Electricity Generation Portfolio Evaluation for Highly Uncertain and Carbon Constrained Future Electricity Industries

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***Abstract*— This paper proposes a stochastic model based on Monte-Carlo simulation to assess the expected costs and risks of different generation portfolios for electricity industries in an increasingly uncertain and carbon constrained world. The approach can incorporate uncertain carbon and fossil-fuel prices of virtually any probability distributions, as well as possible correlations between them. The tool provides expected overall costs and their associated probability distribution for any possible generation portfolio mix. The model is applied to a case study of an electricity industry with coal, CCGT and OCGT generation options that faces uncertain future carbon and fuel prices. Lognormal distributions are used to model fuel and carbon prices uncertainty. Results from the case study highlight some important issues including the potentially significant interactions between carbon and gas prices on portfolio performance. The proposed model enables the tradeoffs between expected system generation cost, associated cost uncertainty and CO_2 emissions among generation portfolios to be identified.**

***Index Terms*—Monte Carlo simulation, electricity generation portfolio, generation investment under uncertainty.**

I. Introduction

UNTIL relatively recently, generation resource planning and investment was commonly carried out by regulated electric utilities under some form of cost recovery regime for what were deemed to be 'economically efficient' choices. This is quite challenging in practice given the nature of generation and network investment in the industry; generally irreversible, lumpy, capital intensive and involving long lead times. The industry must therefore build ahead of time to meet an uncertain and potentially highly variable future demand. Decision support tools in such situation were therefore often focused on estimating the least-cost future generation portfolio mix to meet expected future demand. This, in turn, generally required deterministic assumptions about future uncertainties such as peak demand growth, fuel costs, and plant construction times and costs. Expanded assessment methodologies might include scenarios of different future outcomes for some key uncertainties including consideration of demand-side options.

There are a number of potential challenges with this approach. One is the vexed question of how the necessary assumptions of future demand and fuel costs are determined, particularly where single deterministic values are assumed. Significant financial resources are potentially at risk. Cost recovery regimes may insulate those that make the investment decisions from these risks, if excess costs associated with poor decisions are passed directly through end users. Expensive mistakes have been made, and there have been growing efforts to improve the transparency and allow wider stakeholder input into generation planning and investment processes.

For both regulated and competitive industries, investment decision making has become increasingly challenging due to increased volatility and future uncertainty about fuel prices and growing international concern about climate change since the electricity sector is one of the largest emitters of greenhouse gases. Efforts by many countries to address climate change are based around establishing an environmental externality 'carbon price' on such emissions. The implications for fossil fuel based electricity generation are potentially very great - for example, current emissions permit prices in the EU Emissions Trading Scheme might more than double the operating cost of coal-fired generation in Australia. These uncertainties have often been identified as a cause and a barrier to investment [1].

Investment decision making in the electricity industry is increasingly moving beyond minimizing expected generation costs to more complex assessments incorporating future cost risks. Thus, there is considerable value in formally incorporating risk assessment into decision support tools for electricity industry investment. Incorporating key risks, however, is particularly challenging as drivers such as future demand, fuel prices and possible climate change policy approaches such as emission trading schemes or carbon taxes are highly uncertain and almost certainly correlated. For example, ambitious climate policies might involve high carbon prices that would increase the use and hence cost of lower emission gas in preference to coal, while also resulting in higher electricity prices that reduce demand. Alternatively, a sudden fall in gas prices could increase the competitiveness of gas generation against coal resulting in lower emissions hence reducing the carbon price under an emission trading scheme.

There are many different methods used to support decision making in generation investment. These include the traditional

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optimal generation mix method and approaches to account for risk and uncertainty and they will be explained in Section II.

In this paper, a stochastic model based on Monte Carlo optimization is proposed to account for key uncertainties in electricity industry investment. This model extends traditional deterministic methods for solving optimal generation mix by incorporating uncertainty into key cost assumptions and therefore solving probability distributions of industry costs for different generation technology portfolios. In the work presented here, the proposed model adopts a social welfare perspective therefore concentrating on the overall future industry electricity generation cost. The model also combines the stochastic analysis with generation portfolio-based analysis to determine the expected industry electricity generation cost, risk, and CO_2 emissions of different possible generation technology portfolios. This modeling technique highlights and identifies tradeoffs in these factors among different possible generation portfolios. The potential of this technique in supporting decision making in generation investment under various uncertainties is illustrated using a case study. The impact and contribution of each source of uncertainty is analyzed. Furthermore, the impact of possible changes in the expected carbon prices on generation technology and generation portfolios will also be explored.

II. Electricity Industry Investment

A. Traditional Optimal Generation Mix Method

Under the traditional optimal generation method for solving optimal generation mix, the cost curve of each generation technology under consideration is plotted as a function of capacity factor on top of the Load Duration Curve (LDC). By projecting the intercepts of the cost curves on to the LDC, the optimal capacity of each technology in the generation mix can be determined [2]. This method focuses on solving for the least cost generation mix based on deterministic assumptions about future uncertainties. Although this method is simple, it does not take into account a wide range of relevant issues including sunk existing assets versus possible new plants, reserve requirements, losses and other possible network issues. Extensions to the method can incorporate these issues to at least some extent. More importantly, this approach ignores uncertainties surrounding future fuel prices, energy demand and, now, climate change measures.

