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Modeling Investment Risks and Uncertainties with Real Options Approach

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Dr. Ming Yang is an energy and environment economist in the IEA, and Dr. William Blyth is a consultant. The views expressed in this Working Paper are those of the authors and do not necessarily represent the views or policy of the International Energy Agency or of its individual member countries. As this paper is a Work in Progress, designed to elicit comments and further debate, comments are welcome, directed to the author ming.yang@iea.org.

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Modeling Investment Risks and Uncertainties with Real Options Approach

Ming Yang and William Blyth[1]

Abstract

Changing energy price in competitive energy markets, uncertain future carbon price, uncertain government policy on climate change, and uncertain international regime on climate change mechanism all pose uncertainties to power sector investment. In a process of project investment evaluation, national governments and development banks traditionally use the methodology of discount cash flow (DCF). Unfortunately, this methodology cannot fully quantify these risks and uncertainties. Real Option Analysis (ROA) offers a nuanced approach to strategic investment that quantitatively takes into account investment risks and the value of the open options for budget decision-makers. The objective of this paper is to present a methodology and a computer model developed by the International Energy Agency (IEA) to quantify the impacts of climate change policy uncertainties on power investment using ROA approach. The methodologies include the traditional discounted cash flow approach to calculating project net present value, stochastic simulation to capture the characteristics of uncertain variables, and real options to capture investors' flexibility to optimize the timing of their investment. This paper presents details of the methodology framework, mathematics functions, database, and operation of the model. The results of this analysis are found in Blyth and Yang (2006) and will be included in a forthcoming book of the IEA (2007). Having been applied for case studies, the methodology and modeling have proven effective. This paper concludes that ROA could become a useful tool for the government policy makers and private investors to quantitatively analyze the impacts of climate change policy uncertainty and energy price uncertainty on energy sector investment.

This paper describes the methodology and model used in an information paper of the IEA (Blyth and Yang, 2006) and a forthcoming book of the IEA (2007). The methodology and model will be used in future work investigating the implications of uncertainty for investment decisions. As a reference document, it has not been approved by any IEA committee.

[1] Dr. Ming Yang is an Energy and Environment Economist of the International Energy Agency (IEA) and Dr. William Blyth is a consultant. The authors would like to thank Dr. Richard Bradley of the IEA for his excellent supervision of the study, his detailed instructions to the development and his elegant editing of this paper. Within the IEA, acknowledgement is also due to Richard Baron, Rebecca Gaghen, Sierra Peterson for comments and editing. The authors also greatly appreciate the data collection and comments of experts outside the IEA: Charlie Clark, Tom Wilson and Adam Diamant at Electric Power Research Institute (EPRI), Derek Bunn at the London Business School, Andy Read of E. ON UK, Nikhil Venkateswaren of RWE npower and Russo Eliano of Enel. Finally, the authors are highly indebted to the governments of Canada, the Netherlands and the United Kingdom; the EPRI, Enel, E. ON UK, and RWE npower for their voluntary contributions to this project. Absent such support, the following study would remain but an idea.

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Executive summary

In a competitive energy market, government regulation, development of technologies and uncertain energy and CO_2 prices pose the greatest risk to a sure recovery of energy sector investment. In project evaluation for investment, traditional methodologies such as discounted cash flow (DCF) cannot fully quantify these risks and uncertainties. As presented in this paper, Real Option Analysis (ROA) offers a nuanced approach to strategic investment that considers the value of the opened options for budget decision-makers. The Real Option problem can be viewed as the optimization of available options amidst uncertainty over real assets like project investment capital. In the energy and environment sectors, ROA enables analysis of different risk factors, supporting a direct comparison of CO_2 price uncertainty with other risks.

Over the past 30 years, ROA has emerged from financial economics theory and the appraisal of project investments. A handful of computer models now use ROA in the quantitative analysis of energy and environmental investment, though very few apply ROA to quantify the impacts of climate change policy and uncertain energy and carbon prices on power sector investment. Inspired by the Electric Power Research Institute's (EPRI's) first Greenhouse Gas Emissions Reduction – Cost Analysis Model (GHG-CAM) model, the International Energy Agency (IEA) developed a model to address this lapse.

The IEA model presented in this paper expands the menu of options and adds several new features, including an ability to model carbon price jump and a new plant's construction and development under multiple uncertain factors at the same time. Nowadays, it is widely debated that the carbon price will likely jump at the end of the first 'commitment period' of the Kyoto Protocol due to the international climate change regime and government climate change policy. The carbon price jump will considerably affect decisions of power investors. There is an urgent need to evaluate the impact of carbon price jump on power sector investment. However, our extensive literature reviews show that no modeling research or study has been done to analyze the impact of carbon price jump on investors' decisions.

The IEA's modeling methodology makes also another significant contribution to the ROA literature. As shown in the literature review, the application of ROA modeling has been so far limited to one-stage investment and mostly one stochastic variable. In contrast, the IEA's approach is to model construction or development of a new power plant from a green field with multiple stage investments[2], using stochastic variables simultaneously taking into account uncertainties of energy price and carbon price.

This paper presents the IEA modeling methodology, illustrates its supporting database, states the assumptions in the model, describes the issues that the model can look at, and demonstrates the potential for the model to be used in future projects.

The methodological framework of the IEA's modeling can be divided into four major modules. Module 1 is a database of sorted primary data, such as energy prices, carbon prices and the technologies of power production. Module 2 allows for the development of scenarios and the processing of relevant data. Once treated, these data and scenarios enter Module 3's traditional discounted cash flow analysis and Module 4's real options analysis.

The detailed mathematical equations used in the computer model also appear in this paper. Developed in an MS-Excel environment and supported by commercial software named Real Option Calculator, these equations include those of deterministic method, dynamic and stochastic analysis method, and real option optimization method.

[2] For example, IGCC investment in stage I and CCS investment in stage II.

The IEA's model enables a range of applications: (1) a model without options to estimate the risk premiums of the project; (2) a basic option model to simulate a project from one baseline scenario to a single post-exercise scenario; (3) a multiple options model to account for many risks; (4) a multiple options model with allocated probabilities to specify a probability distribution to indicate the likelihood of each of the target scenarios; and (5) a nested (compound options) model to model a series of investments over time.

To represent carbon price uncertainties, we used Geometric Brownian Motion, an annual random walk model to simulate uncertain prices. As mentioned above, we then developed a special model to simulate climate change policies' effect on uncertain carbon prices, focusing on the effects of a potential jump in carbon prices by between 1% and 200% of prices before the jump.

From historical data of OECD nations, we calculated the correlation coefficients. The results illustrate a parallel between gas prices and electricity prices in several domestic markets, where gas plants are on the margin of the merit order. In other cases, correlation is much more subtle. When applying the model to case studies, we assumed gas plants as at the margin, and set the correlation coefficient between gas and electricity close to 1.

We applied the model and methodology to nine basic case studies and three specific case studies. These case studies involve power generation by using fossil fuels, nuclear energy and carbon capture and storage (CCS) technologies, under different carbon price, energy price and emissions trading schemes. The results show that the methodology and modeling can derive many interesting implications for policy-makers and investment decision-makers in power sector investment. For detailed analysis and results of these case studies, please see Blyth and Yang (2006) and IEA (2007).

With further development of the database and the model in the next phase of study, we will be able to undertake modeling analyses for more complicated issues. These may include:

(1) Applying ROA in a power sector rather than only for a single power technology investment.

(2) Undertaking case studies for energy efficiency and demand side management for end-users.

(3) Modeling investment in renewable energy technologies.

(4) Applying ROA in other sectors such as iron and steel, pulp & paper, aluminum and petrol-chemical industries.

1. Introduction

Worldwide, the power sector faces three major challenges: reforms of power markets to encourage competition, requirements to mitigate greenhouse gas emissions, and rising energy prices. When considered by industrial decision-makers, the risks of a competitive market bear little resemblance to the uncertainties facing the monopolies of integrated power markets. Policies to mitigate climate change have created a marketable value for CO_2 emissions, compelling the new currency's consideration during the process of strategic investment in the power sector. Most electricity producers in Europe now participate in a mandatory emissions trading scheme. Arguably the most efficient form of regulation in terms of its effects on industrial competition, the scheme still introduces the investment risk of carbon price fluctuation. Furthermore, persistently high oil and gas prices have considerably increased production costs and muted energy demand. These regulatory uncertainties and variable prices for energy and CO_2 pose undisputed risks to the sure recovery of energy sector investment.

Risks and uncertainties often compel investment in flexible power production technologies with short periods of return on investment, brief construction times and the capacity to switch between fuels. Economies of scale, however, require investors to develop large power facilities to minimize the cost of unit production. To better navigate these conflicting dynamics, power sector investors have adopted new methods of financial assessment to complement the traditional approach of deterministic discounted cash flow. Such assessments also guide governments' policy formulations to sustain and secure domestic power markets. To inform the decisions of both policy-makers and corporate strategists, the IEA created a new model to address the complex and myriad variables influencing investment in power generation.

Investment in the power sector has three important characteristics. First, the investment is partially or completely irreversible. Once invested, the capital costs become totally or partially sunk. Second, there is always uncertainty over the future return from the investment. Future energy price and carbon price are unpredictable which makes cash inflow of the project return uncertain. Third, the investors have choices to invest at flexible timing. They can invest in a power plant now if they think the return of the investment is high enough to recover all the investment risks, or they can postpone the investment to get better information on the future prices. They will never invest until future major uncertainty is cleared. In other words, investors have the opportunity or option but not the obligation to invest in a project in a period of time. They can also have flexibility to abandon, expand, contract, extend and shorten the operation of the project even after the investment. A good project evaluation methodology or model should incorporate in a quantitative way all the three characteristics: irreversibility, uncertainty and flexibility.

