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Using Renewables to Hedge against Future Electricity Industry Uncertainties – An Australian Case Study

by

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Abstract

A Monte-Carlo based generation portfolio modelling tool was employed to assess the expected costs, cost risk and greenhouse emissions of different generation portfolios, given conditions of highly uncertain gas prices, carbon pricing policy and electricity demand. The Australian National Electricity Market (NEM) was used as a case study, with input assumptions based upon widely accepted future technology cost estimates, electricity demand, fuel costs, carbon prices and their associated uncertainties as well as hourly wind and photovoltaic generation. Outcomes were modelled for 396 possible generating portfolios, each with 10,000 simulations of possible fuel prices, carbon prices and electricity demands. In 2030, the generation portfolio with the lowest expected cost was found to include 60% renewable energy. Increasing the renewable proportion to 75% only very slightly increased expected generation cost (by $0.2/MWh), but decreased the standard deviation of cost (representing the cost risk) by 40%. Increasing the renewable proportion from the present 15% to 75% renewable energy by 2030 is found to decrease expected wholesale electricity costs by $17/MWh. Fossil fuel intensive portfolios are found to have substantial cost risk associated with high uncertainty in future gas and carbon prices. For a 15% renewable energy portfolio, the standard deviation in cost (cost risk) is calculated to be $28-30/MWh. Cost risk is reduced significantly to $8-9/MWh with a 75% renewable portfolio. Therefore, renewable generation is found to effectively mitigate cost risk associated with gas and carbon price uncertainty, with each addition of 10% renewable energy reducing the cost risk by an average of 20%. This is found to be robust to a wide range of carbon pricing assumptions. This modelling suggests that policy mechanisms to promote a managed increase in renewable generation towards a level of 75% by 2030 would minimise costs to consumers, and effectively mitigate the risk of extreme electricity prices due to uncertain gas and carbon prices.

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1. Introduction

There is broad agreement that electricity markets around the world face unprecedented uncertainty on many fronts, such that "uncertainty is the new certainty" (Bhavnagri, 2013). International gas markets are rapidly evolving, climate change concerns continue to grow, carbon pricing has an unclear future, and the emergence of embedded generation and demand-side efficiency technologies has upset long term trends in demand projections in many nations. These multiple sources of uncertainty create great challenges for planning investment decisions in long-lived electricity infrastructure over coming decades.

The National Electricity Market (NEM) on the east-coast of Australia, which covers around 90% of Australian electricity demand (ESAA, 2013), provides a useful case study for exploring these trends. Uncertainty in this market is particularly pronounced in three key areas. Firstly, three major joint ventures are currently in the process of establishing export facilities for Liquefied Natural Gas (LNG) on the east coast of Australia. When these facilities are commissioned (during the period 2014 to 2017), domestic gas prices are anticipated to "rise sharply… as prices converge towards LNG netback prices" (BREE, 2012b). However, the nature of such international price linking remains unclear and international gas markets are themselves highly uncertain looking forward. This creates significant uncertainty over Australia's domestic gas prices over the medium to long term. At present gas-fired generation plays a minimal role in Australia's electricity sector, but with pressure to reduce greenhouse emissions a greater focus on investment in gas-fired plant is possible.

Secondly, Australia has a highly emissions intensive electricity sector, with in excess of 70% of electricity sourced from coal-fired generation, and contributing around 35% of national emissions (BREE, 2013). To provide a long term signal for low carbon investment, a carbon pricing mechanism was introduced on 1 July 2012 by the former Federal Government.[1] However, the current Government has committed to repealing carbon pricing legislation, creating large uncertainty over the extent and manner in which the electricity sector will need to contribute to emissions reductions in the coming decades. Such uncertainty of carbon pricing policy can have significant impact on the electricity industry in terms of higher societal costs due to suboptimal investment decisions (Nelson et al., 2013).

Thirdly, there is large uncertainty over future electricity demand. Repeatedly defying formal industry projections, demand in the NEM has fallen every year since 2009 due to a number of factors including moderate economic growth, increasing electricity prices, energy efficiency measures, changing industrial competitiveness and hence industry structure and an increased penetration of distributed renewable generation (AEMO, 2012b). Australian planning bodies continue to project future growth, although their consistent failure to make accurate predictions has contributed to growing industry scepticism around the likelihood that this will occur.

[1] This commenced with a fixed price of \$23/tCO_2, with the intention of transition to an emissions trading scheme (ETS) with a floating carbon price from 2015. All dollar values in this paper are real 2013 Australian dollars.

Given the high degree of uncertainty facing the electricity sector, it would appear essential that decision making processes appropriately take into account the wide range of possible futures that may eventuate. In particular, rather than simply selecting the lowest cost investment portfolio based upon central assumptions, a risk management approach that protects against the possibility of extremely adverse industry seems wise. Emerging renewable generation technologies, such as wind and solar, have been recognised as low risk investment options since they do not depend on the use of fossil fuels, and do not produce greenhouse emissions (Bhattacharya and Kojima, 2012). Therefore, the inclusion of renewable technologies in generating portfolios may offer an effective hedge against fossil fuel price and carbon price uncertainty. A key question then, is the additional hedging value of higher penetrations of these renewables.

The study presented in this paper intends to assess the value of investing in large-scale renewable generation, particularly photovoltaic (PV) and wind, in mitigating the impacts of uncertainty in future fossil fuel prices, carbon pricing policies, electricity demand and hence overall electricity costs in the Australian NEM. This paper employs a Monte-Carlo based generation portfolio modelling tool first developed in (Vithayasrichareon and MacGill, 2012) to assess different possible future generation portfolios in the NEM by considering different investment scenarios involving gas and renewable generation for 2030. The study adopts a long-term overall societal perspective focusing on overall industry generation costs, associated costs risks and CO_2 emissions of future generation portfolios without considering issues associated with privately undertaken generation investment.

There have been a number of modelling studies exploring high penetrations of renewable generation in international electricity systems, including New Zealand (Mason et al., 2010) , Denmark (Lund, 2006; Lund and Mathiesen, 2009), Ireland (Connolly et al., 2011), Macedonia (Ćosić et al., 2012) and Portugal (Krajačić et al., 2011). In the Australian context, Molyneaux et al. (2012) modelled the costs and greenhouse emissions of two generation portfolios in 2035 (exploring investment in primarily gas-fired generation or renewable generation respectively). Elliston et al. (2013) modelled generation portfolios of 100% renewable energy in 2030 under high and low cost assumptions. The Australian Energy Market Operator (AEMO) modelled 100% renewable energy scenarios in 2030 and 2050 (AEMO, 2013), and annually undertakes a National Transmission Network Development Plan (NTNDP) which explores a small number of scenarios (two were modelled in the 2012 NTNDP) (AEMO, 2012a). Due to modelling constraints, previous studies have typically focused on a small number of generation portfolios, under a few scenarios (where a scenario incorporates various operating conditions including, for example, carbon and gas prices). While such efforts can have considerable value, these studies consider only a very small subset of the possible generating portfolios that might eventuate over time, and sample only a few of the possible market conditions under which those portfolios may need to operate. Sensitivity analyses (assessing the impact of changes in key uncertain variables) or scenario analyses (modelling holistic alternative scenarios) are sometimes conducted to account for some degree of risk and uncertainty. Despite the value of these methods in exploring future uncertainty, there remain inherent limitations in their ability to appropriately account for very significant and interacting uncertainties over important driving factors (Roques et al., 2006a).

As such, they do not provide a detailed analysis of the future risks associated with particular portfolio choices.

There is a growing body of literature applying generation portfolio analysis concepts to account for risk and uncertainty in generation planning. Some studies explicitly examine the role of renewable energy in reducing the risk of generation portfolios in the electricity industry. For example, Bhattacharya and Kojima (2012) apply a portfolio risk optimisation method to examine how renewable energy can minimise the portfolio risk in the Japanese electricity market. Losekann et al. (2013) examine efficient generation portfolios in Brazil in 2020 by assessing costs, risks and CO_2 emissions under different carbon pricing scenarios. Muñoz et al. (2009) present a model for minimising investment risk and maximising investment return of renewable generation portfolios in the Spanish electricity market. Huang and Wu (2008) apply portfolio theory to assess electricity generation portfolios in Taiwan based on the risk-weighted present value of total generation cost. Similar analysis has been conducted for Ireland (Doherty et al., 2006). These studies have found that replacing fossil fuels with renewable generation can often reduce the risk of generation portfolios. However the majority of these studies only model low to moderate levels of renewable generation without exploring the potential implications of high renewable penetrations.

