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A Monte Carlo approach to integrating uncertainty into the levelized cost of electricity☆

Nathaniel Heck[a], Courtney Smith[a,b], Eric Hittinger[b,*]

[a] Department of Chemical Engineering, Rochester Institute of Technology, Rochester, NY, 14618, USA
[b] Department of Public Policy, Rochester Institute of Technology, Rochester, NY, 14618, USA

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ABSTRACT

A Monte Carlo analysis of the levelized cost of electricity yields probability distributions for the costs of major generation technologies rather than the usual point values. A Monte Carlo approach is only slightly more complex than using point values, but provides more realistic information about risk and uncertainty and enables more useful analysis of potential investments in electricity generation.

1. Background

In a deregulated electricity market, investment in new electricity generation is primarily driven by an expectation of profitable operation. In regulated areas, generation planning must consider other factors, such as capacity and the ability to cycle the generation fleet, but is also driven by a desire to meet the electric load at lowest total cost. In either regulatory system, choosing new generation that will minimize the cost of electricity is critical. Levelized cost of electricity (LCOE) is the standard tool used to compare the cost of electricity from different generation sources. However, LCOE is normally calculated using point values for all inputs, effectively neglecting the uncertainty inherent in these generation investment decisions.

The Energy Information Administration estimates that, by the year 2040, 350 GW of new generating capacity will be needed to replace retiring coal and nuclear plants and meet an 18% increase in demand (U.S. Energy Information Administration, 2014a, 2014b, 2014c). Building new electricity generation is a both fundamentally uncertain and capital-intensive business. Though the choice of new generation technologies is normally made with cost minimization as the primary objective, the levelized cost of electricity from a power plant is dependent on several factors that often have significant uncertainty: capital cost, lifetime of the plant, future fuel costs, future carbon prices, and the capacity factor of the plant. The underlying uncertainties are significant in some cases and are affecting current decisions about new generation. For example, one of the major barriers to new nuclear plants in the U.S. is uncertainty over capital costs (Koomey and Hultman, 2007; Rothwell, 2006). Several of the last U.S. nuclear plants to be built, during rate-of-return regulation, had cost overruns of more than 100% (Hirsh, 2002). This is an unacceptable financial risk in deregulated markets and the Department of Energy has offered loan guarantees for new nuclear generation in an attempt to overcome this barrier (Pulizzi and Buurma, 2010). In a similar situation, one of the obstacles to construction of new coal power plants is uncertainty over future carbon policies and prices (Electric Power Research Institute, 1999; Yang et al., 2008; Blyth et al., 2007). It is clear that actual investment decisions are being affected by uncertainty, suggesting that integrating this uncertainty into LCOE estimates would be useful to generation-related planning.

LCOE calculations normally use point values for all inputs. If uncertainty is included at all, it is usually through a simple sensitivity analysis that uses high/low values for each variable to estimate upper and lower bounds on the LCOE. This approach is limited because it does not provide a sense of the likelihood of different outcomes. In contrast, the Monte Carlo approach is a relatively simple and established technique for including uncertainty in quantitative models. In Monte Carlo, a calculation is performed many times, each

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* Corresponding author.
E-mail addresses: nsh8415@rit.edu (N. Heck), cns6240@rit.edu (C. Smith), eshgpt@rit.edu (E. Hittinger).

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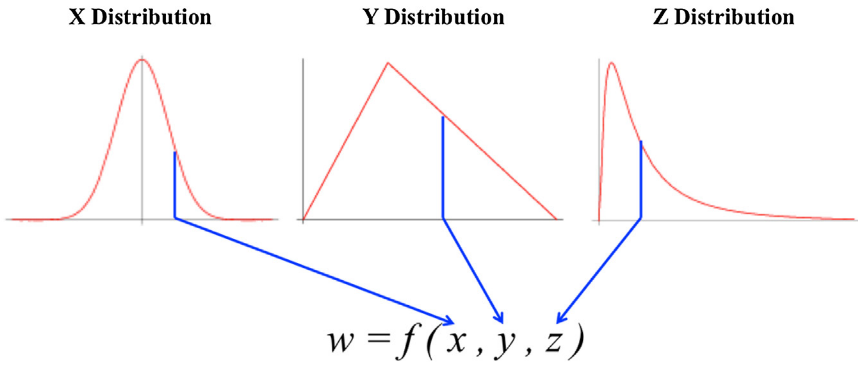

Fig. 1. Example Monte Carlo Iteration. For each distribution, a point is chosen randomly from under the probability density function (PDF), meaning that values from higher-probability areas are more likely to be chosen. The blue lines indicate the value used in a single iteration of the calculation. In Monte Carlo, this process would be repeated many times, each with a different set of inputs chosen from the PDFs of the respective inputs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Coal inputs.

Inputs	Distribution	Range	*A*	*B*	*C*
Capital cost ($/kW)	Log normal	1584–8071	3030	8.182	0.407
Interest rate (yearly %)	Triangular	5	10	15	–
Loan period (yrs)	Constant	40	–	–	–
Fixed O&M ($/kW year)	Normal	19.67–30.80	25.27	2.80	–
Fuel cost ($/MMBtu)	Normal	1.27–2.41	1.84	0.285	–
Heat rate (Btu/kWh)	Normal	8755–12,005	10,380	812.5	–
Variable O&M ($/MWh)	Normal	2.2–6.1	4.15	0.975	–
Capacity factor (%)	Constant	93	–	–	–
Carbon emissions (lbs/MMBtu)	Constant	214	–	–	–

with its own set of inputs chosen randomly from pre-defined distributions for each input variable. In the case of LCOE, the result is a distribution of possible LCOE values, which can be further investigated with a variety of analytical techniques.

