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Evaluation of power investment decisions under uncertain carbon policy: A case study for converting coal fired steam turbine to combined cycle gas turbine plants in Australia

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Abstract

Greenhouse gas (GHG) intensive fuels are currently a major input into the Australian electricity sector. Accordingly, climate change mitigation policies represent a systematic risk to investment in electricity generation assets. Although the Australian government introduced carbon pricing in 2012 and announced a commitment to the continuation of the Kyoto protocol beyond 2012, the opposition at the time signalled that should they be provided the opportunity they would repeal these policies. This paper uses a real options analysis (ROA) framework to investigate the optimal timing of one potential business response to carbon pricing: investment in the conversion of coal plant to lower emission CCGT plant. An American-style option valuation method is used for this purpose. The viewpoint is from that of a private investor assessing three available options for an existing coal plant: (1) to invest in its conversion to CCGT; (2) to abandon it, or; (3) to take no immediate action. The method provides a decision criterion that informs the investor whether or not to delay the investment. The effect of market and political uncertainty is studied for both the Clean Energy Act 2011 (CEA) and high carbon price (HCP) policy scenarios. The results of the modelling suggest that political uncertainty after the implementation of carbon pricing impedes the decision to switch to cleaner technologies. However, this effect can be mitigated by implementing higher expected carbon prices.

Keywords: Energy investment, Real options, Australian climate policy, Decision making, Uncertainty

1. Introduction

With a scientific consensus having formed over the direction and factors that cause global climate change [1], many jurisdictions have implemented policies that promote a reduction in GHG emissions. However, much uncertainty still remains in terms of the range of possible policy responses to the problem. The non-cooperative game nature of global GHG mitigation agreement has accentuated the uncertainty of national policies. Therefore, contemporary energy supply investment is exposed to climate change policy risk in addition to traditional

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risk factors. Emission trading schemes (ETSs) have been designed and implemented to achieve least cost GHG reductions in order to encourage investment in cleaner technologies. However, given the aforementioned policy risk and its potential impact on carbon and energy prices, it is not only current policy settings but also expectations over future policy settings that will influence current investment decisions in long-lived carbon price exposed assets.

The principle aim of this study is to develop an investment decision making framework that incorporates the market and political uncertainty over future carbon prices and the value of waiting until such uncertainty recedes. A case study is developed to evaluate the timing of hypothetical brown-field conversion from an existing coal-fired steam turbine (CFST) to a CCGT plant in New South Wales, Australia.[1] The objective is to measure the influence of current ETS design, and uncertainty surrounding the policy's future, on that decision. Given that a substantial proportion of the capital cost of incumbent coal plants are sunk, their early scrapping and replacement with new low-emission technologies is a costly option. Therefore, brown-field augmentation of CFST with gas turbines, to benefit from a lower emission intensity and higher energy conversion efficiency, is potentially attractive as a means of preserving some of the asset value that was sunk into the original investment.

The case study emphasises two major sources of uncertainty associated with Australia's ETS: market driven carbon price volatility, and political uncertainty over the potential for the policy's repeal, with a focus on the latter. The future of the CEA policy in Australia is still under debate, and will be determined in part by the make-up of both houses of the federal parliament after a national election in late 2013. This paper presents a set of results, and their implications, stemming from the modelling of these uncertainties in the context of the aforementioned investment decision. The method used is real options analysis (ROA). In the

[1] Electricity generation in Australia, which makes use of abundant coal resources, is responsible for over a third of the country's GHG emissions [2].

face of current political uncertainties, investment decisions cannot be solely based on traditional discounted cash flow (DCF) analysis; investors may select to delay the decision rather than making an immediate decision as implied through the use of the DCF technique. Unlike DCF analysis, ROA explicitly accounts for both the value of waiting for more information and the opportunity cost of delaying an investment. This enables the analyst to make a judgement as to the best timing of investment, particularly where cost irreversibility and uncertain payoffs are significant.

Real options theory has been successfully applied in electricity market policy evaluation in two major inter-related research streams: (1) studies that consider a firm's decision to invest in generation technologies in a single-investment framework, and (2) a firm's decision to invest in a portfolio of generation technologies. In research stream (1) Dixit and Pindyck [3] have presented by a simple example how ROA can support taking decisions in electricity planning. Other studies such as Tseng and Barz [4], Deng and Oren [5], and Reuter et al. [6] have focused on operational variability and/or constraints on investment decisions within a short-term horizon. In a recent study, Reuter et al. [7] have compared greenfield investment in wind with coal plants. A subset of studies has shown interest on retrofitting incumbent coal-fired generation with carbon capture and storage (CCS). Reedman et al. [8], Reinelt and Keith [9], Fuss et al. [10, 11], Szolgayová et al.[12], Zhou et al. [13], Zhu and Fan [14], and Zhang et al. [15] have developed case studies to investigate investment into CCS assuming exposure to market and/or political uncertainty. In research stream (2) numerous portfolio optimization studies in the electricity generation sector integrate the real options elements with either a myopic mean-variance portfolio optimization or a dynamic stochastic optimization framework. The standard deviation of the payoffs for investment alternatives, value at risk (VaR) or conditional value at risk (CVaR) are common risk measures applied in the relevant problem formulations. In more recent works, Fortin et al. [16] and Fuss et al.[11]

have developed a static model on a portfolio of various generation technologies. Szolgayová et al. [17] have tried to extend the static portfolio problems to a dynamic formulation. Kumberoglu et al. [18] have integrated ROA approach within a deterministic optimization of the generation mix. A recent study of a dynamic portfolio of generation technologies has been conducted by Min and Chung [19]. They have employed CVaR in designing variability to consider rare events with enormous effects and have found that liquefied natural gas (LNG) or coal can be secure candidates for Korea to reduce its dependency on nuclear energy. Many authors in this research stream combine a present value analysis of costs or benefits with a measure of risk in the relevant objective function used in a stochastic optimization framework under uncertainty.[2]