2. Monte Carlo Based Decision-Support Tool for Generation Investment

The modelling tool employed in this study is intended to complement the existing set of electricity industry modelling tools by incorporating a formal treatment of future uncertainties and assessment of their associated risks.[2]

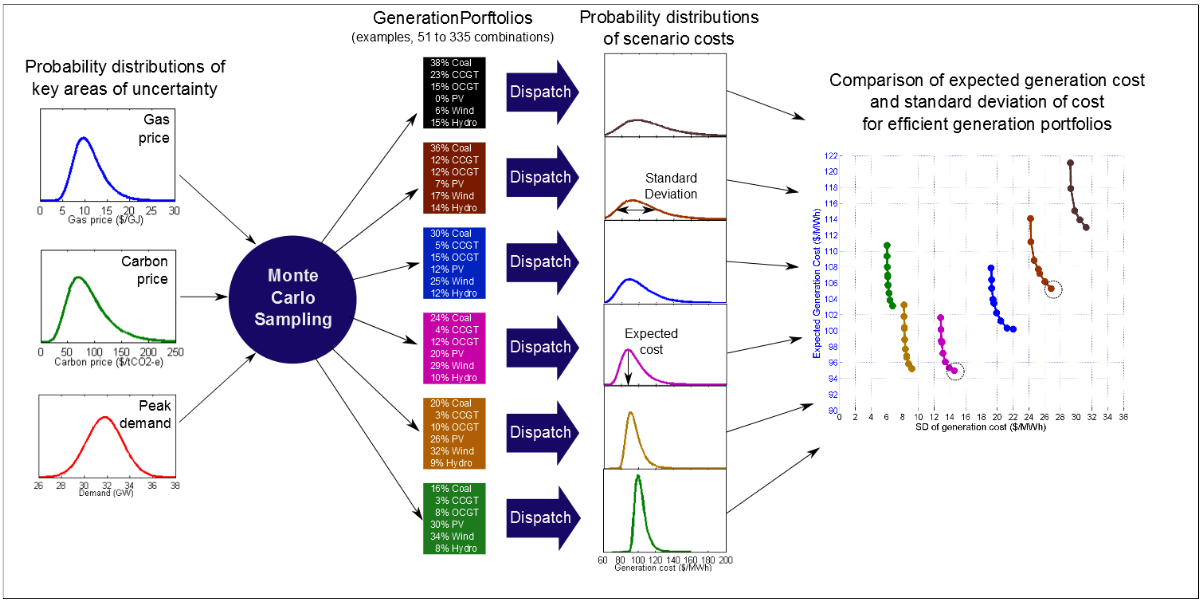
The modelling tool extends the commonly applied load duration curve (LDC) based optimal generation mix techniques by using Monte Carlo Simulation (MCS) to formally incorporate key uncertainties which directly impact overall generation costs and other outcomes, into the assessment. Outputs from the modelling tool consist of many thousands of simulations of overall industry generation costs (annualised fixed and variable costs) and CO_2 emissions for each of the different possible future generation portfolios. These outputs are, therefore, a series of probability distributions that, for relatively simple distributions, can be described as an *expected* future value of annualised industry generation costs and CO_2 emissions, and the *standard deviation* (SD) in these (cost and emissions uncertainty or risk) for each portfolio.

The tool then applies financial portfolio methods to determine an Efficient Frontier (EF) of expected (i.e. mean) costs and the associated cost uncertainty (i.e. SD) for

[2] Notable commercially available tools for generation planning and investment include PLEXOS, MARKAL, WASP-IV and LEAP (Connolly et al., 2010; Foley et al., 2010). These tools rely on deterministic assumptions about highly uncertain future factors such as fuel prices and demand. Expanded assessment methodologies might only include the application of sensitivity and/or scenario analyses. The novel aspects and contributions of this modelling tool are described in detail in (Vithayasrichareon and MacGill, 2012).

each of the different generation portfolios. [3] EF techniques provide a basis for explicitly analysing cost and risk trade-offs among different generation technology portfolios. In particular, the EF is made up of those generation portfolios which offer the lowest expected cost for some level of cost uncertainty. A graphical description of the modelling tool is shown in Figure 1.[4]

Figure 1 - Methodology Monte Carlo based modelling tool.



LDC techniques may use real or simulated demand data. The relationship between time varying renewable generation such as wind and solar, and demand can then be incorporated into the model through the use of residual load duration curve (RLDC) techniques. Here, hourly simulated or measured renewable generation outputs in the time-sequential domain are subtracted from demand over the same time period. This is based on the assumption that variable renewable generation is given the first priority in merit order dispatch due to their low operating costs by comparison with fossil fuel technologies. The resulting residual (net) demand after accounting for renewable generation is then rearranged in descending order of magnitude to obtain a RLDC. It is this curve which has to be met by conventional technologies in the portfolio (Denholm and Margolis, 2007; Doherty et al., 2006; Ummels et al., 2007).

The methodology and mathematical formulation of this modelling tool are described in detail in (Vithayasrichareon and MacGill, 2012). The model has previously been applied to portfolio analysis with wind generation in the context of the NEM (Vithayasrichareon and MacGill, 2013).

[3] The efficient frontier concept is used in the Mean Variance Portfolio (MVP) theory for financial portfolio analysis (Markowitz, 1952).

[4] Since the tool applies MCS techniques, it can support even more sophisticated risk assessments of different generation portfolios such as downside economic risks, value at risk (VAR) and other risk-weighted uncertainty measures. It also does not rely upon the use of a normal distribution to model input uncertainties – any probability distributions can be used.

3. Scenario Descriptions

In this paper, the modelling considers a number of different generation investment scenarios for the NEM in 2030, given assumptions of highly uncertain future fuel prices, carbon prices and electricity demand. These generation scenarios range from investing only in gas generation (no new renewables) to different mixes of renewables and gas investment, through to investing primarily in renewables (with minimal gas). Scenarios with high renewables investment could be driven by factors including expectations of high gas and carbon prices or strong renewable policies. On the other hand, scenarios with high investment in gas-fired generation (with minimal renewables) could occur due to a lack of government support for renewables and an expectation of low gas and carbon prices.

3.1. Generation Investment Scenarios

Four new generation technology options are considered in the model for this study: wind (on shore), utility scale solar PV (single axis tracking), combined cycle gas turbines (CCGT) and open cycle gas turbines (OCGT). The modelling assumes that there will be no new investment in coal-fired generation. There appears to be growing consensus on this given coal generation's high emissions and high capital investment risk (Bloomberg New Energy Finance, 2013). Furthermore, the costs of renewables are becoming increasingly competitive with coal (Bazilian et al., 2012; Bhavnagri, 2013), particularly with a carbon price in place. In addition, the model assumes no new investment in hydro, distillate fuelled plants and cogeneration. Nuclear generation is also excluded as an option; Australia does not have a nuclear energy industry at present, and strong public opposition to the technology seems likely to keep nuclear politically unpalatable in the medium term at least.

Six different investment scenarios for new PV and wind generation were assumed ranging from 0% to 90% combined new PV and wind energy penetration. The modelling assumes that all existing renewable capacity (currently providing an average of 15% of annual energy) will still be in operation in 2030. These investment scenarios and corresponding renewable penetrations are summarised in Table 1. Note that as the renewable penetration level increases, the growing levels of highly variable wind and PV generation does result in growing energy spillage.

Table 1. Different generation investment scenarios.

Renewable Penetration Scenario	Achieved Total Renewable Penetration	% New PV Energy	% New Wind Energy	Spilled PV and Wind	Others (fossil)
15% Renewables	15%	0%	0%	0%	85%
30% Renewables	30%	5%	10%	0%	70%
45% Renewables	44%	10%	20%	1%	56%
60% Renewables	62%	20%	30%	3%	38%
75% Renewables	75%	30%	40%	10%	25%
85% Renewables	83%	40%	50%	22%	17%

The existing NEM generation capacity and possible retirements within this fleet are incorporated as shown in Table 2. As the most emissions intensive generation in the

NEM, existing brown coal is assumed to be entirely retired by 2030 and therefore is excluded from the modelling. Black coal capacity is varied between the portfolios, with the model exploring a range of possible retirements for 2030 (from no retirements to full retirement of all black coal capacity). Existing hydro is assumed to remain in operation at its present levels. All existing gas, distillate, cogeneration, hydro, PV and wind capacity are also assumed to be still operating in 2030. Investment costs of the existing capacity of each technology are considered 'sunk' and therefore are not included in the calculation of annualised industry generation costs.

