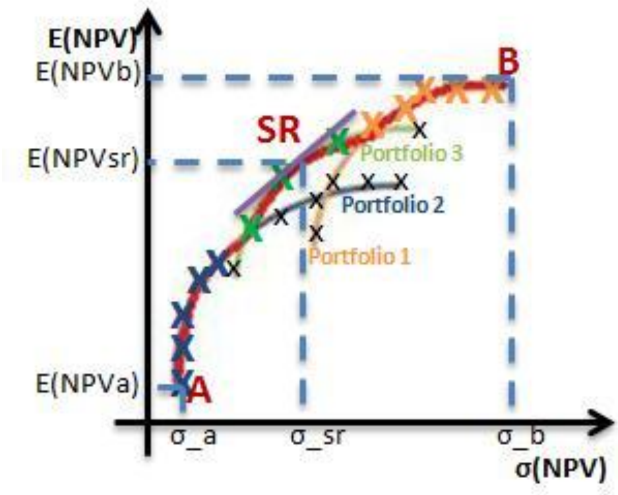

Figura 6. Esempio di Frontiera Efficiente Ottimizzata

La figura soprastante confronta tre diversi portfoli e i punti rappresentati tramite croci rappresentano le performance efficienti ottenute dai singoli portfoli corrispondentemente a diversi valori della soglia d'esercizio.
Solo i portfoli evidenziati con croci di grande dimensione rappresentano però soluzioni effettivamente efficienti poiché appartenenti a una frontiera efficiente ottimizzata ottenuta dalla sovrapposizione delle frontiere efficienti dei tre portfoli presi singolarmente.
Differentemente dal caso precedente dunque il modello fornisce in output non sono la composizione del portfolio che massimizza una qualsiasi funzione obiettivo ma anche la condizione di investimento degli investimenti addizionali che ha avuto rispetto alla sua composizione attuale.

3. Implementazione del Modello

Scopo di questo lavoro come detto è l'estensione del metodo SOET.
Questo capitolo descrive dunque l'idea di evoluzione del modello e della letteratura in ognuna delle tre strade descritte:

1. La modellazione del TTM Effect
2. L'implementazione delle Compound Options
3. L'integrazione tra metodo SOET ed MVP Theory per considerare il portfolio attuale della utility

3.1 La modellazione del TTM Effect

Considerare il Time to Market Effect in ambito energetico vuol dire prendere in considerazione che il tempo trascorso dal momento in cui la decisione di investimento è presa a quando l'impianto inizia a produrre elettricità è superiore al tempo necessario solo alla costruzione dell'impianto.
Questo lavoro, basato su (TIACT, 2005) e (Graber & Rothwell, 2006), descrive tale fase pre – operativa come successione di tre fasi sequenziali la cui durata è mostrata nella tabella sottostante:

Tecnologia	Fase di Studio (site specific)	Fase di Design (site specific)	Fase di Costruzione	TTM
Nuclear PP	1 Anno	2 Anni	6 Anni	9 Anni
SMR PP	1 Anno	2 Anni	5 Anni	8 Anni
Coal PP	1 Anni		4 Anni	5 Anni
CCGT PP	1 Anni		3 Anni	4 Anni

Tabella 7. Paragone tra i diversi TTM dei principali impianti di base load

Tale ipotesi sulla durata di ognuna di queste tre fasi è realistica considerando lo scenario statunitense o lo scenario europeo. Infatti negli USA il processo di ottenimento di licensing nel caso di investimento in impianto nucleare ad esempio richiede una durata di circa tre anni (WNA, 2012), mentre in altri scenari come quello cinese le tempistiche sono inferiori.
La durata della fase pre – operativa è dunque molto significativa nel caso di investimento in un impianto nucleare data la durata elevata di ognuna delle sottofasi di cui è costituita. Analizzando la figura sottostante di (IAEA, 2012) si deduce che tale modellazione sia una semplificazione realistica di quanto accade in realtà poiché:

- La prima fase pre – operativa (chiamata Fase di Studio in questo lavoro) corrisponde alla fase di "Feasibility Study" di (IAEA, 2012)
- La seconda fase pre – operativa (chiamata Fase di Design in questo lavoro) corrisponde alla fase denominata "The detailed site survey; Environmental Impact Assess" in (IAEA, 2012)
- La terza fase pre – operativa(chiamata Fase di Costruzione in questo lavoro) corrisponde all'ultima riga della figura di sotto e cioè alla fase denominata "Site Preparation; Excavation; Construction" in (IAEA, 2012).

La fase di Licensing risulta dunque essere trasversale alle tre fasi qui descritte. Maggior dettaglio alle precise operazioni effettuate in ognuna delle tre fasi è riportata nella Table 9 del lavoro di tesi complessivo.

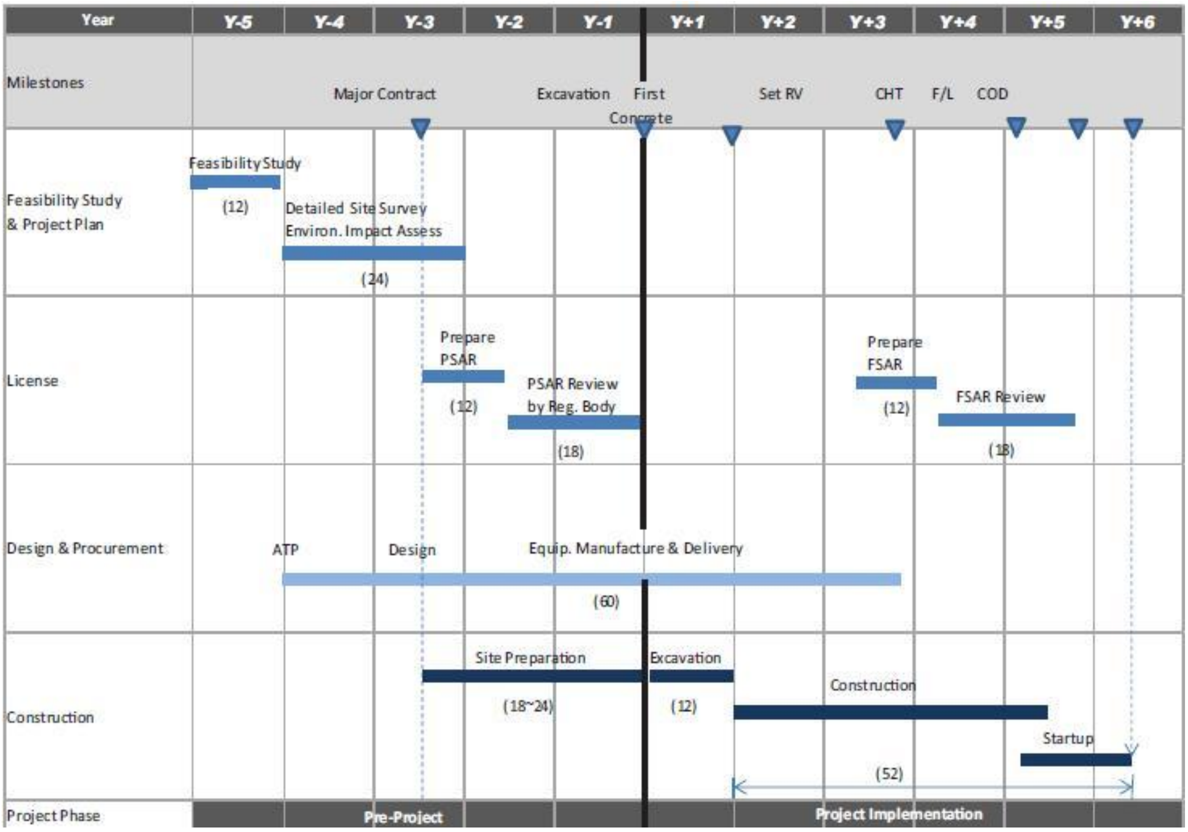

Figura 7. Tipica durata della Fase Pre - Operativa di un impianto nucleare (IAEA, 2012)

Dalla **Tabella 7** si vede come il tempo necessario a diventare operativi nel caso di impianti Coal o CCGT sia relativamente basso, mentre nel caso di impianti nucleari sono necessari diversi anni perché un impianto diventi operativo. Tali tempi si differenziano poi nel caso in cui questo sia il primo impianto a essere costruito o meno dalla utility. Principali esempi di analisi di tale durata pre – operativa sono (Pedraza, 2012) e (Thurner et al., 2014) che ne fanno un'analisi dal punto di vista statistico applicandola a numerosi impianti nucleari "under – construction":

Nome Impianto Nucleare	Dove è localizzato?	Durata Fase Pre - Operativa
Angra 2	Brasile	295 mesi (≈25 anni)
Khmelnitski 2	Ucraina	235 mesi (≈20 anni)
Olkiluoto 3	Finlandia	Dopo 168 mesi (14 anni) non è concluso
CEFR reactor	Cina	135 mesi (più di 11 anni)
TIANWAN-2	Cina	80 mesi (≈7 anni)
Gravelines-4	Francia	63 mesi (5,25 anni)
St.Laurent-B-1	Francia	57 mesi (4,75 anni)
St.Laurent-B-2	Francia	60 mesi (5 anni)
Super-Phoenix	Francia	110 mesi (≈9 anni)
Grafenrheinfeld	Germania	84 mesi (7 anni)
Muelhein-Kaerlich	Germania	135 mesi (più di 11 anni)
This Work	**USA o Europa**	**108 mesi (9 anni)**

Tabella 8. Durata fase pre - operativa impianti nucleari under construction(dati da (Thurner et al., 2014))

Data la grande variabilità evidenziata in **Tabella 7** non si può dunque evitare di modellare la reale fase pre – operativa di un impianto nucleare più dettagliatamente di quanto fatto nei lavori presenti in letteratura. Infatti, considerare solo la fase di costruzione ne andrebbe a sottostimare tempi e costi e potrebbe dunque condurre a decisioni di investimento errate.

3.2 Implementazione delle Compound Options

Da un lato dunque è chiaro come l'implementazione del TTM Effect nel modello nel caso di investimenti in impianti nucleari specialmente abbia da un lato effetto negativo poiché in dieci anni le condizioni finanziarie, economiche e sociali possono variare significativamente rendendo sconveniente un investimento valutato oggi come profittevole.
D'altro lato però (TIACT, 2005), (Graber & Rothwell, 2006) oltre che (IAEA, 2012), nella loro descrizione della fase pre – operativa di un impianto nucleare hanno implicitamente dimostrato che questa è caratterizzata da grande flessibilità.
Come riportato in (Graber & Rothwell, 2006):*"new nuclear power plants are expected to take up to 10 years or more from inception to start-up. There are three sequential phases that characterize the project and each of them is relatively independent to the other. They also must follow in order".*
Questo è come nel campo delle opzioni reali è definita una Compound Option, cioè un progetto d'investimento caratterizzato dalla presenza di più fasi che devono necessariamente seguirsi in ordine, all'inizio di ognuna delle quali l'investitore può scegliere se continuare, posticipare o abbandonare il progetto a seconda dell'evoluzione subita dai principali parametri stocastici caratterizzanti il problema.

Si intende dunque come la fase pre – operativa di una centrale elettrica (data la lunghezza delle fasi specialmente di un impianto nucleare) possa essere modellata come successione di tre compound options in cui terminare una singola fase fornisce all'investitore il diritto ma non l'obbligo di far scattare la successiva.

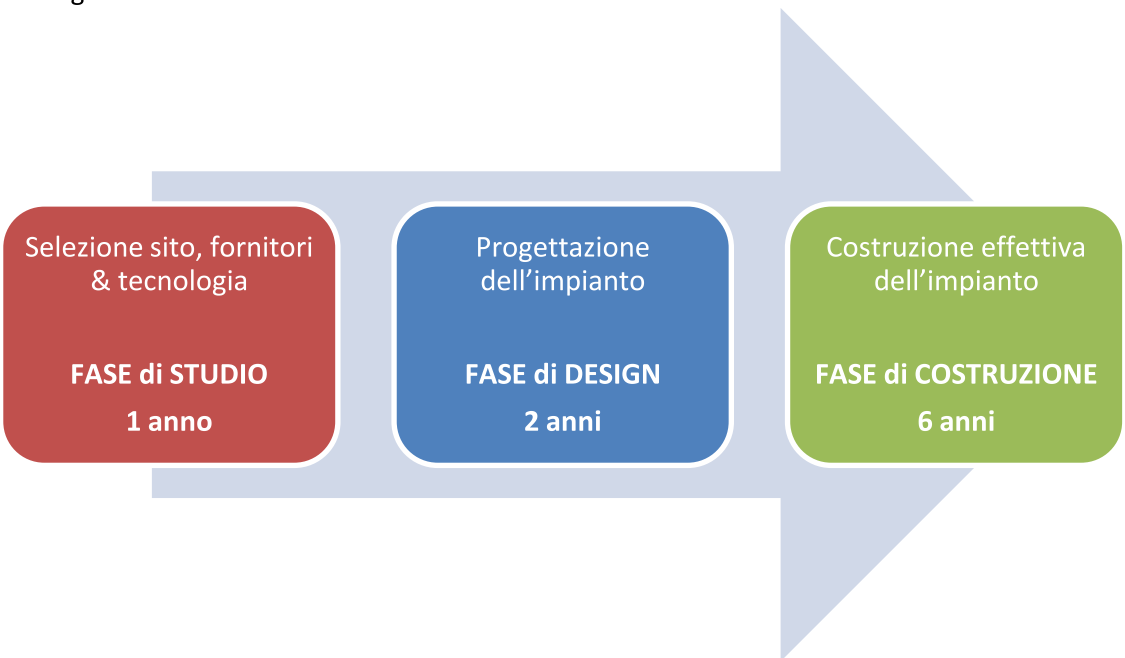

Figura 8. Descrizione fase pre - operativa centrale nucleare come successione di compound options

A seguito della complessità di un modello di applicazione che usi le compound options in letteratura gli esempi recenti che le utilizzano per valutazione di investimenti sono quasi totalmente assenti e quelli che ci sono si limitano a casi semplici che sfruttano come modello di valutazione l'albero binomiale perché di semplice comprensione la condizione che fa scattare l'investimento in una delle fasi considerate (Cheng et al., 2011) e(Siddiqui et al., 2006)[4]. A conferma di ciò (Ghosh & Troutt, 2012), avendo visto che i top managers non adottano metodi di applicazione delle compound options a causa della loro complessità, hanno sviluppato uno schema base da seguire per aiutarli ad una loro implementazione ma per farlo si sono limitati a descrivere casi semplici, poiché la complessità dei metodi esistenti (e.g. LSMC o SGBM) non permetteva di creare un frame work facilmente applicabile per la soluzione di problemi complessi.

Questo lavoro mostra invece come sia possibile applicare il metodo SOET, adatto dunque alla risoluzione di problemi complessi, per la valutazione di compound options in cui sia di semplice intuizione per il management quando e perché far scattare l'investimento in ognuna delle tre fasi sequenziali. Questo obiettivo è raggiunto grazie all'introduzione di una diversa soglia di esercizio per ognuna delle tre fasi in analisi.

Le soglie fisiche considerate sono:

i. Per la Fase di Studio, il Prezzo dell'Elettricità "P_{soglia}"
ii. Per la Fase di Design, il costo atteso di completamento della fase di design "$ECTD_{soglia}$"
iii. Per la Fase di Costruzione, il costo atteso di completamento della fase di costruzione "$ECTC_{soglia}$"

L'ipotesi alla base dell'implementazione delle compound options nel nostro modello è che i costi di completamento tra le fasi siano tra essi correlati.

Parameter	Study Phase	Design Phase	Construction Phase
Cost	1%*K	5%*K	K
Time	1 Year	2 Years	6 Years

Tabella 9. Correlazione tra fasi pre - operazionali di un impianto nucleare (adattato da (Graber & Rothwell, 2006) e (TIACT,2005))

Terminata la fase di studio è possibile prevedere il costo atteso di completamento di quelle di design e di costruzione e dunque se in un determinato momento decisionale:

i. $P_t > P_{soglia}$, allora la Fase di Studio scatta
ii. $ECTD < ECTD_{soglia}$, allora la Fase di Design scatta
iii. $ECTC < ECTC_{soglia}$, allora la Fase di Costruzione scatta

Il prezzo dell'elettricità, essendo la variabile più influente sul risultato dell'investimento(F. a. Roques et al., 2008), è presa in considerazione come variabile di stato che va a costituire direttamente la soglia d'esercizio per la fase di studio. Le soglie fisiche di costo atteso di completamento delle fasi di costruzione e di design invece sono state costruite in maniera più complessa tramite soglie lineari costruite seguendo le seguenti relazioni:

$$ECTD_{soglia} = m_{design} + (P_t - a_{design})$$

$$ECTC_{soglia} = m_{construction} + (P_t - a_{construction})$$

Dove:

- $P_t = Prezzo\ dell'Elettricità\ al\ periodo\ t$

[4] I primi esempi di applicazione delle compound options in letteratura sono (Geske, 1977) e (Geske, 1979) che ne hanno mostrato l'idea e i primi semplici casi di implementazione.

- $m_{[\,]} = Fattore\ Moltiplicativo\ della\ soglia\ lineare\ d'esercizio$
- $a_{[\,]} = Coefficiente\ differenziale\ della\ soglia\ d'esercizio\ lineare$

L'idea che sta alla base di questa scelta è creare un legame tra le soglie fisiche del costo di completamento della fase di design e di costruzione con il prezzo istantaneo dell'elettricità. In tale maniera, prendendo in esempio il caso dell' $ECTC_{soglia}$ si avrà:

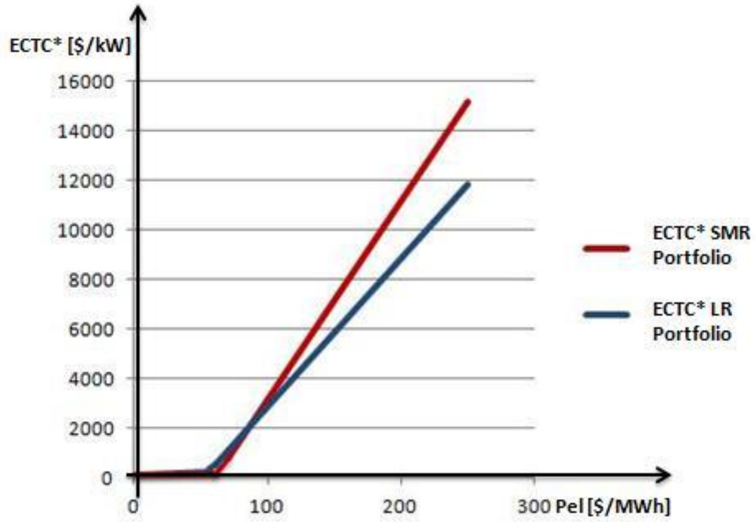

Figura 9. Soglie di Esercizio Lineari

L'idea è stata di creare una soglia che accetti dunque persino un valore elevato di costo di completamento per far scattare l'investimento se anche il prezzo dell'elettricità ha in parallelo un valore alto, poiché tale livello di prezzo garantirà in futuro flussi di cassa positivi in grado di sostenere l'investimento anche costoso.
Se invece il prezzo dell'elettricità è basso la fase successiva potrà scattare solo se il suo costo avrà un valore basso poiché i futuri flussi di cassa entranti altrimenti non sarebbero sufficienti a ripagare l'investimento.

Obiettivo del modello è dunque trovare il valore ottimale per far scattare l'investimento di ognuna delle tre soglie fisiche descritte. Il problema è che si hanno sì tre soglie fisiche ma cinque parametri da ottimizzare per trovare la migliore condizione possibile d'investimento. Applicare i metodi SOET come fatto precedentemente può richiede un tempo troppo elevato per convergere a una soluzione dato l'elevato numero di possibili combinazioni tra questi parametri.

L'idea è effettuare un'analisi del livello di influenza di ognuno dei cinque parametri qui descritti (P_{soglia} ; m_{des}; a_{des}; m_{cos}; a_{cos}) sul risultato dell'intero investimento di modo da verificare se alcuni di essi lo hanno superiore agli altri e costruire così un algoritmo di applicazione del metodo SOET che, conoscendo la natura del problema, non vari in maniera totalmente casuale i valori di tutti i cinque parametri.

L'algoritmo utilizzato per ricavare il livello di influenza dei cinque parametri è riportato qui di seguito:

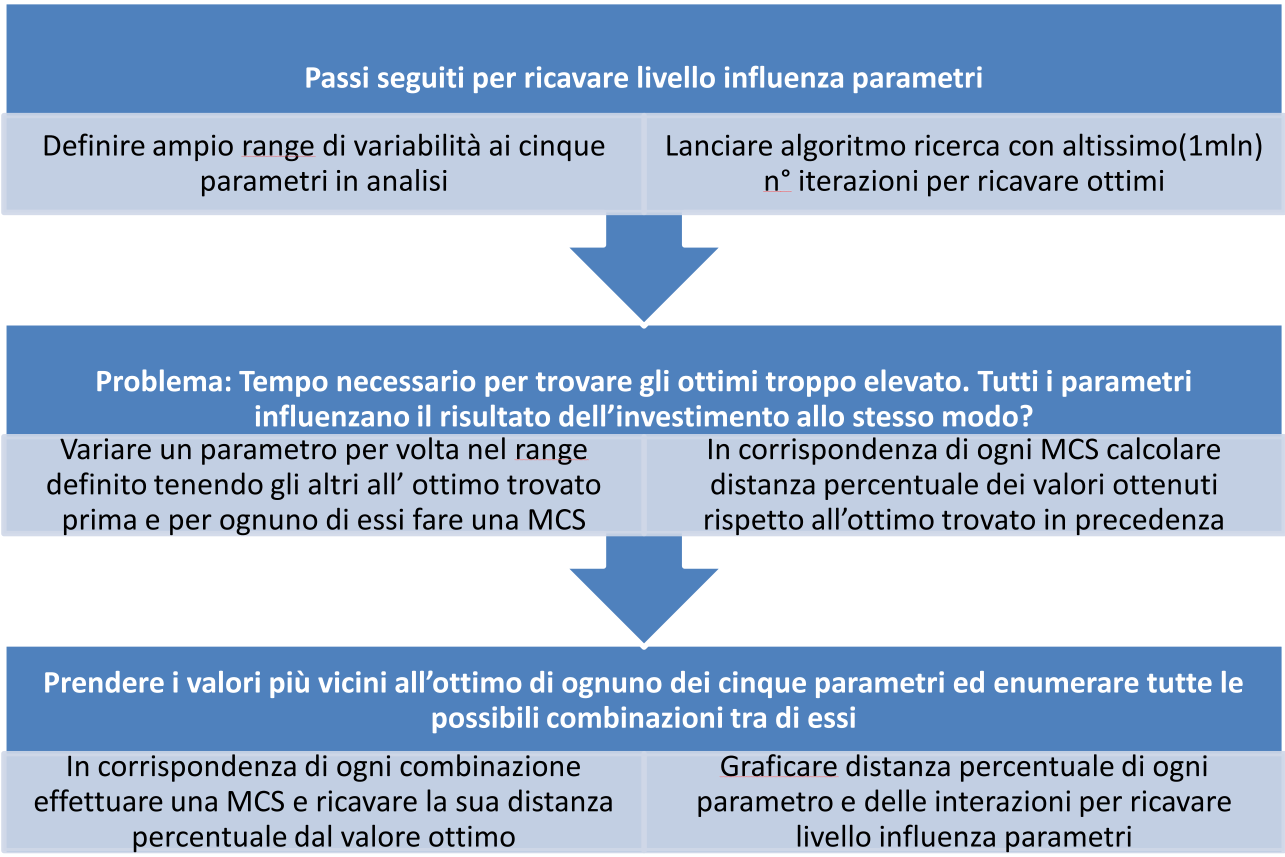

Figura 10. Algoritmo usato per ricavare livello influenza parametri

I risultati ottenuti sono sintetizzati nella seguente tabella:

Parametro	Livello d'influenza
P_{soglia}	Alto
a_{design}	Basso
m_{design}	Basso
$a_{construction}$	Basso
$m_{construction}$	Alto
Interaction	Basso

Tabella 10. Livello Influenza Parametri

I risultati trovati sono confermati se si pensa alla natura del problema in esame. Essendo la fase di costruzione la più costosa e dunque influente sulla bontà dell'investimento è ragionevole che il parametro principale che la caratterizza, cioè m_{cos} lo sia a sua volta assieme al prezzo dell'elettricità.

Ricavato il livello di influenza dei diversi parametri l'algoritmo utilizzato per la valorizzazione di investimenti in impianti nucleari la cui fase pre – operativa è modellata tramite compound options è basato su un evoluzione dell'algoritmo di ricerca:

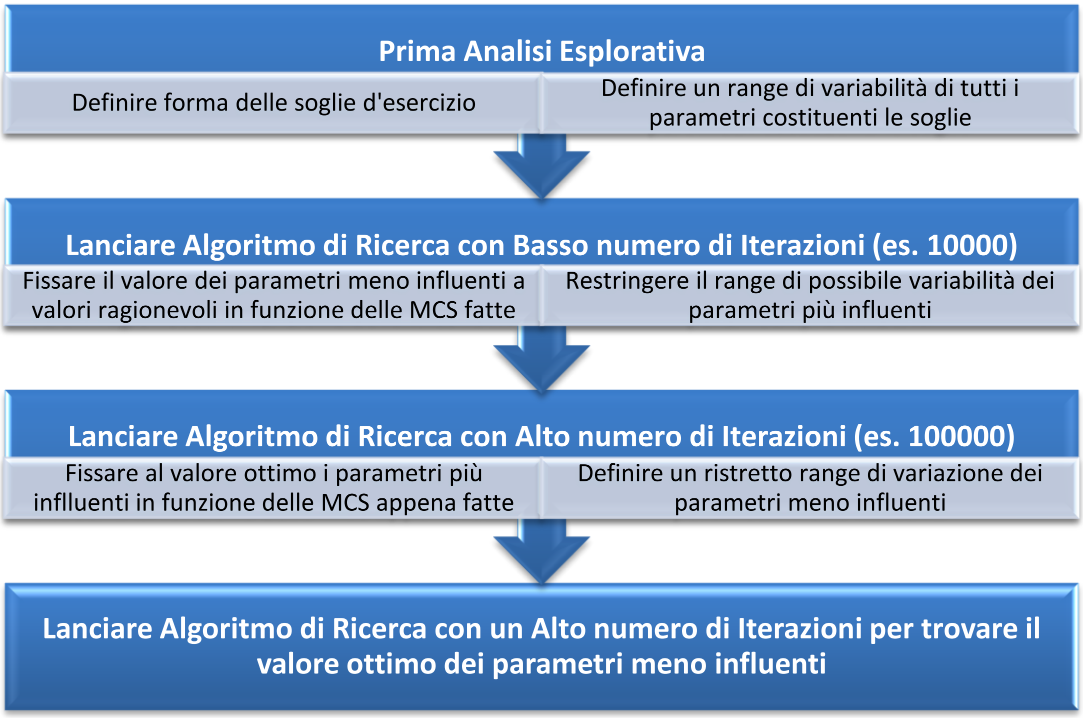

Figura 11. Algoritmo di Ricerca applicato al modello con Compound Options

Nel capitolo 3 della tesi è possibile trovare un'evoluzione anche degli altri due metodi SOET (la discreta enumerazione di tutti i possibili stati e di tutte le possibili soglie) che è stata sviluppata e applicata a questo caso per validare i risultati ottenuti dall'applicazione dell'algoritmo di ricerca.

3.3 Integrazione metodo SOET con MVP Theory

In questo caso, differentemente dal precedente, è nel dettaglio spiegato come integrare con l'MVP Theory uno solo dei tre metodi SOET esistenti, quello della discreta enumerazione dei possibili stati. La modalità con cui applicare le altre due metodologie è presentata nel corpo della tesi.

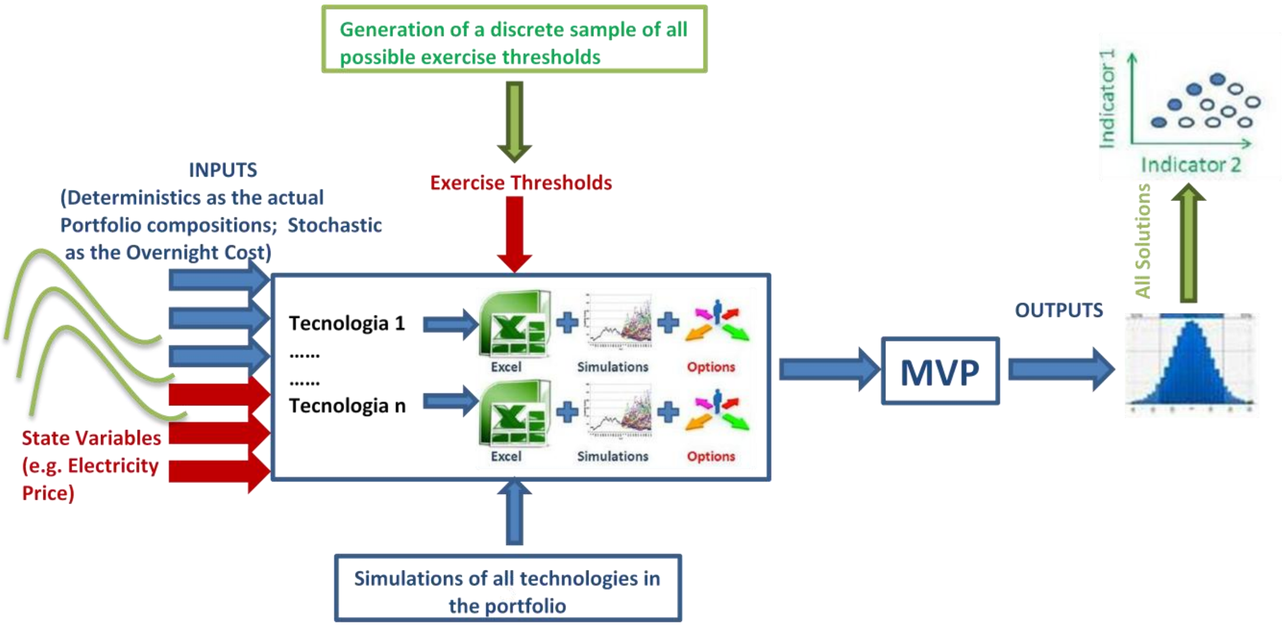

Figura 12. La discreta enumerazione di tutte le possibile soglie integrata con l'MVP Theory

L'idea in questo caso è calcolare innanzitutto grazie ad una MCS la distribuzione di NPV di ogni impianto presente nel portfolio attuale considerato. Successivamente va enumerate un campione di tutte le possibili soglie d'esercizio. Nel caso di una variabile di stato la scelta ricade sul prezzo dell'elettricità con valore iniziale $P_0 = 90\ \$/MWh$, e come soglia di esercizio che faccia scattare l'investimento nell'impianto addizionale il valore P*. Il metodo prevede di provare le soglie P*=0 $/MWh, P*=1 $/MWh fino a P*=600$/MWh e di effettuare in corrispondenza di ognuna di queste una MCS da cui ricavare differenti distribuzioni di NPV per quest'ultimo. Ricavata in corrispondenza di ogni MCS la distribuzione di NPV per l'investimento addizionale è possibile applicare l'MVP Theory per ricavare il valore atteso e il livello di rischio dell'intero nuovo portfolio da esso generato.

Prima di procedere con l'enumerazione sintetica di tutti i passi seguiti nell'implementazione di questo modello è necessario fare una parentesi circa una interessante proprietà che l'opzione "to defer" ha differentemente dall'opzione "to invest".

Nel caso di implementazione della prima si è fatta l'ipotesi che la utility sia obbligata a colmare una richiesta addizionale di 1,5 GW rispetto al suo portfolio attuale entro 20 anni. Nel caso di implementazione invece dell'opzione d'investimento ovviamente questa ipotesi non è necessaria. E' però intuitivo che, se la pura opzione d'investimento è implementata, l'E(NPV) del portfolio attuale sarà superiore di quello con l'impianto addizionale. La ragione è dovuta al fatto che l'MVP calcola l'E(NPV) dell'intero portfolio come media pesata tra tutti gli impianti che lo costituiscono. Se si pensa che per quanto riguarda gli impianti già attualmente attivi la utility però ha già sostenuto i costi di costruzione è semplice intuire che il loro E(NPV) sarà superiore rispetto a quello dell'impianto addizionale. Andando dunque a cercare il valore soglia che massimizzi l'intero portfolio con la nuova tecnologia il modello suggerirà di non investire mai perché il portfolio attuale ha valore superiore, anche nei casi in cui l'investimento addizionale generasse E(NPV) > 0.

In sintesi se è implementata l'opzione di investimento il valore della soglia d'esercizio che massimizza una certa funzione obiettivo(e.g. massimizzazione NPV, minimizzazione rischio, massimizzazione Sharpe Ratio) per l'investimento addizionale preso singolarmente non è lo stesso che massimizza l'intero portfolio in cui si inserisce. Non è dunque possibile applicare l'algoritmo sul portfolio intero ma va implementato solo sulla singola tecnologia e, ricavatane la soglia che ne massimizza il valore, va applicata l'MVP Theory per trovare E(NPV) e livello di rischio dell'intero portfolio in cui è inserita. Il discriminante su cui scegliere se effettuare o meno l'investimento non può cioè essere la performance dell'intero portfolio ma deve essere la singola tecnologia addizionale.

La ragione per cui questo accade è che nell'opzione classica d'investimento a diversi valori della soglia del prezzo dell'elettricità corrisponde una diversa percentuale di iterazioni nei quali l'investimento addizionale è fatto. L'opzione "to defer" invece garantisce di confrontare sempre portfoli costituiti dalla stessa percentuale di ogni tecnologia e dunque possiede l'interessante proprietà che il valore della soglia che massimizza l'investimento addizionale è lo stesso che massimizza l'intero portfolio.

Condizione che permette questa proprietà è che il portfolio analizzato non vari la sua composizione nelle diverse iterazioni. Questo lavoro implementerà dunque anche l'opzione "to defer".

Opzione Implementata	Legame tra impianto addizionale e portfolio intero	Come scegliere l'impianto addizionale?
Opzione to Invest	Il valore delle soglie d'esercizio che massimizzano una certa funzione obiettivo **non** è lo stesso tra l'impianto addizionale e l'intero portfolio	Confrontando solo le distribuzioni di NPV dei diversi possibili investimenti addizionali
Opzione to Defer	Il valore delle soglie d'esercizio che massimizzano una certa funzione obiettivo è lo stesso tra l'impianto addizionale e l'intero portfolio	Equivalentemente confrontando le distribuzioni di NPV dei diversi possibili investimenti addizionali o degli interi portfoli in cui si andrebbero a collocare

Tabella 11. Distinzione tra effetti opzione to defer e to invest

In sintesi dunque si riportano gli step di applicazione del modello qui descritto:

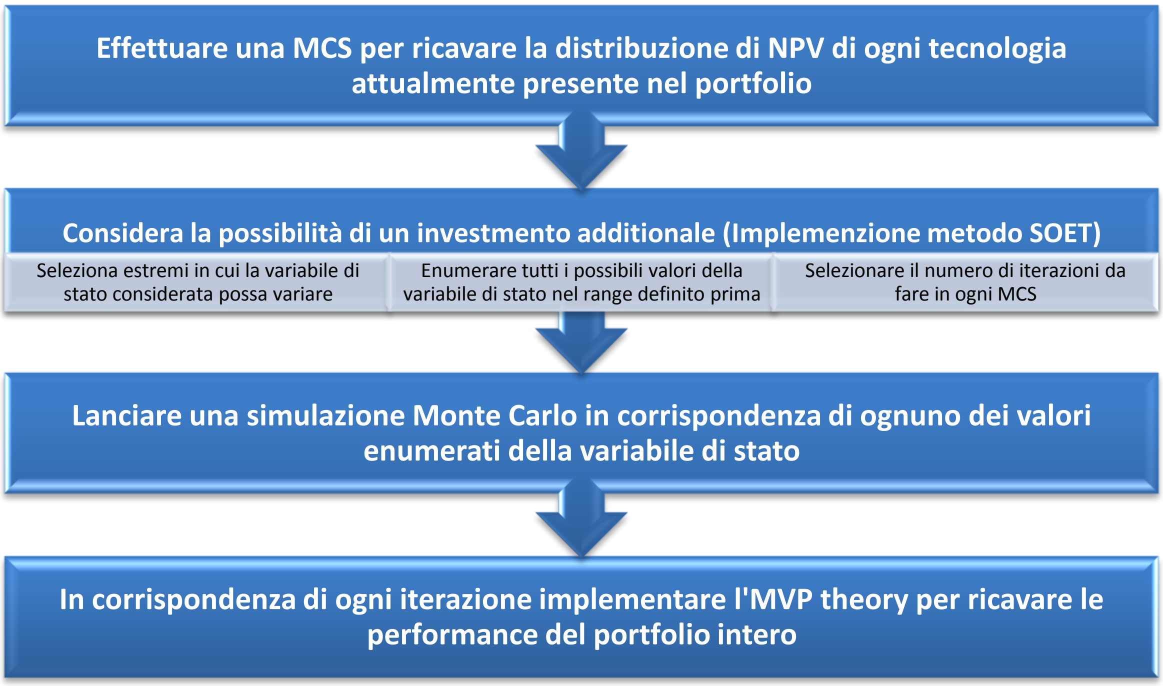

Figura 13. Algoritmo di integrazione discreta enumerazione di tutte le possibili soglie d'esercizio con l'MVP Theory

4. Input

Gli input usati in questo lavoro sono sia deterministici che stocastici. Per gli input deterministici sono state considerate diverse fonti ((EIA, 2012), (IEA NEA, 2010) e (Parsons, 2011)) ed infine è stato scelto di utilizzare quelli forniti da (EIA, 2012) elencati nella tabella sottostante:

Input Deterministici	EIA 2012			
	Nucleare	Coal	CCGT	SMR
Taglia [MW]	1500	750	500	335
Rendimento (%)	85%	85%	85%	95%
Costo Overnight [$/KW]	5335	3220	1003	6362
Costi O&M [$/Mwh]	13,96	13,4	15,03	21,28
Costo Combustibile [$/Mwh]	8,26	22,27	47,4	8,26
Tempo di costruzione [anni]	6	4	3	5
Tempo di studio [anni]	1	/	/	1
Tempo di design [anni]	2	/	/	2
Vita [anni]	60	40	30	60

Tabella 12. Gli input deterministici usati in questo lavoro

Per quanto riguarda l'analisi che tenesse conto del portfolio attuale di una utility questa è stata effettuata in due step, prima implementando il modello a un portfolio fittizio per evidenziarne le proprietà, e successivamente al portfolio attuale di EDF in UK. Le composizione dei due portfoli attuali sono riportate di seguito:

Technology	Capacity Installed [MW]	% in the Overall Actual Portfolio
Nuclear	1500	46,15%
Coal	750	23,08%
CCGT	1000	30,77%

Tabella 13. Composizione Attuale Portfolio Fittizio

Portfolio EDF	
Renewables	116
Nuclear	8741
Coal	3987
Gas	1306
Total Capacity [MW]	**14150**

Tabella 14. Composizione Attuale Portfolio EDF(EDF, 2012)

Come tasso di rendimento è stato usato il 5% come in (Carelli et al., 2010) ad esempio. Questo fattore è difficile da stimare perché riflette il rischio dell'investimento: più alto è il rischio d'investimento, più alto è il tasso di rendimento (Kodukula & Papudescu, 2006) e il suo valore dipende dal tipo di investimento. Si è scelto però un valore costante principalmente poiché questo parametro non riflette il rischio in un analisi che applica le RO

Gli inputs stocastici sono stati descritti più in dettaglio, confrontando i diversi processi stocastici presenti in letteratura ed i possibili valori da utilizzare in questi processi. Per non complicare eccessivamente l'analisi, essendo il focus di questo lavoro il modello più che la precisione nei risultati, sono stati utilizzati processi geometrici browniani senza drift. Come valori iniziali di questi processi sono stati utilizzati per il costo del gas 47,39$/MWh, per il costo del carbone 22,27$/MWh e per l'energia elettrica 90 $/MWh. Per l'implementazione dell'algoritmo è stato usato un add-in di Microsoft Excel 2010: @Risk 5.5.

5. Risultati

Il capitolo dei risultati è costruito con l'obiettivo di mostrare uno di seguito all'altro gli steps di miglioramento modellati in questo lavoro per cui:

- Il paragrafo 5.1 mostra i risultati ottenuti nel caso in cui non sia considerata la presenza di un portfolio attuale di investimenti per evidenziare il TTM Effect e per chiarire l'effetto che l'implementazione delle compound options per modellare la fase pre – operativa delle centrali nucleari hanno sulla decisione d'investimento.
- Il paragrafo 5.2 mostra i risultati ottenuti nel caso in cui sia considerata anche la presenza di un portfolio attuale di investimenti. Dapprima il modello completo sarà applicato a un portfolio fittizio per evidenziarne le potenzialità rispetto ai metodi presenti in letteratura. In seguito poi, il medesimo frame work sarà applicato al portfolio attuale di EDF in UK per identificare la "migliore" decisione d'investimento per colmare una richiesta aggiuntiva di 1,5 GW.

5.1 Risultati TTM EFFECT

Come prima analisi si è applicato il modello precedentemente descritto senza considerare la presenza di un portfolio attuale d'investimenti. L'obiettivo è evidenziare come l'applicazione delle compound options per ricavare la distribuzione di NPV nei casi di centrali nucleari ne migliori ulteriormente le performance e sia dunque il metodo più adatto per una loro efficace valorizzazione.

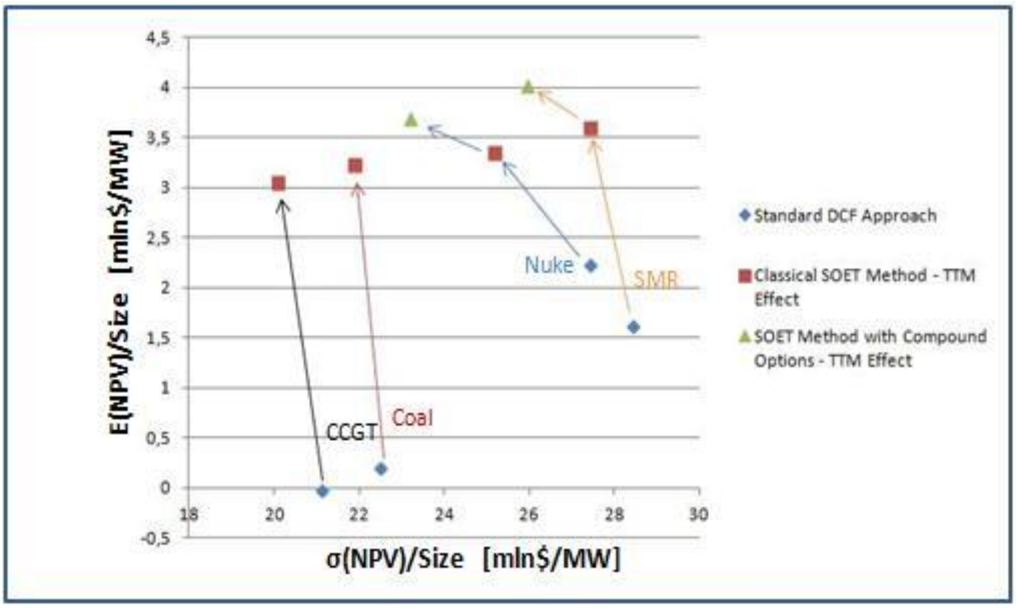

Figura 14. Confronto risultati TTM Effect

Dal grafico di sopra si possono evidenziare i seguenti aspetti:

1. Nel caso di non applicazione delle compound options tutti i possibili impianti appartengono alla frontiera efficiente ma nei casi di investimenti in LR ed SMR i profitti garantiti sono solo leggermente superiori a quelli ottenibili investendo in CCGT o Coal, a scapito però di un livello di rischio decisamente più alto. Hanno cioè Sharpe Ratio molto basso e dunque non sarebbero la scelta d' investimento"migliore"[5].
   Questo è coerente se si considera la differente durata tra la fase pre – operativa di SMR e LR con quella di CCGT e Coal, evidenziata in Tabella 7.
2. Sfruttando la flessibilità intrinseca alla fase pre – operativa di un impianto nucleare tramite le compound options investimenti in queste tecnologie diventano decisamente più interessanti poiché al termine di ogni fase il modello, analizzando l'evoluzione dei parametri stocastici, abbandona o posticipa l'investimento quando lo scenario non è profittevole, migliorandone così l'E(NPV) e riducendone il livello di rischio. Il loro Sharpe Ratio dunque migliora decisamente[6].

Stesso effetto viene ottenuto considerando anche la possibilità di costruire reattori in serie che vadano a colmare un fabbisogno di 1,5 GW da soddisfare poiché la prima centrale prodotta dà, a chi la costruisce, il diritto ma non l'obbligo di costruirne una seconda (ovvero un'opzione to invest). C'è dunque molto valore ad investire nella prima, anche in situazioni non profittevoli, in quanto si ottengono informazioni sui costi di costruzione di un'ipotetica seconda e si potrà quindi in futuro, decidere di investire si confrontano quindi quattro possibilità:

- Un reattore nucleare grande
- Due centrali a carbone
- Tre centrali a gas
- Quattro reattori nucleari piccoli

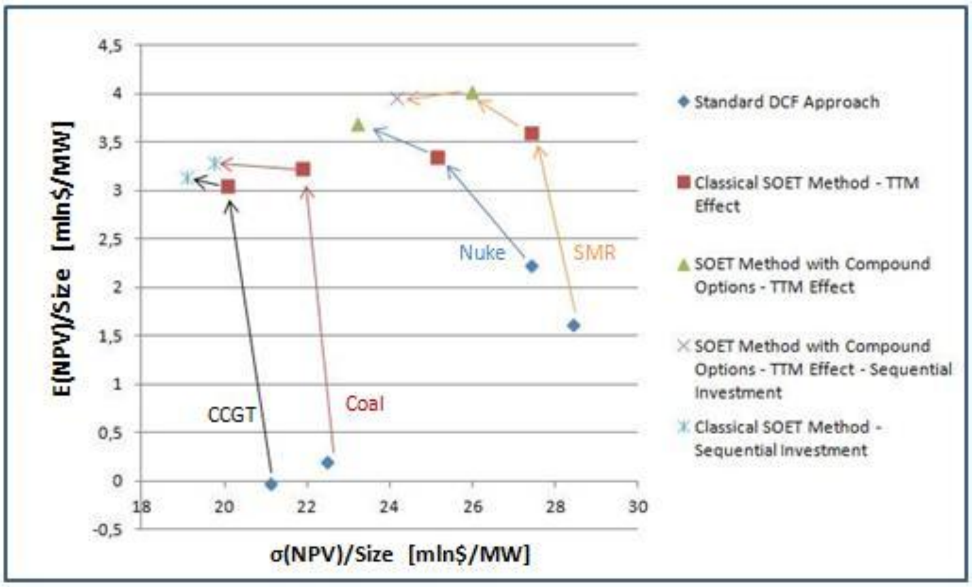

Figura 15. Confronto finale complessivo TTM Effect

[5] L'NPV è misura estensiva e dunque, avendo gli impianti nucleari costo di costruzione molto superiore a coal o CCGT, ne risultano svantaggiati. Tale risultato ha senso nell'ipotesi in cui sia imposto vincolo di mercato di 1,5 GW. Interessante sviluppo futuro sarebbe effettuare l'analisi usando come indicatori anche IRR e Profitability Index.

[6] Le compound options non sono state implementate agli investimenti in coal e CCGT perché il tempo trascorso dal momento in cui la decisione d'investimento è presa a quando inizia la costruzione nei loro casi è di circa solo un anno per cui tale analisi aggiungerebbe poco valore all'investimento. Sarebbero comunque facilmente implementabili.

In questa configurazione si ottengono ancora risultati sulla frontiera efficiente ma i valori dello Sharpe Ratio garantiti da un investimento in un impianto nucleare sono decisamente più bassi di quelli garantiti dalle altre tecnologie.

A ulteriore validazione della bontà di questo modello vi è la grande coerenza tra la percentuale di fasi di design e costruzione fatte sul totale di quelle di studio con il report della World Nuclear Association (WNA, 2014) che analizza i "Reactor under construction".

Tipo di risultati	Percentuale fasi di design fatte	Percentuale fasi costruzione fatte
(WNA, 2014)	55,8%	22,5%
Questo Lavoro	59,7%	22,9%

Tabella 15. Paragone modello sviluppato e Report World Nuclear Association

5.2 Risultati Portfolio Effect

Considerando dapprima il modello a una variabile di stato applicato al portfolio fittizio di investimenti definito nella precedente **Tabella 13. Composizione Attuale Portfolio Fittizio** con la possibilità di investimento addizionale solo di SMR e LR per colmare una richiesta di 1,5 GW è possibile chiarire efficacemente i vantaggi garantiti dal modello sviluppato in questo lavoro rispetto a quanto esiste in letteratura.

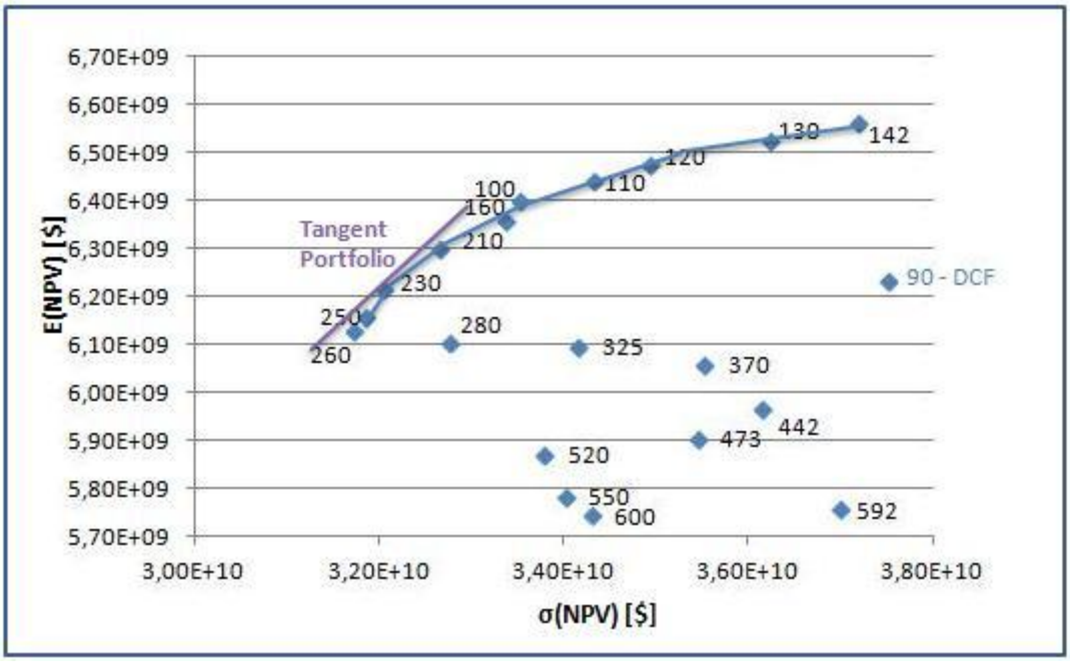

Figura 16. Frontiera Efficiente del Portfolio con LR addizionale

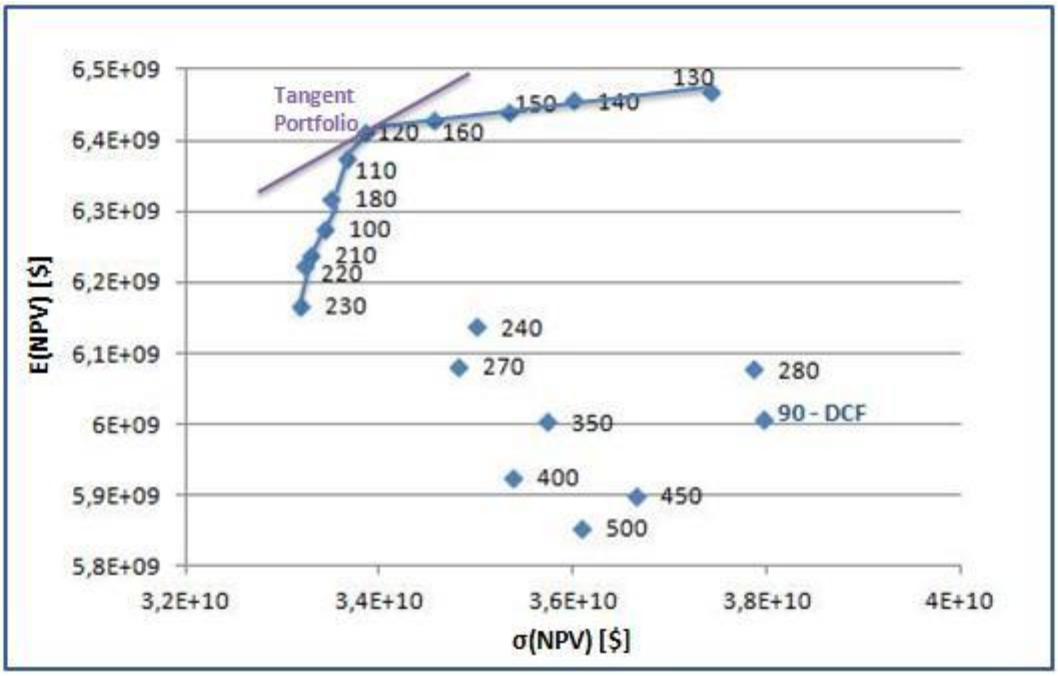

Figura 17. Frontiera Efficiente del Portfolio con SMRs addizionali

Dalle due figure sopra sono identificabili le seguenti proprietà:

i. Questo metodo permette la costruzione di una frontiera efficiente per ogni singolo portfolio in funzione del valore delle soglie d'esercizio che fanno scattare l'investimento addizionale, quando invece i metodi presenti in letteratura ne rappresenterebbero le performance nel piano E(NPV) – σ(NPV) come un singolo e statico punto su di esso (il punto "90 – DCF" di entrambe le frontiere)

ii. La soluzione trovata applicando il metodo standard del DCF integrato con l'MVP Theory porta in questo caso a una soluzione completamente inefficiente poiché il punto 90 – DCF garantisce profitti inferiori con rischi superiori a quelli che si avrebbero attendendo scenari differenti.

iii. I punti sulla frontiera efficiente hanno le seguenti caratteristiche:
   a. L'opzione deve essere esercitata quando $P_{soglia} > P_0$
   b. Esiste un valore assunto dalla soglia detto P_{lim} oltre cui tutti i punti non appartengono più alla frontiera efficiente.

iv. Tutti i punti appartenenti alla frontiera efficiente presentano dunque le seguenti caratteristiche:
   a. La condizione per ottenerli è esercitare l'opzione solo quando $P_0 < P_{soglia} \leq P_{lim}$
   b. Questi punti sono equivalenti tra essi perché massimizzano il valore atteso garantito da un singolo portfolio in corrispondenza di un certo livello di rischio
   c. Possono essere paragonati solo in termini di Sharpe Ratio. Entro il range di valori della soglia d'esercizio che portano alla formazione della frontiera efficiente esiste un valore P_{SR} corrispondentemente al portfolio tangente la frontiera efficiente che ne massimizza lo Sharpe Ratio

Aver ottenuto in output una frontiera efficiente per ogni singolo portfolio analizzato permette dunque di effettuare la scelta tra di essi andando a confrontare non più singoli punti statici come accadeva nel metodo standard per creare così una frontiera efficiente dove ogni singolo punto era un diverso tipo di portfolio.

Questo modello permette infatti la costruzione di una Frontiera Efficiente Ottimizzata: innovativa tipologia di output ottenuta dall'intersezione delle frontiere efficienti di tutti i possibili portfoli, che garantisce di poter "vedere" la soluzione in termini di PP da costruire e di condizione delle soglie d'esercizio che massimizzano una qualsiasi tipologia di funzione obiettivo.

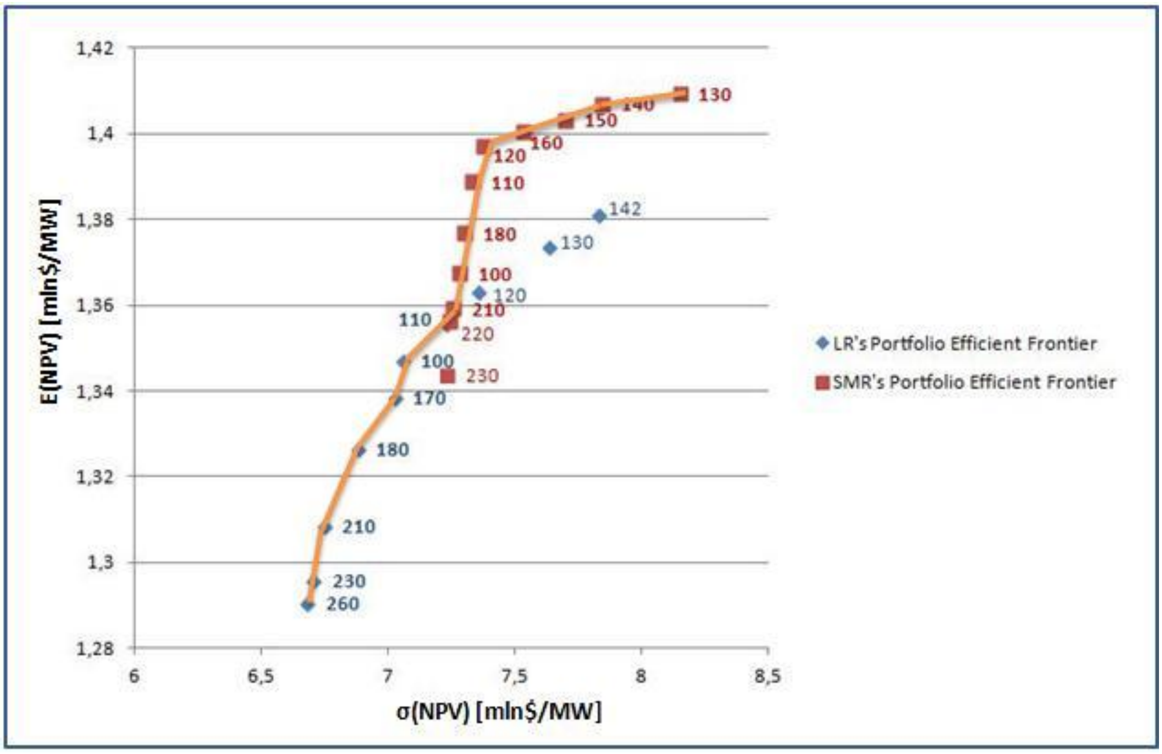

Figura 18. La Frontiera Efficiente Ottimizzata

Si intuisce dunque che non tutte le condizioni efficienti per un singolo portfolio sono condizioni efficienti nel caso in cui tutte le possibilità d'investimento addizionale vengano considerate.

Si vede anche dalla figura soprastante come l'impianto da costruire e le condizioni per farne scattare l'investimento cambino a seconda del diverso obiettivo di una utility:

Funzione Obiettivo	Nucleare	SMR	Impianto Scelto	Condizione d'investimento
Massimizzazione valor medio NPV	E(NPV) = 1,38 mln$/MW	E(NPV) = 1,41 mln$/MW	SMR	$P_{soglia} = 130\ \$/MWh$
Minimizzazione deviazione std NPV	σ(NPV) =6,68 mln$/MW	σ(NPV) = 7,23 mln$/MW	Nucleare	$P_{soglia} = 260\ \$/MWh$
Massimizzazione dello Sharpe Ratio	SR = 0,1933	SR = 0,1895	Nucleare	$P_{soglia} = 230\ \$/MWh$

Tabella 16. Come la scelta del PP addizionale da costruire varia al variare della funzione obiettivo

Dall'analisi della frontiera ottimizzata è inoltre possibile capire quale sia la scelta d'investimento addizionale e le condizioni in cui effettuarlo per massimizzare qualsiasi funzione obiettivo espressa in termini di massimizzazione di profitto per un certo livello di rischio, o minimizzazione del rischio per un livello di profitto obiettivo minimo fissato.
E' dunque evidente come il limite riportato in precedenza sull'MVP sia superato poiché il modello sviluppato, grazie alla costruzione della frontiera efficiente ottimizzata, garantisce di fornire in output la soluzione d'investimento ottimale in funzione dell'istantanea variazione del contesto(viste come istantanea variazione delle variabili di stato e dunque delle soglie d'esercizio).