This paper focuses on research stream (1) as described above.[3] Addressing some of the knowledge gaps in the existing literature, this is the first study, to our knowledge, that models the relationship between the carbon price level and political uncertainty in a post-implementation framework, i.e. with a carbon price scheme already operating. In addition, we focus on the conversion of CFST plants to CCGT since it is a readily available technology. Moreover, in this conversion process, some of the sunk cost of original investment into CFST plant can be preserved. The novelty of our research lies in: (1) simulating electricity price paths based on Treasury forecasts, (2) presenting a new metric, option value ratio (OVR), to assist in determining which investment decision and timing is likely to be most profitable in the presence of uncertainty, and (3) modelling the salvage value of the incumbent CFST plant as a function of the probability of repeal and the corresponding expected repeal times. A comparison of the investment value calculated by standard DCF and ROA methods, along

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[2] For a detailed literature review of long-term electricity planning refer to the recent study by Min and Chung [19].

[3] The focus of this paper is on a single investment decision. An extension of the model to implement a portfolio of generation technologies is currently under consideration.

with the value of flexibility, provides the aforementioned OVR decision criterion that can assist the decision over whether or not to delay the investment.

Among numerous works applying ROA, the most relevant studies to the current analysis are those of, Reedman et al. [8], Laurikka [20], Laurikka and Koljonen [21], Blyth et al. [22], Fuss et al. [10], Zhou et al. [13], and Szolgayová et al. [12]. These authors have investigated the effect of various carbon pricing mechanisms on investment decisions in the electricity sector by implementation of specific scenarios and/or sensitivity analyses.[4] The only Australian study among these by Reedman et al [8], developed a real options model to evaluate the timing of the uptake of a natural gas fuelled plant and various coal technologies, as well as the retrofit of carbon capture facilities in existing plants. However, conversion of an existing coal plant to a CCGT using pre-existing technology was not modelled. They found that the investor's perception of carbon price uncertainty has significant influence on investment decisions, even before the actual enactment of carbon price legislation. Our analysis considers risk in the opposite direction, that of uncertainty over the repeal of existing legislation.

The model formulation developed in this paper conceptually builds on the Dixit and Pindyck [3] dynamic programming approach, draws on International Energy Agency (IEA)'s real options methodology [22] and uses the Monte Carlo simulation type least-squares method developed by Longstaff and Schwarz [24] to value an 'American'-type option.[5] Investment risk evaluation with the real options methodology provides important capabilities, such as separate and integrated elements of risk modelling to assess their relative contribution to overall risk [22].

[4] For a more detailed review of the application of real option analysis in the electricity sector refer to Fernandes et al. [23], Blyth et al. [22].
[5] An 'American'-type option refers to a type of option in which the option can be exercised at any time during its life.

2. Model

This work takes the view of a private investor. It is assumed that a 400MW coal-fired steam turbine power plant has been running for 10 years, and the remaining life of the plant is 40 years from the present time. Under anticipated increasing carbon prices, the investor has the option to invest in the conversion of the plant to a CCGT power plant in response to the looming cost or abandonment of the plant under high future carbon prices. The options available to the investor are: (1) to invest in the plant conversion to CCGT, (2) to abandon the plant, or (3) to take no action. However, with uncertain carbon prices in the future due to either policy regime change or volatility of prices in the liberalized emission trading market, the investor has the option to wait to acquire information about the future, to at least be partially informed about the commitment of the government to the current policies devised. The anticipated carbon price change at some certain time t_j can adversely or favourably affect a project's cash flow, so the investor has the option to wait until after time t_j before making the investment decision. In the case of the decision to wait, a potential loss can be avoided upon adverse market and/or political conditions; however, waiting may forgo some cash flows before $\mathrm{t_j}$ (i.e. opportunity cost of waiting). The options valuation framework provides a suitable method to measure the value of the option to wait.

Other sources of costs in this analysis, such as capital costs are considered to be deterministic. The effect of technical improvements, exchange rate, productivity and commodity variation over the decision horizon has been reflected through forward curves provided by the Australian Energy Technology Assessment (AETA) report 2012 [25]. Fuel and operating and maintenance forecast prices are assumed to be deterministic and data from the Treasury model [26, 27] and an ACIL Tasman report [28] are used. Moreover, it is assumed that once the decision to convert the plant has been made, the plant is built and operated immediately, ignoring construction times. However, this assumption does not affect the quality of the results as they will only shift the pattern of the outputs without considerable impact on the interpretation of the results.