Table 2. Assumed generation capacity and plant retirements

Technology	Existing capacity in 2013 (GW)[a]	Remaining capacity in 2030 (GW)
Black coal	19.8	Varies from 0 to 19.8
Brown coal	7.3	0
CCGT	2.8	2.8
OCGT	7.4	7.4
Hydro	7.7	7.7
Distillate	0.6	0.6
Cogeneration	0.2	0.2
PV (rooftop)	2.8	2.8
Wind	3	3

[a] includes committed capacity

3.2. Installed generation capacity and portfolio determination

For each renewable penetration scenario, the installed capacity of PV and wind were determined based on their targeted energy outputs and a capacity factor of 34% and 41% respectively; this accounts for technology improvement over time above present performance levels (AEMO, 2013). Installed fossil fuel (coal and gas) generation capacity was determined using a probabilistic approach to ensure that there was sufficient capacity to meet the expected demand for at least 99.998% of the time during the year. This is consistent with the current NEM reliability standard of 0.002% of unserved energy per year, measured over the long term. Table 3 shows the installed capacity of PV, wind and conventional generation calculated for each renewable investment scenario for 2030. "Residual peak demand" refers to the peak demand of the net load duration curve (after wind and PV have been subtracted in each hour), and thus incorporates the anticipated contribution of wind and PV to meeting peak demand.

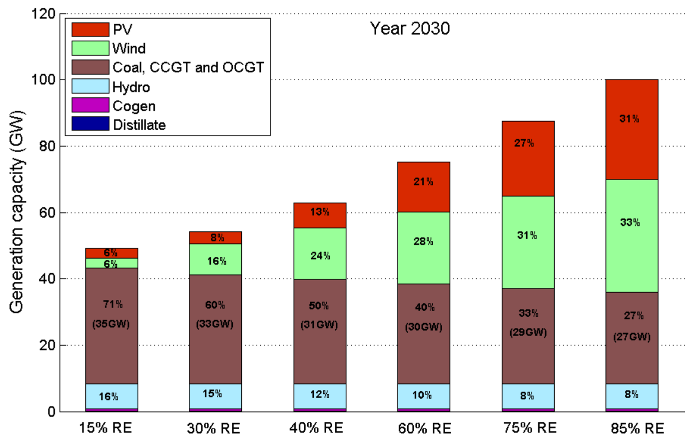
Table 3. Installed generation capacity and residual peak demand for different PV and wind penetrations in 2030.

Achieved Total Renewable Penetration	Investment scenario		Residual peak demand (GW)	Installed capacity (GW)		
	New PV	New Wind		PV	Wind	All other
15% Renewables	0%	0%	30	3	3	44
30% Renewables	5%	10%	29	5	8	42
45% Renewables	10%	20%	27	8	15	40
60% Renewables	20%	30%	26	16	21	39
75% Renewables	30%	40%	25	25	28	38
85% Renewables	40%	50%	24	31	34	36

Remarks: Installed PV and wind capacity includes existing and new capacity

The capacity of each generation technology for each of the renewable scenarios for 2030 is shown in Figure 2. For each renewable scenario, different possible permutations of 'coal, CCGT and OCGT' generation portfolios were considered by varying the share of black coal (existing), CCGT and OCGT in 10% intervals of the combined coal, CCGT and OCGT capacity as shown in Figure 2.[5] This resulted in 66 generation portfolio combinations of coal, CCGT and OCGT for each of the renewable scenarios.[6] For coal, only the existing capacity is considered while the capacity of CCGT and OCGT consists of both new and existing plants. With this approach, the modelling essentially considers different cases of black coal retirements from zero (all plants remain) to 100% (all are retired). The maximum capacity of black coal in 2030 is capped at existing capacity (19.8 GW), with generation portfolios consisting of black coal exceeding this amount removed as infeasible solutions. The amount of existing CCGT, OCGT, distillate, cogeneration, hydro, PV and wind capacity was fixed for every possible generation portfolio, as shown in Table 2.

Figure 2. Installed and the share of technology capacity for each of the investment scenario for 2030.



3.3. Generation Dispatch

For each possible portfolio, generation output of each thermal technology (i.e. coal, CCGT, OCGT, co-generation and distillate) in each period in the LDC (or RLDC) is determined using merit order dispatch based on the short run marginal costs (SRMC) of each thermal technology in 2030.

PV and wind generation is given priority dispatch due to their low operating costs. With this assumption, as noted earlier, PV and wind are considered exogenous and treated as negative load. Hydro generation, however, is relatively unique amongst the technologies being modelled because it is dispatchable, but energy limited. To

[5] The variation is less than 10% of 'total' installed capacity. For example, in the 0% new PV & 0% new wind scenario, the combined share of coal, CCGT and OCGT is 71% (36 GW) of total installed capacity therefore each variation is 7%. Similarly, the variations for the other renewable scenarios are 6%, 5%, 4%, 3% and 3 % respectively.

[6] Total number of possible generation portfolios when combining every renewable scenario is 396 portfolio mixes.

ensure that hydro dispatch within the model was captured appropriately, it was also treated as exogenous to the dispatch. The aggregate hydro generation duration curve (rearranged in order of magnitude) was subtracted from the RLDC in each renewable penetration scenario. With this approach, historical hydro generation patterns were re-mapped onto the new net demand curve, taking account of real operational constraints while better accounting for the fact that the future generation mix will likely be very different from that currently in use, and reordering hydro dispatch by period accordingly. Energy constraints were also maintained at levels considered realistic for future operation (AEMO, 2013a).

To ensure more realistic dispatch outcomes, the modelling assumes a hypothetical minimum of 15% synchronous generation in any one hour period. Synchronous generation is provided by conventional generating plants, which are coal, CCGT, OCGT, hydro, distillate and cogeneration. Previous studies have used this assumption in the NEM, to ensure sufficient system inertia to maintain a stable frequency and satisfy other important system security concerns (such as fault detection) (AEMO, 2013a). This represents the minimum amount to which aggregate conventional generators can be turned down while maintaining system security. Hence, PV and wind generation are 'capped' at 85% of demand in each dispatch interval. For high renewable scenarios, there are periods during which combined PV and wind outputs were greater than total demand. In such cases, energy from PV and wind was spilled. PV was given priority over wind in the dispatch due to the lower variable operating and maintenance costs for PV.

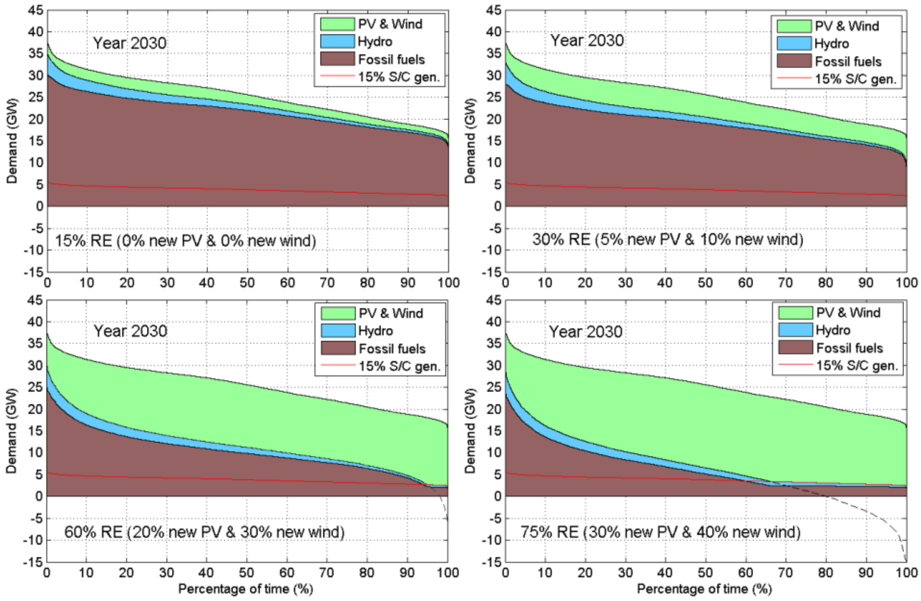
3.4. Demand and generator inputs

Electricity demand, PV and wind profiles

An hourly electricity demand trace for 2029-2030 was obtained from AEMO's 100% renewable energy study in the case of moderate growth, which corresponds to the 50% 'probability of exceedance' (POE) demand projections (AEMO, 2013a). The demand profiles provided by AEMO were based on the shape of the historical 2009-10 demand pattern.

Hourly wind and solar output profiles in 2030 for each renewable investment scenario were simulated based on historical hourly traces of 1-MW on-shore wind and solar PV (single axis tracking) generation in different locations across the NEM provided by AEMO (AEMO, 2013a). To be consistent with the demand profile, 2009-10 data was used as a reference year for these generation profiles. Hourly PV and wind generation was scaled up to the desired penetration level. To construct a hydro duration curve, actual hourly hydro generation output was obtained from AEMO using 2009-10 as the reference year (AEMO, 2012c). Residual load duration curves showing the proportion of PV and wind, hydro and fossil fuel generation for a selection of the scenarios modelled are illustrated in Figure 3.

Figure 3. Residual load duration curve for different renewable scenarios. A minimum of 15% synchronous generation at all times has been assumed. This contributes to additional spilling of the non-synchronous generating technologies (PV and wind).



