Monte-Carlo Optimization Framework for Assessing Electricity Generation Portfolios

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Abstract— **This paper proposes a stochastic approach based on Monte-Carlo Simulation (MCS) to account for various uncertainties when determining the overall generation cost of electricity generation portfolios. This approach extends the traditional deterministic methods for solving optimal generation mix by incorporating uncertainty into key cost assumptions and therefore solving the probability distribution of the expected generation costs for different generation technology portfolios consisting of different generation technologies. The overall cost output is represented by a probability distribution in which the statistical features of mean and standard deviation are used to measure the cost and risk profile for each generation portfolio. The model is applied to a case study of electricity generation portfolios consisting of different mixes of the three most common generation technologies: coal, Combined Cycle Gas Turbine (CCGT) and Open Cycle Gas Turbine (OCGT), taking into account fuel and carbon prices uncertainty. The case study demonstrates the capability of this model in addressing the impact of uncertainty on the cost and risk across different possible electricity generation portfolios. Therefore, it provides a comprehensive basis to assist decision making in generation investment in order to identify appropriate generation technology and/or the generation technology portfolio mixes that most likely to achieve the objectives in terms of expected costs, risks and CO_2 emissions.**

Keywords: Monte-Carlo simulation; generation investment; fuel and carbon prices uncertainty; electricity generation portfolio;

I. INTRODUCTION

The electricity industry faces growing uncertainties including future fuel prices and availability, energy demand and climate change policy. These uncertainties are now having a substantial impact on investment decision making in the industry. These decisions are already extremely challenging given the nature of generation and network investment in the industry which is irreversible, lumpy, capital intensive and involves long lead times. Besides minimising the expected overall generation cost of their electricity generation portfolio, industry investors may also seek to minimise exposure to the economic risks associated with these uncertainties. Risk-averse investors might indeed put more weight on the risks associated with different possible generation portfolios than on their expected costs. For these reasons, there is considerable value in formally incorporating risk assessment into decision support tools for electricity industry investment. However, incorporating these risks is particularly challenging as key drivers such as future demand, fuel prices and possible climate change policy approaches such as emissions trading schemes or carbon taxes are highly uncertain and almost certainly correlated.

This paper proposes a stochastic model based on Monte Carlo Simulation (MCS) to account for various uncertainties when determining the overall generation cost for possible technology portfolios. 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. Such an approach can highlight and identify the tradeoffs between different possible generation portfolios, rather than undertaking a single technology assessment or solving an expected least-cost generation mix. The main reason is that these types of analysis do not indicate the extent to which the additional technology contributes to the overall cost and risk of the existing portfolio of generation technologies. Our proposed model takes into consideration the existing generation portfolios when considering generation investment since adding or removing a particular generation technology subsequently alters the overall cost and risk profile of the existing portfolio.

A. Traditional optimal generation mix method

Under the traditional method for solving optimal generation mix, the cost curve of each generation technology as a function of capacity factor is plotted 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 portfolio can be determined [1]. Fig. 1 shows an example of this traditional optimal generation mix method. For this example, estimates of the fixed and variable non-fuel costs of available generation technologies, future Load Duration Curve (LDC), future fuel prices and an expected price on carbon emissions are all required. For this case, when carbon price is set at $20/t$CO_2$, coal is not an economically viable option, and the optimal generation mix only consists of Combined Cycle Gas Turbine (CCGT) and Open Cycle Gas Turbine (OCGT) plant at 78% and 22% of total capacity respectively.