Applicando dunque questo modello al portfolio fittizio descritto in Tabella 13 considerando anche la modellazione della fase pre – operativa come successione di tre fasi sequenziali il risultato ottenuto è:

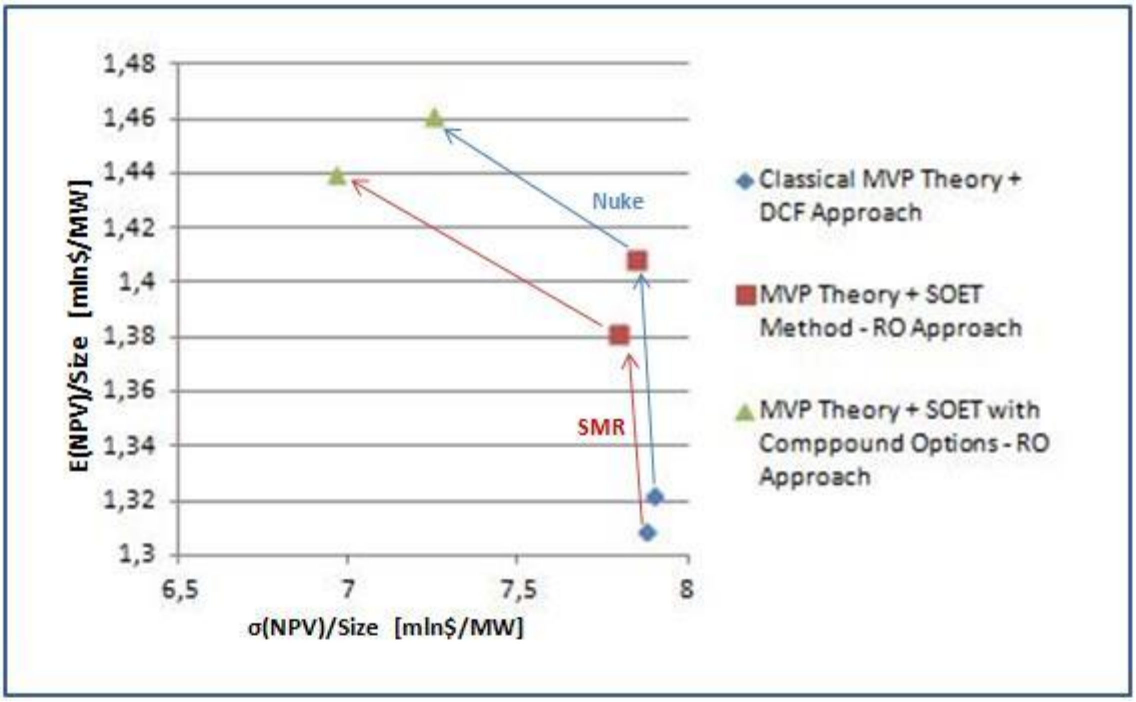

Figura 19. Paragone tra i risultati ottenuti nel caso di portfolio attuale fittizio

Ciò che si deduce dalla figura di sopra è riassunto di seguito:

a. La modellazione che sfrutta le compound options, anche quando si considera un portfolio attuale d'investimenti già esistenti, alza il profitto garantito riducendo il livello di rischio dell'investimento dato che al termine di ogni fase pre – operativa degli impianti nucleari addizionali il modello permette di abbandonare o posticipare l'investimento se lo scenario non è profittevole.
b. A seconda della funzione obiettivo la decisione d'investimento varia:
   i. Se l'obiettivo è la massimizzazione dell'E(NPV) la scelta più adatta è un investimento in un impianto nucleare di grande taglia
   ii. Se l'obiettivo è la minimizzazione della σ(NPV) la scelta più adatta è un investimento in un impianto nucleare di piccola taglia
   iii. Se l'obiettivo è la massimizzazione dello Sharpe ratio la scelta più adatta è un investimento in un impianto nucleare di piccola taglia

Ultimo step dell'analisi è stato applicare il modello di investimenti sviluppato al caso in cui il portfolio attuale della utility sia quello di EDF in UK ipotizzando che si debba colmare un fabbisogno di 1,5 GW addizionali. Le possibili scelte d'investimento sono le stesse enumerate in precedenza.

Il grafico di seguito mostra come varia scelta d'investimento nel caso siano applicati:
- Il classico metodo DCF integrato all'MVP
- Il metodo SOET senza Compound Options integrato all'MVP
- Il metodo SOET con Compound Options integrato all'MVP

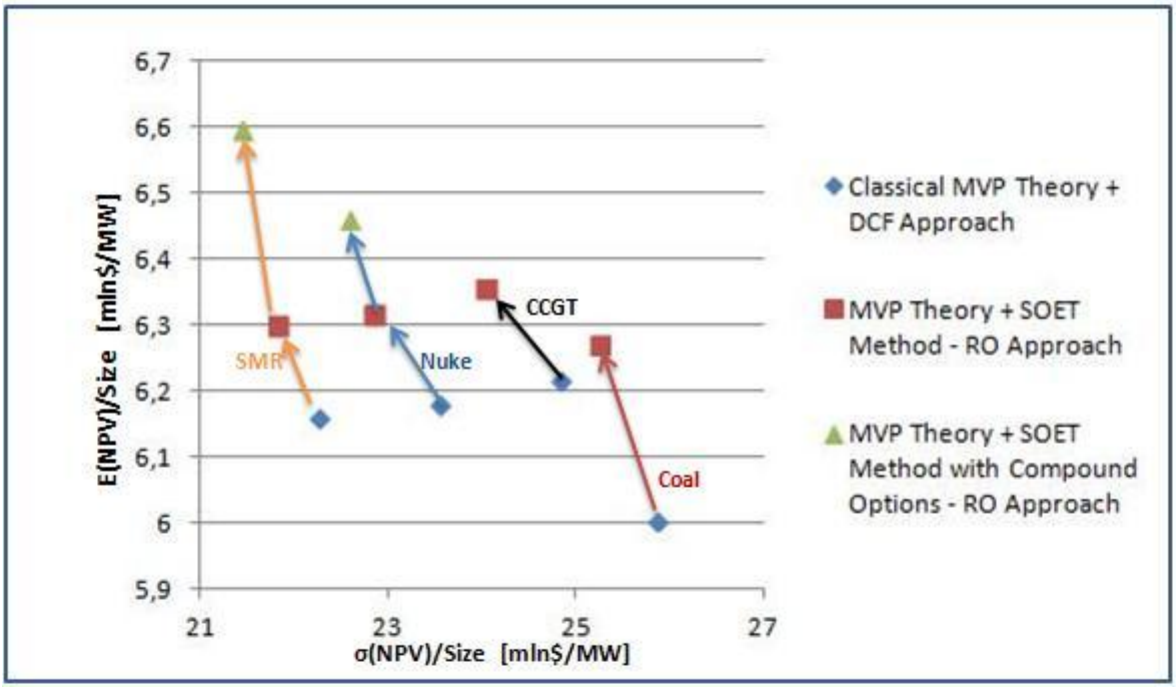

Figura 20. Risultati Ottenuti nel caso di analisi sul portfolio attuale di EDF in UK

Le conclusioni che si possono trarre dal grafico di sopra sono:

- Modellando la fase pre – operativa degli impianti nucleari come successione di tre compound options la scelta d'investimento cambia rispetto ai casi in cui le compound options non sono implementate o all'analisi che applica il metodo DCF nelle quali SMR, LR e CCGT si trovano tutti sulla frontiera efficiente.
- La tecnologia SMR, una volta applicate le compound options, è la sola che si trova sulla frontiera efficiente per cui è la "migliore" soluzione per un investimento addizionale qualsiasi sia la funzione obiettivo che la utility voglia implementare

6. Conclusioni

Questo lavoro ha raggiunto l'obiettivo da un lato di sviluppare un modello realistico per fornire supporto decisionale a una utility nella sua decisione di investimento e dall'altro di mantenere i vantaggi garantiti dal metodo SOET. Infatti:

- Considera l'intera durata della fase pre – operativa di un impianto per la produzione di energia elettrica invece che quella della sola fase di costruzione
- Modella la fase pre – operativa di un impianto nucleare come successione di compound options valutando così nel modo più realistico l'investimento poiché tiene in considerazione la flessibilità che è intrinseca alla fase pre – operativa dell'investimento stesso.
- Considera la presenza di un portfolio attuale di investimenti già esistenti
- Supera il principale limite riguardo l'MVP presente in letteratura perché fornisce la soluzione ottimale qualsiasi sia la funzione obiettivo che la utility voglia massimizzare seguendo l'istantanea variazione del contesto tramite la creazione di un output di forma innovativa: la Frontiera Efficiente Ottimizzata

- Ottimizza gli investimenti, riuscendo a misurare il valore della flessibilità, risolvendo problemi complessi, utilizzando più opzioni reali contemporaneamente e più variabili stocastiche.
- E' implementabile tramite add – ins di Microsoft Excel

Concludendo si riporta dunque la risposta alle domande di ricerca di questo lavoro:

Prima domanda di ricerca: Che effetto ha considerare su un investimento in Base – Load PP l'intero tempo necessario per iniziare a produrre e non solo la fase di costruzione(TTM Effect)?

Risposta: Come spiegato nel capitolo 2 e mostrato nel capitolo 5 l'effetto di considerare l'intero tempo trascorso dal momento in cui la decisione d'investimento è presa a quando la centrale inizia effettivamente a produrre energia ha due effetti opposti:

- Da un lato riduce il valore degli investimenti in impianti nucleari poiché il loro TTM è molto più alto di quello di impianti a carbone o a ciclo combinato
- D'altro lato è possibile distinguere tre fasi sequenziali all'interno di essa

Seconda domanda di ricerca: Come le RO possono aiutarci a modellare questa fase pre – operativa?

Risposta: Modellando tale fase come successione di tre compound options il cui costo è correlato tra esse come evidenziato in Tabella 9 e in Figura 8.

Terza domanda di ricerca: Come le RO possono aiutare una utility a scegliere un investimento in un PP addizionale rispetto ad un portfolio di investimenti già esistente?

Risposta: E' stata ampiamente mostrata la potenzialità che l'integrazione tra il metodo SOET e l'MVP Theory ha sulla decisione d'investimento addizionale a un portfolio già esistente. Rimandiamo al paragrafo 3.3 per la descrizione teorica del metodo usato e al capitolo 6 per comprenderne chiaramente gli effetti che l'applicazione di questo frame work innovativo ha sulla decisione d'investimento.

Quarta domanda di ricerca: Qual è la tecnologia più profittevole per colmare una richiesta di 1,5 GW tenendo conto del portfolio attuale di EDF in UK?

Risposta: Basandoci sullo scenario assunto la tecnologia più profittevole è quella degli SMR qualsiasi sia la funzione obiettivo che la utility possa voler raggiungere. In ogni caso tali risultati dipendono dagli input scelti e non hanno valenza generale poiché obiettivo principale di questo lavoro è la creazione di un frame work innovativo per effettuare una realistica decisione d'investimento nel settore energetico.
Interessante è notare come vari la decisione di investimento nel caso in cui la utility applichi il classico metodo DCF o il metodo SOET integrato all'MVP. Il primo infatti fornisce come decisione ottima l'investimento in CCGT, il secondo in SMR.

7. Sviluppi Futuri

I possibili sviluppi futuri di questo lavoro sono numerosi. Alcune possibili direzioni di sviluppo sono riportate di seguito:

- Applicazione modello a realistico problema di una utility
- Applicazione modello per aiutare la utility nella gestione del suo portfolio attuale di investimenti (si tratta cioè il portfolio non più dal punto di vista produttivo ma manageriale/gestionale)
- Implementazione nel modello di altri parametri in output oltre che l'NPV come IRR e Profitability Index
- Miglioramenti dell'algoritmo di ricerca che, se programmato da zero conoscendo la natura del problema, permetta di trovare più rapidamente l'ottimo valore delle soglie d'esercizio
- Inclusione nel modello della teoria dei giochi per tener conto della presenza di competitor e delle loro politiche nelle decisioni di investimento

Chapter 1 - Introduction

This chapter has the aim to introduce the reader to the main topics of this work. Paragraph 1.1 describes the electrical scenario all over the world focusing on the principal sources of uncertainty that must be kept in mind to evaluate properly an investment in this field. Paragraph 1.2 describes briefly the two main approaches[7] to evaluate investments in the energy field, while instead paragraph 1.3 summarizes the scopes of this work enumerating its research questions.

[7] The discounted cash flow(DCF) method and the Real Option Approach(ROA).

1.1 The Electrical Scenario in the world

Over the last decades, the world electricity consumption has increased remarkably at an average rate of 3,7% from 1971 to 2010, greater than the overall growth in total primary energy supply(fixed to 2,2%). This increase was largely due to more electrical appliances, the development of electrical heating in countries and of rural electrification programs in developing countries.
The following figure shows the evolution of the world electricity production by source of energy along the last four decades.

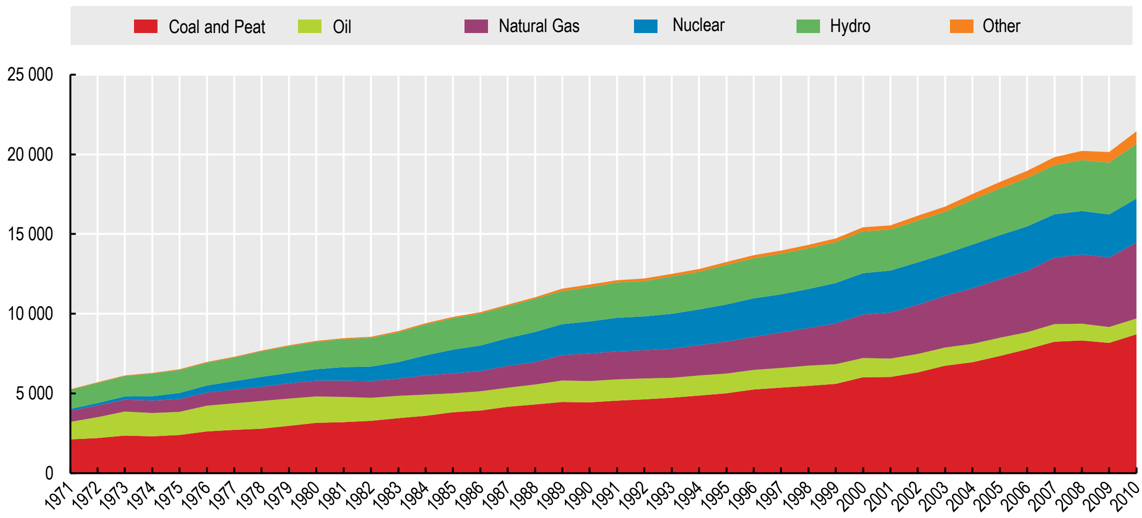

Figure 21. World electricity generation by source of energy (EIA, 2012)

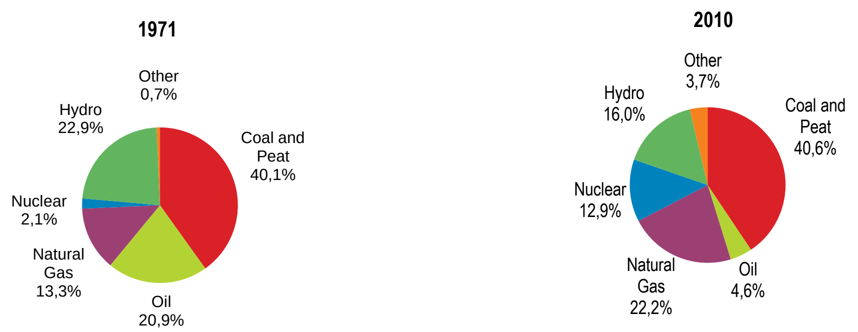

Figure 22. Changes in world electricity generation by source of energy (EIA, 2012)

Figure 22. Changes in world electricity generation by source of energy shows in an easier way how changes the world electricity generation during the last four decades:

- The share of nuclear electricity generation rose from 2,1% to 12,9% even if it is decreasing now because in 1996 it reaches the 17,7%
- The oil production decrease dramatically
- The Natural Gas production increase significantly

This last conclusion is important because it allows us introduce a new form of electricity production that is growing up dramatically in the last few years, especially in the U.S.: the Shale Gas.

The Shale Gas Revolution in the U.S.

The energetic debate in the U.S. has raged for decades because as the country's reliance on fossil fuels has deepened and the environmental concerns have highlighted the need for viable alternative fuel sources. Unfortunately, traditional fossil fuels such as oil, coal, and conventional natural gas all have drawbacks that make them less than ideal to meet the energy needs of the country:

- U.S. reliance on oil comes at the expense of a volatile international market and dependence on unstable foreign economies
- Coal is fraught with dangerous working conditions and high greenhouse emissions
- Natural Gas resources have been largely too expensive to extract
- Nuclear energy production decrease dramatically because of the risks connected to this kind of investment
- The alternative energy sources are currently too insufficient, expensive an unreliable

As a result, energy producers have turned to unconventional fossil fuel extraction from shale gas formations, coal beds, and tight sands as a viable alternative to current U.S. energy supply (EPA, 2011).
In the early 1900s, extractors discovered that if they could create fractures in the shale bed surrounding the gas deposit, the gas would be released from the rock and could be collected through gas wells. Today, the process is called hydraulic fracturing or "fracking," and involves much more sophisticated techniques (L. Lovejoy, 2012). These techniques are not described here because this is not the aim of this work.

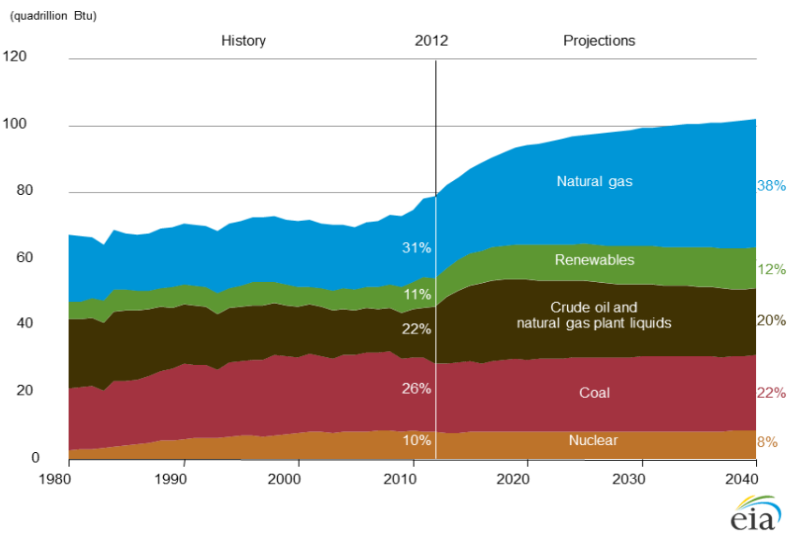

Figure 23. U.S. energy production by fuel, 1980 – 2040 (AEO, 2014)

However this work does not investigate the shale gas technology because it is not widespread all over the world and because there are some problems that are reducing its diffusion, but it is important to know that this innovative technology will play an important role in the future evolution that the electricity production will have.

i. **Surface/Drinking Water Contamination:** it may occur when fracking fluid and natural gas from shale wells escape into the surrounding groundwater, leaching fracking chemicals and methane into the groundwater supply.
ii. **Greenhouse Gas Emissions:** Shale gas has lower greenhouse emissions than oil or coal when used for electricity generation. However, when it is burned for energy

production, it releases CO_2, not methane.

iii. **Transport and infrastructural problems:** since shale gas is often found in remote areas with little existing infrastructure or access to pipelines, many of the resources needed for well completion and usage are brought in using trucks. Depending on the size of the well and technique used, fracking requires between 2 million and 9 million gallons of water. After fracking, the water must be trucked back out for permanent disposal, usually in empty wells. Shale wells require on average 1,000 truck trips during drilling and fracking (Christen, 2010). The high volume of trucks required for fracking adds both to the carbon emissions of the process and decreases air quality in rural areas with shale wells.

iv. **Public Acceptance**

These are the reasons for which we do not investigate this technology in this work, but in the following decade it will surely play an important role and thus its evolution can't be ignored.

Box 1. The Shale Gas Revolution

Furthermore in the last few decades electricity industry has changed significantly in different ways: the electricity and gas markets has been deregulated in many countries in the world and the uncertainty related to the emissions of CO_2 is a new form of uncertainty that must be kept in mind to understand better all the problems and risks connected to an investment in the energy field.

In the following table adapted from (Roques, et al., 2006) we report the most important sources of uncertainty analyzing all of them in function of two factors:

1. The impact of this parameters on the overall result of electricity investments
2. The probability to have changes in the value of these parameters(i.e., their volatility)

Source of Uncertainty	Impact	Volatility
Electricity Price	High	High
Overnight Cost	High	High
Natural Gas Price	High	High
Coal Price	High	High
Carbon Price	High	High
Construction Time	High	High
Nuclear fuel Cost	Low	High
Plant Life	Low	High
Availability Factor	High	Low
Discount Rate	High	Low
Heat Rate	High	Low
O&M Costs	Low	Low
Waste fee	Low	Low

Table 17. Impact and volatility of the sources of risks, adapted from (F. A. Roques et al., 2006)

Obviously the variables with an high volatility and an high impact on the overall profitability of the investment are the most critic.
In literature it is clear that the most influential parameter on the overall profitability of the investment is the electricity price because the revenues generated are directly function of it.

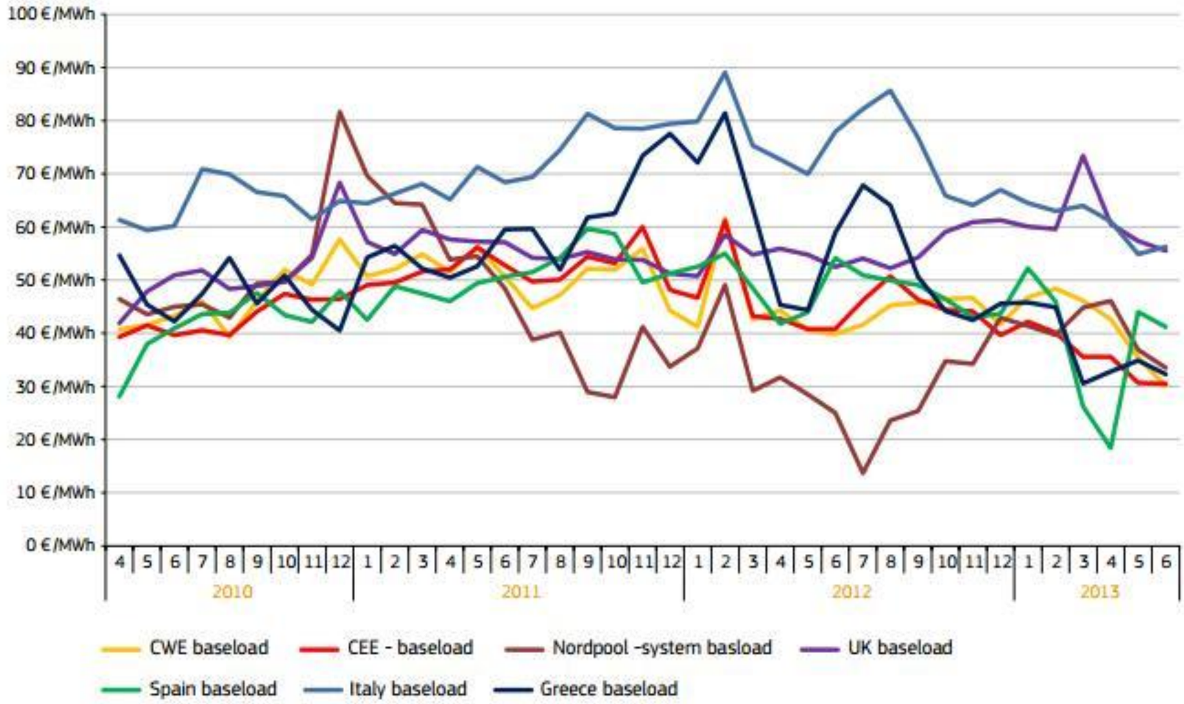

Figure 24. Comparison of monthly electricity base - load prices in regional electricity markets (EC, 2013)

From the figure above we can easily understand how the increasing in the mean value of the electricity price will affect investment in the energy field.

The following instead figures highlight the uncertainty that natural gas cost and coal cost have:

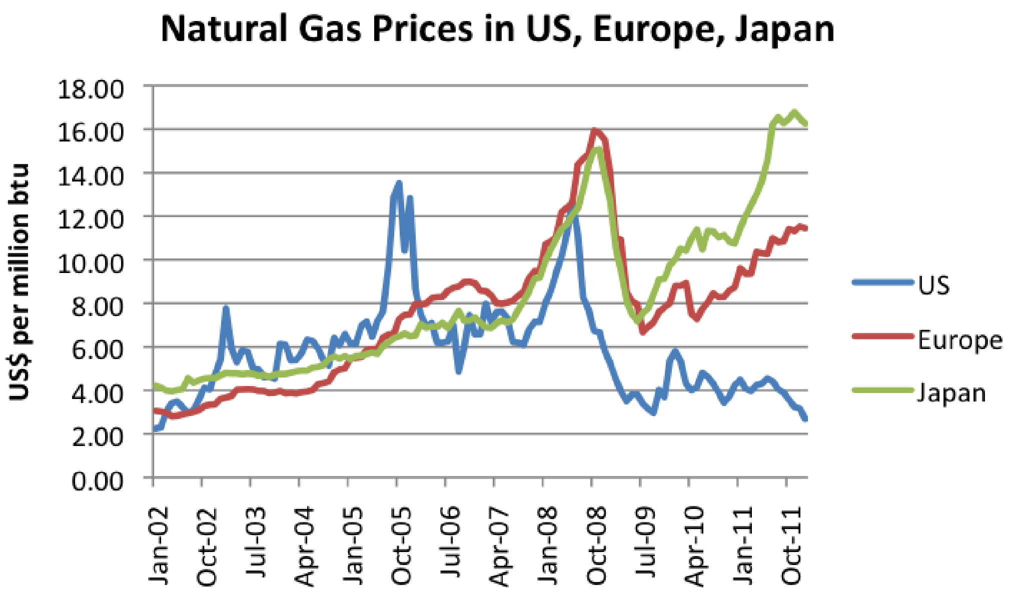

Figure 25. Natural Gas Price in U.S, Japan and Europe (EIA, 2012)

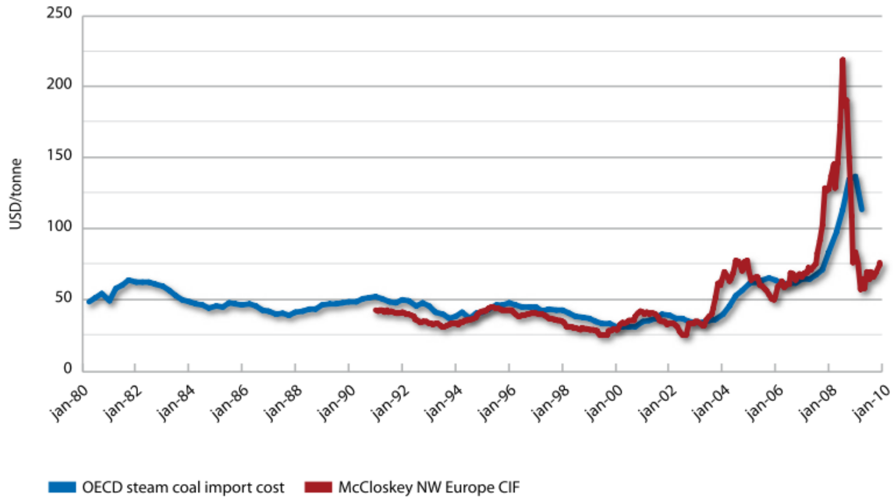

Figure 26. Steam coal quarterly import costs and monthly spot prices (IEA NEA, 2010)

It is clear that we have to model these parameters as stochastic variables if we want to build an effective and useful model to be applied in the energy field.

Indeed the aim of this work is to find, in such an uncertain context, the most profitable power plants, from the point of view of a utility, building an innovative model. Our aim is to build a framework that consider both the entire time elapsed from the moment in which the decision to invest in the PP is taken and the moment in which it starts to produce energy, and the actual portfolio of the utility. To represent this uncertainty this work considers all the critic variables of Table 17.

1.2 Evaluating investments in the energy sector

In literature there are two main approaches that are used to build model with the aim to support a utility in the choice of the best electricity generating technology:

1. The Discounted Cash Flow (DCF), the most used method
2. The Real Options Approach (ROA), considered an expansion of the DCF

The ROA is considered very valuable in uncertain contexts . This is because it considers into the evaluation the possibility to take strategic decisions (like investing or not) in function of the evolution of the uncertain parameters that characterize the uncertain context. This approach considers from the beginning the possibility to react to exogenous variations of the context. The application of this approach adds value to the investment: the value of flexibility. Today, at least in academia, real options theory has been widely accepted as an innovative tool for capital planning and asset valuation(He, 2007). However there are difficulties that have blocked the employment of the ROA. Differently from the DCF, the models based on ROA are mathematically more complex and for this reason there are only few work that apply them to perform a portfolio analysis: the application of the standard RO method is too complex if the actual portfolio of a utility is considered.
This work aims to fill this gap by applying the MVP theory to keep into account the actual portfolio of a utility in an integrated way with the SOET Method[8] that will be properly described in paragraph 2.3.

[8] Simulation with optimized threshold: it is an innovative real option approach developed in (Lotti, 2012).

1.3 Aim of this work and research questions

The aim of this work is to build models of investment that gives in output the best PP to be built considering:

1. The Effect of the real pre-operational time for all base-load PPs(TTM Effect)
2. The Effect of the intrinsic flexibility of the pre-operational phase of a nuclear PP that will be modeled as the succession of three sequential compound options
3. The Effect of the Actual Portfolio on the decision of investment in a new plant

In order to do that we apply an innovative Real Option Approach based on the SOET[9] Method showing how it must be applied in all these three steps of improvement.

The first two effects have been evaluated considering a scenario in which a utility has to face a demand of 1,5 GW[10]. Therefore at that point of the analysis the actual portfolio of the utility will not be taken into account. The actual portfolio will be then considered building an innovative framework that integrate the SOET methods with the MVP Theory to perform effectively a realistic portfolio analysis. We will apply this method to an hypothesized actual portfolio of investment evaluating what is the “best” investment to reach an additional demand of 1,5 GWe according to different objective functions.

Finally, the last step of this work will be to apply this innovative model that consider all these effects to the EDF’s portfolio of investment in UK with the aim to find the most profitable PP that should be built to reach an additional demand of 1,5 GWe.

Therefore this work aims to answer to these research questions:
1. What is the effect of considering the whole time elapsed from the moment in which the decision to invest in a base – load PP is taken and the moment in which it starts to produce energy(TTM Effect)?
2. How can a real option approach helps us to model this pre – operational phase?
3. How can a real option approach helps a utility to choose an investment in an additional PP considering it actual portfolio of already existing investments?
4. What is the best solution for EDF to fulfill an additional demand of 1,5 GW considering its own actual portfolio of investment in UK?

[9] Simulation with Optimized Exercise Thresholds
[10] This expansion can be generated by an increase in the energetic demand or by a decrease in the energetic supply (caused for example by the decommissioning of existing power plants).

Chapter 2 - Literature review: Investment portfolio in the energy sector

This chapter presents the literature review of three main topics: portfolio management in the energy field, Real Option Analysis and Time to Market for power plants.
At first this chapter reviews in paragraph 2.1 several examples of portfolio analysis in the energy field. It starts from an analysis of the most used approaches to perform it, describing their advantages and drawbacks, providing a resume of its applications in the energy industry and explaining why Mean Variance Portfolio Theory(from now MVP) is the most adapted method to our scope(paragraph 2.1.1). Then paragraphs 2.1.2 and 2.1.3 present and describe more specifically the MVP theory, its advantages and its drawbacks. The second part of this chapter describe the Real Option Approach(paragraph 2.2.1), the methods present in literature to perform it (paragraph 2.2.2) and the reasons why it's particularly indicated for this class of problems (paragraph 2.2.3). Instead, paragraph 2.2.4 exploits all the existing examples of application of ROA to a portfolio of investment in the energy sector. Paragraph 2.3 analyzes the SOET method to apply real option to evaluate power plants describing it and comparing it with the other evaluation methods of real options(paragraph 2.3.1). Paragraph 2.3.2 summarizes the main limitations of the SOET method, and describes the two ways we identify to improve it in order to perform a portfolio analysis in the energy field. Paragraphs 2.3.3 introduces the SOET Method considering the TTM Effect. It describes the problem and the idea of the model that we developed. The same approach was then used in paragraph 2.3.4 to describe how the idea of the model vary if the existence of an actual portfolio of investment is considered. Instead paragraph 2.3.5 illustrates the difference between the classical MVP Theory and the framework we developed to integrate MVP with the SOET Method. At the end paragraph 2.4 presents a brief summary of the main messages that this chapter have.

2.1 Portfolio Analysis

Since the main scope of this work regards an improvement of an existent RO Evaluation method in order to take into account the actual portfolio of already existing PPs in the decision of additional investment, this review of the literature mainly concern about the existing applications of the portfolio theory.

2.1.1 Description of all possible methods

Portfolio theories were developed firstly for financial uses and then they have been adapted to the energy sector. In the following table, adapted from (Locatelli & Mancini, 2011), we summarize all the existing method that can be used to perform a portfolio analysis.

METHOD	ADVANTAGES	DISADVANTAGES	NOTES	REFERENCES
Mean-Variance Portfolio theory (MVP)	Easy application. Clarity of result. Improvement direction identifiable. Expandable and adaptable in order to consider additional input	Expensive from a computational point of view, especially with the increasing of the number of considered assets. Requires standard deviations, correlations and expected values of the output	It is the most used technique in electricity generation portfolios. It can be used to optimize different objective function	(Markowitz, 1952); (Bar-lev & Katz, 1976); (Madlener & Wenk, 2008); (Awerbuch, Shimon, Yang, & Spencer, 2007);(Kienzle et al. 2007); (Roques et al. 2007); (Paz et al. 2012); (Abadie, Neufville, & Chamorro, 2014)
Maximization of the geometric mean returns	Identifies the portfolio with the higher probability to reach the maximum return	It does not consider and detect the minimum risk portfolio—identifies only one solution	The efficient portfolio belongs to the range defined by the MVP optimal solutions	(Latanè, 1959), (Young & Trent, 1969); (Weide et al., 1977); (Jean, 1980); (Estrada, 2010); (De Santiago & Estrada, 2011)
Value at Risk (VaR)	Very flexible, it considers variances, co-variances and interactions between factors	Diversification does not permit to reduce risks—considers only the probability of risk neglecting the size of the leak. Subjective, the investor selects the limit value, it does not identify general solutions	It captures extreme and dangerous events providing information on the tail of a distribution	(Deng et al. 2013); (Fortin, Ines et al., 2007); (de Oliveira et al.2011); (Spangardt et al., 2006);(Unger & Luthi, 2002);(Doege et al., 2005)
Safety First (SF)	Very simple and easy, makes a choice based on the probability of returns below a certain threshold	It does not consider co-variances and interactions between factors, too simplistic. Subjective, the investor selects the desired return value, it does not identify a general solution	SF results are almost equivalent to MVP results	(Bawa, 1978); (Roy, 1952); (Dorfleitner & Utz, 2011); (Norkin & Boyko, 2012)

Stochastic dominance(SD)	Ranks and compares the various alternatives by identifying the optimal point in a range of already defined solutions	it does not consider the investor and his aversion to risk— requires a large amount of data. Identifies a single solution	Can be used after the MVP theory application	(Fishburn, 1964), (Bawa, 1982);(Levy, 1992); (Ogryczak & Ruszczyński, 1999)

Table 18. Portfolio Analysis: description of all possible method(adapted from (Locatelli & Mancini, 2011)

In this work we apply the MVP theory to perform the portfolio analysis. We summarize here the reason of this choice:

- It is the most used method in literature because it gives in output the highest amount of information to the model user thanks to the construction of the efficient frontier
- It can be used to find the optimal solution in function of different objective functions
- MVP let us treat a portfolio of investment reporting and evaluating it as an investment in a single technology. This property allows us to integrate in a perfect manner the MVP with the SOET Method (described in paragraph 2.3).
- Each single portfolio can be directly compared to the others in terms of expected NPV and level of risk. We don't have to normalize results if we compare portfolios with different dimensions.
- This method is expandable and adaptable in order to consider additional input.
- MVP can be implemented in an Excel spreadsheet, and it guarantees a remarkable clarity of results.

In the next chapter we will then briefly describe the mathematical law that let us do it.

2.1.2 The MVP Theory

Most of the researches about MVP are a development of seminar paper (Markowitz, 1952). Markowitz was the first to consider diversification as necessary for the construction of efficient portfolios and gave a mathematical formalization of this idea.
In his work he identified a range of optimal solution characterized by the following property: *"maximize the expected return for each risk level".* Optimal portfolios lie on the so-called "*Efficient Frontier*" and all the portfolios that belong to this frontier are considered optimal solutions.

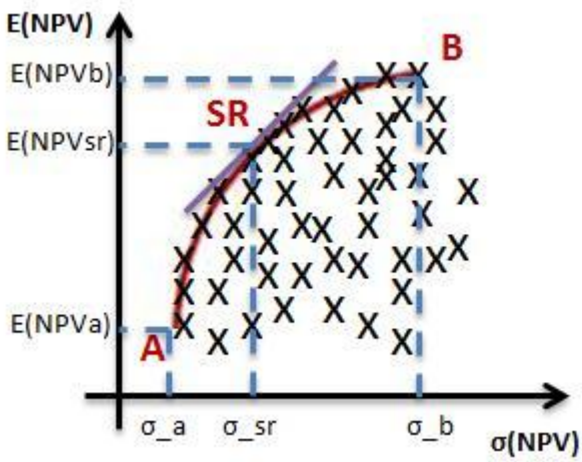

Figure 27. Standard Efficient Frontier

The focus of Markowitz's work was to show a method that an individual or an institution could use to select an optimum portfolio.

(Sharpe, 1966) extended it determining how the aggregate investors will behave, and how market prices and returns are set. The model developed explaining this general equilibrium relationship is the Standard Capital Asset Pricing Model (CAPM).
Subsequently in (Sharpe, 1994) the author, considering his work and all the followed papers existing in Literature based on his findings, summarized the property of his most successful finding: the Sharpe-Ratio.
In order to describe it we will use the description reported in (Stoyanov et al., 2005).
As already said, the classical MVP framework was introduced by Markowitz and it supposes that at time $t_0 = 0$ there is an investor who can choose to invest among n assets. Having made the decision, he keeps the allocations unchanged until the moment t_1 when he can make another investment decision based on the new information accumulated up to t_1.
We define:

$$\boldsymbol{r} = (r_1; r_2; \ldots\ldots; r_n)^T = Vector\ of\ revenues\ of\ each\ asset \text{ (2.1)}$$

$$\boldsymbol{E}(\boldsymbol{r}) = [E(r_1); E(r_2); \ldots.; E(r_n)]^T = Vector\ of\ the\ expected\ value\ of\ each\ asset \text{ (2.2)}$$

The result of the investment is:

$$\boldsymbol{w} = (w_1; w_2; \ldots.; w_n)^T = Portfolio\ Composition \text{ (2.3)}$$

$w_i =$ portfolio weight corresponding to the i-th item, i.e. the share of the initial endowment invested in the i-th asset.

The Expected portfolio return is:

$$\mu_p = \boldsymbol{\Sigma} w_i * \boldsymbol{E}(r_i) = \boldsymbol{w^T} \boldsymbol{E}(\boldsymbol{r}) \quad \text{(2.4)}$$

According to Markowitz's approach then the standard deviation of portfolio return is the measure of risk and it is calculated as follow:

$$\sigma_p{}^2 = \boldsymbol{w^T \Sigma w} \quad \text{(2.5)}$$

Considering for example a portfolio composed of only two technologies, MVP calculates portfolio's performances as follow:

$$E(\mu_p) = w1 * R1 + w2 * R2 \quad \text{(2.6)}$$

$$\sigma_p{}^2 = w1 * \sigma_1{}^2 + w2 * \sigma_2{}^2 + 2 * (w1 * w2 * \rho_{12} * \sigma_1 * \sigma_2) \quad \text{(2.7)}$$

Where $w1 + w2 = 1$, respective percentage of each technology in the portfolio.
The main principle behind the mean-variance analysis can be summarized briefly in two ways:

a. From all feasible portfolios with a given upper bound on σ_p; find the ones with the maximum expected return μ_p
b. From all feasible portfolios with a given lower bound on μ_p; find the ones with the minimum risk σ_p

All the optimal portfolios obtained varying the upper and lower bounds lies on the *Efficient Frontier*.
There's a third way to arrive at the mean-variance efficient set and it is to consider this optimization problem:

$$max_w(\mu_p - \boldsymbol{\lambda} * \sigma_p) \quad \text{(2.8)}$$

Where $\boldsymbol{\lambda} > 0$ is the Risk-Aversion Parameter than in the energy field typically assumes a value between 1,5 and 2 (Ha-Duong & Treich, 2004). In this way the mean-variance efficient set can be obtained by the problem above via varying the risk aversion parameter.
As the portfolios on the efficient frontier are found, an investor have to choose the portfolio composition to reach but, according to MVP theory, all the portfolios lying on the efficient frontier are optimal at the same time. (Sharpe, 1994) described a parameter that let an investor compare them in terms of their expected return for a unit of risk, the so-called *Sharpe Ratio*:

$$SR(w) = \frac{\mu_p}{\sigma_p} \quad (2.9)$$

We would prefer the portfolio on the efficient frontier with the highest expected return for unit of risk(the highest SR). Geometrically the point of the efficient frontier that correspond to the solution of this problem is tangent to the efficient frontier: the optimal portfolio received is called Tangent Portfolio.

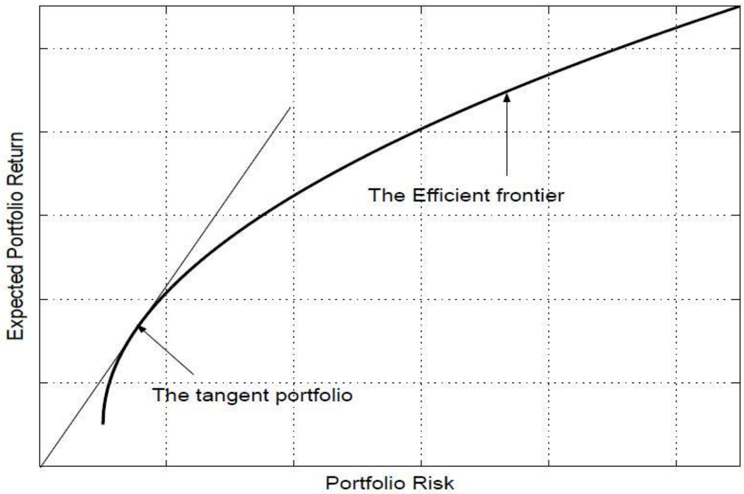

Figure 28. The Efficient frontier and the tangent portfolio (Stoyanov et al., 2005)

For its simplicity and its high diffusion in this field, the Sharpe-Ratio will be one of the parameters considered in this work to compare each different portfolio.

2.1.3 MVP Applications and Drawbacks

The first application of the MVP theory to the energy production business was then developed by (Bar-lev & Katz, 1976). They analyzed fossil fuel procurement in the U.S. electric utility industry comparing the historical price levels and volatilities of oil, natural gas and coal in an MVP approach. They built efficient frontiers for each region in the U.S. and compare them with the actual performance of regional utilities. They found out that, on one hand utilities were efficiently diversified but that, on the other hand, their portfolios were characterized by high risks and high returns.
More recently, (Awerbuch & Berger, 2003) applied the MVP theory to the development of efficient generating portfolios for countries in the European Union. They included the risk of fuel costs, operation and maintenance costs and construction period costs in their analysis and they found out that existing and projected EU generating mix were sub-optimal from a risk-return perspective. Their study showed also that more efficient portfolios could be built adding renewable technologies to the portfolio.

In (Awerbuch et al., 2007) considering the actual portfolio, they were the first to compare it not to all the portfolios on the efficient frontier but on the easiest four portfolios to model and to reach.

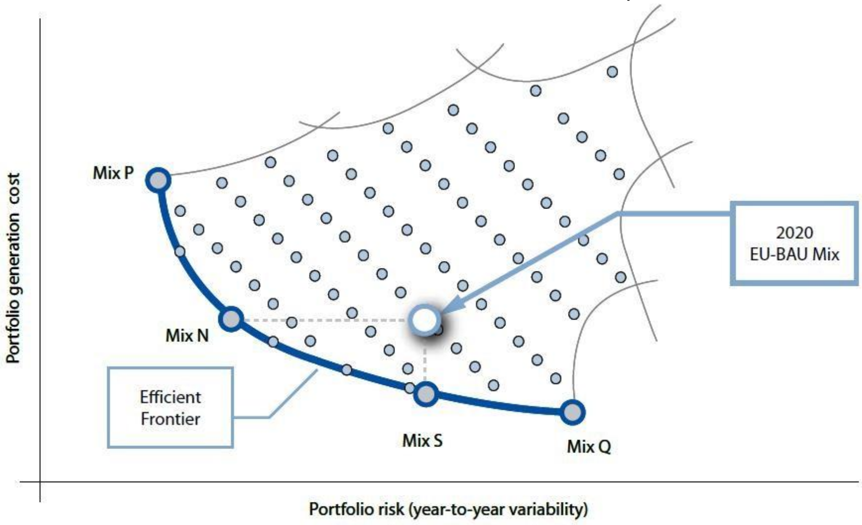

Figure 29. Efficient Frontier and most Remarkable points on it (Awerbuch et al., 2007)

The figure above shows the four portfolios on the efficient frontier that they considered in their paper:

- The portfolio with the minimum at all generation cost(Q)
- The portfolio with the minimum at all level of risk(P)
- The portfolio with the minumum generation cost given fixed the level of risk of the actual portfolio(S)
- The portfolio with the minumum level of risk given fixed the generation cost of the actual portfolio(N)

(Kienzle et al., 2007) developed a theoretical analysis of the implementation of the portfolio theory. They referred their study to the already mentioned work of (Bar-lev & Katz, 1976). They gave a very good definition of the *Portfolio Effect*: *"By diversifying a portfolio, i.e. by dividing investments into 2 or more assets that are less than perfectly correlated, one is able to reduce return at the same time. This is the so-called portfolio effect".* The lower is the Pearson Correlation Coefficient, the greater is the portfolio effect.
Furthermore before them revenues were modeled as follow:

- In the financial world : $Revenues = \frac{Revenues - Expenses}{Expense}$

  "The financial return measure is therefore dimensionless, a property that does not hold for our cost-based return measure: kWh/cent, which becomes dimensionless only if a monetary value is assigned to the numerator" (Awerbuch & Berger, 2003).

- In the energy field, (Awerbuch & Berger, 2003)considered then revenues in an innovative way: $Revenues = \frac{1}{LCOE} * P_{el}$ where P_{el} is the electricity price in the period considered [$/kWh].

In this way then revenues become dimensionless assuming a measure precisely analogous to the financial measure of return.

However, they conclude that this new way of measuring revenues is not positive because the consideration of the electricity price in the short term can lead to future uncertainty in the model. Therefore they modeled revenues in this way:

$$Revenues = -\frac{Cost_t - Cost_{t-1}}{Cost_{t-1}} \quad (2.10)$$

$$Risk = \sigma_{Revenues} \quad (2.11)$$

This implies that the performance would be negative if costs increase. According to (Kienzle et al., 2007), maximizing performance would mean to minimize generation costs' increase or, in the best cases, to maximize their diminution.

Another important work regarding the portfolio analysis is (F. A. Roques, 2007). They applied MVP in two following steps in order to evaluate the optimal energetic portfolio in UK. They analyzed returns and risks associated to investment in base-load power plants: Coal, CCGT and Nuclear power plants were considered. Being in a liberalized market then, they did not focus their analysis on minimizing the generation costs of each technology given a fixed level of risk anymore. Instead they focused on the revenues obtainable using a certain mix of technologies, according to a defined level of risk.
As already said their model followed two steps:

- Firstly they applied the Discounted Cash Flow Method with a Monte Carlo Simulation in order to evaluate the expected value and standard deviation of each uncertain parameters(fuel cost; carbon tax; electricity price).

- Secondly they used the distribution of the parameters evaluated in the first step as an input of the Mean Variance Portfolio theory.

After them (Madlener & Wenk, 2008) considered a Swiss electricity generation utility (AXPO) optimizing its portfolio in terms of maximum return and minimum level of risk.
The evaluation of the efficient frontier was made separately considering a base-load portfolio and a peak-load portfolio. They defined and simulated different scenarios with a different mix of technologies and a different upper and lower bound for each of it. In this way they had been able to find out the profile of risk and the profitability of the mix of technology in each different portfolio.
Furthermore they summarized all the necessary steps of the MVP theory. We report them here because our analysis follows the same framework.

- Identification of the most relevant uncertainties
- Construction of the NPV model for each technology considering the parameter of risk
- Monte Carlo Simulation of each technology in order to find out the NPV distribution and correlations
- Definition of all the constraints of each technology in the portfolio(e.g. demand of energy; maximum output obtainable from each technology)
- Division between base-load and peak-load technologies
- Enumeration of all possible portfolios for base-load and peak-load portfolios
- For both base-load and peak-load cases, evaluation of:
    - Portfolio with the highest profitability
    - Portfolio with the lowest level of risk
    - Efficient Frontier
- Definition of the actual portfolio
- Comparison between the actual portfolio and the portfolios on the efficient frontier

- Final suggests and comments

More recently (Locatelli & Mancini, 2011) performed a portfolio analysis using the Roques' approach. Their framework is reported in the following figure:

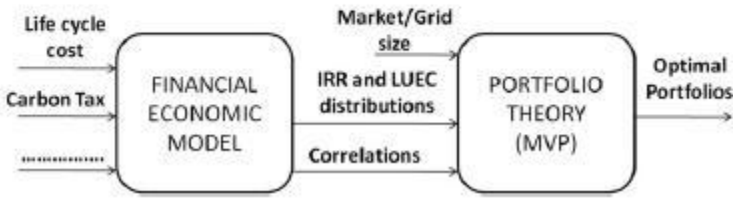

Figure 30. Roques' framework to perform Portfolio Analysis with MVP (Locatelli & Mancini, 2011)

Their work differs to the others about this topic because they considered as output of the financial economic model not only the LUEC distribution, but also the IRR distribution.
They modeled each scenario as a combination of two parameters (the Carbon Tax and the Electricity Price) showing how the mix of technologies in the optimal portfolio varies according to a different level of them. Another application of their framework and their kind of analysis can be found in (Vithayasrichareon et al., 2010) in which the authors employed a stochastic tool based on Monte Carlo Simulation technique to assess the expected generation cost and risk profiles of different electricity generation portfolios of Coal, CCGT and Nuclear plants. They evaluated the economics of this power plants for different portfolio mixes under a number of scenarios of future fuel and carbon prices in the context of the ASEAN region.

Another application of the MVP theory is (Paz et al., 2012) in which the authors applies it to the Spanish energetic portfolio in order to find the optimal generating portfolio for the 2020 considering three different future scenarios. As (Locatelli & Mancini, 2011) they added to the classical parameter analyzed the IRR too because it considers the uncertainty of the electricity price and future risks, differently from the approach described in (Awerbuch & Berger, 2003).

As mentioned then MVP has a broad field of application in finance and have a great popularity in this field. However in literature are reported a series of drawbacks of this methodology that are limiting its use. (Madlener & Wenk, 2008) reported the MVP's main drawback:

"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".

In this work our aim is to show that the application of the MVP theory integrated with a new method of application of the Real Options Analysis will solve this problem.
Indeed in the classical way each portfolio on the efficient frontier is represented as a single static point on it, varying only according to the scenario considered(see Figure 27).
We aim to build as an output of our model an efficient frontier for each single possible portfolio that will be function of the exercise thresholds: each portfolio performances will be then represented as a curve and not as a static point anymore(see Figure 38). In this way we will be able to find the optimal condition to invest for each portfolio according to the future evolution of the uncertainties considered, and we would then be able to compare them showing what is the best solution for the utility. In the following table we report a summary of recent works that perform a portfolio analysis in the energy field applying the MVP Theory.

	This Work	(Locatelli & Mancini, 2011)	(Paz et al., 2012)	(Vithayasrichareon et al., 2010)	(Jain et al., 2013)
INPUT					
Fuel Cost	GBM	Discrete Distribution	Historical Data	Lognormal distribution	GBM
Capital Cost	Differential Eq. (Pindyck, 1992b)	Discrete; Continuous Distribution	Considered but not specified	Lognormal distribution	Differential Eq. (Pindyck, 1992b)
O&M Cost	Deterministic	Discrete Distribution	Considered but not specified	Deterministic	GBM
D&D Cost	Differential Eq.	Deterministic	Considered but not specified	Considered but not specified	Considered but not specified
Technologies	Nuke; Coal; CCGT; SMR, Wind	Coal; CCGT; Nuke	Coal; CCGT; Nuke; Renewable	Coal; CCGT; Nuke	Nuke; SMR
Countries	EDF's portfolio in UK	Europe(OECD)/Italy	Spain	ASEAN Countries	OECD Countries
Emission Cost	GBM	Scenario dependent	Scenario dependent	Lognormal distribution	Not considered
Electricity Price	GBM	Continuous Distribution; Scenario dependent	Historical Data	Lognormal distribution	GBM
METHOD					
TTM Effect	Modeled	Not considered	Not considered	Not considered	Not considered
Pre-Operating Phases	Modeled as the succession of three compound options	Only the construction phase is considered	Not considered	Only the construction phase is considered	Only the construction phase is considered
Actual portfolio of investment	Influence results	Results not influenced	Results not influenced	Results not influenced	Results not influenced
Method used to perform the portfolio analysis	MVP Theory	MVP Theory	MVP Theory	MVP Theory	MVP Theory
Network Size / Market Dimension	Considered	Modeled	Scenario dependent	Not considered	Not considered
Economic Model Type	Real Option Approach (SOET Method)	Cost drivers and DCF considered	Cost drivers and DCF considered	Cost drivers and DCF considered	Real Option Approach (Stochastic Bundling Method – SGBM)
Plant switch off	Not considered for simplicity	Considered	Not considered	Not considered	Considered with option to abandon
Input correlation	Not considered for simplicity	Not considered	Considered	Considered	Not considered
OUTPUT					
Indicators	E(NPV); σ(NPV); Exercise Thresholds; Efficient Frontier 2D for each technology; Efficient Frontier 3D for Portfolio	IRR, LUEC – Efficient Frontier 2D for portfolio in which single technology is a static point on it	Efficient Frontier 2D for portfolio in which single technology is a single static point on it	Classical NPV	Efficient Frontier 2D for portfolio in which single technology is a single static point on it; Value of the option
Benchmarking with actual portfolio	Considered	Considered	Considered	Not considered	Not considered

Table 19. Benchmarking between recent works that apply MVP Theory to perform a Portfolio Analysis

2.2 Real Options Analysis: state of the art

This section presents a brief presentation of Real Option describing its aim and its existing evaluation models. A more complete review of this framework is reported in (Martínez Ceseña et al., 2013)and in (Driouchi & Bennett, 2012).

2.2.1 Introduction to Real Options Approach

The purpose of Real Options(RO) theory is to identify and assess manager's options to adjust projects following the evolution of the uncertain factors regarding their projects. It considers then the ability of managers to modify their projects with the objective of maximizing profits and minimizing risks. In the last decade a remarkable number of researches has focused on the application of the RO theory to electricity generation projects. As (Martínez Ceseña et al., 2013) reports: "*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".*

The basic idea is that standard investment theory relying on NPV calculations generally do not consider the interaction between three important characteristics of investment decisions: the irreversibility of most investments, which implies that a substantial portion of the total investment cost is sunk, the uncertainty surrounding the future cash flows from the investment, which can be affected by the volatility of output or input prices, and the opportunity of timing the investment flexibly (Fortin, Ines et al., 2007);

(Myers, 1977) presented for the first time the term "real options", observing that corporate investment opportunities can be viewed as call options on real assets. More recently, (Pindyck, 1992) explained that a real option is the right, without obligations, to defer, abandon, or adjust a project in response to the evolution of uncertainty. A Real option is any action that management can apply to modify the scheduled project following the variation of the uncertain parameters during the project. The project is flexible if it can be deferred, abandoned, or adjusted in order to obtain a specific objective. Thus, real options offer flexibility, resources and the capability to benefit from the uncertainty surrounding business (Driouchi & Bennett, 2012).

With the real option approach a project is considered an option of the underlying cash flows and the optimal investment strategies are just the optimal exercise rule of the option (He, 2007). The term real options decision-making is thus used to infer that organizational and managerial factors have a role to play in exercising and managerial factors have a role to play in exercising and redeploying a firm's portfolio of real options (Driouchi & Bennett, 2012).

The following figure shows the difference between the classical DCF analysis and the Real Option Approach:

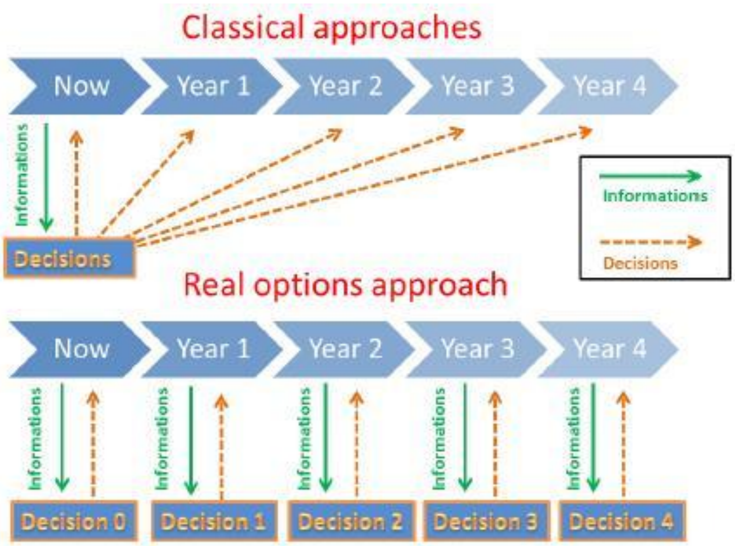

Figure 31. Classical approach and Real Options approach (elaborated from (Cardin & Neufville, 2009))

In this figure we have shown the meaning of the flexibility that is inside in an uncertain investment: taking future actions in function of new information, and not "blindly" at the moment of the evaluation, adds value to the investment.

2.2.2 Real Options Evaluation Models

Real Options take their names from financial options, that are contracts between two parties for a future transaction on an asset. The owner of the option gains the right, but not the obligation, to trade products at a specified price in a specified moment. This is similar to RO that provide to the investor the right, but not the obligation, to adjust the project in order to gain the best performances from it.

The first methodologies to evaluate RO were then developed from financial option valuation. The most common existing approaches are here reported:

i. *Partial Differential Equations(PDE)* : it involves solving a partial differential equation with specific boundary conditions(i.e. type of option, option values at a known point, etc.) that describes the change in option value with respect to measurable changes of certain variable in the market. In a closed form analytical solution to the partial differential equation, the option value is given by one equation. The most famous equation of this type is the Black-Scholes Equation (Black & Scholes, 1973). This approach is highly accurate and inexpensive for simple options, but if the problem is complex this method is useless.
ii. *Trees and Lattices*: It has been firstly presented by (Cox et al., 1979). This method simulate the evolution of uncertainty in discrete scenarios facilitating the modeling of multiple options. This approach is less accurate than the PDE and become prohibitive for large amounts of scenarios. As reported in (Kodukula & Papudescu, 2006) a decision tree shows then a strategic road map, depicting alternative decisions with their property and especially the probability and the payoff of the outcomes. The expected value of an event is then simply the product of its probability of occurrence and its outcome.
iii. *Simulations*: They can be used to model the evolution of uncertainties. Monte-Carlo methods have the advantage that they are more efficient for high-dimensional problems and that the state space need not to be discretized (Hlouskov et al., 2005).

Therefore, it is a robust approach that can handle many types of RO. The most common approach is the Least Square Monte-Carlo Simulation, even if this work apply the Simulation and Optimization with Exercise Threshold(SOET) method developed in (Lotti, 2012).

For a more detailed analysis of the existing method for real option evaluation let us remind to (Kodukula & Papudescu, 2006).

2.2.3. Why the ROA in the Energy Field?

The RO approach is not necessary in every type of investment evaluation: on one hand it is less approximated than the classical DCF method because it considers uncertainty at source, but on the other hand it need a deeper analysis, requiring to model uncertainties and to implement in the model a real option valuation method, i.e. an algorithm that decides for every scenario the best moment to exercise the options to increase an objective function. In general the ROA increases both the expected return and the variability of the DCF. Indeed the most used real options evaluation methods implicitly maximize an objective function that is only the expected return of an investment and therefore they bring to results more profitable but more risky.
A significant number of uncertainties characterize long-term investment in the energy field. Therefore Real Options seems to be the most appropriate evaluation method because they consider opportunities that could arise after the decision of making the investment(e.g. waiting for the most advantageous moment to invest; abandon a not profitable investment; switching from a technology to a more profitable one).
In liberalized energy markets traditional investment calculations are inadequate. ROA is a more sophisticated approach that enables to take into account the “value of waiting” that accrues from the irreversibility of an investment, uncertainty, and the flexibility of postponing an investment in order to obtain more information about the future. Keeping the option alive, i.e. to maintain the feasibility to invest or not to invest, has a value that can be calculated (Madlener & Stoverink, 2012).

(Kulatilaka & Amram, 1999) summarized the circumstances where the real options approach is more fruitful and we report their conclusions here:
- Where 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 consideration. Only the real options approach can correctly value investments in flexibility
- When there will be projects updates and mid-course strategy corrections

A portfolio analysis in the energy field contain all these characteristics because it is high uncertain; flexible and a rational investor has the possibility to wait for making the investment at the more profitable moment, or to abandon the project if necessary. In this way we can consider the value that manager’s flexibility bring to the project evaluating it in a more appropriate way.
Furthermore, as reported in (Martínez Ceseña et al., 2013): *“RO theory acknowledges the ability of managers to modify their projects with the objective of maximizing profits and minimizing risks in a never changing world. The proper application of RO can enhance the expected value of projects under uncertainty. This makes RO theory attractive for the assessment of projects such as electricity generation projects(EGP)and renewable energy projects(REP)”.*
Real options models can support decision making in the electricity industry in three important ways:

first, at the operational level, optimal exercise rules resulting from real options models can be used to
operate a power plant optimally. Second, the real options values can be used to make strategic investment decisions and to choose from various designs which differ in terms of flexibility and marginal
cost of production. Third, profit and loss distributions can be used to integrate physical production assets with financial contracts for the purpose of enterprise-wide risk management (Hlouskova et al., 2005).