Generator data

Existing plant parameters were obtained from the AEMO NTNDP report, calculated as the average for all of the existing plant for each technology type (AEMO, 2012a). New entrant generation parameters for each technology were based on the 2030 cost estimates averaged over all NEM regions from the 2012 Australian Energy Technology Assessment (AETA) report (BREE, 2012a).[7] Annualized capital costs were calculated using a weighted average cost of capital of 10%. Expected fuel prices were also based upon an average of NEM regions for the "medium" projection case from (BREE, 2012a). For OCGTs, an uplift of 20% was applied to the gas price in any investment scenario, accounting for their lower purchasing power given smaller generation volumes. The parameters for new generators are shown in Table 4.

Table 4. Generator parameters for existing and new-entry plants.

Parameters	Existing Generators								New Generators			
	Coal	*CCGT*	*OCGT*	*Hydro*	*PV*	*Wind*	*Distillate*	*Cogen*	*CCGT*	*OCGT*	*Wind*	*PV*
Plant life (years)	N/A								30	30	30	30
Overnight capital cost ($kW)	SUNK								1,113	751	1,800	2,200
Fixed O&M cost ($/MW/yr)	55,700	32,300	17,400	56,000	25,000	23,500	14,000	27,000	10,000	4,000	40,000	32,300
Variable O&M cost ($/MWh)	1.3	1.7	8.8	6.9	0	2.7	10.2	2.1	4	10	14	0
Thermal efficiency (%)	34	46	28	N/A	N/A	N/A	27	70	49.5	35	N/A	N/A
Heat Rate (GJ/MWh)	10.6	7.8	12.9	N/A	N/A	N/A	13.2	9.1	7.3	10.3	N/A	N/A
Emission Factor (tCO_2/MWh)	0.96	0.4	0.7	N/A	0	N/A	0.9	0.5	0.4	0.5	0	0
Expected fuel price ($/GJ)	1.9	11.65	14	N/A	0	N/A	32.3	3.8	11.65	14	0	0

Remarks: Note parameters for existing PV plants are based on non-tracking while those for new PV plants are based on single-axis tracking

[7] It was assumed that any existing fuel contracts will have expired by 2030, such that existing generators will be purchasing fuel at the same prices as new generators.

4. Modelling uncertainties

Key uncertain parameters include fuel prices, carbon prices and demand. Lognormal distributions were applied to model future fuel and carbon prices to reflect the asymmetric downside risks associated with their future value. Electricity demand uncertainty was modelled by assuming a normal distribution of residual peak demand in the RLDC for each scenario of renewable penetration. Both lognormal and normal distributions can be characterised by their mean (expected value) and standard deviation (SD).

4.1. Fuel and carbon price uncertainty

The mean and SD of fuel prices were determined from the 2030 fuel cost estimates provided in the 2012 AETA report, which provides projections for low, medium and high price scenarios (BREE, 2012a). The central projection of fuel costs was applied as the mean, while the SD was approximated based on the spread between the low and high case scenarios, illustrated in Table 5. The SDs obtained via this method were approximately equal to percentage of absolute uncertainty provided in the AETA report.

Table 5. Fuel price estimates for 2030

Fuel	Fuel price ($/GJ)			SD of fuel prices	
	Low	Medium	High	%	Absolute
Black coal	1.78	1.86	1.99	6%	0.1
Natural gas	8.81	11.65	15.83	30%	3.5

For carbon prices, the mean and SDs were obtained from Australian Treasury modelling of carbon prices in Australia in 2030 (Australian Treasury, 2011). This modelling included two scenarios: a low carbon price case (corresponding to a 5% reduction in Australian greenhouse emissions by 2020) and a high carbon price case (corresponding to a 25% reduction in Australian greenhouse emissions by 2020), as illustrated in Table 6. The mean carbon price was based upon a scaling between the high and low scenarios (adjusted by CPI to March 2013 dollars) equivalent to a 17% reduction by 2020. This is less than the 19% target recently recommended by the Australian Government Climate Change Authority in the national Targets and Progress Review (Australian Government, 2014). The SD was obtained using the same approach as the fuel prices.

Table 6. Carbon price estimates for 2030

Year	Carbon price ($/t$CO_2$)			SD of carbon price	
	Low	Medium	High	%	Absolute
2030	54	91	115	40%	36

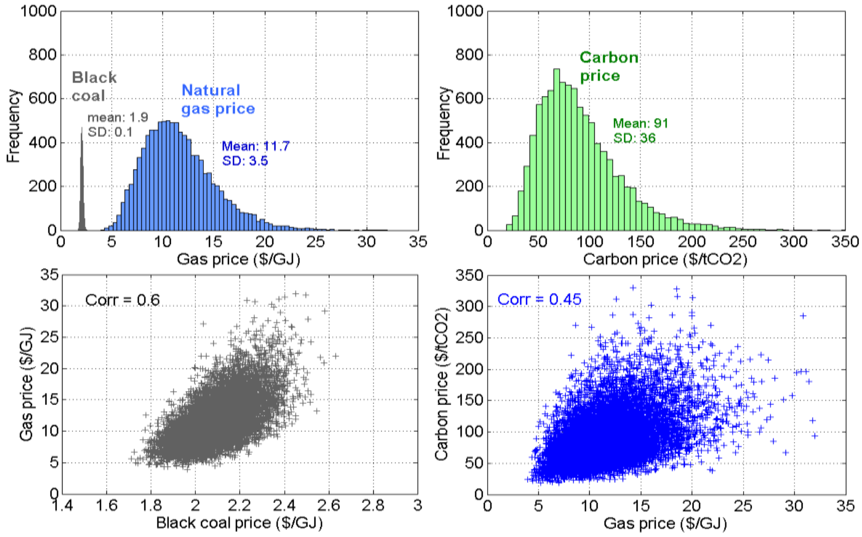
Fuel and carbon prices have exhibited a considerable historical correlation in the EU and UK markets (Roques et al., 2006b). For example, ambitious climate policies might involve high carbon prices that would increase the use and hence cost of lower emission gas in relation to coal, while also resulting in higher electricity prices (Green, 2008). Such correlations may have a significant influence by either moderating or exacerbating the impact of uncertainty. Neglecting them, therefore, can impact overall industry costs and associated cost risks, and subsequently affect the choice of future generation portfolios (Awerbuch and Yang, 2008). Correlations between fuel and carbon prices were accounted in this modelling, estimated based upon historical trends in OECD countries and are shown in Table 7.

Table 7. Correlation coefficients between fuel and carbon prices.

Correlation Coefficient ($\rho_{i,j}$)	Coal price (ρ_{coal})	Gas price (ρ_{gas})	Carbon price (ρ_{carbon})
Black coal price (ρ_{coal})	1	0.6	-0.35
Gas price (ρ_{gas})	0.6	1	0.45
Carbon price (ρ_{carbon})	-0.35	0.45	1

Correlated samples of coal, gas and carbon prices were generated from their marginal lognormal distributions using a multivariate Monte Carlo simulation technique described in (Vithayasrichareon and MacGill, 2012). Histograms showing the distributions of 10,000 simulated coal, gas and carbon prices as well as the scatter plots highlighting their correlations are shown in Figure 4.

Figure 4. Correlated probability distributions and scatter plots of fossil-fuel and carbon prices.



4.2. Electricity demand uncertainty

Demand uncertainty is modelled as the uncertainties in the RLDC for each scenario of renewable penetration based on the POE demand projections in 2029-2030 from AEMO (AEMO, 2013a).

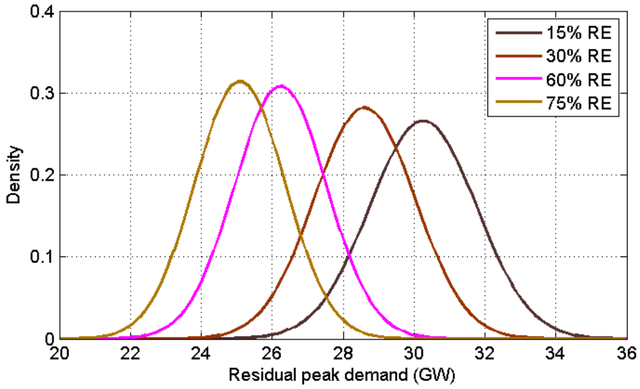
AEMO's forecast 50% POE peak demand was applied as the mean peak demand. The SD of peak demand was determined based the difference between AEMO's 10% POE and 50% POE peak demand estimates. To create the RLDC used in each simulation, the reference RLDC (central projection) for each renewable penetration scenario was then adjusted by scaling the whole net RLDC as required to match the desired peak demand for the particular simulation. The uncertainty in the RLDC was therefore modelled as vertical shifts in the reference RLDC, thus maintaining the same shape.

The peak demand projections for 10% and 50% POE cases and SD for 2030 are shown in Table 8. The probability distributions of 10,000 simulated residual peak demand for a selection of the renewable scenarios modelled are shown in Figure 5.