Despite the advantages of Monte Carlo modeling for LCOE estimation, its use in existing literature is limited. Research using Monte Carlo for LCOE estimates has been focused on one or two energy types, precluding interesting comparisons between technologies. One such study, focused on solar photovoltaic panels, looked at the effects on LCOE of degradation in performance over time, average viable sunlight received, and other variables associated with photovoltaic panels (Darling et al., 2011). Another study, from Spinney and Watkins at Charles River Associates, used a Monte Carlo approach to compare utility options under integrated resource planning, a utility planning system commonly used when the paper was published in 1996 (Spinney and Watkins, 1996). In a third work, Vithayasrichareon uses Monte Carlo techniques to compare the LCOE of German coal and natural gas generation facing uncertain carbon prices in the future (Vithayasrichareon, 2010). We have not found any research in the existing literature that summarizes the Monte Carlo approach for LCOE and presents its advantages and extensions, as we do below. In addition to this conceptual comparison, we apply carefully collected cost and operational data from a variety of sources to estimate LCOE distributions for seven different electricity generation technologies.

2. Methods

We use a Monte Carlo analysis for calculating the LCOE for seven generation technologies: coal, combined cycle natural gas, peaking natural gas (combustion turbine), nuclear, wind, solar photovoltaic, and solar thermal. By changing the inputs to the basic equation for LCOE slightly, different scenarios can be analyzed in proportion to their estimated probability. Examined in this paper are four analyses: one looking at the basic LCOE for each generation technology, another examining the effect that uncertain carbon pricing would have on the expected LCOE of fossil fuel technology, a third separating uncertainty from variability for the renewable generation technologies, and the fourth focusing on the financial risk aversion associated with each technology.

To perform a Monte Carlo estimate of LCOE, the standard LCOE equations are used and quantified with point values. However, unlike a simple calculation of LCOE, the calculation is performed many times (usually hundreds to millions), each time with a different set of inputs selected from pre-defined input distributions. The results are recorded for each calculation, and the resulting distribution in LCOE gives the distribution of possible outcomes.

To calculate a Monte Carlo LCOE, an appropriate range and distribution for each variable is first determined. Distribution types

Table 2
Combined cycle natural gas inputs.

Inputs	Distribution	Range	*A*	*B*	*C*
Capital cost ($/kW)	Log normal	559–1858	931	6.927	0.3
Interest rate (yearly %)	Triangular	5–15	5	10	15
Loan period (years)	Constant	20	–	–	–
Fixed O&M ($/kW year)	Triangular	5.50–15.37	5.50	7.28	15.37
Fuel cost ($/MMBtu)	Triangular	3.42–9.02	3.42	4.50	9.02
Heat rate (Btu/kWh)	Normal	6430–7050	6740	155	–
Variable O&M ($/MWh)	Normal	1.41–3.73	2.57	0.58	–
Capacity factor (%)	Triangular	40–87	40	80	87
Carbon emissions (lbs/MMBtu)	Constant	117	–	–	–

Table 3
Peaking natural gas inputs.

Inputs	Distribution	Range	*A*	*B*	*C*
Capital cost ($/kW)	Triangular	600–1200	600	850	1200
Interest rate (yearly %)	Triangular	5–15	5	10	15
Loan period (years)	Constant	20	–	–	–
Fixed O&M ($/kW year)	Log normal	4.90–24.30	9.30	2.39	0.4
Fuel cost ($/MMBtu)	Triangular	3.42–9.02	3.42	4.50	9.02
Heat rate (Btu/kWh)	Normal	9000–10,850	9925	462.5	–
Variable O&M ($/MWh)	Log normal	3.05–16.22	5.90	1.95	0.418
Capacity factor (%)	Normal	5–10	7.5	1.25	–
Carbon emissions (lbs/MMBtu)	Constant	117	–	–	–

used in this work include normal, log-normal, and triangular. From the distribution for each variable, a random point is chosen from under the curve, and used in the LCOE equation to compute a single LCOE value. This is repeated many times to obtain a final distribution of LCOE for each technology. Fig. 1 illustrates one iteration of Monte Carlo for a result, *w*, that is a function of three variables, *x*, *y*, and *z*, each with its own distribution.

The basic formula for LCOE is given by Eq. (1) (National Renewable Energy Laboratory, 2014). *P* is the yearly payment associated with the initial capital cost to build the generation plant or station, $O\&M_F$ is the fixed operation and maintenance cost, or the cost of paying employees, overhead, and other operating costs, 8760 is the number of hours in a year, C_f is the capacity factor as a percent, or the ratio of the actual energy output of the plant relative to the energy output if it were always running at maximum capacity, F_c is the fuel cost, *Q* is the heat rate of the plant, and $O\&M_V$ is the variable operations and maintenance cost, or the cost associated with how often the plant is operational. All calculations in this work use real 2014 dollars.

$$\mathrm{LCOE} = \frac{P + O\&M_F}{8760 \times C_f} + (F_c \times Q) + O\&M_V \quad (1)$$

P, the yearly payment on capital costs, is given by Eq. (2). C_c is the capital cost of building the generation plant or station, *i* is the interest rate, and *n* is the number of payments, assumed to be the lifetime in years of the plant.

$$P = C_c \times \left[i + \frac{i}{(i+1)^n - 1} \right] \quad (2)$$

In addition to base case results, we include estimates of the effect that carbon price uncertainty has on LCOE of fossil fuel generators. For the carbon pricing scenario, the expected future costs of carbon payments are included, assuming an uncertain carbon price that takes effect at an uncertain point of time in the future. We assumed that any carbon price, once established, would increase at 3% per year, though this variable could also be given and used as a distribution rather than a point value. Eq. (3) is used to calculate the annual CO_2 payment in the first year of the CO_2 pricing regime. P_{CO_2} is the carbon price in $/tonne, Q is the heat rate in MMBTU/MWh, E_{co2} is the emissions intensity of the fuel in tonnes/MMBTU, S_{plant} is the capacity of the plant in MW, and C_f is the capacity factor. Eq. (4) calculates the future value, in the year when the carbon price takes effect, of all carbon payments. In this equation, *g* is the growth rate in CO_2 price, which we fix at 3%, and *m* is the number of years until the carbon price is implemented. Eq. (5) takes the future value of all carbon payments and converts it to a present value, where *i* is assumed to be the same interest rate as in Eq. (2). Eq. (6) illustrates how the carbon payments are included in the LCOE, by taking the present value of all carbon prices and combining it with the capital cost of the system. While conceptually complex, this method amortizes the carbon payments that start in year *m* over all of the electricity produced by the plant.