Traditional appraisal methodologies for project investment can hardly incorporate the above three characteristics. Traditionally, people use pay-back period method and/or discounted cash flow (DCF) method in project appraisals. In a payback period calculation, a decision-maker would estimate the number of years it would take for the income from a particular investment to pay back the costs of the investment. This approach is theoretically flawed because of a couple of shortcomings. First, it puts a fixed time horizon on considering the consequences of the investment. Such a measure may be biased against investments whose most significant benefits come after their payback period. Second, a payback period calculation does not take into account the timing of returns to investment (i.e., the time cost of money). This methodology is simple and used by individuals and/or industrial stakeholders who do not have significant amounts of transactions, or when the time lag between the initiation of the transaction and the cash flow is very short. Examples of the application of the method include retrofitting a part of plant facility or replacing equipment. However, very few people use the method in evaluating a power investment project.

More widely used methodology in project appraisal is the DCF. This approach describes a method to value a project or an entire company. The DCF methods determine the present value of future cash flows by discounting them using an appropriate cost of capital (or discount rate). This is necessary because cash flows in different time periods cannot be directly compared. People prefer money sooner rather than later due to the fact that a dollar in one's hand today is worth more than a dollar one may receive tomorrow. The same logic applies to the difference between certain cash flows and uncertain ones. This is due to opportunity cost and uncertainty over time. DCF can partially take into account risk and uncertainty of future value of currency by using different discount rate. However, it involves at least two problems. First, the forecast of future cash flows is uncertain (due to energy price and carbon prices changes), but the cash flow in DCF is assumed certain. Second, it is difficult to determine the appropriate cost of capital. Users of the methodology argue that they can deal with cash flow uncertainties by raising the discount rate. However, it is hard to justify to which level the discount rate will really incorporate all the future risks.

Stochastic methods and multiple scenarios have been used to deal with uncertain variables in the DCF. When calculating the DCF, investors rest on a series of simplifying assumptions. In the presence of certain types of uncertainty about the future costs and benefits of capital investments, investors have to estimate the likelihood of various future scenarios, calculate the DCF in each of these futures, and sum to find the average expected DCF across the possible futures. For example, if an investor envisions a two-thirds chance of a DCF of $100 and a one-third chance of a DCF of $40, the expected DCFs is $80. However, this methodology still focuses on whether or not to invest the project. It does not tell the investors the best timing of investment. A Real Options Approach (or ROA) can incorporate stochastic variables and multiple scenarios and timing of investment together.

ROA is new in assessing investment in climate change projects. The term "Real Options" can be traced to Myers (1977), who first identified investments in real assets as mere options. A real option is a permit with different value at different time periods to undertake some business decision, typically an option to make a capital investment. For example, an opportunity to invest in the expansion of a firm's factory is a real option. In contrast to financial options a real option is not tradable - e.g. the factory owner cannot sell the right to extend his factory to another party, only he can make this decision. The terminology "real option" is relatively new, whereas business operators have been making capital investment decisions for centuries. However the description of such opportunities as real options has occurred at the same time as thinking about such decisions in new and more analytically-based ways. As such, the terminology "real option" is closely tied to these new methods. ROA offers a nuanced approach to strategic investment that considers the value of the opened options for budget decision-makers.

A firm can use real option to cope with investment uncertainty and flexibility. By purchasing a permit, a firm may have the real option of expanding, downsizing, or abandoning other projects in the future. By investing in R&D, the firm may have real options for further business development, mergers, acquisitions, and licensing (both physical and tangible assets). With such options, the firm will be able to flexibly manage its irreversible investment capitals, and at the same time, taking into account the uncertainties and risks of future cash flow. Because of this, the application of ROA theory and modeling in power sector investment and climate change uncertainty policy is developing quickly.

ROA sees the investment problem and uncertainty in a particular way. It focuses for example on the timing of the decision not on whether to do the project or not. It has a strong ability to explicitly analyse the effects of different sources of uncertainty on the cash-flow, providing a powerful tool for giving insights into the question that motivated climate change policy study. Combining ROA with stochastic methods and multiple scenarios, we will be able to calculate project DCF at different future time milestones. With this methodology, we can explore answers for questions such as (1) “If I do hold on investment for a couple of years when significant risk is gone, what is the DCF at 90% of probability? and (2) Does climate change policy uncertainty pose a significant risk to power sector investments, and if so, how could policy design be improved to reduce these risks”? Because of its ability to do so, ROA has been recently applied in climate change policy analysis.

One example of its application to climate change policy is Laughton et al (2003) which applied ROA to the assessment of geological GHG sequestration, using a simplified model of the option to sequester part of a pure CO_2 stream of to illustrate the process of relevant risk valuation. As Laughton concluded, the employment of a traditional deterministic discount cash flow (DCF) can warp valuation, as the DCF does not account for the complex effects of risk and uncertainty on values. However, as acknowledged by the author, Laughton’s study was quite preliminary, excluding key elements such as price variables from the model. The IEA’s model includes price variables.

Using real option valuation in an environment of uncertain CO_2 price, Sekar (2005) evaluated investments in three coal-fired power generation technologies: pulverized coal, standard Integrated Coal Gasification Combined Cycle (IGCC) and IGCC with pre-investments to reduce the cost of future CCS retrofitting. Sekar developed cash flow models for each of the three technologies, though the simulation’s structure meant that the CO_2 price appeared as the sole uncertain variable in the cash flow. Sekar’s approach combined two elements: market-based valuation to evaluating cash flow uncertainty, and dynamic quantitative modeling of uncertainty. The study used Monte-Carlo cash flow simulation in the place of simple scenarios to incorporate cash flow uncertainty, but energy prices were not modeled as stochastic variables. The IEA’s model includes price stochastic variables.

Using ROA to evaluate risks to the development of new nuclear power plants, Rothwell (2006) modeled three uncertainties: price risk, output risk and cost risk. Using a Monte Carlo simulation, Rothwell derived various risk premiums, between $383/kW and $751/kW that would trigger investment in the United States’ new nuclear power plants. The study, however, did not model uncertain carbon prices and their influence on power sector investment. The IEA’s model includes uncertain CO_2 prices.

Laurikka (2006) presented a simulation model using ROA to quantify the option value of Integrated Gasification Combined Cycle (IGCC) technology within an emissions trading scheme. The study designed and simulated three types of stochastic variable: the price of electricity, the prices of fuel and the price of emission allowances. As Laurikka concluded, (1) a straightforward application of the traditional project appraisal on a scenario of IGCC can bias results for current competitive energy markets regulated by an emissions trading scheme; (2) the potential combination of several uncertainties with real options rendered the European Union Emission Trading Scheme (EU ETS) extraordinarily complex; (3) when accounting for uncertainties, the IGCC technology is not competitive within the EU ETS. However, while simulating CO_2 prices in EU ETS, Laurikka did not consider the possible jump of CO_2 prices. The IEA’s model simulates CO_2 price jump.

Other recent applications of ROA in the energy sector include (1) Siddiqui (2007), which evaluated the United States’ federal strategy for renewable energy research, development, demonstration, and development; (2) Marreco and Carpio (2006), which examined the flexibility of the Brazilian power system; and (3) Kuper and Soest (2006), which evaluated the influence of uncertain oil prices on energy use.

In 2005, the Electric Power Research Institute of the USA (EPRI) developed the Greenhouse Gas Emission Reduction Analysis Model, using a discounted cash flow (DCF) analysis to evaluate the revenues, costs and expected after-tax gross margin accruing from investment in the technology of greenhouse gas reduction. The model relies on sophisticated statistical and economic tools, including Monte Carlo simulation, and methods of real options analysis and decision to enable an evaluation of specific GHG reduction strategies that account for individual risks, uncertainties and real options. The model incorporates energy prices and CO_2 trading prices with correlations. Developed in an MS Excel environment, the model is supported by a commercial software program called Real Option Calculator or ROC. However, as of October 2006, the EPRI has not reported any case study using power firm's real data.

Between August 2005 and October 2006, the International Energy Agency (IEA) undertook a study on quantification of climate change policy uncertainty or risk on power sector investment. In designing the study, the IEA aimed to (1) develop its in-house capability of using ROA approach; (2) analyze the influence of climate change policy uncertainty on individual investments in the power sector; (3) explore the consequences of policy uncertainty on the power sector's evolution and associated risk for policy objectives such as greenhouse gas emission mitigation and energy security; and (4) examine the potential to reduce the effects of uncertain climate change policy through improved policy design.

Within the study, the IEA developed a model called Modeling INvestment with Uncertain ImpacTs (MINUIT). The IEA's model mimics EPRI's first version of the GHG-CAM model. Compared with GHG-CAM, the IEA's model has the following advantages: expanded menu of available options, new modeling module for a new plant's development and construction. In addition, we created a module to model carbon price and energy price jump. The IEA's model with stochastic simulation imitates or evaluates the desired true characteristics of a number of variables in a single run of the model. As such, the model will be able to identify the impacts of not only individual risk factor, but also a group of risk factors such as both uncertain energy price and uncertain carbon price. In that way, we will be able to identify the largest uncertain factor affecting power investment.

We applied the model in a number of case studies that are different from all the previous studies indicated in the literature review. For example, in contrast to Laughton et al (2003), we incorporated and modeled all energy prices with stochastic variables. As in Seker's study, we treat the price of CO_2 as a random variable. In addition, we model the electricity price and the primary energy price as random variables simultaneously which was not modeled in Seker's study.

Within this paper, we present this type of analytical tool as a potential guide for informing policy-makers and investors to the effects of regulatory uncertainty. The purpose of this paper is to provide a detailed explanation of the modeling methodology. Interesting readers can find our case study results in Blyth and Yang (2006) and IEA (2007).