Table 8. Peak demand projections and standard deviation for 2030

Year	Peak demand (GW)		SD of peak demand	
	10% POE	50% POE	%	Absolute
2030	40.8	38.3	5%	1.9

Figure 5. Probability distributions of 10,000 simulated residual peak demand for different renewable scenarios



There were some instances in which the simulated residual peak demands exceeded the installed fossil fuel generation capacity, resulting in unserved energy. Unserved energy was valued at $12,900/MWh, which was the market ceiling price in the NEM in 2012-13.[8] The cost of unserved energy was included in the overall industry cost in each Monte Carlo run.

5. Results

5.1. Optimal Generation Portfolios for 2030

Figure 6 illustrates the modelling outcomes for a selection of the generation portfolios considered. Each dot represents a single generation portfolio, plotting that portfolio's expected cost (against the vertical axis) and the cost risk (SD of cost, plotted against the horizontal axis), calculated over 10,000 simulations of uncertain fuel prices, carbon prices and electricity demands. Different colours are used to represent the different levels of renewable penetration, ranging from 15% renewable generation (in dark brown) to 85% renewable generation (in green).

Only generation portfolios that lie on the "efficient frontier" for each renewable penetration level have been included on the graph (plot of every possible portfolio is

[8] The market price cap for 2013-2014 financial year is $13,100/MWh.

shown later in Figure 12). Generation portfolios on the efficient frontier represent the most optimal options in terms of cost and cost risk (SD of cost) for each renewable penetration scenario. This means that any portfolio that is not on the efficient frontier is necessarily suboptimal (by the measures calculated in this study). The efficient frontiers within each renewable proportion are steep. This suggests that varying the proportion of coal, OCGT and CCGT generation has minimal impact on the cost risk of a portfolio. Given uncertainties around carbon prices and gas prices, operating on any mix of coal and gas-fired electricity carries a similar level of cost risk. Of the factors considered in this study, only the addition of renewable generation significantly reduces the cost risk.

Figure 6. Efficient frontiers containing optimal generation portfolios for different renewable energy (RE) penetrations. The capacity of fossil fuel technologies in each portfolio is presented (GW, in brackets)[9] as well as the percentage share. The coloured boxes show the proportions of each technology by capacity installed

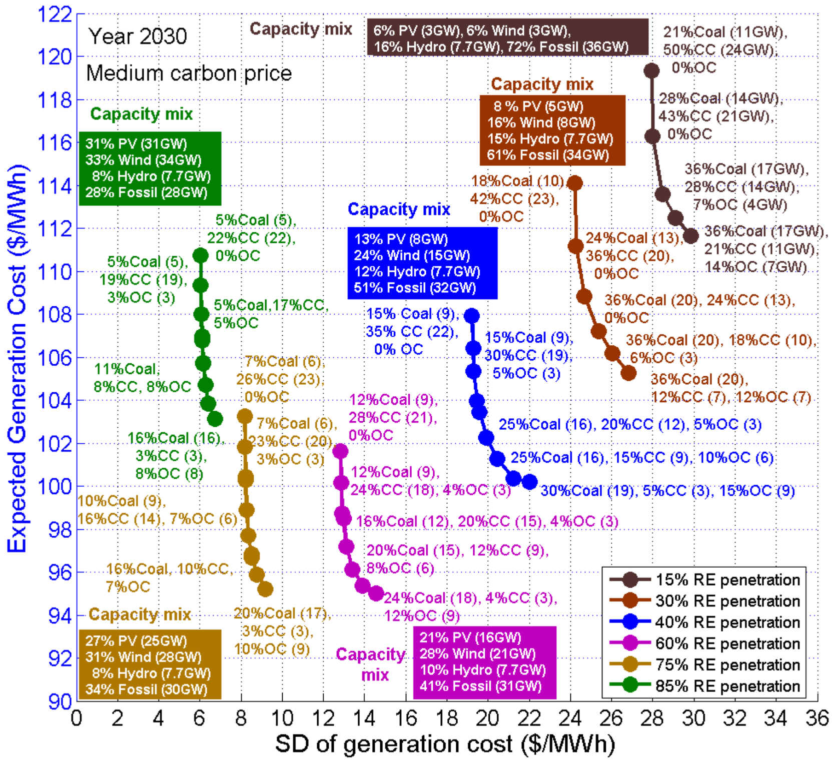


Figure 6 illustrates that in 2030 the generation portfolio with the lowest expected cost is a portfolio with 60% renewable energy. This scenario has an expected generation cost of $95/MWh, and a SD of cost of $15/MWh. Notably, increasing the renewable proportion further to 75% only very slightly increases expected generation cost (by $0.2/MWh), but decreases the SD of cost by 40% to $9/MWh. This is likely to be an attractive option for decision makers, since a very small increase in expected cost produces a large increase in *certainty* around expected cost. This is illustrated in Figure 7, which shows the probability distribution for the lowest cost generating

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[9] Note that the capacity of fossil fuel also accounts for co-generation and distillate with the combined capacity of 0.8 GW. The capacity share of distillate and cogeneration are not explicitly displayed given their low contributions (0.8 GW) but they have been added to the total fossil fuel capacity shown in the coloured box for each renewable penetration.

portfolio at each renewable penetration level considered. Moving from 60% renewable energy to 75% renewable energy significantly reduces the width of the probability distribution, without significantly changing the expected cost of the portfolio.

Figure 7. Probability density distribution of the generation cost for the lowest cost portfolio for each level of renewable penetration considered. The markers on each curve show the expected (average) cost for the distribution. Since lognormal distributions have been applied for the various input assumptions, the expected cost lies to the right of the peak density.

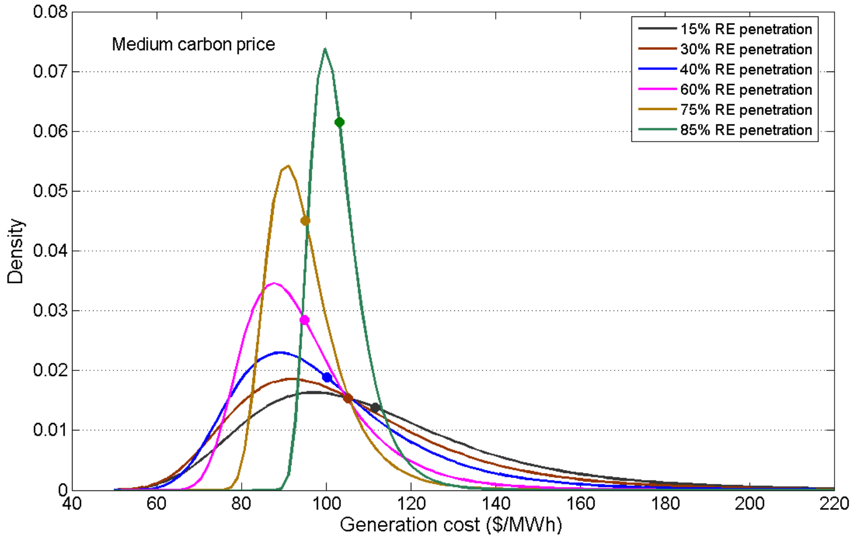
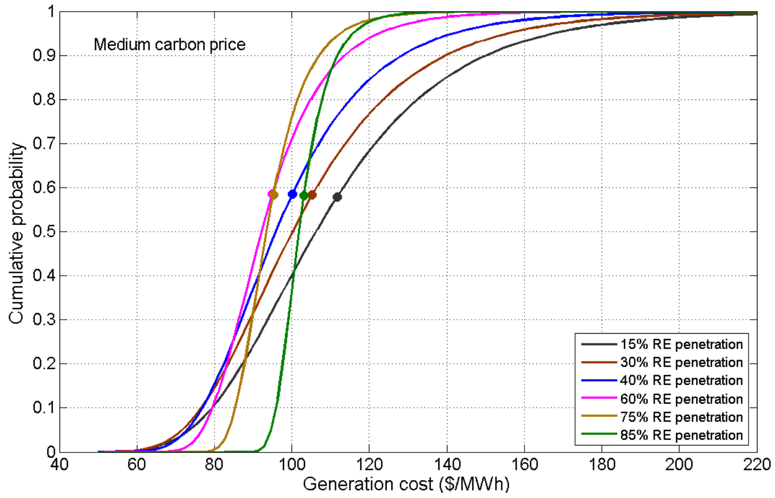


Figure 6 and Figure 7 clearly illustrate that the addition of renewable generation to portfolios is an effective measure to reduce overall cost risk. Portfolios with only 15% renewable energy experience a SD in cost of $28 to $30/MWh, while portfolios with 85% renewable energy experience a SD in cost of only $6 to $7/MWh. Comparing across all levels of renewable penetration, this modelling suggests that each addition of 10% renewable energy reduces the cost risk by around 20%. This is in addition to the fact that the expected cost of 85% renewables is lower than that of scenarios with 15% renewable energy ($103 to $111 /MWh, compared with $112 to $120/MWh for 15% renewables).