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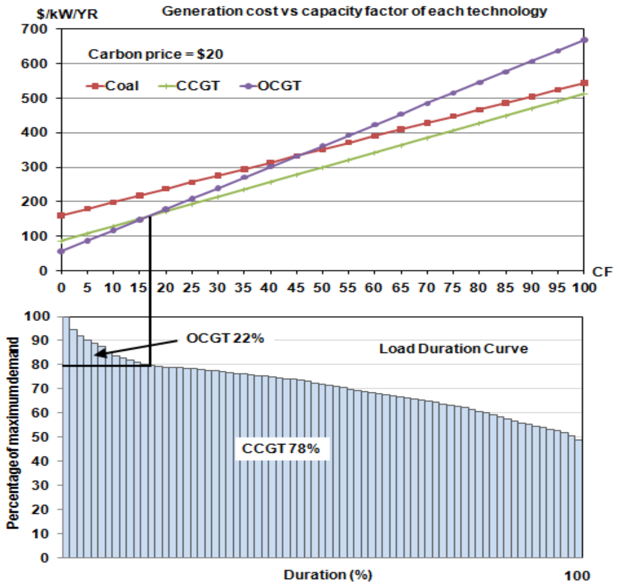

Figure 1. Traditional optimal generation mix for coal, CCGT and OCGT plant under a range of assumptions including a carbon price of $20/tCO_2$

Although this traditional deterministic method is simple and useful, 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. Of particular focus in this paper, the standard approach also does not take into account uncertainties such as future fuel prices, energy demand and climate change measures. This method only solves for the expected least-cost generation mix given deterministic assumptions about future uncertainties. Furthermore, it ignores the existing generation portfolios that the utility or country already operates, which is an important criteria in generation investment since each generation technology contributes differently to the overall generation portfolio in terms of expected costs and risks including, for example, carbon risk.

B. *Stochastic approach for incorporating uncertainty*

There are several methods for implicitly addressing risks and uncertainty in generation investment however it is widely agreed that the Monte-Carlo Simulation (MCS) is the most comprehensive technique and flexible to analyze problems which involve many uncertain parameters having many possible combination of input values [2, 3]. MCS characterizes uncertainty by assigning a probability distribution to uncertain input parameters then generating repeated samples of uncertain inputs to determine the output values which can be represented by the probability distribution. Any distribution can be used including historical data sets. Moreover, correlated input uncertainties can also be incorporated in the MCS. The statistical features of mean and standard deviation can be used to measure the cost-risk profile of the output under conditions of particular assumed probability distributions. The standard deviation is the most widely used method for measuring uncertainty since it is a measure of statistical dispersion which indicates how widely spread the actual spread of the values in the data set [4]. Hence the project with greater risk and uncertainty would have a wider spread of possible outcomes than the project with less uncertainty [5]. For the MCS in our model, stochastic variables are generated repeatedly from their probability distribution in order to calculate the overall generation cost of a particular portfolio of generation technologies. For simplicity, this paper uses normal non-correlated distributions for stochastic input variables. The overall cost output is therefore represented by a probability distribution. The portfolio risk is defined as the standard deviation of expected generation cost of the generation portfolio [6-9]. The results from the Monte-Carlo simulation enables the impact of uncertainty on different generation portfolios to be captured and compared and therefore the significance of each source of uncertainty on each generation portfolio can be identified.

II. METHODOLOGY

A. *Model Framework*

The model is based on the Monte Carlo Simulation (MCS) technique to account for uncertain parameters in order to calculate the expected generation cost of various electricity generation portfolios in a year. The methodology framework is presented in fig. 2.