B. Generation Investment Under Uncertainty

There are several methods for implicitly addressing risk and uncertainty in generation investment. The Monte Carlo simulation technique is widely recognized to be the most comprehensive and flexible technique to analyze problems which involve many uncertainties having many possible combination of input values [3, 4]. Monte Carlo simulation characterizes uncertainty by assigning a probability distribution to uncertain input parameters, which can be determined based on the historical data or expert judgment [3-5]. The stochastic variables are then generated repeatedly from their respective probability distributions in order to calculate the cost output. Any distribution can be used to represent uncertain variables. Moreover, correlated input uncertainties can also be incorporated – for example, a high carbon price might move the probability distribution of the gas price upwards. The output represents a range of possible results which can be represented by a probability distribution. Under conditions of particular assumed probability distributions, the mean and standard deviation can be used to fully describe the cost-risk profile of the output. The standard deviation is the most widely used method for measuring uncertainty since it is a measure of statistical dispersion that indicates how the values are spread in the data set [6]. Hence a project with greater risk and uncertainty would have a wider spread of possible outcomes than a project with less uncertainty [1].

There are, however, a few drawbacks of the Monte Carlo simulation technique [4]. First, the probabilities and correlation among uncertain parameters can be difficult to estimate. Another drawback is the potentially exhaustive computational time when there are a large number of correlated uncertain parameters. As the number of correlated uncertain parameters increase, a higher number of samples and Monte Carlo runs are required to attain a reasonable accuracy.

There are a number of recent studies that have proposed probabilistic frameworks which account for risk and uncertainty to support decision making in generation investment. Many of the proposed probabilistic models focus on stand-alone technology analysis by comparing the economic viability between technologies [7-9]. However, the stand-alone technology analysis does not indicate the extent to which the additional technology contributes to the overall cost and risk of the generation portfolios. This is because adding or removing a particular generation technology will subsequently alter the overall cost-risk profile of the generation portfolio. The capacity planning that is based on stand-alone technology costs is likely to lead to economically inefficient outcomes since it does not recognize the diversity value of different technologies within the generation portfolio [10].

III. Monte Carlo Optimization Model For Assessing Electricity Generation Portfolios

The model proposed in this paper employs the Monte Carlo simulation technique to account for uncertainties when determining the expected generation cost of generation portfolios. The methodology flowchart is shown in Fig. 1.

The model considers a range of generation portfolios by varying the share of each technology in the portfolio from 0% to 100%. The overall generation cost of a generation portfolio is calculated for each set of uncertain parameters. Outputs from the Monte Carlo simulation represent a range of possible generation costs of each generation portfolio, and therefore can be represented by a probability distribution. In this work we assume lognormal distributions and therefore describe them through their mean and standard deviation. Note, however, that the technique does not rely on the use of normal distributions to describe the uncertainty of key input variables.

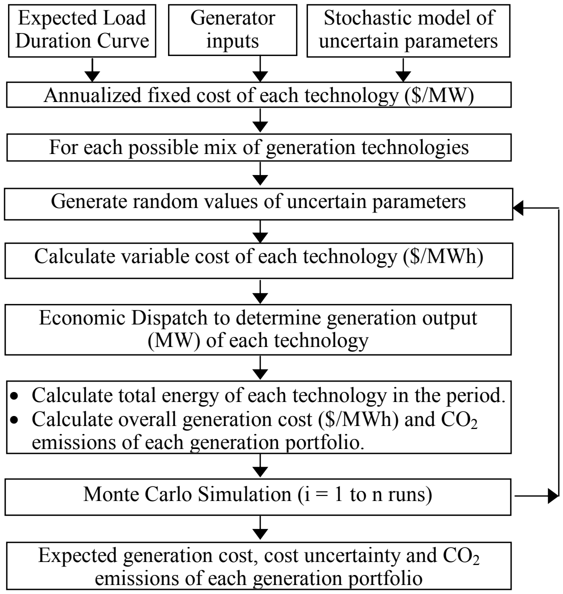

Fig. 1. Methodology Flowchart

In this paper, the cost spread of generation portfolio, represented by the standard deviation, will be referred as 'cost uncertainty'. This term implies a similar meaning as 'risk' in the economic and finance context. The term 'cost uncertainty' is considered to be more suitable with the analysis in engineering context, particularly in this study.

This model incorporates the economic merits of alternative generation types when determining the generation output of each technology therefore it does not have to assume a fixed capacity factor for each technology. With the inclusion of the load profile represented by the load duration curve, the generation output of each technology can be determined using the Economic Dispatch based on the variable cost resulting in the least cost operation. In this way, the generation output and capacity factor of each generation technology can be determined in a more practical and economically efficient manner. Furthermore, results from the model will reflect the value of different type of generation technologies in meeting varying demand; an aspect which has been often overlooked in standard generation portfolio analysis.

For each Monte Carlo run, the values of stochastic input parameters are randomly selected from their respective probability distributions, taking into consideration estimated correlations between them. The generation cost consists of annualized fixed and variable costs. The annualized fixed cost is calculated from the overnight capital cost of each generation technology using the Capital Recovery Factor (CRF), as shown in (1) where *m* is the plant life and *i* is the discount rate. The CRF determines the equal amount of regular payments in a present amount of money [2].

$$CRF = i(1+i)^m / \left((1+i)^m - 1\right) \qquad (1)$$

The generation output of each technology in each period is determined using the economic dispatch resulting in a least cost operation. The variable cost comprises of operation & maintenance, fuel and carbon costs as detailed in (2) and (3).

$$Fuel\ cost = Fuel\ price \times Heat\ Rate \qquad (2)$$

$$Carbon\ cost = EF \times Carbon\ price \qquad (3)$$

where *EF* is the CO_2 emissions factor of each technology.