The following table contains a brief summary of the characteristics of some recent works that apply real options in the energy field:

	(Yu & Tao, 2013)	(Jain et al., 2013)	(Zambujal-Oliveira, 2013)	(Detert & Kotani, 2013)	(Santos et al., 2014)
Scope of Work	Evaluate how all risks and uncertainties impact on the development of new Nuke PP in China	Help a utility determine the value of sequential modular SMR	Analyze different RO model type to assess the best for making investment in the energy sector.	Examine energy switching from non – renewable to renewable technologies in Mongolia	Apply a ROA to a mini-hydro PP case comparing its results with the results obtainable through the classical DCF approach
Real Option Evaluation Method	Partial Differential Equation (PDE)	Dynamic Programming Method	Binomial Tree	Simulation Method	Binomial Tree
Options Considered	Compound Option; Option to Invest; Option to Abandon	Option to Invest; Option to Abandon	Option to defer; Option to invest	Option to Switch	Option to invest
Outputs	Value of the Optio	E(NPV); Classical NPV	Value of the Options	Decision to switch; Option Value	E(NPV); Classical NPV; Option Value

Table 20. Summary of recent works that apply a real option approach in the energy field

One of the principal scopes of this work is to use then real options to make a strategic investment decision because we want to build a model that could help a utility to choose between different power plants, considering its actual portfolio of investments.

2.2.4. Portfolio Analysis with a Real Options Approach

In this section we are going to describe the main works present in literature that perform a portfolio analysis using a real option approach. Before starting we have to say that in literature does not exist a lot of works that apply real option to perform a portfolio analysis. Indeed we can easily find application of real option in the energy field like for example (Yu & Tao, 2013) that apply real option to evaluate the impact of uncertainties and risks on the development of new nuclear power plants in China.
Other works of this type are (Xu et al., 2012); (Takashima et al., 2012); (Gollier et al., 2004).
Because of the fact that in literature several works that report the application of real option analysis in the energy field exist we will not describe it in a detailed way. One example of good

summary of all standard real option application in the energy field is (Martínez Ceseña et al., 2013).

As already said, there are not a lot of works in literature that apply real option to perform a portfolio analysis in the energy field. However the importance of this type of analysis can be easily understood because, from the utility's point of view, every decision of investment in power plant must be analyzed in function of its own actual portfolio. (Hlouskova et al., 2005) implemented a real option model for the unit commitment problem of an electricity producing turbine in the German electricity market. In their work they highlighted the importance of considering the actual portfolio of a utility, mainly from the great influence that it has on the risk position of the company. Indeed they said: *"The risk position of the company is determined by the entire portfolio and the interaction of various positions, i.e., production facilities, financial contracts and also long term customer contracts. Therefore, the decision to enter into new contracts cannot be taken independently from the current portfolio".*
The same conclusion can be found in (Kjærland, 2007) in which the author built a real option evaluation model in order to perform a valuation study of hydropower investment opportunities in the Norwegian context in which there were a potential of 39 TWh not yet developed.

Another example of application of a real option approach to perform a portfolio analysis can be found in (Kumbaroglu et al., 2005). However, we have to say that the scope of their work was not to perform a portfolio analysis but they presented an investment planning model that evaluate investment alternatives in renewable power plants in the Turkish electricity market. Their model works in a recursive manner on a year-by-year basis, guide optimal investment planning in the electricity supply sector and is based on the real option approach to investment.

A remarkable work that develop a Real Option Model to perform a portfolio analysis in the electricity sector is (Fortin, Ines et al., 2007) in which the authors combined a real options framework with portfolio optimization techniques using CVaR as the measure of risk. They developed a real options model to find the optimal timing of investment into carbon capture and storage modules in the case of coal-fired and biomass-fired power plants. Outputs of the real options model are the optimal investment strategy and its implied return distribution; the return distribution, then, was employed as an input into the portfolio optimization. Before them, (Spangardt et al., 2006) presented the idea of optimizing a power portfolio. They did not explicitly suggest a real options framework but their stochastic optimization setup is similar to the real option analysis performed in (Fortin, Ines et al., 2007).
(Doege et al., 2005) and (Unger & Luthi, 2002)used a similar framework to model the operational flexibility of a hydro pump storage plant and showed how to dispatch it to hedge against adverse movements in the portfolio. They maximize expected profit of a given power portfolio while restricting overall risk.

Another work that apply ROA to considering the existence of a portfolio of investment is (Liu, 2012a)in which the author studies the optimal abandonment decision to shut down a power plant in an energy portfolio, with the objective to maximize expected long-term profit over an infinite time horizon. The same framework developed in this work was then used in (Liu, 2012b)in which the author studies a firm that is considering the introduction of a new plant in its actual portfolio as an alternative to generate electricity. The firm's decision includes the optimal entry time for the new plant, and the optimal dispatch between the existing plant and the new plant after it has been constructed to maximize the expected profit over an infinite time horizon. They solved the problem decomposing it into two auxiliaries problems, and they characterized the optimal strategies in closed-form by standard value-matching and smooth-passing conditions.

Most recently (Fuss et al., 2012) analyze the impact of uncertainty on investment decision-making at the plant level in a real options valuation framework, and then use the GGI Scenario Database (IIASA, 2009) as a point of departure for deriving optimal technology portfolios across different socio-economic scenarios for a range of stabilization targets, focusing, in particular, on the new, low-emission targets using alternative risk measures: they applied the CVaR method to perform the portfolio analysis.

Another different and recent work that apply a real option approach in an integrated framework with the MVP theory to perform a portfolio analysis is (Jain et al., 2013). In this work the authors built a two-steps framework to evaluate the effects that risks and uncertainties have on a nuclear power plant:

I. The authors developed a Real Option Approach based on the Stochastic Bundling Method(SGBM)[11] in order to take the decision to invest in a single PP.
II. The authors applied the MVP theory to find the portfolios on the efficient frontier.

Applying the RO the authors evaluated the distribution of the profits that each technology in the portfolio guarantee thanks to a backward approach made performing a Monte Carlo Simulation. Furthermore, in this way, they have been able to find out the optimal policy of investment that a utility should do considering the possibility to abandon an investment if the scenario is not profitable anymore.
After that they discovered the best policy of investment for each possible technology in the portfolio, thanks to a MCS Simulation, they find out the E(NPV) and σ(NPV) of the overall portfolio made up by the technologies considered. As a consequence, the last step of their analysis was to build the efficient frontier and to compare the actual portfolio they hypothesize with it.
Therefore, the output of the MVP Theory are the same obtained before them by all classical works summarized in Table 18. We can say that this kind of method does not use in the most efficient way all the advantages that a RO evaluation model have compared to the classical DCF Approach. Indeed, each technology in the portfolio remains a single static point in the plane E(NPV) – σ(NPV) that vary only in function of the scenario hypothesized(Figure 27).
As a result, they did not solve the main drawback of the MVP Theory expressed in (Madlener & Wenk, 2008) that we report in paragraph 2.1.3.

Applying the SOET method with the MVP theory we aim to solve this problem building a dynamic framework in order to give to the utility the best decision of investment in function of the snapshot variation of the contest. The idea is, when possible, to consider a set of different exercise thresholds and calculate the different effects on the output distribution (e.g. the NPV distribution of the whole portfolio calculated applying the MVP theory).
In practice, as will be illustrated in chapter 3, this method applies SOET to a portfolio of technologies before the MVP. MVP will then calculate as output the NPV distribution of the total portfolio.
According to this value and to a defined objective function we will then use a Search Algorithm to generate the best exercise threshold and for each technology in the portfolio we will calculate, through a MCS, several performance indicators that MVP will summarize in the Expected Mean and the standard deviation of the NPV of the total portfolio.

In the following table we summarize the characteristics of the most recent works that apply a real option approach to perform a portfolio analysis comparing them with this work.

[11] Real Option Evaluation Method quite similar but less used than the LSMC Method

	This Work	(Jain et al., 2013)	(Liu, 2012a); (Liu, 2012b)	(Fuss et al., 2012)	(Kumbaroglu et al., 2005)
MODEL					
RO Evaluation Method	SOET Method	SGBM Method	PDE	Dynamic programming method	Dynamic Programming Formulation
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	Option to invest; option to choose
TTM Effect	Modeled	Not considered	Not considered	Not considered	Not considered
Pre – Operating Phases	Modeled 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	Only the construction phase is considered
Actual Portfolio	Influence results	Results not influenced	Influence results	Results not influenced	Results not influenced
Method used to perform the portfolio analysis	MVP Theory	MVP Theory	Stochastic Dominance	CVaR Method	Not specified
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 PDE 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	Value of the option

Table 21. Summary of recent works that apply a real option approach in the energy field

2.3 Simulation Optimization with Exercise Thresholds (SOET)

The approach developed in (Lotti, 2012) is based on the MCS and then the core of the method is the evaluation model (Figure 32. Classical SOET Method) that generate the distribution of the output variable from the inputs, both deterministic and stochastic.

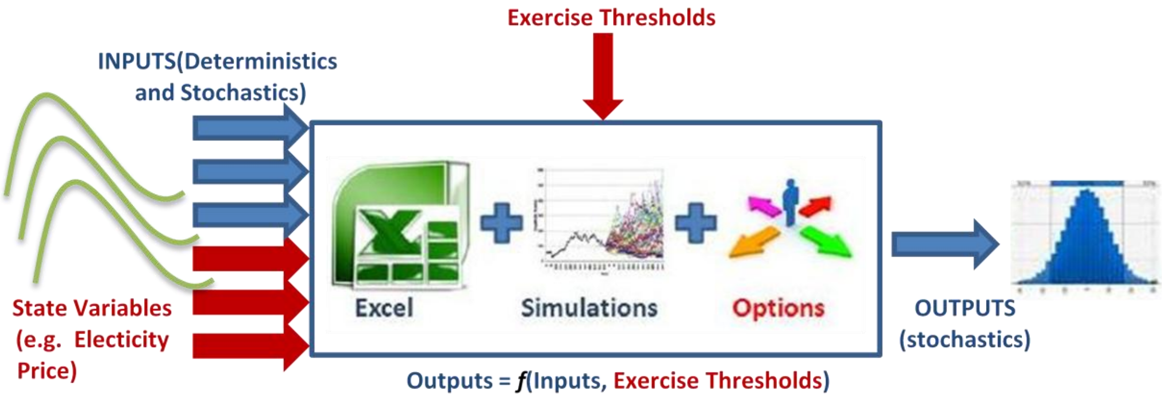

Figure 32. Classical SOET Method (Lotti, 2012)

The idea of this method is to use an exercise threshold in order to trigger the investment. One exercise threshold regulates the moments of exercise of the options, in function of the value of the state variables. Then the output distributions (e.g. the NPV distribution) are not only functions of the inputs, but also of the exercise thresholds. There are then infinite exercise thresholds that can be adopted, and each one of these triggers differently the options. We could have exercise thresholds that trigger the investment only with extremely profitable scenarios, like when the value of the price of the electricity is very high, some other that trigger the investment also in less profitable scenarios, while some others will consider the scenario at time zero sufficient to invest immediately. Then, if the exercise threshold influence the output distribution, we can find the optimal exercise threshold that maximize a specific objective function(e.g. maximum Returns). Therefore, a MCS that uses this exercise threshold would bring to the "best" output distribution. Then the aim of these methods is to compare different exercise thresholds (e.g. the price P* to reach) to find the preferred one.

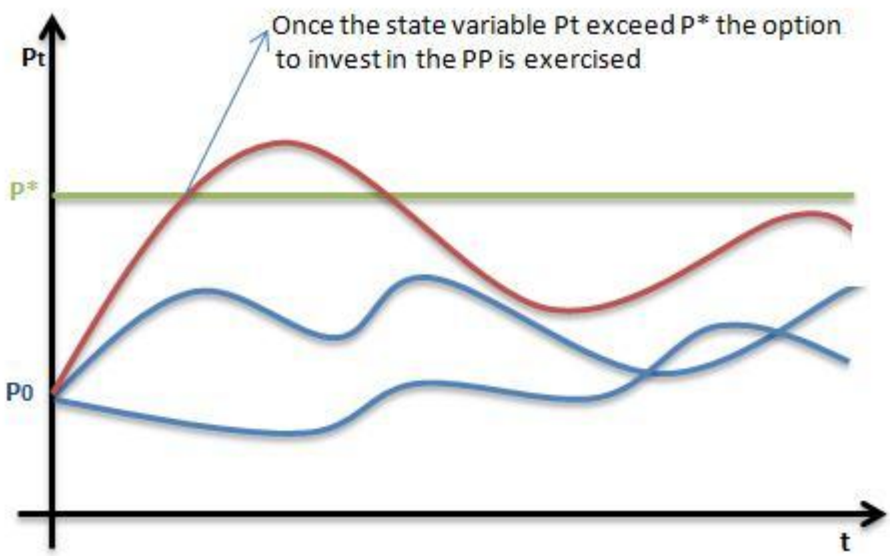

Figure 33. The exercise threshold trigger the option to invest

In summary, different exercise thresholds generate different output distributions (e.g. the NPV) because:

a) The exercise thresholds are conditions that determine the best timing in which exercise the option

b) The timing impacts the output distributions

The advantages of this method, in comparison with other real option methods(e.g. LSMC) are:

- It's simple to be used because it can be easily implemented in an excel spreadsheet thanks to Excel-Add In
- We can have every kind of objective function:
    - Maximization of profits
    - Minimization of risks
    - Maximization of profits given a fixed value of risk
    - Minimization of risks given a fixed value of profits
    - Maximization of the Sharp Ratio Parameter
- It allows to model every uncertain variable without increasing the complexity of the problem but only increasing the computational effort
- It produce two outputs:
    - The expanded NPV distribution
    - The exercise threshold

We report now the differences between the SOET and the LSMC Method, the most diffused RO method to solve complex problems in literature:

	LSMC	SOET
Inputs	Both Deterministic and Stochastic	Both Deterministic and Stochastic
Outputs	Value of options; Total NPV	Exercise Thresholds and the Total NPV
Objective Function	NPV Maximization	You can choose every kind of objective function, including a risk evaluation too
Optimization Mechanism	Dynamic Programming	Global Optimization
Focus	The Value of options	The Exercise Thresholds
Results' Precision	It needs a great amount of iterations to find a result. It happens because the algorithm takes its decisions while it is performing the MCS	When an exercise threshold is found, the method perform a normal MCS and therefore it is very reliable and precise.
Implementation	It must be totally programmed	It can be implemented with excel adds-in
Numbers of options	Theoretically infinite, even if the model becomes very complex if we add interactions between options	Theoretically infinite, there is only a computational limit
Numbers of state variables	Theoretically infinite	Theoretically infinite

Table 22. Comparison between LSMC and SOET Method: adapted from (Lotti, 2012)

2.3.1 Description of all possible methods

The basic idea of the SOET Method is one but there are three methods to implement it. The first method is defined as the discrete enumeration of all possible thresholds; the second is defined as the discrete enumeration of all possible states and the third is the most general and can solve theoretically every kind of problem, with infinite interactive options, state variables, but it's more expensive computationally.

We remind to (Lotti, 2012) for a more specific description of all this method but we report here a table in which we compare the characteristics of all of them.

Voice of Comparison	Discrete Enumeration of all possible thresholds	Discrete Enumeration of all possible states	Search Algorithm
Idea of The Method	It generates a discrete sample of all possible thresholds, and for each one generates, through a MCS, an NPV distribution. Then it calculates some important indicators (e.g. mean and standard deviation) from each NPV distribution, helping the model user to select the exercise thresholds that generate the NPV distribution preferred.	The method aims to simulate every possible "situation", that is every possible combination of the state variables (e.g. all the combinations of the price of electricity). Then, for every possible situation the question is "in which situation is better to invest or to wait?"and not "which value of the state variable is better to wait, given the initial state?".	Given an initial state (the initial value of the state variables), it generates several exercise thresholds and for each one calculates, through a MCS, several performance indicators. This method doesn't enumerate all possible thresholds but searches the best exercise threshold through algorithms. It tries a solution, check its goodness, and in function of this goodness try another one, jumping from one solution to another, searching the best one/s.
Advantages	It allows to compare all possible thresholds directly, understanding the pattern of the problem. It is the best method to solve problems with one state variable	It is the most précis of the method.	It is fast and it is the most general of the method and can solve theoretically every kind of problems, it is the best method to solve problems with several interacting options
Drawbacks	With more than one state variable is difficult to understand the pattern of the problem. It can be applied to problems with several interacting state variables.	It can maximize only the expected NPV and thus it can't show the risk component. It need an algorithm to generate results if it is applied to problem with several state variables	It can offer only one considered "best" solution even if it is not very precise.
Solutions	Multiple. It produces a Pareto frontier.	One. The one that maximize the expected NPV	In the actual development one. The one that maximize the objective function

Table 23. Difference between the existing SOET Method

We have to say that there is not a method that is better than the others but they bring to the same results. An investor have to decide the most appropriate method to be used in function of the type of analysis he is going to perform. Concluding, these methods are complementary and they should be used together, when it's possible, to generate significant results.

2.3.2 Extension of the analysis

Starting from the SOET method and from the existent literature described here we extend the analysis solving some of the limitations that those work have and that does not permit to perform a portfolio analysis in an effective way.

Indeed, in this work our aim is to apply the SOET model extending it to perform a portfolio analysis in the energy sector. Respectively to the classical SOET Method and to the existent literature the model contains the three following innovations:

1. Modeling the Time To Market Effect. It means that we will consider the whole period required after the utility decides to build a new power plant, instead of only the construction period.

2. Considering the intrinsic flexibility of an investment in a nuclear power plant. The pre-operating phase will be modeled as the succession of three sequential phases that we evaluate as compound options.

3. Considering the actual portfolio of a utility. This third step will be made up of two different phases:
    a. To expand an actual hypothesized portfolio following the growth of the demand of energy. The purpose of this analysis is to give an insight to the potential of the SOET Method integrated with the MVP
    b. To apply this new framework to the real EDF's portfolio of investment in UK.

2.3.3. Extension to the SOET Method: modeling the TTM Effect

"Time to Market" is defined in (Pawar et al., 1994) as "the strategy of focusing on reducing the time to introduce new products to market".
Considering the *"TTM effect"* in the energy field means that we have to take into account that the effective time elapsed from the moment in which the final decision to invest is taken and the moment in which the plant starts to produce energy is longer than the time necessary only to build the PP. Table 24 shows this effect. From that table it is easy to notice how this effect is significant in the nuclear case for which the time needed to start the production pass at least from six to nine years.
The problem is that in ten years the financial, economical and social conditions could significantly change making the investment not convenient anymore.

As already said, if we want to create an effective framework to perform a portfolio analysis in the energy field we have to improve the models described in literature that take into account the pre-operating phase of power plants modeling it only considering the construction phase.
This assumption is too unrealistic because we can't expect that a utility begin the construction of the power plant the day after the decision to invest in it is taken.
The purpose of the analysis that we want to make is to give a deeper insight in modeling the pre-operating phase of a power plant. Studying the typical time elapsed from the moment in which the decision to invest in a power plant is taken and the moment in which it begins to produce electricity we noticed a great difference between nuclear power plants and the other power plants.

In the following table we report the so-called "Time to Market" for the base-load power plants that we will consider in our analysis.

Technology	Study Phase	Design Phase	Construction Phase	TTM
Nuclear PP	1 Year	2 Years	6 Years	9 Years
SMR PP	1 Year	2 Years	5 Years	8 Years
Coal PP	1 Year		4 Years	5 Years
CCGT PP	1 Year		3 Years	4 Years

Table 24. Benchmarking between Time to Market base-load power plants

We take the model in three pre-operating phases for the nuclear PP-case from (TIACT, 2005) in which the authors evaluated the feasibility of siting and commissioning a nuclear plant to serve the future energy needs of Texas Gulf Coast and users. Starting from the fact that no nuclear plant has been built in those years, they suggested that the reason for which it happened was the lack of a business model that could overcome the formidable financial risks characterizing an investment of this type. We report now the finding they made and that we use in this work: "*These risks should not inhibit a management team from proceeding with project development. By employing an option approach, the project developer has the ability to delay or abandon the project at any time prior to construction. The investment of development capital, which by design will be small when risks are highest, would be lost but a far greatest lost would be avoided".* Therefore they created an innovative business model that break the project into manageable stages. At each stage the need for development capital is appropriately matched to the level of risk. This approach does not require a one-time, irreversible decision for investors to commit to the multi-billion dollar investment needed to build a new unit. One of the aim of this work is then to develop this model in a more sophisticated way thanks to the SOET Method in which the investment decision in each of the three pre-operating phases we considered is seen as the succession of three compound options. Indeed at the end of each of these phases the investor has the right to continue, to delay or to abandon the investment according to the evolution of social and environmental conditions. A similar approach can be found in (Graber & Rothwell, 2006).

A more detailed description of the three pre-operating phases that we considered is reported in the following table.

Pre-Operating Phase	Information to be acquired or action to be taken before starting it	Information to be acquired or action to be taken before finishing it
Study Phase	• Raise development capital for paying this phase • Assemble a project development team, including supporting legal, engineering and public relations firms. • Develop a strategic plan for the project • Create an ownership consortium	• Enter into an agreement for host site • Prepare a set of technical bid specifications respecting the normative • Request and evaluate bids for total plant supply • Negotiate Engineering Procurement and Construction contract with plant supply team • Initiate the community outreach program • Make initial contacts with lending sources to identify cost of funds and likely obstacles. • Hire a leading environmental firm to prepare and defend the project in terms of environmental and social impacts
Design Phase	• Raise development capital for paying this phase • Have in hand a binding commitment to an EPC cost that yields a total overnight capital cost to be under a defined value • Finalize the site agreement • Develop a plan for preparing and supporting the License application	• Obtain PPAs for balance of plant output not committed to the owners • Prepare and submit the COL(Combined License) Application for NRC(Nuclear Reactor Construction) approval • Develop a legal strategy to combat delays during construction • Develop a strategy to obtain construction funding • Obtain debt financing at least on a tentative basis
Construction Phase	• NRC approval of the Construction License • Obtain construction funding • Permanent financing obtained • Finalize ownership structures	• Construct the plant • Put in place management team either by outsourcing or by recruitment • Load fuel and begin startup • Refinance and adjust permanent capital structure

Table 25. Description of the pre-operating phases characterizing a Nuclear PP. Adapted from (TIACT, 2005)

The assumption we made about the time elapsed from the moment in which the decision to invest in a PP is taken until that it starts to produce energy is realistic considering the USA or European Scenario. Indeed in the USA the NRC is expected to take three years to review each COL application (WNA, 2012), while other countries like China has a faster system that permit to the utility acquire the license in a shorter time.

The description of the pre-operating phase of a nuclear PP as the succession of three sequential stages with fixed length is a realistic simplification of what happen in reality. Indeed (IAEA, 2012) shows a figure that describe in a more appropriate way the time and length of it.

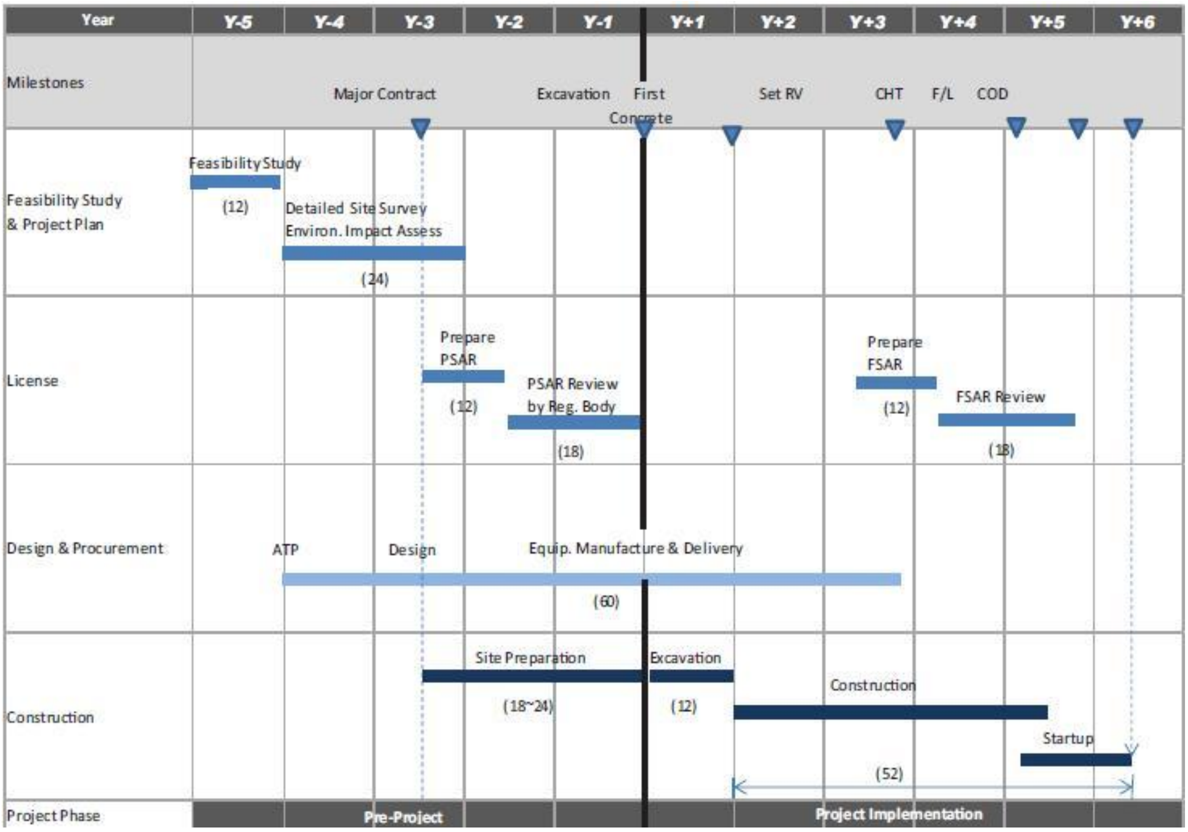

Figure 34. Typical durations for the main contracts (IAEA, 2012)

In this work we will not consider the start-up phase after the construction of the PP is finished but we make the assumption that the PP starts immediately to produce at the maximum of its capacity. The reason of this choice is only to simplify the analysis but it can be implemented in the model in a very easy way considering a lower and specified capacity factor for the first year after the construction is finished.

We can make a parallelism between the phases we described in Table 24 and the stages shown in the figure above.

- The first pre-operating phase (called Study Phase in this work) corresponds to the "Feasibility Study" phase in (IAEA, 2012)
- The second pre-operating phase (called Design Phase in this work) corresponds to "The detailed site survey; Environmental Impact Assess" phase in (IAEA, 2012)
- The third pre-operating phase (called Construction Phase in this work) corresponds to the last row of the figure above: the "Site Preparation; Excavation; Construction" phase in (IAEA, 2012).

From the Table 24 we can see that the time needed to starts to operate for a Coal or a CCGT power plant is relatively short, while a nuclear power plant need several years and this time will depend if this is the first power plant to be built or not.

"*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 power plant project*" (IAEA, 2012).

If this is the first power plant, the a utility need around 10 – 15 years and in some cases even more to build a nuclear power plant because you need to put in place before the construction start the necessary infrastructure, particularly the establishment of the nuclear regulatory authority, the adoption of a national legal framework and the approval of certain international agreements, the indispensable safety infrastructure, the training of the operators, the identification of the financial resources to be used, the necessary nuclear installations to support the implementation of the nuclear power program adopted, to have a size and capacity of the electrical grid that is between 7 and 10 times the capacity of the reactor to be built, among others. If this is not the first nuclear power plant to be built, then you need around 5-6 years to built it, depending of the experience the country has, the type of reactor to be built, among others (Pedraza, 2012). A more detailed description of the typical lengths of the construction phase of a nuclear PP can be found in (Thurner et al., 2014) in which they statistically explain the duration of the construction of all initiated nuclear plant projects.
We report here several example of these differences considering nuclear PP cases studied in (Thurner et al., 2014) in which the authors shows that even within countries there is a significant variations with regard to the construction duration of reactor projects.

Power Plant's Name	Where is located?	Length of the Pre-Operating Phases
Angra 2	Brazil	295 months (≈25 years)
Khmelnitski 2	Ukraine	235 months (≈20 years)
Olkiluoto 3	Finland	After 168 months (14 years) it is not finished
CEFR reactor	China	135 months (more than 11 years)
TIANWAN-2	China	80 months (≈7 years)
Gravelines-4	France	63 months (5,25 years)
St.Laurent-B-1	France	57 months (4,75 years)
St.Laurent-B-2	France	60 months (5 years)
Super-Phoenix	France	110 months (≈9 years)
Grafenrheinfeld	Germany	84 months (7 years)
Muelhein-Kaerlich	Germany	135 months (more than 11 years)
This Work	**USA or Europe**	**108 months (9 years)**

Table 26. Examples of lengths of pre-operating phases of Nuclear PP: data from (Thurner et al., 2014)

(Flyvbjerg, 2006) made an analysis about the major sources of risks incurring in an uncertain project. He analyzed large costs for large transportation infrastructure projects showing that the number of projects in delay or more costly that budgeted is huge. (Thurner et al., 2014) shows that its results can be extended to the energy field too.
He summarized the reasons for this delays in two main reasons called:
- Optimism Bias: "Cognitive predisposition found with most people to judge future events in a more positive light than is warranted by actual experience".
- Strategic Misrepresentation: "Forecasters and managers deliberately and strategically overestimate benefits and underestimate costs in order to increase the like hood that is their projects, and not the competition's, that gain approval and funding".

The aim of our work is not to deepen this factors and to model it but this widespread problem clarify why we can't avoid to model the pre-operating phase of a nuclear power plant in a more detailed way that what is done in the previous works present in literature. Indeed, considering only the construction phase in the evaluation model, underestimate the cost and the length of the pre-operating phase of nuclear power plants.

Considering the *"TTM effect"* in the energy field means that we have to take into account that the time elapsed from the moment in which the final decision to invest is taken and the moment in which the nuclear plant starts to produce energy pass from at least 6 to 9 years. On one hand, the problem is that in ten years the financial, economical and social conditions could significantly change making the investment not convenient anymore. On the other hand, (TIACT, 2005) and (Graber & Rothwell, 2006) showed us that an investment in nuclear power plants is intrinsically flexible.
As already said, they developed a Real Option approach that explicitly takes into account the market risks faced by a nuclear plant developer, as well as the flexibility to continue or abandon the investment as new information become available.
As reported in (Graber & Rothwell, 2006)*"new nuclear power plants are expected to take up to 10 years or more from inception to start-up. There are three sequential phases that characterize the project and each of them is relatively independent to the other. They also must follow in order".*

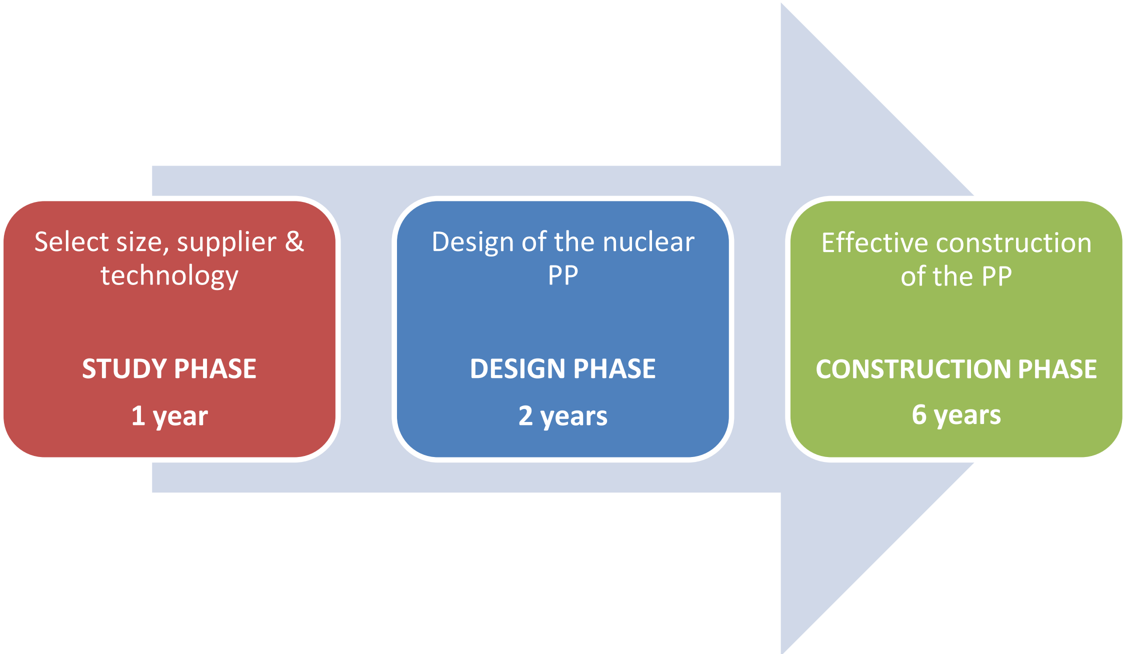

Figure 35. Sequential compound options of the pre-operating phases of a Nuke PP

This is what is called a "*Compound Option*". It is a multistage project investments where management can decide to continue or abandon the project after gaining new information to resolve uncertainty. This capital investment project can either be terminated or continued into the next phase depending upon the market conditions at the end of each phase. These are compound options where exercising one option generates another. A compound option derives its value from another option — not from the underlying asset. The first investment creates the right but not the obligation to make a second investment, which in turn gives you the option to make a third investment (Kodukula & Papudescu, 2006).
Indeed "Sequentially" in this context means that the next option only becomes relevant if the previous one is actually exercised(Madlener & Stoverink, 2012).
In the case in which the project is abandoned the funds expended until that moment are lost.
In the following box we report a brief summary about compound options describing its characteristics and its most remarkable applications present in literature.

Compound Options: a brief description

Many project initiatives (research and development, capacity expansion, launching of new services, etc.) are multistage project investments where management can decide to expand, scale back, maintain the status quo, or abandon the project after gaining new information to resolve uncertainty. For example, a capital investment project divided into multiple phases, including permitting, design, engineering, and construction, can either be terminated or continued into the next phase depending upon the market conditions at the end of each phase (Kodukula & Papudescu, 2006).

These are compound options where exercising one option generates another, thereby making the value of one option contingent upon the value of another option. A compound option derives its value from another option — not from the underlying asset. The first investment creates the right but not the obligation to make a second investment, which in turn gives you the option to make a third investment, and so on.

A compound option can either be sequential or parallel, also known as simultaneous. If you must exercise an option in order to create another one, it is considered a sequential option. For example, you must complete the design phase of a factory before you can start building it. In a parallel option, however,

both options are available at the same time. The life of the independent option is longer than or equal to the dependent option.

It is not easy to find application of this kind of option in literature because of the complexity that the evaluation model assume to apply it.

One of the first application of this kind of option can be found in (Geske, 1977) in which the author applies the technique for valuing compound options to the risky coupon bond problem. Instead, (Geske, 1979) presents a theory for pricing options on options, which means to evaluate a compound option. He showed that the Black-Scholes formula is only a special case of the compound option formula that he derived.

More recently (Siddiqui et al., 2006) developed an approach to determining the option value of research, development, demonstration and deployment (RD^3) programs on renewable energy technology. They apply compound options thanks to a binomial lattice model. (Cheng et al., 2011) built a modified binomial lattice model to apply compound options in order to create a flexible management approach to decide the clean energy strategies that are embedded with a lead time. Thus, they provided a sophisticated approach for the government to make the national clean energy policy and for the electricity industry to map their corresponding measures of meeting the policy.

Instead (Ghosh & Troutt, 2012), starting from the fact that top managers do not appear to share the increasing interest in adopting real options due to the complexity of the existing option pricing models(OPMs), propose a general framework to help practitioners to successfully operationalize complex OPMs developing a layer of abstraction to translate the academic knowledge into procedural knowledge for using the model.

However their purpose was not easy because the only approaches that existed to apply real options to complex problems were the LSMC and the SGBM methods. The problem of these methods is that they are intrinsically complex because both of them must be totally programmed and need a huge amount of iterations to find results. We want to overcome this problem by applying the SOET Method to evaluate the pre-operating phases of nuclear power plants modeling them as the succession of three sequential compound options that can be easily implemented in an excel spreadsheet thanks to existing Excel Add-in.

In this way we aim to create an easy-comprehensible option pricing model that practitioners could use to evaluate investment in the energy sector.

Box 2. The Compound Options

(Madlener & Stoverink, 2012) applied a similar approach to determine the economic feasibility of constructing a 560MW coal-fired power plant in Turkey. In their work they expressed the advantage of modeling the pre-operating phases as the succession of sequential stages as follow: *"The relatively high option value compared to the NPV of the project makes clear that the feasibilities of reacting during project realization, depending on market developments, can be assigned a substantial value. A further advantage of the ROA for a staged or sequential investment lies in the fact that it also delivers, besides the option value of the investment, the optimal strategy for exercising the option"*
Therefore, in this work, we apply the SOET method to this framework and, gaining information about delays and costs incurred in the previous phases of the project investment, we aim to find the best condition (the best exercise thresholds) to decide to continue the investment for each of them. The assumption is made that the decision about continuation of the project realization is made in discrete points in time. We remind you to next chapter for a deeper insight and description in how we model this three sequential phases as compound options.

2.3.4 Extension to the SOET Method: considering an existing Actual Portfolio

The other great limitation that the classical SOET method have is that it is does not consider the presence of an actual portfolio of already existing investment in other power plants. In summary we can't apply the standard methodology to evaluate a real investment in this field. As reported in (Fortin, Ines et al., 2007): "*Large investors would typically want to invest in a portfolio of technologies rather than concentrate on a single technology".*
An evolution of this work would be then to include in the inputs the already existent energetic portfolio, defined as the set of power plants that supply energy to the region analyzed. Therefore we aim to create a totally new and complete framework to evaluate an investment that, from the utility's point of view, is always an investment placed in a wider portfolio of investment in the same sector.

In the first part of this analysis, considered an actual and hypothesized portfolio, we study the influence of adding a single power plant on the return and on the variability of the whole portfolio showing what is the best solution for the utility in terms of return and variability in the case study considered and showing the improvement that the application of the SOET Method integrated with the MVP bring to the classical MVP theory. In the second part of the analysis instead, we apply this new framework to a real case study considering the energetic portfolio of EDF in UK.

As already said, one of the main drawback of the MVP Theory that is limiting its application is reported in (Madlener & Wenk, 2008): "*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".*

Applying the SOET method with the MVP theory we solve this problem and one of the aim of this work is to verify it.

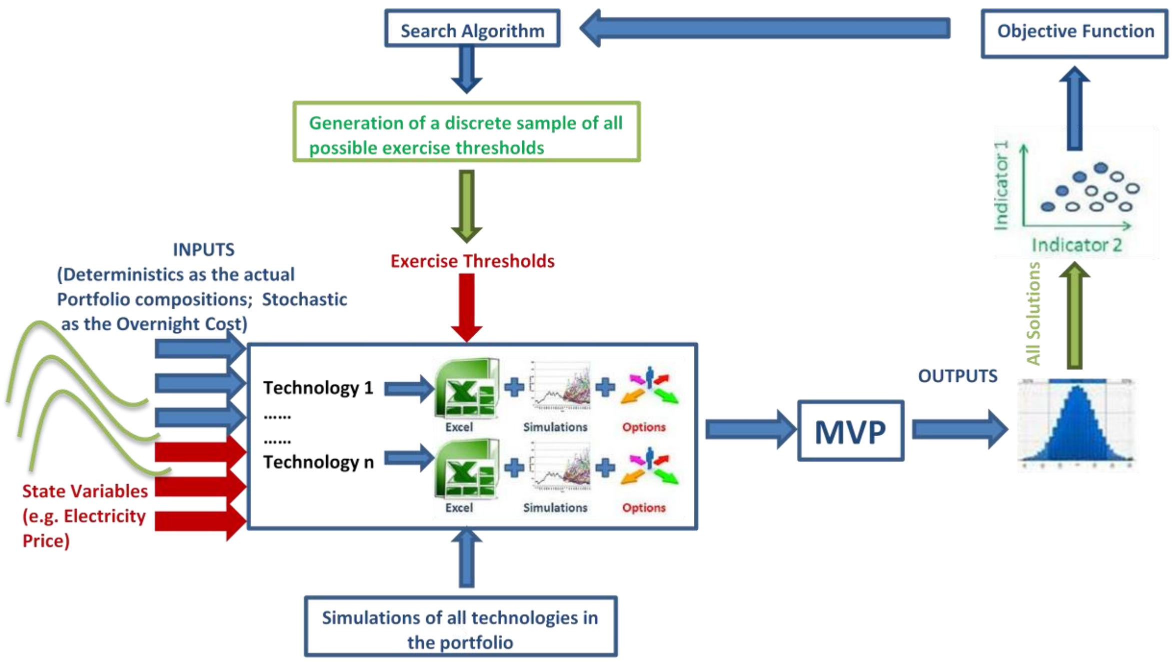

Figure 36. The scheme of the framework that apply the SOET Method to the MVP theory

The idea is, when possible, to consider a set of different exercise thresholds and calculate the different effects on the output distribution(e.g. the NPV distribution of the whole portfolio calculated applying the MVP theory).
In practice, as will be illustrated in chapter 3, this method applies SOET to a portfolio of technologies before the MVP. MVP then calculates as output the NPV distribution of the total portfolio.
According to this value and to a defined objective function we will then use a Search Algorithm to generate the best exercise threshold and for each technology in the portfolio we will calculate, through a MCS, several performance indicators that MVP then summarize in the Expected Mean and the standard deviation of the NPV of the overall portfolio.

We extends the model presented in (Lotti, 2012) considering portfolios in a very similar way than what he did considering single technologies: MVP indeed let us treat the performances of each portfolio as a single power plant and therefore we are able to compare them in terms of expected return and level of risk (see Equation 2.6 and 2.7 for the case of application of the MVP theory to a portfolio of two technologies).
Therefore, starting from the actual portfolio of a utility we apply the option to invest using an exercise threshold to trigger all the additional investments in new power plants to reach the new portfolio composition. With the search algorithm we will then be able to find the best exercise thresholds that maximize a certain objective function(e.g. maximum of total portfolio's return; minimum of total portfolio's standard deviation..) for each different possible portfolio composition.

We already know that the return of an investment in a power plant is function of the exercise threshold that triggers it too and that there is an optimum value at which is better to invest.

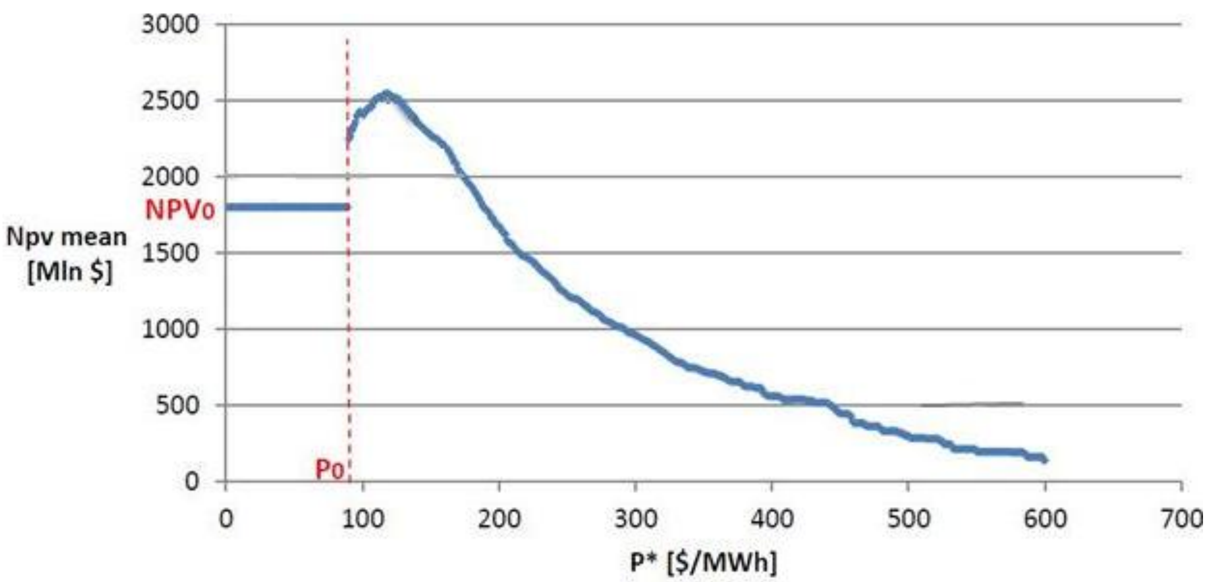

Figure 37. E(NPV) in function of the value of the electricity price(exercise threshold); (Lotti, 2012)

We use the same method to find the exercise thresholds at which each possible portfolio becomes most convenient according to a specific objective function, and then we compare each possible portfolio to find the "best" one for a specific level of risk.
Therefore, this approach could solve the problem described previously: in the classical way each portfolio on the efficient frontier is represented as a single static point on it, varying only according to the scenario considered.
We aim to build as an output of our model an efficient frontier for each single possible portfolio that will be function of the exercise thresholds: each portfolio performances is then represented as a curve and not as a static point anymore. In this way we are able to find the optimum condition to invest for each portfolio according to the future evolution of the uncertainties considered, and we would be then able to compare them thanks to the construction of an Optimized Efficient Frontier showing what is the best solution for the utility.

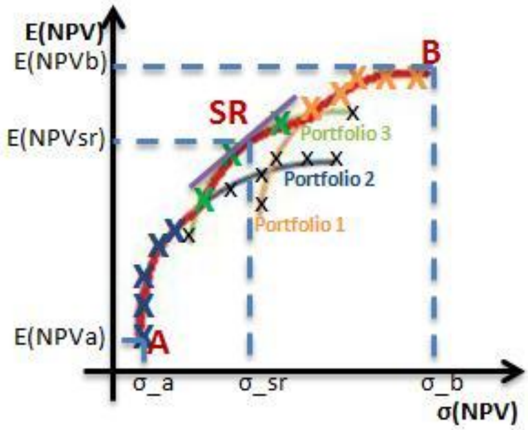

Figure 38. The Optimized Efficient Frontier

2.3.5 Comparison between classical MVP Theory and MVP with SOET Method

In the classical way we can say that:

- Every portfolio on the efficient frontier or, more generally, in the plane E(NPV) – σ(NPV) is represented as a single and static point on it and its position can vary only in function of the scenario hypothesized before the analysis.

- The efficient frontier is a static curve of portfolios equally efficient: each of them guarantee indeed the max return given a specific level of risk. It means that does not exist a portfolio on the efficient frontier that is better than the others: the only indicator we can use to differentiate their value is the Sharpe Ratio presented in (Sharpe, 1966).

- The steps usually followed to perform a portfolio analysis in the energy field are described in (Madlener & Wenk, 2008):

    1. Identification of the most relevant uncertain parameters(e.g. Electricity Price)
    2. Construction of the classical DCF Model that consider the uncertain parameters identified in the previous step for each technology in the portfolio
    3. Monte Carlo Simulation for each technology in order to find the expected mean value, the standard deviation and correlation coefficient between different technologies
    4. Definition of constraints that each technology in the portfolio have to respect (e.g. maximum possible output of a single technology in a certain area)
    5. Division of technologies between base-load power plants and peak-load power plants:
        - Base-Load: Nuke; SMR; Coal
        - Peak-Load: Renewable
        - Both of them: CCGT
    6. Creation of two different portfolios that consider all the existing technology in the portfolio: the first for the base-load and the second for the peak-load
    7. Assumption about possible future scenarios.
    8. Definition of portfolio for each of the hypothesized future scenarios respectively with:
        - Maximum Profit
        - Minimum Risk
        - Construction of the efficient frontier
    9. Construction of the actual portfolio
    10. Comparison between the performance of the actual portfolio and the portfolios on the efficient for every possible future scenarios
    11. Suggestions in order to let to the actual portfolio approach as most as it is possible a portfolio on the efficient frontier

An approach of this type presents several drawbacks that are limiting its use. Indeed all the result obtainable from it are function of the scenario hypothesized and therefore, a portfolio that is thought of as optimal today might be way off the efficient frontier because environmental and social conditions could have significantly changed respective to what a utility could have hypothesized some years before.
In this work our aim is to solve this problem creating a new framework that integrates the classical MVP theory and the application of the real option method with simulated exercise thresholds.
In this way we expect to find this results:

- The output of the model will be an efficient frontier for each single portfolio in function of the value of the exercise threshold. The performance of each portfolio(expected return and risk) will be then represented on a curve and not on a static point anymore.

- We can find the value of the exercise threshold that maximize the value of each portfolio in function of different objective functions (maximization of profit ;minimization of risks;

maximization of the Sharp Ratio value). It will be then possible, in function to different exercise thresholds, to compare different portfolios and to choose the “best” of them for a specific objective function.

- The efficient frontier is not a two-dimensional curve anymore: each point on the curve built in the classical way have its own efficient frontier in function of the exercise thresholds.

- We could find a value of the exercise thresholds that maximize the value of each portfolio in function to the typical objective function that exist in literature:

    - Maximization of the total profit
    - Maximization of the total profit given fixed the actual value of risk
    - Minimization of risks given fixed the actual value of total profit
    - Minimization of total risks
    - Maximization of the Sharp Ratio

We summarize now the differences between the classical MVP theory and the MVP integrated with the SOET Method in the following table:

	CLASSICAL MVP THEORY	MVP + SOET METHOD
Way of Representation of portfolios on E(NPV) – σ(NPV) plane	Static Point	Two-dimensional Curve: each portfolio have its own efficient frontier in function of the exercise threshold
Form of the Efficient Frontier	Two-dimensional 2D Curve	Tri-dimensional 3D curve: the third dimension is represented by the value of the exercise threshold
Does the “best” portfolio exist?	No: each portfolio on the efficient frontier is the optimal.	Yes. We have, in function to the existing environmental condition, a portfolio that is better that the other (relatively to a specific objective function)
Future Scenarios?	Only hypothesized: future environmental condition could be really different that what a utility thought	Simulated through Monte Carlo Simulation: we could find the exercise threshold that maximize the value of each portfolio in function to the snapshot evolution of the environmental conditions.
Robustness and Validity of Results	Results are correct only if future scenarios has been correctly hypothesized. If not, a portfolio that is thought of as optimal today, might already be way off the efficient frontier tomorrow	Theoretically yes. Results are obtained trough thousands of MCS in a dynamic way following the snapshot variation of the contest(in terms of variation of the input values).

Table 27. Comparison between classical MVP Theory and MVP Integrated with SOET Method

Therefore it is becoming clear that the deeper purpose of this analysis is to demonstrate the methodology and the usefulness of the new approach to perform a portfolio analysis, and not to give ad hoc investment advice.

2.4 Conclusions of the chapter

The main messages from this chapter can be summarized as follow:

- Introduction of the most important method to perform a portfolio analysis and detailed description of the classical MVP Theory and of its limitations
- Brief Introduction to the Real Option Approach, to the existing methods to perform it and more detailed description of the SOET Method
- Examples of applications of Real Option Approaches to perform portfolio analysis in the energy field with a detailed descriptions of the limitation they have.
- Brief Description of the compound options and enumeration of works that apply it.
- Introduction to the three different innovations developed in this work to extend the classical SOET Method in order to perform a Portfolio Analysis in the energy field:
    1. Extension of the SOET Method considering the TTM Effect: the pre-operating phase of a nuclear PP is significantly longer than only the construction phase
    2. Modeling of the pre-operating phase of a nuclear PP as the succession of three sequential compound options.
    3. Development of a new framework to perform a portfolio analysis, that consider the actual portfolio of a utility, based on the integration between the SOET Method considering the TTM Effect, the compound options and the MVP Theory.

Chapter 3 - Implementing the model

This chapter presents the models used in this work. The goal is to apply a Real Option Approach (using the SOET Method) in an innovative and integrated way with the MVP Theory in order to perform a realistic portfolio analysis in the energy field.
This chapter contains the description of the models giving a deep and detailed insight to the three main innovations of this works. Therefore, this chapter is organized in this way:

- At first, it describes each of these innovation (paragraph 3.1, 3.2 and 3.3).

- Then, after the description of each innovation is finished, it validates the results obtained in all these three cases by applying an improved version of all the three standard SOET Methods developed in (Lotti, 2012).

A more detailed summary of the topics described in this chapter is reported here:

1. Paragraph 3.1 describes the model used to implement the Real Time elapsed from the moment in which the decision to invest in a PP is taken and the moment in which it starts to produce energy. Paragraph 3.1.1, paragraph 3.1.2 and paragraph 3.1.3 apply all the three standard SOET Methods with one state variable to the nuclear case validating the results of this model.

2. Paragraph 3.2 adds properly to the classical SOET Method three Sequential Compound Options to evaluate the Intrinsic Flexibility of the Pre-Operational phase of a Nuclear PP. Then paragraph 3.2.1, 3.2.2 and 3.2.3 apply the three standard SOET Methods to this case validating the results of this second model.
Instead, paragraph 3.2.4 extends this idea considering the possibility to wait between the pre-operational phases of a PP, while paragraph 3.2.5 shows how the model varies if an investor wants to apply it to evaluate investment in sequential PPs.

3. Paragraph 3.3 describes how we integrate the SOET Method with Compound Options and the MVP Theory in a new and innovative framework to choose which kind of investment in an additional PP is the most adapted in function to the actual portfolio of a utility and to the snapshot evolution of the environmental conditions. Paragraph 3.3.1 applies this method with one State Variable in the case of investment in a Large Nuclear PP in an hypothesized actual portfolio of investment integrating "the discrete enumeration of all possible thresholds" SOET method to the MVP theory. Then, paragraphs 3.3.2 and 3.3.3 validate this result integrating "the discrete enumeration of all possible states" and the "search algorithm" SOET methods with the MVP theory too.

4. Paragraph 3.4 describes briefly how to implement compound options with the option to wait between each of the pre-operational phases of a PP to the SOET Method and how the integration of this model with the MVP Theory must be done.

Finally paragraph 3.5 reports a brief summary of the main messages contained in this chapter.

3.1 Modeling the TTM Effect

The method discussed in this paragraph is the natural consequence of the description of the problem we made in paragraph 2.3.3.
We clarified there that considering the *"TTM effect"* in the energy field means we have to take into account that the effective time elapsed from the moment in which the final decision to invest is taken and the moment in which the plant starts to produce energy is significantly longer than the time necessary only to build the PP.
Table 24 shows how this effect is significant in the Nuclear PP case for which the time needed to start the production pass at least from six to nine years.

As reported in paragraph 2.3.3, the pre-operational phase of a power plant can be schematized as the succession of three sequential phases:

- Study Phase
- Design Phase
- Construction Phase

Therefore at this point of the analysis we want to show how results change applying the classical SOET Method if an investor considers all these phases, and not only the construction phase.
In order to do that, we refer the starting moment of the study phase in function of a particular value of the electricity price. Then, since the first phase is completed, there are information about the TCTD (*Total Cost to Design*) and about the TCTC (*Total Cost to Construction*).
The relationships between the three pre-operational phases that we used in all our analysis are taken by (Graber & Rothwell, 2006)and by (TIACT 2005). We report these relationships in the following table:

Parameter	Study Phase	Design Phase	Construction Phase
Cost	1%*K	5%*K	K
Time	1 Year	2 Years	6 Years

Table 28.Relationship between pre-operational phases of a nuclear PP(adapted from(Graber & Rothwell, 2006)and(TIACT, 2005))

Therefore, the following paragraphs summarize and improve the models developed in (Lotti, 2012) giving a more realistic representation of the pre-operational of a nuclear PP and comparing its results with the results obtained investing in other base-load PPs (e.g. Coal and CCGT).
In order to do that and to verify our results we improve all the three existing SOET methods to this case study considering the application with one state variable.

- The discrete enumeration of all possible thresholds
- The discrete enumeration of all possible states
- The search algorithm

3.1.1 The discrete enumeration of all possible thresholds: application with one state variable

The aim of this section is to apply the discrete enumeration of all possible thresholds' SOET method to evaluate an investment in a large nuclear PP considering all its pre-operational time. The idea is to consider a set of different exercise thresholds and calculate their effects on the output distributions (e.g. the NPV distribution). In practice, as illustrated in Figure 39, this method generates a discrete sample of all possible thresholds, and then for each one generates, through a MCS, an NPV distribution. Then from each NPV distribution are calculated important indicators (e.g. mean and standard deviation) that help the model user to select the exercise thresholds that generate the NPV distributions preferred.

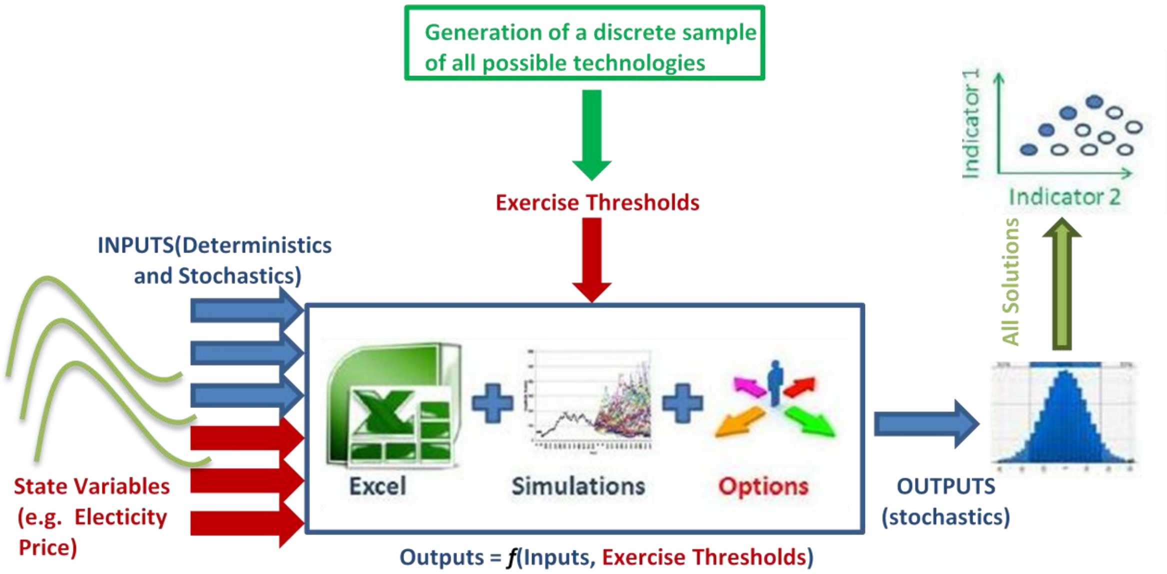

Figure 39. The discrete enumeration of all possible thresholds (Lotti, 2012)

This paragraph contains an example with one state variable to better understand how this method works and then to verify in a simplified way the validity of the results it gives. The most influential input variable is the electricity price and then, with only one state variable, the exercise threshold would be described by the variable P*. Hence, enumerating a discrete sample of all possible exercise thresholds means that we have to generate only different values of P*.

Therefore, let's evaluate the profitability of an investment in a large nuclear reactor both with the DCF approach and with the ROA through the application of the SOET Method with the discrete enumeration of all possible thresholds method presented here.

The DCF approach evaluates the profitability of the investment done at time zero with a MCS. The data used for this case study are properly presented in chapter 4 and are summarized in Table 38[12].

However, supposing that the electricity price follows a Geometric Brownian Motion with initial value $P_0 = 90\ \$/MWh$ and volatility $\sigma = 30\%$, it is possible to generate the stochastic distribution of the NPV of this investment.

[12] The mathematical relations between the inputs and the outputs are implemented in Microsoft Excel 2010 sheets and the simulations are added through a Microsoft Excel add-in: @Risk 5.5 of Palisade Corporation.

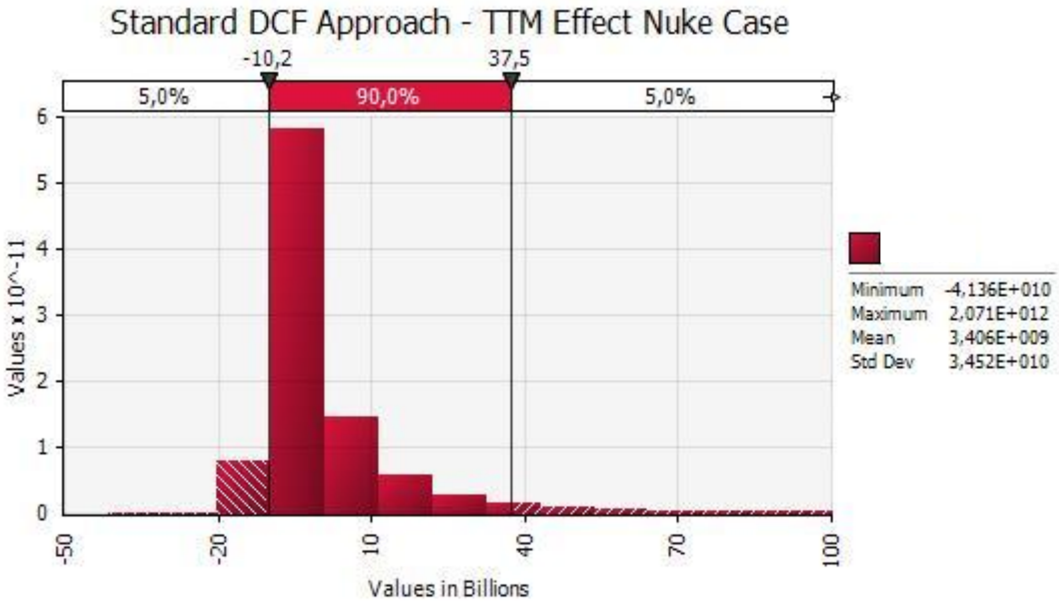

Figure 40. NPV distribution of an investment in a nuclear PP

The mean of the distribution is positive and then the classical DCF approach would suggest to invest. However, thanks to the SOET Method, an investor is able to implement the option to invest. As already said, this option will be exercised only when the value of the electricity price exceeds a specified threshold's value P*. It means that there would be scenarios (represented as iterations of a MCS) in which the option would be exercised and others in which it will not be done.

