POWER GENERATION PORTFOLIO ANALYSIS WITH HIGH PENETRATIONS OF PHOTOVOLTAICS: IMPLICATIONS FOR ENERGY AND CLIMATE POLICIES

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Abstract

Growing concerns over climate change and the security of electricity supply due to uncertainties in fossil-fuel prices and their availability have contributed to the rapid growth of renewable generation over recent decades. Solar photovoltaic (PV) in particular has achieved significant growth given its rapid technology progress and price reductions in recent years. This paper uses a probabilistic generation portfolio modelling tool to assess the value and impacts of high PV penetration in future electricity generation portfolios under multiple policy objectives including generation costs, associated cost risks and CO_2 emissions given a range of future uncertainties. The modelling tool employs Monte Carlo simulation techniques to formally incorporate uncertainty in fossil-fuel price, carbon price, plant capital costs and electricity demand when determining generation cost of each possible generation portfolio. Generation portfolio analysis with the efficient frontier technique is then employed to assess tradeoffs among key objectives for different generating plant portfolios. The tool is applied to a case study of the Australian National Electricity Market (NEM) with five generation options: brown coal, black coal, combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT) and large-scale solar PV. Hourly PV generations across different locations were simulated for different penetration levels based on the actual hourly weather and demand data. Results show that the value of PV in generation portfolios depends largely on the level of future carbon price. Without a carbon price, increasing PV penetration would increase the overall generation cost. However, with a modest carbon price, PV generation can help reducing the overall generation costs in addition to cost risks and greenhouse gas emissions. The study provides insights into a number of important issues particularly the role of PV in addressing the challenges faced by the electricity industry. In addition, the results can be used for assessing specific future generation portfolios that of particular interests to utilities and policy-makers.

1. Introduction

Many electricity industries worldwide face increasing challenges associated with often rapid yet highly uncertain demand growth, energy security concerns and environmental sustainability. Electricity demand is typically driven by economic growth and the recent reduction in demand growth following the Global Financial Crisis has raised doubts on the future prospect of many economies. There is also energy security concern associated with high dependence on fossil-fuels given their future availability and pricing have become increasingly uncertain over recent decades. Coal and gas are the primary fuels for the global electricity industry, both of which have experienced increasing volatility and underlying price growth over the last decade (IEA, 2011). In addition, growing international concerns over climate change have emerged as a new challenge given the significant contribution of the electricity industry to global greenhouse gas emissions. Efforts by many countries in addressing climate change have often been based around establishing an environmental externality ‘carbon price’ on greenhouse gas emissions. These factors have all contributed to the rapid growth of emerging renewable energy (RE) technologies particularly wind and solar power over recent decades.

Solar PV is one of the fastest growing RE technologies worldwide during the past few years due to rapid technological progress and dramatic cost declines. PV has low operating costs and zero carbon emissions. It does not rely on fossil fuels which potentially present a range of energy security concerns. In addition, PV generation outputs are highly correlated with daytime peak electricity demand especially during summer months in many countries. Despite its advantages, PV still makes only a modest contribution to global electricity supply. Relatively high capital costs and investment risk compared with some conventional generation technologies were the main barrier to a wide spread of solar generation technologies (Geoscience Australia, 2010; Singh and Singh, 2010). Although carbon pricing has been viewed as one of the critical factors in driving future generation investment towards RE technologies such as PV, there is still continuing uncertainty surrounding the longer term impacts of climate change policies and the level of future carbon price likely to be required to deliver effective action on climate change. A key policy question, then, is what role might PV play in future generation portfolios in addressing the economic, energy security and environmental challenges facing electricity industries around the world. PV technology offers a new alternative for generation investment but also bring new complexities to analysis due to its unique technical and economic characteristics.

Generation investment and planning decision-making is often influenced by diverse and potentially conflicting criteria involving generation costs, associated cost risks and greenhouse gas emissions. However, the nature of the potential tradeoffs and synergies among these criteria are invariably complex and somewhat context specific. Generation investment and planning criteria is, therefore, increasingly moving beyond minimising generation costs to meet demand towards more complex assessments incorporating risks and uncertainties and a wide range of industry objectives.

This study is intended to provide quantitative analysis and insights into the future role and potential value of large-scale PV in the electricity industry under future uncertainty and multiple industry objectives in the context of the Australian National Electricity Market (NEM). The study employs a probabilistic generation portfolio modelling tool developed in (Vithayasrichareon and MacGill, 2012a) to analyse future generation portfolios with large-scale solar PV under a range of potential future uncertainties including fossil-fuel prices, carbon pricing policy, electricity demand and plant capital costs. The tool has previously been applied to number of case studies; for example the study on the potential impacts and value of high wind penetrations in the NEM (Vithayasrichareon and MacGill, 2013). However, this paper represents its first application to PV.