The installed capacity of each technology is determined from the percentage share of such technology in the generation portfolio. The total generation cost for each generation portfolio during each Monte Carlo run is calculated using (4).

$$TC = \left(\textstyle\sum_{n \in N} (FC_n \times I_n) + (VC_n \times E_n)\right) / \, Annual\ Energy \qquad (4)$$

where FC_n, I_n, VC_n, and E_n is the annualized fixed cost, the installed capacity, the variable cost and the energy of technology n respectively.

The total CO_2 emission for each generation portfolio is determined according to (5).

$$CO_2 = \textstyle\sum_{n \in N} (EF_n \times E_n) \qquad (5)$$

IV. Inputs

A. Expected Load Profile

The load profile used in the simulation is based on the actual half-hourly demand in the State of New South Wales in Australia for 2007, with a peak demand of approximately 14,000 MW. The load duration curve is simplified to 438 segments in which each segment represents the average demand in a 20-hour period to reduce the computation time. This load duration curve is illustrated in fig. 2.

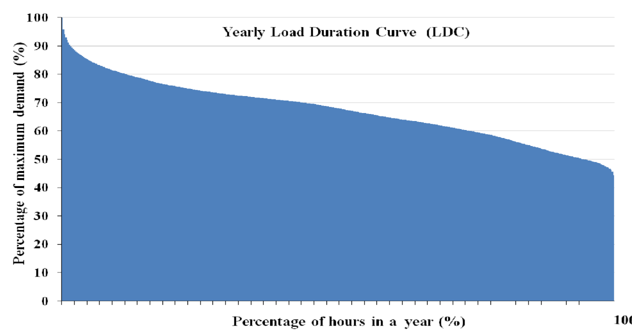

Fig. 2. Load duration curve used for the simulation

B. Generator Inputs

Generation costs and characteristics of each technology used in this study were gathered from [5, 11-14], and are shown in Table I.

TABLE I
TECHNOLOGICAL PARAMETERS

Attributes	Coal	CCGT	OCGT
Plant life (years)	40	25	25
Annualized Capital Cost ($/MW/yr)[1]	117,404	60,891	42,155
Fixed O&M ($/MW/yr)	43,000	25,000	14,000
Average Efficiency (%)	42	58	43
Variable O&M ($/MWh)	3.3	1.5	6.5
CO_2 emission factor (tCO_2/MWh)	0.8	0.35	0.47

[1] Calculated from overnight capital cost using the CRF at 8% discount rate

C. *Stochastic Model of Uncertain Parameters*

Uncertain input parameters in this study consist of gas, coal and carbon prices. In previous work, fuel and carbon prices were modeled using normal distribution [15]. However, fuel and carbon prices are arguably better approximated with fatter-tailed distributions since they allow for greater potential downside risk arising from high price events. The downside risk is of the main concern for risk-averse decision making. Therefore, lognormal distributions are assumed to represent fuel and carbon prices uncertainty.

1) Fuel Price

The mean and standard deviation of fuel prices are defined based on historical fuel prices in [16, 17] . The standard deviation of gas and coal price used in the model is 30% and 10% of their respective mean value. The standard deviation of the coal price is smaller than that of the gas price indicating that the fluctuation of coal price is less than the gas price. The standard deviations of fuel prices are approximately in line with values used in a number of other studies and they are generally between 25-30% of the mean value [18-20].

2) Carbon Price

Since the information on carbon prices is rather limited at this time, the carbon price is assumed to be $20/t$CO_2$ with standard deviation of 50% of the expected value. The model assumes a high value for the standard deviation for carbon price to allow for the possibility that the carbon price may vary significantly due to government policies or other external factors over the expected lifetime of generation assets.

Table II shows the mean and standard deviation of gas, coal and carbon prices used for the simulation.

TABLE II
MEAN AND STANDARD DEVIATION OF UNCERTAIN PARAMETERS

	Carbon price ($/t$CO_2$)	Coal price ($/GJ)	Gas price ($/GJ)
Mean	20	2.85	6.45
Standard deviation	10	0.285	1.935

3) Correlation Between Uncertain Parameters

In practice, the movement of gas, coal and carbon prices has exhibited a considerable correlation as evidenced in EU and UK market, reflecting a rather complex interaction between fuel and carbon markets [21]. The correlation among uncertain input parameters has been identified to have a considerable impact on the cost and risk profile of generation portfolios by either moderating or exacerbating the impact of uncertainty and neglecting such correlation could significantly distort the results [10, 20, 22, 23]. This model, therefore, takes into account the correlations among fuel and carbon prices.

Correlation between gas and coal price is determined based on the historical data and they exhibit a strong positive correlation [16, 17]. However, the empirical correlation between fuel and carbon prices is less evident since the carbon market is yet to fully mature. The evidence in EU carbon market shows that gas and carbon price exhibits a positive correlation while coal and carbon price shows negative correlation. This is as expected, as gas prices increase coal will become more favorable causing the carbon price to rise. Under the emission trading scheme, as coal becomes more favorable, the price of carbon permits should rise in order to reduce the cost advantage of coal therefore providing an incentive for the generators to utilize more gas [24]. On the contrary, with the increase in coal price, electricity generation will shift towards gas, which emits less CO_2 causing the price of CO_2 to fall. The correlation factors among gas, coal and carbon prices determined for this study are shown in Table III. These values are in line with recent studies [10, 20, 24, 25].

