Generation Portfolio Analysis for Low-Carbon Future Electricity Industries with High Wind Power Penetrations

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Abstract— **This paper employs a Monte Carlo based decision-support tool to assess the expected overall generation costs and risks of different thermal plant portfolios with high wind power penetrations. In particular, we present a case study of an electricity industry with Coal, CCGT, OCGT and Wind generation options that faces uncertain future fuel prices, carbon pricing, demand, and plant capital costs. The tool uses half-hourly demand and wind generation data from South Eastern Australia, and Australian estimates of new-build thermal plant costs. It incorporates a Monte-Carlo extension to standard optimal generation mix methods combined with risk weighting techniques from portfolio theory. The implications of different wind penetration levels on the expected costs and risks, and associated emissions of different thermal plant portfolios are explored. Results from the case study highlight the potentially complex interactions between high levels of intermittent generation and the costs, risks and emissions of future electricity industries with different portfolios of Coal and Gas-fired plants.**

I. Introduction

GROWING concerns over energy security, increased uncertainty about fossil fuel prices and climate change have all contributed to the rapid growth of wind power over recent decades. Wind power is becoming a significant generation source worldwide, and particularly in some European countries such as Denmark, Germany and Spain, where it is now contributing greater that 10% of overall electricity generation [1]. Wind also represents the first highly variable and somewhat unpredictable energy source to reach significant penetrations in large power systems [2]. Wind energy, however, possesses very different characteristics from conventional generation sources due to its intermittent and non-storable nature. Given the wind industry's rapid growth, there are increasing concerns regarding the potential operational and economic impacts of incorporating wind power into power systems [3].

Due to the high variability of wind, large-scale deployment of intermittent generation sources such as wind power may have very significant implications for conventional generating plant investment and planning in the industry [4]. Because it provides highly variable, very low cost generation, wind is often modeled as negative load that alters the demand profile of an electricity industry, and therefore the requirements placed on conventional generation capacity [4-6]. Due to its stochastic nature, it has been argued that wind may offer only a modest contribution to reliable generating capacity within the electricity system. This contribution is often referred to as its capacity value or capacity credit, representing the amount of conventional generation that can be replaced with wind generation while maintaining the same reliability level [7]. There are several methods to determine the capacity value of wind generation depending on the context and perspective being considered by the planning body. The range of capacity value for wind has been estimated to lie between 10-25% but is clearly very context specific [8]. Another question, and the focus of this paper, is what impact high wind penetrations might have on the optimal conventional plant mix.

With increasing international concern about climate change, a growing number of countries are establishing policies to support renewable generation and 'price' carbon. Beyond present uncertainties regarding the future of such policies, increased uncertainties about future fossil fuels prices, fluctuating costs for future generation plant and recent reductions in demand growth following the Global Financial Crisis (GFC) have also all increased the challenge for generation investment decision making in the electricity industry.

Wind power is a capital intensive technology but its operating costs are minimal due to its 'free' fuel. Although the direct costs of wind power are currently higher than conventional technologies in most countries, it has been suggested that adding wind can help to hedge against fossil fuel and carbon price uncertainty, and therefore reduce the risk of generation portfolios [9].

This paper employs a novel generation investment decision support tool developed in [10-11] to analyze possible generation portfolios of conventional pulverized coal, Combined Cycle Gas Turbine (CCGT), Open Cycle Gas Turbine (OCGT) and Wind generating plants under future uncertain, coal and gas prices, carbon price, electricity demand and plant capital costs. This study extends previous works by incorporating different wind power penetrations into the possible generation portfolio options.

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Section II describes the decision support tool used and the application of the tool to evaluate generation portfolios with wind generation. Section III provides the description of the case study. The results and analysis are presented in Section IV followed by conclusions in Section V.

II. Monte Carlo Based Decision-Support Tool To Incorporate Wind Generation

The generation investment decision-support tool used in this paper extends deterministic methods for solving optimal generation mixes by incorporating uncertainties for key input cost assumptions through Monte Carlo Simulation (MCS). Some of these uncertainties are correlated – for example, carbon and gas prices. The tool then applies financial portfolios analysis techniques to determine an efficient frontier of expected overall generation costs and associated cost uncertainties for different generation portfolios. The detailed methodology of this tool is presented in [10]. The tool determines a probability distribution of generation costs and CO_2 emissions for each possible generation portfolio from the Monte Carlo simulations. The cost spread of each generation portfolio is represented by a standard deviation and is referred to, here, as 'cost uncertainty'. It has a similar meaning to 'risk' in the economic and financial context.