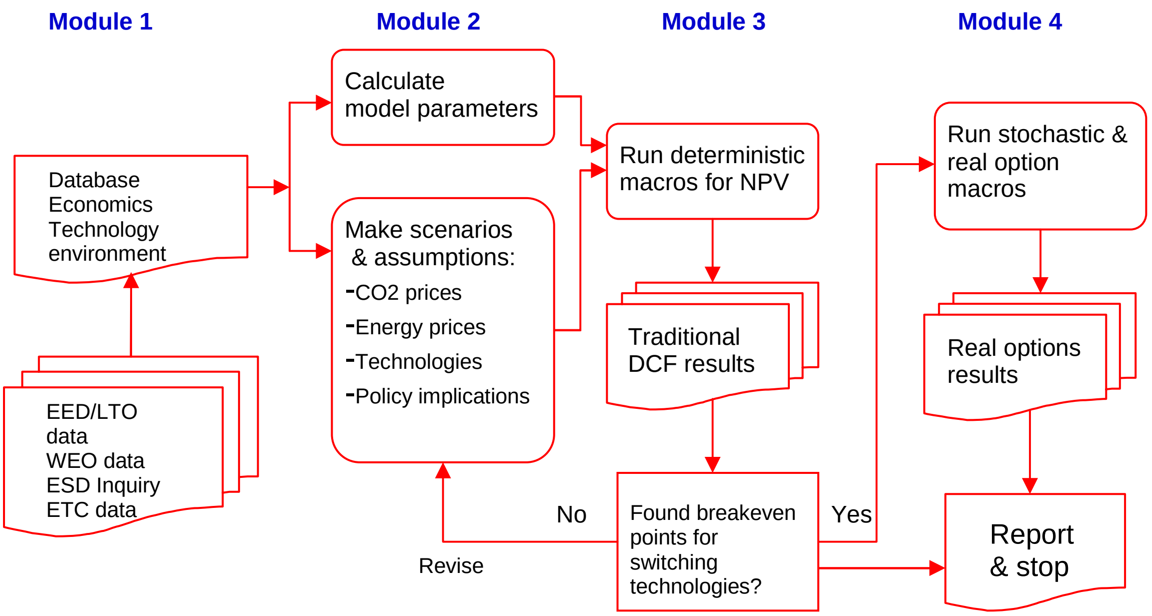
This paper is composed of 8 sections. Following this Introduction, Section 2 presents the methodological framework used in the study. In Section 3, we briefly describe the database to support the model. Parameters to support the uncertainty modeling are calculated in Section 5. Real Options Analysis, a key section in this paper, is presented in Section 6. We show a sub-model for project sensitivity analysis in Section 7. Finally, this paper concludes that ROA could become a useful tool for the government policy makers and investors if they want to incorporate climate change policy uncertainty and energy market uncertainty in their investment policy decision-making.

2. IEA's Modeling methodology framework

The IEA's modeling methodology draws on Dixit and Pindyck (1994). As illustrated in Figure 1, the IEA's modeling methodology divides into four modules. Module 1 is a database of sorted primary data including energy prices, carbon prices and the technology of power production. Module 2 allows for the invention of scenarios and the processing of relevant data. Once treated, these data and scenarios enter Module 3's discounted cash flow (DCF) analysis and Module 4's real options analysis. In Module 3, we developed two macros to perform the traditional DCF analysis and search for breakeven points where power production may switch between generation technologies. Different electricity and carbon prices drive the module running the search. Once the critical points of technology switching appear, the correlating CO_2 price and other data are recorded for reporting and fed into the next module for ROA model running.

In Module 4, while setting the CO_2 and energy prices to change randomly, we calculate the NPVs for all candidate technologies in each of the planning years. We then run the real options calculator, a commercial software programme of real options analysis, to produce the optimal investment options for different technologies during different years. Our sensitivity analysis of the projects' NPVs accounts for the key parameters of capital investment, operation and maintenance (O&M) costs, plant factors, and price volatilities. Finally, by comparing the results from Modules 3 and 4, we estimate and report the risk and uncertainty premiums in the energy sector investments. The following sections detail the IEA methodology and the above-mentioned individual modules.

Figure 1 Methodological framework of the modeling



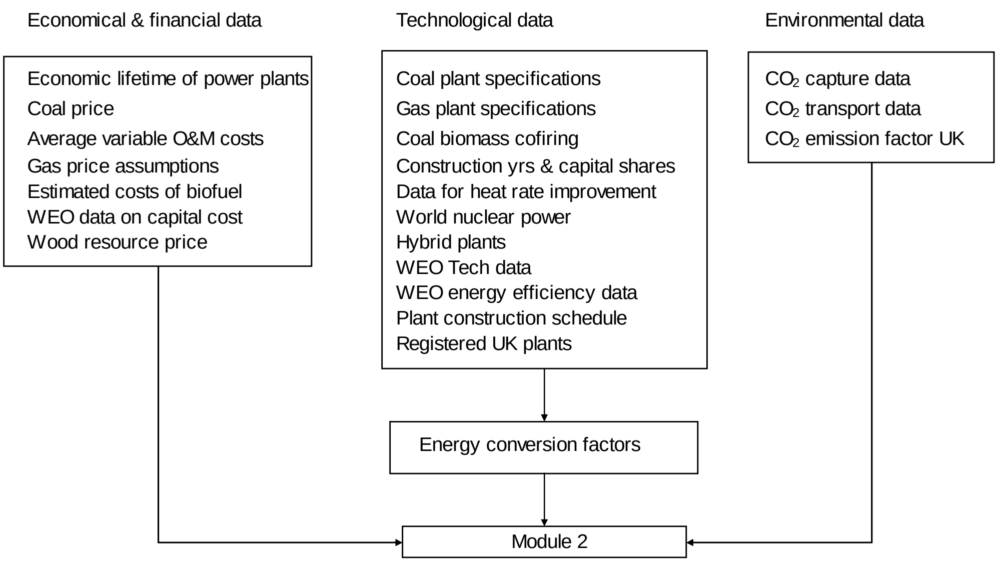
Note: EED – Energy Efficiency and Environment Division of the IEA, WEO – World Energy Outlook; LTO – Long-Term Co-operation and Energy Policy Analysis; ESD – Energy Statistics Division; ETC – Energy Technology Collaboration.

3. Module one: Database Development

The database and its structure for the modeling are shown in Figure 2. The data are collected and stored in three major groups: economic and financial, technical, and environmental. For example, the economic and financial data group include capital investment costs (or option exercise costs), operation and maintenance (O&M) costs, and fuel prices and CO_2 emissions trading prices. We obtained these data mainly from three data sources: the database of the IEA, project funders[3], and the network of the IEA. Some data are collected from multiple resources for cross-checking. While running the model, we used as much as possible the data collected from the IEA database.

We then processed these primary data and assembled them in pre-designed templates for the model to read. We call these data secondary. Illustrated in the first part of Table 1 is a part of the primary data such as energy prices, carbon prices and power technology data. The second part of the table shows the secondary data, processed for modeling. As listed in the first row of the secondary data table, the plant types indicate corresponding technologies. The term "Coal Power" refers to an existing power plant that will generate cash flow without considerable capital investment, while "new" means a new power plant that will replace the old one upon new investment (or upon exercise of the option). If the parameter is "new", the project lifetime will be the economic lifetime of the new power plant: 25 years as indicated in the second row. As illustrated, CO_2 emission factors vary between technologies, ranging from 56 tCO_2/MWh for gas power to 95tCO_2/MWh for coal power.

Figure 2 Structure of the database in Module 1



[3] E. ON UK, RWE npower of UK and Enel of Italy

Table 1 Examples of primary data and secondary data

Primary data

Steam boiler - Coal fired	2000	2001	2002	2003	2004	2005	2006
Capital Cost ($/kW) + FGD	1100	1089	1078	1067	1057	1046	1036
Maintenance Costs ($/kW)	23	23	23	23	23	23	23
Variable O & M (mills/kWh)	3.3	3.3	3.3	3.3	3.3	3.3	3.3
Fuel Cost ($US/toe)	85	85	80	73	66	65	65
Fuel Cost (mills /kWh)	18	18	17	15	14	14	14

Primary data source: World Energy Model of the IEA (2005a)

Project assumptions and calculated operating data

Project Specific Assumptions	Base case - green field	Option 1 - New Coal	Option 2 - New Gas	Option 3 - Existing Coal	Option 4 - Existing Gas	Option 5 - Add CCS to Coal	Option 6 - Add CCS to Gas
Plant duration based on existing plant or new build?	Retrofit	New	New	New	New	Retrofit	Retrofit
Project Lifetime (Years)	0	40	25	40	25	40	25
Capacity Retrofitted (MWe)	472	1,350	1,350	1,350	1,350	1,086	1,208
Capital Cost ($/kW)	0	1,320	589	1,320.00	589.00	810.00	430.00
Construction Period (No. years of capital payment)	0	3	2	3	2	2	2
Capacity/Load Factor	85%	85%	85%	85%	85%	85%	85%
Average annual efficiency of generation	33.0%	46.0%	57.0%	46.0%	57.0%	37.0%	51.0%
% of coal in fuel mix	*100%*	*100%*	*0%*	*100%*	*0%*	*100%*	*0%*
% of oil in fuel mix			*0%*		*0%*	*0%*	*0%*
% of gas in fuel mix		*0%*	*100%*	*0%*	*100%*	*0%*	*100%*
% of biomass in fuel mix			*0%*		*0%*	*0%*	*0%*
% of nuclear in fuel mix			*0%*		*0%*	*0%*	*0%*
% of other in fuel mix			*0%*		*0%*	*0%*	*0%*
CO2 Emissions Factor for Fuel (tCO2/TJ)	95	95	56	95	56	95	56
Fixed Op&Maint ($ /kW-Yr)	30.00	46.8	46.8	46.8	46.8	71.50	71.50
Unit Variable Op&Maint (excluding fuel cost) ($/MWh)	3.00	-	-	-	-	7.40	3.54
Calculated Operating Data	**Base case - green field**	**Option 1 - New Coal**	**Option 2 - New Gas**	**Option 3 - Existing Coal**	**Option 4 - Existing Gas**	**Option 5 - Add CCS to Coal**	**Option 6 - Add CCS to Gas**
Annual Generation (MWh/yr)	3,515,679	10,052,100	10,052,100	10,052,100	10,052,100	8,085,385	8,993,984
CO2 Emissions Rate from Generation (tCO2/MWh)	1.03	0.74	0.35	0.74	0.35	0.13	0.06
Annual CO2 Emission from Generation (tCO2/Yr)	3,628,181	7,442,050	3,561,618	7,442,050	3,561,618	1,079,097	516,435
Fuel Consumption (TJ/Yr)	38,353	78,669	63,487	78,669	63,487	78,669	63,487
Total Capital Cost ($)	-	1,664,240,721	768,271,473	1,664,240,721	768,271,473	849,822,693	501,837,590
Deterministic NPV using mean forecast values for va	-	*- 105,377,700*	*369,364*	*301,146,972*	*300,307,777*	*- 415,185,043*	*- 415,185,043*