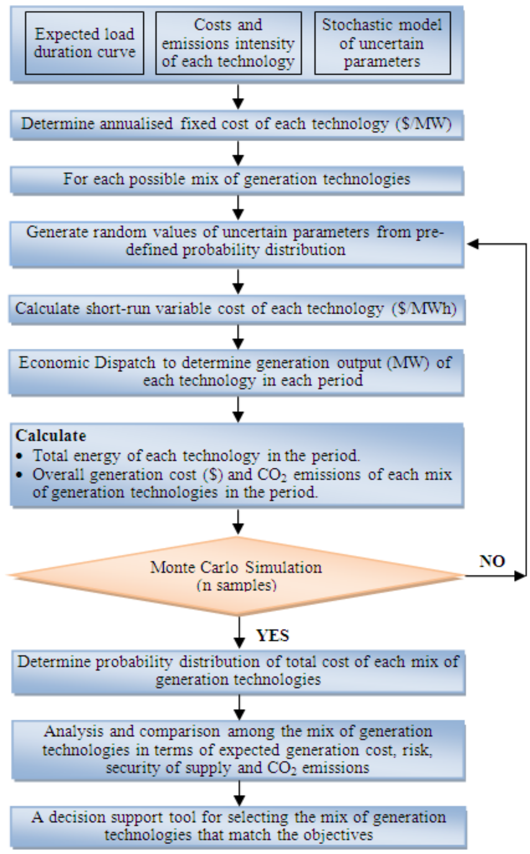

Figure 2. Flowchart of the methodology framework

The generation cost consists of fixed and variable costs. Fixed cost is determined based on annualized cost ($/MW/year) which will be incurred regardless of the amount of energy generated whereas variable costs consist of variable operation and maintenance (O&M), fuel and carbon costs. The amount of energy generated by each available technology in each interval of the LDC is determined using economic dispatch. The overall generation cost of a generation technology portfolio in an entire period is calculated for each set of uncertain parameters. Outputs from MCS represent a range of possible overall generation costs of each portfolio which can be represented by a probability distribution. This study considers a range of generation portfolios for three technologies where each ranges from 0% to 100% of total capacity in 20% increments.

For each Monte-Carlo run, the values of stochastic input parameters are randomly selected from their respective pre-defined probability distributions. The generation cost consists of annualized fixed and variable costs. The annualized fixed cost is calculated from capital cost ($/MW) of each generation technology using the Capital Recovery Factor (CRF) as shown in (1). The CRF determines the equal amount of regular payments in a present amount of money [1].

$$\mathrm{CRF} = \frac{i(1+i)^m}{(1+i)^m - 1} \tag{1}$$

where

m Plant life time (years)

i Discount rate (%)

The variable cost comprises of O&M, fuel and carbon costs as detailed in (2), (3).

$$\text{Fuel cost} = \text{Fuel price (\$/GJ)} \times \text{Heat Rate (GJ/MWh)} \tag{2}$$

$$\text{Carbon cost} = \text{Emissions factor (tCO}_2\text{/MWh)} \times \text{Carbon price (\$/tCO}_2\text{)} \tag{3}$$

The annual energy production of each technology is determined from the sum of generation output of each technology in each segment of the load duration curve (LDC). The area in each segment of the load duration curve represents the energy demanded in a period hence the area under a yearly LDC represents the amount of energy demanded in one year. The load duration curve used in the study is illustrated in fig. 3.

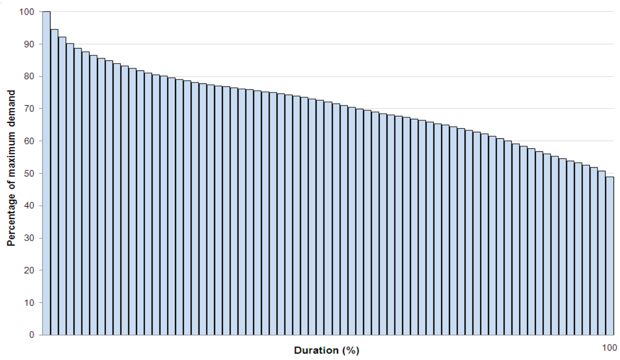

Figure 3. Load Duration Curve

The generation output of each technology in each segment of the LDC is determined based on variable cost of each technology under the economic dispatch resulting in a least-cost operation. The economic dispatch can be formulated according to (4) – (6).

$$\text{Minimize} \quad \sum_{s\in S}\sum_{n\in N} VC_n \times P_{s,n} \tag{4}$$

$$\text{subject to} \quad \sum_{n\in N} P_{s,n} = \mathrm{Demand}_s \tag{5}$$

$$P_{s,n} \le I_n \tag{6}$$

where

N Number of technologies considered;

S Number of segments in the load duration curve;

VC_n Variable operating cost of technology n ($/MWh);

$P_{s,n}$ Output of technology n (MW) in each segment of LDC;

I_n Installed capacity of each technology (MW);