In this paper, wind generation is also incorporated as part of generation portfolios. Wind power is considered exogenous and treated as negative load given that wind generation has very low operating costs and can offset the need to dispatch conventional fossil-fuel generation. The variability of wind is directly incorporated through the use of one year of actual half-hourly wind generation data from around 1,400 MW of installed wind capacity in southeastern Australia, matched against equivalent half-hourly demand over the same period. The resulting residual demand, after accounting for wind, is transformed into a net Load Duration Curve (LDC), referred to as Residual Load Duration Curve (RLDC), which is to be met by conventional fossil-fuel generation technologies in the portfolio. The variability of wind power output, therefore, is incorporated in this technique through increased variability of the LDC. [12]. Although not done here, it would be relatively straightforward to model uncertainty in wind generation as the tool already incorporates demand uncertainty, as illustrated in the next section. Note that while the use of LDC and RLDC has many advantages in investment planning, it does remove the chronology of wind and demand. This tool takes a long-run societal perspective focused on risk assessment. Operational constraints associated with unit commitment such as startup times, ramp rates, or network operation are not currently included. However, these are possible extensions to the method which will be explored in future work.

III. Case Study Description

A case study has been undertaken of an electricity industry with Coal, Combined Cycle Gas Turbine (CCGT), and Open Cycle Gas Turbine (OCGT) and wind generation options. The industry faces significantly uncertain future fuel prices, carbon prices, total electricity demand and new-build plant capital costs. This study assumes that these fuel prices, carbon price and capital cost uncertainties are represented by lognormal distributions. This reflects the asymmetric downside risks of such costs. Electricity demand is represented by a LDC and its uncertainty is modeled using a normal distribution. Note that because the technique is based on MCS, arbitrarily complex probability distributions can be applied. For this case study, however, these uncertain parameters can be described through their mean and standard deviation. The data for this case study including demand and wind generation, fuel and other costs are based on the actual dispatch data and consultancy studies for the states of South Australia (SA), Victoria (VIC) and Tasmania (TAS) in Australia. All monetary values are shown as Australian dollars.

A. *Expected Demand Profile and Wind Generation Data*

The demand and wind generation data used for the simulation are based on the actual combined demand and wind power output in 30-minute interval in the state of SA, VIC, TAS in Australia for 2009. The data was obtained from the Australian Energy Market Operator (AEMO) website [13].

During 2009, the installed wind capacity in these three states increased from 962.65 MW to 1446.65 MW. The actual wind capacity factor in SA-VIC-TAS in 2009 was approximately 28%. In order to simulate for different wind penetrations, the actual wind output is scaled to reflect the full-year installed wind capacity. Fig. 1 shows the actual combined wind power output in these three states in 2009 after scaling.

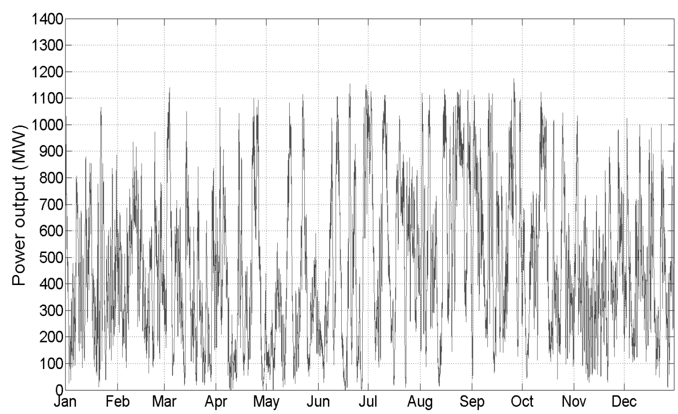


Fig. 1. Actual wind power output in 30-minute interval in SA-VIC-TAS after scaling to reflect the full year installed wind capacity for 2009.