To analyse the effect of electricity price uncertainty along with uncertainty associated with a policy regime change, a mean adjusting and reverting (MAR) process has been used. Mean reverting processes have been applied extensively in similar works, such as Fuss [10], Laurikka[20], and Szolgayová et al. [12]. However, this study accounts for the effect of policy change as a structural break-through in the price path that arises from a carbon price pass-through rate. This work takes the position that once emission trading is introduced, or there is a significant shift in the level of carbon prices, the electricity price development structure changes, and accordingly, the average level of prices will change over the long-run due to technology substitution in the electricity generation sector. Accordingly, electricity output from cleaner technologies will increase and coal plant output will be reduced due to retirement. Cong and Wei [29] have shown theoretically, that implementation of carbon pricing substantially increases electricity prices by internalising environment costs. Yang et al. [30] have shown that the option value created by political uncertainty significantly depends on how carbon price uncertainty passes through to electricity prices in the event of policy change by testing three scenarios. However, the modified MAR process developed here decomposes the electricity price into two parts: (1) electricity price without carbon pricing, $P_{e,base,t}$, and (2) a component that is the result of carbon price pass-through to electricity prices. The mean reverting part of the model uses reversion speed with volatility values extracted from historical data in the national electricity market (NEM), and assumes these parameters remain constant over the planning horizon. The model then adjusts the average base price, $P_{e,base,avg.,t}$, based on forecast values, growing deterministically. To limit the model to generate only positive values, the natural logarithm of prices is used to estimate the model parameters and simulate price paths by the following equation:

$$\ln(P_{e,base,t+1}) = \ln(P_{e,base,t}) + \eta_e.\left(\ln(P_{e,base,avg.,t}) - \ln(P_{e,base,t})\right) + \sigma_e.\tilde{\varepsilon}_{t,e} \quad (1)$$

where η_e is the speed of reversion, $P_{e,base,avg.,t}$ is the average level of $P_{e,base,t}$, that the level of $P_{e,base}$ tends to revert to, $\tilde{\varepsilon}_{t,e}$ is a standard normal random variable, t denotes the time stage and σ_e is volatility in electricity prices.

$P_{e,base,t}$ generated by Eq.1 and initial value, $P_{e,base,1} = 42,$ (see Table 1) is input into the Eq.2 to calculate the total price of electricity. Actually, the decomposition of price has been formulated in order to restructure the electricity price path upon any policy regime reconfiguration as it decomposes the monthly average level of prices, $P_{e,t}$, into a monthly base price net from carbon price pass-through, $P_{e,base,t}$, as calculated in Eq.1, and a portion of price resulting from carbon cost $P_{c,t}$:

$$P_{e,t} = P_{e,base,t} + \gamma_t.P_{c,t} \quad (2)$$

with γ_t being the carbon price pass-through rate at time t, and $P_{c,t}$ the average monthly price of carbon permits at time t. Eq.2 has been used by Laurikka (2006) [20] and Laurikka and Koljonen (2006) [21], however, in contrast to their assumptions, $P_{e,base,t}$ is the monthly average price of electricity less carbon cost pass-through for each time period t, resulting from forecasted values. Likewise, γ_t is the emission factor of a marginal plant in the power system that results from merit-ordering. This study uses forecasted γ_t and $P_{e,base,avg.,t}$ values from policy scenario modelling performed by the Treasury [26, 27].

The model assumes that percentage changes in the carbon price in a short period of time are normally distributed to simulate carbon price paths with a geometric random walk (GRW) process:

$$P_{c,t+1} = P_{c,t} + \mu_c . P_{c,t} + \sigma_c . P_{c,t} . \tilde{\varepsilon}_{t,c} \tag{3}$$

where μ_c is the drift parameter and σ_c is the price volatility. Similar to Yang et al. [30], climate change political uncertainty is modelled inclusively by carbon price. To model the short term correlations between the price of carbon permits and electricity prices in the market, the error terms of the two price processes are correlated. A covariance/correlation matrix has been used to generate linearly correlated data.

To represent the effect of carbon price jumps that result from carbon policy repeal, simulation of the carbon price paths is complemented with a downward jump to zero that has a known probability at certain future times within the decision horizon. The customized model developed here is similar to the one-sided version of carbon price shock model by Yang et al. [30]. Experiments can be conducted by either manipulating the probability of the jump or the time stage in which the jump occurs.

$$P_{c,t_j} = \begin{cases} 0 & , \ r(t_j) < p_j \\ P_{c,t_j} \ (from \ Eq.3), & r(t_j) \geq p_j \end{cases} \tag{4}$$

with $r(t)$ being a random number generated by a random number generator with a uniform probability distribution that is between 0 and 1, and where p_j denotes the probability of a jump occurring at the known jump time t_j. Parameters used in the stochastic modelling of the state variables are presented in Table 1. Technological data for CFST and CCGT plants collected from AETA 2012 and ACILTasman [28] are shown in Table 2.

