Incorporating Performance-based Global Sensitivity and Uncertainty Analysis into LCOE Calculations for Emerging Renewable Energy Technologies

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Abstract

Assessing system costs for power generation is essential for evaluating the economical aspect of energy resources. This paper examines traditional and renewable energy resources under uncertainty and variability of input variables. The levelized cost of electricity (LCOE) of each technology is computed using a global sensitivity analysis. A Monte Carlo approach is utilized to study the thermoeconomics of a variety of power generation methods in the United States: fossil fuel-based, nuclear, developed renewable, and emerging renewable energy resources. The results of this study demonstrate how uncertainties in input data can significantly influence the LCOE values. Power generation from well-developed energy technologies exhibit less variability in LCOE due to established capital costs, operating and maintenance costs, and power generation. On the contrary, emerging renewable energy technologies are subject to high uncertainties in both technical and economic performance, as expected for technologies in early stages of development. A scenario with carbon pricing in power generation is also carried out in the paper. The presence of carbon pricing significantly increases the LCOEs of fossil fuel technologies, and LCOEs of other technologies also experience significant changes when life-cycle carbon assessments are considered. Several cost reduction opportunities are discussed to guide the development of future energy conversion, especially from emerging renewable energy resources.

Keywords:
LCOE, renewable energy, power generation, global sensitivity analysis, carbon pricing

1. Introduction

Power generation from renewable energy systems is increasingly cited as a promising solution for meeting current and future energy demands [1, 2, 3]. Compared to traditional power generation methods, usually from fossil fuels, renewable energy technologies are credited for

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their sustainability, renewable nature and environmental friendliness [4]. On the other hand, renewable energy technologies, especially emerging ones, tend to cost more when generation costs are considered as part of economic evaluations. Levelized cost of electricity (LCOE) is often used as a metric to rank the competitiveness of power generation technologies. LCOE is widely adopted as a standard to compare different technologies [5]. LCOEs are estimated based on the ratio of the total project life-cycle cost and the total lifetime energy production [6]. The LCOE values for traditional power generation methods are more consistent, with less variability because traditional power generation methods have been more widely used over longer periods of time. Contrarily, LCOE values for renewable energy technologies are subjected to estimations since renewable energy technologies have been in use for shorter periods of time.

Quantifying renewable power generation costs can be challenging because of the nature of renewable energy. Renewable energy resources, such as wind and solar energy, are highly intermittent. The available resources for power generation vary at different times. Thus, most renewable energy technologies are non-dispatchable. This can cause variation in generation costs due to the mismatch of energy demand and energy production schedule. Furthermore, renewable energy resources are geographically dependent. Some renewable energy resources are abundant in certain locations, while the same technologies are limited in the same areas [4]. Consequently, generation costs of the same technology can vary among different locations. Other technical limitations such as scalability, energy performance, system lifetime and reliability are also important factors. In short, the performance of renewable energy is significantly influenced by uncertainties.

Estimating LCOEs under uncertainty and variability can be useful for correctly evaluating renewable energy technologies. This topic has been explored in the current literature in various types of analysis. System-level cost evaluations were performed on individual technologies such as biofuels, solar thermal, ocean energy, and solar PV [7, 8, 9, 10]. These studies estimated the LCOE for each individual technology, even though the uncertainties in input variables were not considered. Spinney and Watkins proposed Monte Carlo simulation techniques for analyzing electric power resource decisions and evaluation for merits and risks associated with each decision [11]. Moreover, global sensitivity analysis has been utilized for studying individual energy technologies. However, the scope of these studies is limited in terms of technologies considered and data obtained. For instance, LCOEs of solar PV energy, wind energy, and geothermal were studied, considering various assumptions that go into these calculations [12, 13, 14]. Furthermore, the electricity generation portfolio of future electricity industries was investigated under high uncertainties and carbon constraints [15, 16]. Recently, Heck et al. studied LCOEs of seven energy technologies, including renewable and non-renewable, using a Monte Carlo approach [17]. The analyses in these studies demonstrated the effectiveness of using global sensitivity analysis for evaluating the probability of LCOEs of different technologies under uncertainties.