This region was chosen because of the significant wind generation already in place, and providing a useful basis for simulating high wind penetrations. We have directly scaled the generation data for these simulations of higher wind penetrations than the present 5.2%. Scenarios from 0% to 20% wind energy penetration are undertaken in 5% increments. Note that this approach is likely to over-estimate the actual variability of high wind penetrations as one would expect some benefits from diversity with many more wind farms [14-15]. Fig. 2 shows the electricity demand and wind power for different simulated wind penetration in 30-minute interval.

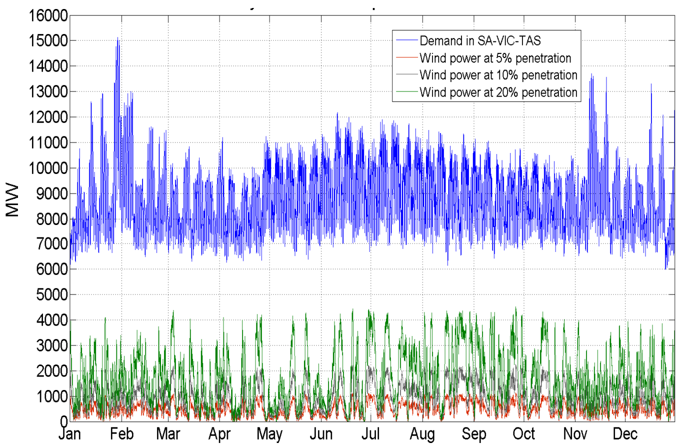


Fig. 2. Demand and wind power output for different wind penetrations

Wind generation is modeled as negative load therefore it is subtracted from the half hourly demand over the year to obtain a residual demand profile. This residual load profile is then rearranged in descending order of magnitude to obtain a Residual Load Duration Curve (RLDC) as shown in Fig. 3. The resulting RLDC is to be served by conventional generation technologies, which in this study are coal, CCGT and OCGT. In order to reduce computational time, the half-hourly LDC and RLDCs are simplified into 876 segments each representing the average demand over those 10 hours.

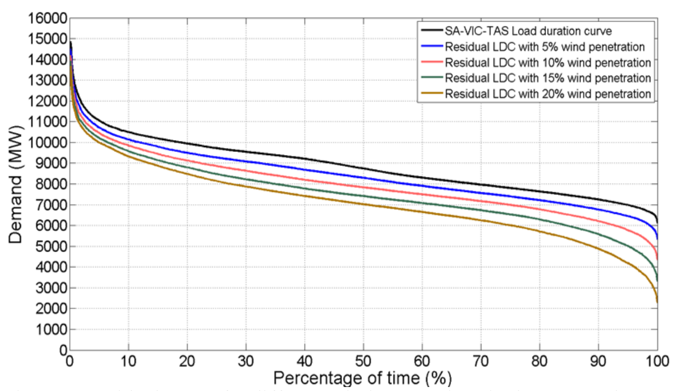


Fig. 3. Residual LDCs for different wind penetrations in the case study.

The installed wind capacity for different wind energy penetrations is determined based on a desired capacity factor, as shown in (1). Typical wind capacity factors for the state of South Australia are consistently between 32% to 40% [15]. Therefore, we assume a 35% wind capacity factor for this study for all wind penetrations.

$$\text{Installed wind capacity} = \frac{\text{Total wind energy}}{\text{Wind capacity factor} \times 8760\,\text{hours}} \quad (1)$$

The installed conventional generation capacity is determined through a probabilistic approach by using a 95% reliability criterion to ensure that there is sufficient conventional generation capacity to meet the expected residual demand for each wind penetration for at least 95% of the 10,000 simulated years.

In this study, demand uncertainty is modeled by assuming a normal distribution of peak demand in the RLDC. The standard deviation of peak demand is approximated based on studies of this region that estimate the likelihood that the maximum demand will exceed projections for any given year using 90%, 50% and 10% 'probability of exceedance' projections as given in [16]. The standard deviation of peak demand is approximated to be 4% of the expected peak demand. Hence, given a normal distribution of peak demand, a 95% reliability criterion is translated to 1.96 standard deviations above the expected peak demand. Table I shows the installed wind capacity, peak demand and its standard deviation, and installed fossil fuel generation capacity for different wind energy penetrations.