$$C_{CO_2} = 8760 \times P_{CO_2} \times Q \times E_{CO_2} \times S_{plant} \times C_f \quad (3)$$

$$\mathrm{FV}_{CO_2} = C_{CO_2} \left[\frac{1 - (1+i+g)^{-(n-m)}}{i+g} \right] \quad (4)$$

$$\mathrm{PV}_{CO_2} = \frac{FV_{CO_2}}{(1+i)^m} \quad (5)$$

$$P = (C_c + \mathrm{PV}_{CO_2}) \times \left[i + \frac{i}{(i+1)^n - 1} \right] \quad (6)$$

An additional benefit of using Monte Carlo estimation is that the results are reported as a quantitative distribution. This allows for quantitative analysis of the risk or uncertainty compared with the average result. For example, a risk averse decision maker might be willing to choose a technology with a slightly higher expected LCOE as long as that LCOE was far more certain than the alternatives. To quantitatively evaluate these possibilities, we use an existing economic model of risk aversion to calculate "certainty equivalent" LCOE for each technology. The certainty equivalent, a function of the decision-maker's risk aversion, indicates a fixed value of LCOE that the decision-maker should be indifferent towards, relative to the uncertain LCOE distribution that they face. Because most entities are risk-averse, the certainty

Table 4
Nuclear inputs.

Inputs	Distribution	Range	*A*	*B*	*C*
Capital cost ($/kW)	Log normal	4146–8691	5801	8.7	0.185
Interest rate (yearly %)	Constant	10	–	–	–
Loan period (years)	Constant	40	–	–	–
Fixed O&M ($/kW year)	Normal	54.19–121.19	87.69	16.75	–
Fuel cost ($/MMBtu)	Constant	0.65	–	–	–
Heat rate (Btu/kWh)	Normal	10,420–10,480	10,450	15	–
Variable O&M ($/MWh)	Triangular	0.42–2.14	0.42	1.28	2.14
Capacity factor (%)	Normal	85–90	87.5	1.25	–
Carbon emissions (lbs/MMBtu)	–	–	–	–	–

Table 5
Wind inputs.

Inputs	Distribution	Range	*A*	*B*	*C*
Capital cost ($/kW)	Normal	1270–2670	1970	350	–
Interest rate (yearly %)	Constant	10	–	–	–
Loan period (yrs)	Constant	20	–	–	–
Fixed O&M ($/kW year)	Triangular	12.00–60.00	12.00	35.00	60.00
Fuel cost ($/MMBtu)	–	–	–	–	–
Heat rate (Btu/kWh)	–	–	–	–	–
Variable O&M ($/MWh)	Log normal	5.86–21.50	10.10	2.418	0.325
Capacity factor (%)	Normal	22.75–50.75	36.75	7	–
Carbon emissions (lbs/MMBtu)	–	–	–	–	–

Table 6
Solar photovoltaic inputs.

Inputs	Distribution	Range	*A*	*B*	*C*
Capital cost ($/kW)	Log normal	1554–5000	2560	7.933	0.292
Interest rate (yearly %)	Constant	10	–	–	–
Loan period (years)	Constant	20	–	–	–
Fixed O&M ($/kW year)	Normal	7.28–34.72	21	6.86	–
Fuel cost ($/MMBtu)	–	–	–	–	–
Heat rate (Btu/kWh)	–	–	–	–	–
Variable O&M ($/MWh)	–	–	–	–	–
Capacity factor (%)	Normal	15.48–28	21.74	3.13	–
Carbon emissions (lbs/MMBtu)	–	–	–	–	–

equivalent is higher than the expected LCOE value. In a sense, the risk-averse decision maker is willing to pay a higher expected cost if the uncertainty is removed. We refer to the difference between the average LCOE and the certainty equivalent as the “risk premium”.

For the associated risk analysis, a constant relative risk aversion function of utility is used to determine the certainty equivalent (Pratt, 1964). Eq. (7) gives risk premium, *RP*, as a function of risk aversion, γ, with LCOE as the LCOE value obtained for each run in the Monte Carlo analysis, and r as the number of runs or iterations. The certainty equivalent, C_{eq}, calculated for each generation technology, is given by Eq. (8). According to Pratt, assuming that the risks considered by a decision-maker vary and the decision-maker’s assets are constant, a proportional or relative risk aversion method can be utilized (Pratt, 1964). The assumption that the relative risk aversion is constant is valid because the utility function of LCOE will be positive and decreasing. The constant relative risk aversion approach is useful here because it quantifies an entity’s risk aversion, γ, where the higher the value, the more

Table 8
Carbon pricing inputs.

Inputs	Distribution	Range	*A*	*B*	*C*
Carbon pricing ($/metric ton)	Triangular	5–50	5	20	50
Years until carbon pricing (years)	Log normal	5–33	10	2.550	0.476

risk-averse one is. A higher risk aversion results in a higher risk premium, and thus a higher certainty equivalent.

$$\mathrm{RP} = \frac{\sum_1^r \mathrm{LCOE}}{r} - \left(\frac{\left(\sum_1^r \frac{(\mathrm{LCOE})^{(1-\gamma)}}{1-\gamma}\right)}{r} \times (1-\gamma) \right)^{(1-\gamma)} \tag{7}$$

$$C_{eq} = \frac{\sum_1^r \mathrm{LCOE}}{r} + \mathrm{RP} \tag{8}$$

Tables 1–8 show the input data used in this work, including both ranges from data sources and the probability distribution parameters chosen to represent the observed distribution from those sources. Data for Tables 1–8 were collected from a variety of sources, including several reports from the U.S. Energy Information Administration (EIA) and the Lazard Capital LCOE study. A complete list of data sources and a compilation of the values extracted from each report are provided in Appendix A. After acquiring several estimated values for each input, we observed the trends in the data points combined with knowledge of the underlying quantity to decide on a distribution type. For most variables that require a distribution, such as heat rate, capacity factor, and fixed O&M, a normal distribution was observed in the collected data. Other variables, especially capital cost, frequently fall in a fairly normal distribution, but have the potential, with a low frequency, to be significantly higher (but not significantly lower). For example, estimates of the cost of new nuclear power follow this trend, due to the possibility of very high capital cost. Since the nuclear power capital cost would more likely have a large

Table 7
Solar thermal inputs.