Table 1
Parameters for price paths modelling

Parameter	Unit	Value
Initial electricity price	A$/MWh	42 [a]
Electricity price volatility	per annum	1.344 [b]
Carbon price volatility	per annum	0.0287 [c]
Electricity price reversion speed	-	0.54 [b]
Correlation coefficient between carbon and electricity price	-	0.7 [d]
Decision horizon (or converted plant life)	years	40
Nominal rate of return	%	9.48[e]
Inflation rate	%	2.5[a]

[a] Data from the Treasury modelling, see references [26, 27]
[b] Electricity price model parameters extracted from historical price data from 1999 to 2012 in the National Electricity Market, NSW, Australia
[c] Similar to Fuss et al. [10] data is taken from GGI scenario database, International Institute of Applied System Analysis, see reference [31]
[d] Similar to Szolgayová et al. [12], a further investigation of the model also shows that it does not affect the direction of the results.
[e] Data form ACIL Tasman report, see reference [28]

Table 2
Power plant data for the CFST and the CCGT plants

Parameter	Unit	CFST	CCGT
Nominal capacity	MW	400	400
Availability	%	83	83
Auxiliary	%	3	3
Sent-out electricity	MWh	2803200	2803200
Emission intensity	tCO2e/MWh	1	0.368
Thermal efficiency (as gen.)	%	33.3	49.5
Fuel consumption	GJ/Year	31441297	21151418
Fixed O&M	A$/year	19,400,000	3,880,000
Variable O&M	A$/year	3,363,840	11,212,800
Capital cost (typical)	A$/kW	2,300	1,062
Remaining life	years	40	-
Economic life	years	50	40
Part of coal plant used in conversion	%	33.3%	-

Availability and auxiliary usage are assumed to be similar in both plants to limit the results of the model that are specifically sensitive to emission rates and efficiencies, allowing outputs to be comparable to each other. It is also assumed a typical 400MW CCGT generation train consists of a 267MW gas turbine coupled with a 133MW steam turbine. Hence, in a typical coal plant conversion, approximately one third of the coal plant's asset value (one steam turbine unit) is used in the converted plant.

A backward dynamic programming technique is applied by starting at the latest decision point and working back to the beginning year, comparing the value of exercising the conversion, the abandonment or taking no action options versus the continuation value, to obtain the optimal exercise policy in order to maximise the sum of the discounted expected future cash flows. The method to obtain the optimal actions resembles the procedure explained in detail by Yang et al. [30, 32], except that the Longstaff and Schwartz [24] valuation method is used to calculate optimal investment rules. To summarize the method developed in this paper, a number of random electricity and carbon prices are simulated for N replicated paths, for each time stage t ($0 < t \leq T$), the investor solves the problem by comparing the value of exercising the conversion, $V_{Conv,t}^{ex}$, abandonment, $V_{AB,t}^{ex}$, or taking no action, $V_{NA,t}$, options for each price path i ($i = 1, \dots, N$) to the expected value of continuing running the CFST for another time stage. The investor exercises the optimal choice only if the expected value of exercising the optimal choice is greater than the expected value of continuing for another period. The continuing value can take an infinite number of potential values (due to uncertainty in the future). Longstaff and Schwarz suggest replacing that quantity with an estimate from a regression model.[6] To run the regression model, discounted optimum values, $e^{-r.\Delta t}.V_{t+1}^{*}(i)$, estimated from the last time stage are used as response variables, and each generated price path at time t represents an explanatory data point. The regression equation for a polynomial basis function with degree of 3 used in this study is:

$$e^{-r.\Delta t}.V_{t+1}^{*}(i) = \beta_0 + \beta_1.P_{e,t}(i) + \beta_2.P_{e,t}(i)^2 + \beta_3.P_{e,t}(i)^3 + \beta_4.P_{c,t}(i) + \beta_5.P_{c,t}(i)^2 + \beta_6.P_{c,t}(i)^3 + \beta_7.P_{e,t}(i).P_{c,t}(i) \quad (5)$$

[6] For a detailed explanation of this method and choice of regression model refer to [24, 33].

After determining regression coefficients, β_k $(k = 0,1, \dots ,7)$, the value of continuing from every state for the underlying simulated prices at time t is approximated and the optimum action for each path simulated is identified.[7] This process is repeated backward from time T, as the boundary condition, to present time $(t = 1)$. Optimum actions taken in these steps form an optimal cash flow matrix with a number of N replicated paths. Discounting all cash flows with an appropriate discount factor and averaging over N simulated paths, the extended net present value, $eNPV$, is obtained.

The Monte Carlo approach to value the investment options has already been applied by Yang et al. (2008) [30], Fuss et. al (2008) [10], Szolgayová et al. (2008) [16], and Zhou et al. [13], however, in contrast to the two stage strategy extraction and picking decisions, the least square method applied in this study delivers the results in a single backward process.[8] The output of the least square Monte Carlo method is a distribution of optimal investment timing along with the extended net present value. To evaluate the value of the option to wait, OV, an estimate of the traditional DCF method standard net present value of the investment decision, $sNPV$, is required as shown by Eq. 6:

$$eNPV = sNPV + OV \tag{6}$$

To take optimum action and estimate $sNPV$ based on DCF analysis, for all simulated price paths, the NPV of converting the existing CFST plant is obtained over the decision horizon and is averaged over N simulated paths, $sNPV_{Conv.,t}$. The optimum standard net present

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[7] There is a controversy over the number of basis functions, Longstaff and Schwarz have argued that the choice of basis functions does not make a significant difference while Glasserman [34] has taken an opposite view. For the purpose of this study, a test of various polynomials showed that the results would not be affected significantly. Moreover, a precise valuation of the option problem is not required here.
[8] The convergence of the simulation algorithm was tested by saving regression functions estimated from one set of price paths and then applied to another set of paths to run the simulation forward. The results were approximately equal, indicating a successful simulation algorithm. This two stage run of simulation mimics the method used by Blyth et al. [22] and Fuss et al. [10].

value for the exercise of the abandonment option is also estimated and the option with the higher value is nominated for exercise. It should be stressed that the DCF methodology presented here uses the simulated price paths used by the ROA method. By choosing the same inputs for both models, the point of difference in their results remains in how the ROA technique accounts for the flexibility that investors have when making investment decisions.