TABLE I
INSTALLED WIND CAPACITY, PEAK DEMAND AND INSTALLED CONVENTIONAL GENERATION CAPACITY FOR DIFFERENT WIND PENETRATIONS

Wind penetration	Installed wind capacity (MW)	Peak demand on the RLDC (MW)	SD of peak demand (MW)	Installed fossil-fuel capacity (MW)
0%	0	14,861	594	16,026
5%	1,263	14,506	580	15,643
10%	2,527	14,202	568	15,316
15%	3,790	13,933	557	15,026
20%	5,053	13,673	547	14,745

B. Generator Data

New entrant generation costs and characteristics of each technology considered in this study are obtained from [17-18] as shown in Table II.

TABLE II
GENERATOR DATA

Attributes	Technology			
	Coal	CCGT	OCGT	Wind
Plant life (years)	40	30	30	30
Capital cost ($/MW)	2,500,000	1,400,000	1,000,000	2,600,000
Fixed O&M ($/MW/yr)	40,000	13,000	7,500	20,000
Variable O&M ($/MWh)	1.2	4.85	7.5	1.6
Average Efficiency (%)	34	52	31	N/A
Heat Rate (GJ/MWh)	10.590	6.922	11.612	N/A
CO_2 emission factor (tCO_2/MWh)	1.00	0.45	0.7	0
Fuel price ($/GJ)	0.6	5.2		0

C. Stochastic Model of Uncertain Parameters

Mean fuel prices are obtained from [18] while their standard deviations of gas and coal price used in this study is 30% and 10% of their respective mean value [10]. The carbon price is assumed at $20/$tCO_2$ with standard deviation of 50% of the expected value. The values for coal, gas and carbon price are shown in Table III.

TABLE III
MEAN AND STANDARD DEVIATION OF COAL, GAS AND CARBON PRICE

	Coal price ($/GJ)	Gas price ($/GJ)	Carbon price ($/$tCO_2$)
Mean	0.6	5.2	20
Standard deviation	0.06	1.56	10

Correlations among fuel and carbon prices are also considered, and are based on historical trends in Europe and some assumptions [10]. These values are shown in Table IV. Whilst not necessarily applicable to the actual fuel supply situation in the region being studies, they do highlight the importance of considering such factors in generation planning.

TABLE IV
CORRELATION COEFFICIENTS BETWEEN FUEL AND CARBON PRICES

Correlation Coefficient ($\rho_{i,j}$)	Coal price (ρ_{coal})	Gas price (ρ_{gas})	Carbon price (ρ_{carbon})
Coal price (ρ_{coal})	1	0.65	-0.32
Gas price (ρ_{gas})	0.65	1	0.45
Carbon price (ρ_{carbon})	-0.32	0.45	1

Correlated samples of gas, coal and carbon prices are generated from their marginal lognormal distributions using a multivariate Monte Carlo simulation procedure. Multivariate simulations reproduce random variables while preserving their marginal distribution properties and correlation structure.

Demand uncertainty is modeled as the variations in the RLDC for each wind penetration level. Each sample RLDC is derived based on each sample of residual peak demand for each wind penetration level. Samples of residual peak demand are generated from its probability distribution with mean and standard deviation as indicated in Table I. The difference between a sample peak demand and the reference peak demand is then used to adjust the demand in every period of the reference RLDC. The uncertainty in the RLDC is modeled as vertical shifts in the reference RLDC thus maintaining the same shape and steepness.

There are some instances that the simulated residual peak demands exceed the installed conventional generation capacity resulting in energy not being served. The value of energy not served used in this study is $12,500/MWh, which is the current market price cap for the Australian National Electricity Market (NEM) [19]. The cost of energy not served is included in the overall industry generation cost during each Monte Carlo run.

The mean capital costs of each technology are obtained from [17-18], while their standard deviations are determined from a range of capital costs of each technology presented in [20]. The standard deviation of capital cost for Coal, CCGT, OCGT and Wind is estimated to be 15%, 10%, 5% and 5% of their mean capital costs respectively. Table V shows the mean and standard deviation of plant capital costs of each option.

TABLE V
MEAN AND STANDARD DEVIATION OF CAPITAL COSTS

($/MW)	Coal	CCGT	OCGT	Wind
Mean	2,500,000	1,400,000	1,000,000	2,600,000
Standard Deviation	375,000	140,000	50,000	130,000

Although the expected capital cost of wind power is high, it is assumed that the capital cost spread of wind plants is relatively low since wind turbines can be installed relatively quickly and the commissioning of wind turbines can be performed sequentially.