The installed capacity of each technology is determined from the percentage share of such technology in the generation portfolio. The total generation cost in a year of each generation portfolio during each Monte-Carlo run is calculated using (7).

$$TC = \sum_{n\in N}(FC_n \times I_n) + (VC_n \times E_n) \tag{7}$$

where

TC Total generation cost in a year ($)

FC_n Annualised fixed cost of technology n ($/MW)

I_n Installed Capacity of technology n (MW)

VC_n Variable O&M cost of technology n ($/MWh)

E_n Energy generated by technology n in a year (MWh)

The amount of CO_2 emissions per year for each generation portfolio is also determined according to (8).

$$CO_2 = \sum_{n\in N} EF_n \times E_n \tag{8}$$

where

EF_n Emission factor of technology n (ton of CO_2/MWh)

The capacity factor (CF) of each technology is defined as the ratio of the actual electrical energy produced in a certain period to the maximum possible energy that could have been produced by the plant or technology in the period.

B. Assumptions

- The model adopts a social welfare maximisation perspective concentrating on the electricity generation cost under uncertainty. It does not attempt to solve electricity pricing.
- This study assumes that the installed capacity is always available for dispatch and there is always sufficient capacity to serve demand. The possibility of outages of generators is not considered.
- This study concentrates on the economic risks arising from fuel price and carbon price uncertainty without considering other technical or operational risks.

One of the important features of this model is the manner in which the capacity factor of each generation technology in the generation portfolio is determined. Unlike the standard probabilistic analysis or discounted cash flow (DCF) approaches in which the capacity factor for each generation technology is assumed to be constant, this model incorporates the economic merits of alternative generation types when determining the capacity factor of each technology. As the load is not uniform, but has hourly, daily, weekly and seasonal variations, therefore different types of generation technology with different economic and operating characteristics should be used to serve demand in different periods [1]. The generation output of each technology in the portfolio is determined by the economic dispatch method which takes into account the load profile represented by the load duration curve and the variable cost of each technology. With this approach, the generation output and capacity factor of each generation technology can be determined in a more practical manner.

III. CASE STUDY: FUEL AND CARBON PRICES UNCERTAINTY

The case study presented here considers the impact of fuel and carbon prices uncertainty on the generation cost of 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 portfolio ranges from 0% to 100% of total capacity in 20% increments, hence there will be 21 combinations of possible generation portfolios as indicated in table I.

TABLE I. POSSIBLE ELECTRICITY GENERATION PORTFOLIOS

No.	Share of technology in generation portfolio (%)			No.	Share of technology in generation portfolio (%)		
	Coal	*CCGT*	*OCGT*		*Coal*	*CCGT*	*OCGT*
1	0	0	100	12	40	0	60
2	0	20	80	13	40	20	40
3	0	40	60	14	40	40	20
4	0	60	40	15	40	60	0
5	0	80	20	16	60	0	40
6	0	100	0	17	60	20	20
7	20	0	80	18	60	40	0
8	20	20	60	19	80	0	20
9	20	40	40	20	80	20	0
10	20	60	20	21	100	0	0
11	20	80	0				

For each generation portfolio, the calculation of cost is repeated for 500 simulated years of uncertain future fuel and carbon prices.

A. Representation of Uncertainties

The normal distribution is assumed to represent fuel and carbon prices uncertainty. Mean and standard deviation of fuel prices are defined based on historical fuel prices provided in [10, 11] . Standard deviation of gas and coal price used in the model is 30% and 10% of their respected mean values. The standard deviation of the coal price is smaller than that of gas price indicating that the fluctuation of coal price is less than the gas price. The standard deviation of fuel prices are approximately in line with values that have been used in a number of previous papers, which are generally between 25-30% of the expected value [12-14]. For the carbon price, however, the information on historical data is rather limited therefore the expected carbon price is assumed to be $20/tCO_2$ with standard deviation of 50% of the expected value. The model assumes a high value of standard deviation 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 value and standard deviation of fuel and carbon prices used for the simulation.