This paper contributes to the existing literature by providing a broader approach in which unproven technologies are also incorporated into the global sensitivity analysis. This approach allows emerging renewable energy technologies to be fairly evaluated in the context of all available energy resources in the U.S. A mathematical framework for levelized generation costs is developed, encompassing situations when operations and maintenance costs, energy performance, lifetime and reliability are uncertain. Global sensitivity analysis based on Monte Carlo approach is used to evaluate the impacts of variability in performance. Furthermore, life-cycle greenhouse gas (GHG) emissions are considered in carbon pricing scenarios [18]. Compared to traditional power generation methods from fossil fuels, nuclear and renewable energy produce considerably less greenhouse gas emissions per unit of electricity generated. Consequently, fossil fuel-based power generation methods are at a disadvantage if there is a cost for the production of greenhouse gases. The competitiveness of low-carbon and carbon-intensive power generation technologies will change dramatically with respect to each other as a result of carbon pricing [19, 20, 21]. This case study provides helpful information about the impact on LCOEs of energy resources if there is a cost for GHG emissions. This paper contributes to the carbon pricing analysis by utilizing the life-cycle GHG emissions for all technologies, as opposed to using simple emission coefficients of different fuels. Finally, cost reduction opportunities are discussed to provide guidance for energy system development decisions. This paper lays the groundwork for global sensitivity analysis and carbon pricing for a wide range of energy technologies, including proven, developed, and emerging energy technologies.

2. Methodology

2.1. Levelized Cost of Electricity

The levelized cost of electricity indicates the cost of each unit of electricity generated, given all required physical assets [22]. The LCOE, often calculated in \$/kWh or \$/MWh, is a useful metric to measure how feasible a power generation technology is for commercial implementation and indicates its competitiveness compared to other technologies [4]. The fundamental definition of LCOE is shown in Equation 1.

$$LCOE = \frac{\textit{Total Lifetime Cost}}{\textit{Total Lifetime Energy Production}} \tag{1}$$

Depending on the type of analysis, the LCOE equation can vary to accommodate necessary changes. For instance, the total lifetime cost in a comprehensive analysis should include a depreciation tax shield and a salvage value of any physical assets at the end of life-cycle. The depreciation tax shield is a tax reduction technique under which depreciation expense is subtracted from taxable income [23]. The majority of LCOE calculations for power generation neglect these two factors. On the other hand, the simple form of the LCOE equation is often used to compute the LCOE [22]. The simple LCOE equation (called LCOE equation for simplicity in this paper) is presented in Equation 2.

$$LCOE = \frac{OCC \times CRF + \textit{Fixed O\&M}}{8,760 \times CF} + FC \times HR + \textit{Variable O\&M} \tag{2}$$

where OCC (\$/kW) is the overnight capital cost, CRF is the capital recovery factor, *Fixed O&M* (\$/kW-yr) is the fixed operation and maintenance costs, CF is the capacity factor, FC (\$/Btu) is the fuel cost, HR (Btu/kWh) is the heat rate, and *Variable O&M* (\$/kWh) is the variable operations and maintenance costs [22]. The units for all LCOEs presented here are $\$/kWh$, which can be converted to $\$/MWh$ if desired.

The capital recovery factor (CRF) is "the ratio of a constant annuity to the present value of receiving that annuity for a given length of time" [22]. In other words, it relates a constant annual payment amount to a single value for the present time. The formula for CRF is expressed in Equation 3.

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{3}$$

where i is interest rate and n is the number of payments, which is assumed to be equal to the lifetime of the project.

2.2. Global Sensitivity Analysis

The Monte Carlo method is utilized in this paper to perform the global sensitivity analysis of the LCOEs. The procedure for this analysis consists of 4 main steps: interpret statistical distributions of input variables, generate random input values based on the distributions, use these input values to compute the LCOE, and aggregate the LCOE results. In short, the Monte Carlo approach can be used to derive many combinations of the inputs by generating stochastic values that conform to the uncertain variables' distributions. Greater numbers of combinations will produce more possible outcomes of LCOE values at the expense of computational complexity and time. These 'what if' scenarios from the global sensitivity analysis reveal what outcomes might be more likely than others and can help an analyst to decide which (if any) might be viable [24]. Furthermore, the results from the global sensitivity analysis can also help to identify which variables might be the most influential ones toward the output. The global sensitivity analysis in this study is conducted by using the Sensitivity Analysis For Everyone (SAFE) toolbox developed at the University of Bristol, United Kingdom [25].