IV. CASE STUDY RESULTS AND ANALYSIS

For each wind penetration level, the calculation of overall industry costs and emissions for each generation portfolio is repeated for 10,000 simulated years of uncertain future fuel prices, carbon price, demand, and capital costs. These provide a basis for comparing the uncertainties of generation portfolio.

Fig.4 shows the distribution of coal, gas and carbon prices. The scatter plots of 10,000 MCS of gas, coal and carbon prices highlighting their correlations are shown in Fig. 5.

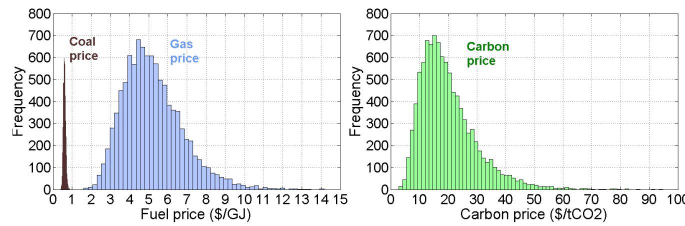


Fig. 4. Distributions of coal, gas and carbon prices over 10,000 simulations

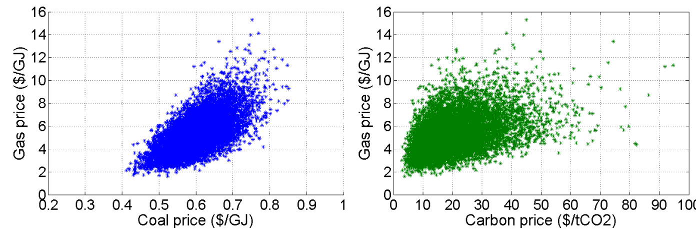


Fig. 5. Scatter plots showing the correlations among coal, gas and carbon price over 10,000 Monte Carlo simulations.

Samples RLDCs for different wind penetrations over 10,000 simulations are shown in Fig. 6.

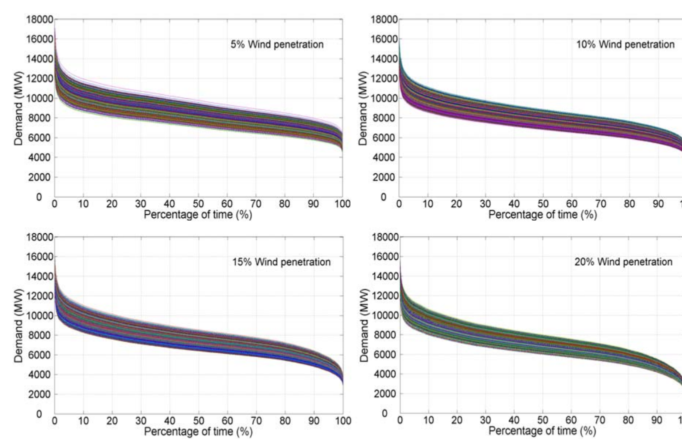


Fig. 6. Random RLDCs for different wind penetration over 10,000 Monte Carlo simulations

The capital cost distribution of each technology for 10,000 Monte Carlo simulations are shown in Fig. 7.

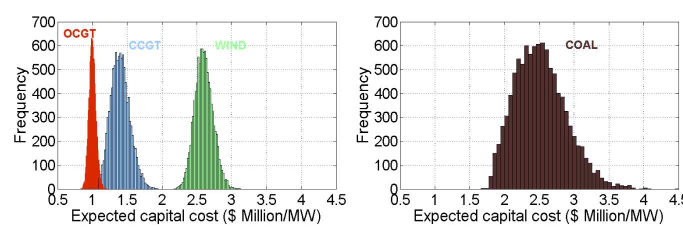
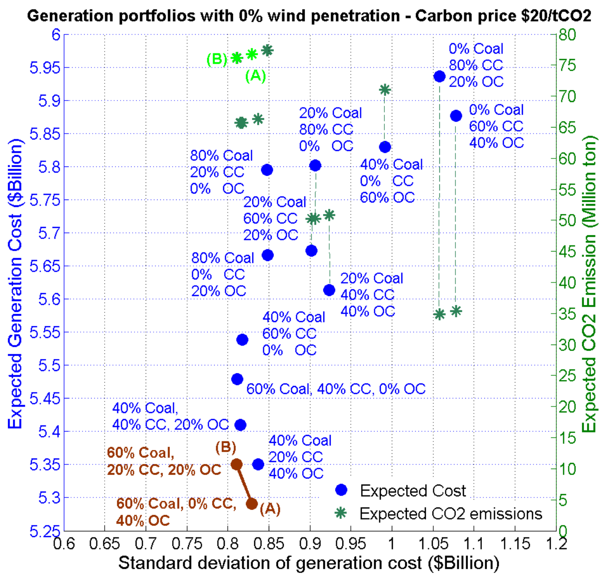