Secondary data: Calculated from the IEA's model MINUIT (2006)

4. Module Two: Parameter calculation and uncertainty modeling

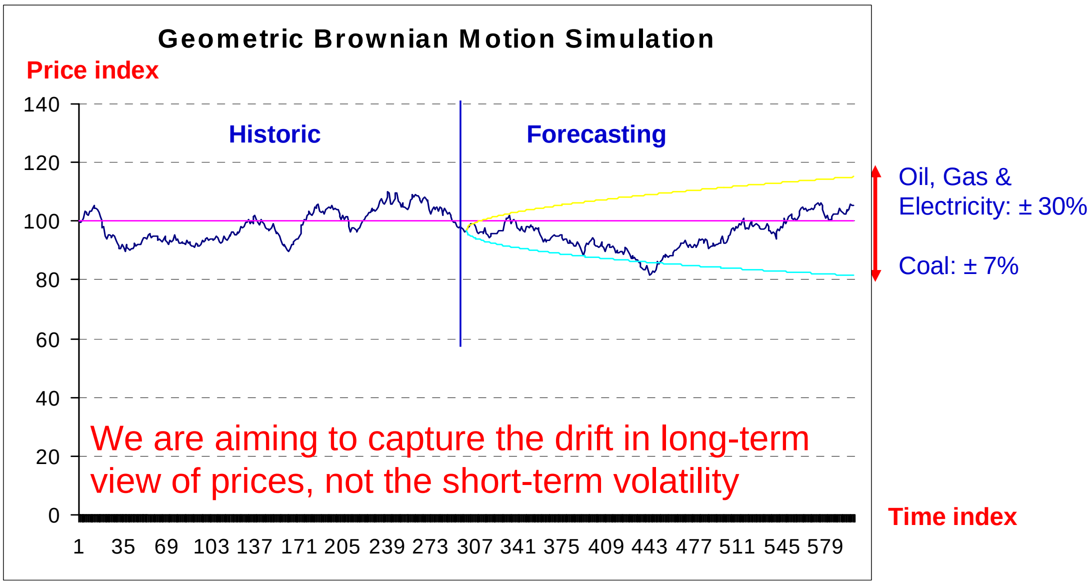
In this module we use collected primary data and processed secondary to calculate various parameters and uncertainty modeling required for running the model. In this document, we do not present in detail all the parameter calculations that are necessary for project economic and financial evaluation. Rather, we only present the calculations and modeling of several key parameters, including price uncertainty, correlation of energy price and CO_2 price.

4.1 Modeling price uncertainties

Figure 3 illustrates the modeling of uncertain fuel prices. The left half of the curve represents the historical price data, while the curve's right half demonstrates how prices evolve stochastically over time during the Monte Carlo simulations[4].

[4] Monte Carlo methods are a widely used class of computational algorithms for simulating the behavior of various physical and mathematical systems, and for other computations. They are distinguished from other simulation methods (such as molecular dynamics) by being stochastic, that is nondeterministic in some manner -

Figure 3 Modeling energy price volatilities



The IEA's model is capable of modeling almost any stochastic process. In the current context, we have chosen to model energy and carbon prices using Geometric Brownian Motion (GBM). In a GBM process, energy price [P(t)] is modeled by the following equation { Dixit A. K. and Pindyck R.S. (1994) pp 71-72, } :

$$d\ln P(t) = (\mu - \frac{1}{2}\sigma^2)dt + \sigma\, dB(t), \quad \textit{if } P(0) = P_0, \textit{ then}$$

$$\varepsilon[P(t)] = P_0 e^{\mu t}, \textit{ and } \; V[P(t)] = P_0^2 e^{2\mu t}(e^{\sigma^2 t} - 1)$$

Where: *μ is the expected growth rate of P(t) between t_{i-1} and t_i. if $y(t_i)$ is the assumed price function that revolves around a certain level in t_i. (long-run marginal cost of production or reduction), then, using the historical data of y(t), we can calculate μ with the following model:*

$$\mu = e^{\frac{\ln\left[\frac{y(t_i)}{y(t_{i-1})}\right]}{t_i - t_{i-1}}} - 1$$

usually by using random numbers (or, more often, pseudo-random numbers) - as opposed to deterministic algorithms. Because of the repetition of algorithms and the large number of calculations involved, Monte Carlo is a method suited to calculation using a computer, utilizing many techniques of computer simulation.

σ is the annual expected volatility of the price expressed as a percentage change. Similarly, using the historical data of *y(t),* we can calculate σ with the following equation[5]:

$$\sigma = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\{\frac{[y(t_i)-y(t_{i-1})]}{y(t_{i-1})}-(\overline{\frac{y(t_i)-y(t_{i-1})}{y(t_{i-1})}})\}^2}$$

It is the standard deviation of the yearly variances of the historical price data. Finally, B(t) is a stochastic (randomised) function generated by the computer.

P(0) = P_0 means that we know the price value at the beginning of the planning period. ε*[P(t)]* is the expected value of price at time *t*. *V[P(t)]* is the variance of the price at time *t*.

The above model is dynamic, stochastic, and log-normal, ensuring a simulated distribution above zero for forecasted prices for energy and carbon.

In using these parameters, we aim to capture the long-term price drifts rather than short-term volatility, as investment strategy considers long-term price changes, rather than price spikes over a short period. In the current IEA model, we set the annual price volatilities to 1.8% for coal and 7.75% for the prices of other fuels and CO_2. The standard deviation of price distribution under a random walk process evolves as the square root of time. We chose this level of annual volatility to provide a mid- to long-term standard deviation in prices after 15 years of ±7% for coal and ±30% for oil and gas, approximating the range between the IEA's high and low price scenarios indicated in IEA (2005b). Assuming that gas prices drive electricity prices, we use the same volatility for electricity. For consistency, we take this same volatility for carbon price.

4.2 Modeling carbon price jump

To complement the simulation of long-term carbon price drifts, we simulate possible carbon price shocks to represent policy-related events. In our modeling, we can simulate a symmetrical jump in carbon prices, either positive or negative, with an equal probability of being anywhere within the range. Both the size of the jump and the year in which the jump occurs can be varied. In our basic case studies, we have set the size of the jump to be 100% (i.e. the price after the jump could be anywhere in the range of almost zero to double the previous price before the jump). The year of the jump is taken to be year 11, giving 10 years of 'normal' cash flow before the jump. See Figure 4.

The mathematics function used in the model for the percentage of carbon price jump appears in a simplified version as follows:

$$P_{cj\%}(t) = [2 \times R(t) - 1] \times J\%$$

Where:

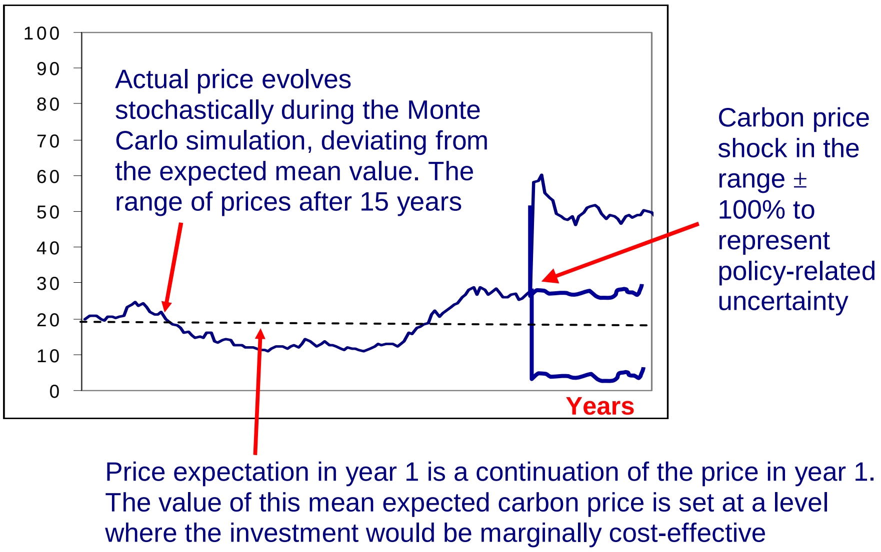
5 This parameter can be calculated in several ways; using the projected future data, one also arrives at this parameter.

$P_{cj\%}(t)$ is the volume of the carbon price jump in percentage, calculated randomly by the model according to the user's expectation. It has a value between -100% and 100%.