TABLE II. MEAN AND STANDARD DEVIATION OF UNCERTAIN PARAMETERS

	Carbon Price ($/tCO$_2$)	Coal Price ($/GJ)	Gas Price ($/GJ)
Mean	20	2.85[a]	6.45
Standard Deviation	10	0.285	1.935

a. Based on coal price of $72.8/ton with the average net calorific value of 25,500 MJ/ton

This study does not take into account the correlation among fuel prices and carbon prices, and therefore assumes their movement to be independent even though the correlation has been identified to have a considerable impact on the cost-risk profile of generation portfolios [7, 14]. Fuel and carbon prices are assumed to have a minimum threshold value in which it is impractical for the price to be below such threshold value. On the high side, however, there is no maximum limit due to the possibility of price spikes. The minimum threshold for gas price is assumed to be $2/GJ. As for the coal price, the minimum threshold has not been set due to its relatively low standard deviation. The distribution of sample uncertain parameters of gas, coal, and carbon prices over the 500 trials are shown in fig. 4. Since the uncertain variables are normally distributed, therefore the simulated distribution of cost output will be close to normal.

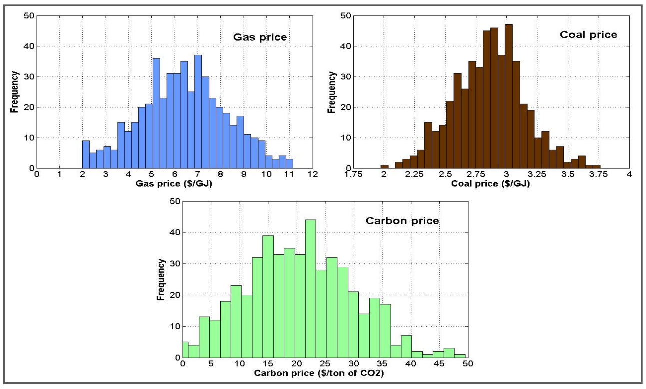

Figure 4. Distribution of sample uncertain parameters

B. Technological Parameters

The parameters for each technology are given in Table III. These parameters are compiled from sources [9, 15-20].

TABLE III. TECHNOLOGICAL PARAMETERS

Attributes	Plant Type		
	Coal	*CCGT*	*OCGT*
Plant life (years)	40	25	25
Capital cost ($/MW)	1,400,000	650,000	450,000
Fixed O&M ($/MW/yr)	43,000	25,000	14,000
Annualized fixed cost ($/MW/yr)[a]	160,500	86,000	56,200
Average Efficiency (%)	42	58	43
Variable O&M ($/MWh)	3.3	1.5	6.5
Emission factor (tCO$_2$/MWh)	0.8	0.35	0.47

a. determined from the capital cost using the method in section II, assuming an 8% discount rate.

C. *Load Profiles*

The load profile used in this simulation is based on a half-hourly demand in New South Wales (NSW) in 2007, with peak demand of approximately 14,000 MW. Since a half-hourly LDC contains a large number of data points and could pose a problem in terms of computation time, the interval of LDC is reduced to 438 segments in which each segment represents the average demand in 20-hour period.

IV. CASE STUDY RESULTS

The overall generation cost for each generation portfolio is simulated assuming combined fuel prices and carbon prices uncertainty. This scenario reflects the likely situation that electricity industries around the world will be required to confront in the near future. The results from the model consist of the expected generation cost, standard deviation of the generation cost, which represents the volatility or risk, and CO_2 emissions of each generation portfolio.

