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# Climate policy uncertainty and power generation investments: A real options-CVaR portfolio optimization approach

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**Abstract**

A decision support framework has been provided to assist investors with long-term decision-making for investment choices in power generation assets under uncertain climate policy. The model combines real options analysis and modern portfolio optimization theory. A long-term correlation between carbon and renewable portfolio standard certificate prices is used to model the interaction of climate policies, with a case study being developed to investigate the optimal choice of capacity additions to an existing mix of power generation assets in Australia. The findings show that there is potential for investors to fully hedge their existing fossil fuel based generation assets through the addition of on-shore wind capacity. The model developed allows for (1) the investigation of investment risk and return under uncertain climate policies, and (2) the study of interaction among green policies.


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*Keywords:* Real options, CVaR portfolio optimization, Electricity generation investment, Climate policy uncertainty

## 1. Introduction

The focus of investors interested in power generation has been captured by restructuring of the electricity sector, climate change and energy security. These factors have rendered '*a time of unprecedented uncertainty for the energy sector*', as recognized by the World Energy Council (WEC) [1]. In the context of this volatile decision-making environment, orthodox investment decision techniques have not been successful in accounting for the influence of uncertainty, nor have they captured the proactive responses of managers to changing market conditions. There is a gap between the intuitive reflections of decision-makers and traditional investment decision techniques in uncertain situations.

Decision criteria such as the levelized cost of energy (LCOE) are not sufficient to rank feasible projects in an unbundled power market setting where investment risk passes back to investors. The


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generation of electricity has become competitive and a risk-return balance has emerged as a key investment driver. Additionally, electricity generation has proved to be a GHG intensive industry, thus, policy makers have intervened in the imperfect market to attempt to internalize negative externalities. However, a balanced, stable and predictable policy framework has been beleaguered by two diverging points: (1) a divergence between profit maximizing private firms and social welfare, and (2) a global disagreement over the issue of climate change [2].

Numerous studies have applied portfolio optimization theory in power generation investment decision-making under uncertainty. Mean variance portfolio theory (MVP) and relative variations incorporating various risk measures have been widely used [3-10].[a] A second stream of studies, more relevant to the study in this paper, has recently attempted to combine real options analysis (ROA) with portfolio optimization theories to address the effects of irreversibility and uncertainty in power generation investments. The standard deviation of the payoffs for investment alternatives, value at risk (VaR) and conditional value at risk (CVaR) are common risk measures applied in the relevant problem formulations. In more recent works in this stream, Fortin et al.[11] and Fuss et al.[12] developed a static model for a portfolio of various generation technologies using CVaR as the measure of risk. They use total discounted income divided by total discounted cost as the measure of return as they focus on the effect that $CO_2$ price volatility has on the composition of a generation portfolio. Szolgayová et al. [13, 14] have tried to extend the static portfolio problems to a dynamic formulation. This extension is non-trivial since the understanding of the correlation of portfolios at different time points is not intuitive.

This study builds on the second research stream as it attempts to provide a decision support framework to assist power generation investors in identifying optimal capacity additions to an existing generation mix. In comparison with other works we use an Australian case study to focus on:

(1) power mix rebalancing; identification of optimal capacity additions considering an existing portfolio,
(2) capacity constraints; the results of capacity constrained model are superimposed on a conventional budget constrained portfolio optimization model, and
(3) the interaction between the renewable portfolio standard mechanism in Australia, called the Large-scale Renewable Energy Target (LRET), and carbon pricing policy.

The case study is developed to assess the effect of post-implementation uncertainty, regarding the future of carbon pricing policy, on investment decisions in electricity generation in Australia. A choice of renewable and non-renewable technologies as additional capacity is available to the investor that can be appended to their existing mix of coal-fired and combined cycle gas turbine (CCGT) investments.

## 2. Method

A portfolio in the context of power generation planning is specified as either generation capacity holdings or value weights in each individual generation technology from the asset universe, herein called technology choices. The decision model is developed at three distinctive levels, as shown in Figure 1.