This modelling also suggests that increasing the renewable proportion from the present 15% to 75% renewable energy by 2030 would decrease expected wholesale electricity costs by around $17/MWh given current Government estimates of future generation technology, gas, coal and carbon prices. For a typical Australian household with four people (using 7400 kWh per annum) this equates to a cost saving per household of $126 per annum (Acil Tasman, 2011). Furthermore, the SD in cost is reduced by $20/MWh.

To put the cost risk into perspective, Figure 8 compares the cumulative probability distributions for generation costs of the lowest cost portfolios for the renewable energy proportions considered. For the 75% renewable portfolio there is a 90% probability that costs will remain below $108/MWh. By comparison, for the 15% renewable portfolio, there remains a 10% probability that costs could exceed $151/MWh.

Figure 8. Cumulative probability of the lowest cost portfolio at each level of renewable penetration. The markers on each curve show the expected (average) cost for the distribution.



The risk associated with choosing between the 15% and 75% renewable portfolios can be quantified through cumulative probability of their cost differences, as shown in Figure 9. The figure suggests that there is 80% probability that the 15% renewable portfolio would experience higher costs than the 75% renewable portfolio and their cost difference could be as high as $100/MWh. For a typical Australian household that equates to the risk of an additional cost of more than $730 per annum, in addition to the expected cost being $126 per annum higher.

Figure 9. Cumulative probability of the difference in generation cost between portfolios with 15% and 75% renewable energy

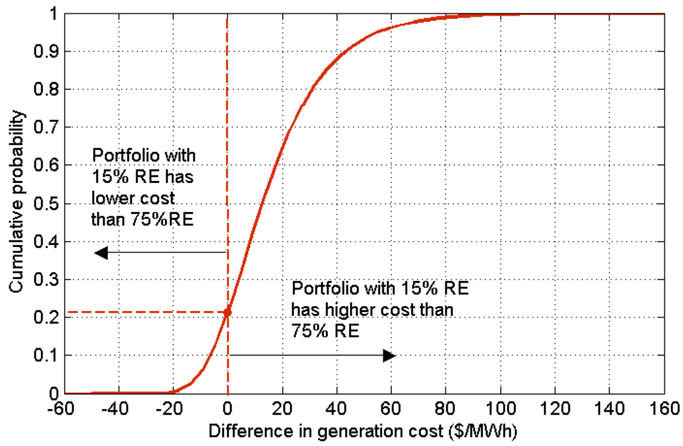


Figure 10 and Figure 11 provide further details on the lowest cost portfolios from each renewable proportion. Notably, there is very minimal retirement of coal-fired capacity across all of the lowest cost portfolios at each renewable penetration level, such that the installed capacity of coal-fired generation remains similar (16-20 GW). This is because the capital cost of existing coal-fired generation has been modelled as sunk. Retirement of coal-fired generation necessitates costly replacement with other types of firm capacity. Therefore, the lowest cost portfolios in 2030 retain a significant proportion of existing coal-fired capacity.

However, as the proportion of renewable generation increases this coal-fired generation operates at a significantly lower capacity factor, reducing from around 0.9 in the 15% renewable scenario to about 0.2 in the 85% renewable scenario. This implies that the existing coal capacity could transition into an intermediate and peaking role in the high renewable scenarios. This reduces greenhouse emissions significantly, and also contributes to the reduction in cost risk by minimising exposure to uncertain carbon prices. The modelling suggests that continuing operation of existing coal-fired plant at low capacity factors is preferable in terms of cost and cost risk, compared with investment in significant quantities of gas-fired plant (which would be exposed to high and uncertain gas prices in addition to carbon prices).

Figure 10. Installed capacity, expected costs, standard deviation (SD) of generation costs (cost risk) and CO_2 emissions of the least cost portfolio in each renewable penetration scenario for 2030. Percentages indicate the % of energy sourced from each technology.

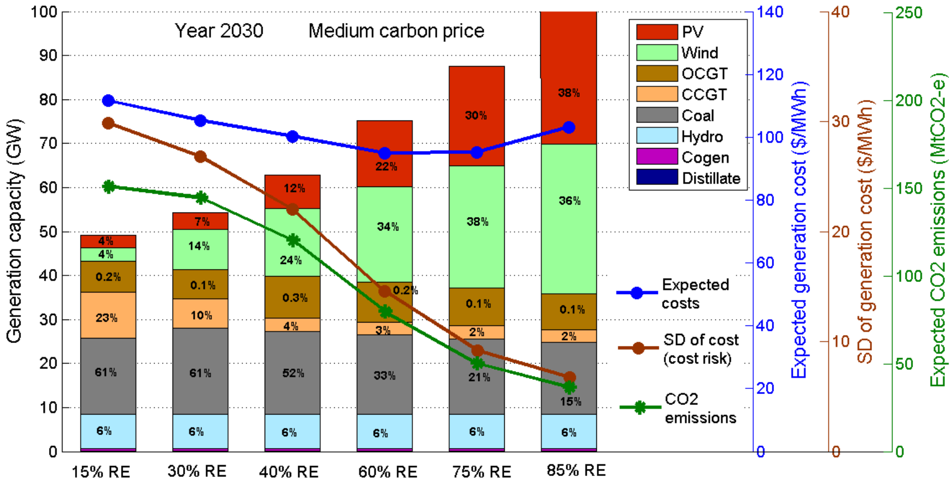
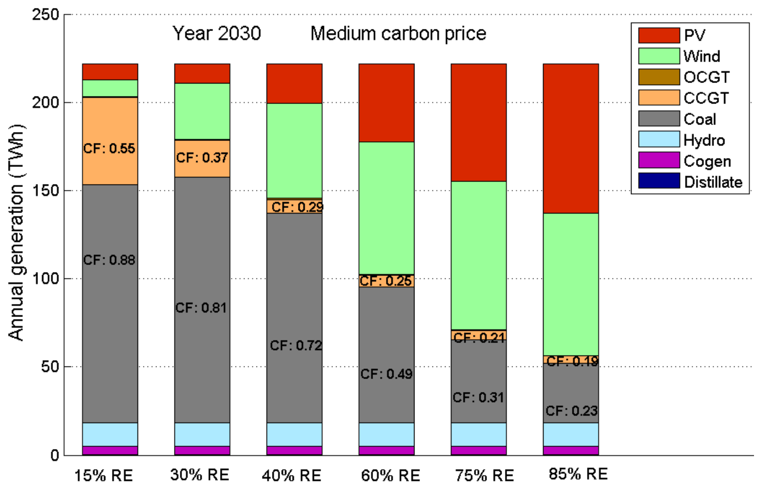


Figure 11. Annual generation and capacity factor (CF) of each technology in the least cost portfolio in each renewable penetration scenario for 2030.



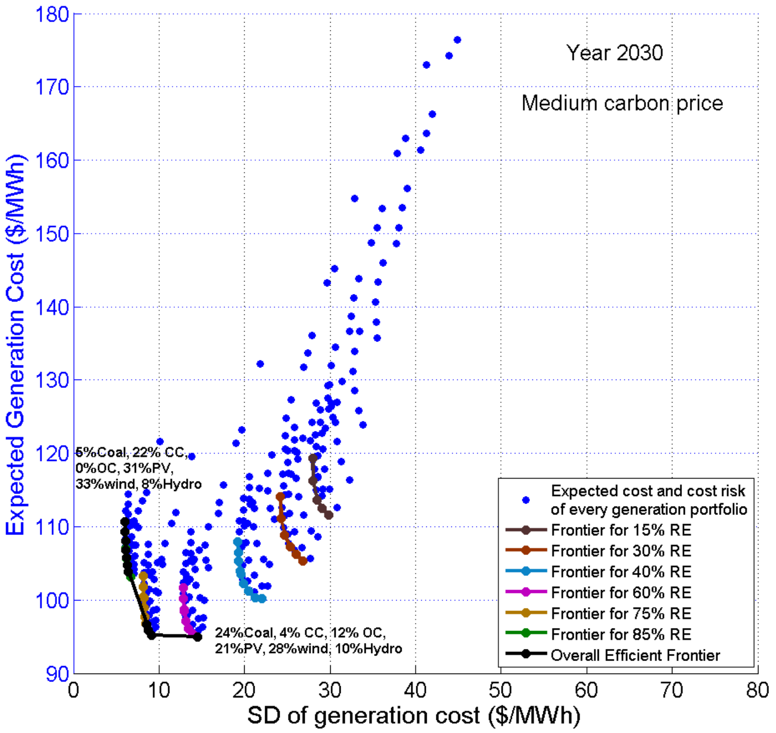
This modelling has not directly examined the technical ability of coal-fired plant to operate at very low capacity factors. It is likely that this plant will need to cycle more frequently, ramp more frequently, and achieve lower turn down rates. The potential for the existing coal-fired assets in Australia to operate in this fashion is likely to be varied. However, analysis of coal-fired plant in the USA suggests that even plant initially designed to operate in a baseload role can move to very flexible peaking operation, at least in some cases (Cochran et al., 2013). This warrants further analysis in the Australian market.