2. Probabilistic Generation Portfolio Modelling Tool

The modelling tool employed in this paper is a simulation based tool that can assess future generation portfolios with PV against multiple objectives given a range of potential future uncertainties. The tool adopts a long-term societal perspective and thus concentrates on overall future industry-wide outcomes for different electricity generation portfolios. The modelling tool extends the 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 into the assessment. Outputs from the tool are the complete range of individual simulations of annual generation costs and CO_2 emissions for each possible generation portfolio, which can, therefore, be represented by a series of probability distributions. The "expected" generation cost and CO_2 emissions for a particular portfolio represents the average of all these simulated generation costs and CO_2 emissions from every Monte Carlo run for a single year in the future. The cost spread for a generation portfolio is denoted by the standard deviation (SD), which represents associated 'cost risk' and is referred to as 'cost uncertainty' in this paper.[1] The tool then applies portfolio analysis techniques to determine the cost-risk efficient frontier (EF) [2] by mapping the expected generation cost and cost uncertainty for different generation portfolios in the value-risk space. Generation portfolios that are not on the EF are considered suboptimal in terms of cost-risk. Such techniques provide a basis for analysing cost and risk tradeoffs among different generation technology portfolios.[3]

Inputs into the tool consist of economic and operating parameters of each generation option as well as probability distributions of key uncertain parameters which are fossil-fuel prices, carbon price, hourly electricity demand and plant capital costs. Demand is represented by a Load Duration Curve (LDC) where estimated hourly demand over a year is arranged in descending order of magnitude. For each Monte Carlo run, the total annual generation cost of each generation portfolio consists of total annual fixed costs and variable costs. The annual fixed cost is determined based on the installed generation capacity of each technology in the portfolio. The fixed cost is made up of annualised plant capital cost, fixed operation & maintenance (O&M) and annualised costs of upgrading or building new transmission networks to accommodate such portfolio. The annual variable cost of generation portfolio is calculated based on annual energy (MWh) generated by each technology in the portfolio given a LDC. The variable cost comprises variable O&M, fuel costs and carbon costs. The generation output of each technology in the portfolio in each period of the LDC is determined using simulated partial economic dispatch with the objective to minimise operating costs subjected to demand and capacity constraints. Note that transmission and other possible inter-temporal operating constraints such as ramp rates and minimum operating levels of generating units are not taken into consideration. Total annual CO_2 emissions of generation portfolios are calculated from the annual energy and emission intensity of each technology.

In the tool, RE generations such as PV are given the first priority in the dispatch as they can offset the need to dispatch fossil-fuel generation. With this assumption, the actual or simulated hourly renewable generation is

[1] Since the tool applies MCS techniques which can incorporate virtually any type of input probability distribution, it can support sophisticated risk assessments including for example downside economic risks and other forms of risk-weighted uncertainty measures that suit particular risk preferences as shown in (Vithayasrichareon and MacGill, 2012a). This paper, however, only focuses on standard deviation as a measure of cost risk.

[2] The efficient frontier concept is used in the Mean Variance Portfolio (MVP) theory for financial portfolio optimisation (Markowitz, 1952). It has been increasing applied to future generation portfolio planning frameworks (Awerbuch, 2006).

[3] Modifications of this EF approach can also be used to highlight other potential tradeoffs between different generation portfolios such as their expected overall costs versus CO_2 emissions as demonstrated in (Vithayasrichareon and MacGill, 2012b).

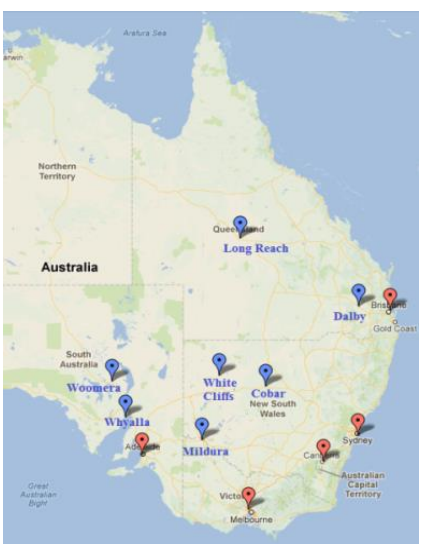
subtracted from hourly demand over a year. The resulting residual (net) demand, after accounting for RE generation, is then rearranged in descending order of magnitude to obtain a residual load duration curve (RLDC), which is to be served by conventional technologies in the portfolio. This technique has been widely in generation planning frameworks (Denholm and Margolis, 2007; Delarue et al., 2011).