Inputs	Distribution	Range	*A*	*B*	*C*
Capital cost ($/kW)	Log normal	4250–9000	5800	8.713	0.198
Interest rate (yearly %)	Constant	10	–	–	–
Loan period (years)	Constant	40	–	–	–
Fixed O&M ($/kW year)	Normal	46.98–79.48	63.23	8.125	–
Fuel cost ($/MMBtu)	–	–	–	–	–
Heat rate (Btu/kWh)	–	–	–	–	–
Variable O&M ($/MWh)	Triangular	0.71–3.00	0.71	2.5	3.00
Capacity factor (%)	Normal	20.5–43.5	32	5.75	–
Carbon emissions (lbs/MMBtu)	–	–	–	–	–

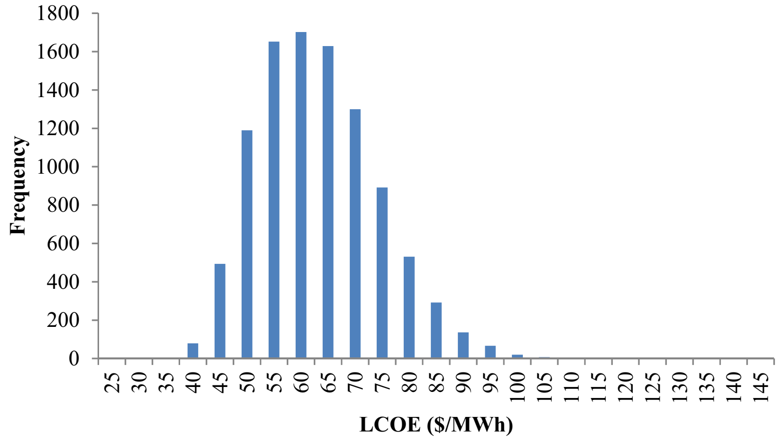

Fig. 2. Histogram of natural gas combined cycle LCOE values. 10,000 iterations, using the inputs from Table 2, are included in this figure. The distribution has a mean of $63.12/MWh, a standard deviation of $11.33/MWh, a median of $62.05/MWh, and a mode of $60.72/MWh.

range but have a higher frequency in the lower values, we used a log normal distribution. Other variables were assumed to fall in a specific range with nearly zero probability of falling out of that range. Natural gas prices follow this pattern. With the unprecedented growth in hydrofracturing in recent years, the price of natural gas is at such a low price that it cannot fall much below this value due to the costs of production. There is the possibility that legislative or social pressures could halt hydrofracturing operations, causing a rise in price of natural gas, but within certain bounds. Most likely, the price will be somewhere closer to the lower end of the range for the natural gas fuel price, so we chose a triangular distribution with a longer tail on the high price side.

For all analysis presented in this work, a 10,000-iteration Monte Carlo simulation is performed using the equations above and data ranges and distributions given in Tables 1–8. The values of *A*–*C* in these tables represent different inputs for the three types of distributions. For a normal distribution, *A* is the mean, and *B* is the standard deviation. For a log normal distribution, *A* is the mode, *B* is the μ parameter, and *C* is the σ parameter. For the triangular distribution, *A* is the low end of the distribution, *B* is the peak, and *C* is the high end of the distribution. The range is also reported, which is two standard deviations for a normal distribution, two geometric standard deviations for a log normal distribution, and the full range for a triangular distribution. For constant inputs, the range represents the value used. While the range for normal and log normal distributions only report two standard deviations from the respective means, in the Monte Carlo iterations the normal distribution is unbounded on both sides and log normal distributions are unbounded on the positive side (and start at zero).

An example of the application of Monte Carlo LCOE evaluation is shown in Fig. 2 for a combined cycle natural gas plant. Using the inputs described in Table 2 and the LCOE equations, over 10,000 iterations we acquire a distribution of possible LCOE values for a combined cycle natural gas plant, which we present here as a histogram.

3. Results

We first apply the equations and inputs described above to generate base case distributions of the LCOE of seven different electricity generation technologies. All values are in real

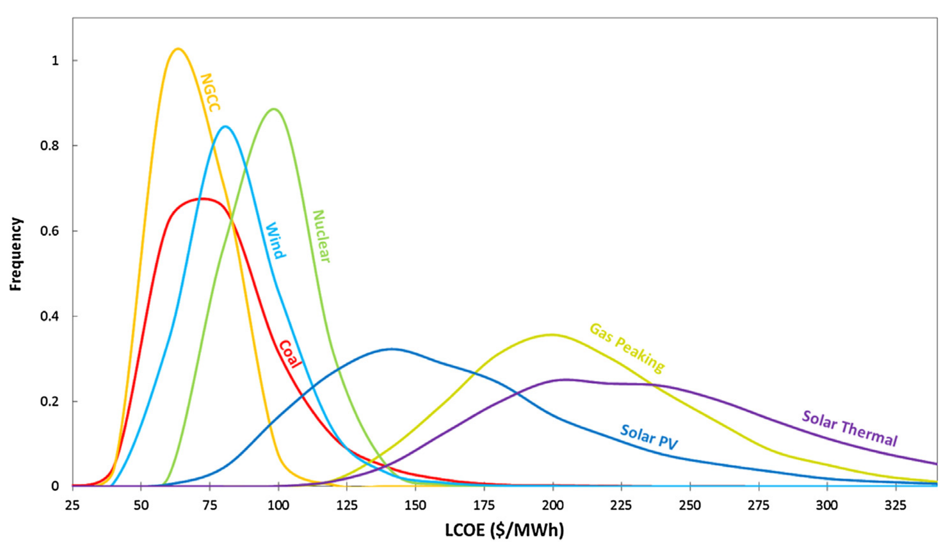

Fig. 3. Base case LCOE distributions for seven generation technologies based on 10,000 iterations of the LCOE equation for each technology. Subsidies, carbon prices, or other adjustments are not included in these calculations.