R (t) is a random function which generates a random number between 0 and 1 with uniform probability distribution in between.

J% is the size of the carbon price jump expected by the user. It has a value between 0% and 100%. In our model, we set J% = 100%

Figure 4 Modeling uncertain CO_2 price jump



Adding the above additional carbon price jump scale to the carbon price function, the new carbon prices $P_{cjp}(t)$, as shown in the following formula, will randomly change between 0% and 200% of the carbon price prior to the jump P_c(t):

$$P_{cjp}(t) = P_c(t) \times \{1 + P_{cj\%}(t)\ \} = P_c(t) \times \{1 + [2 \times R(t) - 1] \times J\%\}$$

Where: $P_{cjp}(t)$ is the carbon price at year t with the jump effect, and $P_c(t)$ is the carbon price without the jump effect. Other parameters are the same as those of the previous formula.

4.3 Modeling price correlations

In developed energy markets around the world, prices for various fuels are highly correlated to each other. In most OECD countries, electricity prices mirror gas prices, as demonstrated in Figure 5's illustration of price correlation in 14 OECD nations[6]. The figure's three graphs track the quarterly electricity prices and gas prices between 2003 and 2005 within Finland, the UK and the average data of the 14 OECD countries. We chose Finland and the UK as examples of the lowest and highest correlation coefficients between gas prices and electricity prices. As indicated in the Figure's first two graphs, each marking the same time

[6] Finland, France, Greece, Hungary, Ireland, Mexico, New Zealand, Poland, Portugal, Slovak Republic, Switzerland, Turkey, United Kingdom and United States. There is a data shortage for other OECD countries.

period, the gas prices and electricity prices in Finland change independently with a correlation coefficient of 0.33, while the electricity prices closely mimic gas prices in the UK with a correlation coefficient of 0.989. Across the OECD, average electricity prices followed average gas prices, with a correlation factor of 0.763.

We used a simple model to calculate the correlation coefficients. Let P_g and P_e represent the gas and electricity prices in two arrays, namely:

$$P_g = \{p_{g1}, p_{g2}, \dots p_{gt} \; \dots . \; p_{gn}\} \quad and \quad P_e = \{p_{e1}, p_{e2}, \dots \; p_{et} \dots . \; p_{en}\}$$

Then, the correlation coefficient can be calculated as follows:

$$\rho_{g,e} = \frac{Cov\ (G,E)}{\sigma_g \times \sigma_e}$$

where:

$$Cov\ (G,E) = \frac{1}{n} \sum_{i=1}^{n} (p_{gi} - \mu_g) \times (p_{ei} - \mu_e)$$

σ_g and σ_e are the standard deviations of the arrays of P_g and P_e respectively. μ_g and μ_e are the mean values of the arrays of P_g and P_e.

Applying the above methodology to the energy and carbon price arrays, we calculated the average correlation coefficients in the OECD, as appearing in Figure 5. Note that the correlation factors of oil prices to the electricity, gas and carbon prices are calculated from the national average data of Italy, because Italy is the only country in the OECD using significant amounts of oil for power generation.

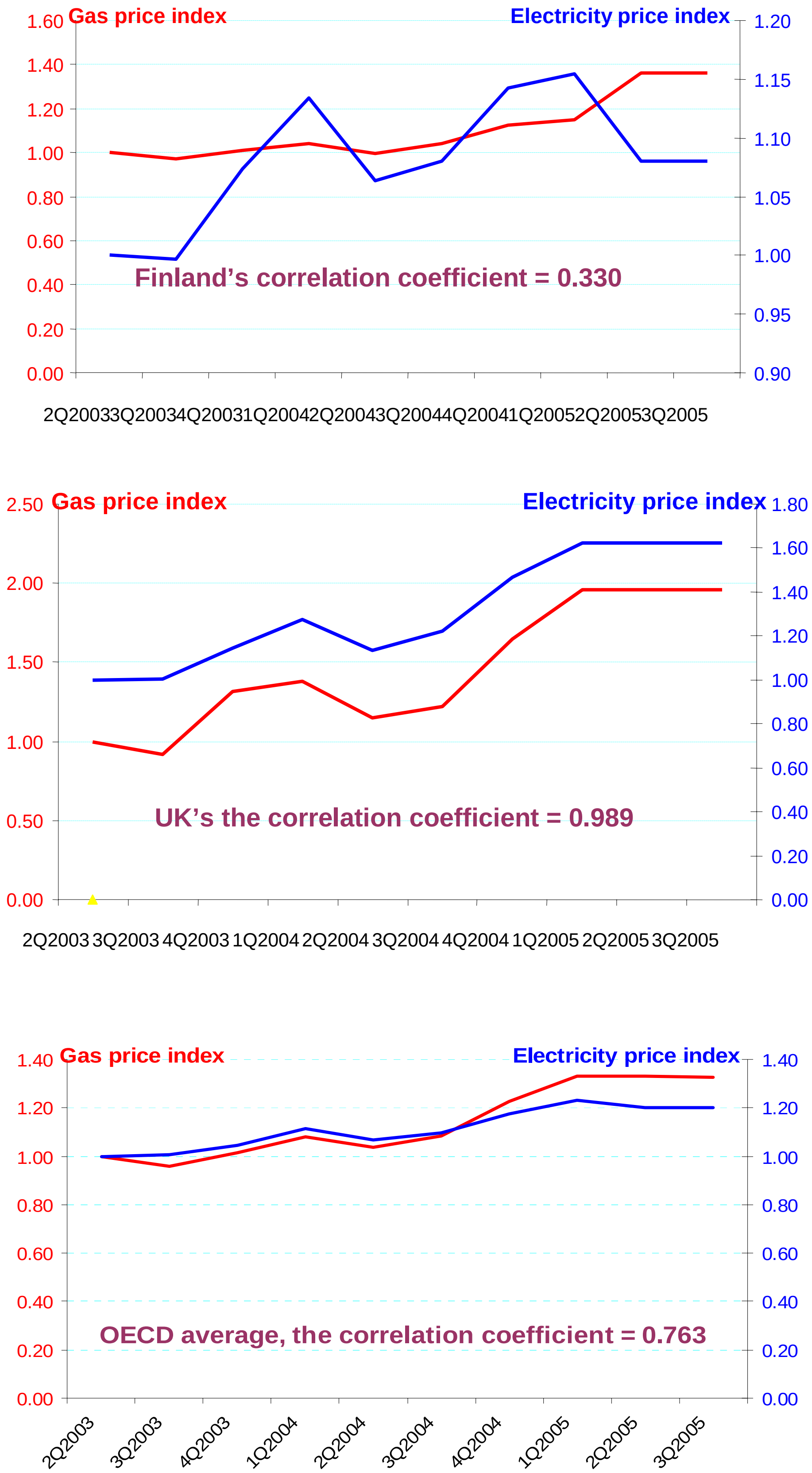
Table 2 Correlation coefficients

	Electricity price	Natural gas price		CO_2 price		Oil price
		OECD	Used	OECD	Used	Not used
Electricity price	1	**0.76**	**0.99**	**0.37**	**0.37**	**0.73**
Gas price		1	1	**0.48**	**0.48**	**0.21**
CO2 price				1	1	**0.87**
Oil prices						1

Note: OECD – calculated from the historical data of the OECD; Used – the actual data used in the model. Oil price data has not yet been used as we made no case study on oil power.

The correlation coefficients shown in the above-mentioned figure are calculated on the basis of the historical and short-term (three-year) data. This figure in the UK was very high, approaching to 1, while it was low in Finland, only 0.33. The reason is that in UK gas power generation is dominant while in Finland (together with Sweden), nuclear power and hydro power are dominant. To better simulate the price correlation relationship in long-term planning, we actually revised the correlation coefficients to a higher degree. As such, assuming the electricity prices will closely follow the gas prices during the next 25 years, we set the correlation coefficient in our model at 0.99 rather than at 0.76. See Table 2.

Figure 5 Correlation coefficients of electricity and gas prices 2003-2005



Source: Calculated from IEA Beyond2020 (2005)

5. Module Three: Calculating Deterministic NPV

In a traditional project assessment, evaluation of a project's costs and expected gross margin or profits often involves a deterministic analysis, which fixes and discounts future cash flow to calculate a project's present values. Net present values (NPVs) or levelised costs per unit of output are the key criteria for assessing a project's financial viability. The deterministic method assumes full knowledge of each central variable, including future energy prices and future carbon trading prices, and discounts the future cash flow by the weighted average cost of capital (WACC) of a firm. In discounted cash flow (DCF) analysis, if the project revenue value is higher than the costs of the project investment and operations, the project may be ripe for investment. A mathematics function below shows the examples of the modeling results from Module 3. A more detailed description of how to calculate DCF, WACC and complete the DCF analysis can be found in ADB (2002).

$$NPV = \sum_{t=1}^{T} \frac{C(P_c)_t}{(1+r)^t} - C_0 \quad in \quad Module \quad 3$$

Where:

C_0 is the unit construction costs;

P_c is the carbon price. Changing with a yearly growth rate, its yearly volatility is zero;

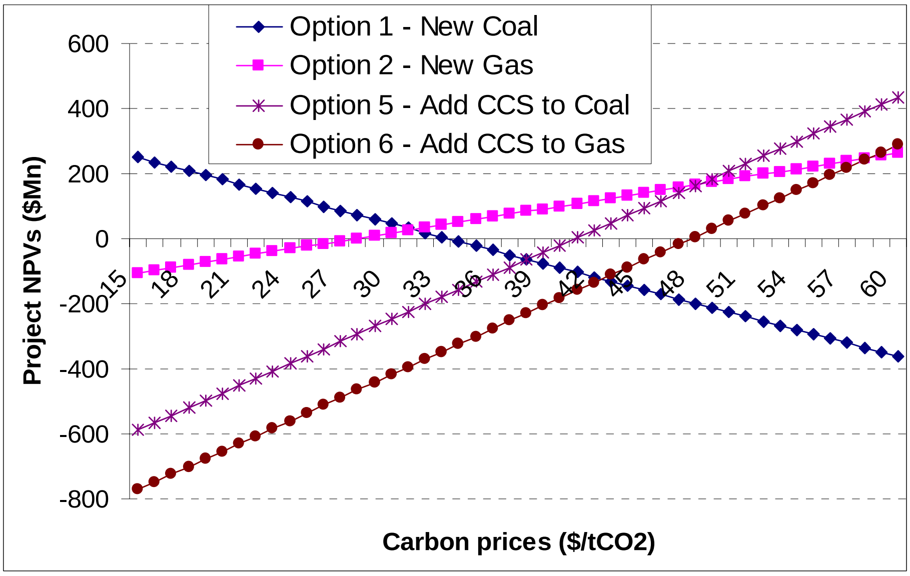
$C(P_c)_t$ is the cash in-flow of the project at year t. It is the function of P_c.