3. The Australian National Electricity Market (NEM) Case Study

This paper considers a case study of the Australian National Electricity Market (NEM) that faces highly uncertain future fuel prices, carbon prices, electricity demand and new-build plant capital costs. It is assumed that there are five generation options: brown coal, black coal, combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT) and PV. Hourly electricity demand and PV generation are the actual and simulated data for the NEM in 2010. The year 2010 was chosen since weather records for this year are largely complete, and therefore would provide relatively accurate simulations of hourly PV generation across different locations in the NEM. Generator characteristics and cost parameters used for the simulations are based on the 2030 cost estimates obtained from the Australian Energy Technology Assessment (AETA) report by the Bureau of Resources and Energy Economics (BREE) (BREE, 2012). Transmission costs were estimated from the National Transmission Network Development Plan (NTNDP) by the Australian Energy Market Operator (AEMO) (AEMO, 2011a). Different PV penetrations from 0% to 25% are simulated for all possible thermal generating plant portfolios. Each input parameter for this specific case study is described in the following subsections. These inputs include demand and PV generation, transmission cost estimates, generator data and the stochastic models of uncertain fuel and carbon prices, demand and new-build plant capital costs.

3.1 Hourly electricity demand and solar PV modelling

Hourly demand for the NEM in 2010 was obtained by aggregating actual half-hourly demand data for each state provided by AEMO and averaging them into aggregate hourly values (AEMO, 2010). Twelve locations comprising of major cities and regional locations in each state of the NEM were selected to model hourly PV generation for 2010. By modelling PV plants in both cities and regional locations, the diversity value of PV plants across different locations in the NEM can be captured. Fig. 1 shows a map of the selected sites for large-scale PV plants for the simulation where the red symbols indicate major cities while the blue symbols indicate regional locations.



For the major cities, it is assumed there is no requirement for building new or upgrading existing networks to accommodate high PV penetrations. On the other hand, centralised PV plants in the selected regional sites would require new transmission lines or network augmentations. Hence, additional transmission costs associated with centralised PV plants in these regional locations are also taken into consideration. System Advisor Model (SAM) software was used to model hourly PV generation outputs in 2010 for the selected locations. SAM is a tool developed by the National Renewable Energy Laboratory (NREL) to model the performance and cost of grid-connected renewable generation technologies, with a particular focus on solar technologies (NREL, 2012). Using hourly weather data for a given location, SAM estimates hourly electricity generation output for any selected solar technology systems. The hourly PV generation in each location was modelled based on a 1-MW fixed flat plate solar PV plant, with north-facing arrays and tilted at latitude angle. The hourly PV generation is scaled up for a desired PV penetration level.

Fig. 1. Locations of PV plants for the simulation.

This study considers 0%-25% PV penetration levels in 5% increments and assuming the same installed PV capacity for each of the selected locations. Fig. 2 illustrates the simulated hourly PV generation for all the selected locations at 20% PV energy penetration as well as the actual NEM hourly electricity demand in 2010. Hourly simulated PV generation was subtracted from the demand to obtain a residual demand profile which was then rearranged to obtain a Residual Load Duration Curve (RLDC), which is to be served by thermal generation technologies. The RLDCs for different PV penetrations are shown in Fig. 3. The figure shows that the RLDCs drop sharply after the top 70% for high PV penetrations. This is because higher PV penetration would only increase daytime PV outputs while the outputs during any other times are still zero. Therefore, the contribution of PV plants in reducing high demand on winter evenings is rather limited. This study assumes that PV plants always generate when available.[4]

[4] In practice, minimum operating levels, startup times and ramp rate limits for thermal plants might necessitate curtailments.

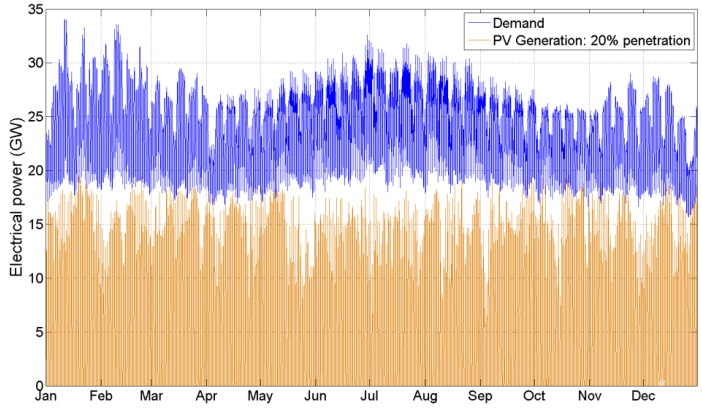


Fig. 2. NEM hourly demand and simulated PV generation at 20% penetration in 2010.

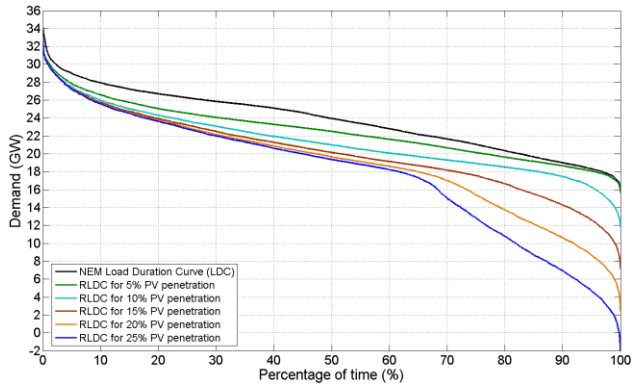


Fig. 3. Residual load duration curves for different PV penetrations.