2.3. Stochastic Model of Uncertain Variables

Variables that go into the LCOE equation (Equation 2) are highly uncertain. The LCOE values can vary significantly as a result of uncertain inputs. In order to accurately estimate the economics of a certain technology, characterizing model inputs is a crucial initial step. Uncertain variables, such as energy performance, capital costs, O&M costs, system lifetime, and economics in the LCOE model are presented in this section. These variables have significant impacts on the LCOEs due to their highly uncertain nature. Investigating these variables can identify the significance of each parameter toward generation costs and guide developments of these technologies.

2.3.1. Energy Performance

Energy performance reveals the amount of energy converted from a certain type of technology, including its energy efficiency or energy return on energy invested. The actual amount of energy conversion is based on the type of technology, the scale of the system, the capacity factor, and the dispatchability of the technology. During the lifetime of a project, the energy performance is crucial for determining the LCOE. Higher energy production reduces the LCOE, and vice versa. The energy performance can be estimated more accurately if information on each actual power plant is readily available. For traditional methods of power generation (fossil fuels) and well-developed renewable energy technologies (solar PV and wind), energy performances can be more readily obtained. On the contrary, the energy performance of emerging renewable energy technologies, such as ocean energy, are difficult to evaluate since the technologies themselves are still under development.

As seen in Equation 2, the energy performance is connected to the capacity factor (CF), which is defined as the ratio of the actual output to the maximum potential output. Using the capacity factor along with the nameplate capacity of a power plant, the energy performance can be obtained. Furthermore, the capacity factor also indirectly includes information about the dispatchability and reliability of a certain technology. Power plants with higher capacity factors tend to be more dispatchable and reliable. Therefore, the LCOEs from these power plants are more likely to be affordable. However, the actual run time of a power plant can also depend on the energy demand and dispatching strategy used while the power plant is in service.

2.3.2. Capital Costs

Capital costs for renewable energy systems can vary across technologies, system sizes, and geographic locations. Capital costs are expected to reduce over time because of the increasing popularity of renewable energy technologies. For example, the price of solar PV has declined significantly due to the adaptation of the technology for power generation. Furthermore, capital costs are also a major contributor to the total project lifetime cost as the O&M costs are insignificant for the many renewable energy technologies. For this reason, accurately calculating the capital costs for renewable energy projects is crucial for accurately evaluating the LCOEs.

2.3.3. Operations and Maintenance Costs

O&M costs vary closely with system sizes. For renewable energy technologies, O&M costs tend to be much smaller than the capital costs due to the low maintenance requirements when compared with traditional thermoelectric generators. Moreover, most O&M costs from renewable energy systems are fixed O&M costs. Notable variable O&M costs exist in systems such as biomass energy systems, where the fuel cost could vary over time. The unit for fixed O&M costs is given on an annual basis based on capacity in \$/kW-yr while the unit for variable O&M costs is given per unit of energy generated in \$/kWh.

2.3.4. Lifetime

Project lifetime determines how long an energy system can be used for power generation. Energy systems with longer lifetimes can provide more economic benefit since more power can be generated while the generator is in service. Renewable energy system lifetimes are often estimated since they are newer and have less historical data, and fewer installations. The project lifetimes directly impact the total energy production and total O&M costs. Uncertainty in the project lifetimes can result in large ranges for possible LCOE values.

Furthermore, the number of capital cost payments is often determined based on the lifetime of the project.

2.3.5. Economics

The economic uncertainty described in this section refers to the interest rate. Interest rates exponentially influence the total lifetime cost for a particular energy system because of their compounding, or year-over-year, nature. The interest rate becomes important when comparing many energy systems with different project lifetimes. The interest rate allows comparison between many technologies at the present value. Thus, the actual economic value of each technology can be estimated with consideration of how the time value of money influences its present-day value. The interest rate in this study is part of the stochastic model and is assumed to be between 3% and 10%, which is commonly seen in other studies.