For estimation of the salvage value of the old plant, it is assumed that the plant can be sold for a portion of its book value. The market value of the plant will be affected by the carbon price level and the probability of policy repeal. As a result, a simple linear model is developed to estimate the salvage value of the coal plant $SV_{Coal,t}$ as a function of the probability of a policy repeal, p_j, the carbon price to break even carbon price ratio, $\frac{P_{c,t}}{\bar{P}_{c,t}^{B.E.}}$, the jump time, t_j, and the book value,

$$SV_{Coal,t} = BV_{Coal,t}.A.B \qquad t<t_j \tag{7}$$

$$A = 1 - \frac{P_{c,t}}{\bar{P}_{c,t}^{B.E.}}(1 - p_j)$$

$$B = 1 + \left(\frac{\left(1 - \frac{P_{c,t}}{\bar{P}_{c,t}^{B.E.}}\right)}{A} - 1 \right) . \frac{t_j - t - 1}{T - 1}$$

A double declining balance (DDB) depreciation method is used to calculate the book value of the coal plant over the planning horizon, $BV_{Coal,t}$. For $t \geq t_j$, $B = 1$, and A reduces to:

$$A = 1 - \frac{P_{c,t}}{\bar{P}_{c,t}^{B.E.}} \qquad t \geq t_j$$

To calculate $\bar{P}_{c,t}^{B.E.}$ for each price path it is assumed that at each time stage t the present value of revenues less the present value of non-carbon costs equals the net present value of emissions. Therefore,

$$\bar{P}_{c,t}^{B.E.} = \frac{\sum_{i=t}^{T} \pi_{NA,i}^{non-carbon} . e^{-r(i-t)}}{q_{Coal,c} . (T - t + 1)}$$

where $\pi_{NA}^{non-carbon}$ is net operating cash flows neglecting emission costs of the power plant.

Coal plant steam turbine modules are assumed to face more wear and tear over time, so the investor must pay an excess amount of capital cost to convert an older steam turbine module in the converted plant as modelled by the following equations:

$$K_{Conv,t} = K_{GT,t} + K_{ST,t}$$

$$K_{ST,t} = \alpha_{Conv.} . (SV_{Coal,1} - SV_{Coal,t})/2$$

Where $\alpha_{Conv.}$ denotes part of the existing CFST used in the converted plant. $K_{GT,t}$, $K_{ST,t}$ and $K_{Conv,t}$ are gas turbine capital cost, transferred asset value from the CFST to the CCGT and total capital expenditure required for conversion, respectively.

3. Results

Two independent policy scenarios were assessed in this paper: (1) the current established CEA program, and (2) the HCP policy scenario developed in Treasury modelling. The starting carbon price and its drift rate assumptions are listed in Table 3.

Table 3
Carbon policy scenario parameters

Parameter	Unit	Scenario "HCP"	Scenario "CEA"
Initial carbon price [a]	A$/tCO2	30	23
Carbon price drift rate	-	0.087	0.045

Data derived from the Treasury forecast [26, 27]

Forecast data for γ_t and $P_{e,base,t}$, used for the simulation of electricity price paths, was taken from Treasury modelling [26, 27] and for simplicity average values within each year were used.[9]

Each scenario was investigated through three stages.

1. Optimisation under perfect foresight (i.e. deterministic modelling), an evaluation of the economic feasibility and optimum timing of the option to convert the plant in the absence of political and market uncertainty.
2. Optimisation under market uncertainty, where electricity and carbon price volatilities were added to the model to simulate the effect of market uncertainty.
3. Optimisation under market and political uncertainty, where the effect of policy repeal was studied for various anticipated arrival times in the future. Each policy scenario was run 15×11 times, i.e. across 15 expected arrival stages from 18 to 102 months (in 6 month increments) and across 11 jump probabilities ranging from 0 to 1 in increments of 0.1. For each run, the option value of waiting for a resolution of policy repeal uncertainty was compared to the standard NPV to derive the OVR decision criterion (see Section 3.3).

3.1.Stage one: Optimisation under perfect foresight (deterministic modelling)

In this situation, use of the standard $NPV > 0$ decision criterion would trigger an immediate conversion to a CCGT plant at time $t = 1$. However, there is an opportunity cost of immediate investment that is related to the higher returns that could be attained through delayed investment. The ROA technique explicitly indicates that maximum profits are obtained when investment in the CCGT plant is delayed for 180 months. A rational investor

[9] Emission intensity of the marginal plant can be calculated based on the technology mix available in each year and the merit ordering. However, in the context of the current analysis a constant average value within each year has been assumed based on the results of the treasury model [26, 27].

would convert the plant at this time. Relatively low carbon prices near the beginning of the planning horizon make the CFST plant initially more profitable in comparison to early CCGT plant conversion.

These results are sensitive to natural gas prices as shown in Table 4. Under the high gas price scenario two, investment in the CCGT plant is hindered by the high price of natural gas, altering the optimum decision from conversion to abandonment at time period 465, when its current operations cease. Note that for the remaining analysis in this study natural gas price scenario one is assumed.