3.2 Generator data

New entrant generation data for each technology were obtained from the 2012 AETA report based on the 2030 cost estimates (BREE, 2012). Annualised capital costs for each technology are determined using a 5% discount rate.

Table 1: Generator data

Parameters	Technology				
	Brown Coal	Black coal	CCGT	OCGT	Solar PV
Plant life (years)	50	50	40	30	30
Typical size (MW)	750	750	386	564	100
Capital cost ($million/MW)	3.8	3.0	1.1	0.8	1.6
Fixed O&M ($/MW/yr)	60,500	50,500	10,000	4,000	25,000
Variable O&M ($/MWh)	8	7	4	10	0*
Thermal Efficiency (%)	32.3	41.9	49.5	35	N/A
Heat Rate (GJ/MWh)	11.144	8.591	7.272	10.285	N/A
Emission factor (tCO_2/MWh)	1.024	0.773	0.368	0.515	0

Remark: *Variable O&M cost for PV has been accounted for in fixed O&M cost.

3.3 Transmission cost estimates

The study assumes new transmission lines would be required for PV plants in the selected regional areas while those in the major cities do not require new networks or upgrades of existing networks. Associated transmission costs for centralised PV plants in the regional sites are determined based on their distances to the nearest load centres or major transmission hubs, maximum PV outputs and indicative transmission cost estimates provided by AEMO (AEMO, 2011a). Transmission cost estimate for high voltage AC lines used in this study is $700/MW/km. Total associated transmission cost for each regional location is determined for each case of PV penetration level. Annualised transmission cost is calculated assuming economic lifetime of transmission line is 50 years and a 5% discount rate.

3.4 Modelling uncertainties

This study considers key cost parameters to be highly uncertain, which is a reasonable assumption given the future cost estimates are used. These parameters include fuel prices carbon price and plant capital costs. In addition, the

electricity demand is assumed to be uncertain. Fuel prices and capital cost uncertainties were modelled based on the percentage uncertainty of these costs. Demand uncertainty was modelled as the uncertainties in the RLDC for each PV penetration. Fuel prices, carbon price and capital cost uncertainties are modelled by lognormal distributions to reflect the asymmetric downside risk of such costs which demand uncertainty is modelled by a normal distribution. Both types of distributions can be characterised by mean (expected value) and standard deviation (SD). The expected fuel prices and plant capital costs were obtained from the 2030 estimates for the NEM while their SDs were estimated from the percentage uncertainty for fuel prices and capital costs provided in (BREE, 2012).

The number of simulations is set at 10,000 each of which consists of a set of sample fuel and carbon prices, plant capital costs and RLDC. These 10,000 set of simulated fuel and carbon prices, capital costs and RLDCs are used for calculating the annual generation costs and emissions for each possible generation portfolio considered.

3.4.1 Modelling fuel price and carbon price uncertainties

SDs of brown coal, black coal and natural gas price were estimated to be 29%, 6% and 30% of their expected values respectively. Table 2 summarises the expected fuel prices and their SDs for each fuel type.

Table 2: Expected price and SD for each fuel type

	Fuel price ($/GJ)		
	Brown coal	Black coal	Natural gas
Mean	0.5	1.65	8
SD	0.15	0.1	2.4

Correlations among fuel and carbon prices are also taken into account when modelling these uncertainties. This is a particularly important aspect given that the movement of gas, coal and carbon prices has exhibited considerable correlations as evidenced in EU and UK market. Such correlations have been demonstrated to influence the impact of uncertainty (Awerbuch and Yang, 2008; Vithayasrichareon, 2012). The correlation coefficients among fuel and carbon prices used in this study are shown in Table 3. These values were estimated from historical trends in OECD countries and a number of previous studies[5] (IEA, 2012).

Table 3: Correlation coefficients among fuel and carbon prices.

Brown coal & Black coal price	Coal & gas price	Gas & carbon price	Coal & carbon price
0.95	0.6	0.45	-0.35

Multivariate Monte Carlo simulation technique is used to generate correlated samples of brown coal, black coal, gas and carbon prices[6]. Histograms of correlated fuel and carbon prices over 10,000 MCS runs for a $20/t$CO_2$ scenario based on the mean, SD and correlation values from Table 2 and Table 3 are shown in Fig. 4. Scatter plots of 10,000 correlated samples are also shown in the figure highlighting the correlations among fuel and carbon prices.