Level 1, models stochastic variables representing uncertainty in the framework; carbon, electricity and renewable energy certificate (REC) prices. The modelling uses the expanded carbon and electricity price models previously described by the authors [15, 16]. However, in contrast to the MRV process, the average base price of electricity in this work is modelled through a regime switching model developed by Higgs and Worthington [17] for the state of New South Wales, Australia. The level of discretization of the underlying variables has been expanded to average daily values (from a monthly average) to increase

[a] See [10] for a recent and detailed literature review of the application of modern portfolio theory to power planning.

the precision of the model and to provide insight into how the model can be further developed to incorporate hourly or half-hourly spot prices.[b]

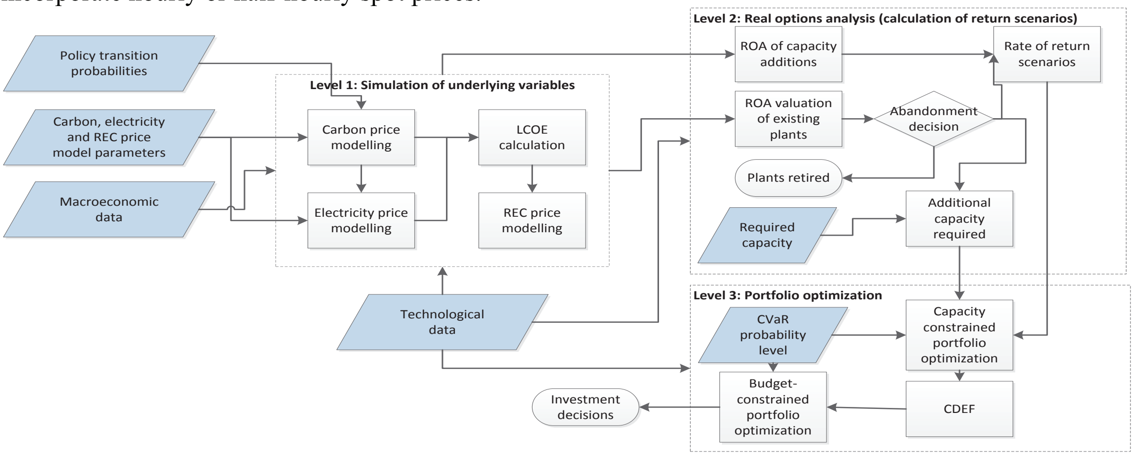


Figure 1. The three-level investment decision-making model

In Australia, the LRET mandated by the Renewable Energy (Electricity) Act 2000 established a target for large-scale renewable electricity supply to ramp up to 41000 GWh by 2020. This scheme requires electricity retailers to purchase large-scale green certificates (LGCs), also called RECs, from the renewable energy technology (RET) generators, which have a dollar value per MWh. Ideally, the value of RECs should reflect the difference between the lowest LCOE for power generation among RETs and the average wholesale price of electricity [18, 19].[c] A model is also required for REC prices as the investment portfolio includes RETs. Although REC prices, $P_{REC,i,t}$, are traded in a market, it is assumed here that their average price is equal to the difference between the least generation cost among RETs, $LCOE^*_{i,t}$, and the average wholesale electricity price in the market at each time stage $t$, $\bar{P}_{e,t}$, calculated for all simulation replications, $i$, as defined below,

$$\begin{aligned} P_{REC,i,t} &= LCOE^*_{i,t} - \bar{P}_{e,t} \\ LCOE^*_{i,t} &= \min\{LCOE_{g,t} \big| \, g \in RETs\} \end{aligned} \tag{1}$$

where $\bar{P}_{e,t}$ is derived from the electricity price model developed.

In Level 2 an ROA is conducted to specify the proxies for portfolio return and risk. The difference between the present value (PV) of net operating cash flows and investment expenditure is divided by the investment expenditure to define an investment return proxy. This measure of return is similar to the holding period (rate of) return (HPR) introduced by Seitz [21]. To calculate net operating cash flows a real option analysis (ROA) model is used. It is assumed that the investor invests in the relevant choice of technologies; however, they have the option to abandon the plant at an optimal point in the future.[d] For this purpose, the American option valuation model developed in our previous works [15, 16] is used. In the case of existing plants, the investment expenditure is replaced by the market value of the incumbent

[b] To include peak generators with relevant spark-spread option in the model, a finer time discretization of electricity prices along with a unit commitment model is required.

[c] see a recent study of the LRET policy in [20].

[d] Other range of options such as retrofitting with carbon capture and storage (CCS) units can be considered to address the potential flexibility of fossil fuel burning plants in mitigation of GHG emissions.

assets. It is assumed that the market values of the incumbent plants are equal to the PV of their net operating cash flows averaged over all simulated replications.[e] Consequently, HPR for incumbent plants is zero. The ROA valuation framework suggests that the investor operates the existing plants over their remaining life unless the expected PV of net operating cash flows is sufficiently close to zero. In the latter case, the investor is better to abandon the existing plant and replace it with an optimal choice of generation technologies. This assumption is plausible considering that in the case of existing assets, a substantial part of the financial risk is eliminated as the investment expenditure is already sunk. Any decision relating to existing generation plants has to be justified by their expected future cash flows.