2.4. Greenhouse Gas Emissions

This section integrates carbon pricing into the calculation of LCOE to assess the influence of incorporating an emission penalty to power generation. The life-cycle GHG emissions data is obtained from NREL's life-cycle assessment meta-analysis, in which NREL reviews and harmonizes life-cycle assessments of electricity generation technologies from a number of studies [18]. Furthermore, the CO_2 equivalent lifetime GHG emissions (CO_2eq) used in this paper are within the interquartile range (between 75th and 25th percentiles) to eliminate shifts due to outliers. The CO_2eq takes into account emissions from other greenhouse gases using factors that correlate the radiative forcing potential of a given gas molecule to that of a CO_2 molecule, converting the emissions of that gas into equivalent CO_2 emissions as if they were CO_2 [26].

Carbon pricing can be included in the LCOE equation by introducing an additional cost to the system costs shown in Equation 2. The following equations illustrate the procedure used to assess the impact of carbon pricing on the LCOE. These equations are adapted from Heck et al. [17].

$$C_{CO_2} = CP \times HR \times EC \times CF \times 8,760 \times 10^{-9} \tag{4}$$

Equation 4 computes the first annual CO_2 payment, where CP (\$/metric ton) is the carbon price, HR (Btu/kWh) is the heat rate, EC (kg/MMBtu) is the life-cycle GHG emissions coefficient of the technology, and CF is the capacity factor. The constants within the equation account for unit conversations so that C_{CO_2} will have units of \$/kW-yr. 8,760 is the number of hours in a year, and 10^{-9} accounts for conversions between MMBtu and Btu as well between metric tons and kg of CO_2. Other unit conversions should be used if the units of the variables are different from listed. This study considers the carbon prices between \$5/metric ton and \$30/metric ton, which is comparable to other studies [17, 27, 28, 29]. This quantity is another uncertain variable considered in Equation 4. The distribution of the carbon price is taken to be uniform in this study; that is, the randomly selected values will be taken between \$5/metric ton and \$30/metric ton, as the implementation of carbon pricing in the U.S. is hypothetical at present.

Using the first annual CO_2 payment, C_{CO_2}, in Equation 4, future annual CO_2 payments can be calculated using Equation 5.

$$FV_{CO_2} = C_{CO_2} \times \frac{(1+i+k)^n - 1}{i+k} \tag{5}$$

where FV_{CO_2} is the future payment, i is the interest rate, n is the payment year, and the variable k accounts for the carbon price increase year over year. This annual price change is assumed to be between 3% and 5%.

The future CO_2 payments are then converted and combined into a present value as shown in Equation 6, so that the CO_2 payments can be incorporated into the LCOE equation.

$$PV_{CO_2} = \sum_{n=1}^{n} \frac{FV_{CO_2}}{(1+i)^n} \tag{6}$$

where PV_{CO_2} is the present value.

Finally, the LCOE equation with integrated carbon pricing is shown in Equation 7.

$$LCOE = \frac{(OCC + PV_{CO_2}) \times CRF + \mathit{Fixed\ O\&M}}{8,760 \times CF} + FC \times HR + \mathit{Variable\ O\&M} \tag{7}$$

3. Data

Case studies using a Monte Carlo approach for the global sensitivity analysis are applied here to access renewable energy technologies ranging from well-developed to new and emerging ones. Furthermore, traditional power generation from fossil fuels and nuclear power are also included for comparison with renewable energy technologies. The data for the case studies in following tables are obtained from various sources, including the U.S. Energy Information Administration (EIA), the National Renewable Energy Laboratory (NREL), and relevant literature. To account for the rapid pace of change among emerging technologies (i.e. solar PV and onshore wind), the capital costs of these emerging technologies were only considered within the last 10 years. This approach eliminates some older data points that might unreasonably increase the LCOEs. Furthermore, the distributions for input variables are characterized based on the available data. Input arguments (minimum, maximum, mean, standard deviation, etc.) associated with each distribution are computed for the global sensitivity analysis. The following analyses are applicable for power generation in the U.S., although the methodology can be expanded to any region provided the appropriate data is available.