This modelling has also not directly examined the financial potential for coal-fired plant to operate at lower capacity factors. Moving into a peaking role is likely to significantly reduce the revenues of these plants, compared with baseload operation. However, if this capacity provides value to the market (as this modelling indicates it would) it should be able to secure peaking contracts with retailers seeking to avoid exposure to the very high Market Price Cap ($13,100/MWh in the NEM at present) in scarcity periods when wind and solar generation are not operating. It is likely that the asset value would need to be significantly written down, but it is unlikely to be economically rational to retire the plant entirely, provided it can operate in this fashion.

A similar capacity of OCGT plant is installed in all the lowest cost portfolios (7-9GW), providing peaking generation at low cost. By contrast, the proportion of CCGT plant in the lowest cost portfolios decreases as more renewable generation is installed, reducing from around 10 GW to less than 3 GW (which is the amount of existing CCGT capacity) as the renewable penetration increases from 15% to 40%. CCGT are also observed to operate less in scenarios with the highest renewable penetrations; the capacity factor reduces from around 0.6 in the 15% renewable scenario to less than 0.2 in the 85% renewable scenario. This reflects the fact that the higher capacity factor gas-fired plant is of lesser value when bulk energy is being provided by variable renewables. Scenarios with less CCGT plant show the lowest SD in cost; although CCGT plant offers somewhat lower exposure to uncertain carbon prices than coal-fired plant, it is strongly exposed to uncertain gas prices.

Figure 12 shows the expected cost and cost risk of every possible generation portfolio in all of the renewable scenarios. The efficient frontier for each renewable scenario (as shown in Figure 6) and the overall efficient frontier when combining every renewable scenario are also shown. The portfolios on the overall efficient frontier involve those from the 60%, 75% and 85% renewable scenarios, implying these are the most optimum renewable penetrations.

Figure 12. Expected costs and cost risk of every generation portfolio combining every renewable penetration scenario. The overall efficient frontier is shown by the black solid line.



5.2. Sensitivity analysis for different expected carbon prices

The uncertainty around future carbon prices is considerable, and is the source of significant disagreement in Australia at present. Although the previous modelling captures a large degree of uncertainty in possible future carbon prices, based upon modelling by the Australian Treasury (Australian Treasury, 2011), other analysis may disagree on the choice of expected carbon price applied. Some may argue that the present Australian Government is, and is likely to remain, opposed to carbon pricing, which gives a higher degree of certainty that the carbon price applying to the electricity sector will be zero or very low in future. In contrast, others argue that the evidence around climate change is mounting over time (IPCC, 2014), and that a "social tipping point" may be reached in the near future (Wheeler, 2012). This could create a rapid shift towards strong global mitigation activities, and mean that the modelling by the Australian Treasury underestimates the carbon price range that is likely to apply in 2030.

To address the potential for disagreement, the model has been applied with a range of different probability distributions for the carbon price. In addition to the medium estimate of carbon price, which is centered around $91/tCO2 in 2030, a sensitivity analysis considered four alternative probability distributions for expected carbon prices, as illustrated in Figure 13. High and low carbon prices centred around $115/tCO2 and $54/tCO2 respectively were modelled. These prices were centered around the high and low carbon price projections from the Australian Treasury modelling as shown in Table 6 (Australian Treasury, 2011). In addition, a very low carbon price centered around $20/tCO2 was also modelled in order to examine outcomes in the case where there is high confidence of an absence of Government action to mitigate climate change in the electricity sector.

A sensitivity was also conducted for a zero carbon price case; this assumes complete certainty that there will not be any form of carbon price applying to the electricity sector and is included only for comparison purposes.

Figure 13. Assumed probability distributions of different expected carbon prices.[10]

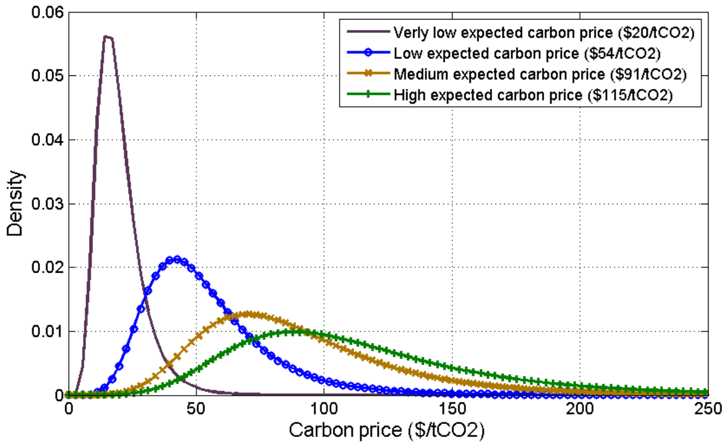


Figure 14 displays the overall least cost generation portfolios for different carbon price probability distributions in 2030. The capacity of coal and CCGT in the least cost portfolios is approximately the same for all of the expected carbon prices; these amounts represent the existing coal and CCGT capacity. No new CCGT is installed in the least cost portfolio at any level of carbon price. This suggests that investment in new PV and wind will be more attractive than new CCGT investment, regardless of carbon price. CCGT plants are exposed to high and uncertain gas prices, and therefore play a very small role in the least cost portfolios, in terms of both capacity and annual generation, even when carbon pricing is not applied.

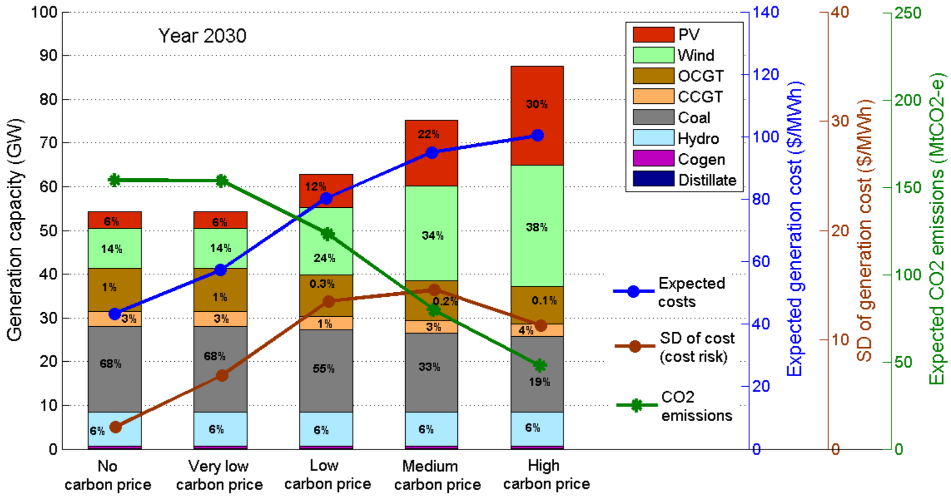
There is minimal difference in the least cost generating portfolios between the zero and very low carbon pricing scenarios. A very low carbon price (i.e. in the range of $20/tCO_2$) does not have an impact on the technology share in the least cost portfolio and the overall CO_2 emissions compared to the case without a carbon price. This implies that a very low carbon price is unlikely to provide sufficient investment incentive for low carbon alternatives and is unlikely to result in significant emission reductions.

It should be noted that the expected generation costs illustrated in Figure 14 should be interpreted with caution, especially when comparing between different carbon pricing scenarios. The cost to generators of paying the carbon price is included in the total cost, meaning that the difference in cost between portfolios is heavily driven by the different carbon price distribution applied in each scenario. The costs illustrated in Figure 14 are included since they represent the likely pass-through of the

[10] Note that for the case without a carbon price, the modelling assumes there is no carbon price uncertainty.