Identification of portfolios in terms of budget (or value) weights is conventional, although in generation planning, meeting electricity demand or required capacity is the major concern of investors. Therefore, capacity holding in each individual asset gains more significance in comparison with a budget constrained specified portfolio. The problem takes the form of a complex optimization problem to meet a required demand/capacity within the constraints of a conventional budget. The portfolio optimization is thus approached in two steps (as shown in Level 3, Figure 1): (1) a portfolio optimization based upon a link between investment expenditures/asset values and capacity/demand values, herein referred to as the capacity/demand constrained optimization, and (2) a conventional budget constrained portfolio optimization. In the first step, a portfolio optimization determines the range of efficient portfolios subject to capacity/demand limitations, herein referred to as the constant demand efficient frontier (CDEF). These portfolios are the result of adding new capacity to the existing generation mix with their risk estimated based on the minimum CVaR at a range of feasible constant returns. At this stage, the total budget required to invest in each technology choice is determined. The budget weights of the portfolios on the CDEF are calculated based on the results of step (1) and are fed into the results of a conventional budget constrained portfolio optimization in step (2). This enables the comparison of CDEF portfolios with portfolios on the conventional efficient frontier (EF) obtained by the budget constrained portfolio optimization.

In step (1), the objective function for a CVaR portfolio optimization problem is written as,

$$\min_{\boldsymbol{b}_g} CVaR_{1-\varepsilon} \tag{2}$$

where $\boldsymbol{b}_g$ is the budget/value invested in technology choice $g$, and $\varepsilon$ is the probability level that is set at $\varepsilon = 0.95$. The result of this optimization provides the CDEF for the choice of technologies. In order to run the portfolio optimization under capacity/demand constraints, a relationship between the investment budget and generation capacity is required (as shown in Eq. 3). It is assumed that existing plants supply electricity as long as the PV of their net operating cash flows is not close to zero (a threshold can be defined to decide if a plant should be abandoned, however, in this study the limit is set to zero). Finally, the constraints are written as,

$$\begin{aligned} &\sum_{g=1}^{G} b_g \frac{\alpha_g}{mv_g} = D \quad , \quad b_g \geq 0 \\ &b_g \frac{\alpha_g}{mv_g} = S_g \quad \forall\, g \in E \end{aligned} \tag{3}$$

[e] Many profitable investments cannot be sold for their present value of net operating cash flows. The selling transaction of these assets is subject to incurring a substantial loss. Further work might be conducted to integrate the risk associated with asset selling into portfolio optimization framework.

where $E$ is the set of all existing power plants, $S_g$ is sent-out capacity, $D$ is required capacity, $\alpha_g$ is output factor adjusted for auxiliary load, and $mv_g$is the unit market value (in A$ per nominal capacity installed) for technology $g$. The second constraint limits the lower bound of budgeted investment expenditure (i.e. $b_g \geq 0$).

In step (2), a conventional budget-constrained portfolio optimization is conducted as per the objective function and constraints below,

$$\min_{w} CVaR_{1-\varepsilon} \qquad s.t.\ \ \boldsymbol{w}'\boldsymbol{\iota} = 1 \tag{4}$$

where $\boldsymbol{w}$ is a vector of technology budget weights and $\boldsymbol{\iota}$ a vector array of ones. The result of this optimization provides the conventional EF for the choice of technologies. As mentioned, the CDEF, i.e. the results of the capacity-constrained portfolio optimization, will be overlaid on the results of this stage.

The CVaR optimization is conducted through a reformulation suggested by Rockafellar and Uryasev [22], who replace the objective function with an auxiliary function that has more tractable computational properties.

## 3. Case study

It is assumed that an investor's existing generation mix consists of 5 incumbent plants operating at time $t = 1$ (the beginning of the planning horizon): $2{\times}400$ MW black-coal steam turbines with a remaining economic life of 10 years (bkCFST10), $2{\times}400$ MW black-coal steam turbines with a remaining economic life of 20 years and 30 years (bkCFST20, bkCFST30), and $1{\times}374$ MW combined cycle gas turbine plant with a remaining economic life of 30 years (CCGT30). The total sent-out capacity of these existing plants amounts to 1579.2 MW.

To meet a total required sent-out capacity of $C_1 = 2000$ MW, the investor has a choice of investment in a mix of the following technologies: (1) black coal-fired steam turbine (bkCFST), combined cycle gas turbine (CCGT), on-shore wind (onWind), or non-tracking photovoltaic (nonTrackPV). Table 1 shows technological data for the above technology choices.