With the above model, we calculated deterministic NPVs for various technologies. While doing so, we set the carbon price to change from USD 0/tCO_2 to USD 100/tCO_2. Because NPVs are functions of carbon prices and different technologies will have different responses to carbon prices, we are able to find the breakeven points of NPVs among different technologies. These points are critical because an investor may switch from investing in one technology to another if the carbon price is beyond or below that critical point. Figure 6 shows a part of our modeling results in Module 3. It demonstrates the change of NPVs of four technologies along with the changing CO_2 prices: new coal power, new gas power, adding CCS to a coal power plant, and adding CCS to a gas power plant. If carbon price is low, a power investor prefers to invest in a new coal power plant because the NPV of the new coal power plant is higher than any other technologies. However, with the growth of carbon price, the NPV of the new coal power plant decreases accordingly. The breakeven point of carbon price for the NPVs of a new coal plant and a new gas plant is about USD 33/tCO_2. If carbon price is beyond this point, a power investor would be better off if he invested in a new gas power plant. If carbon price reaches USD 39/tCO_2 and USD 60/tCO_2, a power investor will consider the installation of CCS technologies to a coal power plant and a gas power plant respectively.

It should be stressed again that the above analysis is on the basis of DCF methodology. The nature of price change in a stochastic way is not incorporated in the calculation. A DCF analysis incorporates an aspect of project risk evaluation simply by setting higher discount rates. This method is best suited to inform the investment decisions of a mature company operating in a stable environment, one that enables the semi-exact forecasting of the next year's cash flows. Such certainty may be difficult to secure in a dynamic market or in the period of a new power generation technology's launch, when uncertainties about the raw materials, primary energy prices and CO_2 trading prices confound a determination of potential revenue. In any case, the blunt use of a single parameter (discount rate) to represent many different sources of risk exacerbates the difficulty of choosing an appropriate discount rate, particularly in novel situations where risk premiums are not well established.

Most importantly, the DCF does not account for the flexibility that investors must often select when making investments. For example, a new power plant with carbon capture and storage may not be cost-effective under current economic and technical conditions. However, as these circumstances change, the project may become cost-effective. The DCF analysis may close this project opportunity, whereas a real options method may steer the project developer to postpone the investment, while keeping the option alive. For the purposes of policy analysis, ROA is particularly useful, as the different elements of risk can be identified and modeled separately, and investors' investment flexibility can also be modeled.

Figure 6 Modeling results from Module 3



6. Module Four: Real Options Analysis

Module 4 of the IEA's real options analysis (ROA) model consists of two key elements: scenarios and options. Figure 7 shows the relationship between the scenarios and the options. A scenario shown in circles in the figure describes a particular mode of operation of a technology. For example, a power plant performance characteristics before and after investment to improve energy efficiency can be considered as two distinct operational scenarios. Corresponding to a particular mode of operation, a cash-flow forecast for each period characterizes each scenario. Underlying this cash-flow forecast is a spreadsheet model that incorporates the relationships and assumptions relevant to a given mode of operation. As a scenario's cash flow usually depends on the relationship of different variables, some of which are stochastic and random forecasts, scenarios' future cash flows can therefore be uncertain. Traditional NPV analysis can always be regarded as a project's single scenario cash flow without uncertain forecasts of costs or prices.

An option defines the opportunity of switching irreversibly from one scenario to another. In Figure 7, the arrows represent options, meaning that for all the years during which an option is active, one can switch scenarios. An option may be available only during specific years or throughout the entire lifetime of a project. The action of switching scenarios is known as exercising the option or, in practical terms, investing in the project. Therefore, this exercise generally entails a cost, often investment capital itself.

An option always has a source scenario and at least one target scenario. A source scenario can be either an existing project such as a coal-fired power plant which is generating cash flow without additional capital investment, or a green field on which a new power plant can be built. A target scenario can be either the existing coal power plant with improved energy efficiency or a new power plant such as CCGT or clean coal technology. A target scenario can also serve as the source scenario for another target scenario. For example, in Figure 7 Scenario D-1 is both a target scenario of Scenario A and the source scenario of Scenario D-2. While the project is operating under the source scenario and if the option is active, the option may be exercised, switching the operating scenario to the target scenario. The IEA's model monitors uncertainty surrounding an uncertain forecast to determining circumstances under which it is optimal to exercise the options for each year during the whole planning period. The model delivers a sequence of optimal exercise rules that maximises the investment value of the project regardless of the uncertainty's resolution over time.

Assuming the source scenario is the current scenario, the model will determine for each active year whether it is optimal to switch. Optimization of the exercise decision also accounts for all future exercise opportunities and, in more complex models, the presence of other options. In the model one may allow an option to aim for more than one target scenario. In this case, upon option exercise, the project will randomly switch to one of the target scenarios according to a set of pre-defined probabilities or switch within a set of predefined probabilities.

With the features described above, the model allows one to quantify and optimize investment opportunities in different manners and categories. These include:

a. Optionless models. The model is useful in the valuation of simple, single scenario models as it extends traditional discounted cash-flow (DCF) analysis by incorporating the effects of uncertainty. The model provides multiple risk measures including variance, value at risk, percentile analysis and value cumulative distribution function (CDF). By comparing the NPVs of the technologies under two studies, i.e. "with" and "without" setting the price variable uncertainty, one can estimate the risk premiums of the project.

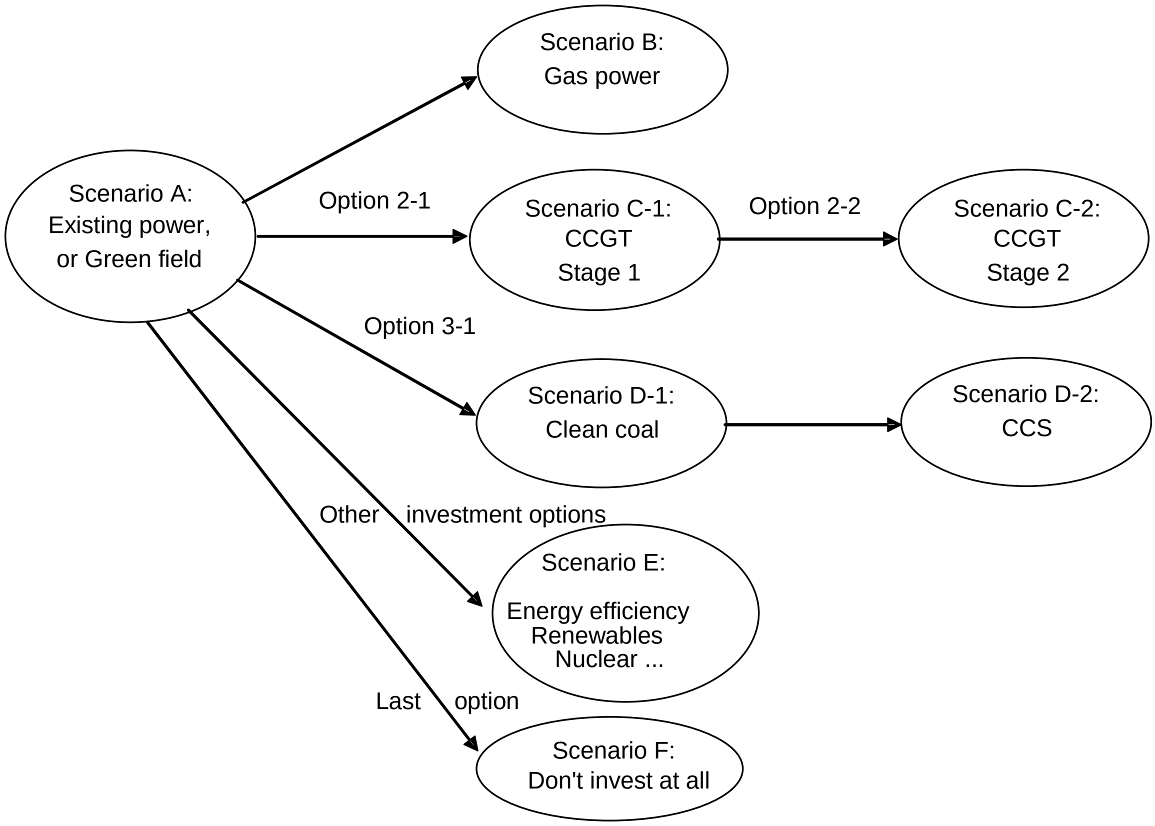
b. Basic option models. This category encompasses most models in current real options practice where a key strategic decision is to be made during the life of a project that would move a project from one baseline scenario to one single post-exercise scenario.

c. Multiple options. The basic option model can also be extended by incorporating many options. As such, multiple options with the same source scenario may coexist. Eventually, only one of such options may be exercised. Recall that investments in power technologies are irreversible, meaning that once the capital is invested it becomes a sunk cost. When a firm makes irreversible investment, it exercises or kills all its other options to invest in any other technologies. This lost option value is an opportunity cost that should be included when calculating the investment's cost. Exercising a single option may lead to any one, but only one, of the option's target scenarios.

d. Multiple options with allocated probabilities. We can also specify a probability distribution that indicates the likelihood of each of the target scenarios. This modeling approach is useful in scenario analyses. For instance, if we want to model the influences of different CO_2 prices under different probabilities on the same technology, we can simply duplicate the target scenario data to form the other target scenario data, change the CO_2 price, set both of the target scenarios, allocate a different probability to each of the target scenarios, and run the model. Note that the sum of the probabilities should always be equal to one.

e. Nested (compound options). By compound options we refer to the situation where a strategic option becomes available only upon prior exercise of a different option. This kind of analysis often arises in applications with management strategies composed of many sequential steps. The IEA model uses a nested approach to model the retrofit of carbon capture and storage to existing coal and gas power plants.