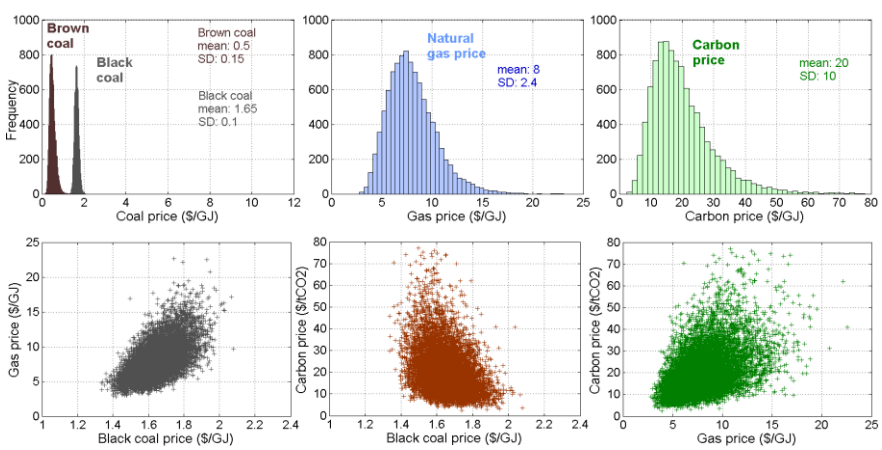


Fig. 4. Histograms of 10000 samples of correlated fuel and carbon prices and their scatter plots.

[5] Although the correlation coefficients are not necessarily applicable to the actual fuel supply situation in the NEM, they do highlight the importance of considering such factors in generation investment and planning.

[6] Multivariate simulation technique is used for reproducing random samples of uncertain parameters while preserving their respective marginal distribution properties and correlation structure.

3.4.2 Modelling capital cost uncertainty

SDs of the capital costs of brown coal, black coal CCGT, OCGT and PV plants were estimated to be 36%, 41%, 28%, 30% and 60% of their expected values respectively. The expected capital costs and SDs for each technology used in the simulation are shown in Table 4.

Table 4: Expected capital cost and SD for each generation technology

	Capital cost ($million/MW)				
	Brown coal	Black coal	CCGT	OCGT	PV
Mean	3.8	3	1.1	0.8	1.6
SD (value)	1.36	1.2	0.32	0.23	0.94

3.4.3 Modelling electricity demand uncertainty

Demand uncertainty is modelled by assuming a normal distribution of residual peak demand (peak demand RLDC) for each PV penetration. The SD of residual peak demand is estimated based on 90%, 50% and 10% 'probability of exceedence' (POE) provided by AEMO which indicate the likelihood that the maximum demand will exceed projections (AEMO, 2011b). The POE projections are used to determine the SD of the expected peak demand, which is approximately 4% of the expected value. For each PV penetration, each random RLDC is derived from each sample of residual peak demand. The difference between a random residual peak demand and the expected peak demand is then used to adjust the demand in every period of the expected RLDC to obtain a random RLDC for each PV penetration. The uncertainty in the RLDC is therefore modelled as vertical shifts in the expected RLDC thus maintaining the same shape and steepness. Such concept is illustrated in Fig. 5, which shows the histograms of 10,000 residual peak demand and random RLDCs for 5% and 20% PV penetrations. There are some periods when the simulated residual demand exceeded the installed generation capacity. The costs of energy not served in those periods are included in the calculation of the overall generation cost during each Monte Carlo run. The value of energy not served used is $12,900/MWh, which corresponds to the spot market price cap in the NEM.

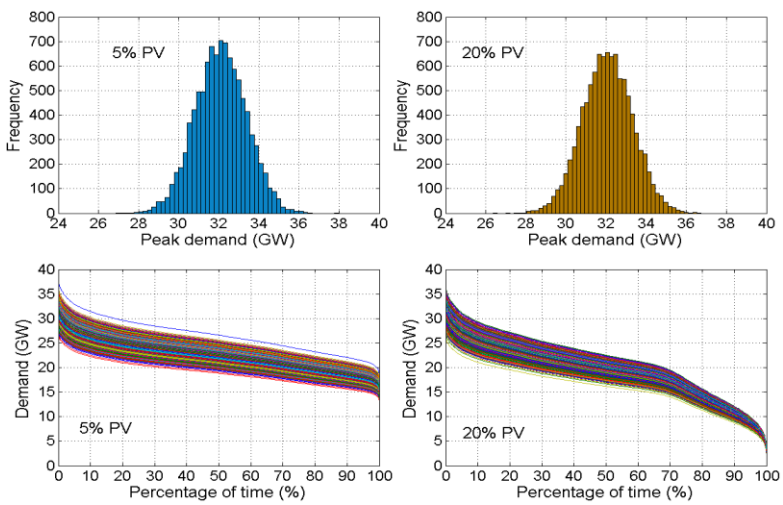


Fig. 5. Histograms of peak demand and associated RLDCs over 10,000 simulations for 5% and 20% PV