The modelling in the case study offers a distinctive perspective that reflects an investor's exposure to political uncertainty, both carbon pricing and post-implementation uncertainty i.e. the investor is exposed to an established carbon pricing policy (and volatility in carbon prices) but with an uncertain future (post-implementation uncertainty) regarding the stability of that policy. The model also assumes the existence of a relatively stable renewable portfolio standard regulation to subsidize power supply from renewable sources (in the Australian context this is the LRET mechanism[f] ).

Table 2 summarizes the statistical characteristics of HPR distributions for the choice of existing and new technologies. These HPR distributions are derived from the result of the ROA model explained in section 0, and are used as return scenarios in the portfolio optimization stage. Notice that green-field CCGT investment has the highest HPR dispersion among the choice of new technologies and existing assets. While it has the largest maximum HPR value, the magnitude of its negative outcomes makes it a risky investment, as also indicated by its VaR and CVaR. Green-field wind investment has the highest expected HPR, with relatively stable and non-negative HPR outcomes. This signals that wind generation may be a dominant investment among the efficient portfolios to be calculated in the next section, whereas CCGT, bkCFST and nonTrackPV technologies have less potential for inclusion in efficient portfolios.

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[f] Other perspectives may include uncertainty over the future of LRET mechanism, as is a current issue in Australian climate policy. However, in order to maintain our focus on the framework development we intend to consider such viewpoints in further studies.

Table 1. Typical technological data for the choice of technologies

| Technology | Nominal Capacity (MW) | Capacity Factor (%) | Auxiliary (%) | Emission Intensity ($tCO_2$/MWh) | Thermal Efficiency (%) | FOM (mA$/y) | VOM (mA$/y) | Economic Life (year) |
|---|---|---|---|---|---|---|---|---|
| bkCFST | 400 | 83 | 3 | 1 | 33.3 | 19.40 | 3.36 | 40 |
| CCGT | 374 | 83 | 3 | 0.368 | 49.5 | 3.63 | 10.48 | 40 |
| onWind | 100 | 38 | 0.5 | 0 | - | 3.98 | 3.94 | 30 |
| nonTrackPV | 100 | 21 | 0 | 0 | - | 2.50 | 0 | 40 |

Technological data collected from [23-25]. All other data including fuel prices, macroeconomic, and parameters used in price models are similar to that used in the authors' previous work [16].

Table 2. Statistical characteristics of HPR distributions

| Technology | mean | min | max | skewness | VaR | CVaR |
|---|---|---|---|---|---|---|
| bkCFST | 0.110 | -0.482 | 0.318 | -1.600 | -0.062 | -0.178 |
| CCGT | 0.151 | -0.528 | 1.990 | 1.617 | -0.438 | -0.477 |
| onWind | 0.367 | 0.279 | 0.460 | -0.425 | 0.285 | 0.283 |
| nonTrackPV | -0.252 | -0.321 | -0.188 | -0.499 | -0.319 | -0.320 |
| bkCFST10 | 0 | -0.155 | 0.237 | 0.5777 | -0.122 | -0.136 |
| bkCFST20 | 0 | -0.383 | 0.162 | -0.328 | -0.085 | -0.149 |
| bkCFST30 | 0 | -0.508 | 0.098 | -2.993 | -0.109 | -0.219 |
| CCGT30 | 0 | -0.581 | 1.235 | 0.850 | -0.500 | -0.535 |

The result of the capacity-constrained portfolio optimization is shown in Figure 2, Panel 1. The CDEF is depicted by the solid line.[g] Note that the efficient portfolios on the CDEF do not have the same budget, which is in contrast to the EF from a classical budget-constrained portfolio optimization. Thus, the CDEF line does not represent the positively sloped risk-return trade-off found in the conventional EF as estimated by budget-constrained optimizations.

In order to understand how the optimization model has identified optimal portfolios, 1000 random portfolios are generated and depicted on the same graph (Figure 2, Panel 1). These randomized portfolios are generated in such a way that the total sent-out capacity equals the required amount. A further examination of the randomized portfolios reveals that those with a higher CVaR and lower return, moving to the lower right, are mainly dominated by nonTrackPV generation capacity. Towards the upper left, portfolios gain a higher return and lower CVaR risk by the addition of onWind generation to the existing mix of technologies. The upper end of the CDEF line consists of a portfolio of existing assets and 100% of the additional capacity requirement met by onWind. Aside from the extremes of the CDEF line there is a third portfolio region where the portfolio CVaR risk approaches zero. In this region the investor has the opportunity to almost fully hedge their set of existing assets in the face of uncertain carbon pricing policy through their choice of additional capacity. Generally, a significant portion of such portfolios consists of

[g] Note that the CDEF frontier is not necessarily a continuous smooth curve, given the limited size of the asset universe in our case study. In this analysis, however, we have chosen to draw the solid line based on 20 optimal portfolios to appropriately present the results.

onWind generation, although this capacity is quite variable (385 to 730 MW of nominal capacity), and the remainder is allocated to other green-field investment choices under various proportions.