The steps to implement this method are reported here:

I. Consider a range of possible values of P*, defined by a lower and an upper bound. The lower bound has to be significantly lower than the actual electricity price, while the upper bound has to be significantly higher than it(highly improbable to be reached). In this example we choose $P^*_{LB} = 1\ \$/MWh$ and $P^*_{UB} = 600\ \$/MWh$.
II. Select all the values of P* in the range defined before for which a MCS would be performed. Implementing a step of 1 between one value of P* and the successive and then performing 600 simulations brings to optimal result, but we have to say that considering a larger step of 10 and then performing only 60 simulations brings to good result too.
III. Select the number of iterations for each simulation. In order to obtain a robust result at least 100000 iterations should be implemented.
IV. From each NPV distribution (each one obtained from a MCS) several statistical indicators are available. In this example these indicators are the mean and the standard deviation.

We can summarize the steps described above thanks to the following flow – chart:

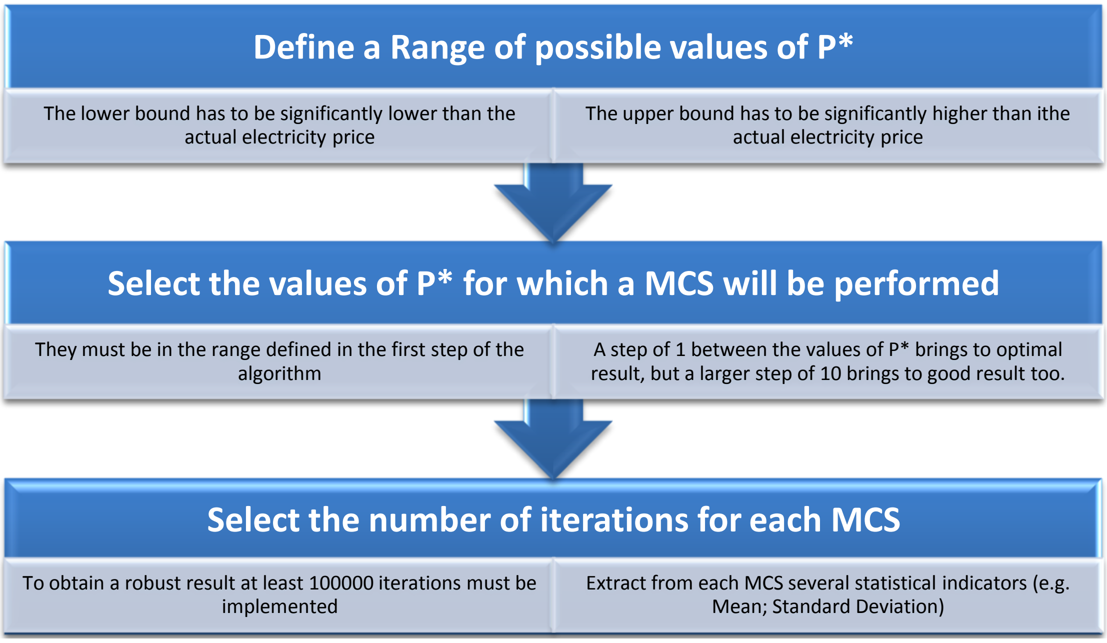

Figure 41. Steps of the discrete enumeration of all possible thresholds algorithm

The results are then obtained and the following figures represents the relation between P* and the NPV Mean and between P* and the NPV standard deviation. Those figures are obtained performing 60 MCS[13] with 100000 iterations for each simulation.

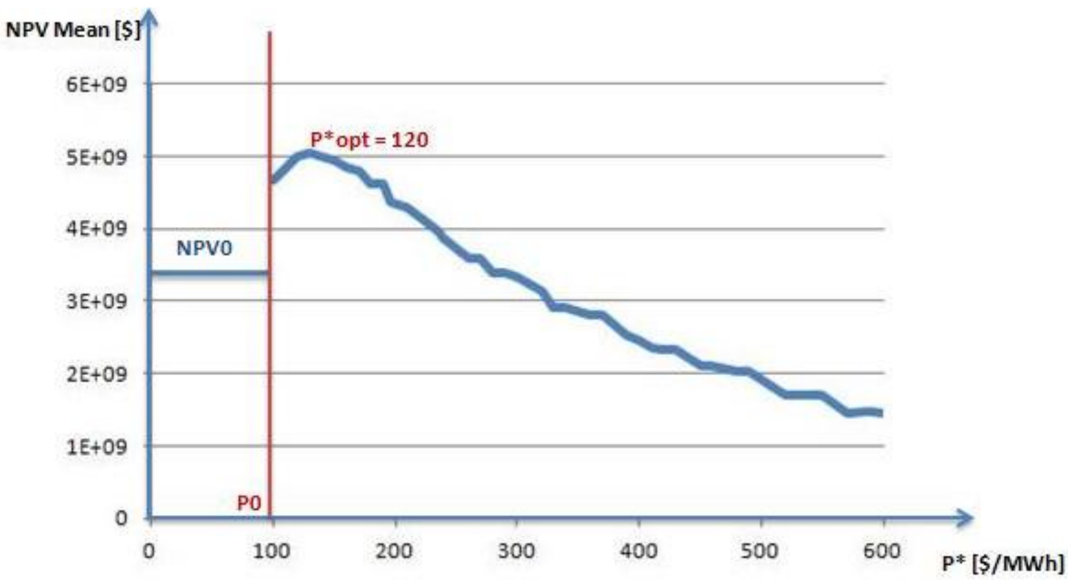

Figure 42. How the value of P* impacts on the NPV distribution

Some properties could be noticed from this figure:

[13] One for each value of P* considered.

I. When $P^* \leq P_0 = 90\ \$/MWh$ the option to invest is exercised immediately since P_0 already exceeds P^* and then all the NPV means obtained in this range are the same and are equal to the NPV_0 obtained applying the classical DCF Approach
II. When P^* is very high the figure converges to zero because the probability to reach those high value of P^* is very low and then the probability to not invest(e.g. to have a null NPV) is significantly high.
III. There is a value of P^* that maximize the NPV mean of the investment. If the model user has the aim to maximize its profit he has to find this value and wait for this level of the electricity price to trigger the investment.
IV. There is a discontinuity after $P^* = P_0$. Indeed waiting for a value greater than P_0 means to not invest at time zero. Acquiring information about the evolution of the environmental conditions (e.g. knowing the evolution of the electricity price) means that there would be more or less the 50% of probability to not invest in the next time and to a probability of the 20% to never invest. Therefore the value of the NPV mean increases and the standard deviation of the NPV distribution decreases because the model suggest to not invest in the less profitable scenarios.

The maximum of the curve (e.g. the maximum of the NPV mean) represented above is then obtained in correspondence to the value of $P^* = 120\ \$/MWh$.

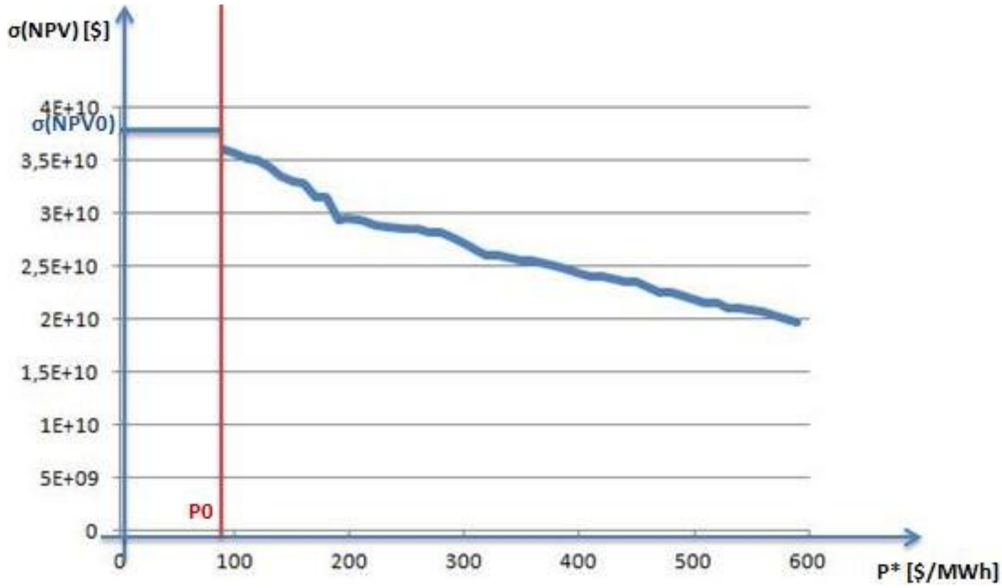

Figure 43. How the P* impacts on the standard deviation of the NPV distribution

This figure shows that as more as P^* increases as more the level of risk[14] connected to the investment decreases. Waiting for an higher value of the electricity price means that the investment in less profitable scenarios is avoided and then that the probability to have a negative NPV is quite null in this case, while investing now it is significantly higher.

[14] Measured using as indicator the standard deviation of the NPV distribution

3.1.2 The discrete enumeration of all possible states: application with one state variable

This paragraph verifies the result obtained in paragraph 3.1.1 applying the second existing SOET Method to the nuclear case of investment. The advantages of this method are that it gives solutions that are quite more precise, with less computational effort. The method simulates every possible "situation", that is every possible combination of the state variables (e.g. all the combinations of the price of electricity). Then, for every possible situation the question is "in this situation is better to invest or to wait?" and not, as before "which value of the state variables is better to wait, given the initial state?".
In Figure 42 we showed that the relationship between the NPV mean and the value of the threshold P* presents a peak in correspondence to the optimal value of P*. Then we have two trends in the function:

- When $P_{opt} > P^*$ the trend is positive and the NPV mean increases with the increase of P^*
- When $P_{opt} < P^*$ the trend is negative and the NPV mean decreases with the increase of P^*

This method then calculates for each possible value of the exercise threshold the difference between investing immediately and waiting for a value slightly greater. Following the description made here we expect as results then:

- When $P_{opt} > P^*$ this difference will be positive since it is better to wait (the trend is positive).
- When $P_{opt} < P^*$ this difference will be negative since it is better to invest (the trend is negative).
- When $P_{opt} = P^*$ this difference will be zero and then this is the condition to find the optimal value of the exercise threshold with this second method

A flow – chart representing the idea of this second method is reported here:

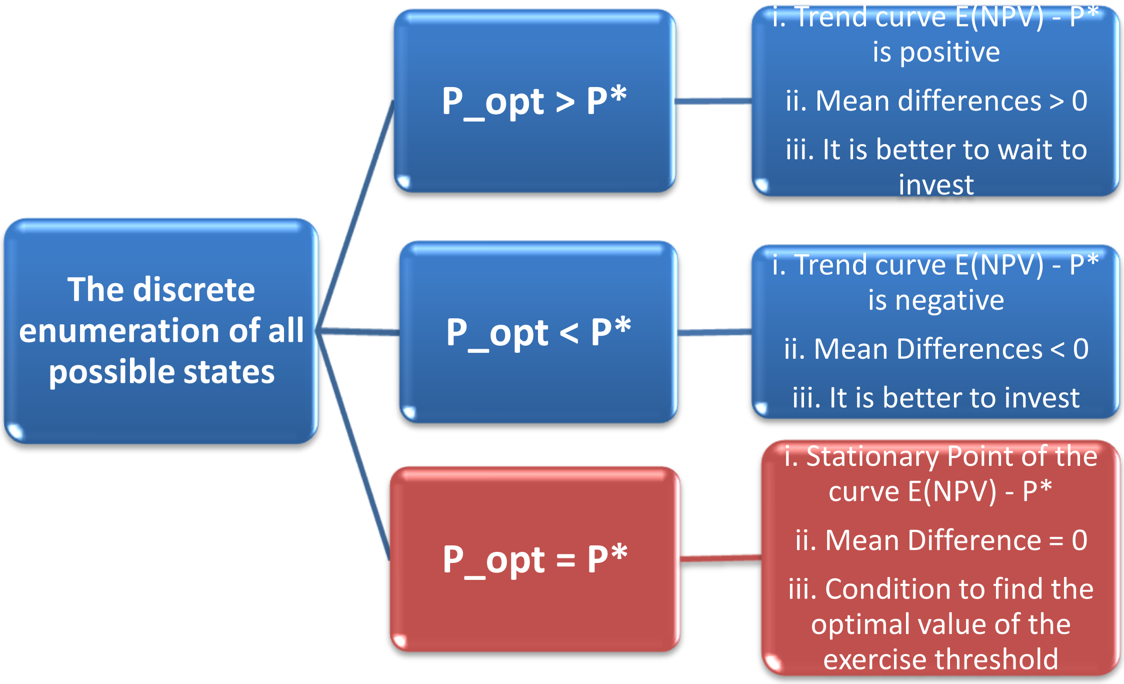

Figure 44. The idea of the discrete enumeration of all possible states SOET Method

Before the description of the steps that must be followed to implement this idea we have to say that this method is the most precise one but that it can be applied only when the objective function is the maximization of the NPV mean because it does not take into account risk.

The step of this method are reported here:

I. Consider a range of possible values of P*, defined by a lower and an upper bound. The lower bound has to be significantly lower than the actual electricity price, while the upper bound has to be significantly higher than it (highly improbable to be reached). In this example we choose again $P^*_{LB} = 1\ \$/MWh$ and $P^*_{UB} = 600\ \$/MWh$.
II. Select the number of values that have to be analyzed. As before, an optimal result would be obtained performing for this case study 600 simulations, but 60 simulations bring to a good result too. In this work we perform 60 simulations in correspondence to these values of the electricity price: {10,20…..590,600}. In example, the first value $P_0 = 10\ \$/MWh$ is considered and a MCS is launched considering this value of the initial price of electricity and hence the investment is done immediately. A second simulation is then performed in which is waited the value $P^* = 10{,}0001\ \$/MWh$. For each value of the electricity price considered are then obtained two NPV distributions and then two NPV means. In this way the model user is able to see if it is better to invest or to wait for that possible state variable[15].

The following figure shows the decreasing behavior of the difference between the investing now NPV and the NPV obtained waiting for a slightly greater value of P*.

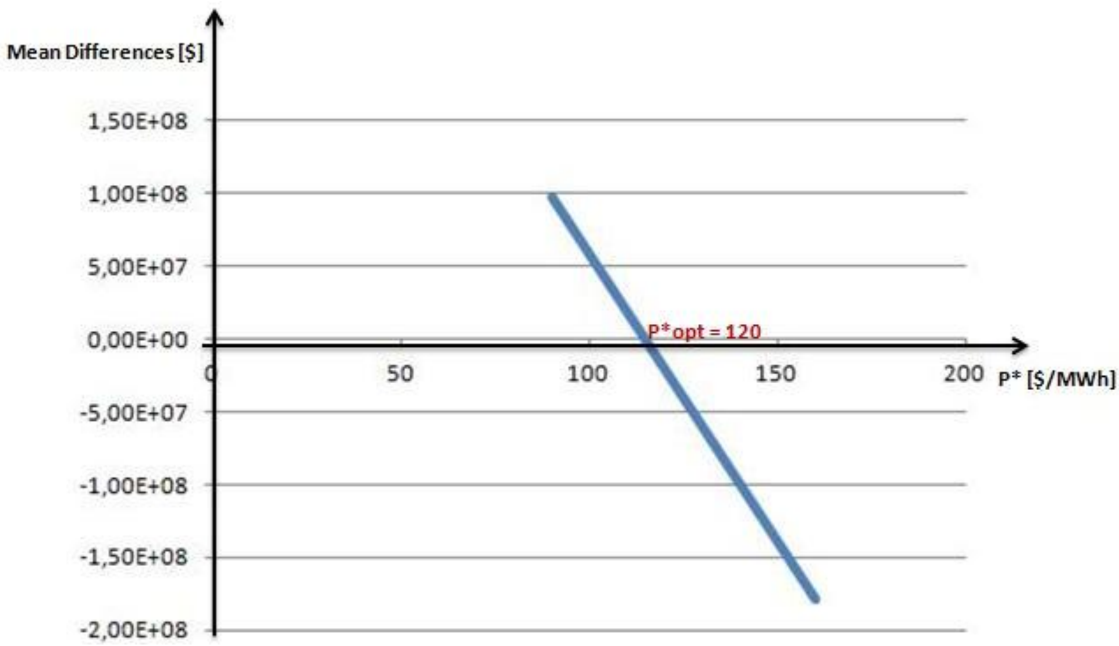

Figure 45. How P* impacts on the mean differences

This method validate the discrete enumeration of all possible thresholds because the solution that they found (the value of the exercise threshold that maximize the NPV mean) are the same.

[15] This result is true because the value of the exercise threshold that maximize the NPV Mean is independent from the actual value of the electricity price. We remind to (Lotti, 2012) for the demonstration of this property.

3.1.3 The search algorithm: application with one state variable

Differently from the discrete enumeration of all possible threshold, given an initial state (the initial value of the state variables), this method generates several exercise thresholds thanks to a search algorithm and for each one calculates, through a MCS, several performance indicators (i.e. Expected NPV and Standard Deviation of the PP considered).
These algorithms try a solution (that is performing a MCS given an exercise threshold), check its goodness, and in function of this goodness try another one, jumping from one solution to another, searching the best one, according to a specific objective function. Therefore the optimization problem is to find the values of the exercise thresholds that maximize this objective function. These thresholds are then the decision variables that must be found in the optimization problem.
As already said, to resolve this optimization problem we use a search algorithm. This algorithm generates different exercise thresholds , and each exercise threshold becomes an input of the evaluation model. Then the evaluation model generates an output distribution from the inputs and from that exercise threshold . After that the value of the objective function from the output distribution is calculated and, in function of this value, the optimization algorithm generates new thresholds, searching the best ones.

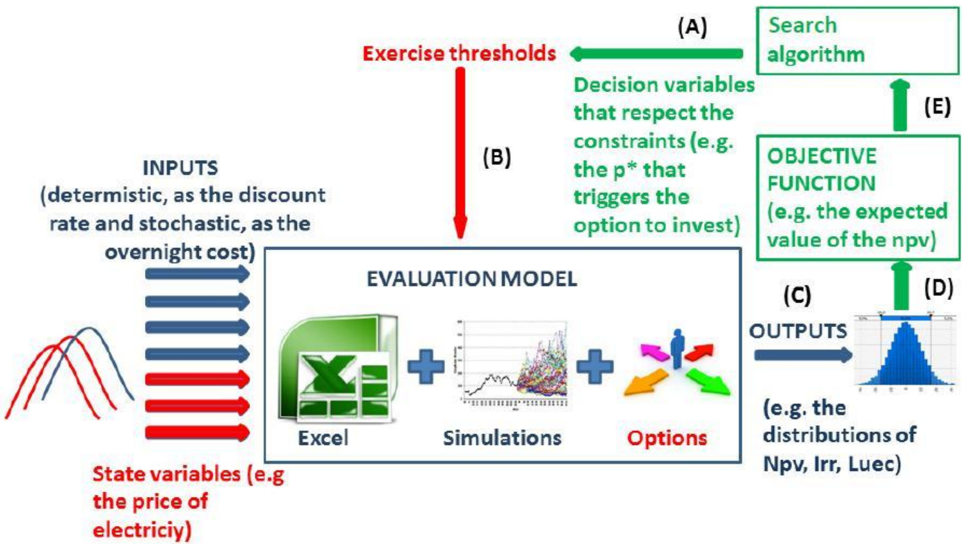

Figure 46. The scheme of the Model (Lotti, 2012)

We can say that this method is an evolution of the discrete enumeration of all possible thresholds as it searches the optimal exercise threshold without listing all its possible values but only the ones that the algorithm considers more interesting.
The steps for the model user to implement this idea are reported here:

I. Define an objective function (e.g. maximize the NPV mean; minimize the NPV standard deviation)

II. Define a lower and an upper bound for the interval in which P^* could vary.

III. Select the dimension *n* of the number of iterations per simulation. In order to obtain a robust result empirically we can affirm that at least 100000 iterations should be performed.

Then, the algorithm will search for the solution (the exercise threshold) that maximizes the objective function and when the algorithm is stopped it returns the best solution it found.

Considering our example with only one state variable we can deep into the steps of the algorithm described here showing how even with this method the same optimal value of P^* is found.

a. The P* interval is divided into a little number of candidate solutions, for example {50, 100,…,600 }. This idea gives to the algorithm (but not to the user, that doesn't look into the algorithm process) insights about the shape of the curve shown before in Figure 42. Then the algorithm perceive that there is a local maximum (not knowing that is the global maximum) between $P^* = 100\ \$/MWh$ and $P^* = 150\ \$/MWh$.

b. Once the sub-interval containing the optimal value of the threshold has been isolated the algorithm redoes the previous step with dividing this sub-interval into other candidate solution, for example {100, 110,…,150}.
c. Apply again this idea until the optimal value of the exercise threshold is found[16].

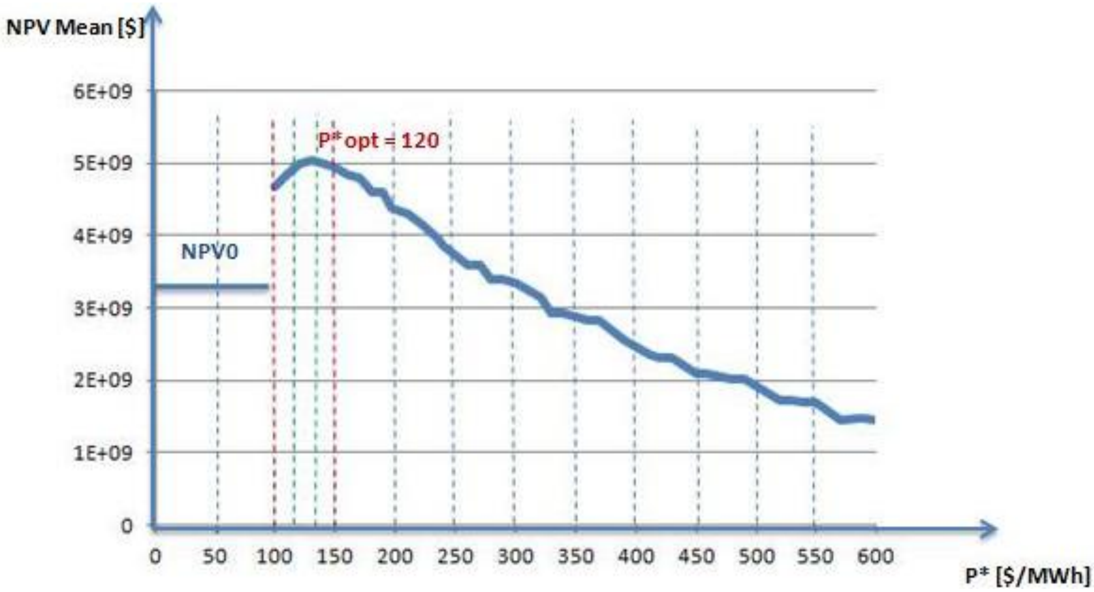

Figure 47. The candidate solutions method followed by the search algorithm to find the optimal value of P*

Applying in this way the search algorithm we find out always the same value of the electricity price that triggers the investment in the nuclear PP in the most profitable way.

3.2 TTM Effect: Modeling Compound Options

This section provides a deeper insight in the effect that the flexibility in the pre-operational phases of a PP has on the overall investment and it is one of the most important improvement that this work have.
Respectively to the analysis described before in which our aim was only to show the effect of considering the whole time elapsed from the moment in which the decision to invest is taken and the moment in which the plant starts to produce electricity, our scopes here are:

[16] It is the same idea of the bisection method used to find the roots of a complex curve whose mathematical formula is unknown.

- Demonstrate that the pre-operational phase of a PP can be modeled as the succession of three sequential compound options.

- Show how to apply this idea and how results improve implementing it.

As already said, in order to evaluate this flexibility we built a model based on the succession of three sequential compound options.

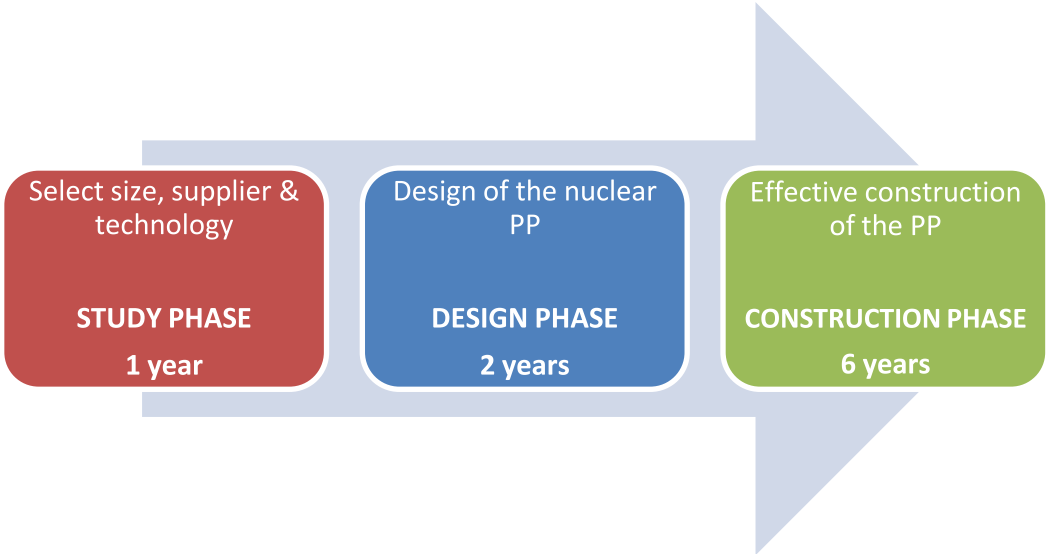

Figure 48. Sequential compound options of the pre-operating phases of a Nuke PP

The idea to implement the compound options in the model is based on the assumption that the cost of completion of the first phase is correlated to the Total Cost of the second and of the third one. Therefore we refer the starting of the following phases in accordance to the expected cost to design and to construction and if:

$ECTD < ECTD_{threshold}$ → The design phase begin; if not, at this point of the analysis, the investment in the PP is abandoned.

$ECTC < ECTC_{threshold}$ → The construction phase begin; if not, at this point of the analysis, the investment in the PP is abandoned.

Our aim now is to add to the analysis performed in paragraph 3.1 the possibility for the utility, at the beginning of the design and of the construction phase, to abandon the investment if the scenario is not convenient anymore. Paragraph 3.2.4 shows how model vary adding the possibility to wait between each of the pre-operational phases[17].

It is clear now that this model allows the application of more than one state variable. In this way it is possible to implement in the analysis exercise thresholds with multiple state variables, both the expected cost to complete each of the pre-operational phases, and the electricity price. We created a linear exercise threshold for the ECTD and the ECTC of this type (the reasons of this choice are reported in Box 3):

[17] Modeling effectively the pre-operational phase of a nuclear PP as three sequential compound option. However, the implementation of the compound options is made using the same kind of thresholds described here.

$$ECTD^* = m_{design} + (P_t - a_{design}) \qquad (3.1)$$

$$ECTC^* = m_{construction} + (P_t - a_{construction}) \qquad (3.2)$$

In which we have:

- $P_t = Electricity\ Price\ Value\ at\ time\ "t"$
- $m_{[\ ]} = "Multiplication\ Factor"\ of\ a\ Linear\ Exercise\ Threshold$
- $a_{[\ ]} = "Difference\ Coefficient"\ of\ a\ Linear\ Exercise\ Threshold$

As it is possible to see from the equations above, the ECTC and ECTD thresholds are then function of the electricity price of each decisional moment; "*m*" and "*a*" are the two parameters of the linear exercise threshold that remain constant during the single simulation. The focus of our considerations is then based on P_t : indeed the value of P_t gives to $ECTC_{threshold}$ the variability, and therefore it is in function of P_t's variability that the value of the $ECTC_{threshold}$ changes during each simulation.

The idea of the SOET method we applied is that there will be iterations in which the state variable is under the exercise threshold, and others in which the utility will not exercise the option because the state variable is above that value.
The difference with the Standard SOET Method developed in (Lotti, 2012) is in the evaluation model. Indeed, we model the pre-operational phase of a nuclear power plant as the succession of three sequential phases and therefore we build a model with multiple state variables. Having three pre-operating phases means that we have a different exercise threshold for each of them, while the algorithm of the classical SOET Method works with only one state variable (The Electricity Price).

In this work:

- The study phase will be triggered by a single specific value of the electricity price;

- The beginning of the design phase and of the construction phase is function of the value of multiple state variables.

Thus, we create a complex algorithm that gives in output the value of five different parameters (P*; m_{des} ; a_{des} ; m_{cos} ; a_{cos}) that maximize a specific objective function (e.g. Maximize the NPV Mean).

Before describing it, the following box resumes the steps that must be followed in the case in which we have a single state variable that trigger the investment (it means that the exercise threshold is made up by a single value), and in the case in which we have one multiple state variable (i.e., we have to maximize the value of a specific objective function varying two parameters at least).

The Search Algorithm: steps to find a solution

1. Algorithm with one state variable:
   - Define a specific objective function (e.g. maximization of the Expected NPV)
   - In this case an interval of possible values of P* is defined by two values, the lower and the upper bound
   - Select the number of iteration for each different simulation

- Run the algorithm that will automatically search for the solution(e.g. the exercise threshold P*) that maximize the objective function

2. Algorithm with two state variables:
    - Assume a shape for the exercise threshold. The most common and the most efficient shape is the linear exercise threshold, defined by two parameters “m” and “a”.
    - Define a lower bound and an upper bound for the parameters “m” and “a”
    - Select the number of iteration for each different simulation
    - Run the algorithm that will automatically search for the solution (the parameters “m” and “a”) that maximize the objective function

The result would be then the “best” exercise threshold (defined by the values “m” and “a”). Once the solution is found a full MCS is performed, returning the NPV distribution. In this way the model user can analyze all the output variables he wants: the NPV mean, the NPV standard deviation and so on.
We have to say that the possible shapes of the exercise thresholds are theoretically infinite. For instance they can be:

1. Edge-Shaped
2. Linear
3. Non-Linear and Not Edge-Shaped (for example logarithmical, exponential and so on).

A non-linear exercise threshold allows to find the real shape of the exercise threshold but we decide to use a linear exercise threshold modeled as shown in equations (3.1) and (3.2), because:

1. The improvement guaranteed with the use of a non-linear threshold is only slightly greater than the result obtainable with a linear one, while the model becomes extremely more complex.

2. The model user should understand that the exercise thresholds provided by the model do not represent the real ones, but an approximation. Using linear thresholds with two parameters “m” and “a” then avoids this misunderstanding, which is thinking that the exercise thresholds provided are the real ones.

Box 3. The Search Algorithm: steps to find a solution

As already said, in order to consider properly the TTM Effect, we model the pre-operating phase of a nuclear PP as the succession of three sequential phases. Thus, we have to create an algorithm to optimize the research of the optimal value of five different parameters.
The steps of the algorithm applied considering the presence of five state variables in the standard way are:

- Assume a shape for all the exercise thresholds considered (e.g. linear)

- Define an upper and a lower bound for all the parameters that must be maximized. In our case for instance, according to the Total Cost to Construction and to Design(defined in paragraph 4.1.2) we consider that:
    - The Electricity Price must be between 0 $/MWh and 600 $/MWh
    - The m_{des} parameter must be between 1 and 10
    - The a_{des} parameter must be between 5 and 80
    - The m_{cos} parameter must be between 10 and 110
    - The a_{cos} parameter must be between 5 and 80

- Select the number of iteration for each different simulation

- Run the algorithm that will automatically search for the optimal values of the five parameters that maximize the objective function implemented.

It is easy to understand the complexity of finding these optimal values, even with the use of a search algorithm. Indeed, the possibilities that should be analyzed are:

$$N°_{possibilities} = 601 * 11 * 81 * 91 * 81 = 3.947.104.161\, possibilities \quad (3.3)$$

We have quite 4 billions of combinations in our case study, and, as we did, if the possibility to build four sequential SMRs is considered this number increase to quite 10 billions of possible combinations.
It is clear that we can't apply "The Discrete Enumeration of all possible thresholds" and "The Discrete Enumeration of all possible states" SOET Methods or the classical RO evaluation models present in literature(LSMC; SGBM; Binomial Tree; PDE) because of the complexity of the problem in a standard way. Thus firstly we apply the "SOET Method with the search algorithm" and then, thanks to a simplified version of the discrete enumeration of all possible states and thresholds, we verify its results.

3.2.1 Modeling Compound Options with the search algorithm SOET Method

As reported above the problem of this method is that the search algorithm could need a significant amount of time to find the optimal solution. Thus, if we want to apply it in an effective way we have "to help" the search algorithm understanding the nature of the problem we are studying. It means that there are parameters that influence results more than the others and that, in a first approximation, we can fix the value of those parameters that are less influential[18].

The steps performed in our analysis are these:

- Assume a shape for all the exercise thresholds considered (e.g. linear)

- Define an upper and a lower bound for all the parameters that must be maximized. See the list above for the value used at this point of the analysis

- Select a low number of iterations for each different simulation (for example 10000): in this way the model user is able to restrict the range of possible variation of all the parameters considered

- "Understand the nature of the problem" and fix the value of the less influential parameter to a possible value. For instance in this case, according to the explorative simulation performed in the previous step of the analysis, we consider:
    - $m_{des} = 4$
    - $a_{des} = a_{cos} = 20$
- Define a new and more restricted range of possible variations for the P* and m_{cos} parameter. In this case, according to the explorative simulation performed in the previous step of the analysis, we consider that:
    - The m_{cos} parameter must be between 40 and 70
    - The Electricity Price must be between 100 €/MWh and 150 €/MWh

[18] See Appendix 8.2 for the method used to distinct between less influential parameters and most influential ones.

- Select an high number of iterations for each different simulation to find the optimal value of the most influential parameters (for example 100000).

- Run the algorithm that will automatically search for the optimal values of the most influential parameters that maximize the objective function implemented.

- Fix the value of the most influential parameters and define a restricted range of possible variation for the others. In this case we have:
    - The m_{des} parameter must be between 3 and 6.
      The $a_{cos} = a_{des}$ parameter must be between 15 and 30.

- Select an high number of iterations for each different simulation (for example 100000)

- Run the algorithm that will automatically search for the optimal values of the less influential parameters too.

- Run a simulation with a huge amount of iterations (for example one million) with the optimal value of all the exercise thresholds considered in order to find out all the parameters that describe the goodness of the investment (Expected NPV; Level of risk; Sharpe Ratio).

The following figure reports the steps presented here in a flowchart:

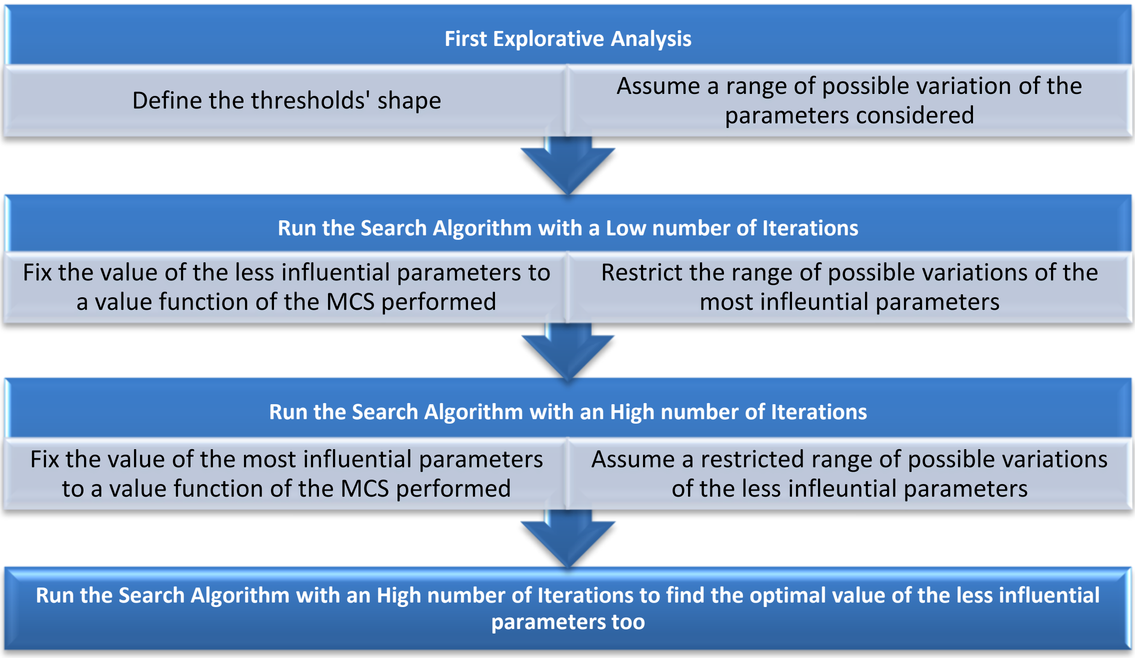

Figure 49. Steps of the algorithm used in this work

Therefore in this analysis we made an approximation because we did not vary at the same time all the parameters that characterize each exercise threshold. We assume that the interaction between those parameters has a low influence on the overall result[19]. In any case a utility should have the computational strength to deal with the effort needed in this case and thus, the search algorithm without this simplification can easily find the optimal solution.

[19] See Appendix 8.2 The Level of Influence of the linear exercise thresholds' parameters used to model compound options to understand how we validate this assumption

However our aim is to improve a model showing the potentialities of the innovative framework that we built in order to perform a realistic portfolio analysis in the energy field and hence this algorithm is sufficient to reach our scope. Indeed in summary, we want to show:

- The Effect of considering the real pre-operational time for all base-load PPs
- The Effect of considering the intrinsic flexibility of the pre-operational phase of a nuclear PP modeling it as the succession of three sequential compound options
- The Effect of considering the Actual Portfolio on the decision of investment in a new plant

The chosen of the most influential parameters must be done in function of the nature of the problem. In this case it means that we have to know that the construction phase is the most uncertain and most costly pre-operational phase of a nuclear power plant. It means that the profit guaranteed by the overall investment is mainly function of the impact that the Total Capital Construction Cost has on it.
Thus, we have to pay a great attention to the $ECTC_{treshold}$: we have to build a model that effectively allow to abandon the investment if the scenario is not convenient anymore. Furthermore, because of the fact that in this case there is not the possibility to wait between the three pre-operational phases, triggering the study phase all the investment is triggered too. It means that even the threshold that trigger the study phase (e.g. the electricity price) has great influence on the overall investment.

The result (i.e., the E(NPV) and the exercise thresholds) obtained applying this method to the large nuclear case of investment are reported here[20]:

Method	P*	ECTD*	ECTC*	Expected NPV [mln€]
SOET Method – Compound Options	115	5*(P_t - 25)	80*(P_t - 25)	5003,998

Table 29. Result of the Search Algorithm SOET Method implemented with Compound Options

Paragraph 5.2 contains the robustness analysis of our model in which our results are compared with the current status of nuclear reactor under construction, and in addition it shows also how these results change by varying the cost relationship between all the pre-operational phases of the nuclear PP.

3.2.2 Modeling Compound Options with the discrete enumeration of all possible thresholds SOET Method

As reported in the previous paragraph we have five parameters that characterize the exercise thresholds with quite 4 billions of possible combinations between each of them. Thus we can't enumerate all these possible combinations but we have to apply this method with the same simplification made applying the search algorithm. It means that, knowing the nature of our case study we have to fix the value of the less influential parameters to realistic values and then we can enumerate all the possible combinations between all the most influential parameters performing a MCS for each of this value.

Thus, as we did before, the five parameters are modeled in this way:

[20] A more detailed description of how this result is obtained is reported in paragraph 5.1.1

Parameter	Level of Influence[21]	Way of modeling
P*	High	Free to vary between a lower and an upper bound
a_{design}	Low	Fixed to a reasonable value in its possible range of variation
m_{design}	Low	Fixed to a reasonable value in its possible range of variation
$a_{construction}$	Low	Fixed to a reasonable value in its possible range of variation
$m_{construction}$	High	Free to vary between a lower and an upper bound

Table 30. Description of the parameters characterizing the exercise thresholds implemented

Thus with this simplification we approximate the model with two state variables (i.e. P* and m_{cos}). Then, instead of exploring a sample of the values of one state variable we have to explore a sample of the combinations of these two parameters.
As in paragraph 3.1.1, for every exercise threshold there is a different NPV distribution and then different means and standard deviations. The difference here is that the exercise thresholds depend on two variables and then the method will use tables to represent the result of the example.

The steps of this method are summarized here:

I. Define the interval of the possible exercise thresholds (P*; m_{cos}). The combinations used in this analysis are 90 < P* < 250 and 10 < m_{cos} < 110
II. This interval is divided into the possible exercise thresholds, for example the combinations (P*; m_{cos}) = {(90;10),(90;20)….(100;10),(100;20)….(250;110)} for a total of 200 simulations (with a number of 100000 iterations for each simulation).
III. For each exercise threshold is performed a MCS and it's obtained an NPV distribution, that is the result of waiting for that exercise threshold.
IV. From each one of these NPV distributions (each one obtained from a MCS) several statistical indicators are obtained. In this example these indicators are the mean and the standard deviations.

The following two figures shows how the different combinations of the parameters impact on the mean and on the standard deviation of the NPV distribution.

[21] This level of influence of each parameter of the linear exercise thresholds implemented to the overall result of the investment is demonstrated in appendix 8.2

P* [$/MWh] \ m_cos	10	20	30	40	50	60	70	80	90	100	110
90	-3,92E+08	-1,14E+08	1,01E+09	2,13E+09	3,18E+09	3,67E+09	4,05E+09	4,18E+09	4,21E+09	4,44E+09	4,40E+09
100	-2,43E+08	7,71E+08	2,28E+09	3,71E+09	4,14E+09	4,73E+09	4,81E+09	4,94E+09	4,94E+09	4,88E+09	4,92E+09
110	-1,97E+08	1,02E+09	2,71E+09	3,95E+09	4,53E+09	4,93E+09	4,79E+09	4,92E+09	4,97E+09	4,95E+09	4,93E+09
115	-1,56E+08	1,22E+09	2,99E+09	4,05E+09	4,46E+09	4,89E+09	4,92E+09	5,01E+09	4,88E+09	4,93E+09	4,94E+09
120	-1,11E+08	1,41E+09	2,99E+09	4,02E+09	4,48E+09	4,92E+09	5,00E+09	4,95E+09	4,99E+09	4,96E+09	4,93E+09
130	-4,69E+07	1,68E+09	3,36E+09	4,21E+09	4,91E+09	4,75E+09	5,01E+09	4,95E+09	4,84E+09	4,95E+09	4,96E+09
140	9,70E+06	1,91E+09	3,55E+09	4,38E+09	4,54E+09	4,70E+09	4,98E+09	4,96E+09	5,01E+09	4,90E+09	4,98E+09
150	1,25E+08	2,11E+09	3,77E+09	4,48E+09	4,86E+09	4,63E+09	4,76E+09	4,96E+09	4,96E+09	4,91E+09	4,96E+09
160	3,07E+08	2,30E+09	3,62E+09	4,06E+09	4,84E+09	4,61E+09	4,60E+09	4,72E+09	4,81E+09	4,68E+09	4,84E+09
170	3,58E+08	2,54E+09	4,17E+09	4,12E+09	4,44E+09	4,58E+09	4,68E+09	4,82E+09	4,62E+09	4,60E+09	4,73E+09
180	4,76E+08	2,80E+09	3,85E+09	4,16E+09	4,39E+09	4,66E+09	4,52E+09	4,59E+09	4,41E+09	4,49E+09	4,55E+09
190	5,09E+08	2,86E+09	3,84E+09	4,23E+09	4,39E+09	4,30E+09	4,36E+09	4,43E+09	4,42E+09	4,44E+09	4,32E+09
200	6,02E+08	3,22E+09	3,62E+09	4,04E+09	4,29E+09	4,32E+09	4,37E+09	4,43E+09	4,36E+09	4,42E+09	4,27E+09
210	8,95E+08	2,80E+09	3,71E+09	4,09E+09	4,16E+09	4,06E+09	3,83E+09	4,18E+09	4,18E+09	4,09E+09	3,96E+09
220	8,88E+08	2,82E+09	3,57E+09	3,78E+09	4,08E+09	4,01E+09	3,94E+09	4,21E+09	4,09E+09	4,15E+09	3,98E+09
230	9,19E+08	2,94E+09	3,63E+09	3,78E+09	3,89E+09	4,17E+09	3,81E+09	3,91E+09	3,77E+09	3,94E+09	4,08E+09
240	9,99E+08	2,99E+09	3,55E+09	3,66E+09	4,03E+09	3,80E+09	3,72E+09	4,03E+09	3,83E+09	3,81E+09	3,78E+09
250	1,11E+09	2,95E+09	3,50E+09	3,68E+09	3,57E+09	3,72E+09	3,67E+09	3,89E+09	3,72E+09	3,74E+09	3,83E+09

Figure 50. How the values of P* and m_cos impact on the mean of the NPV distribution

P* [$/MWh] \ m_cos	10	20	30	40	50	60	70	80	90	100	110
90	1,48E+08	8,23E+09	1,55E+10	2,18E+10	2,42E+10	2,54E+10	3,46E+10	3,41E+10	3,28E+10	3,26E+10	3,13E+10
100	1,21E+09	1,44E+10	2,48E+10	2,53E+10	2,90E+10	3,01E+10	3,57E+10	3,54E+10	3,52E+10	3,50E+10	3,43E+10
110	1,79E+09	1,66E+10	2,67E+10	2,71E+10	3,35E+10	3,63E+10	3,81E+10	3,79E+10	3,71E+10	3,67E+10	3,64E+10
115	4,27E+09	2,25E+10	2,88E+10	2,76E+10	3,62E+10	3,66E+10	3,89E+10	3,96E+10	3,84E+10	3,63E+10	3,60E+10
120	6,15E+09	2,26E+10	2,49E+10	2,77E+10	3,51E+10	3,86E+10	3,91E+10	3,92E+10	3,79E+10	3,74E+10	3,71E+10
130	4,58E+09	2,21E+10	2,88E+10	3,07E+10	3,56E+10	3,62E+10	3,64E+10	3,73E+10	3,63E+10	3,80E+10	3,70E+10
140	5,88E+09	1,98E+10	2,84E+10	3,14E+10	3,62E+10	3,52E+10	3,61E+10	3,65E+10	3,68E+10	3,68E+10	3,68E+10
150	7,40E+09	2,16E+10	2,95E+10	3,22E+10	3,50E+10	3,50E+10	3,58E+10	3,69E+10	3,59E+10	3,53E+10	3,62E+10
160	1,37E+10	2,25E+10	2,51E+10	2,64E+10	3,49E+10	3,46E+10	3,45E+10	3,63E+10	3,53E+10	3,45E+10	3,58E+10
170	1,09E+10	2,37E+10	2,97E+10	2,94E+10	3,38E+10	3,59E+10	3,41E+10	3,61E+10	3,40E+10	3,35E+10	3,42E+10
180	1,26E+10	2,63E+10	3,09E+10	3,08E+10	3,21E+10	3,59E+10	3,47E+10	3,32E+10	3,33E+10	3,30E+10	3,35E+10
190	1,05E+10	2,59E+10	2,84E+10	3,07E+10	3,20E+10	3,32E+10	3,19E+10	3,25E+10	3,28E+10	3,27E+10	3,27E+10
200	1,15E+10	2,38E+10	2,71E+10	3,17E+10	3,08E+10	3,29E+10	3,16E+10	3,22E+10	3,16E+10	3,15E+10	3,17E+10
210	1,29E+10	2,66E+10	2,92E+10	3,03E+10	3,04E+10	3,12E+10	3,01E+10	3,04E+10	2,95E+10	3,10E+10	3,02E+10
220	1,60E+10	2,34E+10	2,93E+10	2,96E+10	2,99E+10	3,11E+10	2,90E+10	3,06E+10	2,94E+10	3,07E+10	2,95E+10
230	1,84E+10	2,44E+10	3,09E+10	2,83E+10	2,86E+10	3,23E+10	2,95E+10	2,96E+10	2,92E+10	3,06E+10	2,92E+10
240	1,60E+10	2,75E+10	3,10E+10	2,70E+10	2,75E+10	3,17E+10	3,00E+10	3,01E+10	2,91E+10	3,12E+10	2,85E+10
250	1,68E+10	2,52E+10	3,08E+10	2,53E+10	2,56E+10	3,09E+10	2,89E+10	2,93E+10	2,93E+10	3,01E+10	2,86E+10

Figure 51. How the values of P* and m_cos impact on the standard deviation of the NPV distribution

If the objective function considered is the maximization of the NPV mean the discrete enumeration method built in this way brings as result the same obtained applying the search algorithm SOET Method presented before:

$$P^*_{opt} = 115\ \$/MWh$$

$$m_{\cos\ \_opt} = 80\ MWh/kW$$

3.2.3 Modeling Compound Options with the discrete enumeration of all possible states SOET Method

This paragraph verifies the results obtained applying the search algorithm and "the discrete enumeration of all possible thresholds" SOET Method and modeling the pre-operational phase of a nuclear PP as the succession of three sequential compound options.
Therefore "the discrete enumeration of all possible states" SOET Method has been applied to this case study too. In this analysis we have to extend the model presented in paragraph 3.1.2 to multiple state variables. Hence, instead of exploring a sample of the values of one state variable it is needed to explore a sample of the combination of more state variables. The assumption made here is the same used in paragraphs 3.2.1 and 3.2.2 for which there is a distinction between the less influential parameters and the most influential ones (see Table 30).

It would be required to perform a MCS for all possible combinations of P_0 and m_{cos} . For this case study we considered as possible combinations: (P_0 ; m_{cos}) = {(90,10);(90,20);…;(100,10);…;(250,100)}. Once this is done, for every combination is valued the NPV means of investing and of waiting for an improvement, that is an increase in the price of electricity or a decrease of the expected cost to construction. In other words for every possible combination, for example (P_0 ; m_{cos}) = (90,10), is valued the NPV mean of investing immediately and the NPV mean of waiting, investing only if $P_t > 90{,}0001\ \$/MWh$ or if $m_{cos} < 9{,}999\ MWh/kW$.
Then the difference between the NPV means is calculated and when it is positive is better to wait while when it becomes null that's the optimal moment to invest.

This method has been applied to this case study and the result obtained is shown in the following figure. The symbol '-' represents the states for which it is better to invest immediately, while the symbol '+' represents the cases for which waiting for a value slightly different of the states variables increases the value of the investment:

P* [$/MWh] \ m_cos	9,9999	19,9999	29,9999	39,9999	49,9999	59,9999	69,9999	79,9999	89,9999	99,9999
90,0001	+	+	+	+	+	+	+	+	+	+
100,0001	+	+	+	+	+	+	+	+	+	-
110,0001	+	+	+	+	+	+	+	+	-	-
115,0001	+	+	+	+	+	+	+	-	-	-
120,0001	+	+	+	+	+	+	-	-	-	-
130,0001	+	+	+	+	+	-	-	-	-	-
140,0001	+	+	+	+	-	-	-	-	-	-
150,0001	+	+	+	-	-	-	-	-	-	-
160,0001	+	+	-	-	-	-	-	-	-	-
170,0001	+	-	-	-	-	-	-	-	-	-
180,0001	-	-	-	-	-	-	-	-	-	-
190,0001	-	-	-	-	-	-	-	-	-	-
200,0001	-	-	-	-	-	-	-	-	-	-
210,0001	-	-	-	-	-	-	-	-	-	-
220,0001	-	-	-	-	-	-	-	-	-	-
230,0001	-	-	-	-	-	-	-	-	-	-
240,0001	-	-	-	-	-	-	-	-	-	-
250,0001	-	-	-	-	-	-	-	-	-	-

Figure 52. The NPV mean difference between investing now and waiting for a value slightly greater of P* and smaller of m_cos

The figure above shows that the value of P* and m_{cos} obtained with the other methods are correct because there is a change in the trend of the function according to them. Furthermore it is easy to notice that, having two state variables, we do not find a single point in which the trend of the function changes but we found a series of points.

The values found before ($P_{opt} = 115\ \$/MWh\ ;\ m_{cos} = 80\ MWh/kW$) represent the values of this series of point that maximize the NPV Mean.

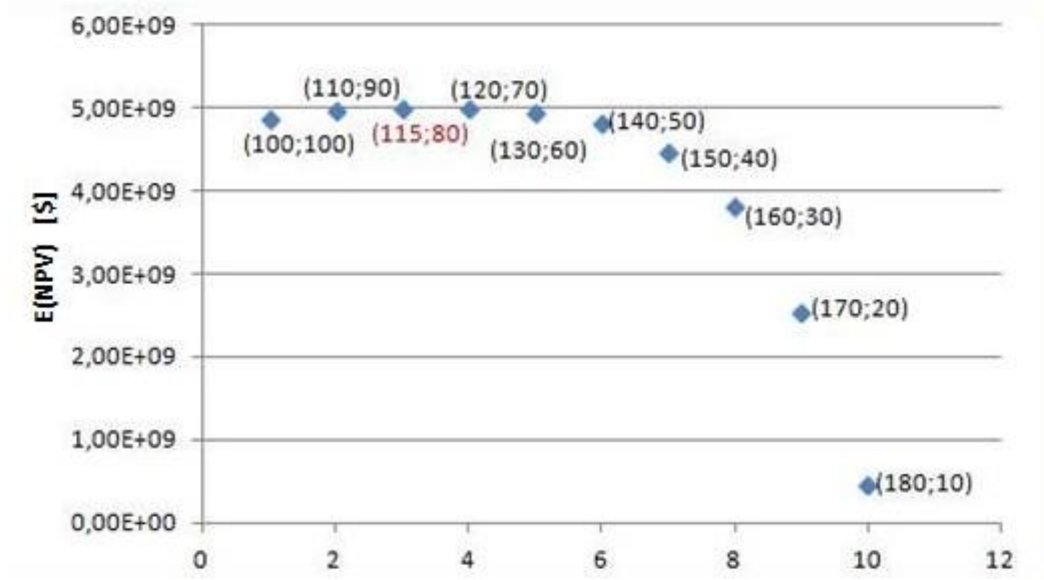

Figure 53. Discrete Enumeration of the combination of states that maximize the NPV Mean

3.2.4 Modeling Compound Options: implementing the option to wait between pre-operational phases

The Figure 48 shows what a compound option is. At the end of the study phase and of the design phase, the investor gains respectively the right, without obligation, to invest in the design or in the construction phase. Therefore this is a complex and multiple option because an investor can decide to continue, to abandon or to delay the investment following the evolution of the environmental conditions around him.
The exercise thresholds that trigger the beginning of each phase are built with the same criteria described before (see equation 3.1 and 3.2), and the step of the algorithm that must be followed to apply the SOET Method in order to find their optimal value are the same too.
The difference here is in the nature of the problem we are considering and therefore in the way in which the model user should "help" the search algorithm to find those optimal values in a reasonable amount of time.

Indeed in this case compound options are completely implemented, and thus there is the possibility to wait between each of the pre-operational phase. It means that, being the construction phase the most costly and the most uncertain period of the investment, this phase influences in the most significant way the overall investment. In other words we can expect the first two pre-operational phases of the investment to be performed in an explorative way to see if the scenario is evolving in a profitable way for the investment[22].
Selecting a low number of iterations for each different simulation with the aim to restrict the range of possible variation of all the parameters considered confirm this assumption and let us define their upper and their lower bound in a lower range helping the model to optimize the problem.
We remind to chapter 5 for the description of the result obtained for this case – study.

[22] See appendix 8.2 for a deeper insight in the level of influence of all the parameters for this case study.

3.2.5 Modeling Compound Options with Sequential Investment in Power Plants

This paragraph contains the steps that should be followed to implement the SOET Method with the search algorithm in order to evaluate the TTM Effect with Compound Options for investments in sequential power plants. In fact since the different PPs have different capacities, it is more correct to compare them when they supply the same power installed. Furthermore, this analysis is necessary to exploit all the advantages of an investment in SMR, in terms of modularity effect (e.g. reducing capital cost of investment, encouraging local contest and so on..), economy of multiples, learning effect (see (Carelli et al., 2010) and (Locatelli, Bingham, & Mancini, 2014) for a more detailed description of these properties). The problem of this analysis in which compound options are implemented for all the SMR PPs that could be built is the huge amount of possible combinations of the parameters that characterize the exercise thresholds of the model. In order to find out the optimal value of these parameters the model user, knowing the nature of the problem, have to make some approximations to “help” the search algorithm.
The assumption we made are reported here:

- At the beginning of the construction phase of a PP, the study phase of the successive PP is triggered too.

- The design phase of all the PP after the first can be performed only before the construction phase of the previous PP is finished.
    - These two assumptions are reasonable because one of the advantage of an investment in SMRs is that they have a lower capital construction cost than the LR’s one. Thus, an investor can face an investment in an SMR after the first being financed by the electricity produced and sold by the first one. It means that we have to give to the model user the possibility to trigger the most costly phase of the investment in an additional SMR immediately after the first one is completed.

- The most influential parameters are again the $m_{construction,i}$ parameters in which:
    - $m_{construction,i}$ = Construction Phase’s “Multiplication Factor” of the i-th SMR

- In function of the nature of the problem all the Construction Phase’s “Multiplication Factors” should be linked between each other. In this way the model user can “help” the search algorithm to find those optimal values in a reasonable amount of time. The relationships used in our analysis are:

    - $m_{construction,2} = m_{construction,1} - 40$
    - $m_{construction,3} = m_{construction,1} - 30$
    - $m_{construction,4} = m_{construction,1} - 20$

        - The reason of this idea is that the first investment in SMR should be done in an explorative way (and thus it has the highest multiplication factor for the ECTC threshold) in order to see the evolution of the scenario and to properly decide if it is reasonable to invest in additional power plants.
        - Other kind of relationships are obviously possible but always following the idea described in the previous point. For example, knowing that exploiting the learning factor, that reduces the total cost of construction the model user could implement:

            - $m_{construction,2} = m_{construction,1} * LE_2$
            - $m_{construction,3} = m_{construction,1} * LE_3$

- $m_{construction,4} = m_{construction,1} * LE_4$

In which the LE_i is the “Learning Effect” parameter that describe the reduction in the total cost of construction that there is for the i-th PP (a more detailed description of it is reported in paragraph 4.1.5). Moreover this relationship is an help for the model user have to understand that the exercise thresholds provided by the model do not represent the real ones, but an approximation and, using thresholds of this kind avoids this misunderstanding.

- After those relationships between the parameters that characterize the exercise thresholds are built, the steps to implement the SOET Method with compound options are the same described previously for the case of investment in a single power plant. The level of influence between these parameters are reported here:

Parameter	Description	Level of Influence	Way of modeling
P*	Trigger the study phase of the first PP to be built	Medium	At the beginning it’s free to vary. It is fixed after the optimal value is found in order to find the optimal values of the less influential parameters too.
$\boldsymbol{a_{design,i}}$	Difference Coefficient of the linear exercise threshold that trigger the design phase of the i-th PP to be built	Low	After the first explorative simulation it is fixed to a reasonable value to reduce the computational effort required by the model, “helping” it to find the optimal values of the most uncertain parameters
$\boldsymbol{m_{design,i}}$	Multiplication Coefficient of the linear exercise threshold that trigger the design phase of the i-th PP to be built	Low	After the first explorative simulation it is fixed to a reasonable value to reduce the computational effort required by the model, “helping” it to find the optimal values of the most uncertain parameters
$\boldsymbol{a_{construction,i}}$	Difference Coefficient of the linear exercise threshold that trigger the construction phase of the i-th PP to be built	Low	After the first explorative simulation it is fixed to a reasonable value to reduce the computational effort required by the model, “helping” it to find the optimal values of the most uncertain parameters
$\boldsymbol{m_{construction,i}}$	Multiplication Coefficient of the linear exercise threshold that trigger the construction phase of the i-th PP to be built	High	At the beginning it is free to vary. It is fixed after the optimal value is found in order to find the optimal values of the less influential parameters too.

Table 31. Description of the parameters characterizing the exercise thresholds implemented

- The last step of the algorithm is to vary the relationships implemented before in order to verify it gives in output the best result respectively to the objective function maximized.

3.3 The Integration between the SOET Methods and the MVP Theory to perform a Portfolio Analysis

The aim of this paragraph is to clarify how we integrate the SOET Method with the MVP Theory in order to consider an investment in a new power plant that, from the utility's point of view, is always an investment in an already existent portfolio of investments.

Differently from several classical works that apply the financial economic model and then the MVP (e.g. (F. A. Roques, 2007); (Locatelli & Mancini, 2011); (Paz et al., 2012)) to evaluate the performances of the portfolio, this work applies the SOET Method to a portfolio of technologies before the MVP. Then, MVP calculates as output the NPV distribution of the total portfolio.