Table 4
Natural gas forecast price scenarios (A$/GJ)

Scenarios	2012	2020	2030	2040	2050	2100
(1) Medium price [a]	4.63	5.86	7.86	10.07	12.89	44.31
(2) High price	6.36	10.44	18.26	23.37	29.92	102.86

[a] Based on North NSW prices forecasted by [28] and a multiplier index of 1.06. For a detailed description of the multiplier index refer to this reference.

In the HCP scenario, due to the higher starting point and drift rate associated with carbon prices as compared to the CEA case, the optimum action recommended by ROA technique was to exercise conversion of the plant at time stage 72 months. Note there is not a significant value in delaying the investment decision as the OVR shows (see Table 5, $OVR = 3.4\%$), the higher carbon price causes a rational investor to immediately exercise the conversion.

3.2.Stage two: Optimisation under market uncertainty

Electricity and carbon price volatilities were introduced in stage two of the modelling, with the number of iterations, N, set to 1000. From this modelling, none of the iterations indicated that abandonment of the CFST plant was optimal. In the case where an iteration did not involve plant abandonment as the optimal result, that result was allocated to one of eleven bins shown in Fig. 1, Panel 4. Similarly, none of the iterations indicated ‘no action’, i.e. that the optimal decision was to continue with production from the CFST plant. The bulk of the iterations indicated that the optimal decision was to convert to a CCGT plant in the first 1-4 years of the planning horizon. As such, compared to the stage one modelling results, price volatility tended to expedite conversion to the CCGT plant. This finding was consistent with the observation of Fuss et al. (2008) that imperfect foresight results in a different optimal strategy to that which would be employed under perfect foresight. The distributions of modelled MAR electricity and GRW carbon price paths were positively skewed, i.e. mean prices above long-term median prices. Even though long-term median electricity and carbon prices in both cases were the same, favourable deviations in the stochastic modelling rewarded early investment. To put it another way, volatilities in the carbon and electricity price paths added value to the project, given that ROA accounted for these deviations in the valuation process.

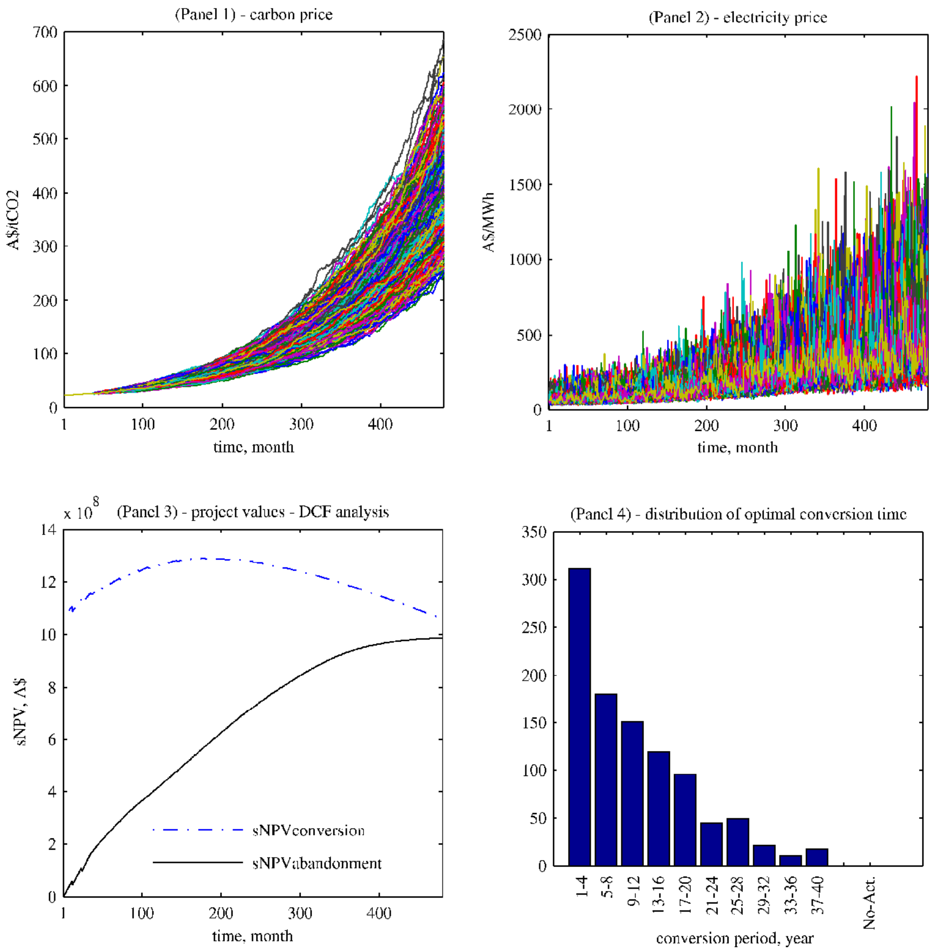

Fig. 1. Model output for optimization of timing of the investment options (CEA Scenario-Market Uncertainty).

Panel 3: DCF technique recommends conversion of the plant immediately ($at\ t = 1$) as $sNPV_{Conv.,1} > 0$.

The results of the analysis for the HCP scenario were similar to those for the CEA scenario, suggesting that the optimum decision under market uncertainty was to convert the plant early in the planning horizon, 1-4 years. To compare the effects of market price uncertainty on the two scenarios (CEA and HCP), Table 5 lists the different project values, with corresponding option premium measures. Market price uncertainty increased the value of the project in both cases by ~20% when compared with the results of the deterministic analysis. In the HCP scenario, where the OVR was very low, there was little value in delaying the plant conversion investment, as the higher carbon price eroded cash flows more significantly than under the CEA scenario.