TABLE III
CORRELATION COEFFICIENTS BETWEEN FUEL AND CARBON PRICES

Correlation Coefficient	Coal price	Gas price	Carbon price
Coal price	1	0.65	-0.32
Gas price	0.65	1	0.45
Carbon price	-0.32	0.45	1

The multivariate lognormal simulation is employed to generate correlated sets of random gas, coal and carbon prices from their respective lognormal distribution.

The scatter plot of 5,000 samples of gas, coal and carbon prices are shown in Fig. 3. Correlations were verified to be the same as the values specified in Table III.

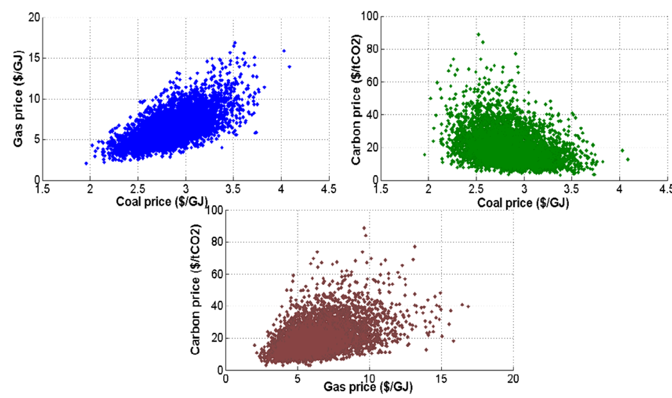

Fig. 3. Scattered plot of 5,000 samples of gas, coal and carbon prices

V. CASE STUDY

The case study considers generation portfolios consisting of different mixes of three technologies: coal, Combined Cycle Gas Turbine (CCGT), and Open Cycle Gas Turbine (OCGT). The share of each technology in the generation portfolios ranges from 0% to 100% of total capacity in 20% increments, and therefore there are 21 possible combinations of generation portfolios to be considered. The overall generation cost of each generation portfolio is simulated given combined carbon and fuel prices uncertainty. The impact and contribution of different sources of uncertainties on generation portfolios will also be explored. The calculation of generation cost for each generation portfolio is repeated for 5,000 simulated years of uncertain future fuel and carbon prices. The impact of carbon pricing on generation portfolios is also explored by running the simulation for different expected carbon prices.

VI. Simulation Results and Analysis

The simulation results consist of the expected generation cost, standard deviation of generation cost, which represents the cost uncertainty, and CO_2 emissions of each generation portfolio. The average simulation time for 5,000 sets of correlated random parameters on 2.0GHz Intel Dual Core CPU is 258 seconds, using MATLAB R2007b.

The distribution of the sampled gas, coal and carbon prices over 5,000 runs are also shown in Fig. 4. The distribution of coal price is less spread and closely resembles the normal distribution due to the low volatility. The distributions of gas and carbon prices exhibit longer tail due to higher variances.

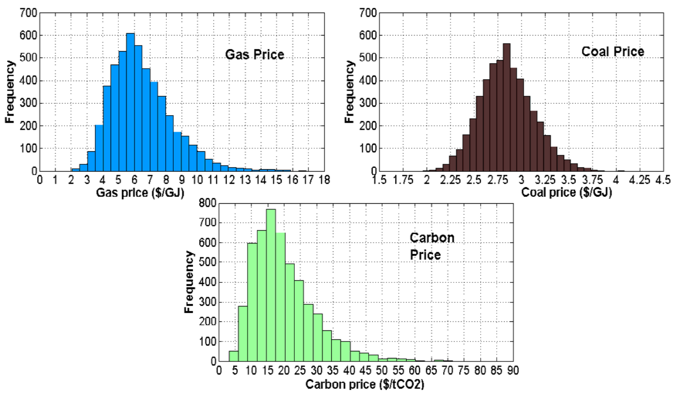

Fig. 4. Distribution of sample gas, coal and carbon prices

A. *With combined fuel and carbon prices uncertainty*

In this case, the generation cost of each generation portfolio is simulated given that fuel and carbon prices are uncertain. This scenario reflects the likely situation that electricity industries around the world will be required to confront in the near future. The correlations among gas, coal and carbon prices are also taken into account. The expected generation cost, CO_2 emissions of every generation portfolio is plotted against its standard deviation, as shown in Fig. 5.

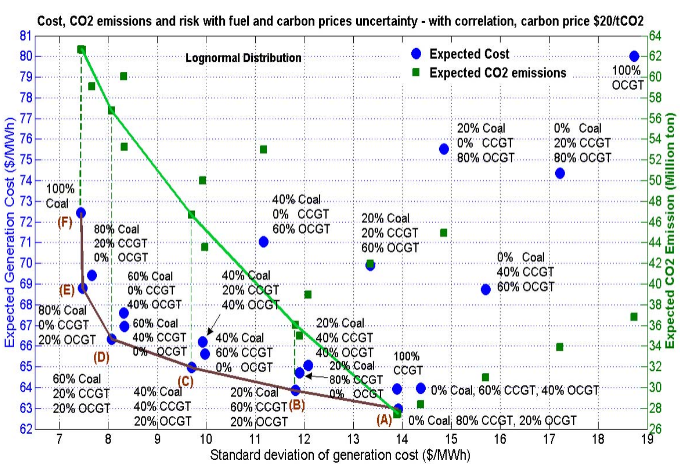

Fig. 5. Expected generation cost, cost uncertainty and CO_2 emissions

In this case, it is possible to construct the Efficient Frontier[1] which contains the optimal generation portfolios, as shown by the brown solid line in Fig. 5. Along the efficient frontier line, generation cost cannot be reduced without increasing the cost uncertainty, or the cost uncertainty cannot be reduced without increasing the generation cost. Generation portfolios that are not on the efficient frontier can be disregarded, either because their expected generation cost are too high relative to the cost uncertainty, or the cost uncertainty is too high relative to the expected generation cost.