3.1. Coal

Coal-fired power plants are among the most popular choice for power generation in the U.S. [30]. Within the electric power sector, energy consumption from coal-fired power plants took one third of the total electric power sector energy consumption in 2016 (12,966 trillion Btu out of 37,762 trillion Btu or 3,780 million MWh out of 11,067 million MWh) (Figure

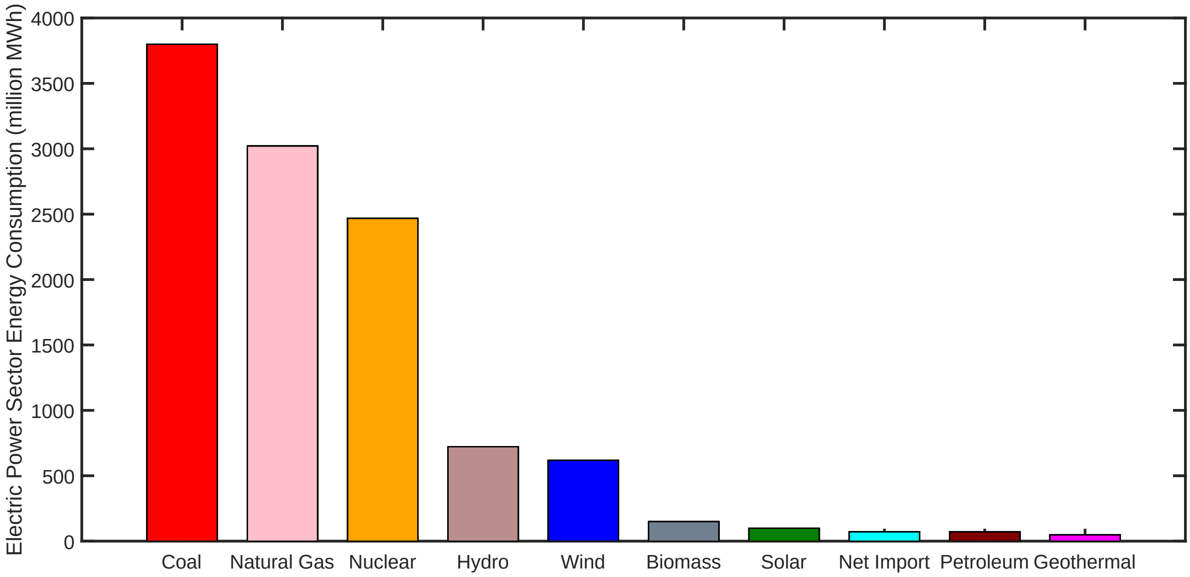

Figure 1: U.S. electric power sector energy consumption by technology for 2016 [30].

1) [30]. Even though the electric power sector energy consumption from coal-fired power plants is gradually decreasing within the last decade, coal-fired power plants are still an important part of power generation. This is because coal is relatively cheap, dispatchable, and well-established. Table 1 details the uncertain variables used for coal-fired power plants.

Table 1: Coal uncertain variables [31, 32, 33, 34].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	1,920 – 11,000	Log-normal	Log mean (μ) = 8.32 & Log s.d. (σ) = 0.53
Fixed O&M cost ($/kW-yr)	20.40 – 80.00	Exponential	Mean (μ) = 42.79
Variable O&M cost ($/MWh)	2.00 – 10.00	Exponential	Mean (μ) = 5.55
Capacity factor (%)	75.0 – 93.0	Uniform	Min. (a) = 75.0 & Max. (b) = 93.0
Lifetime (years)	50 – 100	Uniform	Min. (a) = 50 & Max. (b) = 100
Fuel cost ($/MMBtu)	1.27 – 2.41 ($4.33 – 8.23/MWh)	Uniform	Min. (a) = 1.27 & Max. (b) = 2.41
Heat rate (Btu/kWh)	8,755 – 12,005 (2.57 – 3.52 kWh/kWh)	Uniform	Min. (a) = 8,755 & Max. (b) = 12,005
Life-cycle GHG emissions (g CO_2eq/kWh)	930 - 1,050	Uniform	Min. (a) = 930 & Max. (b) = 1,050

3.2. Natural Gas

Natural gas-fired power plants have surpassed nuclear electric power to become the second most consumed energy source in the electric power sector in recent years [30]. The electric power sector energy consumption from natural gas-fired power plants was 10,309 trillion Btu in 2016 (3,021 million MWh) [30]. The rise of natural gas-fired power plants is a result of the reduction in price of natural gas. Consequently, natural gas-fired power plants are a vital part of the future of the U.S. energy sector. Table 2 details the uncertain variables used for natural gas-fired power plants.