Table 5
A Comparison of the different project values for the CEA and the HCP scenarios

	$eNPV$	$sNPV_{Conv.,1}$	OV	OVR%
CEA scenario				
Deterministic	1.02×10^{9}	8.12×10^{8}	2.11×10^{8}	26.0%
Market uncertainty	1.21×10^{9}	1.05×10^{9}	1.59×10^{8}	15.1%
HCP scenario				
Deterministic	9.91×10^{8}	9.58×10^{8}	3.29×10^{7}	3.4%
Market Uncertainty	1.21×10^{9}	1.20×10^{9}	8.18×10^{6}	0.7%

3.3.Stage three: Optimization under market and political uncertainty

In this stage of the analysis a series of 15 expected policy jump arrival times, evenly distributed over the domain $18 \leq t_j \leq 102$, were analysed with constant probabilities of jump p_j. Note that the $eNPV$s as estimated by the ROA exceeded the $sNPV$s estimated by the standard DCF method. To measure the magnitude of the value of holding the option and waiting to exercise, an option value ratio (OVR) was defined as the percentage of option value (OV), as calculated by Eq. 6, to the project's value $sNPV_{Conv.,1}$. Intuitively, the OVR's magnitude represented the premium gained by delaying the investment until a portion of the uncertainty was resolved; a higher OVR suggested a higher premium relative to the base case valuation. By comparison, the $sNPV_{Conv.,1} \geq 0$ decision criterion, which if met would trigger immediate investment at time stage $t = 1$, did not provide any information about the optimal timing of the decision.

Typically, a higher expected probability of policy repeal decreased both the $eNPV$ and $sNPV$ of the plant conversion. However, the value of holding the option increased with higher expected probabilities of repeal. The option value ratio ranges from ~15 % at a 0% probability of repeal, to ~138% at a 100% probability of repeal. A low OVR may not alter the decision that would have been made using the $sNPV$ criterion. A visual inspection of the distributions of optimum exercise times such as those presented in Fig. 2 indicated that OVRs of 25% or lower corresponded to immediate exercise of the investment decision; low OVRs imply low premiums for delaying the decision. The 25% threshold margin is a judgement inferred from the full set of distributions (of which Fig. 1 presents a subset) for CEA scenario. For example, at $p_j = 10\%$ and $t_j = 54$ the first panel in Fig. 2 shows a single significant peak at the beginning of the planning horizon which indicates immediate investment. Conversely, in Panel 3, where the $OVR = 41.6\%$ there is not a single significant peak at the beginning, rather the majority of cases suggest delaying the decision. The optimal decision cannot be derived from the diagram because expected $eNPV$ is a weighted average of all the iterations of each simulation.

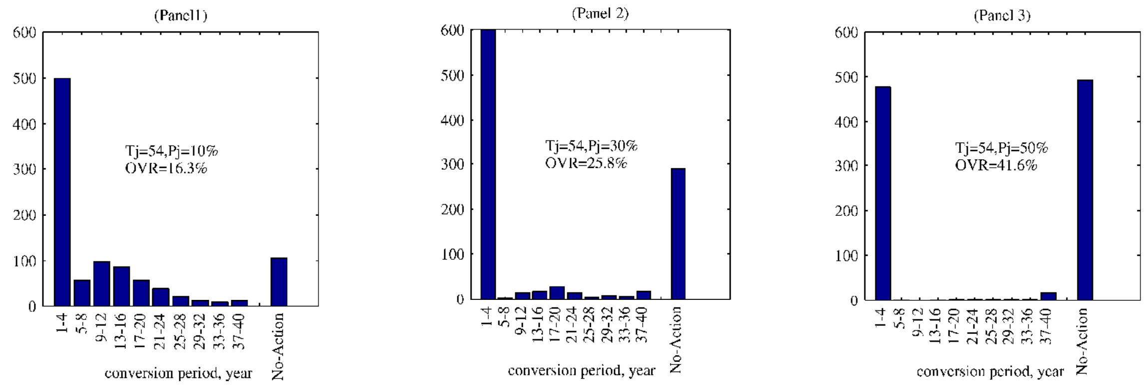

Fig. 2. A comparison of the optimal exercise times (CEA scenario)

Fig. 3 provides a visual representation of the relationship between OVR, probability of repeal and the expected month of repeal for 162 runs of the simulation. It shows that higher repeal probabilities, occurring at earlier expected policy repeal times, resulted in higher OVRs. In other words, larger option premiums were attained by waiting until the expected policy repeal time for the resolution of uncertainty when the probability of repeal was relatively high and/or the expected repeal time was relatively early. Realistically, the more distant the expected repeal time, the more difficult it would be to make a subjective judgement over the probability of repeal. Therefore, the main focus is on the short or mid-term expected policy repeal times. However, long-term expected policy repeal times were still incorporated in the model.