As indicated in Fig. 5, generation portfolio A, which contains 0% coal, 80% CCGT and 20% OCGT has the lowest expected cost. This portfolio, however, exhibits a relatively high cost uncertainty as indicated by its standard deviation. The next lowest cost generation portfolios on the efficient frontier is portfolio B. By changing the technology mix from portfolio A to portfolio B so that the portfolio now contains 20% coal, 60% CCGT and 20% OCGT, the cost uncertainty can be reduced by 15% while the expected cost will increase by only 1% in relation to portfolio A. However, the expected CO_2 emission of portfolio B is 30% higher than that of portfolio A. Similarly, by changing the technology shares from portfolio A to portfolio C so that the portfolio now contains a mix of 40% coal, 40% CCGT and 20% OCGT, the cost uncertainty can be reduced by 30% while the generation cost will increase by only 3%. However, changing the technology share from portfolio A to portfolio C will significantly increase the CO_2 emissions by 66%. In terms of cost uncertainty, portfolio F which consists entirely of coal has the least cost uncertainty. Its cost uncertainty is 53% lower than that of portfolio A, while the generation cost is 15% higher. However, the amount of CO_2 emissions of portfolio F is more than double of the amount emitted by portfolio A. Generation portfolios can be assessed by analyzing the cost, cost uncertainty and CO_2 emissions tradeoffs among optimal generation portfolios on the efficient frontier.

Based on the same concept as the cost-risk efficient frontier illustrated previously, the CO_2 emissions frontier[2] showing the tradeoff between CO_2 emissions and cost uncertainty among optimal generation portfolios can be constructed. Along the CO_2 emissions efficient frontier, the amount of CO_2 emissions cannot be reduced without increasing the cost uncertainty. The green solid line in Fig. 5 displays the CO_2 efficient frontiers.

In addition to the standard cost-risk efficient frontier, the CO_2 efficient frontier can be used to provide additional support in decision making in terms of environmental sustainability aspects. For instance, generation portfolio A has the lowest expected CO_2 emissions but exhibits considerable cost uncertainty. By changing the technology share to portfolio B, the cost uncertainty can be reduced by 15%, however it causes the expected CO_2 emissions to increase by about 29%, which is moderately higher than the reduction in cost uncertainty. Similar comparisons can be made by analyzing the

[1] Efficient Frontier is the concept used in the Mean-Variance Portfolio (MVP) theory developed by [26] for financial portfolio optimization to analyze the expected returns and risks of financial portfolios.

[2] The notion of CO_2 emissions frontier is not fully compatible with a standard efficient frontier since the vertical and horizontal axes have different dimensions. However, it effectively shows the tradeoffs between CO_2 emissions and cost uncertainty of generation portfolios.

tradeoffs between CO_2 emissions and cost uncertainty among the optimal generation portfolios on the efficient frontier. The CO_2 emissions frontier can be used as the additional criteria to support decision making in terms of environmental aspect.

The result also demonstrates the importance of the contribution of each technology to the generation cost and cost uncertainty of the generation portfolio. Intuitively, adding a more costly technology to the portfolio should increase the portfolio cost and similarly, adding a less costly technology should reduce the cost of generation portfolio. However, this is not always the case. For example, considering portfolio F and E, by increasing the share of OCGT, which is the most expensive technology, from 0% to 20% in the otherwise 100% Coal portfolio, so that the portfolio now contains 80% coal, 0% CCGT and 20% OCGT, can reduce the portfolio cost considerably while the cost uncertainty is relatively unchanged. This may seem counterintuitive since adding a more expensive technology should increase the cost of the generation portfolio. However, since the load is not uniform therefore the tradeoffs between fixed and variable costs enable each generation technology to play a valuable role in a generation portfolio in meeting demand in different periods.

The upper graph of Fig. 6 displays the cost distributions of single technology while the lower graph compares the cost distributions of optimal generation portfolios on the efficient frontier. The figure shows that OCGT is the most susceptible technology to fuel and carbon prices uncertainty as it exhibits the largest cost spread. Coal, on the other hand, has the least cost uncertainty while CCGT is in the middle.