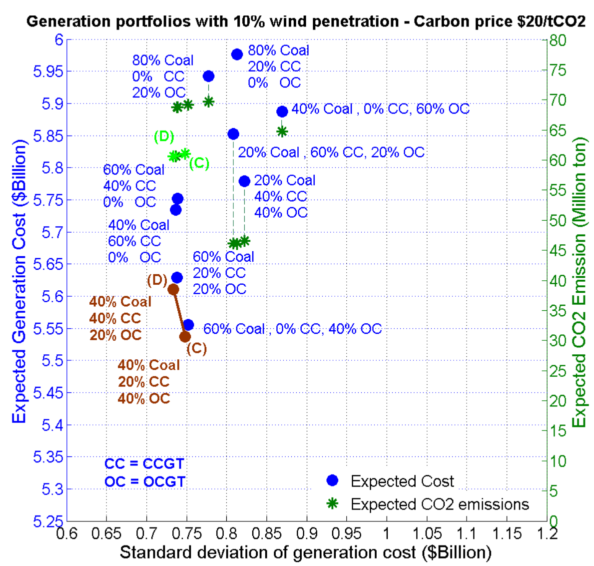
Fig. 7. Distribution of capital costs for the generating plants

These samples of correlated fuel and carbon prices, demand and capital costs are then used for the calculation of expected generation cost, cost uncertainty and CO_2 emissions of each generation portfolio for different wind penetrations. The proportion of coal, CCGT and OCGT are varied in 20% increments meaning 21 possible combinations of generation portfolios.

The expected annual generation cost, CO_2 emissions and cost uncertainty of each of the possible thermal generation portfolios for the 0% and 10% wind penetration scenarios are illustrated in Fig. 8. Note that not every generation portfolio is presented on the graphs to aid clarity.



(a)



(b)

Fig. 8. Expected cost, cost uncertainty and CO_2 emissions of generation portfolios for an expected carbon price of $20/tCO_2 with (a) 0% wind penetration and (b) 10% wind penetration. The expected generation costs are represented by the circles and the CO_2 emissions of the corresponding portfolios are represented by the asterisks in the same vertical line. The efficient frontier of optimal portfolios representing the lowest possible expected costs and cost uncertainty tradeoffs are represented by the red line.

The Efficient Frontiers (EF)[1] containing the optimal generation portfolios are also presented on the graphs. Along the EF, expected generation costs cannot be reduced without increasing the cost uncertainty and vice versa. As wind penetration increases from 0% to 10%, the optimal generation portfolios on the EF change from portfolios (A) and (B) in Fig. 8(a) to (C) and (D) in Fig. 8(b). The optimal generation portfolios which contain a significant share of coal are replaced by the portfolios that have lesser shares of coal and larger shares of CCGT. Although the overall expected industry generation cost increases as a result of a 10% wind penetration (recall that wind generation has high capital costs despite its low operating costs), the overall cost uncertainty and CO_2 emissions can be reduced quite significantly. This occurs, of course, since wind power is not susceptible to fuel and carbon price fluctuations. The analysis of the expected cost, cost uncertainty and CO_2 emissions tradeoffs among the generation portfolios are provided in detail in [10], although not in the context of generation portfolios with wind penetrations.

Generally, as wind penetration increases, the expected cost of most of the generation portfolios also increases while their cost uncertainty and CO_2 emissions decrease. Interestingly, however, there are some portfolios where expected costs decrease under some circumstances as shown in Fig. 9.