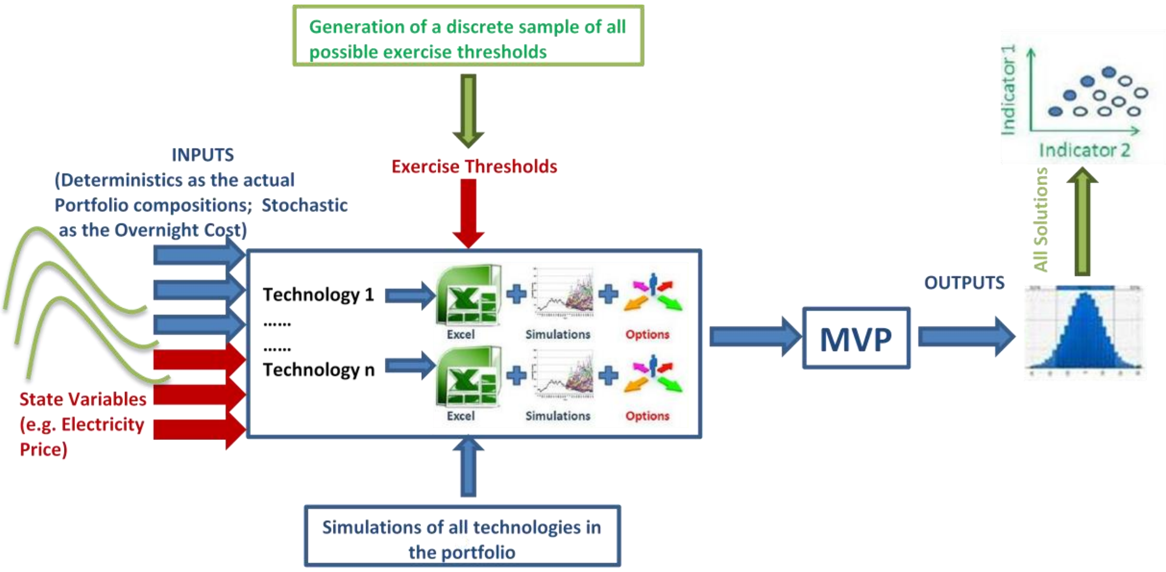

Figure 54. The discrete enumeration of all possible thresholds SOET Method integrated with the MVP Theory

This paragraph describes how we integrate all the three standard SOET Method with the MVP Theory and, in order to validate the results obtained, applies all these method with one state variable evaluating an investment in a nuclear PP considering an hypothesized actual portfolio of the utility and the real time elapsed from the moment the decision to invest in the PP is taken and the moment in which it starts to produce energy.

3.3.1 Application with One State Variable: the discrete enumeration of all possible thresholds integrated with the MVP theory.

Let's evaluate the profitability of an investment in a large nuclear reactor considering the presence of an actual portfolio of investment in this field with the DCF approach integrated with the MVP theory and with the ROA through the integration between the SOET Method and the MVP (both with and without modeling its pre-operational phase as the succession of three sequential compound options).

The DCF approach evaluates the profitability of the additional investment done at time zero with a MCS. The actual portfolio of investments and the data used for this analysis are properly presented in Chapter 4. However, supposing that the electricity price follows a Geometric Brownian Motion with initial value $P_0 = 90\ \$/MWh$ and volatility $\sigma = 30\%$ and that the hypothesized composition of the actual portfolio of a utility is the same reported in the following table, it is possible to generate the stochastic distribution of the total portfolio considering this additional investment.

Technology	MW Installed	Percentage in the overall Actual Portfolio
Large Nuclear PP	1500	46,15%
Coal PP	750	23,08%
CCGT PP	1000	30,77%

Table 32. Composition of an hypothesized actual portfolio of a utility

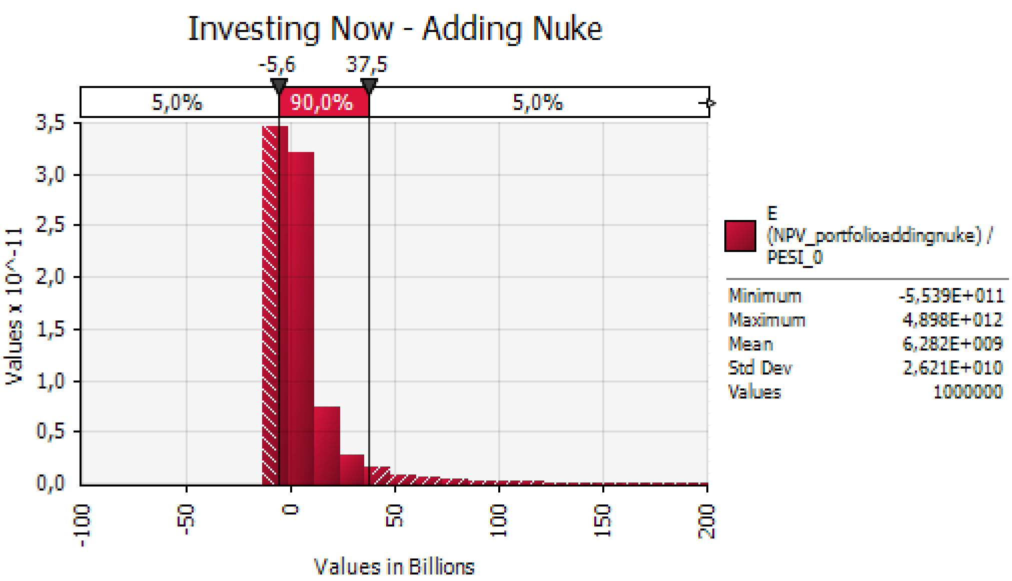

Figure 55. NPV distribution of the portfolio of a utility considering an additional investment in a Nuke PP

The results of the overall portfolio considering an additional investment in a large nuclear PP obtained applying the classical DCF Approach (e.g. Investing now) integrated with the MVP theory are reported in the following table:

Evaluation Method	E(NPV) [mln $]	σ(NPV) [mln $]
Classical DCF Approach + MVP	6282	37506

Table 33. Results of a Portfolio considering an additional Nuke PP(DCF Approach – Classical MVP)

Instead with the SOET Method the investor has the possibility to implement in the analysis the option to defer or the option to invest in the additional Nuke PP and this option will be exercised only when the value of the electricity price will exceed a threshold P*. At this point of the analysis the pre-operational phase of the nuclear PP is not modeled as the succession of three sequential compound options, because our aim here is only to describe how the integration between all the standard SOET Methods with the real Time to Market and the MVP Theory must be done.

In order to properly integrate a Real Option Approach with the MVP Theory when the option to defer is implemented, we have to make the assumption that the utility is obliged to fulfill a request of 1,5 GW in addition to their actual output. Indeed it is obvious that, considering the profitability of the actual portfolio without this additional investment, its E(NPV) will be greater than the one of the portfolio in which the new investment is made. The reason of this effect is that MVP gives in output the E(NPV) of the overall portfolio as the weighted average between the profitability of each power plant in the portfolio. Taking into account the fact that the utility has already borne the construction costs of the PPs in the actual portfolio, it is easy to understand that their E(NPV) will be greater than the E(NPV) of the new PP for which those costs are not still incurred, and thus the E(NPV) of the overall portfolio without the additional investment will be greater than the one with it. If we do not make this assumption, the application of a ROA thanks to the SOET Method with the objective function of maximizing the E(NPV) of the overall portfolio will suggest as best choice to never perform this investment and the analysis becomes useless[23]. This effect is avoided implementing in the model the assumption that the utility is obliged to start the investment in the additional PP after 20 years from this moment.
Therefore the analysis of the option to defer is interesting because it let us transfer directly the result of the additional PP to the result of the overall portfolio[24] while the option to invest[25] would not do it.

The steps of the method to achieve this results are:

1. Evaluation of the NPV distribution of power plants in the actual portfolio of the utility

2. In order to apply the option to invest in the additional nuke PP, consider an interval of P* defined by a lower and an upper bound. The property of the extreme of the range considered are simple to understand:
    a. The Lower Bound has to be lower than the actual electricity price (for example P*=1)
    b. The Upper Bound has to be significantly higher than the actual electricity price (for example P*=600)

3. Select all the values of P* in the range defined before for which a MCS would be performed. Implementing a step of 1 between one value of P* and the successive and then performing 600 simulations brings to optimal result, but we have to say that considering a larger step of 10 and then performing only 60 simulations brings to good result here too.

4. Select the number of iterations for each simulation. In order to obtain a robust result at least 100000 iterations should be implemented.

5. In correspondence to each simulation implement the MVP Theory to find out the performances of the overall portfolio in function of the value of the exercise threshold and to build the efficient frontier of the portfolio with this additional investment.

[23] If you want to implement properly the option to invest, the objective function has to be the maximization of the NPV mean of the additional investment, and not of the overall portfolio. Only after that value has been found the model user has to apply the MVP theory to find out the NPV mean and standard deviation of the overall portfolio
[24] It means that the value of the exercise threshold that maximize the NPV mean of the additional PP is the same that maximize the NPV mean of the overall portfolio
[25] It means that the value of the exercise threshold that maximize the NPV mean of the additional PP is not the same that maximize the NPV mean of the overall portfolio

The steps of the algorithm described above can be summarized in the following flow – chart:

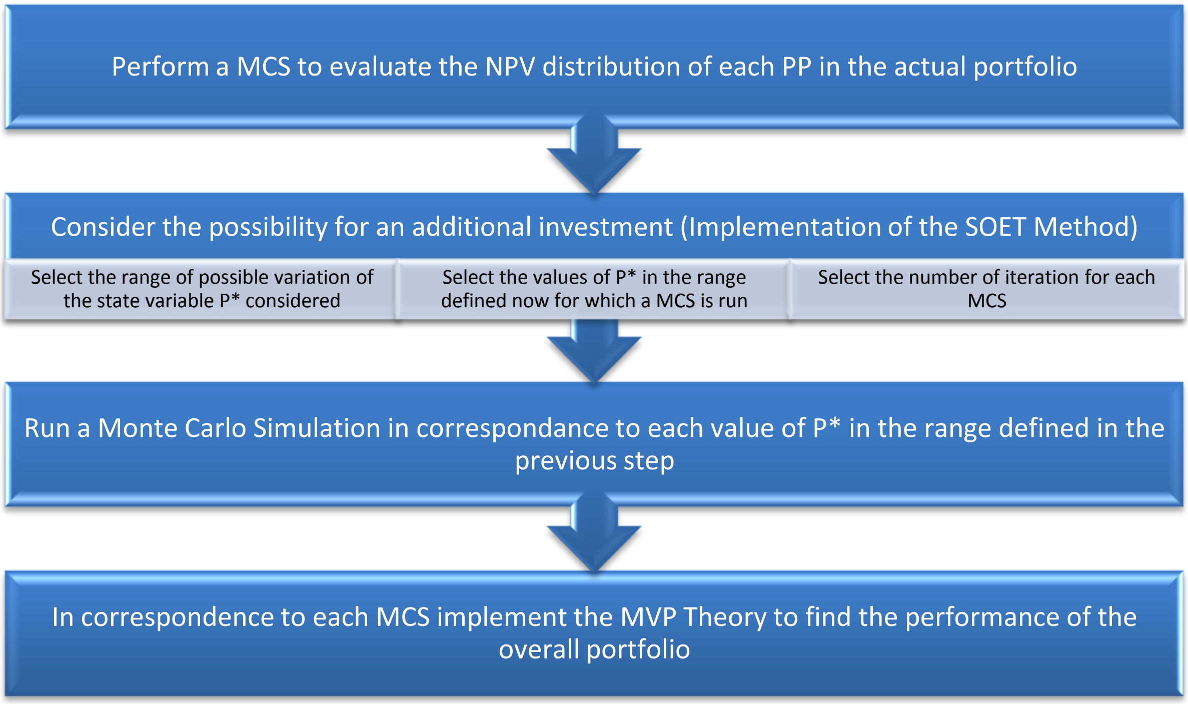

Figure 56. Steps of the algorithm used to integrate the discrete enumeration of all possible threshold SOET Method with the MVP Theory in the application with one state variable

The results of this analysis are reported in the following figures that shows the relationship between the E(NPV) of the portfolio with the exercise threshold P* and the efficient frontier of the portfolio considered.

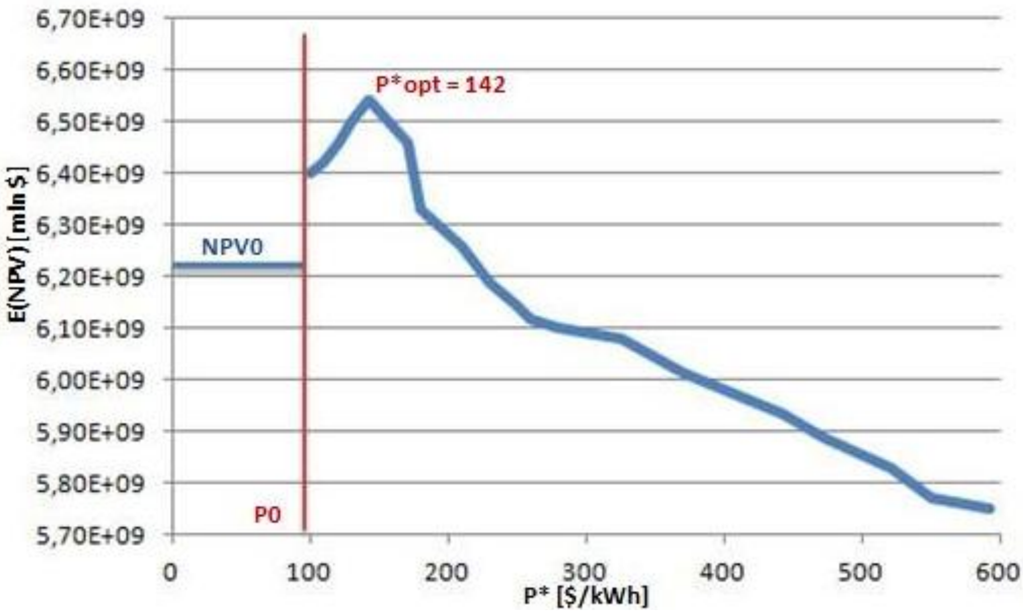

Figure 57. How the value of P* impacts on the NPV distribution of the overall portfolio

It is possible to notice several things from this function:

I. There's a great analogy between this relationship and the one between a single PP and the exercise threshold (see Figure 42)

II. When $P^* < P_0$ the option to invest is exercised at time zero. All the values of the E(NPV) of the portfolio are the same: NPV_0 as in the standard DCF analysis.

III. When P^* is very high the value of the E(NPV) decreases significantly. That's because when P^* is very high the probability that the price of electricity will reach this value is very low. Then the probability to invest only after 20 years is very high, and not triggering the investment before that moment equals to merely fix the investment after 20 years.

IV. Between these two extreme conditions exists an exercise threshold in which the mean of the NPV distribution is maximized. That's what in ROA is called the Expanded NPV and the difference between this and the NPV_0 is the value of the option to invest.

V. There is a discontinuity of the second type after $P^* = P_0$. Indeed waiting for a greater value than P_0 means to not invest at time zero, and thus to acquire more information about the investment increasing its value and reducing its level of risk.

The following figure shows the efficient frontier for the portfolio considering the option to invest in an additional large nuclear power plants. The points on the figure are found evaluating the investment in function of different values of the exercise threshold.

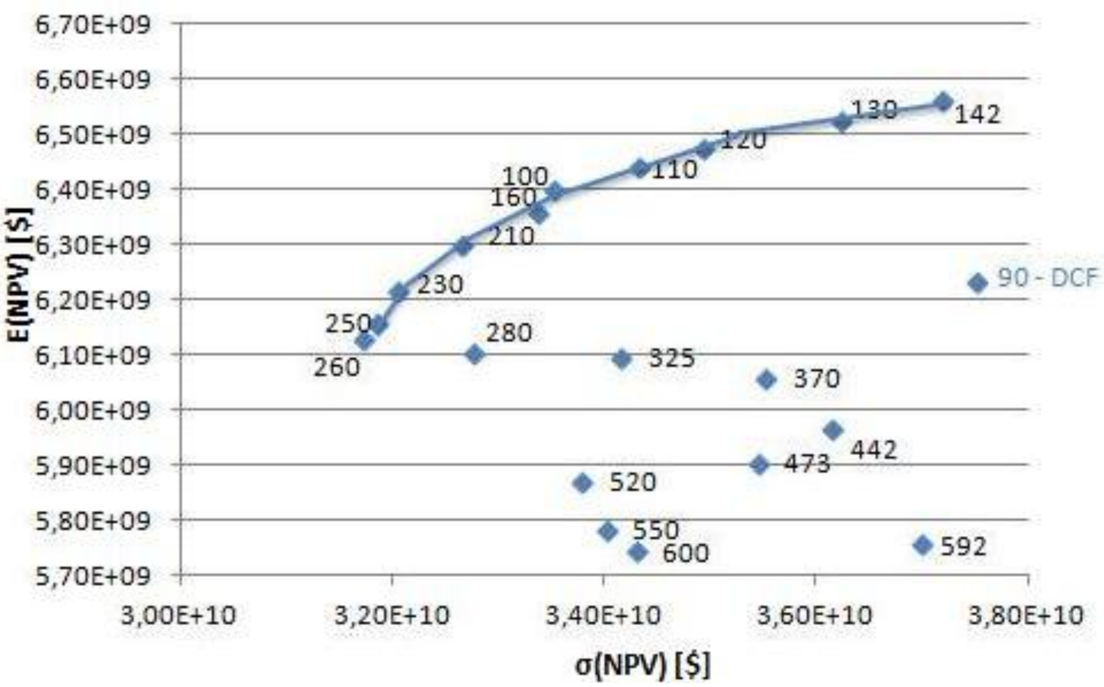

Figure 58. Efficient Frontier for the Adding Nuke Portfolio Case

It is easy to notice that, evaluating the performance of the portfolio with a ROA thanks to the integration between the SOET Method and the MVP Theory, we are able to create a curve on the plane E(NPV) – σ(NPV) differently from the output obtainable applying the classical DCF Approach with the MVP in which the performance of the portfolio is represented by a single static point on the plane E(NPV) - σ(NPV).

From the figure above some things can be noticed:

I. When $P^* \leq P_0$ the option to invest is exercised at time zero and the investment does not belong to the efficient frontier. As a consequence it means that the investor should wait to begin the investment because in this way the profitability of the investment increases while the risk connected to it decreases. Thus the DCF Approach integrated with the classical MVP Theory brings to a completely inefficient result[26]. It confirms the good nature of our choice of modeling this kind of investment thanks to a Real Option Approach.

II. The points on the efficient frontier have all these characteristics:
   a. The option to invest has to be exercised when $P^* > P_0$
   b. There is a value $P^* = P_{lim}$ after whose value all the points does not belong to the efficient frontier anymore (in this example the point is $P_{lim} = 260\ \$/kWh$).

III. All the points that belong to the efficient frontier have these properties:
   a. The condition to find them is to exercise the option to invest only when $P_0 < P^* \leq P_{lim}$
   b. Those points are equivalent because they maximize the E(NPV) accordingly to their specific level of risk
   c. They can be compared only in term of Sharp Ratio, which means in term of the ratio between the E(NPV) and the level of risk connected to the investment. In this case study the point that maximize the Sharp Ratio Value is obtained when the option to invest in the additional PP is exercised at $P^* = P_{SR} = 230\ \$/kWh$

The potentiality of this method becomes clear if we think that the efficient frontiers of all the different possible portfolios can be compared between each other. It means that the model user can find the optimal solution in function to the snapshot evolution of the environmental conditions around him (i.e. in function to the specific value of P* that trigger the investment) building a sort of *Optimized Efficient Frontier* of the Portfolio considering all the possibilities for the additional investment(see for example Figure 38).
Therefore, applying this model, the investor is able to find out what is the most adapted PP to be added in the actual portfolio (or what are effectively the technologies on the efficient frontier) according to the specific evolution of the environmental conditions.

3.3.2 Application with one state variable: the Discrete Enumeration of all Possible States integrated with the MVP Theory

In order to validate the result obtained in the previous paragraph we integrate now "the Discrete Enumeration of all Possible States" SOET Method with the MVP Theory.
Figure 57 shows that there is a great analogy between how P* impacts on the NPV mean of the overall portfolio and how it impacts on the NPV mean of a single investment without considering the actual portfolio of a utility.
Having the two curves the same properties, we can apply the discrete enumeration of all possible states as we did in paragraph 3.1.2 analyzing the TTM Effect on a nuclear PP.

Therefore this method calculates for each possible value of the exercise threshold the difference between investing immediately and waiting for a value slightly greater. Following this description we expect as results that:

- When $P_{opt} > P^*$ this difference will be positive since it is better to wait (the trend is positive).

[26] The main drawback of the MVP Theory reported in (Madlener & Wenk, 2008) is true but our model solve it.

- When $P_{opt} < P^*$ this difference will be negative since it is better to invest (the trend is negative).
- When $P_{opt} = P^*$ this difference will be zero and then this is the condition to find the optimal value of the exercise threshold with this second method

Hence, the step of this method are reported here:

I. Consider a range of possible values of P*, defined by a lower and an upper bound. The lower bound has to be significantly lower than the actual electricity price, while the upper bound has to be significantly higher than it(highly improbable to be reached). In this example we choose again $P^*_{LB} = 1\ \$/MWh$ and $P^*_{UB} = 600\ \$/MWh$.
II. Select the number of values that have to be analyzed. As before, an optimal result would be obtained performing for this case study 600 simulations, but 60 simulations bring to a good result too. In this work we perform 60 simulations in correspondence to these values of the electricity price: {10,20…..590,600}. In example, the first value $P_0 = 10\ \$/MWh$ is considered and a MCS is launched considering this value of the initial price of electricity and hence the additional investment is done immediately. A second simulation is then performed in which is waited the value $P^* = 10{,}0001\ \$/MWh$. For each value of the electricity price considered are then obtained two NPV distributions and then two NPV means.
III. Apply the MVP Theory for both the two MCS performed in the previous step in order to see if it is more profitable to invest immediately in the additional PP or to delay it.

The following figure shows the decreasing behavior of the difference between the investing now $NPV_{portfolio}$ and the $NPV_{portfolio}$ obtained waiting for a slightly greater value of P*.

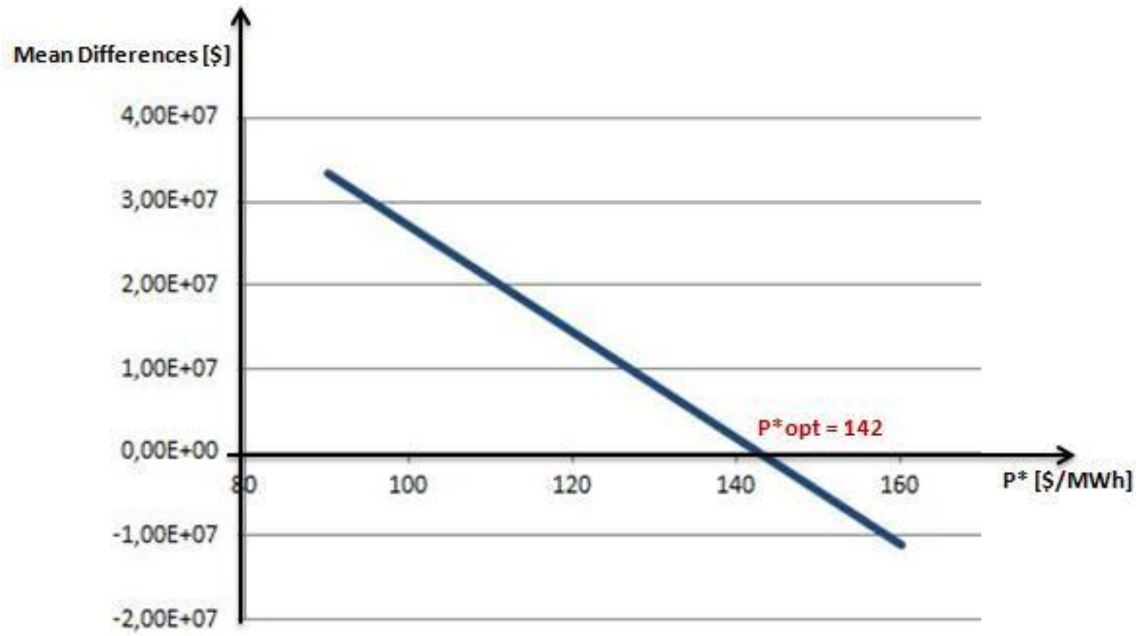

Figure 59. How P* impacts on the mean differences of the overall Portfolio

This method validate the discrete enumeration of all possible thresholds because the solution that they found (the value of the exercise threshold that maximize the NPV mean) are the same(e.g. P* = 142 $/MWh).

3.3.3 Application with one state variable: the search algorithm integrated with the MVP Theory

As already said, this work applies the SOET Method to a portfolio of technologies before the MVP. Then, MVP calculates as output the NPV distribution of the total portfolio. After this calculation, a search algorithm allows the generation of the optimal exercise thresholds and for each different technology in the portfolio the model calculates, through a MCS, several performance indicators that MVP summarizes in the Expected Mean and in the Standard Deviation of the NPV of the overall portfolio.

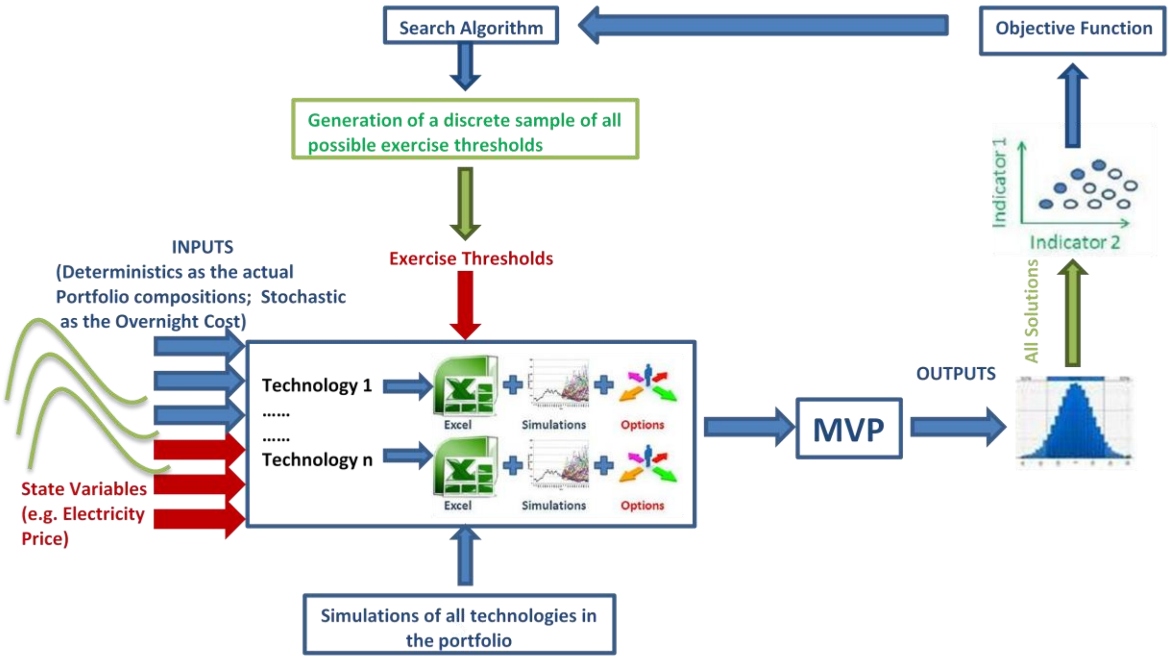

Figure 60. The scheme of the framework that apply the SOET Method to the MVP theory

The idea is, when possible, to consider a set of different exercise thresholds and calculate the different effects on the output distribution (e.g. the NPV distribution of the whole portfolio calculated applying the MVP theory).
According to this value and to a defined objective function we will then use a Search Algorithm to generate the best exercise threshold and for each technology in the portfolio we will calculate, through a MCS, several performance indicators that MVP then summarize in the Expected Mean and the standard deviation of the NPV of the total portfolio.

The steps of the method to achieve this results are:

1. Evaluate the NPV distribution of all the power plants in the actual portfolio of the utility
2. Define an objective function for the overall portfolio considered
3. In order to apply the option to invest in the additional nuke PP, consider an interval of P* defined by a lower and an upper bound. The property of the extremes of the range considered are the same described before:
    a. The Lower Bound has to be lower than the actual electricity price (for example P*=1)
    b. The Upper Bound has to be significantly higher than the actual electricity price (for example P*=600)

4. As seen in paragraph 3.1.3 , the P* interval is divided into a little number of candidate solutions, for example {50, 100,…,600 }. This idea gives to the algorithm (but not to the user, that doesn't look into the algorithm process) insights about the shape of the curve. Then apply the algorithm with a low number of iterations (e.g. 10000).
5. In correspondence to each simulation implement the MVP Theory to find out the performances of the overall portfolio in function of the value of the exercise threshold and to build the efficient frontier of the portfolio with this additional investment.
   In this way the algorithm perceives that there is a local maximum (not knowing that is the global maximum) between $P^* = 100\ \$/MWh$ and $P^* = 150\ \$/MWh$.
6. Restrict this new range of P* with other candidate solution, for example {100,110,…,150 } and implement an higher number of iterations (e.g. 100000).
   In this way, thanks to the application of the MVP Theory, the algorithm perceives that there is a local maximum between $P^* = 140\ \$/MWh$ and $P^* = 150\ \$/MWh$.

These steps are summarized in the following flow – chart in order to help the reader to understand better the logic of this algorithm:

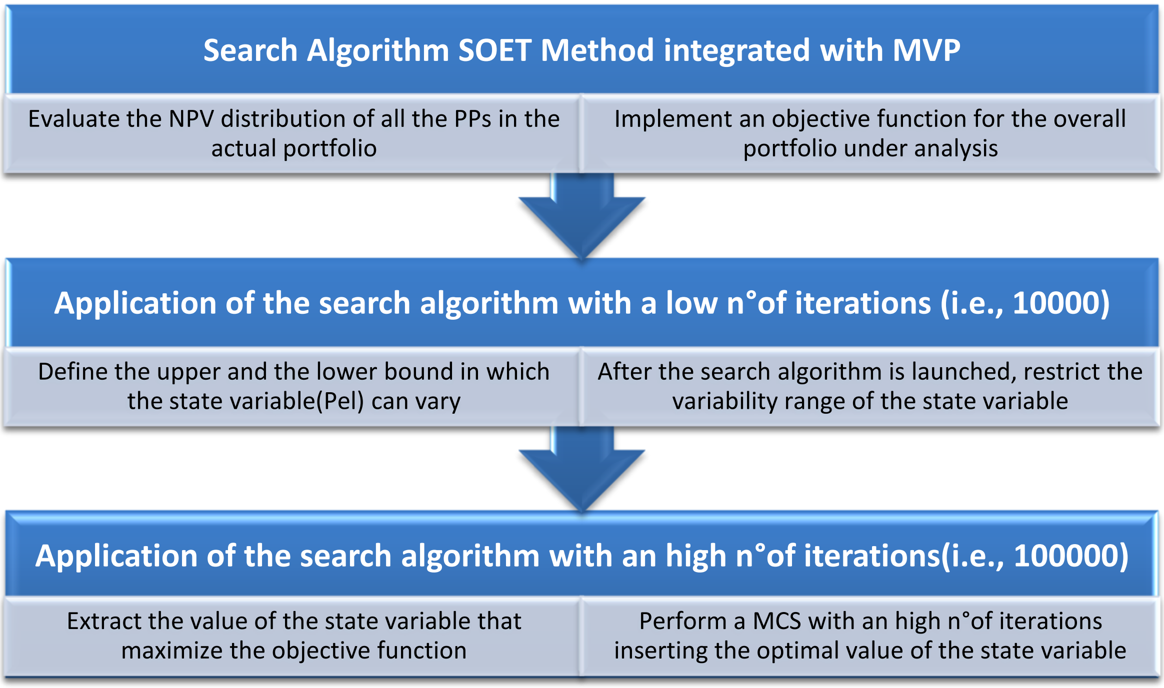

Figure 61. Steps of the search algorithm SOET Method integrated with the MVP Theory

Following these steps the search algorithm SOET Method integrated with the MVP Theory finds out the same value of the electricity price ($P^* = 142\ \$/MWh$) that triggers the investment in the nuclear PP in the most profitable way.

3.4 The Integration between the SOET Methods with Compound Options and the MVP Theory to perform a Portfolio Analysis

The aim of this paragraph is to clarify how the integration between the SOET Method with Compound Options and the MVP Theory in order to perform a realistic portfolio analysis in the energy field could be done.

If an investor wanted to apply this model to an investment in a nuclear PP considering the actual portfolio of a utility, the steps that must be followed are the same presented in paragraph 3.2 for all the three standard SOET Methods. Indeed we would have five values to be optimized but, as done before, the analysis can reasonably be simplified by fixing the less influential parameters (e.g. a_{des}; a_{cos}; m_{cos}) and by varying only the most influential ones (e.g. P* and m_{cos}) in order to discover their optimal value and their impact on the NPV distribution.
Hence, we remind to paragraph 3.2 to deepen insight into the algorithms that should be used to integrate all the three SOET Methods with Compound Options. The only difference is that, at the end of each MCS, the MVP Theory must always be applied to find out the NPV distribution of the overall portfolio.

3.5 Conclusions of the chapter

The main messages of this chapter can be summarized as follow:

- The description of how all the three standard SOET Method should be modified in order to implement the three steps of improvement from literature that this work have:
    - The Effect of considering the real pre-operational time for a nuclear PP
    - The Effect of considering the intrinsic flexibility of the pre-operational phase of a nuclear PP modeling it as the succession of three sequential compound options
    - The Effect of considering the Actual Portfolio on the decision of investment in an additional plant
- The validation of the results obtained thanks to the application of all the three standard SOET Method to each of these steps

Chapter 4 - The Implementation: building the static MVP evaluation model

This chapter aims to present the inputs used in the model (paragraph 4.1). The inputs analysed can be divided in deterministic and stochastic, where the stochastic inputs are the most influential variables in the analysis and are properly described from paragraph 4.1.1 to paragraph 4.1.4, while the other data employed in the analysis are the deterministic ones and are presented in paragraph 4.1.5.
Furthermore, we apply the model to a real energy portfolio present in UK to develop a more realistic and complete analysis that take into account all type of PPs and the renewable technology not considered before, and thus paragraph 4.1.6 contains the actual composition of the EDF's portfolio of technologies in UK. Then, paragraph 4.2 reports the output obtainable applying all the models developed in this work.
Paragraph 4.3 contains a list of all the requirements and assumptions, and the reasons for these choices, while at the end paragraph 4.4 reports a brief summary of the main messages this chapter have.

4.1 Inputs

The inputs data have to be divided in two groups: the deterministic and the random ones. The deterministic data are those that can be described by an explicit mathematical relationship while the random data are subject to variation due to chance, therefore they can take a set of different values.
In addition, the random variables can also be divided in state variables, that are the variables that describe the future response of a system given a present state, and not state variables.
The last step is to determine which of the random variables has to be considered to decide when exercise the option.

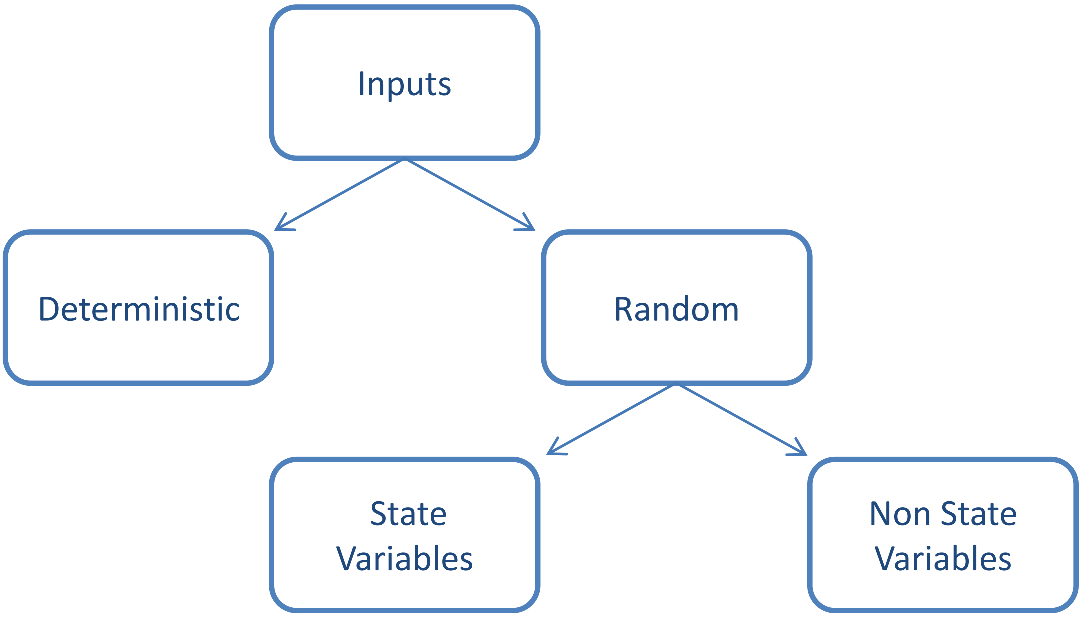

Figure 62. Classification of the inputs

As in (F. a. Roques et al., 2008), we use as state variables the most influential data and the data that give more information to “help” the model user in the decision of investment.
In this work we implement as input variables the price of electricity, the total capital investment cost, the fuel cost and the carbon tax because these variables have a greater impact than the others on the NPV distribution of the overall investment.
Therefore, the following paragraphs contains the description of all these variables and the way in which we model each of them.

4.1.1 The price of electricity

Liberalisation of energy markets, climate policy and the promotion of renewable energy have changed the framework conditions of the formerly strictly regulated energy markets.
The need for decision support tools in the energy business, mainly based on operation research models, has therefore significantly increased. In order to cope with different uncertain parameters, several stochastic modelling approaches have been developed in the last few years for liberalised energy markets (Möst & Keles, 2010).

We report here the most important features that must be kept in mind to model the electricity price, taking them from (Möst & Keles, 2010):

- Transportation of electricity requires a physical link (transmission lines).
- Electricity cannot be directly stored on a large scale, which necessitates that supply and demand are equalised at all times.
- Electricity can only be substituted to a limited extent, as the functioning of private, public and economic life in industrialised countries depends on a reliable electricity supply.

(Möst & Keles, 2010) report also some characteristics that electricity generation plants have, which can be summarized as follow:

- A long-term technical useful life between 40 and 60 years depending on power plant type;
- An high capital intensity for investment projects combined with long-term amortisation times;
- Undesirable by-products such as CO2, ash, fumes, heat, etc.

Furthermore it is easy to understand that the model have to take into account the characteristics of the price of electricity. We report its most important properties here taking them from (Burger et al., 2004):

- **Seasonal Patterns and Periodicities**: All markets show seasonal patterns of electricity demand over the course of the day, week and year.
- **Price Spikes**: Electricity spot prices typically exhibit extreme spikes. The spikes reflect the fact that the central dispatch process needs to rely on the bids of the high marginal cost of production generators in order to satisfy demand (Christensen et al., 2011).
- **Mean Reversion:** Prices have the tendency to revert rapidly from price spikes to a mean level. Characteristic times of mean reversion have a magnitude of days or at most weeks and can be explained with changes of weather conditions or recovery from power plant outages.
- **Price Dependent Volatilities:** It turns out that in all markets there is a strong correlation between price levels and levels of volatility.
- **Long-Term Non-Stationary:** Due to the increasing uncertainty about factors such as supply and demand or fuel costs in the long-term future, a non-stationary model seems more appropriate. A non-stationary is also needed for a model to be consistent with the observed dynamics of futures prices.

In literature there are many model that try to take into account different theoretical characteristic to explain the features of this variable.
In this work we use the Geometric Brownian Motion Process(from now GBM) to model the electricity price. Indeed both the Geometric Brownian Motion and the Mean Reversion Process deal with the volatility of the electricity prices, and can be used especially for the evaluation of real options in energy markets (Hirsch, 2009).

The Geometrical Brownian Model's functional form is:

$$dp = \alpha p dt + \sigma p dz \quad (4.1)$$

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.

Therefore this model do not consider the Mean Reversion, Spike Jumps and Price Proportional Volatility. The reasons for which we implement this model in this work are reported here:

I. The mathematical simplification of the model.
Indeed 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 thanks to a GBM process, this price value at time zero is the expected value for the future too, while the volatility at time t for the price in the future time t + n can be easily found out thanks to the following relationships:

$$E(P_{t+n}) = P_t \quad (4.2)$$

$$Var(P_{t+n}) = {P_t}^2(e^{\sigma^2}n - 1) \quad (4.3)$$

In addition this approximation has a low impact on the overall result; indeed the short term effects as Spike Jumps and Seasonal Patterns do not influence the investment decisions: these types of analysis are based on long-term expectations. Furthermore GBM is particularly adapt to reflect Long-Term uncertainty.

II. The model is simple to be used and to be implemented in an excel spreadsheet. There are only few parameters that must be modelled (e.g. three or two if the drift is removed)

III. It is true that on one hand the removal of the mean reversion and of jumps simplify the model, but on the other hand it is not so far from a realistic description of this variable because the weight of these two parameters in a long period of evaluation is negligible.

After all the descriptions and the assumptions presented previously we can then model the electricity price with the following expression:

$$P_{t+1} = P_t + \sigma P_t W_t \quad (4.4)$$

Where P_t is the electricity price at time t and W_t is a standard normal variable.

The value of P_t is taken from Italian scenario because it varies from country to country, and (GME, 2012) suggests for this case 90 $/MWh.

The choice of the last parameter σ is taken from (Locatelli & Mancini, 2011) that suggested a value if $\sigma = 0{,}3$ because it can be considered an intermediate value for its own historical value as well as for the other studies reported in the literature.

4.1.2 The Total Capital Investment Cost

A power plant generator incurs in three principal costs:

1. The Total Capital Costs of Construction (Construction Costs including Research & Development)
2. The Operating Costs (Fuel and Operation and Maintenance Costs)
3. The Decommissioning Costs.

In this section we make attention on the first of these three voices. The Total Capital Investment Cost (TCIC) can be divided in another three components too: the overnight costs, the interest during construction costs and the escalation costs. The overnight cost is the cost of the construction project if no interest was incurred during construction, as if the project was

completed “overnight”. Instead the interests during construction represent the financial costs incurred during the construction, while the escalation costs represent the increase in the costs, for example of equipment, labor and materials.
In this work we take into account only the first type of cost and we do not consider escalation costs and interest during construction.
As reported previously, for the nuclear and for the SMR PPs, we do not consider only the Construction Phase, but their pre-operational phase is described as the sequential succession of three phases:

- The Study phase
- The Design Phase
- The Construction Phase.

For this reason this work contains also as input variables the Total Capital Study Cost(TCSC) and the Total Capital Design Cost(TCDC) and not only the Total Capital Investment Cost (TCIC) . All these variables are modelled in the same way and thus we describe the functional form used only in one case taking as example the TCIC.

The use of total capital investments costs and of ECTD and ECDC

We introduce the ECTD and ECDC to implement the compound options in the analysis. These options help the model user to take the optimal decision, between invest or not, at the beginning of the Design Phase and Construction Phase acquiring information about the evolution of the environmental conditions around him (i.e. in function to the evolution of the random variables). TCIC is not relevant because it does not take into account the variations of the parameters when the investment has already been triggered. In correspondence to each decisional moment, the value of the investment of completion of the phase has to be compared with the expected cost to complete it and if its value is below this threshold the investment in this phase can reasonably be done. Hence, the value of ECTD and ECTC is correlated with the cost of completion of the first pre-operational phase with the Total Cost of the second and of the third one.
Thus the beginning of the second and of the third phases is evaluated in accordance to the expected cost to design and to construction, as explained in the Table 28, where the study cost and construction cost are respectively 1% and 5% of the TCIC.

Box 4. The use of total capital investments costs and of ECTD and ECDC

“*The cost of an investment is more uncertain than the future value of its payoff*”(Pindyck, 1992). This is the case for large projects that take considerable time to build. An example is a nuclear power plant, where total construction costs are very hard to predict due to both engineering and regulatory uncertainties.

During the time project, two different kinds of uncertainty arise (Pindyck, 1992):

- The first, called **Technical Uncertainty**, relates to the physical difficulty of completing a project. The project costs from time to time turn out to be greater or less than anticipated, but the total cost of the investment is only known for certain when the project is complete. This uncertainty came from the inability to predict perfectly how difficult a project will be.
- The second kind of uncertainty relates to input costs (called **Market Uncertainty**). Some costs, as materials required for a project, or changes in government regulations, can modify the project costs. Input costs uncertainty is particularly important for projects that are likely to take a long time to complete.

In this work we take the model from (Pindyck, 1992) because it contains both the uncertainties described:

$$dK = -Idt + \sigma(IK)^{1/2}dz + \gamma Kdw \quad (4.5)$$

where K is the remaining cost; *dz* and *dw* are the increments of uncorrelated Wiener processes, I is the investment rate, σ is the volatility of technical uncertainty and γ is the volatility of input costs uncertainty.

It is possible to see that in the equation above the first term is deterministic, while the second term represents the technical uncertainty and the third one the inputs' uncertainty. Thus, if no variability is considered (e.g. *dz* and *dw* are nulls) the cost of construction is a deterministic input. In our model we do not consider the inputs' uncertainty, in fact in power plants investment the second term of the formula is predominant on the third one and this kind of uncertainty is external to the project, it arises because input prices for work and materials fluctuate over time (Espinosa, 2005).

For this reason we adopt the model simplified as (Schwartz, 2002) taken from (Pindyck, 1992):

$$dK = -\,Idt + \sigma(IK)^{1/2}\,dz \quad (4.6)$$

The first term is the control of the diffusion process: as investment proceeds, the estimated remaining cost to completion decreases, while the second term corresponds to technical uncertainty. The advantage of the simplification in equation 4.6 is that it gives rise to a bang-bang solution (Schwartz, 2002) for the optimal control of the investment[27].

As in (Schwartz, 2002) the mean and the variance of the TCIC are described by these relationships:

$$E(TCIC) = K \quad (4.7)$$

$$Var(TCIC) = \frac{\sigma^2 K^2}{2-\sigma} \quad (4.8)$$

The relationship of $Var(TCIC)$ has been used to model the technical volatility of projects that take time to build and for which information is only available prior to project initiation.

Since the evaluation model is discrete-time based this stochastic process is modeled with:

$$K_{t+1} = K_t - I + \sigma(IK)^{1/2}W_t \quad (4.9)$$

Where W_t is a standard normal variable that gives the variability to this data.

The data used in the model are then reported in the table below, where K is the Mean of the Overnight Cost (Locatelli & Mancini, 2011), and σ^2 is calculated from equation (4.8).

[27] It means that the optimal solution is to continue at the maximum possible rate or at zero.

Plant	K[=E(TCIC)]	σ^2
Nuke	5335	0,041804
CCGT	1003	0,091407
Coal	3220	0,028319
SMR	6362	0,073334

Table 34. The σ^2 obtained

As reported above, to define K in a correct way, we have to consider the Total Capital Study Cost and the Total Capital Design Cost for both a large nuclear PP and an SMR PP. The values of these two parameters are modeled with the same functional form described here for the TCIC and their expected values are reported in the following table:

Input	Nuke	SMR
Study Cost	1%*K(Nuke)	1%*K(SMR)
Design Cost	5%*K(Nuke)	5%*K(SMR)

Table 35. Overnight Cost for Study Phase and Design Phase

4.1.3 The Fuel Costs

Power generation investments will ultimately be driven by their view of electricity and fuel prices, in fact electricity and fuel price risks in most markets are stronger than climate policy risks.
As reported in (IEA, 2007), there are three possible sources of fuel cost's variability:

- **Short-Term Volatility** (less than one years), when prices fluctuate quite rapidly according to snapshot variation of market's conditions.
- **Longer-Term Price Uncertainty** (greater than one year). This uncertainty is related to weather, technology costs and market conditions.
- **Climate Policy Uncertainty**, for example jump in price at some known time in the future.

In our model we take into account only the longer-term price uncertainties that is described very well with a Geometric Brownian Motion model.
In this way we model the price of electricity and the fuel costs in the same way of the electricity price for the same reasons described in paragraph 4.1.1.
To model the fuel costs we use the data taken from (Blyth et al., 2007) and thus, the annual standard deviation for gas price is ± 7.75% and for coal price is a ± 1.8%.
This gives a standard deviation from the expected mean after 15 years of ± 30% for gas and oil and ± 7% for coal, approximately in line with the IEA's predictions. As we can see in the Table 38 in paragraph 4.1.5 the starting Fuel Cost for a CCGT PP and for a Coal PP are taken from (EIA, 2012) and their values are respectively 22,3 $/MWh and 47,4 $/MWh.

4.1.4 The Carbon Tax

The cost of CO_2, as electricity price variations, is an important variable that should be considered to properly evaluate this kind of investment. The investment risks vary according to the technology being considered, with nuclear power appearing to be particularly exposed to fuel and CO_2 price risks. Furthermore, because different technologies emit different amounts of greenhouse gases per unit of electricity generated, climate policy risk introduces a new factor into this investment decision.

Whether climate change policies are introduced through a price mechanism (Carbon Tax) or through some other regulatory mechanism, the current and potential future cost of emissions needs to be included in the investment analysis (Yang et al., 2008). As in (Yang, 2007) we use GBM model to represent carbon price uncertainties, as done for price of electricity and fuel costs.
In the following table are reassumed some values taken from literature about the modelling of this variable, especially for our work the expected mean carbon cost chosen is 30 $/t and its volatility is 10%.

Authors	Mean	Volatility
(Wickart & Madlener, 2007)	40 €/t	/
(Blyth et al., 2007)	25 $/t	7.75%
(Van ’t Veld & Plantinga, 2005)	26.5 $/t	/
(Chen & Tseng, 2011)	15 $/t	38%
(Heather Mclean, 2012)	30 $/t	/

Table 36. Different value of carbon tax in Literature

4.1.5 Deterministic inputs

This paragraph contains the deterministic inputs chosen to analyze the data.
The first deterministic input described is the **Discount Rate**. This factor is difficult to estimate because it reflects the risk of the investment, indeed the higher the perceived risk, the higher is the Discount Rate too (Kodukula & Papudescu, 2006), and its value change depending on the type of investment.
In this work we choose a constant discount rate, irrespective of the fact that the specific risk strongly varies with the technology concerned and also over time (Rohlfs & Madlener, 2012).
Another reason for which we choose a constant value of the discount rate is that for these type of analysis it is not a parameter that reflects the risks in ROA analysis. As (Locatelli & Mancini, 2010), we use a discount rate of 5% in all this work.
For modelling the **Decommissioning Costs** the default values of (IEA NEA, 2010) are used. As already said, escalation costs and interest during construction are not considered and thus, Decommissioning Costs can be evaluated as a percentage of the total cost of construction, in particular: 15% for Nuke and SMR and 5% for Coal, CCGT and Wind power plants.
Moreover, in this model we consider the **Learning Effect** too. The construction costs of the second power plant built are only the 85% of the first, the third only 80% and the fourth 75%.
The **Capacity Factor** follows a standard value for PPs that operate in base-load and it is 85%. Only the Wind Technology have a different value of this parameters, it is 35% according to (IEA NEA, 2010).

As it happened for the power requirements, a comparison between costs reported in literature is done. The data are summarized in this table and taken from (EIA, 2012), (IEA NEA, 2010) and (Parsons, 2011).

Deterministic Inputs	EIA 2012			NEA 2010			PARSON 2011		
	Nuclear	Coal	CCGT	Nuclear	Coal	CCGT	Nuclear	Coal	CCGT
Capacity [MW]	2236	1200	400	1400	750	480	3300	1600	850
Capacity factor [%]	85%	85%	85%	85%	85%	85%	91%	95%	93%
Overnights cost [$/KW]	5335	3220	1003	4101,5	2133,5	1069	5518,8	2553,9	1036,8
O&M [$/Mwh]	13,9	13,4	15	14,74	6,02	4,48	12,741	6,1845	35,932
Fuel [$/Mwh]	8,26	22,3	47,4	9,33	18,21	61,12	7,75	35,805	72,08
Carbon cost [$/Mwh]	0	23,96	10,54	0	23,96	10,54	0	8,835	3,782
Construction Time [years]	6	4	3	7	4	2	6	3	4,3
Life [years]	60	40	30	60	40	30	40	35	30

Table 37. Inputs Data used in literature

This work uses the inputs of (EIA, 2012) for the large reactors and add the SMR technology inputs through the INCAS model (Locatelli & Mancini, 2011) in order to maintain the same proportions between the Large Nuclear reactors and the SMRs.
In the SMR technology the only parameters that change significantly from LR are the O&M cost and the Capital cost, the other remain approximately similar for all the base-load power plants considered.

Deterministic Inputs	EIA 2012			
	Nuclear	Coal	CCGT	SMR
Capacity [MW]	1500	750	500	335
Capacity factor (%)	85%	85%	85%	95%
Overnights Cost [$/KW]	5335	3220	1003	6362
O&M Cost [$/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

Table 38. Deterministic Inputs used in this work

In the table below, extracted from Table 19 we summarize the model we used to describe the input variables used in this work comparing them with the input used in literature.

	This Work	(Locatelli & Mancini, 2011)	(Paz et al., 2012)	(Vithayasrichareon et al., 2010)	(Jain et al., 2013)
INPUT					
Fuel Cost	GBM	Discrete Distribution	Historical Data	Lognormal distribution	GBM
Construction Cost	Differential Eq. (Pindyck, 1992)	Discrete; Continuous Distribution	Considered but not specified	Lognormal distribution	Differential Eq. (Pindyck, 1992)
Design Cost	Differential Eq. (Pindyck, 1992)	Not considered	Not considered	Not considered	Not considered
Study Cost	Differential Eq. (Pindyck, 1992)	Not considered	Not considered	Not considered	Not considered
O&M Cost	Deterministic	Discrete Distribution	Considered but not specified	Deterministic	GBM
D&D Cost	Differential Eq.	Deterministic	Considered but not specified	Considered but not specified	Considered but not specified
Technologies	Nuke; Coal; CCGT; SMR, Wind	Coal; CCGT; Nuke	Coal; CCGT; Nuke; Renewable	Coal; CCGT; Nuke	Nuke; SMR
Countries	EDF's portfolio in UK	Europe(OECD)/Italy	Spain	ASEAN Countries	OECD Countries
Emission Cost	GBM	Scenario dependent	Scenario dependent	Lognormal distribution	Not considered
Electricity Price	GBM	Continuous Distribution; Scenario dependent	Historical Data	Lognormal distribution	GBM

Table 39. Comparison between the inputs used in this work and in Literature

4.1.6 Actual Portfolio EDF Composition

The last step of this work has the aim to perform a complete and realistic portfolio analysis in the energy field. The analysis has been conducted on the EDF's portfolio of investments in UK.
We use this portfolio because EDF is one of the largest energy companies that works in UK, and it invests on all the types of power plants used in our analysis. We choose this portfolio because EDF invests in a remarkable way on Nuke PPs and Renewable technologies which are key factors in our work and are not always used by other companies. In particular we summarize the EDF Portfolio in UK in the tables below.
The data are taken from (EDF, 2012).

Nuke		Coal		CCGT	
Name	Capacity [MW]	Name	Capacity [MW]	Name	Capacity [MW]
Hinkley Point B	870	Cottam	2000	West Burton	1300
Hunterston B	890	West Burton	2000	Sutton Bridge B	1800
Dungeness B	1040				
Heysham 1	1160				
Hartlepool	1180				
Torness	1190				
Heysham 2	1220				
Sizewell B	1191				
Total	**8741**	**Total**	**4000**	**Total**	**3100**

Table 40. Composition of Actual EDF's Portfolio in UK

In this analysis we introduce another technology that is becoming more and more important in recent years: the renewable one.
The price of electricity for these technologies do not follow the laws of the traditional power plants. Indeed those price are pre-determined by the UK's government in form of incentives to the construction of renewable power plants. Therefore there is no sense in modelling the electricity price with the GBM Model described before to evaluate them, but in this case we model it as a fixed price because it is more reasonable and more coherent to reality.
This is in contrast with the logic of a wholesale market price determined by variable costs; the new policy is called feed in tariff, where the renewable generators are characterized by virtually zero variable cost. In summary the feed – in – tariff policy encourages investment in renewable technologies because:

- It eliminates market risk
- It guarantees to the investor revenues with an increasing positive trend

Feed in Tariff

In the last two decades, feed-in tariffs (from now FIT) emerged as the dominant policy instrument for supporting electricity from renewable sources in the European Union (Klein & Hons, 2012) and is gaining popularity as a policy option for encouraging renewable energy development. FIT policies offer a long-term guarantee of payments to renewable energy developers for the electricity they produce and it can be implemented to support all renewable technologies including wind, solar photovoltaic, solar thermal, geothermal, biogas, biomass, fuel cells, and tidal and wave power. The level of risks and uncertainties in this kind of investment is then significantly lower than investments in the classical base-load PPs.
The success of FIT policies around the world, notably in Europe, suggests that they will continue to grow in importance in the United States as evidence mounts that they provide an effective framework for the promotion of renewable energy development and job creation (Couture et al.,2009).
FIT policies can be understood as an advanced form of production-based incentive, where a payment is awarded for the actual electricity produced ($/kWh).
Initial evidence suggests that there are two primary reasons for which feed in tariff policies are more cost-efficient than other policies.

Firstly, policies using competitive solicitations like Renewable Portfolio standard involve an higher degree of risk for the developer. The reduction of these investment-level risks under FIT policies can also help to reduce Capital Costs, ultimately reducing the cost of renewable electricity.
Secondly, projects tend to be financed by larger institutional or corporate investors who provide equity as opposed to debt financing because they are under a competitive solicitation processes (Couture & Cory, 2009).
A further advantage of feed in tariff policies is that they tend to reduce the social opposition to renewable energies development because average citizens and business owners can participate. This could be an important condition for an higher expansion of renewable technologies.

Energy Source	Scale	Tariff(p/kWh)	
		<31/3/14	>1/4/14
Wind	<100 kW	22,23	17,32
Wind	>100-500 kW	18,53	14,43
Wind	>500-1500 kW	10,05	7,83
Wind	>1500-5000 kW	2,26	3,32

Table 41. Table: payment for wind electricity in the UK (UK Government, 2014)

Box 5. Feed – In - Tariff in UK

EDF have many plants of renewable technologies and they install more than 20 wind turbine in the UK, all the plants are summarized in the table below, we take the data from (EDF, 2012).

Renewable Generation					
Wind Turbine	Power (MW)	Wind Turbine	Power (MW)	Wind Turbine	Power (MW)
Kirkheaton	1,8	Longpark	38	Llangwyryfon	9,35
Trimond	5,2	Broom Hill	8	Cemmaes	15,3
Fallago rig	144	Langley	8	Great Orton	3,96
Glassmoor Ext	12,3	High Hedley Hope II	5,2	Walkway	14
Green Rigg	36	High Hedley Hope	2,4	Red Tile	24
Buondary Lane	6	Cold Northcott	6,6	Red House	12
Burnfoot Hill	26	Deeping St. Nicholas	16	Glassmoor	16
Fairfield	6,5	Teesside(Offshore)	62,1	Longpark	38
Rusholme	24	Bicker Fen	26		
				Total	528,71

Table 42. Renewable plants of EDF portfolio in UK

In our work for simplicity we consider all these Wind Plants as a single Plant that produce 116 MW per year (EDF, 2012). (528,71 are the theoretical total output that all the Renewable plants can produce together).
In the table below we summarize the deterministic inputs, already presented in the chapter, used in the model to evaluate the performance of the Wind Technology.

Deterministic Inputs	
Electricity Price [$/MWh]	33,2
Capacity [MW]	116
Capacity factor (%)	35%
O&M Cost [$/Kw]	28,07
Life [years]	30
Decommissiong Costs [$/KW]	121,85

Table 43. Deterministic data Renewable Technology

Furthermore (Awerbuch et al., 2007) explained that year-to-year fluctuations in electricity output from a wind farm is an unsystematic risk and is probably not relevant for portfolio purposes since it is uncorrelated to the risk of other portfolio cost streams – though this unsystematic risk presents a potential risk to the owner of the wind farm. While it is possible to measure the standard deviation of the yearly wind resource at a given location, its correlation to the output of other wind farms, or to most other generating cost components, is arguably zero (that is, $\rho = 0$). Thus, wind variability does not contribute significantly to portfolio risk.
Therefore, for a complete description of the input used in this work, we report now the table containing all the correlation coefficients between the technologies modeled in this work, bringing them from (Roques et al., 2008).

Technology	Nuke	SMR	Coal	CCGT	Wind
Nuke	1				
SMR	1	1			
Coal	0,953	0,953	1		
CCGT	0,797	0,797	0,789	1	
Wind	0	0	0	0	1

Table 44. Correlation coefficients between technologies (adapted from (F. a. Roques et al., 2008))

Finally, the last step for this section is to summarize the sizes of all the technologies present in the EDF's portfolio.

EDF's Portfolio in UK	
Renewables	116
Nuclear	8741
Coal	3987
Gas	1306
Total Capacity [MW]	**14150**

Table 45. EDF's Portfolio in UK used in the model

4.2 Outputs

Firstly we report here a table to make a comparison between the outputs obtainable applying the models described in this work and the ones obtained in the principal works present in literature.