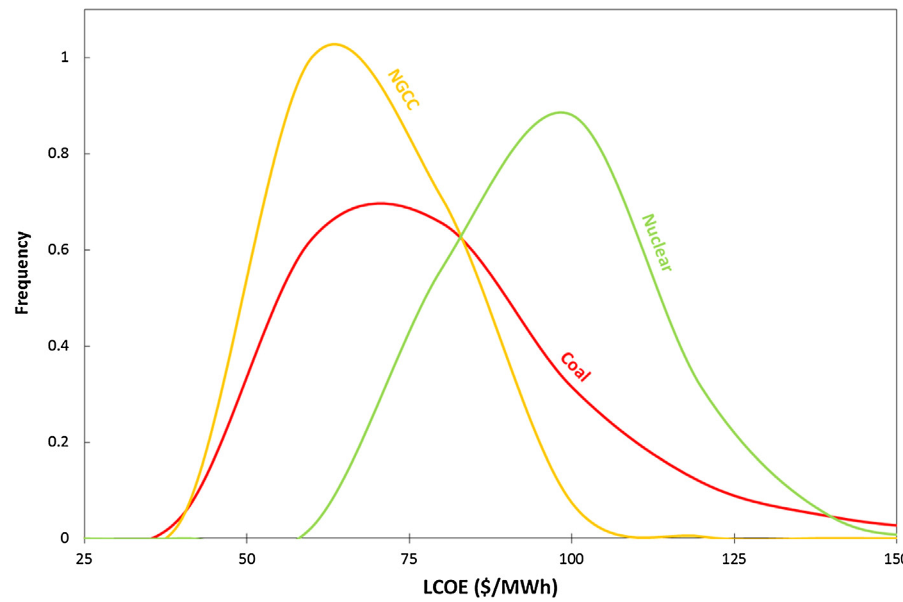

Fig. 4. Base case LCOE distributions for baseload generation technologies. This figure shows the same data as Fig. 3, at a different scale on the *x*-axis.

2014 dollars and assume plant construction starting in 2014. In addition to providing a range of LCOE values, the figures below show the uncertainty distribution for each generation type. Wider curves and lower peaks indicate a wider range of possible outcomes and a greater uncertainty associated with investment in that technology. For ease of comparison, the *y*-axis of each figure has been scaled so that the highest value is assigned a frequency of one.

Fig. 3 shows that several technologies are clustered together with relatively narrow distributions on the lower-cost side of the plot: natural gas combined cycle, coal, wind, and nuclear. Three other technologies (solar photovoltaic, solar thermal, and peaking natural gas) have LCOE distributions that are both significantly higher on average and more uncertain.

When comparing the baseload technologies (Fig. 4), coal has the widest distribution, meaning it has the highest uncertainty compared to the other baseload technologies, even without taking carbon prices or policies into account. Both nuclear and coal have long “tails” on the right side, mainly due to a higher uncertainty of possible capital costs. When comparing the renewable technologies in Fig. 5, wind is significantly less expensive than either solar technology, with less variability in LCOE. Overall, these results are compatible with observed trends in new construction of electricity generation, which is predominantly in the form of natural gas and wind generation.

From the box and whisker plot (Fig. 6), different comparisons can be made than with the overlapped distribution curves alone. This figure more clearly demonstrates the long “tails” for both coal and nuclear compared to NGCC. Gas peaking plants, a generation

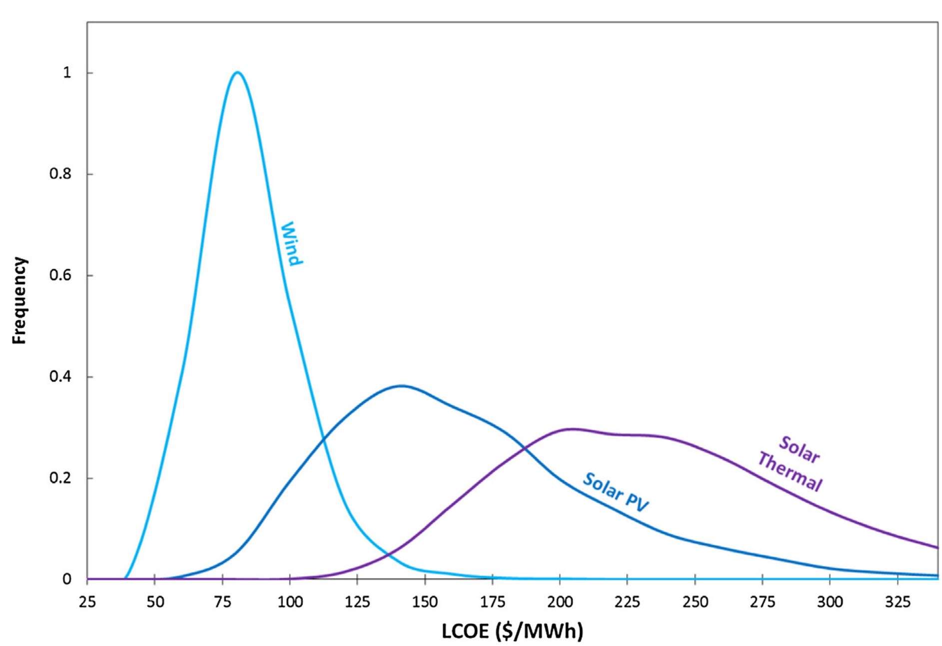

Fig. 5. Base case LCOE distributions for renewable generation technologies. This figure shows the same data as Fig. 3.

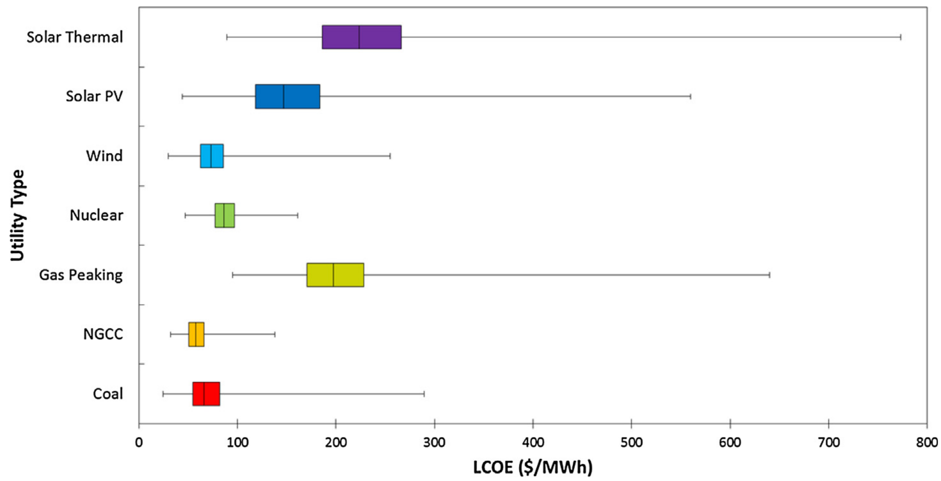

Fig. 6. Box and whisker plots for base case LCOE of the seven examined generation technologies. The box indicates the inter-quartile range while the extent of the whisker indicates the 95% confidence interval.