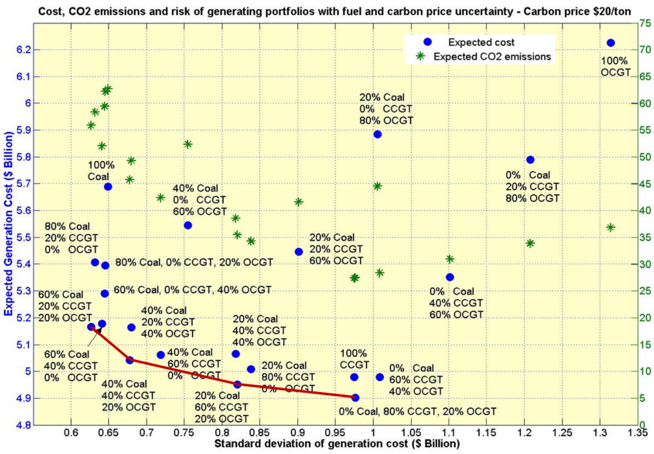

Figure 5. Expected generation cost, SD and CO_2 emissions of each portfolio

Fig. 5 shows the plot of the expected annual generation cost, CO_2 emissions of every generation portfolio against its standard deviation. With the combined fuel and carbon prices uncertainties assumed in this study, OCGT is the most susceptible technology to uncertainty as it exhibits the largest cost spread, as indicated by the standard deviation. Coal has the least cost uncertainty, while CCGT is in the middle. Hence, the generation portfolios that consist of a majority of coal would have less cost uncertainty. In terms of generation cost, in the case where a single technology represents the entire generation portfolio, OCGT is the most costly while CCGT is the least costly technology.

Although, the volatility of carbon price is greater than that of gas price and coal price, as explained in section III, the impact of gas price uncertainty on OCGT and CCGT is still more influential than the impact of carbon price uncertainty on coal since fuel cost is the largest cost component of OCGT and CCGT. Based on the expected fuel and carbon prices in this study, fuel cost constitutes about 80% of variable costs for CCGT and OCGT whereas it accounts for about 55% for coal. Carbon costs, on the other hand, account for around 14% of variable costs for CCGT and OCGT while it accounts for about 37% for coal. Consequently, given the combined fuel price and carbon price uncertainty, the generation portfolios that contain a large share of coal exhibit a lower uncertainty compared with the portfolios that are dominated by CCGT or OCGT.

It is also possible to establish the efficient frontier that consists of optimal generation portfolios. Along the efficient frontier, the generation cost cannot be reduced without increasing the uncertainty [6, 7]. The solid line in fig. 5 indicates the efficient frontier. There are four generation portfolios on the efficient frontier, and the lowest expected cost is for the portfolio of 0% coal, 80% CCGT and 20% OCGT mix. However this mix also exhibits a relatively high cost uncertainty. By increasing the share of coal from 0% to 20% of the portfolio, replacing the share of CCGT so that the portfolio now contains a mix of 20% coal, 60% CCGT and 20% OCGT, the cost uncertainty can be reduced by 15% while the generation costs will increase by only 1%. However, the CO_2 emissions will increase by 30% relative to the lowest expected cost generation portfolio. In terms of cost uncertainty, the least uncertain cost generation portfolio is the 60% coal, 20% CCGT and 20% OCGT mix as the risk is 35% lower and the generation cost is about 6% higher in relation to the lowest expected cost generation portfolio. However, the amount of CO_2 emissions is more than double of the amount emitted by the lowest expected cost generation portfolio. Similar comparisons can be made by analysing the cost, risk and CO_2 emissions tradeoffs among generation portfolios.

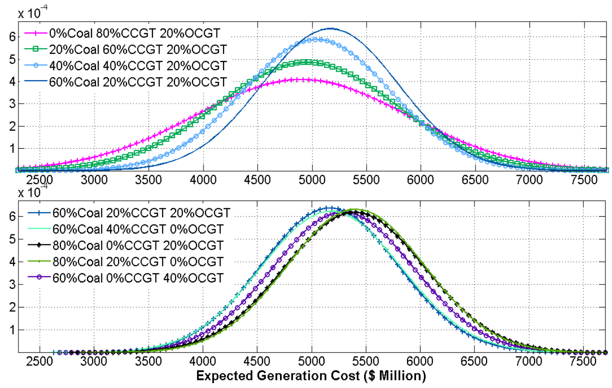

Figure 6. Probability distributions for different generation portfolios

The upper graph of fig. 6 displays the probability distributions of generation portfolios that are on the efficient frontier while the lower graph shows the distributions of generation portfolios with low cost uncertainty.