OUTPUT	This Work	(Locatelli & Mancini, 2011)	(Paz et al., 2012)	(Vithayasrichareon et al., 2010)	(Jain et al., 2013)
Indicators	E(NPV); σ(NPV); Exercise Thresholds; Efficient Frontier 2D for each technology; Efficient Frontier 3D for Portfolio	IRR, LUEC – Efficient Frontier 2D for portfolio in which single technology is a static point on it	Efficient Frontier 2D for portfolio in which single technology is a single static point on it	Classical NPV	Efficient Frontier 2D for portfolio in which single technology is a single static point on it; Value of the option
Benchmarking with actual portfolio	Considered	Considered	Considered	Not considered	Not considered

Table 46. Comparison between the outputs used in this work and in Literature

In our work there are then two different types of outputs generated from the model:

- Outputs obtainable from DCF models. These outputs permit to obtain many different statistical indicators as the mean, the standard deviation and the NPV distributions. These outputs are the firsts and the more important parameters to evaluate the result during the analysis.

- Outputs obtainable with RO approach. The outputs of this point are extracted from the SOET model and are dependent to Exercise Thresholds used, indeed the model is built to use the optimization algorithm that find the best threshold.

We obtain these two outputs described above in all the analyses performed in this work, but to describe the main scope of this work it is now useful to divide the outputs obtainable with a ROA's description in two different section:
- Outputs obtained in TTM Analysis(both with and without compound options)
- Outputs achieved in Portfolio Analysis.

1. Outputs TTM Analysis:

a. Exercise Thresholds: this output permit to find out all the parameters that described the goodness of the investment as expected NPV and level of risk.
The Exercise Threshold allow to understand how the state variables impact on the investment and the best moment to maximize a specific objective function.

b. Efficient frontier 2D for each possible technology: it will be function of the exercise thresholds.

2. **Outputs Portfolio Analysis:**

   a. Exercise Thresholds: this output permit to find out all the parameters that described the goodness of the additional investment as expected NPV and level of risk of the overall portfolio in which it is positioned.
   b. Efficient Frontier 3D for Portfolio: it is a graph where each point on the curve have its own efficient frontier in function of the exercise threshold, the third dimension is given by the value of the exercise threshold, through this graph we find a value of the exercise thresholds that maximize the value of each portfolio taking into account the level of risk.

4.3 Requirements and Assumptions

In this paragraph we report the most important assumptions used in this work:

1. There is not inflation.
2. The investors do not take debt after the investment. There are not interest during construction.
3. The escalation cost are not considered, the only cost considered during construction are the overnight costs.
4. The time horizon considered is very broad (60 or more years), but the model can take the decision once a year.
5. The stochastic variables are not correlated in order to simplify the model.
6. The variables modelled with the Geometric Brownian Motion have no drift in order to simplify the analysis. For this reason the stochastic variables have a fixed volatility during the all period considered.
7. After that a power plant is finished to be built, it starts immediately to produce energy. Thus, we do not consider the initial period when the power plant is not working at full power (Start-Up Phase (EIA 2012)) and the period of maintenance during the life of the plant.
8. We do not consider the financial risks, the public acceptance and the environment related risks.
9. In order to properly evaluate investments in “sequential power plants”, the construction of the second PP can begin only when the construction of the first one is finished.
10. Another effect derived from the precedent assumption is that the study phase and the design phase of the second power plant have to finish before the construction phase of the first power plant is finished too. The same condition occurs for the second, for the third and for all the subsequent plants that could be built.
11. Each type technology in the actual of the EDF’s portfolio is modelled as a single large PP that gives in output the sum of all the outputs of the PPs of that technology in the portfolio.
12. The time horizon in which the model user can take the decision to invest is defined as follow:
    - In the TTM Model, the last moment in which the decision of investment is after 20 years from now. After this moment the investment can’t be performed anymore.
    - In the TTM Sequential Model, the investment in the second power plants can start in the first 10 years after the decision to realized the first plant, the same process is used for the third and for the fourth plant.
    - In the Portfolio Model when the option to defer is implemented, the investment starts after 20 years if the conditions in the firsts 20 years are not favourable. See paragraph 3.3.1 for a more detailed description of this assumption.

4.4 Conclusions of the chapter

The main messages this chapter contains are summarized here:

- The description of all the random and of all the deterministic variables used in this work.
- The description of the actual EDF's portfolio of investment in UK with a detailed description of the feed-in-tariff policy present in UK to evaluate investment in renewable technology.
- The main outputs obtainable applying the models presented in this work with their comparison with the outputs obtained in the principal works present in literature.
- The requirements and the assumptions we made in this work.

Chapter 5 - Time to Market results

This chapter presents the results obtained from the application of the SOET Method considering the TTM Effect. Paragraph 5.1 shows the investment analysis on the Large nuclear PP evaluating it with the classical DCF approach and with the classical SOET Method considering only the possibility for the utility to abandon the investment after having performed the study and the design phase(paragraph 5.1.1). Paragraph 5.1.2 adds to this analysis the real TTM Effect implementing the three sequential compound options: a utility has the possibility to wait for the best environmental conditions before starting with the successive pre-operational phase considered. Paragraph 5.2 proves the robustness of the model we built, while paragraph 5.3 applies the same kind of analysis performed for the large nuclear case, to the SMR too. Paragraph 5.4 contains the benchmarking between all the base-load technologies considering the presence of sequential investment in the SMR, in the Coal and in the CCGT case. At the end paragraph 5.5 reports the main messages contained in the chapter.

5.1 TTM Effect: The Large Nuclear Power Plant case

In this paragraph we evaluate the performances of an investment in a Large Nuclear Power Plant. In the first part of this chapter the analysis will be performed applying the classical DCF Approach and the SOET Method considering the possibility to abandon the investment at the beginning of each of the pre - operational phases but not to wait for the best moment between each of these phases. This limitation will be removed in the second part of this chapter in which the SOET Method considering the TTM Effect will be properly applied modeling the pre-operational phase as the succession of three sequential compound options.

5.1.1 The Sequential phase effect on a large nuclear PP: "no wait TTM" case

This section contains the comparison between the results obtained applying the classical DCF Method and the results obtained from our model that consider the intrinsic flexibility of an investment in a nuclear power plant. It shows that, modeling the pre-operational phase as the succession of three sequential phases, adds value to the investment. However, in this paragraph we make the assumption that it is not possible to wait between each of the three pre-operational phase: this result is then obtained applying the classical SOET method described in paragraph 3.1 considering the option to abandon at the beginning of each of the pre-operating phases considered and the real pre-operating time of a Nuclear PP reported previously in Table 24. Benchmarking between Time to Market base-load power plants.
Instead, the following paragraph shows the effect of considering the possibility of waiting between the three pre-operating phases that therefore are properly modeled as compound options.

The NPV distributions are obtained making 1000000 iterations and they are represented in Figure 63 (DCF Method), Figure 64 (SOET Method - investing now) and Figure 65 (Classical SOET Method).

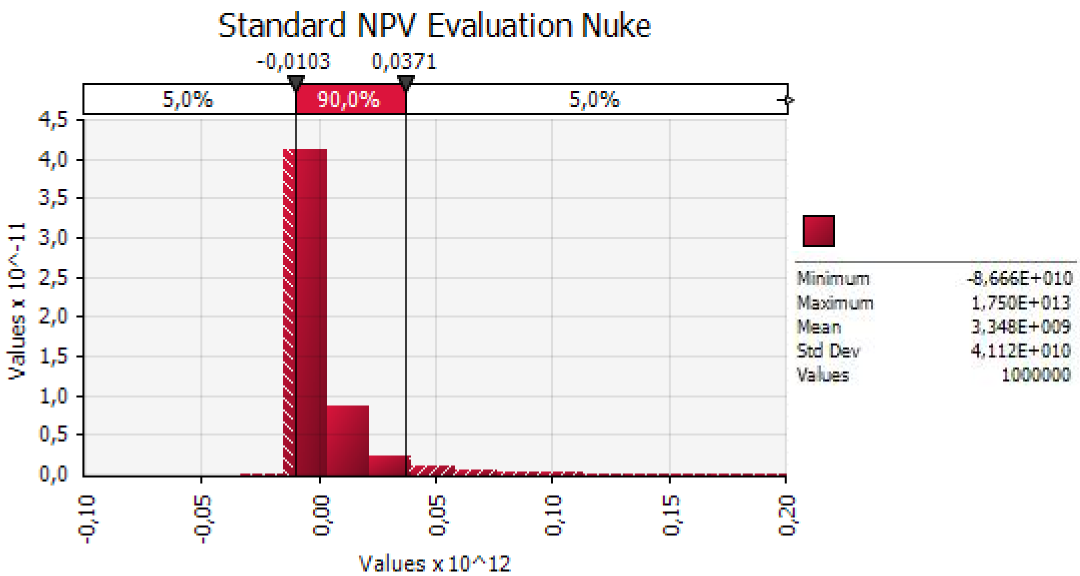

Figure 63. Probability Distribution of the NPV(DCF Method-No TTM Effect-Investing now)

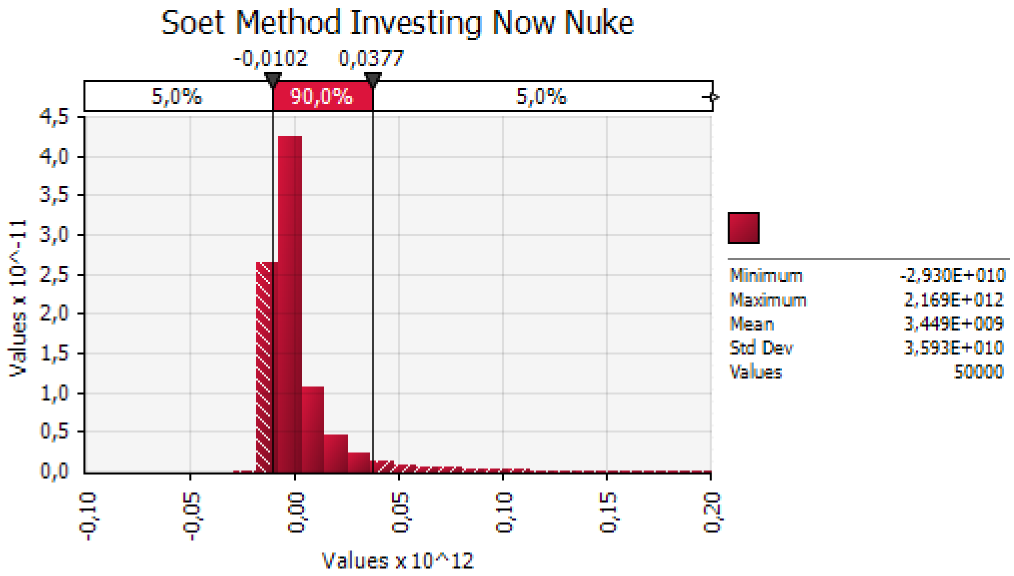

Figure 64. Probability Distribution of the Expected NPV(Sequential Method TTM Effect - Investing now)

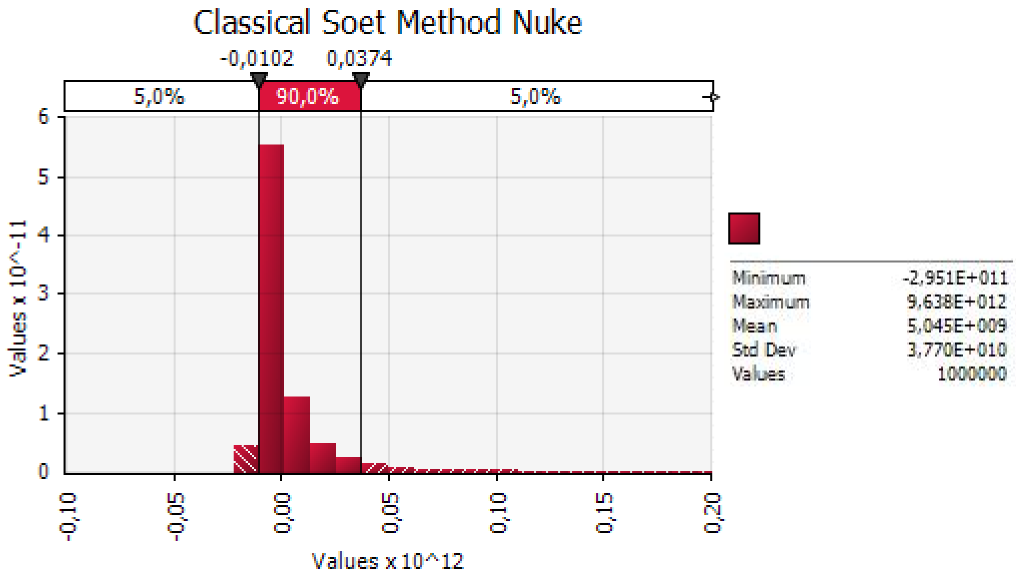

Figure 65. Probability Distribution of the Expected NPV(Sequential Method TTM Effect – Classical SOET Method considering the Option to Wait only for the study phase)

Figure 63 shows the probability distribution of the NPV if the investment is made immediately without considering the pre-operational phase as the succession of three sequential steps but implementing in the model the real pre-operational time of a nuclear PP. Therefore we evaluated the profitability of the investment with the classical DCF Method here.

Figure 64 analyzes again the case of immediate investment, but in this analysis we took into account the intrinsic flexibility of the pre-operational phase modeling it as the succession of three sequential phases. We noticed that the expected NPV grows up in this case. The reason of this increase is that at the beginning of the design and of the construction phase there are more information about uncertainties and our model let us abandon the investment if it is not convenient anymore (it happens when ECTD or ECTC are below their respective threshold).

Figure 65 adds to the model the option to wait for the best moment in which begin the study phase too. Therefore we are able to acquire more information triggering the investment only in the most profitable scenarios. As already said, in this case we applied the classical SOET method considering the option to abandon because we wait for the best moment to begin each of the pre-operational phases(the ECTD and ECTC thresholds can be seen as the only possible moment in which abandon the investment if it is not convenient anymore).
In the next paragraph we extend this analysis adding the option to wait between each phase and the option to abandon at the beginning of the design and of the construction phase.

As expected, the following table confirms that, considering the possibility to abandon the investment at the beginning of each of the pre-operating phases and then adding the option to wait for the beginning of the study phase, has a positive impact on the profitability of the investment.

Method	P*	ECTD*	ECTC*	Expected NPV[mln$]	Opt. Value[mln$]
DCF Method – Investing Now	90	None	None	3337,651	/
Sequential SOET Method (Opt to Abandon) – Investing Now	90	5*(P_t - 25)	80*(P_t - 25)	4225,398	887,747
Sequential SOET Method (Opt to Abandon) – Waiting Study	115	5*(P_t - 25)	80*(P_t - 25)	5003,998	1666,347

Table 47. Results "No Wait TTM" case

5.1.2 The Sequential Effect on a large nuclear PP: Modeling the pre-operating phase as the succession of three Compound Options

This section shows how the expected NPV of the investment improves if we consider the intrinsic flexibility in the pre-operational phase of a nuclear plant adding the option to wait between each of our phases(i.e. modeling it as compound options). Therefore this is the result obtained applying the new framework of the SOET Method that model properly the pre-operational phase of a nuclear PP as the succession of three sequential compound options.

Results are shown in the following figure:

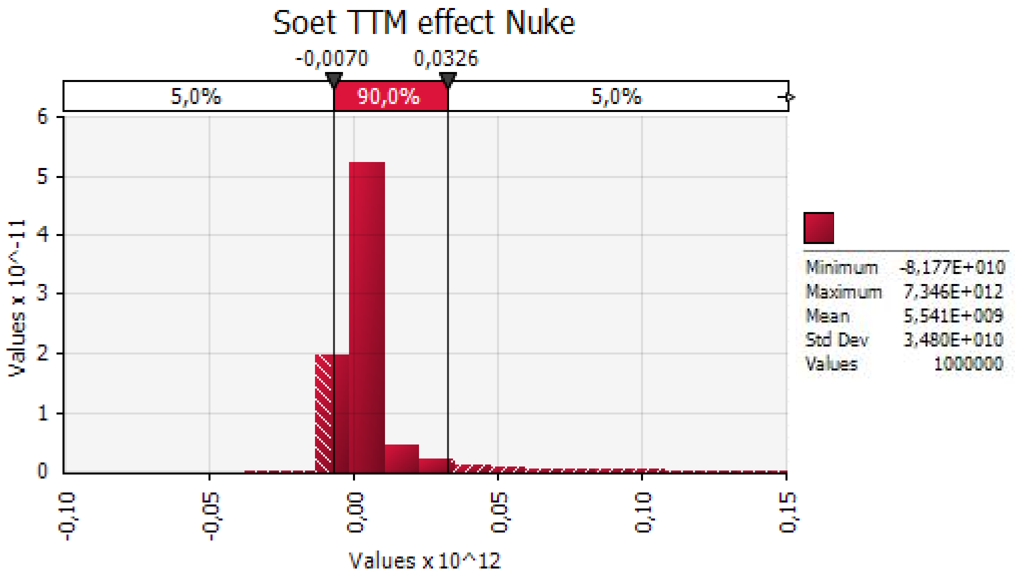

Figure 66. Probability Distribution of the Expected NPV(Sequential Method considering TTM Effect with Compound Options between each of the pre-operating phases)

We report our results in the following table in which we show the value of exercise thresholds and of the expected NPV obtained. As we expected the application of the SOET method with compound options to model the value of the intrinsic flexibility of the pre-operational phases of a nuclear power plant adds a great value to the investment.

Method	P*	ECTD*	ECTC*	Expected NPV[mln$]	Opt. Value[mln$]
DCF Method – Investing Now	90	None	None	3337,651	/
Sequential SOET Method (Opt to Abandon) – Investing Now	90	5*(P_t - 25)	80*(P_t - 25)	4225,398	887,747
Sequential SOET Method (Opt to Abandon) – Waiting Study	115	5*(P_t - 25)	80*(P_t - 25)	5003,998	1666,347
Sequential SOET Method – Compound Options	95	5*(P_t - 55)	60*(P_t - 55)	5596,253	2258,602

Table 48. Results with option to Wait between pre- operating phases

Therefore we can conclude that if an investor wants to invest in a nuclear power plant he has to consider all the time elapsed from the moment in which he decides to invest and the moment in which the power plant starts to produce energy, not only the construction phase.

On one hand this kind of investment has the drawback that the time needed to start to produce energy is significantly higher than the time necessary to start to produce energy for a Coal or a CCGT power plant; and as a consequence, environmental conditions could change making not profitable anymore this kind of investment. On the other hand this investment has a great intrinsic flexibility in the pre-operational phase: a utility that want to invest in a nuclear power plant have to consider it, like our model does with the implementation of three sequential compound options.

In most of the cases, the first two pre-operating phases have not a great cost, especially if we compare it with the total cost to construction. Therefore an investor could think to make quite always those phases in order to acquire more information and thus, to begin the most uncertain phase(the construction phase) only in the most profitable scenarios.

The result we obtained confirms this assumption because the study phase is triggered with a low value of the electricity price threshold: the following figure shows how vary the probability of begin each phase along years. The first two phases are made in the early, while the construction phase has a significantly lower level of probability to be started. It is reasonable because the construction phase has the greatest impact on the overall profitability and is the more uncertain phase of the investment.

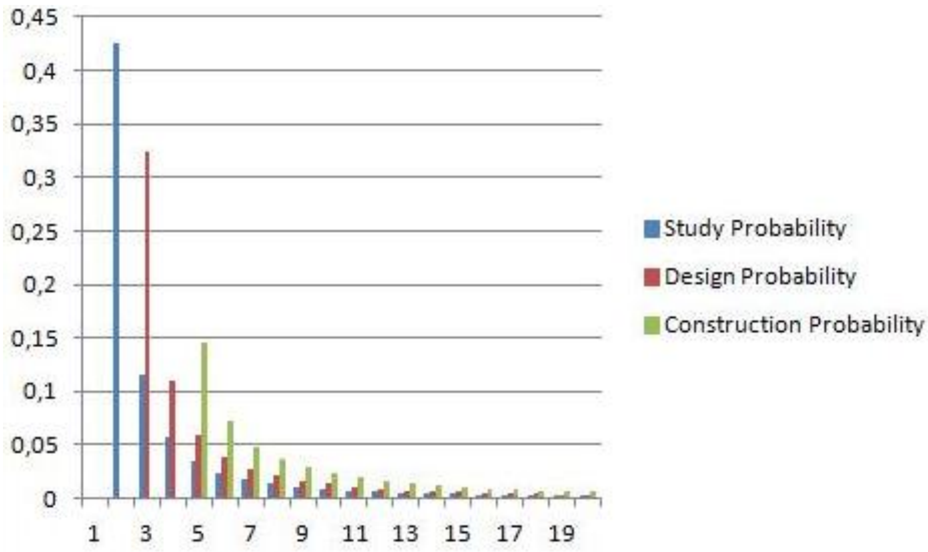

Figure 67. Probability Distribution of beginning each phase along years

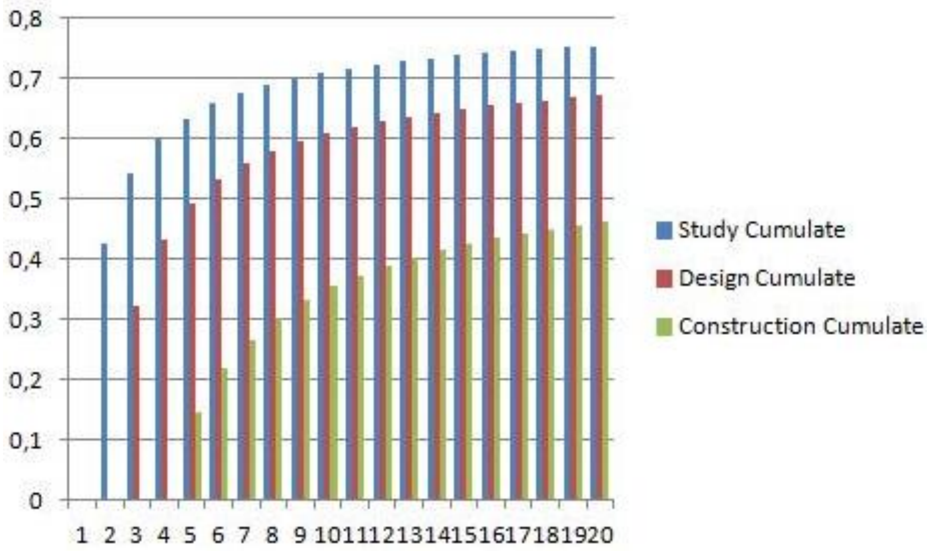

Figure 68. Cumulate Probability Distribution of the Pre-Operating phases

The results we showed here are confirmed by (WNA, 2014) in which the World Nuclear Association describes the status of the so-called Nuclear Power Plant “Under Construction”. The percentage of nuclear PP whose construction has started is only 22,5% of the nuclear PP for which they made a study, and the percentage of Nuclear PP for which the design phase is made are the 60% of the nuclear PP for which the study was made. The comparison between the (WNA, 2014) results and our results are reported in the following table:

Kind of Results	Percentage of design phase made	Percentage of construction phase made
WNA 2014	55,8%	22,5%
Our Results	59,7%	22,9%

Table 49. Comparison between our results and WNA 2014 report

5.2 Robustness Analysis of the TTM Model

In this section we change the relationship between the cost of pre-operating phase to verify the robustness of the model implemented. The next table describes the analysis that we performed and the expected result that we would like to find applying them in our model.

KIND OF ANALYSIS	STUDY COST PERCENTAGE	DESIGN COST PERCENTAGE	EXPECTED RESULTS
Standard Analysis	$1\% * Construction\ Cost$	$5\% * Construction\ Cost$	See previous paragraph
High Study Cost Case	$90\% * Construction\ Cost$	$5\% * Construction\ Cost$	The investment must be made only in the most profitable scenarios. We expect then to find a greater value of the electricity price threshold that triggers this phase and a lower probability level of starting the study phase.
High Design Cost Case	$1\% * Construction\ Cost$	$90\% * Construction\ Cost$	The study phase can be made quite always because it has a low cost and let the investor acquire more information about the evolution of the uncertain parameter. Instead the design phase should be performed only in the most profitable scenarios.

Table 50. Expected Results of our study cases

5.2.1 The High Study Cost Case

The results we obtain are shown in Figure 69 (Exercise Threshold and Expected NPV), Figure 70(NPV distribution), Figure 71(Cumulate Probability Distribution along years of Beginning study and design phase), Figure 72(Probability Distribution of beginning study and design phase in each year).

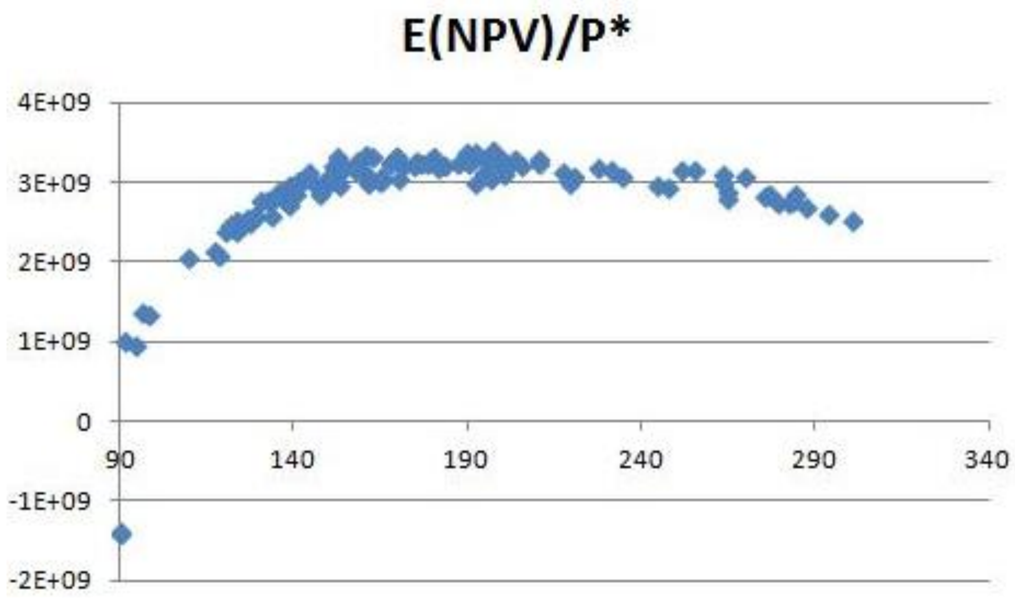

Figure 69. Value of The Expected NPV obtained varying the electricity price threshold

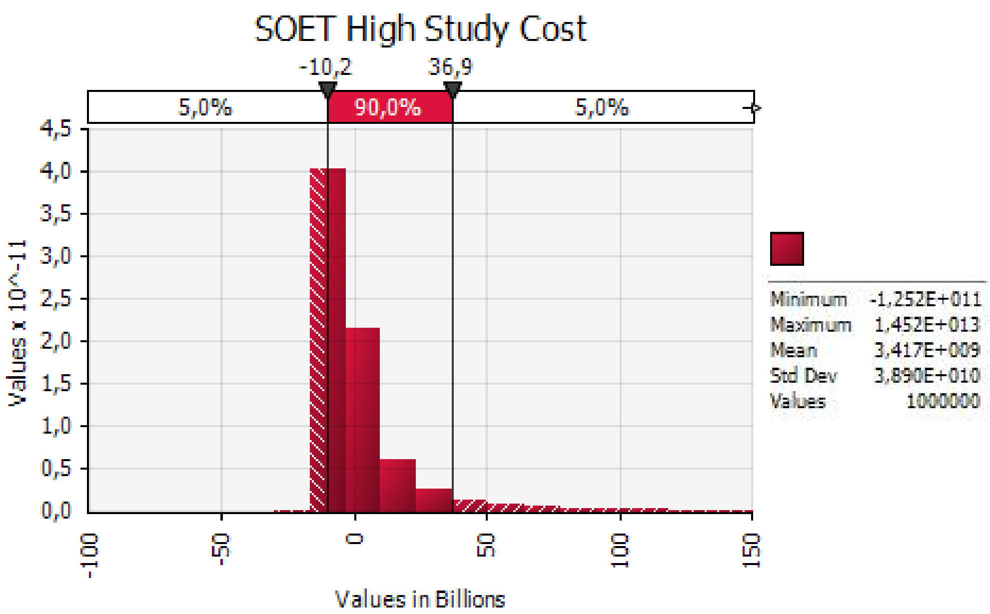

Figure 70. Probability Distribution of the Expected NPV in the “High Study Cost Case”

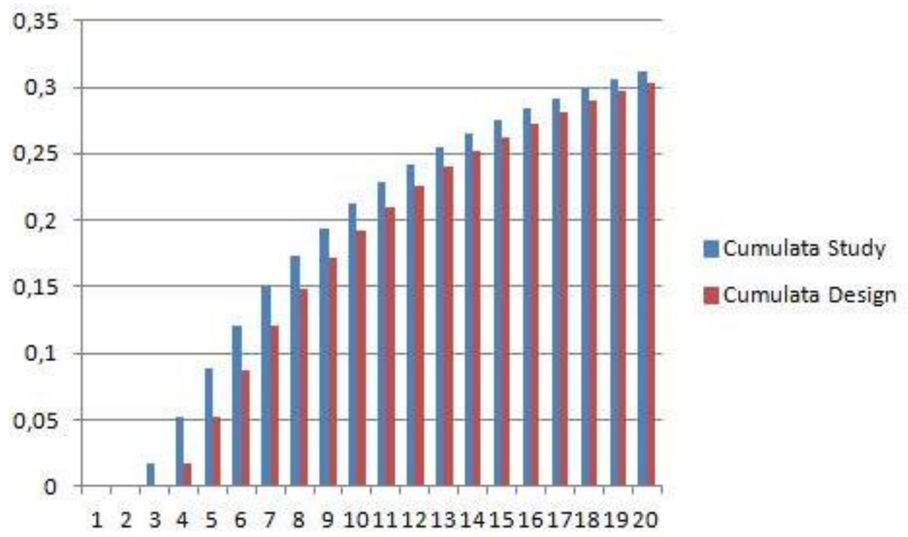

Figure 71. Cumulate Probability Distribution of the Study and the Design Phase(High Study Cost)

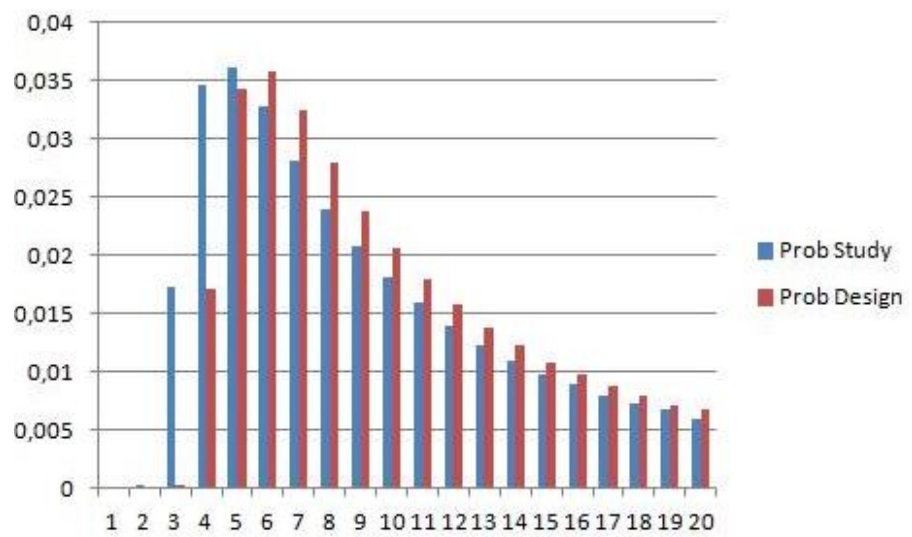

Figure 72. Probability Distribution of beginning the study and the design phase along years(High Study Cost)

The result shown in the previous figures are summarized in the following table:

Case Study	P*	ECTD*	ECTC*	Expected NPV [mln$]
High Study Cost Case	185	$5 * (P_t - 25)$	$80 * (P_t - 25)$	3416,565

Table 51. Results of the High Study Cost Case

Figure 69 confirms our assumptions showing how the optimal electricity price that trigger the study phase is significantly higher that the value obtained in the standard analysis. Furthermore the optimal solution seems to be "never invest" because the expected NPV always grows up at the increase of the electricity price threshold. The reason for which we found an optimal value of the threshold is only that, having an high value of it means to begin the investment later.

Therefore the effect of the discount factor become always more important letting us find an optimal value of the exercise threshold.
Figure 71 and Figure 72 let us find out that our assumptions about the probability to invest in the study and design phase along years is very different than the one obtained in the standard analysis. Indeed the probability level of the study phase is far below the probability obtained in the standard analysis. Furthermore we can see how the probability level of the design phase is quite equal to the probability of the study phase in the previous year(because the design phase begin the year after the beginning of the study phase). Therefore we can conclude that all our ex-ante expectations about this case are confirmed and we can summarize them here:

- The study phase starts only in the most profitable scenarios(the probability of doing it in 20 years is about 30% instead the 70% obtained in the standard case)
- The design phase is always made if the study phase is performed because it has a very lower impact on the overall profitability of the investment than it.

5.2.2 The High Design Cost Phase

The result that we obtain are shown in Figure 73 (NPV distribution), Figure 74(Cumulate Probability Distribution along years of Beginning study and design phase), Figure 75(Probability Distribution of beginning study and design phase in each year).

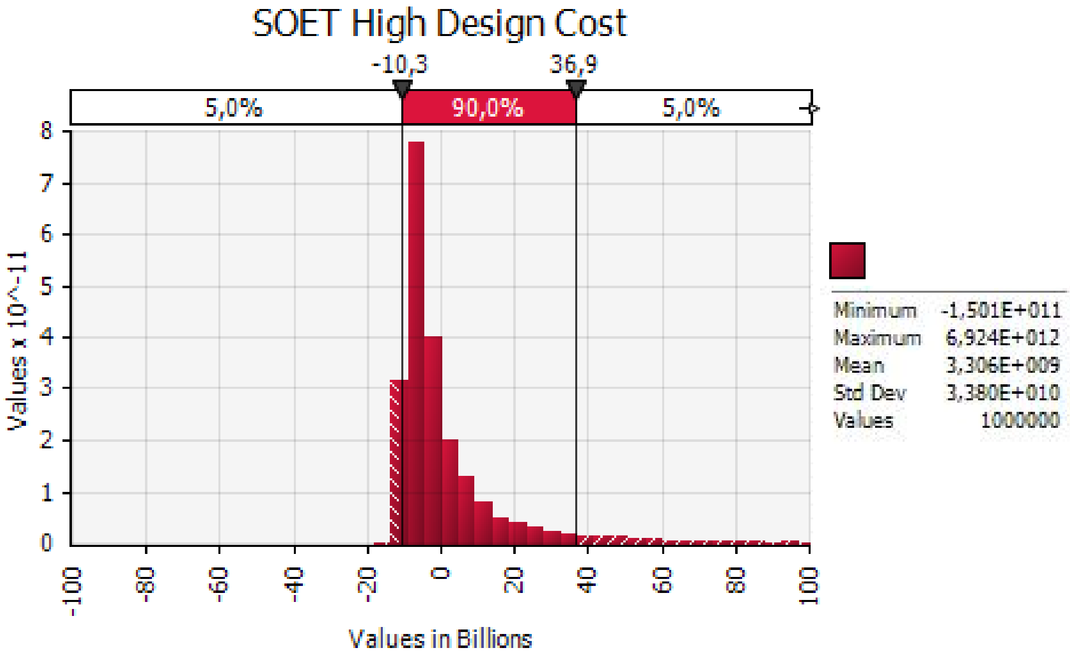

Figure 73. Probability Distribution of the Expected NPV in the "High Design Cost Case"

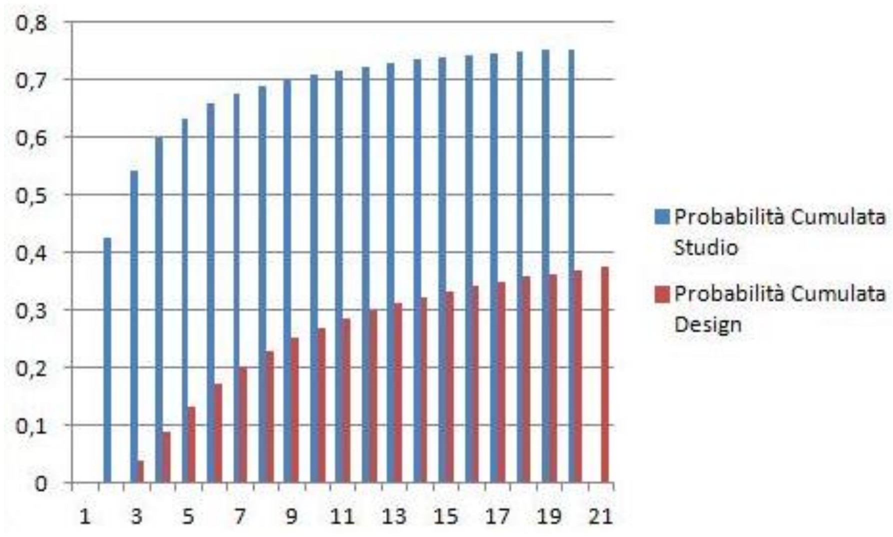

Figure 74. Cumulate Probability Distribution of the Study and the Design Phase(High Design Cost)

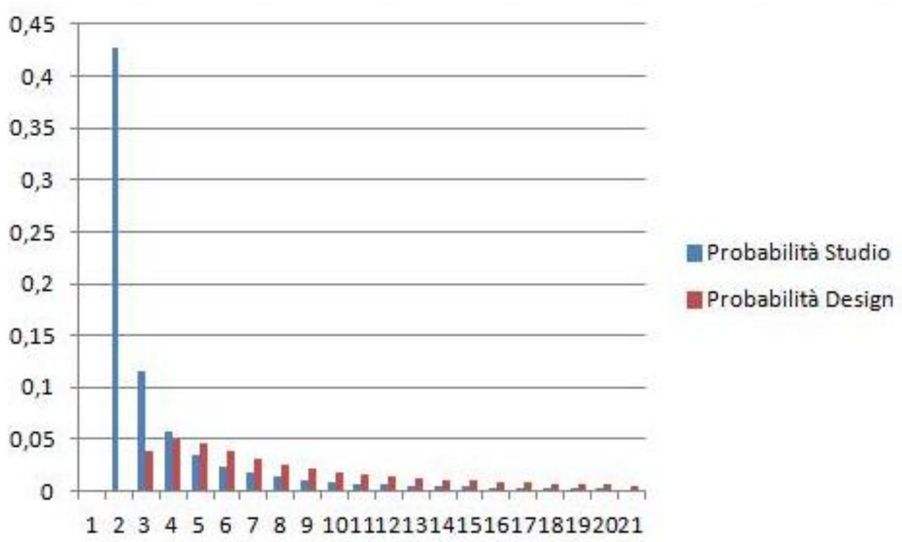

Figure 75. Probability Distribution of beginning the study and the design phase along years(High Design Cost)

The result shown in the previous figures are summarized in the following table:

Case Study	P*	ECTD*	ECTC*	Expected NPV [mln$]
High Design Cost Case	95	$20 * (P_t - 25)$	$80 * (P_t - 25)$	3306,28

Table 52. Results of the High Design Cost Case

The results shown in the previous table and figures are deeply different than the results obtained in the “High Study Cost Case”. Indeed here we can immediately see that the electricity price that trigger the investment in the study phase is very low(P* = 95$/MWh). Therefore in Figure 74 and in Figure 75 we can see two easy consequences of this results:

- The study phase starts quite in all scenarios and it begins in the early(the probability of doing it in 20 years is quite 80% instead of the 30% obtained in the *"High Study Cost Case"*).
- The design phase is made only in the more profitable scenarios because it has a greater impact on the profitability of the overall investment: in Figure 74 and in Figure 75 we can see how low is the probability value of investing in this phase if we compare it to the probability of investing in the study phase

All the results we obtained can be summarized in the following table:

Case Study	P*	ECTD*	ECTC*	Expected NPV [mln$]
Standard Analysis	95	$5*(P_t-55)$	$60*(P_t-25)$	5596,253
High Study Cost Case	185	$5*(P_t-25)$	$80*(P_t-25)$	3416,565
High Design Cost Case	95	$20*(P_t-25)$	$80*(P_t-25)$	3306,28

Table 53. Summary of Results

We can conclude that the model we built is robust because the results that we obtained confirm all the expected result that we summarized in Table 50. Expected Results of our study cases.

5.3 Time to Market Effect: the SMR case

The same analysis made for the Large Nuclear case has been made for the SMR case too. The results are reported in the following figures:

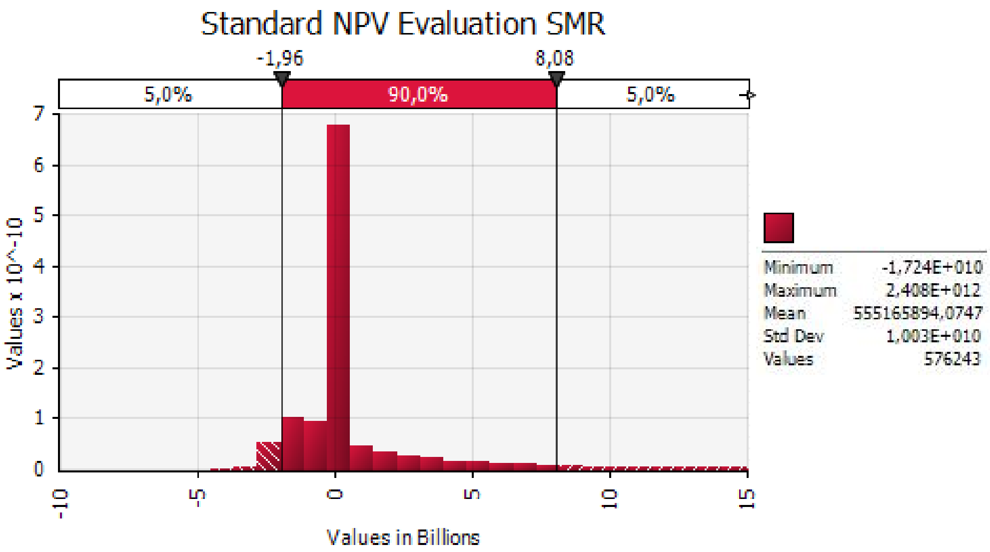

Figure 76. Probability Distribution of the NPV(DCF Method-No TTM Effect-Investing now-SMR case)

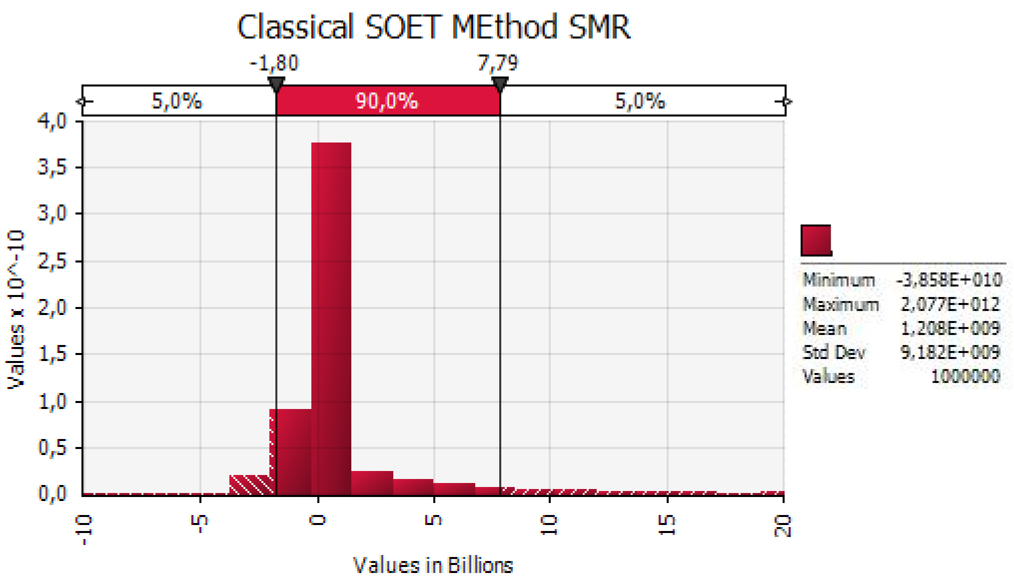

Figure 77. Probability Distribution of the Expected NPV(Sequential SOET Method-SMR case)

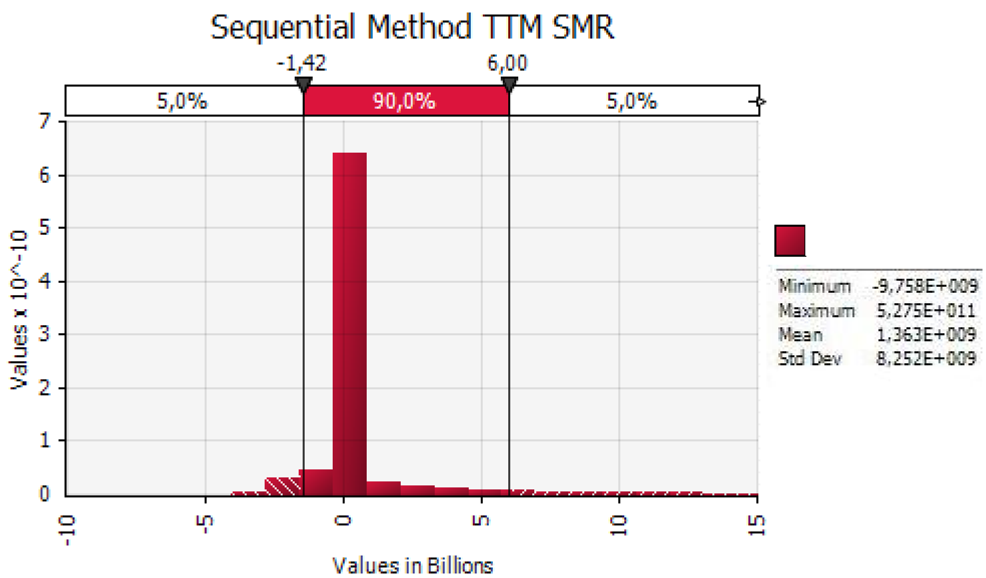

Figure 78. Probability Distribution of the Expected NPV(Sequential Method TTM Effect with Compound Option to Wait between each of the pre-operating phases-SMR case)

The results shown in the previous figures, in terms of expanded NPV and exercise thresholds for each of the analysis performed, are summarized in the following table:

Kind of Analysis	P*	ECTD*	ECTC*	E(NPV) [mln $]	Option Value [mln $]
Standard NPV Evaluation	90	None	None	547,5826	None
Classical SOET Method	120	$5 * (P_t - 15)$	$70 * (P_t - 15)$	1207,562	659,98
SOET Method with Compound Options – TTM Effect	96	$5 * (P_t - 20)$	$45 * (P_t - 20)$	1345,173	797,59

Table 54. SMR's results summary

At this point of the analysis it is becoming interesting the comparison between the results obtained in the SMR case and in the Large Nuclear case and we report them in the following table:

Kind of Analysis	Size [MW]	E(NPV) [mln$]	σ(NPV) [mln$]	E(NPV)/Size	σ(NPV)/Size
Standard NPV Nuke	1500	3347,794	41120,03	2,2319	27,4134
Standard NPV SMR	335	547,5826	9521,823	1,6346	28,4234
Classical SOET Nuke	1500	5045,32	37703,51	3,3636	25,1357
Classical SOET SMR	335	1207,562	9181,715	3,6047	27,4081
SOET with Compound Options(TTM Effect) Nuke	1500	5540,954	34804,97	3,6940	23,2033
SOET with Compound Options(TTM Effect) SMR	335	1345,173	8692,039	4,0154	25,9464

Table 55. Benchmarking between Nuke's result and SMR's result

In order to be properly compared, we normalized in function of their size the results obtained for both the large nuclear and the SMR case.
In the following figure we want to show how results, in terms of profit and risks connected to the investment, change in function of the kind of technique that we used to evaluate them.

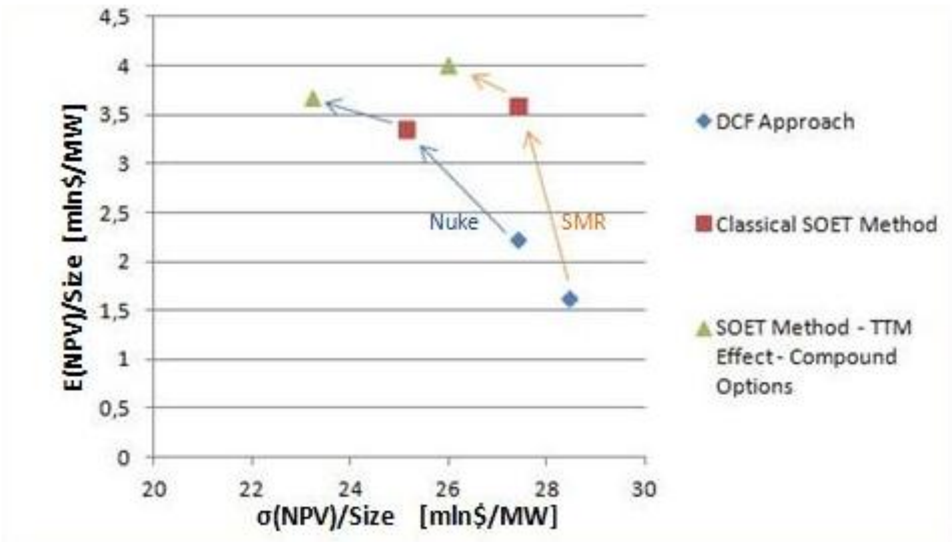

Figure 79. Benchmarking between Nuke's results and SMR's results in terms of mean and standard deviation

We can see that both the Large Nuclear PP and the SMR PP belong to the efficient frontier. Indeed if a utility decides to invest in an SMR they will have a greater profitability than investing in a LR but the investment will have a greater level of risk too.

However, the real purpose of this analysis was to show how results vary if we apply the SOET method modeling the pre-operational phase of a nuclear power plant as the succession of three sequential compound options or with the classical SOET method that doesn't model the intrinsic flexibility of these phases.

We can see that modeling it as the succession of three sequential compound options adds value to the investment. Furthermore, because of the fact that a utility have three different decisional moment, at the beginning of the design and of the construction phase they have more information about uncertainties and our model let abandon the investment if it is not convenient anymore(it happens when ECTD or ECTC are below their respective exercise thresholds).
Therefore we can conclude this analysis saying that real option are the best approach to describe and evaluate a power plant because of the intrinsic flexibility of their pre-operational phases, and that the SOET Method let us model it as three compound options in a very effective way.

In the following sections we compare this results with the results obtained in the case a utility decides to invest in a single Coal or CCGT power plant and in sequential power plants in order to reach the capacity of the Large Nuclear Reactor considered(1500 MW).

5.4 Time to Market Effect: comparing all base – load technologies

The first part of this section shows the results we obtained applying the standard NPV evaluation and the classical SOET Method to the case of CCGT and Coal-Fired Power Plants.
Because of the fact that the pre-operational phases of CCGT and of Coal power plants are far shorter and less risky that the pre-construction phases of nuclear PP, we have not applied the SOET Method with compound options to these cases.

In this way we aim to make a real comparison between nuclear power plants and the others base-load power plants considering as a negative effect the longer time that must be elapsed in the nuclear case after a utility decides to invest in it.
Our results are reported in the following figures:

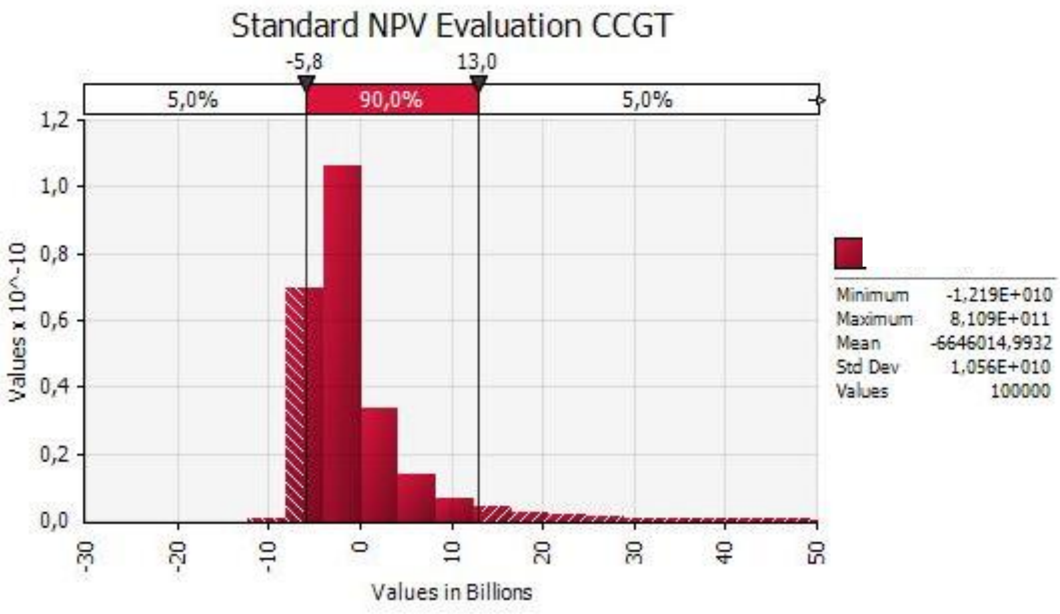

Figure 80. Probability Distribution of the NPV(DCF Method-No TTM Effect-Investing now-CCGT case)

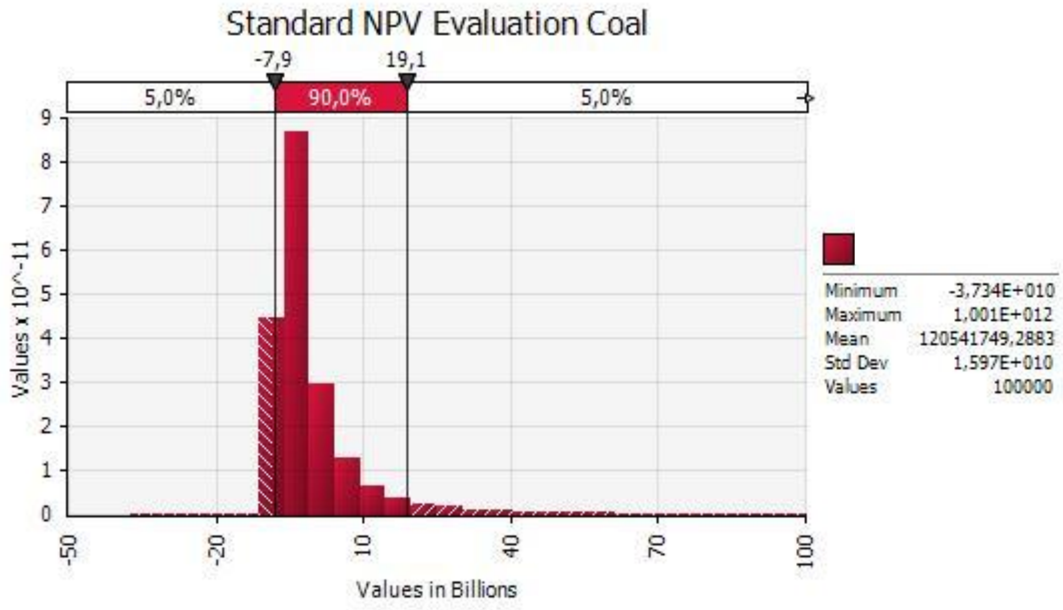

Figure 81. Probability Distribution of the NPV(DCF Method-No TTM Effect-Investing now-Coal case)

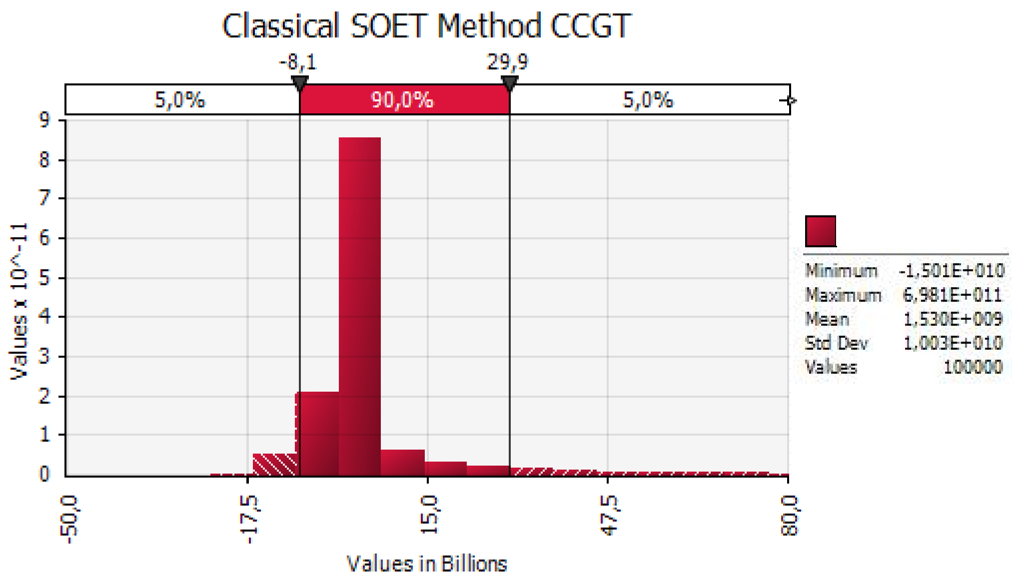

Figure 82. Probability Distribution of the Expected NPV(Sequential SOET Method-CCGT case)

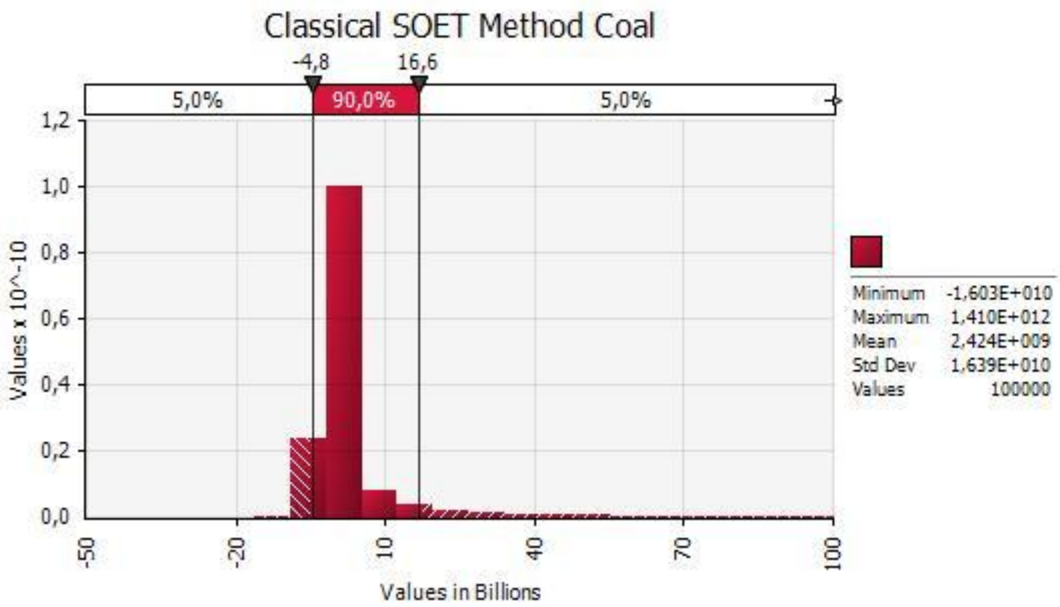

Figure 83. Probability Distribution of the Expected NPV(Sequential SOET Method-Coal case)

The results we found are summarized in the following table and the comparisons between these results and the results obtained for the SMR's and Nuke's case of investment is shown in Figure 84.