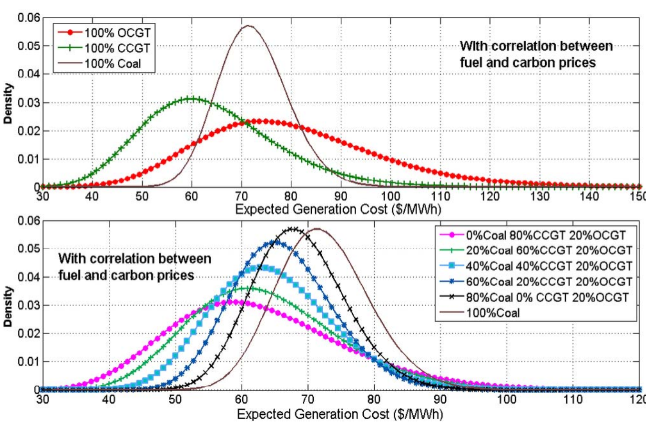

Fig. 6. Cost distributions of different generation portfolios

In terms of the expected cost, OCGT has the highest cost, followed by coal while CCGT has the lowest generation cost. The lower graph shows that, among the optimal generation portfolios on the efficient frontier, increasing the share of coal to replace the share of CCGT in the portfolio leads to considerable reduction in cost uncertainty as illustrated by the less spread cost distributions. However, it comes at the expense of increased overall electricity generation cost and greater environmental stress due to substantial increase in CO_2 emissions. On the other hand, reducing the share of coal in the generation portfolio would have dual benefits in terms of cost reduction and less environmental damage.

B. The Impact of Different Sources of Uncertainties

The results from the case study suggest that the impact of each source of uncertainty varies according to the type of generation technology. The relative contributions of different sources of uncertainty for each technology will be explored by simulating the results for three cases of uncertainty, namely only fuel price uncertainty, only carbon price uncertainty and combined fuel and carbon prices uncertainty.

The cost distributions of single technology portfolios for three difference cases of uncertainty are compared in Fig. 7.

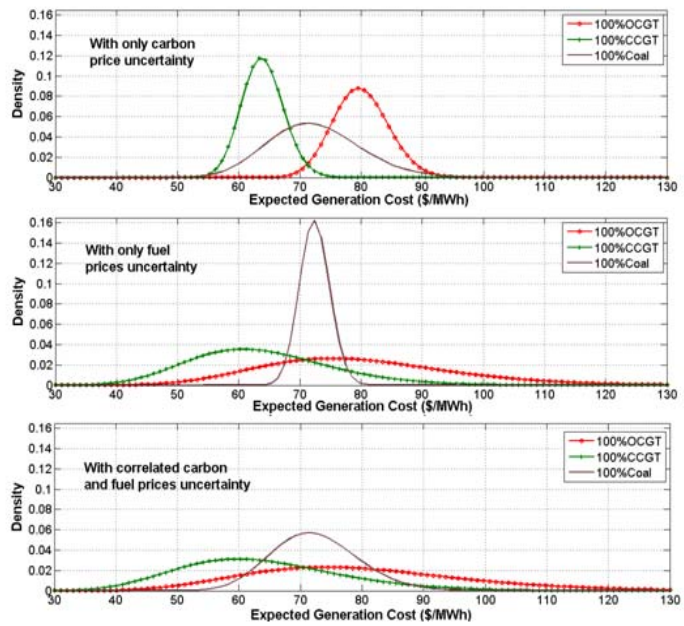

Fig. 7. Cost distributions for different cases of uncertainty

The top graph shows the cost distributions when carbon price is the only source of uncertainty. In this case, coal has a moderately flatter cost distribution than CCGT and OCGT, which indicates that carbon price uncertainty has a greater affect on coal than on CCGT and OCGT. With only uncertainty in gas and coal price, as shown in the middle graph, the cost spread of CCGT and OCGT are significantly larger than that of coal, which imply that CCGT and OCGT are highly sensitive to gas price fluctuation while coal is minimally affected by uncertainty in coal price.

Comparing between the middle and bottom graphs, the cost distributions of CCGT and OCGT in the case where there is only fuel price uncertainty are fairly similar to those in the in the case with combined fuel and carbon prices uncertainty, while the cost spread of coal increases considerably as the carbon price uncertainty is introduced. Such an occurrence suggests that CCGT and OCGT are relatively insensitive to carbon price fluctuation whereas coal is particularly sensitive to carbon price fluctuation while only minimally affected by the volatility of the coal price. Hence, the main source of uncertainty for CCGT and OCGT is fuel price while the dominant source of uncertainty for coal is caused by carbon price fluctuation due to its high emissions.

The impact of gas price uncertainty on CCGT and OCGT is more influential than the impact of carbon price uncertainty on coal even though the volatility of carbon price is greater than that of gas and coal prices as indicated in Section IV. This is because fuel cost is by far the largest cost component of CCGT and OCGT. Based on the expected fuel and carbon prices in this study, the proportion of variable cost components in each technology is depicted in Fig. 8. Given the combined fuel and carbon prices uncertainty, generation portfolios that contain a large share of coal exhibit a lower cost uncertainty compared with the portfolios that are dominated by CCGT or OCGT.

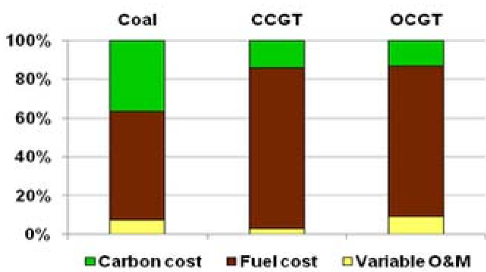

Fig. 8. Variable cost components of each generation technology

C. *The Impact of Carbon Pricing*

The case study presented so far has assumed an expected carbon price of $\$20/tCO_2$. However, setting different carbon prices will have impacts on the relative costs and cost uncertainty among generation portfolios. This section investigates the effect of varying expected carbon prices on the expected generation cost, cost uncertainty and CO_2 emissions of generation portfolios. Results are simulated for different expected carbon prices of \$10, \$20, \$30 and $\$40/tCO_2$ with standard deviation of 50% of the expected prices and the efficient frontiers for each carbon price are shown in Fig. 9.