Figure 7 Model structure of Real Options



Note: Clean coal stands for clean coal power technologies

Each appearing in Figure 7, these model structures may be combined into a larger model. For example, we craft a nested option model with multiple options available for a given scenario or build multi-target nested options.

The above scenarios, options and their related uncertain prices are modeled with mathematical functions and supported by computer software programming. The following paragraphs present these functions and programming in more detail.

6.1 Dynamic stochastic analysis method

A stochastic analysis method uses Monte Carlo simulation to incorporate the estimations of uncertainties into the model variables. In our model, we present input data such as primary randomized energy prices, electricity prices and carbon trading prices with some statistical distribution rather than fixed and known price points. As a result, the IEA's model calculates stochastic project NPVs. The following formula is used in Module 4 to calculate the project NPV:

$$NPV = \sum_{t=1}^{T} \frac{C\,(Stochastic \quad P_c \;\&\; P_e)_t}{(1+r)^t} - C_0 \quad in \quad Module \quad 4$$

Where:

C_0 is the unit construction costs;

P_c and P_e are the carbon prices and energy prices. They change stochastically in the model;

C(Stochastic P_c & $P_e)_t$ is the cash in-flow of the project at year t. It is the function of P_c and P_e.

As shown in the above mathematical formulas, the NPVs in Module 4 are a function of the fluctuating carbon price and electricity price. Figure 10 illustrates examples of Module 4's modeling results.

We use stochastic analysis to assess how variations in price affect project profitability, selecting equations describing variations in price that leave unchanged the expected mean price – within the chosen equations increases in price are as probable as decreases in price. If variations in price are small, the project valuation will return results similar to that of the DCF valuation, since average prices are unaffected. However, as variations in price become larger, the project valuation can change if a project's gross margin is a non-linear function of price.

Stochastic analysis is particularly useful when assessing the value of operational flexibility, as in the capacity to run a plant during favourable price conditions and extinguish operations during adverse price conditions. In an environment of fluctuating prices, this operational flexibility increase overall plant profitability, relative to a static DCF analysis. For further detail on this dynamic, see Blyth and Yang (2006).

6.2 Real option optimization method in this study

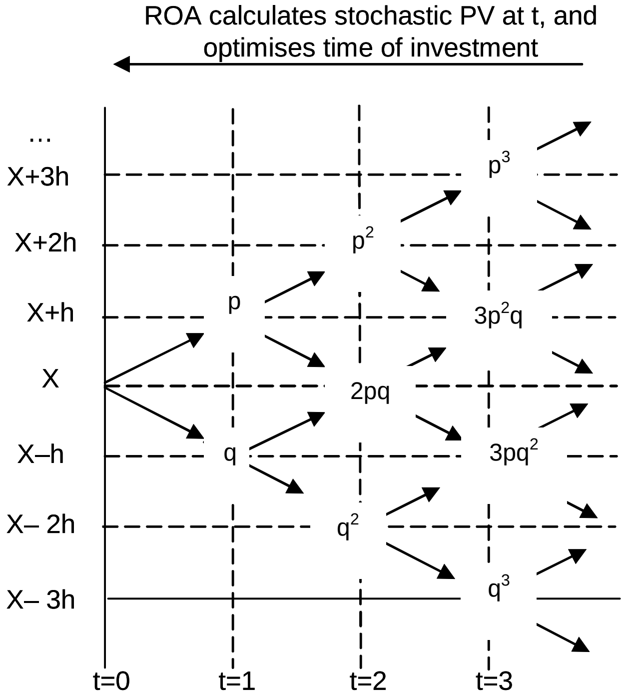
Optimal timing under uncertainty can manifest itself in two ways. First, consider projects that appear not to be cost-effective (i.e. have a negative NPV when measured using a standard DCF approach). A project valuation that does not account for price uncertainty produces a decision never to invest in the technology. However, following resolution of these uncertainties, this same investment opportunity may actually be cost-effective. In this case, the effect of optimal timing would be not to forgo the project opportunity.

Conversely, if an investor considers a power project that returns a positive NPV following a DCF assessment, standard investment wisdom would compel an immediate investment. However, a real options analysis that accounts for price uncertainty might foretell the earning of greater profits by waiting for more optimal price conditions. In this case, the effect of optimal timing would be to delay the investment, relative to an assessment ignoring price uncertainty.

Timing of investment and choice of technology are of principal interest to policy-makers, particularly those governing the power sector, where investment is crucial to balancing supply and demand for electricity. Changes in the timing of investment could therefore strongly influence power prices. The IEA's model may inform the strategy of investors and policy-makers alike, given the model's capacity to derive an optimal investment rule that accounts for the uncertainties in costs and revenues, as well as the flexibility of investment timing.

The IEA's model is structured as a "decision tree", and the real option optimization compels a search of the best time to invest and calculates investment risk premiums from the top to the bottom of the tree. At time *t*, the model will look at the NPV of the project taking into account wide likelihoods of carbon and energy price volatilities under two scenarios: either invest now or hold on the investment until next period. The model will compare all the NPVs at all the time periods under the two scenarios, and tell the best time of investments. Figure 8 illustrates the methodology of such a modeling operation. We divide time up into discrete periods of length Δt, and assume that in each period NPV (X as in the figure) either moves up or down by an amount *h*. Let the probability that it moves up be *p*, and the probability that it moves down be *q=1-p*. The figure shows the possible values of NPVs (X, X+h, X+2h, X+3h, X-h, X-2h, and X-3h) in each of three periods (t=1, t=2, and t=3) with different probabilities (p, q, p^2, 2pq, q^2, p^3, $3p^2q$, $3pq^2$ and q^3) assuming that it begins at the point X. More detailed descriptions about dynamic optimisation of the process will be given later in this document.

Figure 8 Stochastic value and optimization tree of ROA



Source: Adapted from Dixit & Pindyck (1994)

To better demonstrate the optimization process, we start with a case study of switching an old inefficient coal-fired power plant to other technologies. We denoted the current coal power plant status as a Base Scenario (BS). One of the options available to BS is to switch the power plant to a CCGT, which we call the target scenario (TS)[7]. We assumed that the project investment would take place within a period of t years { $t=1, . . . , T$}. The capital investment in CCGT (or the cost of exercising the option) is K. We denoted $C_{B(t)}$ and $C_{T(t)}$ cash flows corresponding to BS and TS at year t respectively. Within our discount curve, $d(t_1, t_2)$ denotes the discount factor applied at time t_1 to cash flows occurring at time t_2. By definition, we have $d(t_1, t_1) = 1$.

The optimal exercise policy is derived by estimating the value of exercise versus the continuation value using top-down dynamic programming techniques (Dixit and Pindyck 1994). We begin solving the problem at the latest year and work back to the beginning year. For the latest year in our project, the policy problem in the model is to

$$Exercise,\ if\quad V_{(T)} = C_{T(T)} - C_{B(T)} > K_{x(T)}$$

$$Do\ not\ exercise,\ if\quad V_{(T)} = C_{T(T)} - C_{B(T)} \leq K_{x(T)}$$

Correspondingly, we have the optimization relationship at year T:

$$V^{*}_{(T)} = \max\{C_{T(T)};\ (C_{B(T)} + K_{x(T)})\}$$

In any year t ($0 < t < T$), the random value of exercising the target option is the present value of the target scenario's cash flow, that is:

$$V^{ex}_{(t)} = \sum_{k=t}^{T} d(t,k)\, C_{T(k)}$$

The continuation value, that is, the value of the project if one chooses not to exercise the option in period t, is given by:

$$V^{cont}_{(t)} = C_{B(t)} + d(t,\ t+1)\, V^{*}_{(t+1)}$$

Where $V^{*}_{(t+1)}$ is the summed cash flows of the base scenario project under the optimal conditions during year $t+1, t+2, \dots T-1, T$, discounted back to year $t+1$.

Under ROA, the optimal exercise (or investment) timing is derived by comparing the value of exercise versus the expected value of continuation of the project, which is highly dependent on future uncertain information such as the stochastic prices of carbon, energy and electricity. We denote the expected value as $E[V^{*}_{(t+1)}]$. At any time t, the computer model simulates the random prices and conveys information to t about the way manner in which uncertainty has been resolved, along with the provision of future profit outlooks for the different scenarios.

[7] Other options include (1) switching to biomass coal co-firing; (2) improving the heat rate; (3) expanding the lifetime of the power plant; (4) early retirement of the power plant; (5) completely re-building a new coal-fired power plant or gas power plant, etc.