technology that is not directly comparable with other technologies, is shown to have large uncertainty in prices. This results from the uncertainty in frequency of operation as well as inefficiencies that arise from a peaking plant's erratic operational schedule. These results can be compared with other LCOE studies, such as the Lazard Capital Levelized Cost of Energy Analysis (Lazard Capital, 2013) (a comparison we provide in Appendix B).

We next investigate the effect that carbon prices have upon the base case results (Fig. 7). In this scenario, we include an uncertain carbon price (triangular distribution between $5 and $50/tonne of CO_2, with a mode of $20/tonne) that occurs at an uncertain future date (log normal distribution between 5 and 35 years from now, with a mode of 10 years). Integrating this carbon price scenario into fossil fuel LCOE estimates has only a minor effect on the distribution. As expected, coal is most affected by the carbon price. While using higher carbon prices would produce more notable shifts in LCOE, we based the carbon price scenario on actual estimates of the magnitude and start date of effective carbon pricing in the U.S. (see Appendix A). As noted above, the carbon price did not have a large effect on the LCOE cost. The average LCOE for a new coal plant without a carbon tax is $62/MWh, and it only increased to $80/MWh with the carbon tax. This is due mostly to the delay we chose to start implementing the carbon tax, which was variable with the greatest likelihood of starting 10 years into the future. If the carbon tax was implemented immediately, it would have a larger effect on the coal LCOE cost. For example, if we force the carbon price delay to zero, the average LCOE for a coal plant increases to $104/MWh, more than doubling the effect of the carbon price on levelized cost.

For renewable generation technologies, the base case LCOE distributions reflect both uncertainty in financial parameters and variability due to the location of the plant. Specifically, because renewable energy is limited by available wind or solar resource and generally used whenever available (because of its near-zero marginal cost), capacity factor is related to location in a direct and predictable way. This is in contrast to fossil fuel or nuclear generation, for which location has little effect on the plant availability but can affect the capacity factor through uncertain local market conditions. In Figs. 8–10, we illustrate the effect that location-based capacity factor variability has on the overall uncertainty of LCOE for the three renewable technologies examined. In these figures, we perform a new estimation using fixed values for capacity factor, rather than sampling from a distribution. We show results for an average capacity factor as well

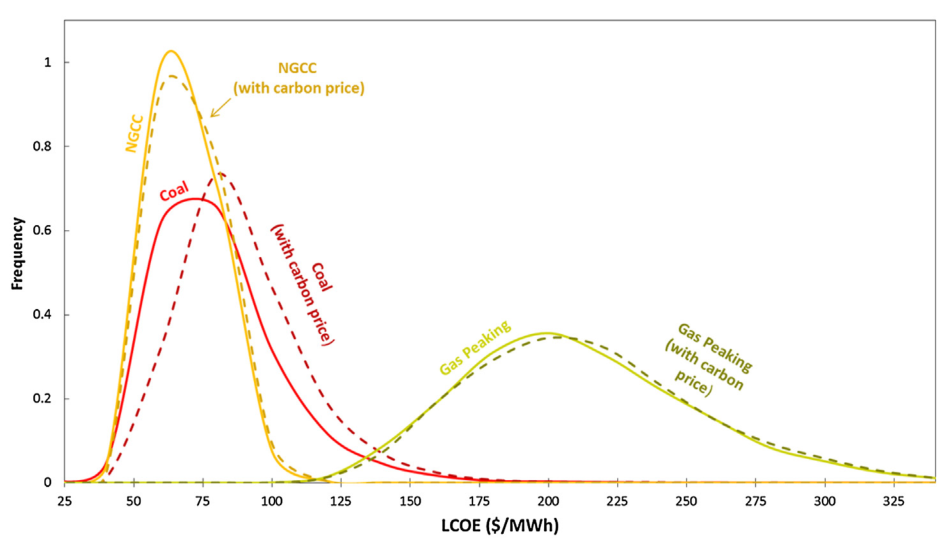

Fig. 7. LCOE distributions of fossil fuels with carbon price.

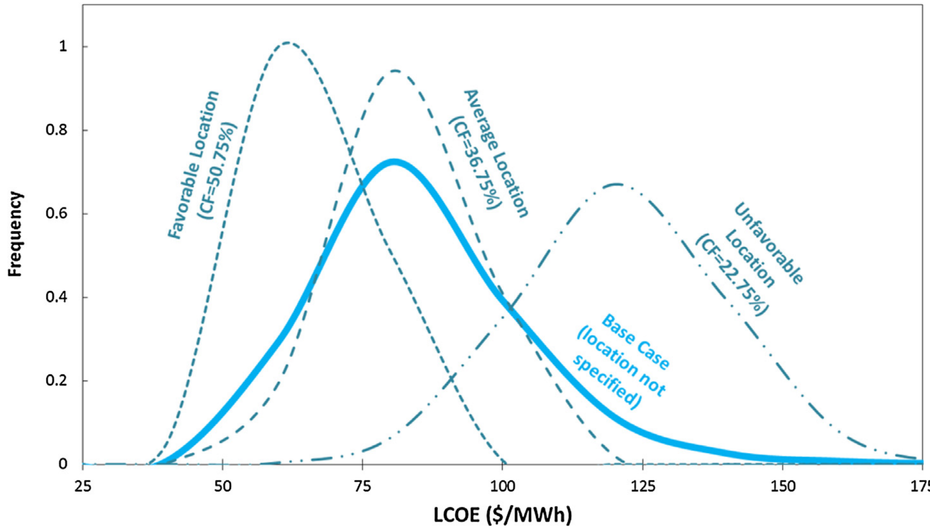

Fig. 8. Location-adjusted LCOE distributions for wind generation. These curves deconvolute the effect of location on the uncertainty in wind LCOE by assuming a fixed capacity factor rather than a capacity factor drawn from under the input distribution. Note that these three curves do not reflect equally likely or available scenarios: for example, there are few locations where a 50% wind capacity factor can be achieved.

as values that are ± 2 standard deviations from the mean used in our input distributions.