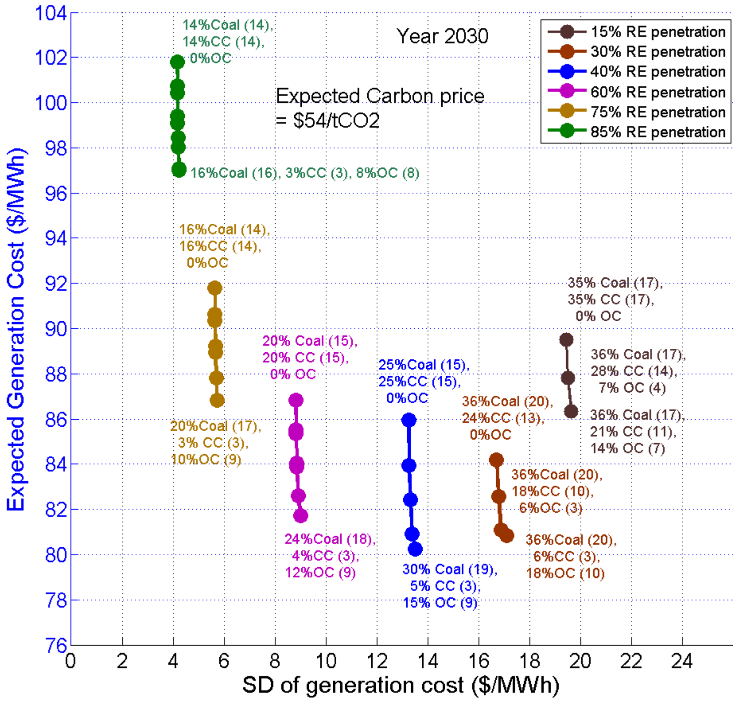
carbon price in electricity prices, but it should be noted that consumers would see this carbon revenue returned in other forms (such as reduced taxation in other areas, or Government investment in public infrastructure). The increasing SD in cost as the carbon price increases similarly is driven by the rising carbon price.

Figure 14. Installed capacity, expected costs, standard deviation (SD) of generation costs (cost risk) and CO_2 emissions of the least cost generation portfolios for different expected carbon prices for 2030. Percentages indicate the % of energy sourced from each technology.



Importantly, even with lower carbon price assumptions, renewable energy still appears to provide effective cost risk mitigation. For example, Figure 15 illustrates the efficient frontier portfolios for the low carbon price sensitivity. It is clear that increasing the proportion of renewable energy significantly reduces the SD of cost, while varying the proportion of coal and gas-fired generation has almost no effect on the SD in cost. Comparing the cost outcomes for all portfolios modelled reveals that the addition of 10% renewable energy consistently reduces the cost risk by around 20%, for any level of assumed carbon price. This indicates that renewables offer an effective hedge against the possibility of extreme prices, regardless of perspectives on future carbon price probabilities.

Figure 15. Efficient frontiers containing optimal generation portfolios for different renewable energy (RE) penetrations for 2030, for the low carbon price probability distribution.



5.3. Modelling Limitations

As with other modelling exercises, these findings need to be considered with appropriate caution since the modelling outcomes are highly dependent on input assumptions, and the modelling tool itself has important limitations. The modelling is static since it only assesses the performance of future generation portfolios in 2030 without taking into account the dynamic and multi-stage process of generation planning and investment. System costs have been calculated based upon capital investment costs for each technology projected for the year 2030; in reality investment will progress over time, and the generation capacity installed earlier will likely have higher costs. Previous assessments have suggested that the additional cost from this "investment trajectory" could be on the order of 10-20% for the move to a 100% renewable power system by 2030 (Riesz et al., 2013).

The costs of building new or upgrading existing transmission facilities to access new renewable generation is not included in these simulations. However, the costs of transmission are estimated to be relatively minor compared with the capital cost of generation in a move to a high renewable system (AEMO, 2013a).

Operation of the power system with very high proportions of renewables has not been considered in detail, beyond a relatively simple balancing of demand and supply in each modelling period (although a 15% minimum of synchronous generation was modelled to account for operational constraints around fault feed in levels and system inertia). The operation of the electricity market was also not considered in detail; for example, no potential for exercise of market power was included in the modelling. These aspects may well influence the relative costs and cost risks of generation portfolios.

6. Discussions and Policy Implications

This modelling indicates that a renewable penetration level of around 75% is likely to be optimal for the NEM in 2030, both on the basis of lower expected cost (given widely accepted central projections for gas and carbon prices) and lower cost risk. Investment in renewable generation is found to be preferable (lower cost and lower cost risk) to investment in gas-fired generation regardless of the carbon price, due to the anticipated high and uncertain gas prices.

This modelling indicates that investment in renewables provides an effective hedge against risks associated with future uncertainty in gas and carbon prices. Investment in renewables could therefore be considered a kind of "insurance" against potentially extreme future electricity prices. The additional cost of investing now in renewable technologies effectively insures industry stakeholders against future high prices. In contrast, continuing to operate with an emissions intensive coal-fired generation portfolio, or moving to a predominantly gas-fired generating portfolio is likely to significantly increase industry costs and cost risk.

6.1. The need for policy intervention

Some might argue that there is no need for Government intervention, since the electricity market should respond to these anticipated price signals, and developers would invest appropriately. Expectations of high and uncertain gas and carbon prices should entice developers to invest in renewable generation, and those that do will ultimately be able to undercut their competitors by supplying customers with lower cost contracts.

However, renewables cannot compete at present wholesale electricity prices in the absence of explicit support; gas prices and carbon prices will need to rise to the anticipated levels before a rational investor would bring a renewable project to market. At that point, the long lead times for the development of electricity infrastructure will mean that transforming the entire infrastructure base will take many years. If the goal is to achieve 75% renewable energy by 2030, it is almost certain that this is more likely to be achieved if development begins immediately. If there are no mechanisms to support the managed growth of renewable generation, this modelling suggests that consumers could be exposed to extended periods of very high electricity prices while the industry "catches up" to the high gas and carbon prices that are likely to eventuate.

The 75% renewable energy portfolio modelled in this study is composed of 25 GW of PV and 28 GW of wind in 2030. This is far in excess of the 3 GW of each installed at present, but could be achieved incrementally by adding 1.6 GW of wind and 1.4 GW of PV each year to the NEM from the present time. This is likely to be achievable. 1.3 GW of rooftop PV was installed in the NEM in the one year from 2011-12 to 2012-13. The Australian Energy Market Operator predicts that under present policy settings rooftop PV installations alone are likely to reach 14 GW by 2030, and may be has high as 23 GW (AEMO, 2013b). Utility scale investment such as the 103 MW PV solar farm in Nyngan, and the 20 MW Royalla Solar Farm, both currently under construction, would be additional to this investment. With regards to wind generation, there is already 16 GW of announced projects proposed for development (AEMO, 2014).

An expansion of this mechanism to 75% renewable energy by 2030 may be a suitable policy response, given the results of this modelling. Alternatively, a sufficiently high and assured carbon price could produce the required result.

6.2. Promoting Plant Retirement

This modelling also suggests that promoting the closure or full retirement of coal-fired plant may not be a desirable policy goal. Where these assets can move into an intermediate or peaking role, they can provide low cost firm capacity that supports reliable supply of electricity from large quantities of variable renewable generation. By operating at very low capacity factors, these coal-fired plants would contribute only modestly to greenhouse emissions, but would avoid expenditure on new generating capacity (such as dedicated new peaking plant). Rather than promoting closure of coal-fired plant (through schemes such as the previous Government's "Contracts for Closure" mechanism), it may be preferable to explore market adjustments that ensure coal-fired plant are exposed to appropriate incentives to operate in a more flexible manner, and can earn sufficient market revenue to remain profitably operational as peaking plant. This is suggested as a topic for future analysis.

7. Conclusions

This paper provides an analysis of the role of coal, gas and renewables in future generation portfolios in the Australian NEM for 2030 under highly uncertain gas prices, carbon pricing policy and electricity demand. A Monte-Carlo based generation portfolio modelling was employed to assess the expected costs, associated cost risk and greenhouse emissions of different possible generation portfolios. The analysis is based upon the widely accepted future technology cost estimates, electricity demand, fuel costs, carbon price and hourly wind and PV generation outputs. Sensitivity analysis with different expected carbon prices has also been considered.

The modelling results suggest that a generation portfolio with 60% renewable has the lowest cost in 2030. Increasing the renewable proportion further to 75% only very slightly increases expected generation cost, but significantly decreases the cost risk and greenhouse emissions. Increasing the renewable proportion from the present 15% to 75% in the NEM by 2030 would decrease expected wholesale costs by around $17/MWh, suggesting that policies to promote a managed increase in renewable generation towards the level of 75% by 2030 are warranted on a cost minimisation basis for consumers.

This modelling indicates that renewable generation effectively mitigates the potential for extreme electricity prices caused by high and uncertain carbon and gas prices. The addition of 10% renewable energy to the NEM reduces the cost risk by around 20%, regardless of the assumed carbon price probability. Therefore, the additional cost of investing in renewable generation at present can be accurately framed as an "insurance" or hedge against future extreme prices, in addition to a cost minimisation measure.

The modelling results also show that investment in CCGT is undesirable compared to renewable generation. Future generation portfolios with a large share of gas-fired generation, particularly CCGT, and far less renewables are likely to be exposed to considerable cost risk due to gas and carbon price uncertainties.

Existing coal-fired plants are shown to have the potential to continue to play an important role in all of the least cost power systems in 2030 by moving into a peaking role. In this manner, coal and gas-fired plant can effectively complement variable renewables, providing firm capacity without contributing significant emissions, cost or cost risk.

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