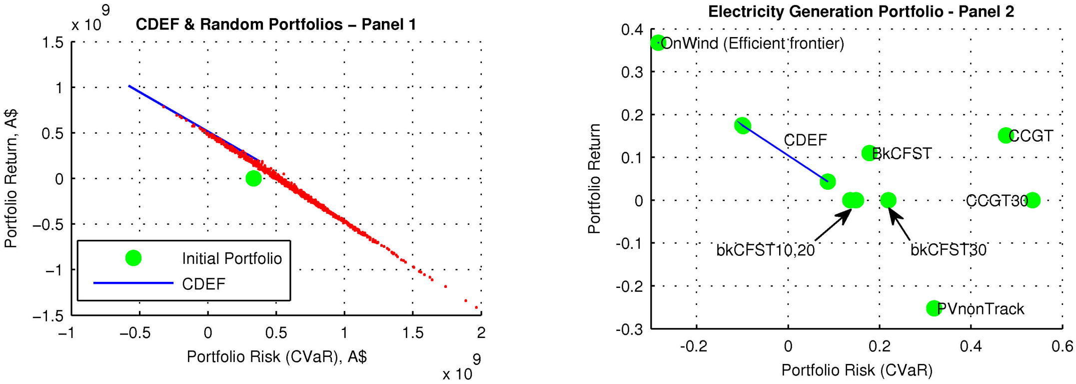


Figure 2. The results of portfolio optimization: Panel 1, capacity-constrained portfolio optimization; Panel 2, budget-constrained portfolio optimization

Finally, by superimposing the results of the capacity-constrained optimization, i.e. the CDEF portfolios, onto the conventional budget-constrained portfolios, we arrive at a model to better conceive the results of the capacity constrained optimization. For this purpose, the portfolio capacity weights are converted to value weights. The results of this step are shown in terms of risk-return dimensions in Figure 2, Panel 2. Note that the risk and return scales on this graph are different from those on Figure 2, Panel 1. In Figure 2, Panel 2, portfolios are scaled based on their rate of return. The associated risk is the portion of those returns in terms of CVaR (rather than total return and absolute amount of CVaR in Figure 2, Panel 1).

The efficient frontier, calculated among green-field investments, consists of 100% onWind generation. For comparison, other generation assets are shown on the same scale. Note how wind generation has the highest rate of return among the choice of generation assets. One of the most noticeable results, however, is in how the direction of CVaR risk in wind generation differs from other technologies. This is the result of a constantly positive return distribution for wind generation across all the various outcomes.

## 4. Conclusion

A decision support framework has been developed through a combination of a CVaR portfolio optimization and ROA and assists investors in evaluating their investment decisions for additional capacity, considering their existing power generation assets and uncertainty regarding the future of climate policies. The findings show that opportunities may exist for investors to fully hedge their generation assets against potential policy changes. A lower cost renewable technology, i.e. onshore wind generation, looks to be an attractive choice of technology for additional capacity. This result, however, should be seen in the light of shortcomings of the research, which is based on a particular case study.

In conclusion, REC prices are correlated to carbon and electricity prices. This represents the interaction between the emission trading and the LRET scheme in Australia. Notwithstanding the ideal model developed here, the findings suggest that a clash of objectives between these GHG reduction schemes can be detrimental to the achievement of socially optimal GHG abatement costs. The model developed in this research has the potential to be combined with reliability analysis models and expanded to a dynamic model. The model developed for the correlation between carbon and REC prices can be further extended in order to investigate the effect of interaction among climate policies. The uncertainty regarding the future of the LRET mechanism in Australia can also be added to the model.

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Conclusions and recommendations noted in this paper are those of the authors and are not necessarily the views of the Murdoch University, Curtin University, the Centre for Exploration Targeting or Ernst & Young.

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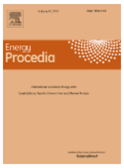


**Biography**

Mahdi ShahNazari is a PhD candidate at Murdoch University, Department of Physics and Energy, Perth, Australia. His research interests include energy and resources economics, finance and strategic investment decision making. He holds a bachelor’s degree in chemical engineering and a master of business administration (MBA).