We denote:

$$E[V_{(t)}] = E[V_{(t)}^{ex} - V_{(t)}^{cont}]$$

At any time *t*, the optimal exercise (or investment) policy will adhere to the following rules:

$$Exercise,\ if\ \ E[V_{(t)}] > \ K_{x(t)}$$

$$Do\ not\ \ exercise,\ if\ \ E[V_{(t)}] \leq \ K_{x(t)}$$

Correspondingly, the optimization relationship between the expected values of the existing project (or none for a green field) and future potential projects appears as:

$$V_{(t)}^{*} = \max\{E_t[(V_{(t)}^{ex}];\ \ E_t\ [C_{B(t)}\ \ + d(t,\ t+1)\,V_{(t+1)}^{*} +\ K_{x(t)}]\}$$

The above optimization relationship is essential to our model's simulation of the new investment rule under ROA. The rule states: "In year t, the investor should not invest in any new project (wait for at least one year) unless the expected value of the discounted future cash flows of the new plant ($E[V^{ex}_{(t)}]$) is greater than the expected cash flow of the existing plant in year t ($E[C_{B(t)}]$) plus the expected discounted optimization value of the options of the project in year t+1 ($E[d(t, t+1)\ V^*_{(t+1)}]$) and expected capital costs (or investment cost) ($E[K_{x(t)}]$)." If the option is not exercised in year t, the option holder will have two options in the next year: exercise it or wait for a better opportunity. Once the option holder exercises the option at t, future options close and the option holder receives the optional value of the project: $V^*_{(t)} = E[V^{ex}_{(t+1)}]$. The risk premium relates directly to the options of the project: the higher the uncertainty, the higher the project's option value. Thus, more uncertain carbon and energy prices create higher option values for the project, or in other words, higher thresholds for new investment. In Blyth and Yang (2006), we demonstrate quantitatively how the uncertainties surrounding climate change and energy prices raise the threshold for investments in various power generation technologies.

The above optimization process is multiple and dynamic, which will be carried out by a computer programme from T, via T-1, … t, t-1, .. until t=1. Figure 9 illustrates the optimization process. Though the previous example centres on a single target technology, the IEA's model can optimize multiple options, calculating one NPV at year t ($V_{(t)}$) for each of the technologies, comparing these values and choosing the largest one as $V^*_{(t)}$.

Figure 9 Real option optimization flow chart

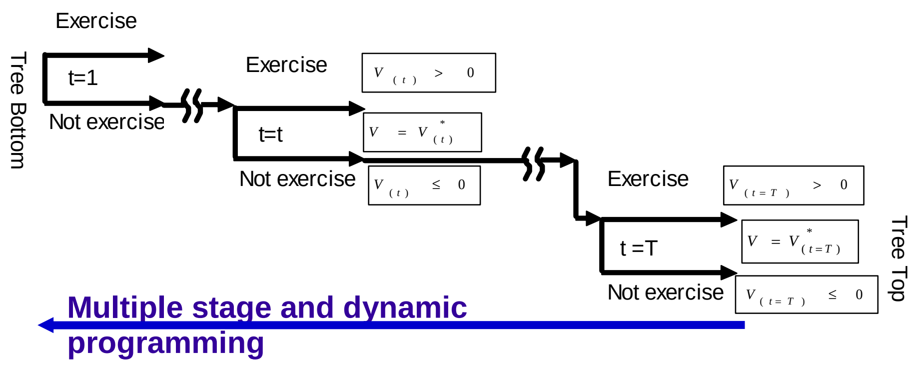


Figure 10 Optimization of future cash flows using Real Options

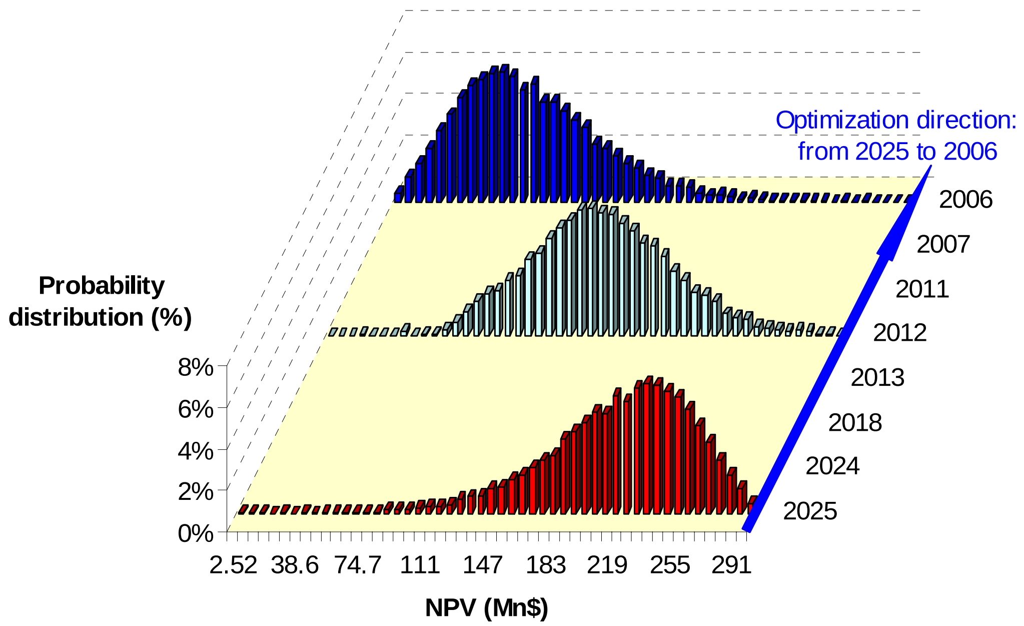


Figure 10 further demonstrates how the IEA model derives the rules of investment from the real options optimization. Starting at the end of the planning period, in each year, the model will calculate the NPVs for the projects, including the existing equipment and all potential new technologies. Note that the NPVs will have forms of random distribution due to the stochastic prices for energy and CO_2. As exemplified by the red-colored distribution, each of the NPV distributions represent the optimal NPV as selected from a cluster of the NPVs. We use the mean NPV values to represent the NPVs of the projects. Accounting for all price volatility in each year of the investment planning period, the computer model generates optimal investment rules for each candidate technology for each year. These investment rules then inform the Monte Carlo simulation, which runs forward from 2006 to determine the optimal date to switch from the existing technology to any new technology. In this study, we particularly concentrate on the value of these investment rules produced by the model: the ROA's investment rules typically exceed the normal DCF breakeven point by a margin which we interpret as an investment threshold further raised by uncertainty.

7. Computer software programming

The IEA's model uses a Real Option Calculator (ROC) Excel Add-in software programme also used by the Electric Power Research Institute (EPRI) for their real option analysis work. The ROC uses the Monte Carlo simulation tool and runs the optimization routines. When this study started, the software was commercially available from Onward Inc. (Onward 2004). As Onward's product is no longer sold, other commercially available decision-support software programming could be used for similar analyses.

8. Sensitivity analyses

This study's sensitivity analysis involved two methodologies for the range of variables. In the traditional methodology of project sensitivity analysis, the dependent variable is the project NPV. Independent variables generally appear as the project's capital costs, operation and maintenance (O&M) costs, discount rate, and the time period of the project construction (ADB, 2002). In this study, we used this traditional methodology to analyze the sensitivity of two major variables: capital investment costs, and O&M cost.

With another method, we also assessed the sensitivity of a random variable: the volatility of the carbon price. During the assessment, we used the expected threshold values of the stochastic NPVs, rather than the deterministic project NPVs, as the traditional methodology of sensitivity evaluation cannot capture the change of stochastic variables and thus is not applicable to such uncertainty analysis. The formulas used for our study's sensitivity analysis are expressed as follows:

$$Sensitivity\ of\ NPV\ (\%) = (\frac{NPV\ under\ the\ revised\ scenario}{NPV\ under\ the\ base\ scenario} - 1) \times 100\%$$

for the variables of capital investment and O&M cost; and

$$Threshold\ change = (\frac{Annual\ NPV\ threadhold\ under\ the\ revised\ scenario}{Annual\ NPV\ threadhold\ under\ baseline\ scenario} - 1) \times 100\%$$ *for the variable of volatility of carbon prices.*

We followed the procedures listed in ADB (2002) when conducting the sensitivity study for the two variables, calculating first the NPVs for all options under the baseline scenario. Then, we set the capital investment costs and O&M costs to each increase by 10%, and again calculated the NPVs. Substituting the two calculated values in the first formula, we estimated the sensitivity of NPVs and calculated the sensitivity of carbon price volatility using the second formula.

9. Conclusions

Assessment of how carbon and energy prices affect project risk and investment strategy compels the development of new methodologies and models to quantify the influence of climate change policy and uncertain energy prices on energy sector investment. This paper describes the technical details of such a model developed by the IEA: Real Options Analysis approach.

The methodology and modeling of Real Options Analysis is still developing. The IEA's modeling methodology applies real options as a novel tool in policy analysis. This application of real options enables modeling of individual risk factors, thus informing a comparison of the relative influence of uncertainty in CO_2 price vs. fuel price. With such a tool, we can critically compare the effects of different policy designs, and compare the impact of climate change policy uncertainty with the impact of market uncertainty on power investment. More importantly, we model both the energy prices and carbon prices with stochastic variables and use nested modules to model multiple-stage investments, which is still a gap in the modeling the impact of climate change policy in power investment.

The methodology and model presented in this paper have proven effective and applicable. We have applied this methodology and model in nine general case studies and three specific case studies. The research results of the case studies have been well accepted and acknowledged by the project funders that include three national governments of OECD countries and three power companies. Details about these studies and result discussions appear in a separate paper. See Blyth and Yang (2006), and IEA (2007).

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