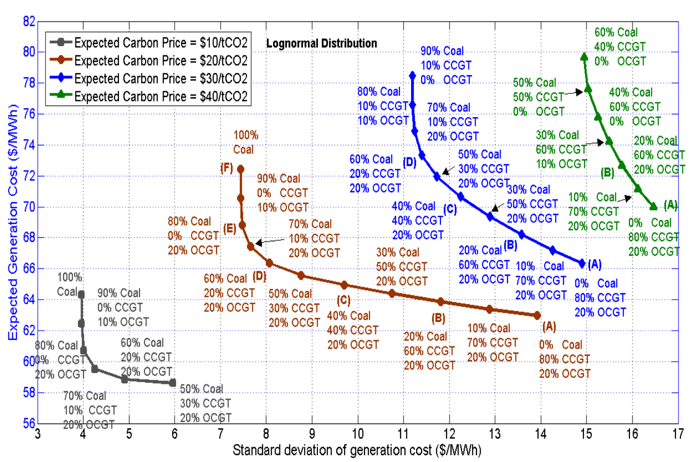

Fig. 9. Efficient frontier for different expected carbon prices

In order to show a smoother efficient frontier, results are simulated for the generation portfolios ranges from 0% to 100% of total capacity in 10% increments.

As illustrated in the Fig. 9, the efficient frontier moves diagonally upward as the carbon price increases, indicating that both the generation cost and cost uncertainty of generation portfolios increase with the increase in the expected carbon prices. Furthermore, as the carbon price increases, the efficient frontiers become more compressed with respect to the standard deviation of cost, implying that the difference between relative cost uncertainty among the optimal generation portfolios on the efficient frontier is getting smaller while the cost difference among generation portfolios becomes larger. For example, for the expected carbon price of $\$20/tCO_2$, the cost difference between generation portfolio A, which is the lowest cost portfolio, and portfolio B is about 1.6% while the difference in cost uncertainty is 16%. As the expected carbon price increases to $\$30/tCO_2$, the cost difference between portfolio A and B increases to 2.8% while the difference in cost uncertainty reduces to 8.8%. As the expected carbon price is increased to $\$40/tCO_2$, the cost difference between portfolio A and B is further increased to 3.6% while the difference in cost uncertainty is further reduced to 4.8%.

Another finding is the influence of carbon price on the type of generation portfolios on the efficient frontier. Different carbon prices lead to different types of optimal generation portfolios being presented on the efficient frontier. As the carbon price increases, the generation portfolios that contain a large share of coal become less favorable in terms of both generation cost and cost uncertainty, and therefore such portfolios tend to lie outside the efficient frontier. With high carbon prices, the optimal generation portfolios on the efficient frontier are those that have a smaller share of coal. For instance, as the carbon price increases from \$20 to $\$30/tCO_2$, portfolio F, which consists entirely of coal, is no longer on the efficient frontier which means that there are other generation portfolios that have lower expected cost as well less cost uncertainty. Similarly, as the carbon price increases to $\$40/tCO_2$, the generation portfolio on the efficient frontier with the largest share of coal is the 60% coal, 40% CCGT and 0% OCGT mix while other optimal portfolios consist mainly of CCGT. On the other hand, with a low carbon price, the generation portfolios on the efficient frontier consist of a majority of coal.

The increase in carbon price will ultimately increase the overall industry electricity generation cost as well as cost uncertainty. Coal has been illustrated to have considerable sensitivity to the change in carbon prices. With high carbon prices, generation portfolios that contain a smaller share of coal will become more favorable.

VII. CONCLUSIONS

This paper has presented a novel approach to select generation portfolios by combining stochastic analysis using the Monte Carlo simulation technique with the generation portfolio analysis to account for uncertainty. The proposed model can effectively solve for the expected electricity generation cost, cost uncertainty and CO_2 emissions of different generation technologies portfolios given probability distributions and associated correlations for coal, gas and carbon prices.

Results from the case study indicate that the impact of fuel and carbon prices uncertainty on generation technologies depends on the proportion of fuel and carbon cost in total generation cost, and the volatility of fuel and carbon prices. For the cost assumptions used in the case study, CCGT and OCGT are predominantly impacted by fuel price uncertainty since fuel cost is by far their largest cost component. Coal, on the other hand, is mainly affected by the uncertainty in carbon price while minimally impacted by fuel price uncertainty due to its high CO_2 emissions. Generation portfolios with a majority share of coal have a lower cost uncertainty compared with the portfolios that are dominated by CCGT or OCGT. However, portfolios with a larger share of coal will cause greater environmental damage due to the associated substantial increase in CO_2 emissions. As the carbon price increases, both the generation cost and cost uncertainty of generation portfolios also increase. With higher carbon prices, generation portfolios with a larger share of coal become less favorable as they tend to lie outside the efficient frontier.

Results also show that each type of generation technology has a valuable contribution to the generation cost and cost uncertainty of the generation portfolio since adding a more expensive technology to the portfolio does not necessarily increase the overall portfolio cost and vice versa. This is because load is not uniform therefore the tradeoffs between fixed and variable costs enable each generation technology, especially the peak-load technology to play a valuable role in a generation portfolio in meeting varying demand.