The results illustrate two effects. First, locations that are significantly better or worse than average can shift the LCOE estimates by large ($\sim$50%) amounts. Second, while the residual uncertainty in LCOE tends to decrease slightly, it is clear that location-dependent capacity factor variability is not the primary driver of overall LCOE uncertainty. Risk associated with renewable utility investments is also dependent on location. Figs. 8–10 show how the risk deviates depending on how favorable a location is for that technology. As the plant is put in a more favorable location, not only does the expected cost decrease but the uncertainty around that cost decreases as well.

Table 9 illustrates the effect of LCOE uncertainty on a risk adverse decision-maker. The table shows the calculated uncertainty premium and certainty equivalent for a decision-maker with constant relative risk aversion and $\gamma = 2$. The uncertainty premium represents the amount that a person would "pay" to eliminate the uncertainty, and is a way to monetize the risk of investing in an uncertain outcome. Technologies with wider LCOE distributions have higher uncertainty premiums. The certainty equivalent is a fixed and certain price that the decision-maker ($\gamma = 2$) would be indifferent towards relative to the existing uncertainty distribution. These calculation illustrate the additional capabilities of a Monte Carlo approach to estimating LCOE, as they can only be evaluated when LCOE is expressed as a distribution.

In Table 10, we use the results from our base case calculations to determine the probability that one generation technology will be cheaper than another. These results are similar to visual comparisons from Fig. 3, but are here quantitatively determined. This is accomplished by random pairwise comparisons of individual Monte Carlo iterations of two technologies, checking which of the technologies has a lower LCOE. By repeating this process, one can calculate the percent of all scenarios in which

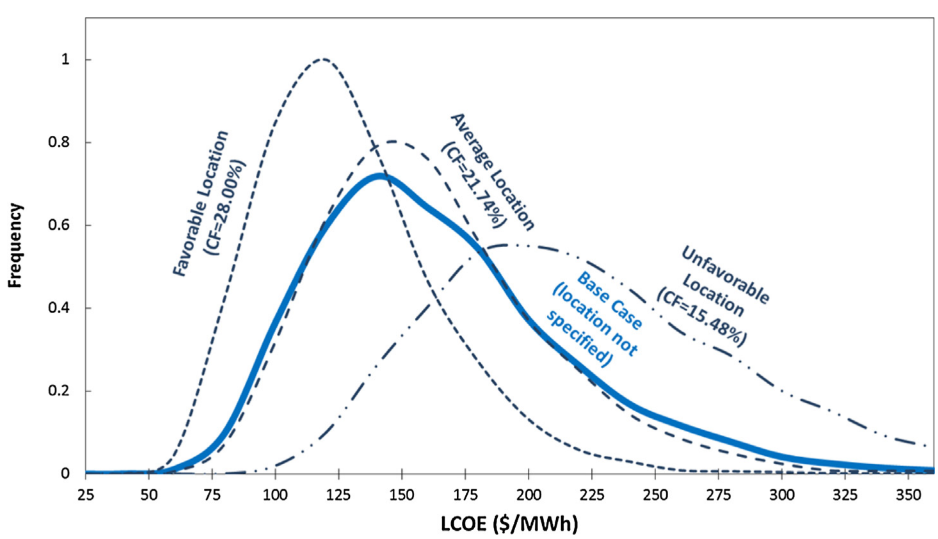

Fig. 9. Location-adjusted LCOE distributions for solar photovoltaic generation. These curves deconvolute the effect of location on the uncertainty in solar PV LCOE by assuming a fixed capacity factor rather than a capacity factor drawn from under the input distribution.

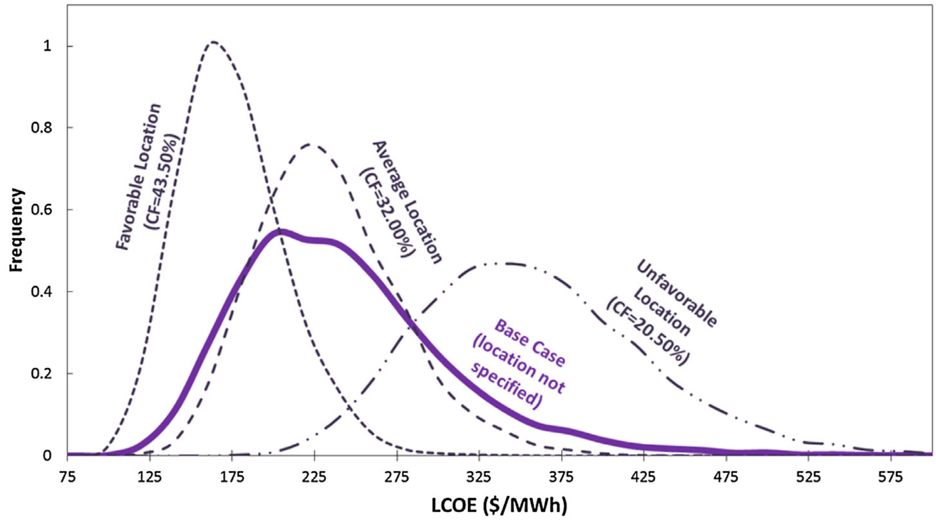

Fig. 10. Location-adjusted LCOE distributions for solar thermal generation. These curves deconvolute the effect of location on the uncertainty in solar thermal LCOE by assuming a fixed capacity factor rather than a capacity factor drawn from under the input distribution.

Table 9
Tabulation of risk premium and certainty equivalent LCOE estimates for seven generation technologies. These results assume a decision-maker with a constant relative risk aversion with $\gamma = 2$. Expected value shows the mean of the LCOE distribution. The uncertainty premium is the equivalent additional cost related to the uncertainty in LCOE. The certainty equivalent is the sum of the expected value and the uncertainty premium.