4. Simulation Results

The overall yearly generation costs and CO_2 emissions of every generation portfolio were calculated for 10,000 simulated future fuel and carbon prices, demand and plant capital costs. The portfolio costs and emissions during each Monte Carlo run (each set of uncertain parameters) were determined based on the installed capacity and annual energy generated by each technology in the portfolio.[7] The expected cost and CO_2 emissions of each generation portfolio are the average values of costs and emissions over the 10,000 Monte Carlo runs. SD of generation costs, as well as higher statistical moments, of the cost distributions can be determined since the results provide a full spectrum of possible generation costs of each portfolio. Hence the results can be used to analyse the downside risks of generation portfolios, which indicated by the magnitude of rare but high cost outcomes. This is particular importance given that the distributions of energy commodity prices have been frequently observed to exhibit major deviations from normality due to their asymmetry and tail fatness (Eydeland and Wolyniec, 2003). However, only SD as a measure of cost risk is considered in this paper.

[7] Note that, a change in merit order dispatch can occur during each Monte Carlo run. For example, a particular set of uncertain parameters may produce low gas price, high coal and carbon prices which result in CCGT to have the lowest variable costs compared with the other technologies.

4.1 Portfolio expected cost, cost uncertainty and CO_2 emissions

Fig. **6** uses a scenario of an expected carbon price of $20/t$CO_2$ to show the expected costs, cost uncertainty and expected CO_2 emissions of different thermal generation portfolios for 5% and 20% PV penetrations. Expected cost and CO_2 emissions of each generation portfolio are plotted against its SD, which represents cost uncertainty.[8] The circles represent the expected generation costs while the CO_2 emissions of the corresponding portfolios are represented by the asterisks in the same vertical plane. The efficient frontier (EF)[9] is shown by the solid line.

The portfolio expected cost, cost uncertainty and emissions change for different PV penetration. As illustrated in the figure, for an expected carbon price of $20/t$CO_2$, higher PV penetration would appear to increase the portfolio expected costs and cost uncertainties. However, greater PV penetration would reduce the portfolio expected CO_2 emissions. In the examples shown in
Fig. **6**, the technology mixes in the optimal generation portfolios on the EF change slightly for different PV penetrations. The optimal portfolios change from portfolios *A*, *B*, *C*, *D* and *E* for the case of 5% PV to portfolios *B*, *C*, *F* and *G* for the case of 20% PV.

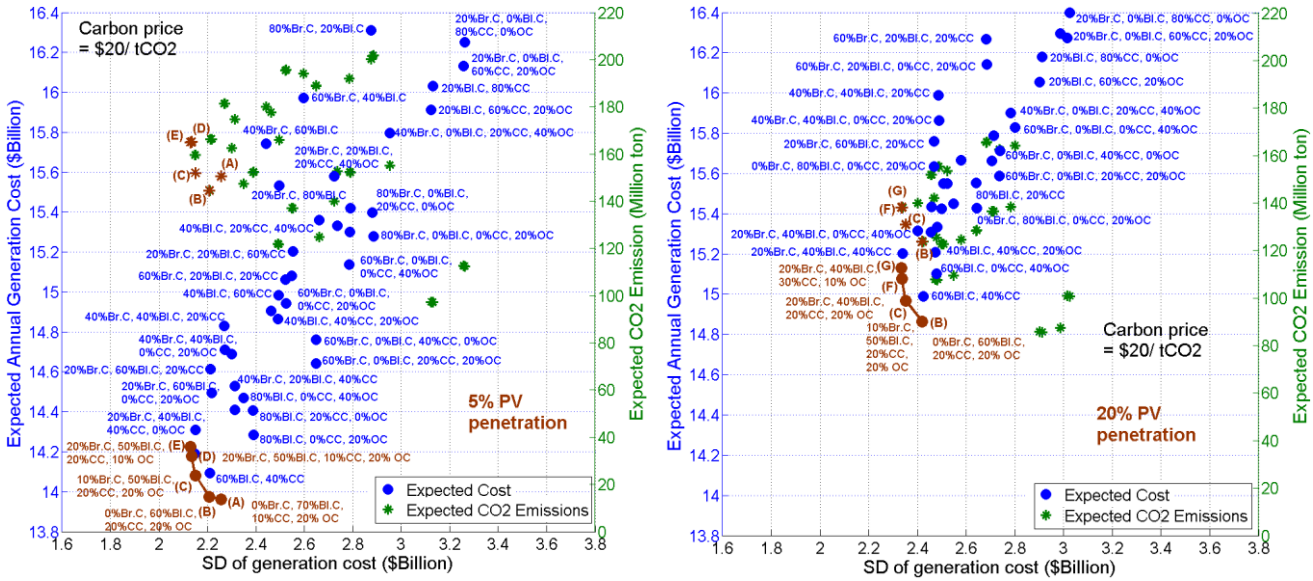


Fig. 6. Expected cost, cost uncertainty and CO_2 emissions of the thermal generation portfolios for an expected carbon price of $20/t$CO_2$ with 5% PV penetration (left) and 20% PV penetration (right).