	Coal	CCGT
Exercise Threshold	Pel > 145	Pel > 150

Table 56. Exercise Threshold for the Coal and the CCGT case

Kind of Analysis	Size [MW]	E(NPV) [mln$]	σ(NPV) [mln$]	E(NPV)/Size	σ(NPV)/Size
Standard NPV Nuke	1500	3347,794	41120,03	2,2319	27,4134
Standard NPV SMR	335	547,5826	9521,823	1,6346	28,4234
Standard NPV CCGT	500	-6,6460	10564,24	-0,01329	21,1285
Standard NPV Coal	750	153,9154	16855,75	0,20522	22,4743
Classical SOET Nuke	1500	5045,32	37703,51	3,3636	25,1357
Classical SOET SMR	335	1207,562	9181,715	3,6047	27,4081
Classical SOET CCGT	500	1529,605	10033,08	3,0592	20,0662
Classical SOET Coal	750	2424,323	16389,37	3,2324	21,8525
SOET with Compound Options(TTM Effect) Nuke	1500	5540,954	34804,97	3,6940	23,2033
SOET with Compound Options(TTM Effect) SMR	335	1345,173	8692,039	4,0154	25,9464

Table 57. Benchmarking between all base-load technologies' results

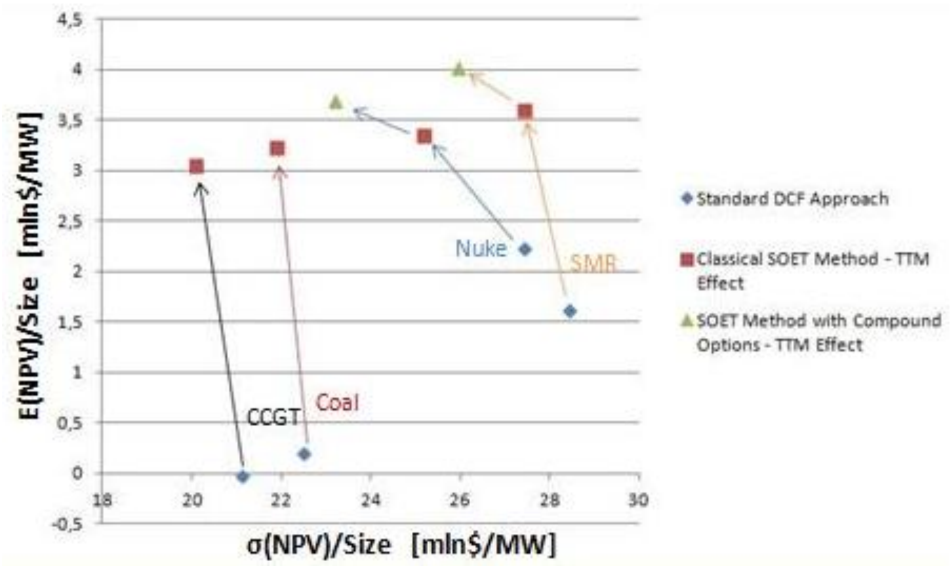

Figure 84. Benchmarking between all base-load technologies' results in terms of mean and standard deviation

From the previous figure and table we can easily notice that all technologies lies on the efficient frontier because SMR is the most profitable technology but the most risky too, while CCGT guarantees the lowest level of profit but the lowest level of risk too.
Furthermore, if we compare only the results obtained applying the classical SOET Method without modeling the TTM Effect, we can see that the negative consequence of an investment in a nuclear PP that we hypothesize in paragraph 2.3.3 was correct.
We said that considering only the construction phase in the evaluation model, underestimate the cost and the length of the pre-operating phase of nuclear power plants.
Considering the *"TTM effect"* in the energy field means that we have to take into account that the time elapsed from the moment in which the final decision to invest is taken and the moment in which the nuclear plant starts to produce energy pass from at least 6 to 9 years, while for the case of CCGT and Coal PP is only 4 and 5 years(see Table 24).
Indeed it is true that all technologies belongs to an efficient frontier, like (Lotti, 2012) shows, but considering the real time elapsed from the moment the decision to invest is taken and the moment in which the power plant starts effectively to produce energy, the difference in term of expected NPV between technologies is really low while investments in Coal and CCGT power plants are significantly less risky than investment in SMR or in LR making them not so interesting anymore.
An investment in nuclear power plants comes back to be interesting only if we model its pre-operational phase as the succession of three sequential phases in which the utility brings the right, without obligation, to acquire information and go on with the effective construction of the power plant only in the most profitable scenarios.

In this way we have verified the assumptions we made in chapter 2: considering the whole time required for a power plant from the moment a utility decides to invest in it and the moment in which it starts to produce energy, has a negative effect on nuclear power plants that have an high complex study and design phase. Nevertheless the intrinsic flexibility that characterize the nature of the pre-operating phases of a nuclear power plants let us model it with a real option approach as the succession of three sequential compound options. In this way we treat this kind of investment as a multistage project investments where management can decide to continue or abandon the project after gaining new information to resolve uncertainty at the end of the study and of the design phase.
We can now answer to the question reported before in this work.

QUESTIONS	EXPECTED ANSWER	RESULTS OBTAINED
How much is the effect of the longer time needed for a Nuke PP to start produce energy after a utility decides to invest in it?	Large Nuclear and SMR PPs becomes less profitable and more risky than in the case reported in (Lotti, 2012) if compared with CCGT or Coal PPs	The expected answer is verified because both LR and SMR has quite the same level of profitability than CCGT and Coal but they are far more risky than them. Thus, an investment in a nuclear PP seems to be not interesting.
Can Real Option help us to exploit the intrinsic flexibility of the pre-operational phases of an investment in a nuclear PP?	Yes. Modeling it as the succession of three sequential phases, a utility is able to acquire information and start the construction of the PP only in the most profitable scenario.	The expected answer is verified because both LR and SMR increase their profit and decrease their level of risk than if we evaluate them with the classical SOET Method. Thus, apply real option to model the pre-operating phases of a nuclear PP, adds value to this kind of investment making it interesting again.

Table 58. Questions about the TTM Effect

The second part of this section considers the possibility for a utility to invest in sequential SMR, Coal and CCGT in order to obtain an output directly comparable with the output produced by the LR. The construction of the exercise thresholds has been complex in the SMR case because we implemented the SOET Method considering the TTM Effect for all the sequential PP that a utility could build. We remind to chapter 3 for a wide description of the methodology that we used. However, in all the study cases of this section the reactors that follow the first one receive an additional advantage: similarly than the method we used to find the exercise threshold in the case application of the SOET Method considering the TTM Effect on a single PP, since the first reactor is completed there are information about the TCIC, because the cost of completion of the first reactor is correlated to the TCIC of the second reactor and so on. In this way is possible to implement in the analysis exercise thresholds with multiple state variables, with both the price of electricity and the TCIC. This is valid only for the reactors after the first, since with the first there will be no information about the TCIC.
The following tables contains the exercise thresholds for all the PP considered in the analysis.

	First Reactor	Second Reactor	Third Reactor	Fourth Reactor
Study Phase	Pel > 92	$ECTC_1$ < 118*(Pt – 50)	$ECTC_2$ < 78*(Pt – 45)	$ECTC_3$ < 88*(Pt – 40)
Design Phase	$ECTD_1$ < 4*(Pt – 50)	None	None	None
Constr Phase	$ECTC_1$ < 118*(Pt – 50)	$ECTC_2$ < 78*(Pt – 45)	$ECTC_3$ < 88*(Pt – 40)	$ECTC_4$ < 98*(Pt – 40)

Table 59. Exercise threshold: Sequential SMR PP

	First CCGT	Second CCGT	Third CCGT
Exercise Threshold	Pel > 139	$ECTC_1$ < 30*(Pt – 20)	$ECTC_2$ < 25*(Pt – 20)

Table 60. Exercise threshold: Sequential CCGT PP

	First Coal PP	Second Coal PP
Exercise Threshold	Pel > 120	$ECTC_2 < 11*(Pt - 20)$

Table 61. Exercise threshold: Sequential Coal PP

As expected, exploiting the learning factor, that reduces the total cost, and the fact that modularity gives information useful in a ROA approach to take decisions better, the results of an investment in coal or CCGT are furthermore increased.

Instead, in the SMR case we can see that results obtained in the sequential case are really similar in terms of expected NPV than the results obtained in the application of the SOET Method considering the TTM Effect in the case of a single SMR. Indeed, partitioning the pre-operational phases of the SMR after the first, does not add a great value to the investment. It is the construction of the first SMR that allow to acquire information in order to start the construction of the other PP only in the most profitable scenarios. However, this kind of analysis reduces in a significant way the level of risk connected to this kind of investment, making it more interesting to be performed. It can be seen in the significant increase in the value of the sharp ratio in the case of sequential SMR, whose parameter becomes higher than the SR of the LR and get closer to the value that the SR has in the case of coal and CCGT PPs. We have not considered in our analysis the case of sequential large nuclear reactors because, even if it could happen, an investment of this type would require a huge investment. The following figure and table show all the results we obtain in our analysis.

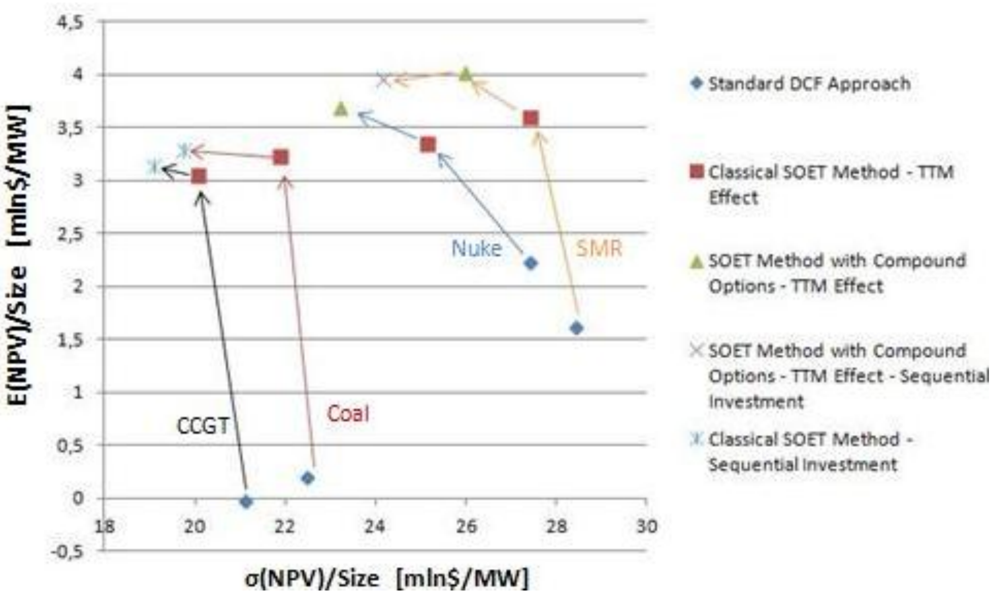

Figure 85. Final Benchmarking between all results obtained – TTM Analysis

Kind of Analysis	Size [MW]	E(NPV) [mln$]	σ(NPV) [mln$]	E(NPV)/Size	σ(NPV)/Size	SR
Standard NPV Nuke	1500	3347,794	41120,03	2,2319	27,4134	0,081
Standard NPV SMR	335	547,5826	9521,823	1,6346	28,4234	0,058
Standard NPV CCGT	500	-6,6460	10564,24	-0,01329	21,1285	-0,0006
Standard NPV Coal	750	153,9154	16855,75	0,20522	22,4743	0,0091
Classical SOET Nuke	1500	5045,32	37703,51	3,3636	25,1357	0,1338
Classical SOET SMR	335	1207,562	9181,715	3,6047	27,4081	0,1315
Classical SOET CCGT	500	1529,605	10033,08	3,0592	20,0662	0,1525
Classical SOET Coal	750	2424,323	16389,37	3,2324	21,8525	0,1479
SOET with Compound Options(TTM Effect) Nuke	1500	5540,954	34804,97	3,6940	23,2033	0,1592
SOET with Compound Options(TTM Effect) SMR	335	1345,173	8692,039	4,0154	25,9464	0,1548
SOET with Compound Options(TTM Effect) Sequential SMR	1340	5310,875	32374,4	3,9633	24,16	0,16405
Classical SOET Sequential CCGT	1500	4719,309	28595,44	3,1462	19,0636	0,16504
Classical SOET Sequential Coal	1500	4928,918	29553,51	3,2859	19,7023	0,1668

Table 62. Benchmarking between all base-load technologies' results considering sequential investments

It is easy to notice that all technologies considered belongs to the efficient frontier, and therefore that none of them should be considered to be better than the others.

5.5 Conclusions of the chapter

The main messages of this chapter can be summarized as follow:

- It shows how results improve considering the TTM Effect to the classical SOET Method
- It proves the robustness of the model thanks to two case studies and to the comparison of our results and the report (WNA, 2014) that considers all reactors under construction.
- It describes the effect that a longer TTM has on the profitability of a PP and the value that the considering three sequential pre-operational phases (modeled as sequential compound options) add to it.
- It compares all base-load technologies considering the TTM Effect and sequential investment building the plane E(NPV) – σ(NPV) and the efficient frontier for our case study.

Chapter 6 - Results Portfolio Analysis

This chapter presents the results obtained applying the SOET Method integrated with the MVP Theory in order to choose which PP is the most profitable to build considering the actual portfolio of a utility.
Firstly, paragraph 6.1 applies our framework to a dummy actual portfolio of investment in order to help the reader to understand the power of this method comparing its results with the ones obtainable applying the classical MVP Theory.
Then, paragraph 6.2 applies our model to the EDF's actual portfolio of investment in UK with the aim to find out which is the best PP to be built with the assumption that an additional demand of 1,5 GW must be guaranteed by the utility. Finally paragraph 6.3 reports the main messages of this chapter.

6.1 Application to a dummy actual portfolio of investment

As reported previously, this chapter shows the results obtained applying our method to a dummy actual portfolio of investment with the assumption that the utility has to build a new PP in order to reach an additional demand of 1,5 GW.

The aim of this analysis is to show the potentiality of this method and thus it compares the result obtained if the decision of investment is taken applying:

1. The classical DCF approach with the MVP Theory(the static evaluation of paragraph 6.1.1)

2. The SOET method without the compound options with the option to defer (paragraph 6.1.2)

3. The SOET method modeling the pre – operational phase of the additional nuclear PP as the succession of three sequential compound options with the option to defer (paragraph 6.1.3)

4. The SOET method both with and without modeling the pre – operational phase of the additional PP as the succession of three sequential compound options when the option to invest is implemented (paragraph 6.1.4).

Therefore, at this point of the analysis, the chosen of new technology is limited to the SMR's one and to the Nuke's one because they are the only two technology whose pre – operational phase is modeled as the succession of three sequential compound options. Being the capacity of the SMR remarkably different than the LR's one, in this analysis we consider that four SMRs will be built one after in order to properly choose the best investment from the utility's point of view.
This assumption is reasonable we consider that the aim of the utility is not the reduction of the financial exposure but the maximization of its profit.[28]
Others base – load technologies as the Coal and the CCGT ones will be considered in paragraph 6.2 that apply our method to the actual EDF's portfolio of investment in UK.

The composition of the dummy actual portfolio of investment is reported in the following table:

Technology	Capacity Installed [MW]	% in the Overall Actual Portfolio
Nuclear	1500	46,15%
Coal	750	23,08%
CCGT	1000	30,77%

Table 63. Dummy Actual Portfolio of Investment

[28] If it is true the utility will not wait for a PP to be built to start the construction of the successive because the construction of all the PP in the same area and one after the other increases the learning effect, the capacity to use infrastructure, reduces the design cost of the PP and anticipates revenues because all the PPs start to produce energy before than the case in which the construction of each of them starts only if the previous one has been finished.

6.1.1 The Static Evaluation

In this case there is no optimization and the investments are evaluated as they are made at time zero and never abandoned. This is then a static evaluation and it is done as a standard MVP analysis where the investment in the additional PP is done applying the classical DCF approach. The NPV distributions are then obtained and represented in Figure 86 for the Large Nuclear power plant and Figure 87 for the Small Nuclear power plant.

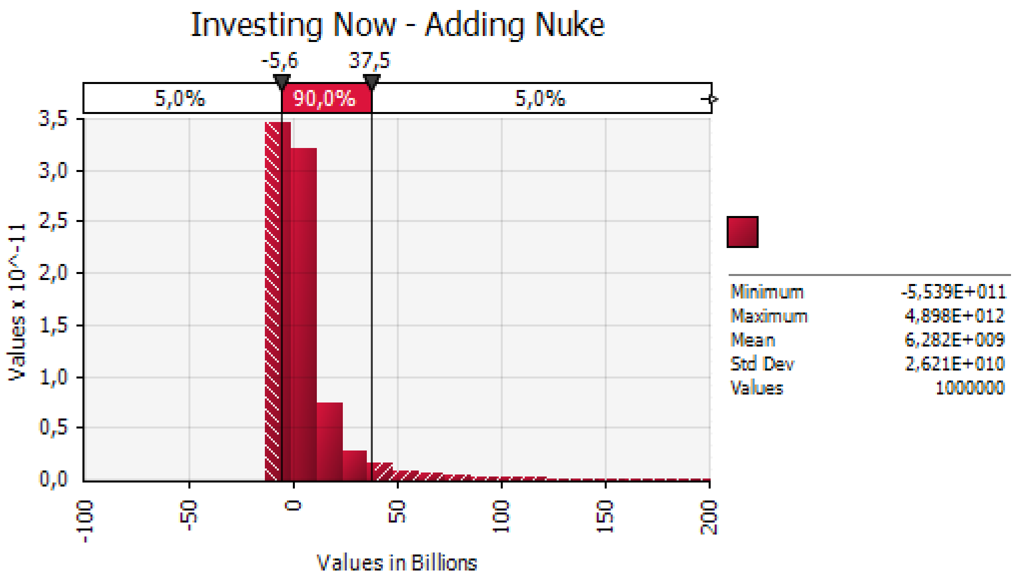

Figure 86. The Overall Portfolio with an additional LR's NPV distribution

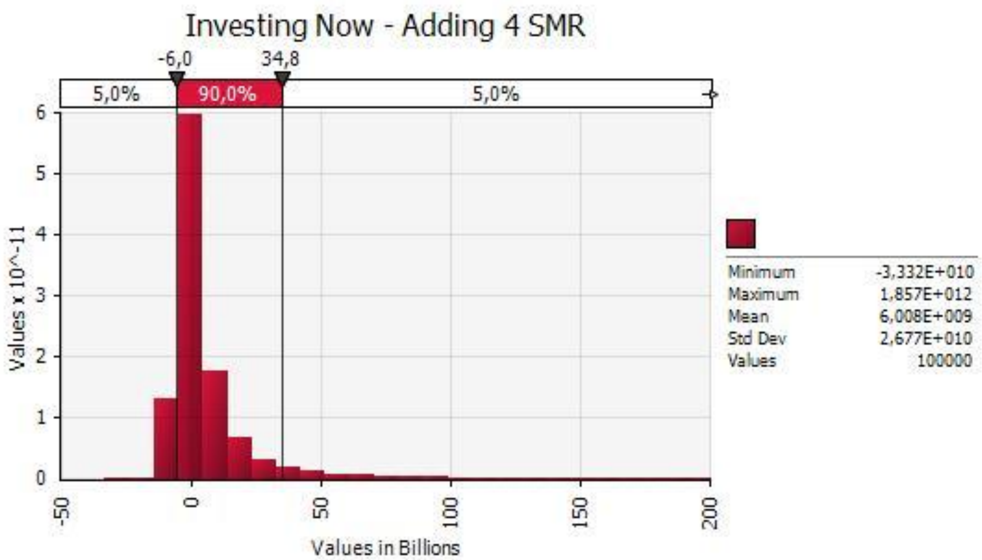

Figure 87. The Overall Portfolio with Four additional SMRs' NPV distribution

These distributions are represented with bins because they are approximated by MCS (with n=100000 iterations). Their results in terms of NPV mean and standard deviation of the overall portfolio are[29]:

Technology	NPV Mean [mln $/MW]	σ(NPV) [mln $/MW]	Sharpe Ratio[30]
Large Nuclear	1,323	7,9	0,1675
Small Modular Reactor	1,309	7,88	0,1661

Table 64. Static Evaluation Results of the dummy portfolio with an additional PP

From the table above it is easy to understand that, if the decision to invest is taken applying the classical approach that apply the MVP theory with the DCF approach, the PP that would be built is certainly the Large Nuclear one. Indeed it has an higher value of the NPV Mean and an higher value of the Sharpe Ratio too(i.e., the NPV generated per unit of risk is greater in the LR's case of investment).

6.1.2 Option to defer with one state variable: the SOET Method integrated with the MVP Theory

This paragraph adds the option to defer the investment and it uses as state variable the electricity price. The model optimizes the mean of the NPV distribution of the overall portfolio using as decision variable the exercise threshold , that is the value of the price of electricity P* waited to invest. To obtain this maximized mean the search algorithm is used. The search algorithm finds the P* which maximize the NPV means and as output it gives the NPV distributions (with maximized NPV mean) and the P* used to obtain these results.
The following figures then shows the results obtained if only the option to defer is implemented and thus the investment has to be triggered in 20 years from now.

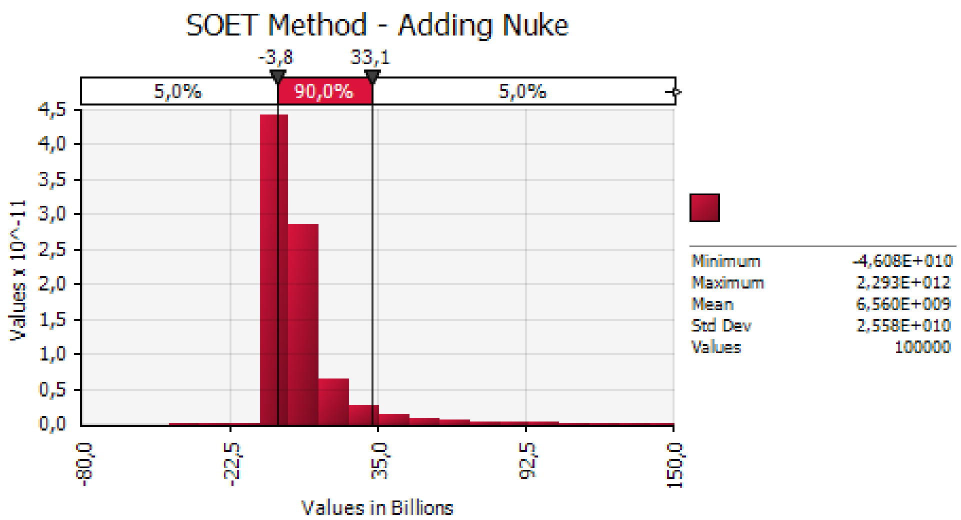

Figure 88. The Overall Portfolio with an Additional LR's NPV distribution obtained with the SOET Method – Option to defer

[29] The results must be reported in table because the standard deviation reported on the figure is not the standard deviation of the overall portfolio. Indeed it is evaluated thanks to the MVP Theory after the MCS is finished.
[30] It is the ratio between the value of the E(NPV) and the σ(NPV). For a detailed description of its meaning see paragraph 2.1.2

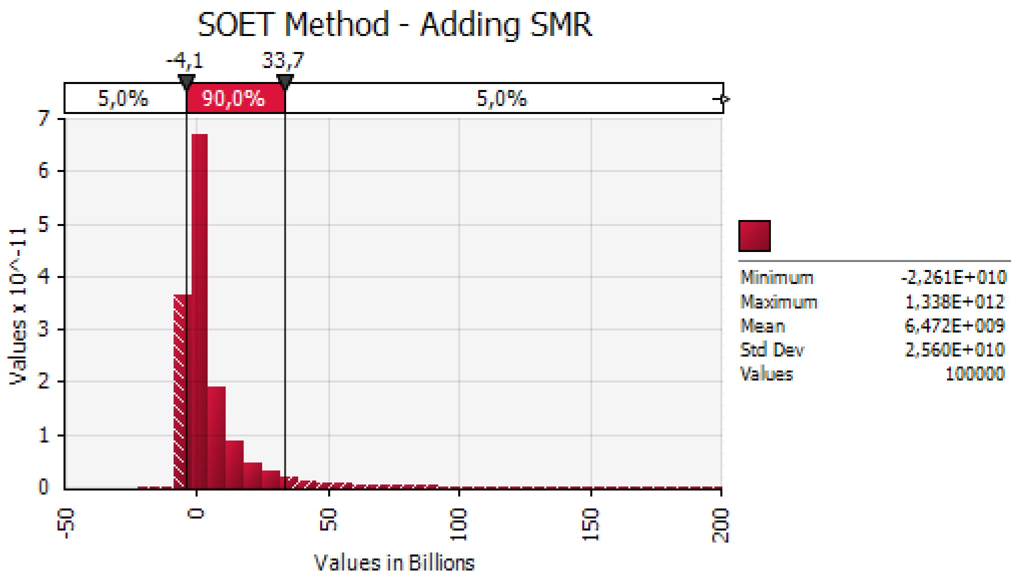

Figure 89. The Overall Portfolio with Four Additional SMR's NPV distribution obtained with the SOET Method – Option to defer

Taking into account the overall portfolio the results obtained in these two cases are:

Technology	NPV Mean [mln $/MW]	σ(NPV) [mln $/MW]	Sharpe Ratio	Exercise Threshold
Large Nuclear	1,38	7,79	0,1796	$P_{el} > 142\ \$/MWh$
Small Modular Reactor	1,41	7,84	0,1773	$P_{el} > 130\ \$/MWh$

Table 65. RO Results of the dummy portfolio with an additional investment – Option to defer

From the results above it is easy to understand that the application of a Real Option Approach increases the value of the NPV Mean of the overall portfolio and reduces its level of risk too.
It is correct because the application of a real option approach to evaluate the investment in an additional PP adds value to its specific NPV Mean and reduces its level of risk.

One of the innovation of this work is that it integrates this approach with the MVP Theory and then in this way the improvement guaranteed by evaluating the investment on a single PP thanks to a ROA is transferred to the results of the overall portfolio. In this way the model user is able to take into account for the decision of investment the actual portfolio of a utility that has great influence both in the value of the NPV Mean and in the value of the standard deviation.

Another interesting output guaranteed by our model when it is applied with one state variable is the tri – dimensional efficient frontier for each single portfolio. Indeed the performance of the overall portfolio in terms of E(NPV) and σ(NPV) are function of the value of the electricity price that trigger the investment.
As reported in chapter 3 the output obtainable applying the MVP Theory to a portfolio in the classical way is a single static point on the plane E(NPV) - σ(NPV).

Then the following two figures aim to how the output and the information it guarantees improve by applying our model:

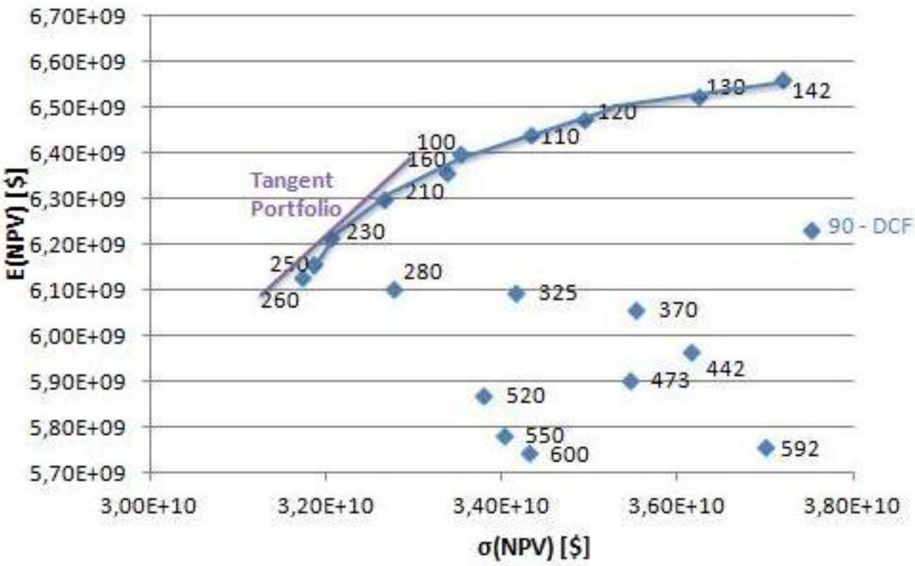

Figure 90. Efficient Frontier of the Portfolio with the additional LR PP

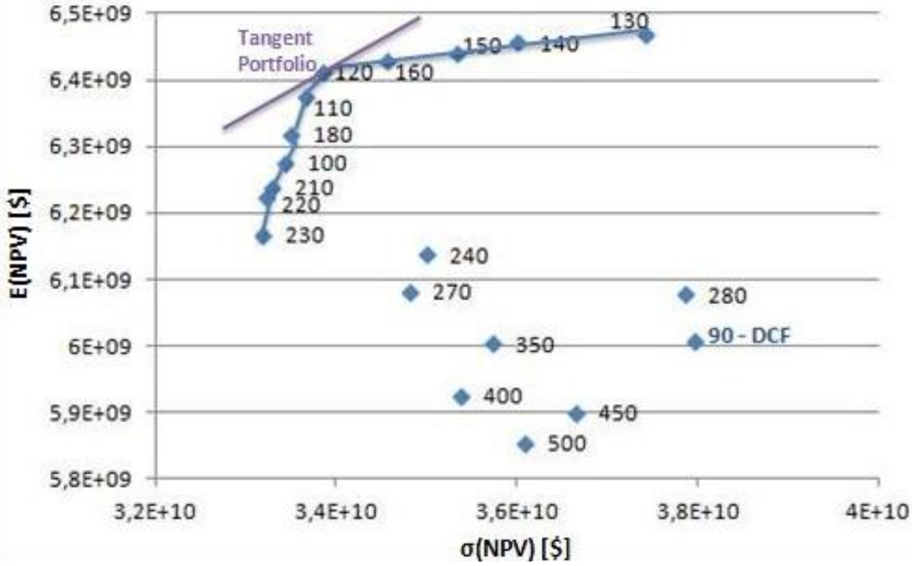

Figure 91. Efficient Frontier of the Portfolio with the additional SMR PP

The results shown above have been summarized in the following tables to help the reader understand how the level of information is increased and what PP is the most adapted to be built if different objective function are considered:

Additional PP	Lower Bound Efficient Frontier	Upper Bound Efficient Frontier	Tangent Portfolio Condition
Large Nuclear	$P^*_{LB} = 100\$/MWh$	$P^*_{UB} = 260\$/MWh$	$P^*_{SR} = 230\$/MWh$
SMR	$P^*_{LB} = 100\$/MWh$	$P^*_{UB} = 230\$/MWh$	$P^*_{SR} = 120\$/MWh$

Table 66. Remarkable value of the state value in the two portfolio under analysis

Additional PP	Maximization of NPV Mean	Minimization of NPV standard deviation	Maximization of the Sharpe Ratio value
Large Nuclear	$P^*_{maxNPV} = 142\$/MWh$	$P^*_{min\sigma} = 260\$/MWh$	$P^*_{SR} = 230\$/MWh$
SMR	$P^*_{maxNPV} = 130\$/MWh$	$P^*_{min\sigma} = 230\$/MWh$	$P^*_{SR} = 120\$/MWh$

Table 67. Value of the state value in the two portfolio under analysis that maximize different objective function

The information reported in the two table above can be summarized as follow:

- The investment in the additional Large Nuclear PP to the actual portfolio has to be made only if the electricity price has a value between P* = 100 $/MWh and P* = 260 $/MWh because, according to other value of the electricity price it is not efficient anymore.
- Instead in the case in which the additional investment is an SMR PP, this kind of investment is efficient only if the value of the electricity price is between P* = 100 $/MWh and P* = 230 $/MWh.

At this point the following table shows how the decision to invest vary according to different specific objective function:

Objective Function	Large Reactor's Results	SMR's Results	PP Chosen	Condition of investment
Maximization of NPV Mean	E(NPV) = 1,38 mln$/MW	E(NPV) = 1,41 mln$/MW	SMR	$P^* = 130\$/MWh$
Minimization of NPV Standard Deviation	σ(NPV) =6,68 mln$/MW	σ(NPV) = 7,23 mln$/MW	Large Reactor	$P^* = 260\$/MWh$
Maximization of the Sharpe Ratio Value	SR = 0,1933	SR = 0,1895	Large Reactor	$P^* = 230\$/MWh$

Table 68. How the chosen of the additional PP vary in function of the objective function

From the table above it is becoming always more and more clear the potentiality of this method because it allow to find out the best solution for the utility according to completely different objective functions:

- If the objective function is the maximization of the NPV Mean of the overall portfolio an additional SMR must be built and the condition to start this investment is P* = 130 $/MWh

- If the objective function is the minimization of the NPV Standard Deviation of the overall portfolio an additional LR must be built and the condition to start this investment is P* = 260 $/MWh

- If the objective function is the maximization of the Sharpe Ratio Value of the overall portfolio an additional LR must be built and the condition to start this investment is P* = 230 $/MWh

But what if the utility want to build a PP according to a specific level of risk and it does not have one of the three objective function defined above?

In that case the efficient frontier shown in Figure 90 and Figure 91 must be compared directly and an Optimized Efficient Frontier must be built.

The following figure reports this innovative result:

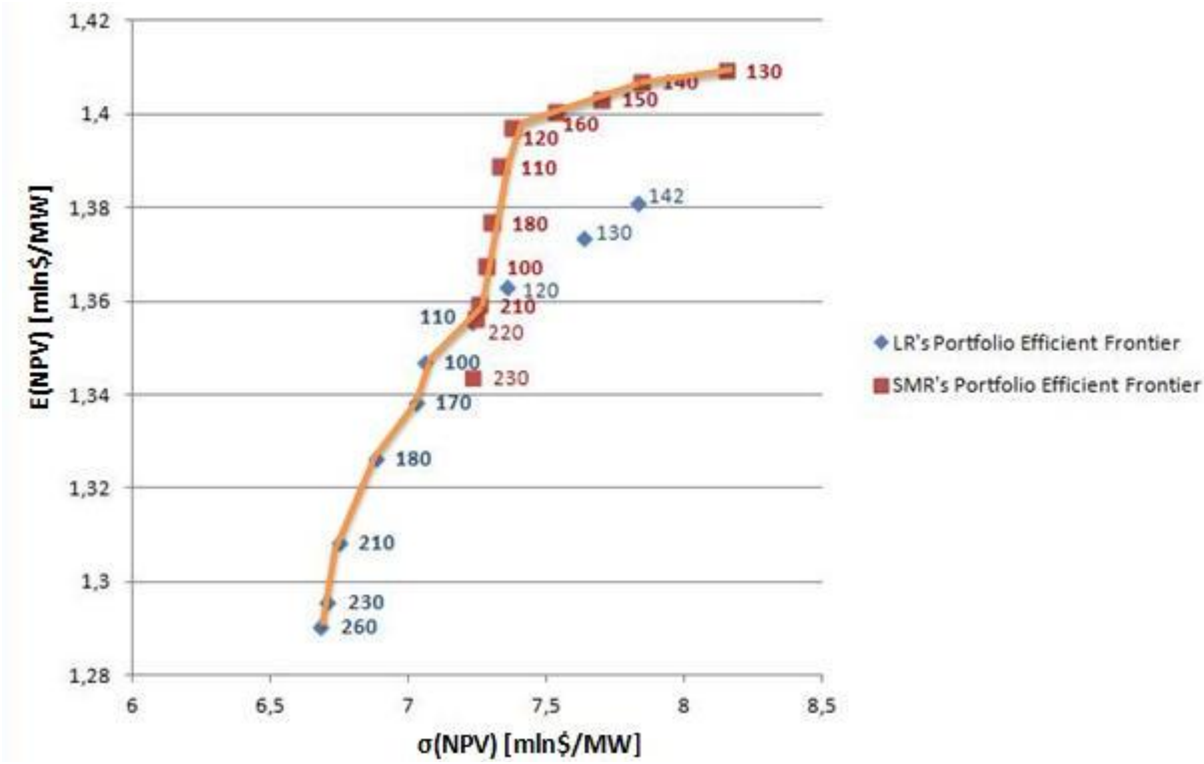

Figure 92. The Optimized Efficient Frontier

Thanks to the optimized efficient frontier shown above a utility obtains further important information:

1. It can choose which PP is the most adapted and in which condition the investment has to be triggered in function to every specific level of risk.

2. There are values on the efficient frontier of the single portfolio that does not belong on the optimized efficient frontier.

We remind now the main drawback contained in literature about the MVP theory:
"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 & Wenk, 2008).

It is clear now that this problem has been solved by integrating our improved version of the SOET Method with the MVP Theory because the optimized efficient frontier guarantee the best solution for the utility following the snapshot evolution of the environmental condition around it(represented by the snapshot evolution of the electricity price in this case).

6.1.3 Option to Defer with Compound Options

This paragraph extends our method modeling the pre – operational phase of the PP under analysis as the succession of three sequential compound options. The following figures then shows the results obtained applying this model if the additional PP is a LR or an SMR PP and if only the option to defer is implemented and thus the investment has to begin in 20 years from now.

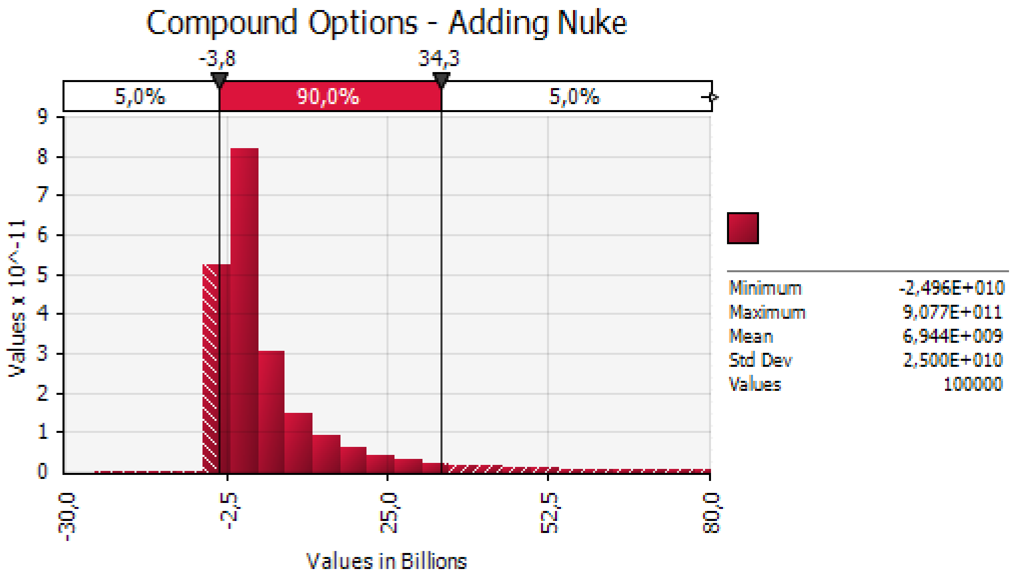

Figure 93. The Overall Portfolio with an additional LR's NPV distribution obtained with the SOET Method with Compound Options – Option to defer

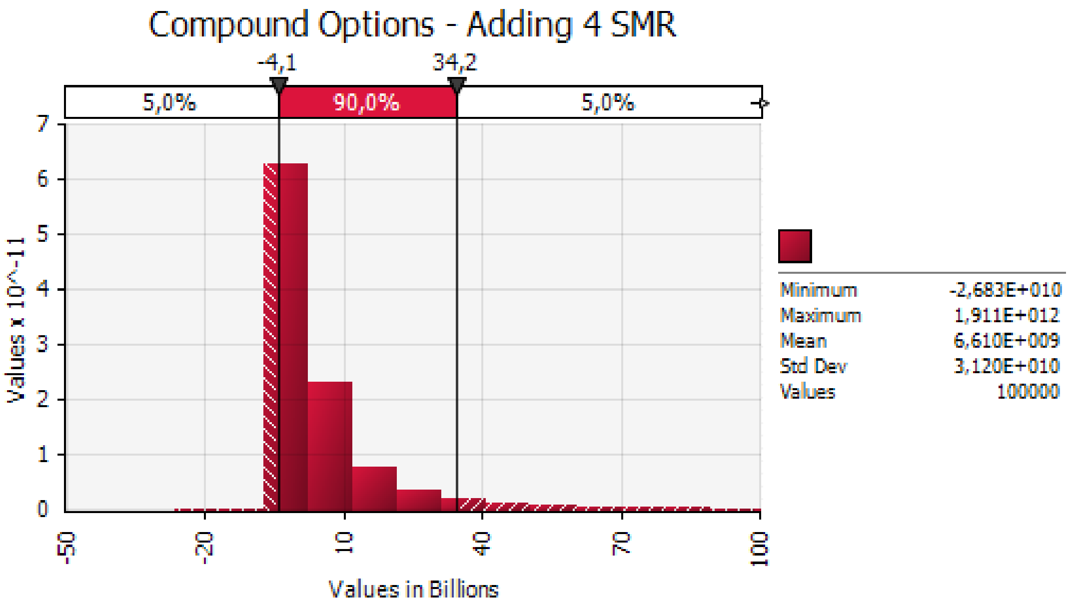

Figure 94. The Overall Portfolio with Four additional SMRs' NPV distribution obtained with the SOET Method with Compound Options – Option to defer

The NPV distribution shown above has been obtained thanks to a search algorithm and the steps that should be used in this case has been described in chapter 3 and are summarized in Figure 61. Steps of the search algorithm SOET Method integrated with the MVP Theory. The model, as already said, gives in output not only the NPV distribution of the portfolio but the values of the exercise thresholds that trigger the investment in the additional PP too. In this case it is a complex multi - stage problem and thus the exercise thresholds are complex too. We report here their equations both for the LR's and for the SMR's case of investment:

Technology	Study Phase Threshold	Design Phase Threshold	Construction Phase Threshold
Large Nuclear	$P_{el} > 95\ \$/MWh$	$ECTD^* < 5 * (P_t - 45)$	$ECTC^* < 60 * (P_t - 52)$
Small Modular Reactor	$P_{el} > 100\ \$/MWh$	$ECTD^* < 4 * (P_t - 25)$	$ECTC^* < 80 * (P_t - 60)$

Table 69. Value of the exercise thresholds of the additional PP – Option to defer

These exercise thresholds are reported in the following two figures:

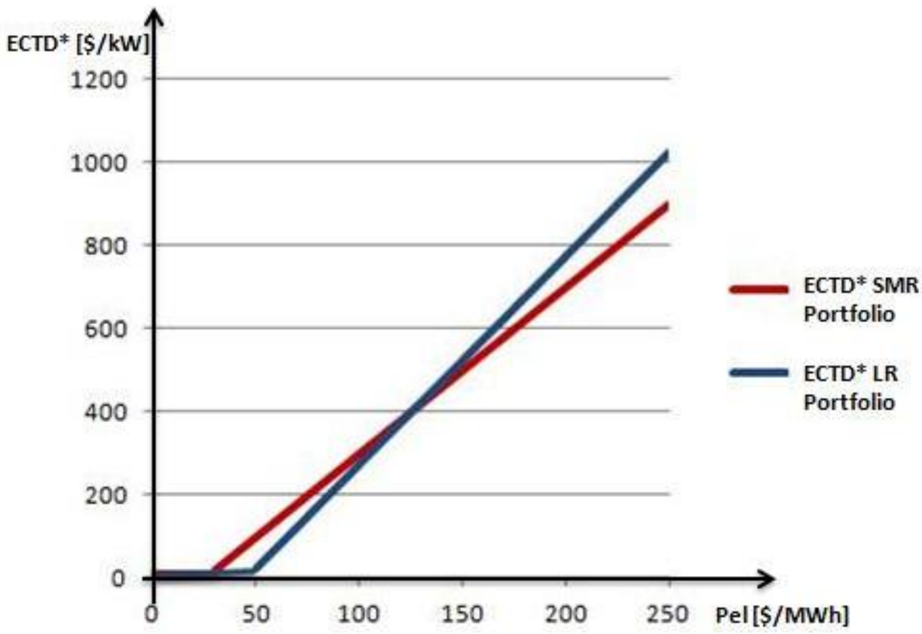

Figure 95. Value of the exercise thresholds of the design phase in the SMR and LR case

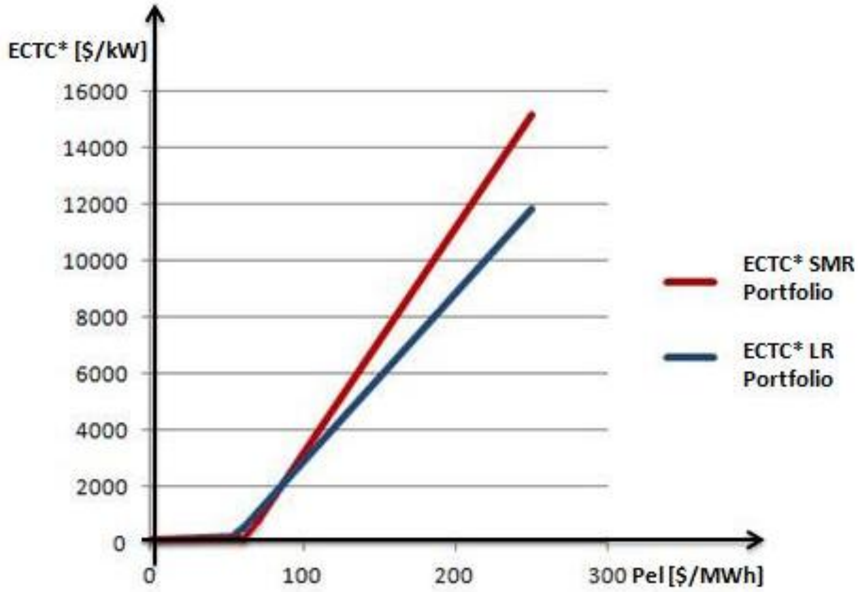

Figure 96. Value of the exercise thresholds of the design phase in the SMR and LR case

From these two figure it is easy to understand the existing relationship between the exercise threshold that trigger both the design and the construction phase with the snapshot evolution of the electricity price's value. Taking as example the construction phase, it means that the value of the expected cost to completion that trigger this phase can be high if the actual value of the electricity price is high because it would mean that the probability for the investment to generate a great amount of revenues is high too.
Instead, if the electricity price is low the expected cost to completion must be low too because in that scenario the positive cash – flow would not be sufficiently high to guarantee a good result for the investment.

The results obtained modeling the pre – operational phase of these PP in this way are shown in the following table:

Technology	NPV Mean [mln $/MW]	σ(NPV) [mln $/MW]	Sharpe Ratio
Large Nuclear	1,462	7,251	0,2016
Small Modular Reactor	1,44	6,966	0,2067

Table 70. RO Results of the dummy portfolio with an additional investment whose pre – operational phase is modeled as the succession of three sequential compound options

From the table above we can see that the LR nuclear case of additional investment to the actual portfolio guarantees again the maximum level of profit to the utility but modeling the pre – operational phase thanks to the compound options reduces remarkably the level of risk of the SMR PP and its Sharpe Ratio indeed becomes higher than the Sharpe Ratio of the portfolio with the LR PP.

It means that if the aim of the utility is to maximize the Sharpe ratio value[31](e.g. the profit for unit of risk) the best solution would be to add to this dummy actual portfolio an SMR PP. Instead if the objective function is to maximize the NPV Mean the Large Nuclear PP is the best solution for the utility.
The following figure illustrates the means and standard deviations of the distributions in all the three different ways in which the investment has been modeled:

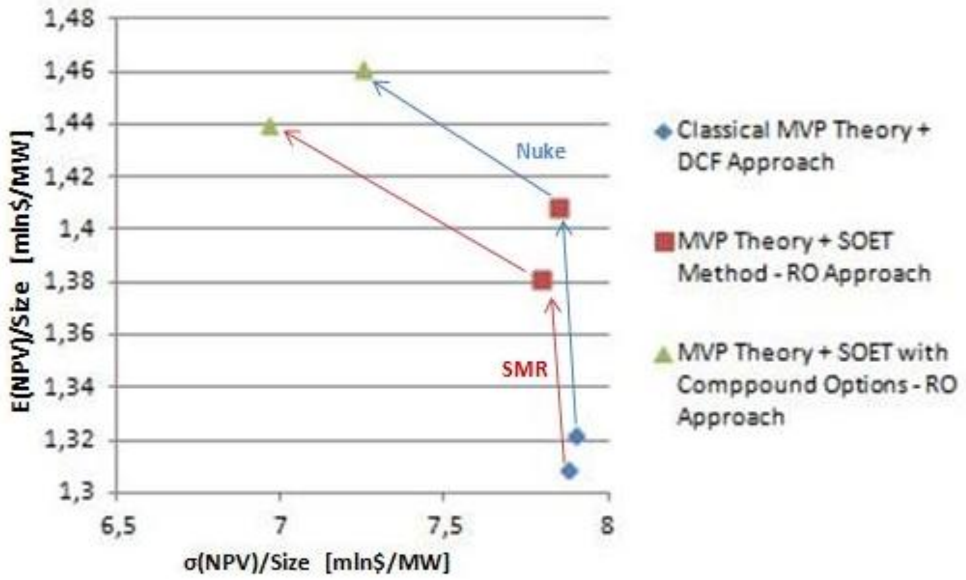

Figure 97. Benchmarking between results of new portfolio obtained applying the three evaluation models described in this work

6.1.4 Implementing properly the option to invest

As reported in paragraph 3.3.1 the option to defer has a special property if the actual portfolio is considered in the decision of investment because the effect that the value of the state variable considered has on the additional investment is the same it has on the overall portfolio[32].

Instead the option to invest has not the same property and thus the value of all the new possible portfolios can't be directly compared as we did in the previous paragraph.
Hence, the discriminating that must be used in this case is directly the value of the additional investment. The following two figures show how the value of the additional investment increases if the option to invest is considered both in the LR's and in the SMR's case of additional investment.

[31] Being the analysis made considering the presence of an actual portfolio of investment, the maximization of the Sharpe Ratio value is the most adapted criteria to choose between alternative additional investment because it takes into account the position of risk of the utility.
[32] The value of the exercise threshold that maximize the NPV mean of the additional PP is the same that maximize the E(NPV) of the overall portfolio. And it is the same for every possible objective function the utility would implement

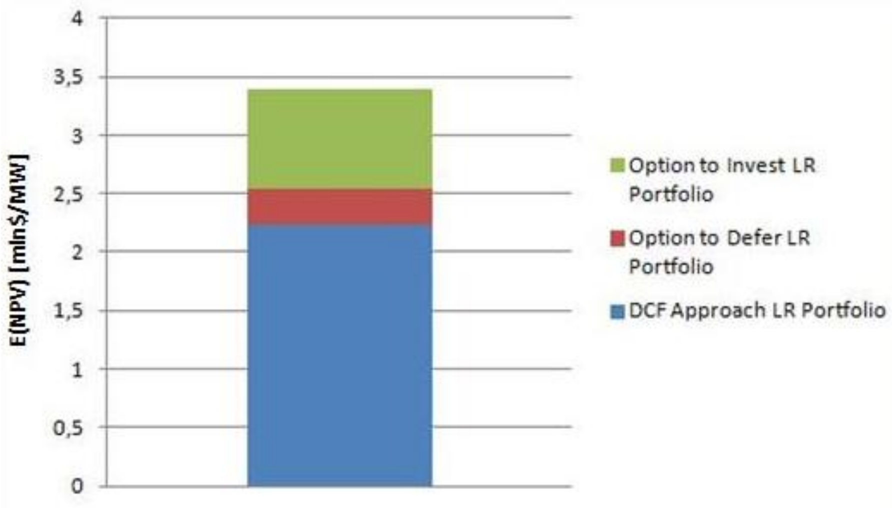

Figure 98. Value of options in the case of the additional LR

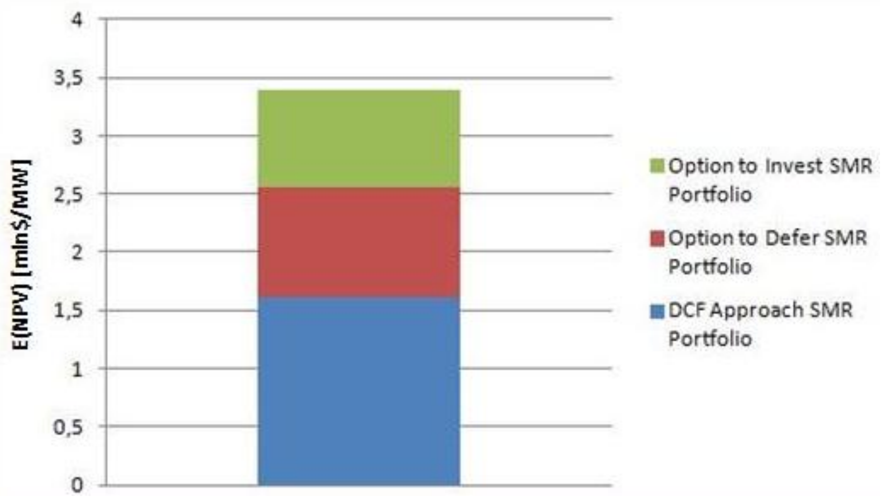

Figure 99. Value of options in the case of the additional SMR

It is clear that the implementation of the option to invest increases remarkably the additional investment both in the SMR and in the LR case. It means that it is the best method to evaluate the single investment in an additional PP because it permits to not perform the investment if the scenario is not convenient. However its result are not directly linked to the result of the overall portfolio[33] while that relationship exists when the option to defer is implemented. This is the reason for which the analysis on the portfolio and the construction of the optimized efficient frontier has been done when the option to defer is implemented.
The results obtained when the option to invest is implemented and the pre – operational phase of the PPs is not modeled as the succession of three sequential phases are shown in the following figures and are summarized in the table below them:

[33] The value of the exercise threshold that maximize a specific objective function for the additional PP is not the same that maximize the same objective function in the overall portfolio if the option to invest is implemented.

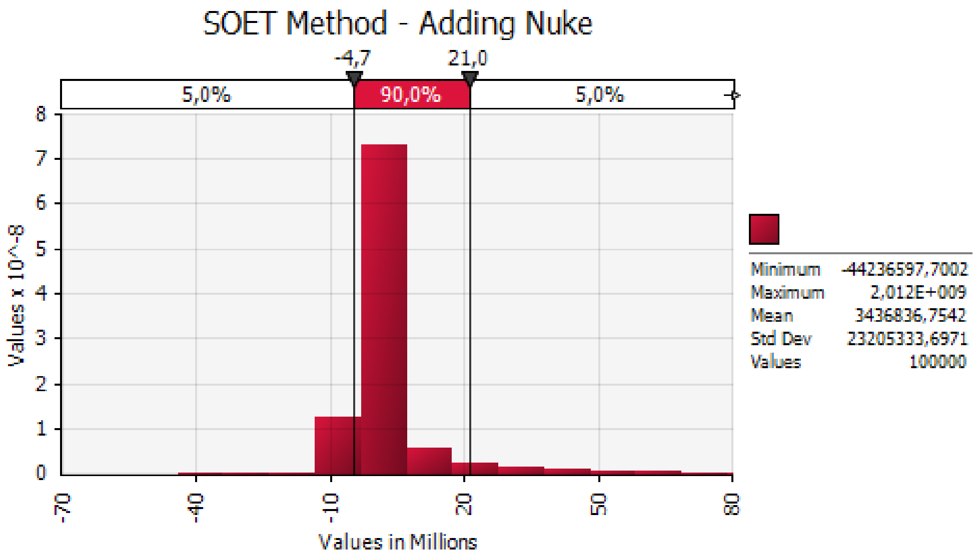

Figure 100. NPV distribution of the additional LR – SOET Method

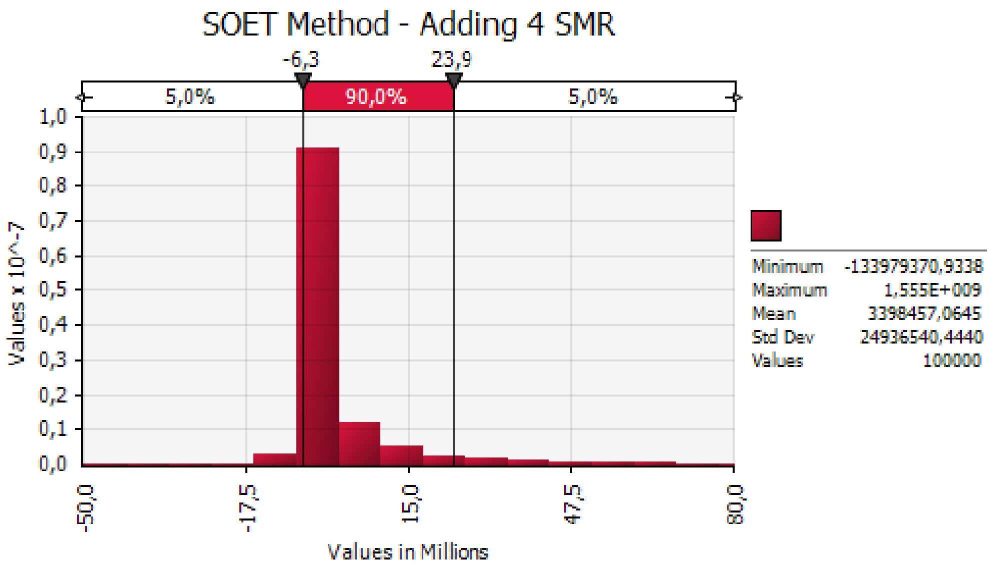

Figure 101. NPV distribution of the additional four SMRs – SOET Method

Additional PP	$E(NPV_{technology})$	$\sigma(NPV_{technology})$	Exercise Threshold
Large Reactor	3,39 mln$/MW	24,58 mln$/MW	$P^* = 120\ \$/MWh$
SMRs	3,4 mln$/MW	24,94 mln$/MW	$P^* = 125\ \$/MWh$

Table 71. Results of the additional PP when the option to invest is implemented

After the results of the single technology have been found the model user can apply the MVP Theory and find out the value of the overall portfolio.

Then in summary the difference between the case in which the option to invest in implemented from the case in which the option to defer is implemented are:

Option implemented	Link between additional PP and overall portfolio	How the additional PP must be chosen?
Option to Invest	The value of the exercise thresholds that maximize a specific objective function is not the same between the new PP and the overall portfolio	By only comparing the results of the new additional PP[34]
Option to Defer	The value of the exercise thresholds that maximize a specific objective function is the same between the new PP and the overall portfolio	By comparing the results of the new additional PP or by comparing the ones of the overall portfolio

Table 72. Distinction between the effect of the different kind of options implemented

6.2 Application to the EDF's actual portfolio of investment in UK

The aim of this paragraph is to apply our model to a real actual portfolio of investment. The assumption made to perform the analysis is the same made in all this work and thus it is that EDF has to build a base – load PP[35] to face an additional demand of 1,5 GW.
The steps of the analysis are the same made in paragraph 6.1 for the application to a dummy actual portfolio of investment and thus this paragraph contains these results:

1. The classical DCF approach with the MVP Theory for each of the possible additional PP(the static evaluation of paragraph 6.2.1)

2. The SOET method without the compound options with the option to defer for each of the possible additional PP (paragraph 6.2.2)

3. The SOET method modeling the pre – operational phase of the additional nuclear and SMR PPs as the succession of three sequential compound options with the option to defer (paragraph 6.2.3)

The possibility we assume the utility has to fulfill the request of 1,5 GW are reported here[36]. It can build:

a. A single Large Nuclear Reactor Power Plant
b. Two Coal Power Plants
c. Three CCGT Power Plants
d. Four SMR Power Plants

[34] In that case the performance of the overall portfolio can be found only after the value of the new technology has been found by applying the MVP Theory

[35] The possible PPs that can be built are LR, SMR, CCGT and Coal PP whose data have been described in paragraph 4.1.5

[36] The possibility for new PPs could be different than the ones we enumerate but the main scope of this work is to describe and show the potentiality of this method and not to give a real suggestion to EDF. The application of this model to a real case will be a future development of this work.

6.2.1 EDF: The static evaluation

As we did in paragraph 6.1.1, in this case the investments are evaluated as they are made at time zero and the option to abandon them is not implemented. This is then a static evaluation and it is done as a standard MVP analysis where the investment in the additional PP is done applying the classical DCF approach. The NPV distributions are then obtained and represented in the following figures for all the four possibility to fulfill the additional request of 1,5 GW.