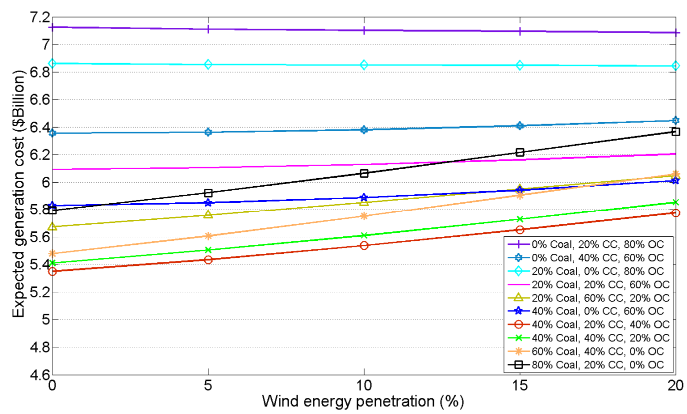


Fig. 9. Expected generation cost of some selected generation portfolios for different wind penetrations for an expected carbon price of $20/tCO_2.

The expected generation costs of portfolios which contain a majority of OCGT (greater than 60%) reduce or increase only very slightly with increasing wind penetration when the expected carbon price is $20/tCO_2. In these cases, the variable costs of the generation portfolios are very high. Hence, the reduction in variable cost of such portfolios with wind exceeds the increase in fixed costs resulting in reduced expected costs.

The results also suggest that increased wind penetrations reduce the overall CO_2 emissions of every generation portfolio significantly and by around the same rate, as shown in Fig. 10

[1]Efficient Frontier (EF) is the concept used in the Mean Variance Portfolio (MVP) theory developed by [21] for financial portfolio optimization.

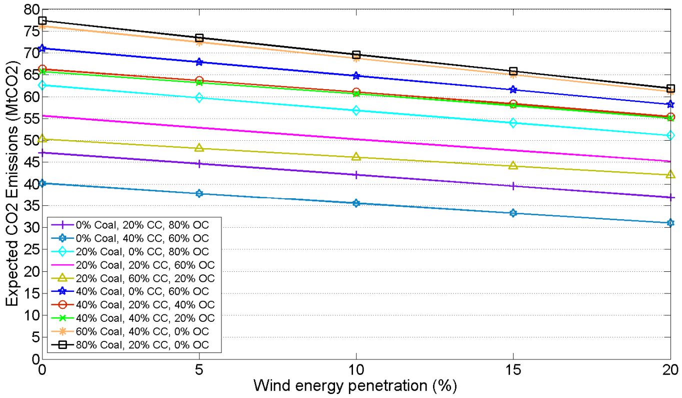


Fig. 10. Expected CO_2 emissions of generation portfolios for different wind penetrations for an expected carbon price of \$20/tCO_2.

V. Conclusions

This paper demonstrates the application of a Monte Carlo simulation based decision-support tool to perform high level analysis of the costs, risks and greenhouse emissions of possible thermal generation plant portfolios in the context of varying wind penetrations. The technique incorporates real or simulated half hourly wind data and electricity demand to create a Residual Load Duration Curve under different wind penetrations. A stochastic MCS extension to standard optimal generation mix methods and the use of Portfolio theory allows the tool to provide estimated overall generation costs and associated cost uncertainty, and greenhouse emissions for different possible thermal plant portfolios and wind penetrations. The tool was demonstrated on a case study based on wind generation and demand within South Eastern Australia, and coal, CCGT and OCGT generation investment options. The study included uncertainties on future coal and gas prices, carbon price, electricity demand and plant costs.

Results from the case study highlighted that, for the given carbon price of \$20/tCO_2, high wind penetrations increase overall expected generation costs but reduce their associated uncertainty as a result of wind's high capital costs but 'free' fuel and zero carbon emissions. Furthermore wind power can reduce the overall CO_2 emissions significantly for all thermal plant portfolios. Wind power can, therefore, play an important role in hedging against future fuel and carbon prices volatility.

The extent to which wind generation affects the expected cost and exposure to risk for portfolios depends on their proportion of fixed and variable costs. The case study highlighted the synergies between OCGT and wind generation. In conclusion, the competitiveness of wind in future electricity industries will be primarily influenced by the particular portfolio of conventional generation plant within the electricity industry, and the level of any 'carbon' price.

VI. Acknowledgement

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VIII. Biographies

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