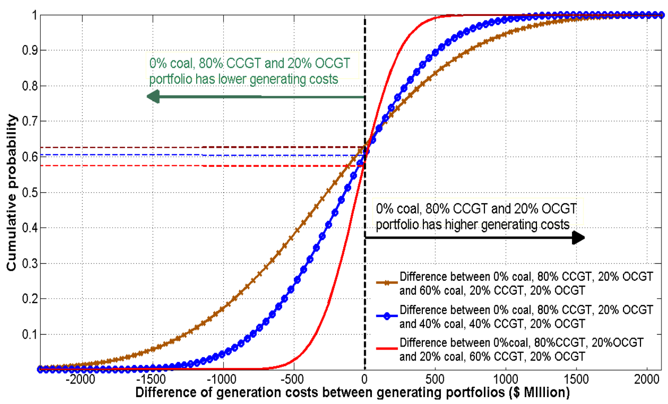

Figure 7. Cumulative probability of the optimal generation portfolios

The cumulative probability distribution can be used to statistically compare different generation portfolios. Fig. 7 shows the cumulative probabilities of the difference of generation costs between the generation portfolio that contain 0% coal, 80% CCGT and 20% OCGT share, which is the least cost portfolio, with other portfolios that are on the efficient frontier. According to the figure, there is 58% chance that the least expected cost generation portfolio will have lower cost than the portfolio that contains 20% coal, 60% CCGT and 20% OCGT share. Similarly, there is 63% chance that its cost will be lower than the portfolio that contains 60% coal, 20% CCGT and 20% OCGT share. Similar comparisons can be made between the optimal portfolios on the efficient frontier in order to statistically quantify the cost-risk trade-off between them.

The results from the case study reveal several important aspects, in particular the contribution of each technology to the generation cost and risk of the generation portfolio. Intuitively, adding a more costly technology, at an assumed capacity factor, to the portfolio should increase the portfolio cost and similarly, adding a less costly technology should reduce the portfolio cost. However, this is not always true, as indicated in the case study. For example, introducing OCGT, which is the most costly technology at an assumed capacity factor, to the otherwise 100% CCGT portfolio can reduce portfolio cost while the risk is relatively unchanged. Similarly, by increasing the share of OCGT from 0% to 20%, replacing the share of coal in the otherwise 100% coal portfolio, can reduce the expected generation cost considerably without increasing the cost uncertainty. This may seem counterintuitive since adding a more expensive technology should increase the portfolio cost. However, since the load is not uniform throughout the year therefore the trade-off between fixed and variable costs enables each generation technology to play a valuable role in a generation portfolio in meeting demand during different periods.

The results also demonstrate that although OCGT and CCGT are less affected by carbon price uncertainty than coal, they face a much higher fuel price uncertainty since fuel cost is by far the largest cost component, causing both technologies to have higher cost uncertainty than coal. With the carbon price assumed to be $20/t$CO_2$, coal is the least uncertain cost technology. However, with a rise in carbon price, coal will become more expensive and susceptible to cost uncertainty relative to CCGT and OCGT.

V. CONCLUSIONS

This paper has presented an approach that extends the traditional deterministic method for solving optimal generation mix by employing a stochastic approach of MCS to incorporate uncertainty into key cost assumptions and therefore solving probability distributions of expected generation cost for different generation technology portfolios. The model is applied to the case study of generation portfolios consisting of different mixes of coal, CCGT and OCGT, under fuel and carbon prices uncertainty. The results from the model help to understand the impact of uncertainties on different generation technologies and generation technology portfolio mixes. The cost-risk profile and CO_2 emissions across various generation portfolios can be compared and therefore enabling the tradeoffs among generation portfolios to be highlighted and quantified.

This model is powerful yet flexible since it is capable of accommodating a number of uncertainties, varied types of generation technology, load profile and any form of probability distribution for the stochastic parameters as well as possible correlation between them. This model appears to have a significant potential to support decision making in generation investment under various uncertainties, and therefore enabling the appropriate generation technology and generation portfolios to be identified.

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