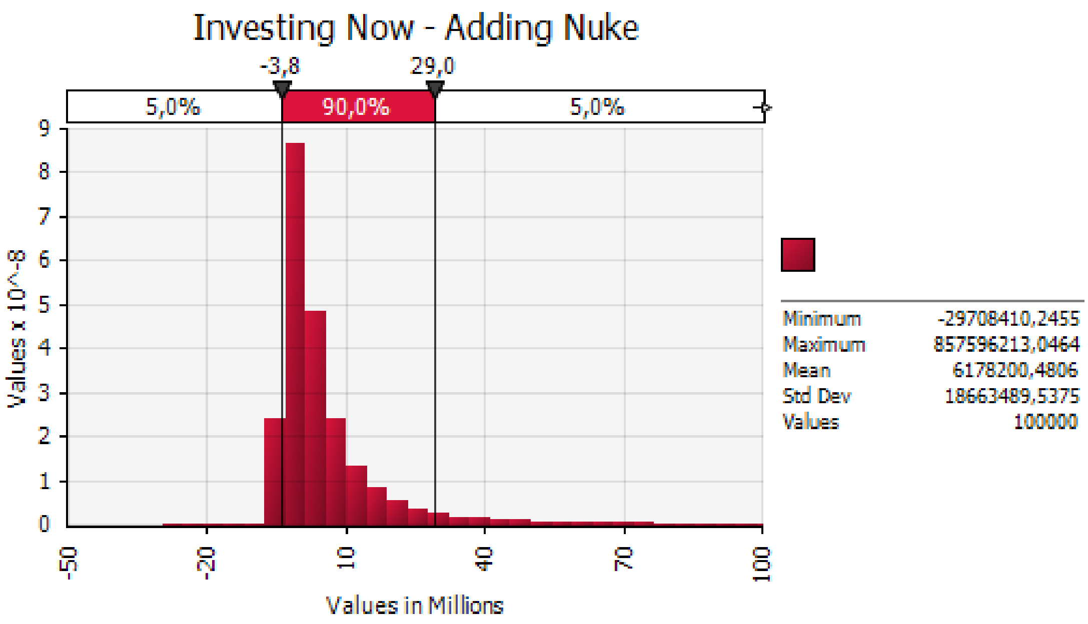

Figure 102. The static evaluation of the EDF's portfolio with an additional LR PP

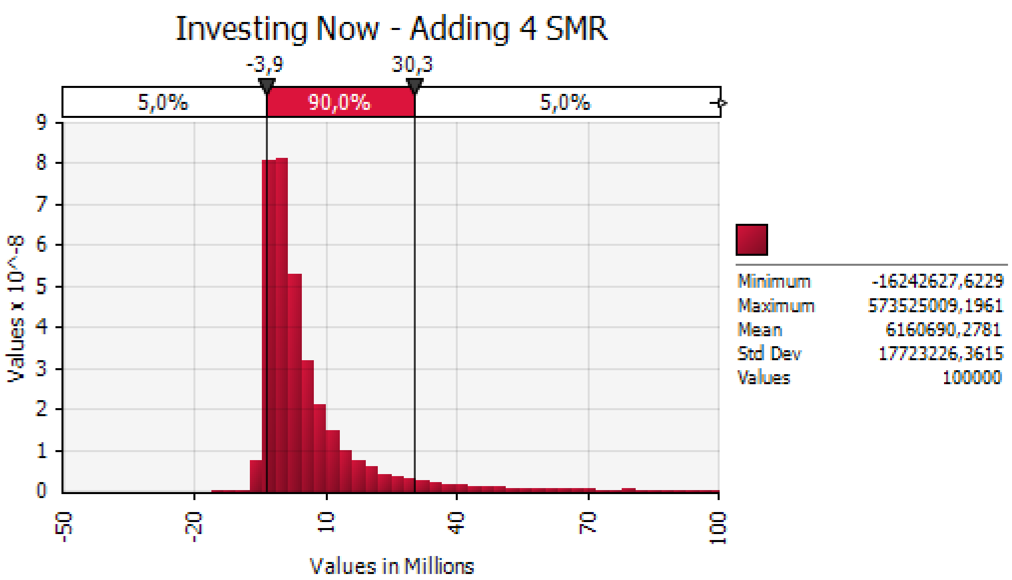

Figure 103. The static evaluation of the EDF's portfolio with Four additional SMR PPs

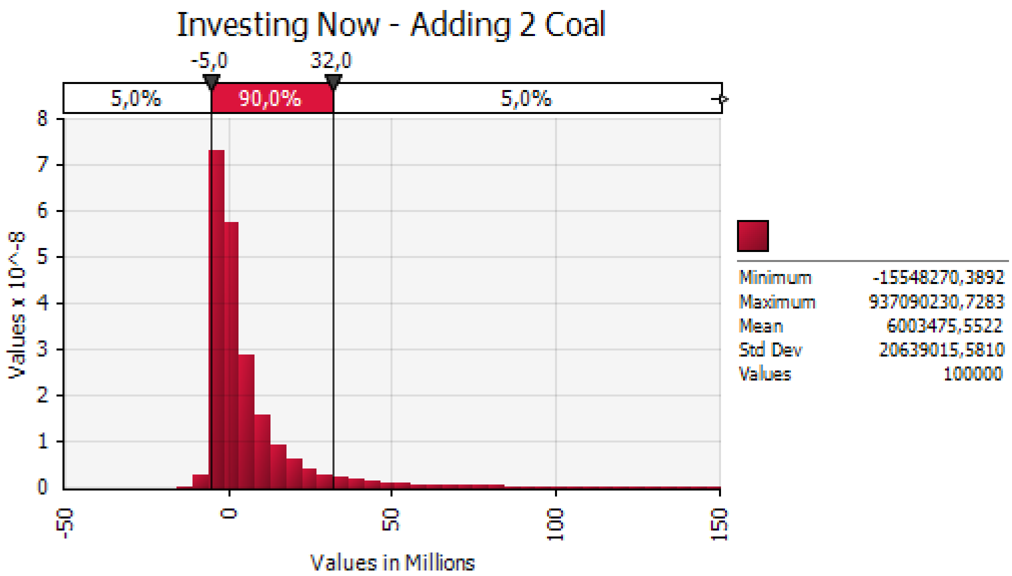

Figure 104. The static evaluation of the EDF's portfolio with Two additional Coal PPs

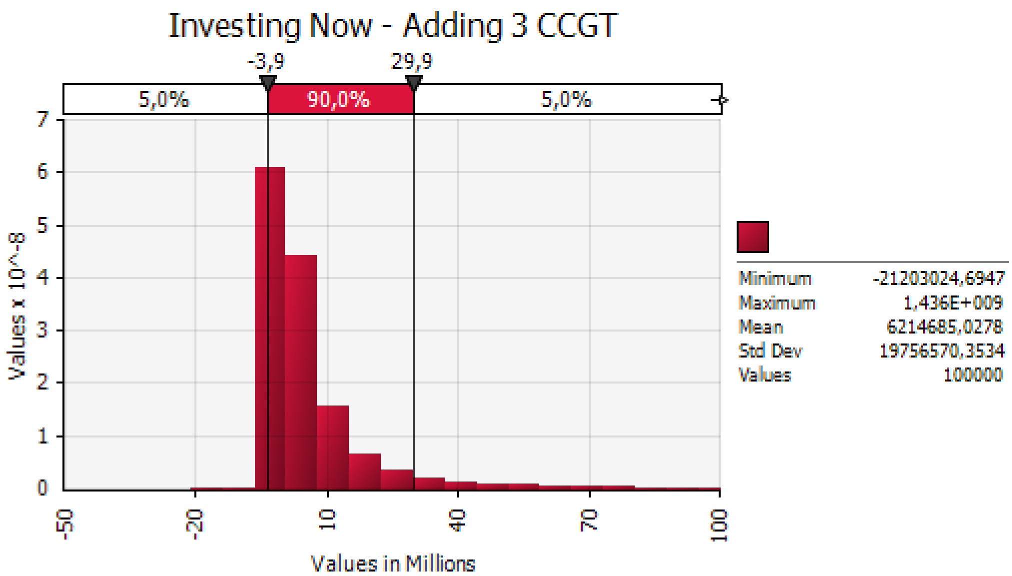

Figure 105. The static evaluation of the EDF's portfolio with Three additional CCGT PPs

The results obtained applying the MVP Theory integrated with the classical DCF approach on the EDF's overall portfolio with the additional PPs shown above have been summarized in the following table:

Additional Technology	$E(NPV_{portfolio})$	$\sigma(NPV_{portfolio})$	Sharpe Ratio
Large Reactor	6,18 mln$/MW	23,53 mln $/MW	0,2626
SMRs	6,16 mln$/MW	22,27 mln$/MW	0,2767
Coals	6,00 mln$/MW	25,86 mln$/MW	0,2322
CCGTs	6,21 mln$/MW	24,82 mln$/MW	0,2504

Table 73. Static Evaluation's results

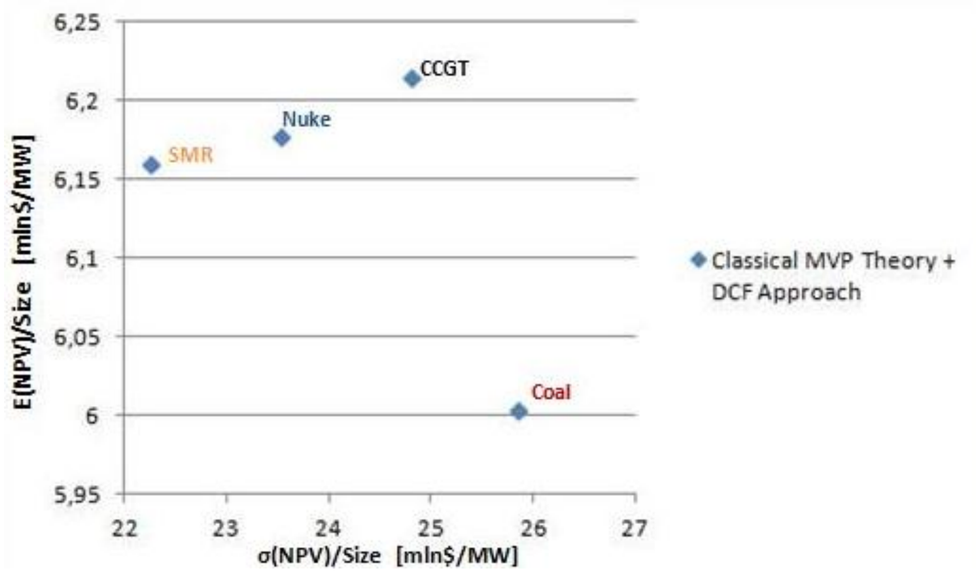

Figure 106. Benchmarking between Portfolio's results of the static evaluation

From the table and the figure above we can conclude that if the additional investment is evaluated thanks to the MVP Theory integrated with the classical DCF approach the best solution for the utility is:

- To not build Two Coal PPs because that possibility is not on the efficient frontier in the plane E(NPV) – σ(NPV)
- To build Three CCGT PPs if its objective function is the maximization of the NPV Mean of the overall portfolio
- To build Four SMR PPs if its objective function is the minimization of the NPV Standard Deviation of the overall portfolio
- To build Four SMR PPs if its objective function is the Maximization of the Sharpe Ratio Value of the overall portfolio

6.2.2 EDF: The Option to defer with one state variable case

This paragraph integrates the SOET Method with the MVP Theory with the aim to add the option to defer the additional investment. The model evaluates the mean of the NPV distribution of the overall portfolio using as decision variable the exercise threshold , that is the value of the price of electricity P* waited to invest. To obtain this maximized mean and the optimal value of the electricity price P* the search algorithm is used. The output the model gives are therefore the NPV distributions (with maximized NPV mean) and the P* used to obtain these results.

The following figures contains the results obtained in all the four possibility of additional investments considered in this work:

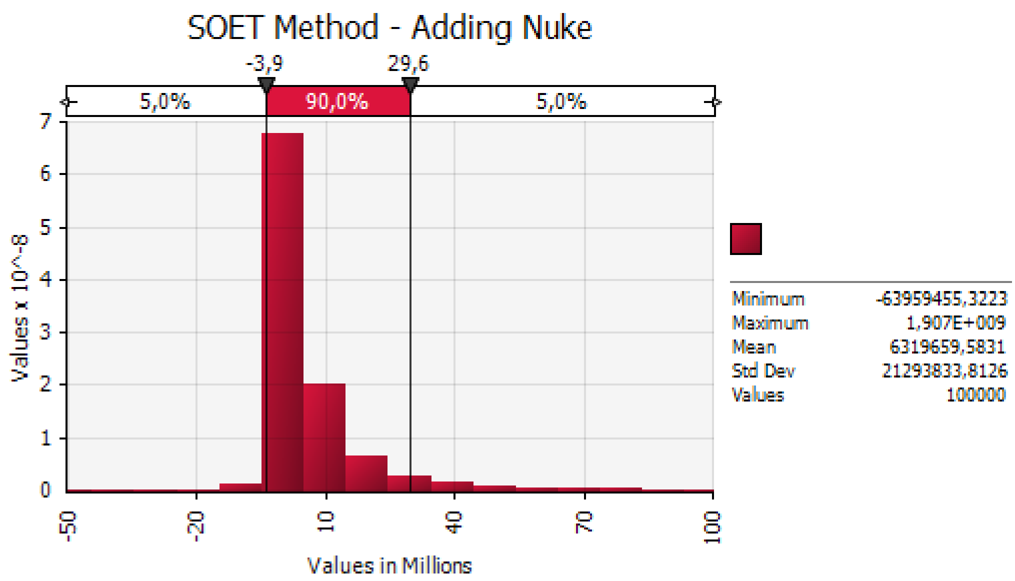

Figure 107. The Overall Portfolio with an additional LR's NPV distribution obtained with the SOET Method – Option to defer

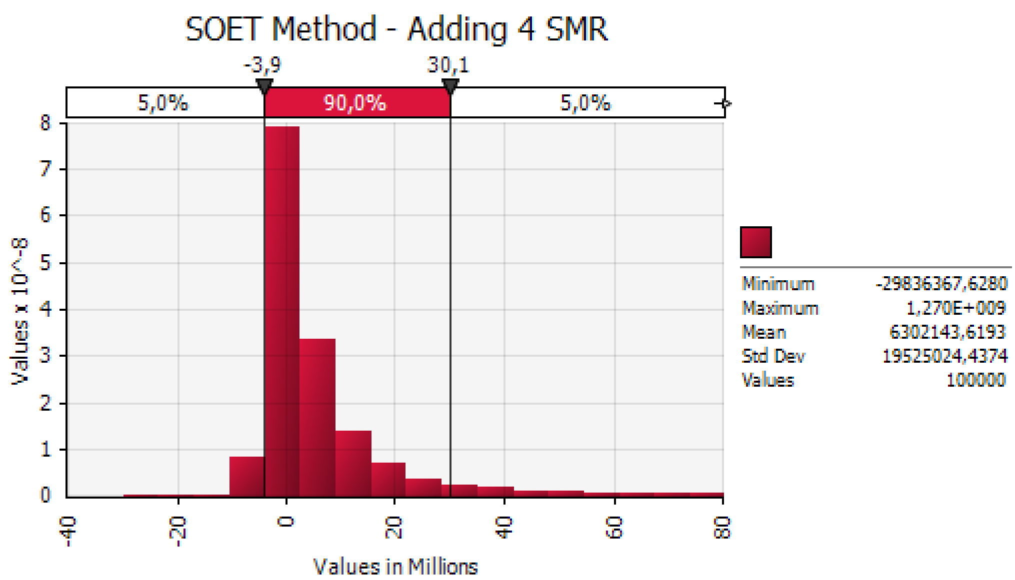

Figure 108. The Overall Portfolio with Four additional SMRs' NPV distribution obtained with the SOET Method – Option to defer

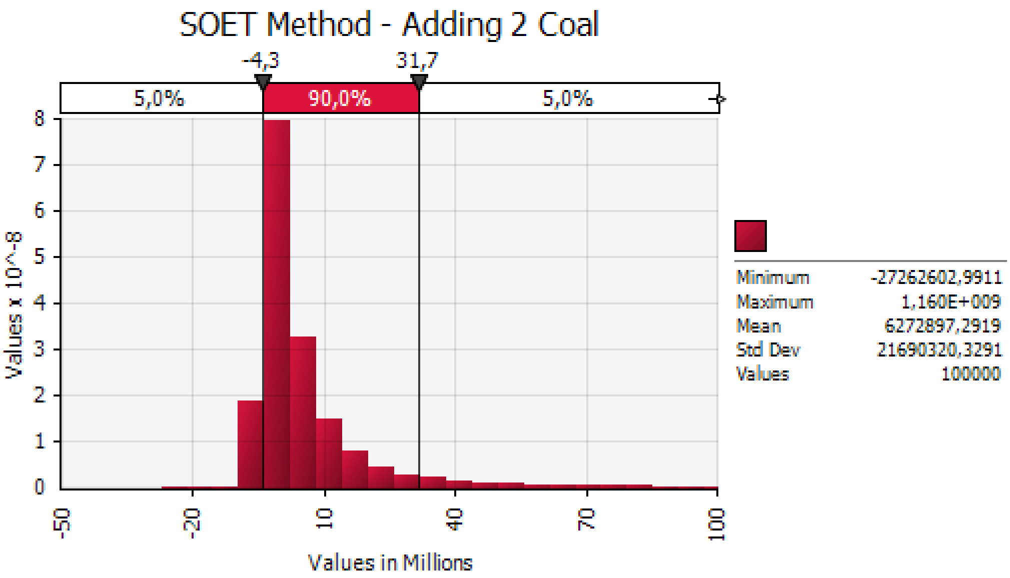

Figure 109. The Overall Portfolio with two additional Coals' NPV distribution obtained with the SOET Method – Option to defer

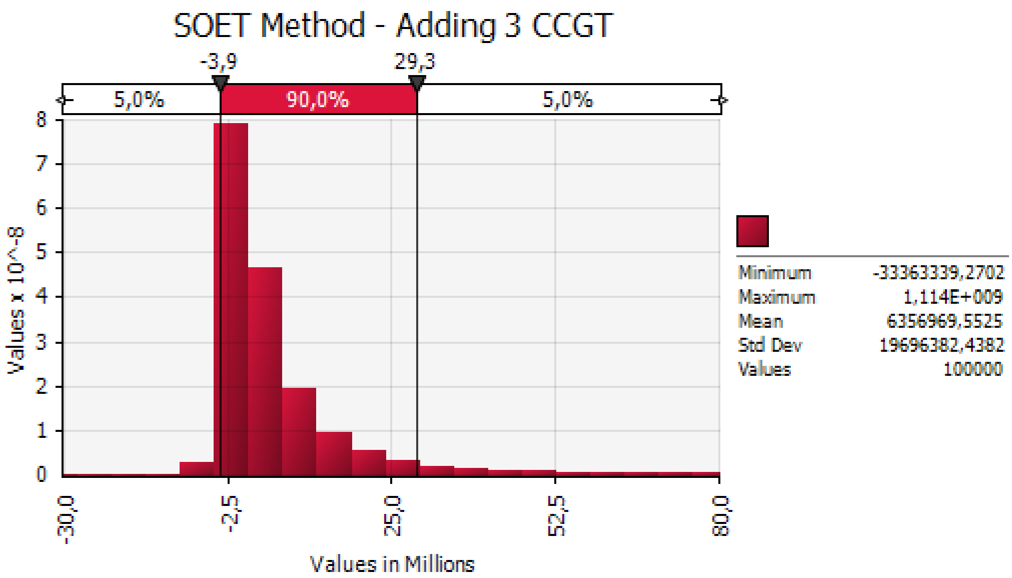

Figure 110. The Overall Portfolio with three additional CCGTs' NPV distribution obtained with the SOET Method – Option to defer

The results obtained by integrating the SOET Method with the MVP theory shown above have been now summarized in the following table in terms of E(NPV), σ(NPV) of the overall portfolio and value of the exercise threshold P* that guarantee that distribution as output.

Additional Technology	$E(NPV_{portfolio})$	$\sigma(NPV_{portfolio})$	Sharpe Ratio	Exercise Threshold
Large Reactor	6,32 mln$/MW	22,84 mln$/MW	0,2767	$P^* = 140\ \$/MWh$
SMRs	6,30 mln$/MW	21,83 mln$/MW	0,2888	$P^* = 130\ \$/MWh$
Coals	6,35 mln$/MW	24,04 mln$/MW	0,2644	$P^* = 145\ \$/MWh$
CCGTs	6,27 mln$/MW	25,25 mln$/MW	0,2484	$P^* = 125\ \$/MWh$

Table 74. Option to Defer results

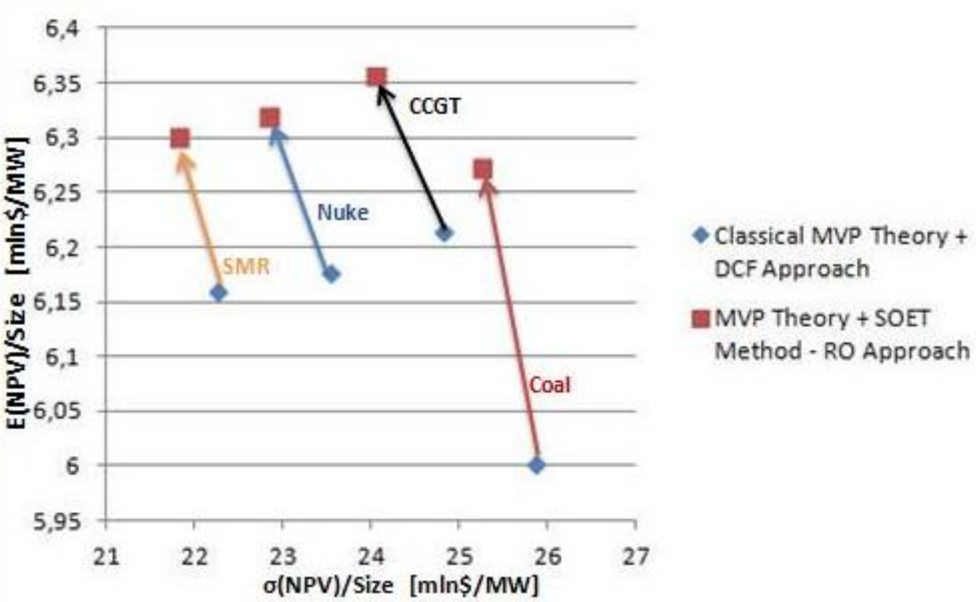

Figure 111. Benchmarking between Portfolio results with SOET Method

From the table and from the figure above we can immediately see that the application of a real option method to evaluate a portfolio with an additional investment adds the E(NPV) of the overall portfolio and reduces its level of risk.
However, by applying the SOET Method integrated with the MVP Theory the utility has to choose again:

- To not build two Coal PPs because that solution is not on the efficient frontier
- To build three CCGT PPs if the objective function is the maximization of the NPV Mean of the overall portfolio
- To build four SMR PPs if the objective function is the minimization of the NPV Standard Deviation of the overall portfolio
- To build four SMR PPs if the objective function is the maximization of the Sharpe Ratio Value of the overall portfolio

6.2.3 EDF: Option to defer with Compound Options

Finally, in order to extend the model to all the potentialities described in this work, we evaluate now the intrinsic flexibility of the nuclear and of the SMR PPs modeling their pre – operational phase as the succession of three sequential compound options.
The results obtained are reported in the following two figures and are summarized in the two tables below them:

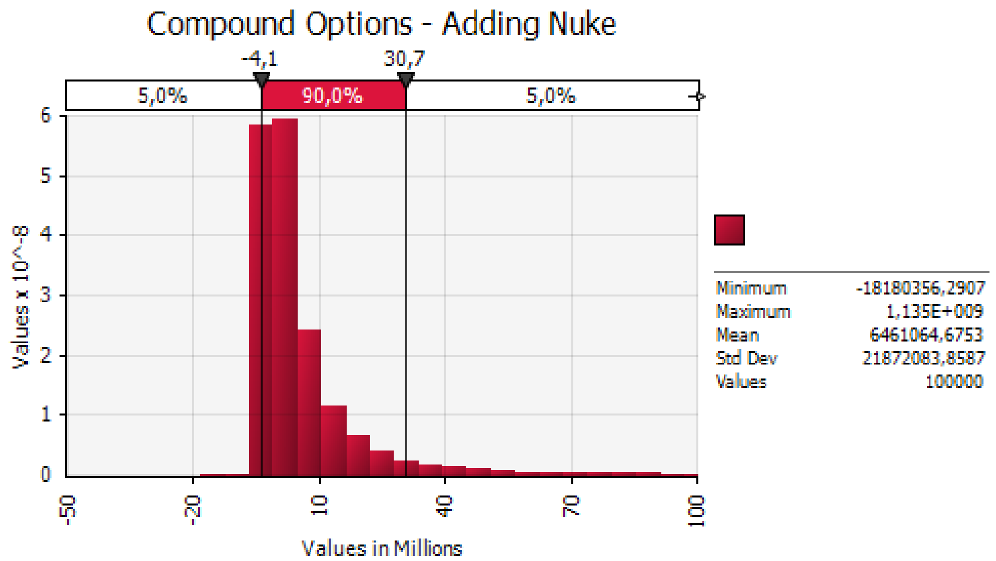

Figure 112. NPV distribution of the Overall Portfolio with an additional LR - SOET Method with Compound Options

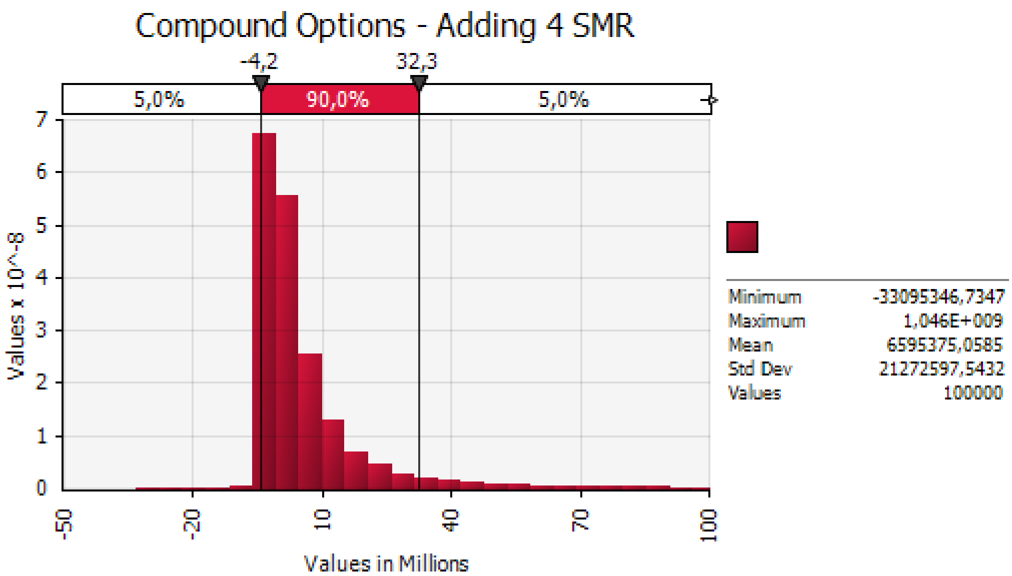

Figure 113. NPV distribution of the Overall Portfolio with an additional LR - SOET Method with Compound Options

Additional Technology	Study Phase Threshold	Design Phase Threshold	Construction Phase Threshold
Large Nuclear	$P_{el} > 92\ \$/MWh$	$ECTD^* < 5 * (P_t - 45)$	$ECTC^* < 78 * (P_t - 58)$
Small Modular Reactors	$P_{el} > 93\ \$/MWh$	$ECTD^* < 5 * (P_t - 30)$	$ECTC^* < 70 * (P_t - 25)$

Table 75. The value of the exercise thresholds

Additional Technology	NPV Mean [mln $/MW]	σ(NPV) [mln $/MW]	Sharpe Ratio
Large Nuclear	6,46	22,57	0,2862
Small Modular Reactor	6,60	21,44	0,3077

Table 76. The Overall Portfolio results with compound options implemented

From the table above it is clear that the implementation of the compound options in the model increases remarkably the goodness of additional investment and therefore the result of the overall portfolio because for both the two cases considered:

- The value of the NPV Mean of the overall portfolio increases
- The value of the NPV Standard Deviation of the overall portfolio decreases
- The value of the Sharpe Ratio increases

The following figure shows this conclusions:

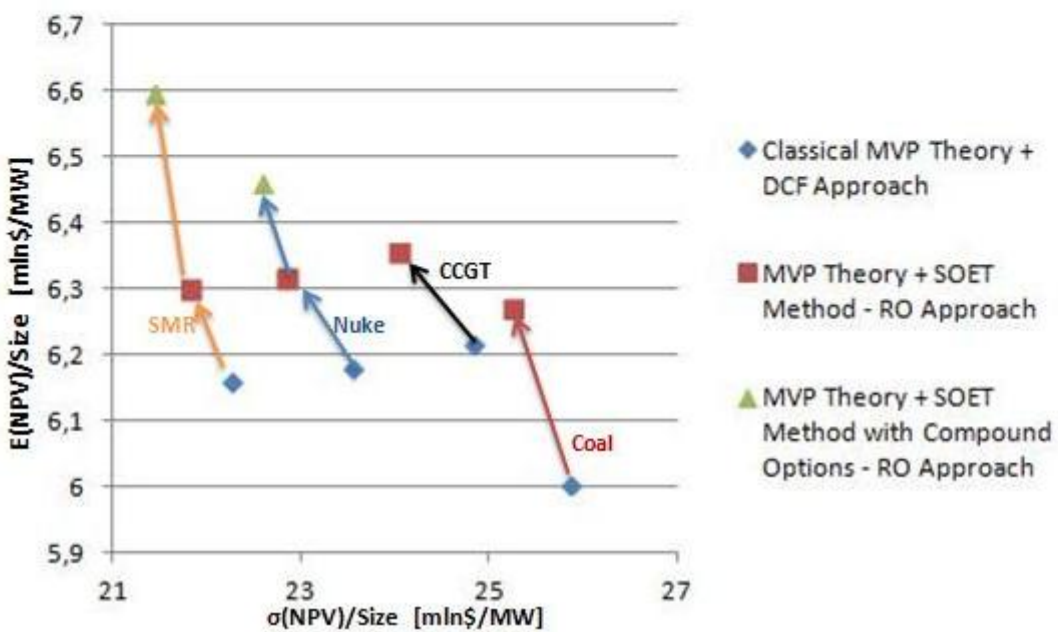

Figure 114. Final Benchmarking between all the base – load technologies under analysis

From the table above the conclusion we can make is that:

- Modeling the pre – operational phase of the nuclear and of the SMR PP is necessary to take the decision of the investment with the greatest number of information about it.

Indeed the chosen of the additional technology change respectively to the case in which compound options are not implemented.

- The SMR technology is the only technology on the efficient frontier and thus it is the "best" solution of additional investment for each of the three most used objective function that a utility could consider[37].

6.3 Conclusions of the chapter

The main messages contained in this chapter are:

- The integration between the SOET Method and the MVP Theory gives in output an Optimized Efficient Frontier from which the utility can choose the best PP to be built according to every possible objective function
- Modeling the pre - operational time of a nuclear PP as the succession of three compound options change the decision of investment
- If the analysis of an additional investment to an actual portfolio is performed implementing the option to defer there is a direct link between the additional PP and the overall portfolio. It means that:
    - If the option to defer is implemented the values of the exercise thresholds that maximize a specific objective function of the additional PP are the same that maximize the value of the overall portfolio. Therefore the decision of investment can be taken by comparing the results of all the possible new additional PPs or by directly comparing their overall portfolio.
    - If the option to invest is implemented the values of the exercise thresholds that maximize a specific objective function of the additional PP are the same that maximize the value of the overall portfolio. The criteria to choose the investment in that case must be the additional PP and not the overall portfolio. After the NPV distribution of the new PPs has been found, the MVP Theory has to be applied to find out the performance of the overall portfolio.

[37] Maximization of the NPV Mean or minimization of the NPV standard deviation or maximization of the Sharpe Ratio value of the overall portfolio with the additional PPs.

Chapter 7 - Conclusions

The conclusions of this work are several and can be differentiated in these voices:

- Conclusions about the models developed in this work (paragraph 7.1)
- General conclusions not influenced by the choice of the input data and then that have general value (paragraph 7.2)
- Conclusions about the results obtained that highly depend on the input chosen in this work (paragraph 7.3)
- Conclusions about the research question asked in chapter 1 (paragraph 7.4)
- Conclusions regarding future possible developments that this work and the innovations it contains could have (paragraph 7.5)

7.1 Conclusions about the models

In this paragraph are reported the principal strengths all the models developed here have:

- It confirms all the conclusions contained in (Lotti, 2012). Indeed the evaluation of the TTM Effect without modeling the pre – operational phase of nuclear PPs as the succession of three sequential compound options is a simple extension of that work that let us say that :
    - The SOET Method works and optimizes the investments. Observing the figures of chapter 5 is proved how the method can measure the value of flexibility, resolving complex problems, with more than one real option and more state variables.
    - It gives several information about the pattern of the problems, suggesting, through its exercise thresholds what a firm should do to improve their investments.
    - It gives the possibility to compare different solutions(expressed by the exercise thresholds).
    - It's possible to define a custom objective function, making considerations about the risk profile of the investments
    - It's possible to be implemented through excel add-ins

- The modeling of the pre – operational phase of nuclear PPs as the succession of three compound options (one of the most important innovation this work contains) adds these points of strength to the model:
    - It shows how to model compound options to solve complex problems. In literature there are only few works that model them and none of them solve complex problems because of their complexity.
    - It gives a more realistic representation of modeling the pre – operational phase of a nuclear PP because:
        - On one hand considering the whole time required for a PP to start produce electricity from the moment in which the decision to invest is taken reduces remarkably the value of nuclear PP because their TTM is remarkably higher than the Coal's or the CCGT's ones.
        - On the other hand modeling their pre – operational phase as the succession of three sequential compound options (which means considering the intrinsic flexibility this kind of investment have) adds great value to that investment
    - It gives several information to the model user, suggesting, through its exercise thresholds, what are the conditions that trigger each of the pre – operational phases.

- This model shows how to consider the actual portfolio of a utility giving a more realistic representation of an investment in the energy field[38].

The principal point of weakness instead is the computational time needed to find out the optimal value of the exercise thresholds when complex problems are considered.

[38] An investment in the energy field, from the utility's point of view, is always an investment in a wider portfolio of already existing PPs

7.2 General Conclusions

This paragraph contains the general conclusions this work have (i.e., the conclusions that not depend on the inputs chosen).

- The RO theory has been respected, showing its already theoretically proven aspects. It has been shown how there is value in flexibility and that this value is maximized as more as there is volatility ad as more as the investments NPV is close to zero. In fact it is shown how the NPV of investment with a value close to zero is highly increased.
- The integration between the SOET Method and the MVP theory solves the principal drawback[39] that the MVP Theory have and that was limiting its use and that does not let to evaluate investment in the energy field considering the actual portfolio of a utility

	CLASSICAL MVP THEORY	MVP + SOET METHOD
Way of Representation of portfolios on E(NPV) – σ(NPV) plane	Static Point	Two-dimensional Curve: each portfolio have its own efficient frontier in function of the exercise threshold
Form of the Efficient Frontier	Two-dimensional 2D Curve	Tri-dimensional 3D curve: the third dimension is represented by the value of the exercise threshold (see for example Figure 90)
Does the "best" portfolio exist?	No: each portfolio on the efficient frontier is the optimal.	Yes. There is, in function to the existing environmental condition, a portfolio that is better that the other relatively to a specific objective function (see the optimized efficient frontier of Figure 92)
Future Scenarios?	Only hypothesized: future environmental condition could be really different that what a utility thought	Simulated through Monte Carlo Simulation: we could find the exercise threshold that maximize the value of each portfolio in every different future scenario.

Table 77. General conclusions about the improvement on a portfolio analysis guaranteed by integrating the SOET Method with the MVP Theory

[39] Reported in (Madlener & Wenk, 2008).

7.3 Conclusions depending on Inputs

These conclusions highly depend on the input chosen (EIA, 2012) and then have not a general value.

- The use of the model with these inputs modeling the pre – operational time of nuclear PPs with compound options and not considering the presence of an actual portfolio of already existing PPs(see Figure 85 in chapter 5) show how:
  - The SMR technology is the most valuable if the objective function is the maximization of the NPV Mean of the overall portfolio
  - The CCGT technology is the most valuable if the objective function is the minimization of the NPV Standard Deviation of the overall portfolio
  - The Coal technology is the most valuable if the objective function is the maximization of the Sharpe Ratio value of the overall portfolio

- The use of the model with these inputs modeling the pre – operational time of nuclear PPs with compound options and considering the presence of an actual dummy portfolio of already existing PP(see Figure 97 and Figure 92 in chapter 6) shows how:
  - The SMR technology is the most valuable if the objective function is the maximization of the NPV Mean of the overall portfolio
  - The Large Nuclear Reactor technology is the most valuable if the objective function is the minimization of the NPV Standard Deviation of the overall portfolio
  - The Large Nuclear Reactor technology is the most valuable if the objective function is the maximization of the Sharpe Ratio value of the overall portfolio

- The use of the model with these inputs modeling the pre – operational time of nuclear PPs with compound options and considering the EDF's actual portfolio of already existing PPs in UK(see Figure 114 in chapter 6) shows how:
  - The SMR technology is the most valuable if the objective function is the maximization of the NPV Mean of the overall portfolio
  - The SMR technology is the most valuable if the objective function is the minimization of the NPV Standard Deviation of the overall portfolio
  - The SMR technology is the most valuable if the objective function is the maximization of the Sharpe Ratio value of the overall portfolio

7.4 Research questions conclusions

This paragraph answers to the research questions asked in paragraph 1.3.

First Research Question: What is the effect of considering the whole time elapsed from the moment in which the decision to invest in a base – load PP is taken and the moment in which it starts to produce energy(TTM Effect)?

How explained in chapter 2 and shown in chapter 5 the effect of considering the whole time elapsed from the moment in which the decision to invest is taken and the moment in which the PP starts effectively to produce energy has two opposite effects:

  - On one hand it reduces the value of nuclear PPs' investments because their TTM is remarkably higher than the Coal's or the CCGT's ones.
  - On the other hand this pre – operational phase can be described as the succession of three sequential phases

Second Research Question: How can a real option approach helps us to model this pre – operational phase?

By modeling that phase thanks to three sequential compound options whose cost is correlated between each other. We remind to paragraph 2.3.3 for the detailed description of the model we built to implement them.

Third Research Question: How can a real option approach helps a utility to choose an investment in an additional PP considering it actual portfolio of already existing investments?

It is widely explained in this work the potentiality that the integration between the SOET Method and the MVP Theory has on the decision of investment if the presence of an actual portfolio of investment is considered. We remind to chapter 3.3 for the theoretical description of the model we built and to chapter Results Portfolio Analysis to see the effect that the application of this innovative framework has on the decision of investment

Fourth Research Question: What is the best solution for EDF to fulfill an additional demand of 1,5 GW considering its own actual portfolio of investment in UK?

Based on the assumed scenario the technology that would be more profitable is the SMRs according to all the three classical objective function present in literature(see paragraph 6.2.3). However these results are very dependent on the input chosen and then have not a general value because the aim of this work is the creation of an innovative framework to perform a realistic decision of investment in the energy field.

7.5 Future developments

The possible future developments of this work are several. We report here some of the directions in which this work can be developed in future:

- The models and their idea could be used to help a utility in a realistic decision of investment according to their specific needs (which can be implemented as objective function). In this way a realistic set of data could be used in input and an effective solution to the utility's problem could be given in output.
- Several assumptions of this work can be removed or reduced.
    - The stochastic processes assumed (chapter 4) are simplified to not complicate the work, since the aim of the work was to test the model and not to provide very realistic results. The stochastic process that most of all needs to be improved is the price of electricity, that doesn't change in function of the power plants present in the market.
    - The start – up phase is not considered after the construction of the PP is finished. That assumption is easy to be correct because a lower value of the capacity factor should be used in the first year of production of electricity, but it was not done for simplicity
    - These stochastic processes are not correlated and there is no inflation/escalation. Those are easy to correct but weren't made for simplicity.
    - The assumption that the firms do not take debt to make the investments is very strong but it was made because hypothesis about the debt structure of the firm are arbitrary. However, since the debt structure changes the results considerably

(e.g. through the interests during construction) this assumption must be removed if this model want to be used in a real case.
  - The assumption that the volatility is fixed is too strict for the model user. It has to be modeled as state variable in order to take better decisions.
- Another direction in which this work can be improved is through the inclusion of the game theory in the analysis to take into account the behavior of competitors. For example, waiting for an high value of the price of electricity could bring to sub-optimal results since some competitor would fill the energy demand while the firm is waiting. Considering, through the game theory, these aspects would deepen the analysis. Furthermore more objective function like the conquer of a specific market share could be implemented and taken into account thanks to the fact that this model consider the presence of an actual portfolio of investment.
- This model can be used to analyze a portfolio of investment not from a productive point of view but from a managerial one. Indeed the modification of an energetic portfolio needs a huge amount of time to be done and the possible modifications are limited too. If we consider as fixed the actual portfolio of a utility(because their PPs produce always more energy than the requests) the idea would be to apply this real option approach integrated with the MVP Theory to decide, from a managerial point of view, the percentage of each technology in the portfolio that guarantee to fulfill the request of energy in the most efficient way(the idea would be to partialize PPs that give in output too MW). In this way a different portfolio that maximize a specific objective function can be built in correspondence to each iteration made by a MCS. In this way the efficient frontier becomes variable in function to the different output that the utility want to guarantee. An idea would be then to use as state variable the percentage of each technology in the managerial portfolio and apply a very similar framework to the one described in this work.
- The most powerful tool of this work is the search algorithm and this algorithm is not made especially for this work but implemented from a ready-made algorithm[40].The problem is that the algorithm does not know anything about the nature of the problem and if the number of parameters that must be maximized increases it could need a huge amount of time to find a good solution. In this work we interact in the search process manually addressing the search in the direction of proposed solution but if the complexity of the problem increase this solution won't be sufficient anymore to find an optimal solution. Therefore a possible evolution of this work would be to improve the algorithm, building it from zero through language programming:
  - The algorithm has to be improved to reduce the statistical imprecision of the model. In other words instead of considering a solution better than other one for its mean, the model has to consider the stochastic nature of the outputs it produces through MCS and then use confidence intervals.
  - The value of the exercise threshold has to be linked: the exercise thresholds "has to talk" between each others[41]. Indeed if the number of parameters that must be maximized increase too much a possible idea would be to link with function each of these parameters through others and to optimize them. The only rule that must be followed is to reduce the number of parameters that the search algorithm has to maximize and, being less this number, the optimal solution will be found more rapidly.

[40] We used Risk Optimizer contained in @Risk 5.5 of Palisade Corporation

[41] See an example of this possible relationships between different exercise thresholds in paragraph 3.2.5

Chapter 8 - Appendix

This chapter contains useful information to help the reader to understand better the main concepts of this work. Firstly paragraph 8.1 reports all the acronyms used in the previous chapters and then paragraph 8.2 gives a detailed description about the steps we followed to demonstrate the level of influence that the parameters of the exercise thresholds have in the case in which the pre – operational phase of a nuclear PP is modeled as the succession of three sequential compound options.

8.1 Acronyms

We report now the entire list of acronyms used in this work:

PP: Power Plant
SMR: Small Modular reactor
LR: Large Reactor
CCGT: Combined Cycle Gas Turbine
NPV: Net Present Value
DCF: Discounted Cash Flow
ROA: Real Option Approach
RO: Real Options
MCS: Monte Carlo Simulations
SOET: Simulation with Optimized Exercise Thresholds
LSMC: Least Square Monte Carlo
SGBM: Stochastic Grid Bundling Method
PDE: Partial Derivative Equations
ECTC: Expected Cost to Completion
ECTD: Expected Cost to Design
TCIC: Total Capital Investment Cost
TCDC: Total Capital Design Cost
TCSC: Total Capital Study Cost
MVP: Mean Variance Portfolio
VaR: Value at Risk
CVaR: Conditional Value at Risk
SF: Safety First
SD: Stochastic Dominance
SR: Sharpe Ratio
IRR: International Rate of Return
LUEC: Levelised Unit Electicity Cost
GBM: Geometrical Brownian Motion

8.2 The Level of Influence of the linear exercise thresholds' parameters used to model compound options

As reported in equation 3.3 in chapter 3, the number of possible combinations that must be analyzed is huge in the model that describe the pre – operational phase of a nuclear PP as the succession of three sequential compound options.
Therefore, the model user have to "help" the algorithm understanding the nature of the problem by fixing to a reasonable value the less influential parameters and by exploiting then all the possible combinations of only the more influential ones.
We report now the two main assumptions we made in order to show how we validate all of them:

i. There is a difference between the level of influence of each of the five parameters that characterize the exercise thresholds necessary to model three sequential compound options:

Parameter	Level of Influence
P*	High
a_{design}	Low
m_{design}	Low
$a_{construction}$	Low
$m_{construction}$	High

Table 78. Level of Influence of the exercise thresholds' parameters

ii. The interaction between the five parameters above have a low influence on the overall NPV distribution of the investment

The following two paragraphs demonstrate the validity of the assumption we made verifying the level of influence of each single parameter and of the interaction between all of them in the case of investment in a large nuclear PP.

8.2.1 The level of influence of each single parameter

In order to find out the level of influence of each of the five parameters described before we performed here five different analysis following the same steps for each of them:

1. Select the parameter whose level of influence is the objective of the analysis
2. Define a wide range of variability for each of the parameters considered
3. Run the search algorithm with a huge number of iteration (i.e., 1000000) to find out the optimal values of all the parameters
4. Vary one parameter in its defined range keeping the others stuck to their optimal value and perform a MCS for each of them
5. Enumerate all the possible values of the parameter under analysis
6. Perform a Monte Carlo Simulation for each of these values with an high number of iteration (i.e. 100000) and save all their NPV Mean into an excel spreadsheet.
7. Evaluate for each different simulation the "percentage distance" between the value obtained in that specific simulation with the optimal one.
8. Build a graph to understand how the variation of the parameter influence the overall result of the investment.

In the following five figures we represent then this "percentage distance" in function of all the parameters under analysis. We found these graphs applying the SOET Method with Compound Options to the large nuclear case of investment.

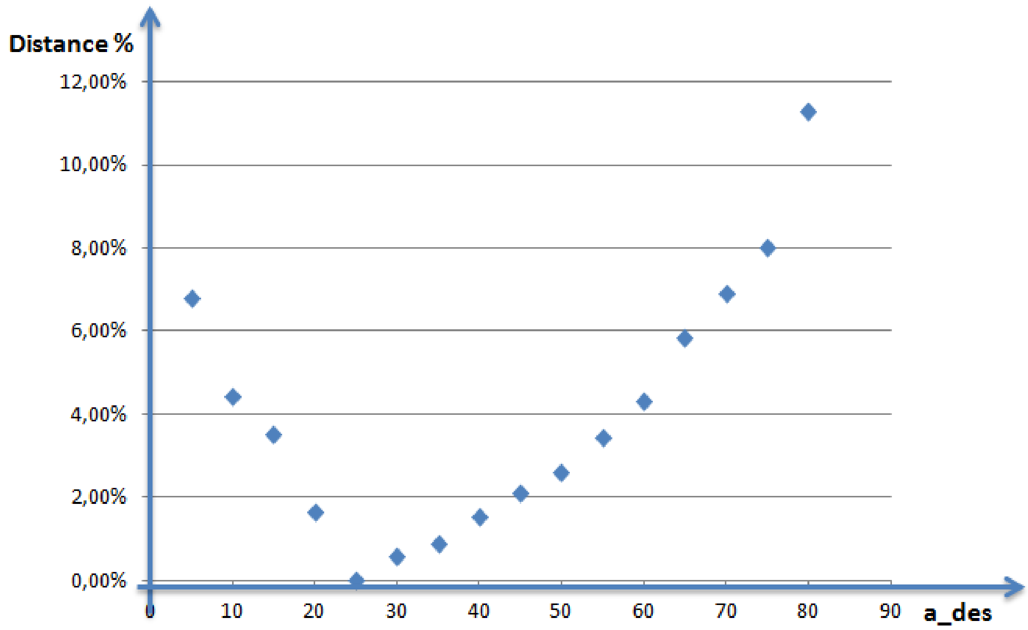

Figure 115. Percentage Distance of the Difference Coefficient of the Design Phase Linear Exercise threshold

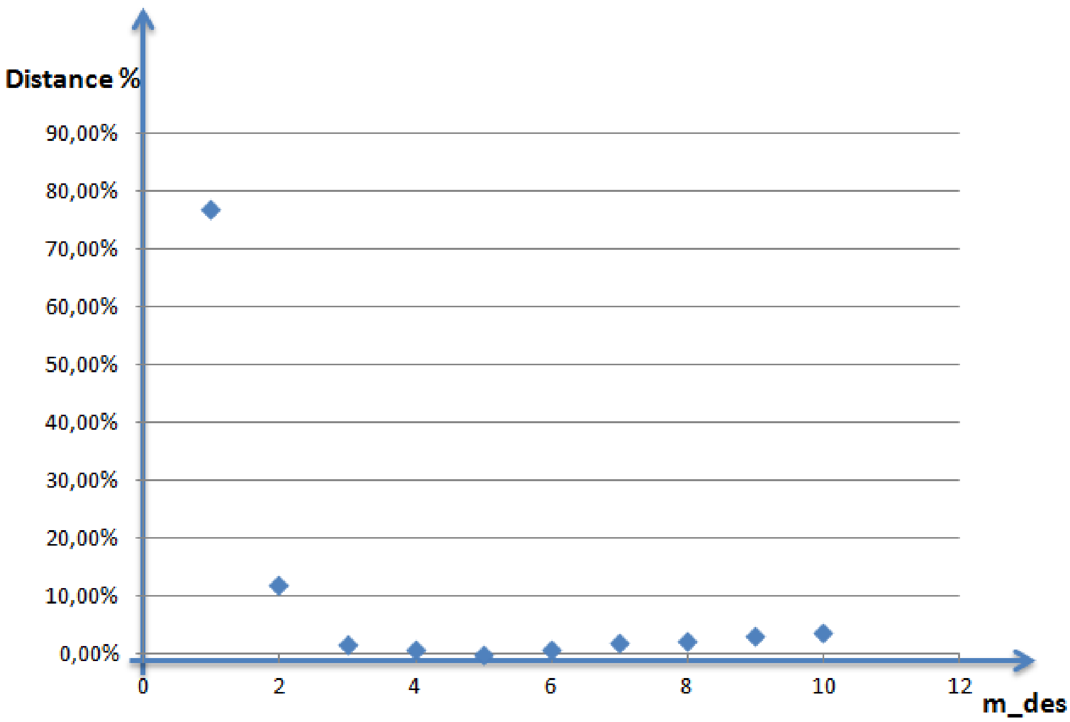

Figure 116. Percentage Distance of the Multiplication Factor of the Design Phase Linear Exercise threshold

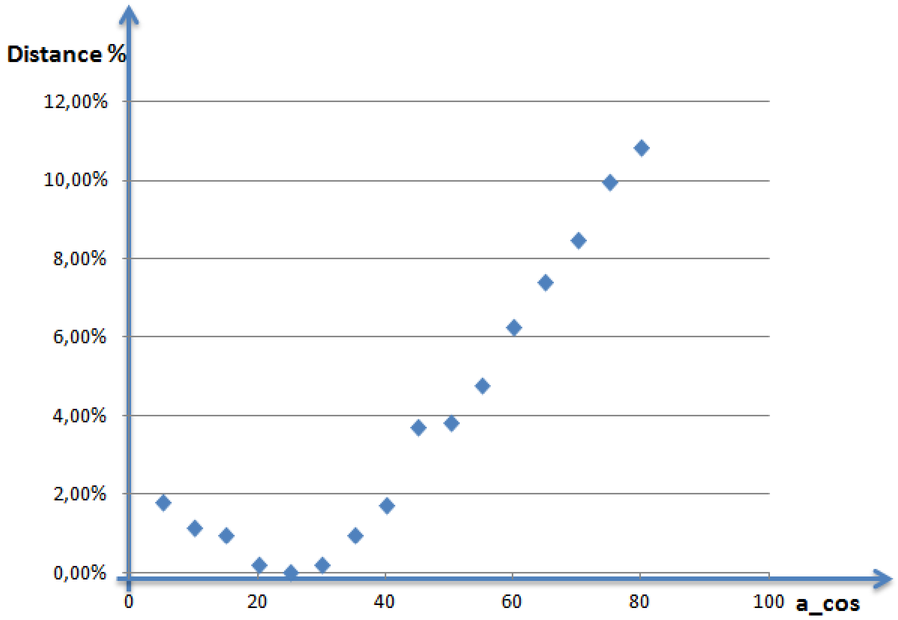

Figure 117. Percentage Distance of the Difference Coefficient of the Construction Phase Linear Exercise threshold

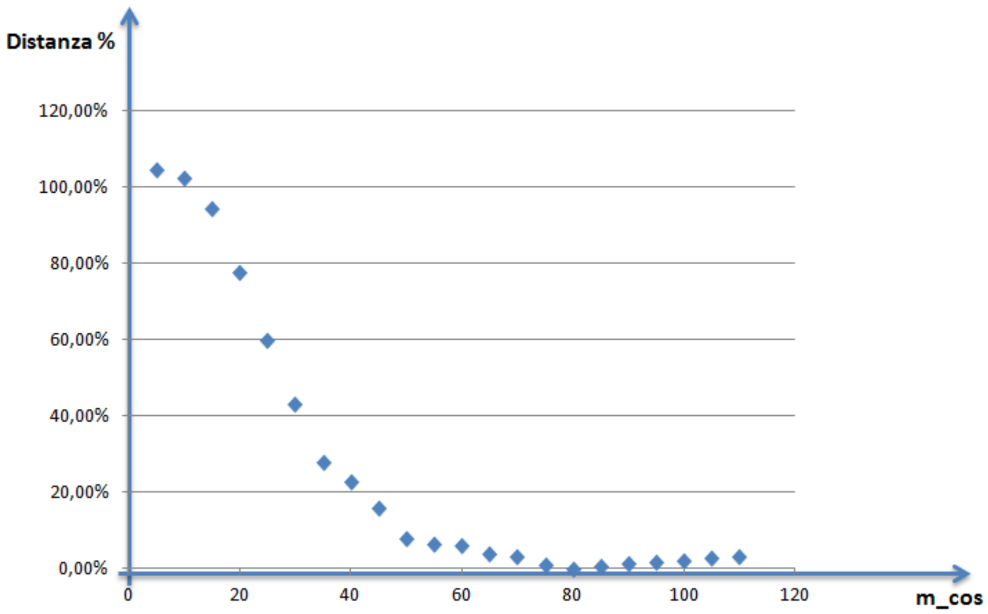

Figure 118. Percentage Distance of the Multiplication Factor of the Construction Phase Linear Exercise threshold

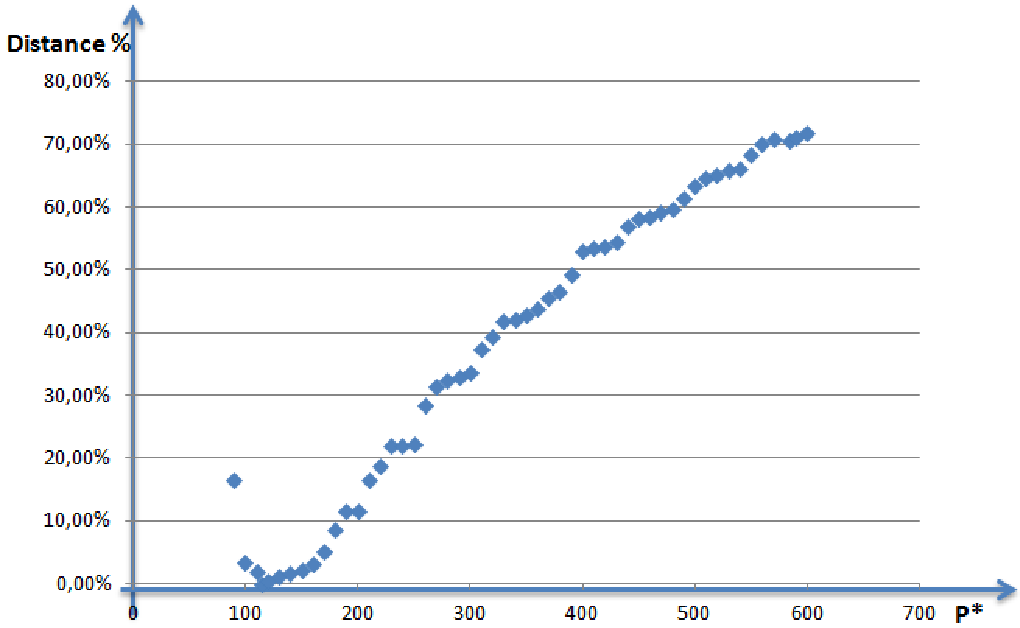

Figure 119. Percentage Distance of the Electricity Price(Exercise threshold that trigger the study phase)

We can summarize the results shown in the figures above in the following table:

Parameter	Distance Percentage	Level of Influence
P*	It reaches a value greater than 70%	High
a_{des}	It is always under 12%	Low
m_{des}	It is always under 10%(expect the first value)	Low
a_{cos}	It is always under 12%	Low
m_{cos}	It reaches a value greater than 100%	High

Table 79. Level of Influence of the parameters under analysis

It is becoming clear that the distinction between less influential parameters and more influential ones is reasonable because the value of the NPV Mean is remarkably influenced only by the electricity price and the multiplication factor of the construction phase's exercise threshold.

8.2.2 Level of Influence of the Interaction between the parameters

The aim of this paragraph is to demonstrate that even the interaction between the five parameters under analysis is low. This test is important because it will let us to build the algorithm to model the pre – operational phase of a nuclear PP as the succession of three sequential compound options in which the optimal value of the parameters that characterize their exercise thresholds can be found applying the algorithm described in the flowchart of Figure 49.
In order to verify it we followed this algorithm:

1. Build the percentage distance graphs for all the parameters under analysis

2. Enumerate the values of each parameter that guarantee a value of the NPV Mean close to the optimal one(in this analysis we consider three possible optimal value for each parameter)
3. Enumerate all the possible combinations between all the possible values of the parameters
4. Perform a MCS according to all the combinations found out in the previous step of the analysis and save their NPV Mean into an excel spreadsheet
5. Evaluate for each different simulation the "percentage distance" between the value obtained in that specific simulation with the optimal one.
6. Build a graph to understand how the interaction between the parameter influence the overall result of the investment.

Then the following figure represent the influence that the interaction between all these five parameters has on the NPV Mean:

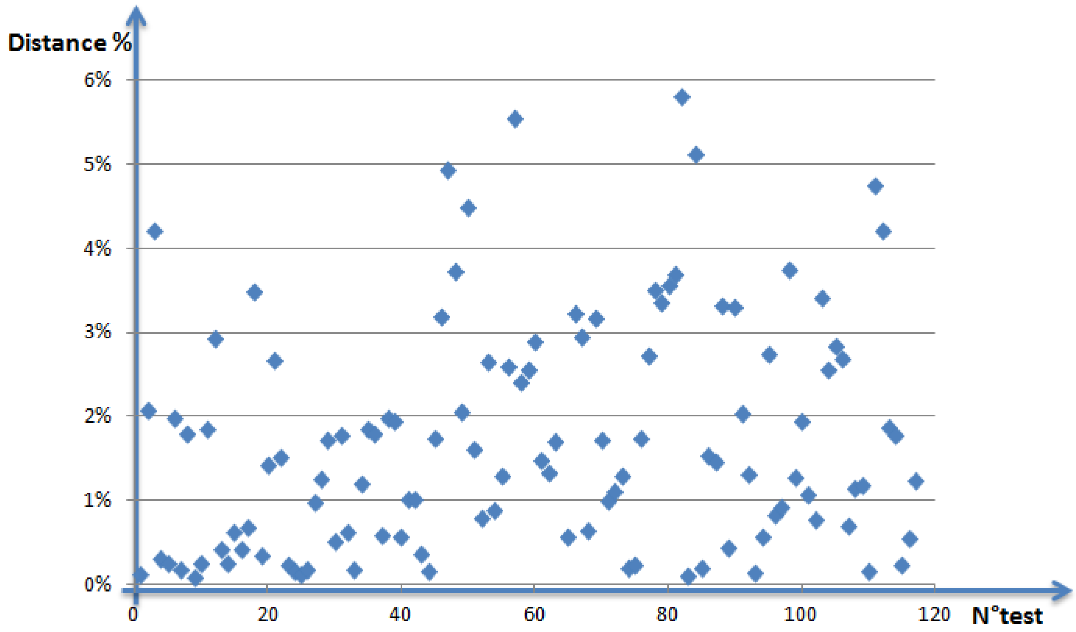

Figure 120. The Percentage Distance of the Interaction between the parameters

From the figure above we can see that the percentage distance of the interaction between the five parameters under analysis is always under 6%. It means that it has a low influence on the overall NPV distribution of the investment and then that the assumption we made in chapter 3 is true.

The following flowchart helps the reader understand the algorithm used to find out the level of influence of this parameters:

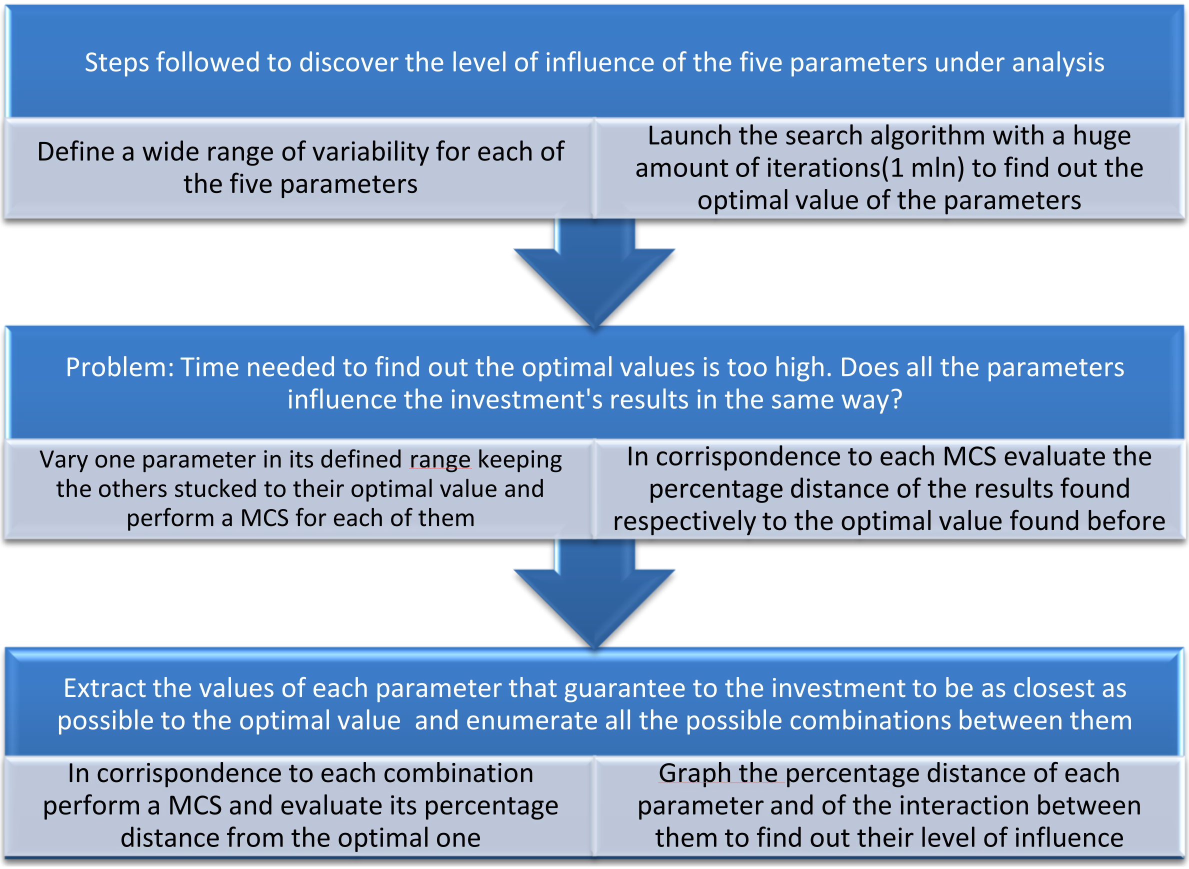

Figure 121. Steps of the algorithm followed to find out the level of influence of the parameter

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