This model has a potential to support decision making in generation investment and planning under uncertainty, and therefore allowing the appropriate generation technology and generation portfolios that optimize among expected cost, cost uncertainty and CO_2 emissions to be identified.

VIII. REFERENCES

[1] IEA, "Climate Policy Uncertainty and Investment Risk," OECD/IEA, Paris, Paris2007.
[2] H. G. Stoll, *Least-Cost Electric Utility Planning*: John Wiley & Sons, 1989.
[3] F. A. Roques, W. J. Nuttall, and D. Newbery, "Using Probabilistic Analysis to Value Power Generation Investments under Uncertainty," EPRG Working Paper2006.
[4] P. J. Spinney and G. C. Watkins, "Monte Carlo simulation techniques and electric utility resource decisions," *Energy Policy,* vol. 24, pp. 155-163, 1996.
[5] R. Doherty, H. Outhred, and M. O'Malley, "Establishing the Role That Wind Generation May Have in Future Generation Portfolios," *IEEE Transactions on Power Systems,* vol. 21, pp. 1415-1422, August 2006.
[6] S. T. Rachev, S. V. Stoyanov, and F. J. Fabozzi, *Advanced Stochastic Models, Risk Assessment, and Portfolio Optimization: The Ideal Risk, Uncertainty and Performance Measures*: John Wiley & Sons, Inc., Hoboken, 2008.
[7] Z. Tomsic, D. Feretic, and N. Debrecin, "Comparison of Power Plants Competitiveness Using Stochastic Methods," in *8th International Conference on Probabilistic Methods Applied to Power Systems* Iowa State University, Ames, Iowa, 2004.
[8] J. Su and F. F. Wu, "Evaluation of generation expansion investment under competitive market environment," in *Power Engineering Society General Meeting, 2005. IEEE*, 2005, pp. 2136-2140 Vol. 3.
[9] T. R. Limbu, T. K. Saha, and J. D. F. McDonald, "Probabilistic cost benefit analysis of generation investment in a deregulated electricity market," in *Power Engineering Society General Meeting, 2006. IEEE*, 2006, p. 7 pp.
[10] S. Awerbuch and M. Yang, "Efficient Electricity Generating Portfolios for Europe," in *Analytical Methods for Energy Diversity and Security: A tribute to Shimon Awerbuch* M. Bazilian and F. A. Roques, Eds. London: Elsevier, 2008.
[11] M. Yang, W. Blyth, R. Bradley, D. Bunn, C. Clarke, and T. Wilson, "Evaluating the power investment options with uncertainty in climate policy," *Energy Economics,* vol. 30, pp. 1933-1950, 2008.
[12] NEA/IEA, "Projected Costs of Generating Electricity, 2005 Update," OECD Publisher, Paris, Paris2005.
[13] IEA, "Energy Technology Perspectives 2008: Scenario & Strategies to 2050," OECD/IEA, Paris2008.
[14] IEA, "Fossil Fuel-Fired Power Generation: Case Studies of Recently Constructed Coal- and Gas-Fired Power Plants," OECD/IEA, Paris2007.
[15] P. Vithayasrichareon, I. MacGill, and F. Wen, "Monte-Carlo Optimization Framework for Assessing Electricity Generation Portfolios," presented at Australasian Universities Power Engineering Conference 2009. AUPEC '09, Adelaide, 2009
[16] IEA, "Coal Information 2008," OECD/IEA, Paris, Paris2008.
[17] IEA, "Gas Information 2008," OECD/IEA, Paris2008.
[18] H. Laurikka, "Option value of gasification technology within an emissions trading scheme," *Energy Policy,* vol. 34, pp. 3916-3928, 2006.
[19] W. Blyth, "Use of Real Options as a Policy Analysis Tool," in *Analytical Methods for Energy Diversity and Security*, M. Bazilian and F. A. Roques, Eds. London: Elsevier, 2008, pp. 69-83.
[20] F. A. Roques, D. M. Newbery, and W. J. Nuttall, "Fuel mix diversification incentives in liberalized electricity markets: A Mean-Variance Portfolio theory approach," *Energy Economics,* vol. 30, pp. 1831-1849, 2008.
[21] F. A. Roques, W. J. Nuttall, D. Newbery, and R. D. Neufville, "Nuclear Power: A Hedge Against Uncertain Gas and Carbon Prices," 2005.
[22] C.-H. Chang, Y.-K. TUng, and J.-C. Yang, "Monte Carlo Simulation for Correlated Variables with Marginal Distributions," *Journal of Hydraulic Engineering,* vol. 120, pp. 313-331, 1994.
[23] D. C. Rode, P. S. Fischbeck, and S. R. Dean, "Monte Carlo Methods for Appraisal and Valuation: A Case Study of a Nuclear Power Plant," *Journal of Structured and Project Finance,* vol. 7, pp. 38-48, 2001.
[24] R. Green, "Carbon tax or carbon permits:The impact on generators' risks," Institute for Energy Research and Policy, University of Birmingham2007.
[25] M. Yang and W. Blyth, "Modelling Investment Risks and Uncertainties with Real Options Approach," International Energy Agency 2007.
[26] H. Markowitz, "Portfolio Selection," *The Journal of Finance,* vol. 7, pp. 77-91, 1952.

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