4.2 The impact of carbon pricing and different PV penetrations

The frontiers showing cost-risk tradeoffs among optimal generation portfolios for different expected carbon prices and PV penetrations are shown in Fig. 7. For a low carbon price (i.e. $20/t$CO_2$) as shown on the left graph of Fig. 7, higher PV penetrations increase overall industry costs and cost risk as indicated by the upward movements of the EF as PV increases. With a low carbon price, the optimal conventional generation portfolios consist mainly of brown and/or black coal. For higher carbon prices (i.e. from $50/t$CO_2$), however, it is possible for the overall industry costs and associated cost risks to fall as PV penetration increases. In this case the EFs are shifted diagonally downwards as the PV penetrations increases implying lower industry costs and associated cost uncertainties. The reason is that PV reduces fossil fuel consumption and emissions, and hence the impacts of uncertain fossil fuel and carbon prices. For high carbon prices, the optimal mix of conventional generation changes as PV penetration increases– in particular, away from coal and towards gas generation.

[8] Note that not every generation portfolio in the simulation is presented on the graphs to aid clarity. Except for those on the EF, only generation portfolios with 20% increments on technology shares are shown. Furthermore, portfolios which have high expected cost and cost uncertainty were omitted in order to expand the resolutions of the axes.

[9] Efficient Frontier (EF) represents the lowest possible expected costs and cost uncertainty tradeoffs. Along the EF, the overall expected costs can only be reduced by accepting higher cost uncertainties among the portfolios.

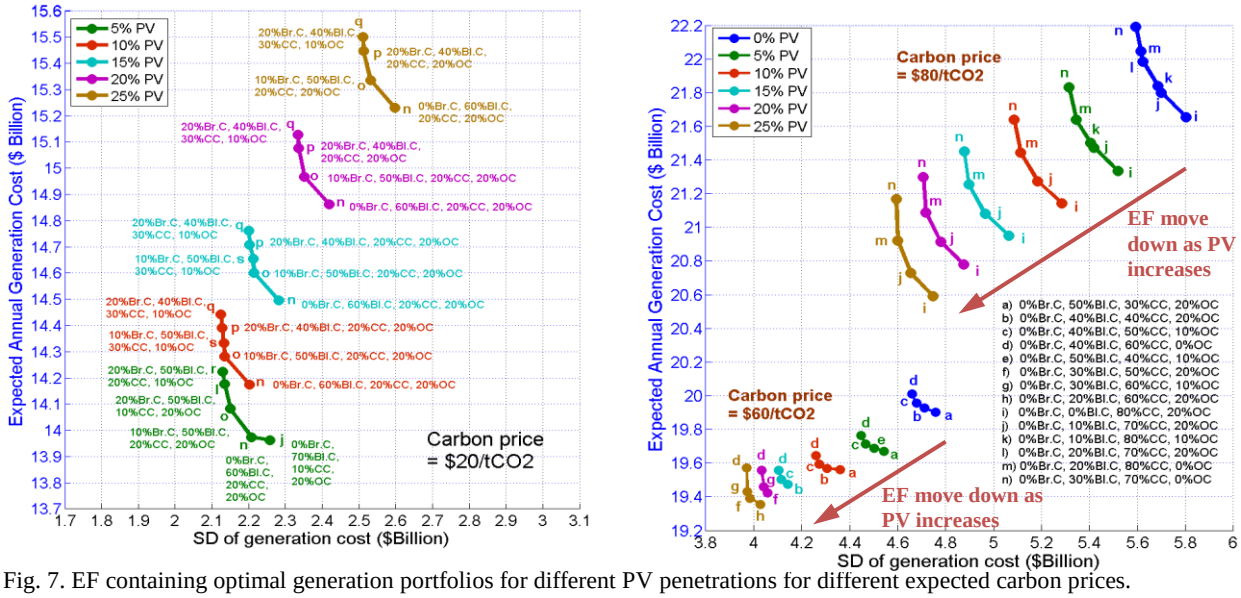


Fig. 7. EF containing optimal generation portfolios for different PV penetrations for different expected carbon prices.

Fig. 8 shows that portfolio generation costs generally increase with increased PV penetration for a range of carbon prices. However, the cost increases become smaller as carbon price increases until at a "threshold" carbon price where the portfolio costs are the same for any PV penetration level. Beyond the threshold carbon price, the portfolio expected costs would begin to fall as PV increases. The higher the carbon price, the more cost reductions can be achieved with a higher share of PV. The level of threshold carbon price is influenced by the share of gas-fired generation. Portfolios with high proportions of combined brown and black coal would require higher threshold carbon price compared with those that comprise mostly of CCGT and/or OCGT.