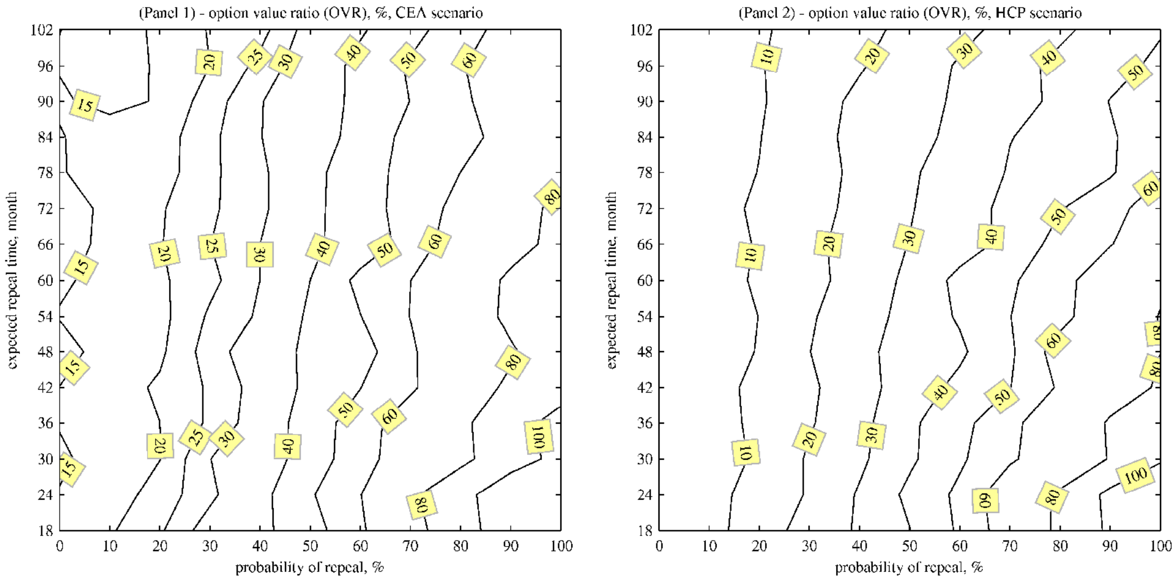

Fig. 3. Option value ratio (OVR) calculated for various expected policy collapse time stage and probability for CEA scenario (Panel 1) and HCP Scenario (Panel 2)

Under both the CEA and HCP scenarios the model generated similar results. A higher expected probability of repeal decreased both the $eNPV$ and the $sNPV$, as well as increased the value of holding the option. Panel 2 of Fig. 3 provides an OVR contour plot of the results for the HCP scenario. Again, a higher probability of repeal, coupled with an earlier expected policy collapse time, resulted in higher OVRs. These results show that the closer in time a change in policy is expected, the higher the perceived risk by the investor, and consequently the decision to convert the plant may be delayed until after the legislative repeal, which agrees with previous findings by Blyth et al. [22] and Fuss et al. [10].

A comparison of Panels 1 and 2 of Fig. 3 reveals that the OVR surface for the HCP scenario lies under that of the CEA scenario. This provides insight into how the carbon pricing level may affect the timing of the investment; for any given probability and expected time of policy repeal, the investment decision was less likely to be delayed under the HCP scenario. In other words, OVR values were scaled down under the assumption of a more ambitious carbon price trajectory. This result of the modelling show that political uncertainty can have a substantial impact on the decision to delay carbon price exposed investments. This finding complements that of Reedman et al. [8] who argue that political uncertainty prior to the implementation of carbon pricing also affects investment decisions. Therefore, political uncertainty prior to the implementation of carbon pricing creates an incentive for investment that is aligned with the objectives of the policy, whereas political uncertainty after implementation of carbon pricing creates a disincentive that works against those same objectives.

4. Conclusion

There is a chance that the change in the Australian Federal Government will result in repeal of the current CEA carbon pricing legislation, exacerbating the market uncertainties already affecting electricity and carbon price forecasts. This paper developed a real options valuation model to assess the effect of such political uncertainty on electricity generation investment decisions. The value of flexibility associated with the timing of the investment decision was recognised through the use of a ROA.

The model developed herein can be used with a range of technologies and options to assess the effect of political risks and various price scenarios. For the purposes of this paper, a hypothetical situation was developed where the restructuring of stochastic carbon and electricity prices was factored into the net cash-flows of an incumbent CFST plant and an augmented CCGT plant. The option to convert the CFST plant to the cleaner CCGT plant offers natural insurance against the risk of high future carbon, and thus electricity prices. In this modelling the uncertainty over the CEA's future was simulated by probabilistic jumps in the carbon price that flowed through to electricity prices via an emission intensity factor. These jumps, representing the occurrence of legislative repeal, were modelled at a range of various arrival times and probabilities over many iterations. Three levels of carbon and electricity price uncertainty were analysed for both the CEA and the HCP scenarios. From this modelling, a quantitative factor, OVR, was introduced to provide investors with a decision criterion that can be used to recommend the optimal investment timing.

The research results suggest that political uncertainty after the implementation of carbon pricing impedes the decision to switch to cleaner technologies. However, the results also suggest that this effect can be mitigated by high carbon prices. These findings should be seen in the light of the limitations of the study. A principal limitation of the study was that the model was developed for a single investment option. Further work is planned to look at a portfolio of investment options, including greenfield investments to hedge against the looming uncertainty over carbon pricing policies.

Two recommendations to policy makers arise from the analysis presented in this paper. The first is that those who are serious about meeting carbon policy objectives should try to create a more stable political environment, as controversy over the survival of carbon pricing legislation may be detrimental to a desired investment in cleaner technologies. The second is that setting a higher carbon price may dampen the effects of political uncertainty should a more stable environment not be found.

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