	Coal	Coal with carbon price	NGCC	NGCC with carbon price	Gas peaking	Gas peaking with carbon price	Nuclear	Wind	Solar PV	Solar thermal
Expected value	71.00	79.50	58.97	60.32	202.57	204.34	87.94	75.72	156.09	232.43
Uncertainty premium	6.15	5.73	2.08	2.01	9.26	9.07	2.45	4.10	15.83	16.20
Certainty equivalent	77.15	85.23	61.04	62.33	211.83	213.41	90.39	79.82	171.91	248.63

technology A is cheaper than technology B. This calculation is another example of a quantitative comparison that is possible only when the LCOE is expressed as a distribution. For the baseload technologies, in 34% of the scenarios coal is cheaper than NGCC. Nuclear is less likely to be competitive with either of the other two technologies: a 23% chance of being cheaper than coal and only a 5% chance of attaining a lower LCOE than NGCC. Wind is relatively competitive with all three baseload technologies, with an estimated 21% chance of being cheaper than NGCC, 40% chance of being cheaper than coal, and a 72% chance of being cheaper than nuclear generation.

4. Discussion

Most evaluations of LCOE use point values for each input without taking into consideration the uncertainty associated with each variable, resulting in a "best estimate" value that provides little or no appreciation for the role that uncertainty plays in generation investment decisions. Because investment in new generation is a capital-intensive long-term investment, an adequate inclusion of uncertainty is important. Inputs, such as capital cost, fuel prices, variable O&M, and carbon pricing, are affected by numerous factors that can change the value of these inputs dramatically, within a few years' time. While using a point value usually corresponds to the most likely outcome for an input, it cannot take into consideration the effects of changing even one of the factors listed above. Monte Carlo is capable of overcoming this limitation by considering a variety of scenarios in proportion to their likelihood. This produces a probability distribution of different outcomes for LCOE, providing a more accurate representation than the single most likely outcome for point values. Furthermore, using a Monte Carlo approach to LCOE calculation allows the user to incorporate uncertainty in a way that allows for additional quantitative analysis and comparisons.

One of the greatest advantages of Monte Carlo is the relative simplicity of the technique. While more complex than a point value

Table 10
Comparison of the LCOE distributions of different technologies, showing the probability that each technology will be more expensive than other technologies. Each cell shows the probability the technology above it (along the top row) will be more expensive than the technology to the left (along the first column).

Probability that top row LCOE is greater than left column LCOE	NGCC	Gas peaking	Nuclear	Wind	PV solar	Solar thermal
Coal	34%	~100%	77%	60%	96%	~100%
NGCC		~100%	95%	79%	99%	~100%
Gas peaking			0%	0%	23%	64%
Nuclear				28%	93%	~100%
Wind					96%	~100%
PV solar						83%

calculation, modern quantitative analysis software (such as Microsoft Excel or MATLAB) can easily handle the required calculations. By modeling the distributions for each LCOE input independently, and then calculating the final LCOE for each case, a large data set can be populated quickly and efficiently with this method. From there, simple statistical analysis of the generated data set provides a plethora of useful information that point value evaluation would be incapable of providing. In addition to the relative ease of generating a data set quickly, the use of quantitative analysis software allows users to easily adjust the modeled input distributions if more accurate information becomes available. As prices change or policy initiatives are enacted, a simple adjustment to that input will adjust the LCOE distribution for that technology accordingly.

Since the Monte Carlo analysis gives an LCOE distribution for each generation technology, a more sophisticated analysis can be completed. If the distributions for two technologies cross, a user can evaluate the probability that one generation type will be cheaper than the other. This is most useful when the two generation technologies have differently shaped probability distributions. The analysis can be pursued even further by studying the individual scenarios in which one technology is cheaper, with an expanded qualitative discussion of the real-world economic or policy scenarios that may lead to those outcomes.

The structure of the Monte Carlo process allows for relationships between uncertain parameters to be accounted for easily. This compounded uncertainty is useful in a variety of circumstances, such as determining the effect of carbon pricing on the LCOE of fossil fuel plants. The amount paid by a generator for carbon emissions is affected by both the price for the emissions and the amount of time that the plant is operational (the capacity factor) under the carbon pricing policy. The carbon price and the year that the policy takes effect are determined based on their respective distributions, generating a value for the total cost the generator will have to pay for emissions, which is then used in the final LCOE calculation for that scenario. While seemingly complex, this only requires a couple of extra steps in the Monte Carlo process that can be added easily, without much extra configuration of the process.

As we demonstrated above, Monte Carlo also allows for an uncertain investment risk to be quantitatively evaluated based on an individual's risk aversion. The certainty equivalent value for each LCOE iteration was calculated using a gamma equal to 2. Similar to any other input, the gamma value can be easily adjusted to account for the risk aversion of an individual decision-maker. While we used a gamma value of 2, a more risk-averse decision-maker may be modeled using a higher gamma and a less risk-averse person a lower. Using point values or traditional sensitivity analysis to explore LCOE does not provide enough information to quantitatively compare the average LCOE with the uncertainty surrounding that value. Risk and risk aversion play an important role in decision making for investments in new generation plants, and using Monte Carlo analysis of LCOE allows for an additional quantitative analytical approach.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.tej.2016.04.001.

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Nathaniel Heck is pursuing a B.S. in Chemical Engineering at Rochester Institute of Technology. He has experience working in research and development in the polymer industry, focusing mainly on polytetrafluorethylene (PTFE) products.

Courtney Smith is currently a student at the Rochester Institute of Technology, completing degrees in Mechanical Engineering and Public Policy. She has experience as an energy analyst through her internship with the City of Rochester and industry experience with General Electric.

Eric Hittinger is an Assistant Professor of Public Policy at Rochester Institute of Technology. He has a background in energy economics and power system engineering, and a variety of publications on the topic of energy system economics. He has worked as a consultant for several battery companies and is the primary developer of the Energy Systems Model (ESM) microgrid software. His Ph.D. is in Engineering and Public Policy from Carnegie Mellon University, where he worked in the Carnegie Mellon Electricity Industry Center.