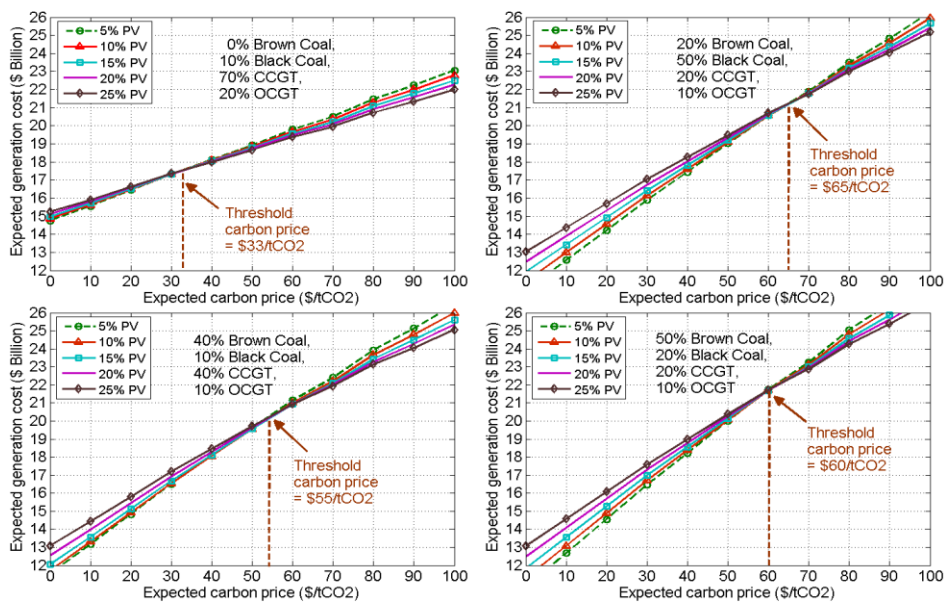


Fig. 8. Expected portfolio costs for different carbon prices and PV penetrations for some selected thermal generation portfolios.

This impact appears to depend largely on the proportion of fixed and variable costs in the portfolios. Portfolios with a majority of CCGT and/or OCGT have high proportion of variable costs compared to their fixed costs while it is vice verso for those that comprises mainly of brown and/or black coal. Therefore, the reduction in variable costs for gas-dominated generation portfolios would exceed the increase in fixed costs resulting in a reduction of the overall generation costs.

5. Conclusions

The results show that PV generation can play a valuable role in hedging against uncertain future fossil-fuel prices and carbon pricing policies which subsequently reduce the risk of generation portfolios. The paper also illustrates that increasing the share of PV generation would reduce the overall CO_2 emissions. More importantly, the results suggest that the imposition of a sufficient carbon price would enhance the economic value and encourage more

investment in large-scale solar PV even when the transmission cost estimates were included. For higher carbon prices (i.e. from \$50/tCO_2), the optimal generation portfolios on the EFs would also contain less coal and more gas-fired generation technologies resulting in lower industry CO_2 emissions. Such carbon price would provide incentives for utilities to move away from emission-intensive technologies, particularly coal-fired plants, or at least improve the efficiency of existing generating plants in order to minimise the costs of carbon emissions, and subsequently reduce the overall industry carbon emissions.

Typically, PV generation, although have relatively high fixed cost compared to CCGT and OCGT, would help reduce variable operating costs of generation portfolios given its zero fuel and carbon costs. As carbon price increases, the reduction in the operating costs would become more dominant and eventually outweighs the increase in fixed costs as PV penetration increases. For gas-dominated portfolios, the threshold carbon price could be as low as around \$30/tCO_2. On the contrary, portfolios with large shares of coal, as is currently the case in the NEM, have higher threshold carbon prices of around \$55-\$60/tCO_2. This level of carbon price is considered very modest compared to many modelled estimates of future carbon prices required to effectively address climate change (Australian Treasury, 2011; IEA, 2011). Given a sufficient future carbon price, large scale PV generation can play a significant role in reducing the overall industry generation cost and exposure to cost risk due to uncertainties in fossil-fuel and carbon prices. In addition to the level of future carbon price, the value of PV generation in future generation portfolios will also be influenced by the mix of generation technologies in the portfolios.

The findings appear to be valuable for energy and climate policy decision-making in the electricity industry particularly with regard to large-scale PV generation and carbon pricing. In addition, the results can be used for assessing specific future generation portfolios that of particular interests to utilities and policy-makers. Although the case study data is Australian specific, the results highlighted the potential implications of different PV penetrations and carbon prices for a largely conventional coal- and gas-fuelled electricity industry, which has relevance to many countries.

There are, however, some limitations to this study. The analysis is static in the sense that it considers the performance of different generation portfolios over a specific year without taking account the dynamic and multi-stage process of generation planning and investment over the medium to longer term. Since the modelling tool is based on the use of LDC and RLDC techniques, the time-varying nature of electricity demand was ignored. As a result short-term inter-temporal operational implications associated with different generation portfolios, such as startup/shutdown times and ramp rate constraints, were not taken into consideration. In addition, issues relating with network constraints were not considered in the study.

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