Table 2: Natural gas uncertain variables [31, 32, 33, 35].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	750 – 1680	Log-normal	Log mean (μ) = 7.05 & Log s.d. (σ) = 0.21
Fixed O&M cost ($/kW-yr)	5.01 – 34.56	Exponential	Mean (μ) = 13.01
Variable O&M cost ($/MWh)	0.61 – 6.37	Log-normal	Log mean (μ) = 0.94 & Log s.d. (σ) = 0.52
Capacity factor (%)	40.0 – 93.0	Uniform	Min. (a) = 40.0 & Max. (b) = 93.0
Lifetime (years)	50 – 100	Uniform	Min. (a) = 50 & Max. (b) = 100
Fuel cost ($/MMBtu)	3.42 – 9.02 ($11.67 – 30.78/MWh)	Uniform	Min. (a) = 3.42 & Max. (b) = 9.02
Heat rate (Btu/kWh)	6,430 – 7,050 (1.88 – 2.07 kWh/kWh)	Uniform	Min. (a) = 6,430 & Max. (b) = 7,050
Life-cycle GHG emissions (g CO_2eq/kWh)	430 - 560	Uniform	Min. (a) = 430 & Max. (b) = 560

3.3. Nuclear

Commercial nuclear power plants in the U.S. have been around since late 1950s [36]. Nuclear electric power contributed 8,422 trillion Btu (2,468 million MWh) of electricity generated in 2016 [30]. Even though the rate of development of nuclear energy has slowed down, nuclear power plants are still an important part of electricity generation in the U.S. for the foreseeable future. Uncertain variables for nuclear power plants are presented in Table 3.

Table 3: Nuclear uncertain variables [31, 32, 33, 37].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	2,870 – 8,200	Uniform	Min. (a) = 2,870 & Max. (b) = 8,200
Fixed O&M cost ($/kW-yr)	12.80 – 127.00	Normal	Mean (μ) = 84.50 & S.d. (σ) = 36.92
Variable O&M cost ($/MWh)	0.25 – 6.00	Log-normal	Log mean (μ) = -0.22 & Log s.d. (σ) = 1.00
Capacity factor (%)	85.0 – 90.0	Uniform	Min. (a) = 85.0 & Max. (b) = 90.0
Lifetime (years)	50 – 100	Uniform	Min. (a) = 50 & Max. (b) = 100
Fuel cost ($/MMBtu)	0.60 – 0.65 ($2.05 – 2.22/MWh)	Uniform	Min. (a) = 0.60 & Max. (b) = 0.65
Heat rate (Btu/kWh)	10,420 – 10,480 (3.05 – 3.07 kWh/kWh)	Uniform	Min. (a) = 10,420 & Max. (b) = 10,480
Life-cycle GHG emissions (g CO_2eq/kWh)	6.2 - 33	Uniform	Min. (a) = 6.2 & Max. (b) = 33

3.4. Solar PV

Solar PV is among the fastest growing renewable energy technologies. Solar PV panels have been installed in various system sizes, ranging from residential scale (<10 kW) to utility size (1 - 10 MW) [38]. The cost of solar PV panels has decreased significantly in recent years, driving LCOE values for solar PV down to grid parity in some locations. The LCOE of solar PV itself is also varying because of the wide variety of solar PV technologies and system sizes. Uncertain variables for solar PV are presented in Table 4.

3.5. Solar Thermal

Concentrating solar power (CSP) is also an important part of solar power. Together with solar PV, solar energy accounted for 337 trillion Btu (98.8 million MWh) for energy consumption in the electric power sector in the U.S. in 2016 [30]. Unlike solar PV, the system size of CSP is more suitable at medium to large scales (such as utility applications) than at

Table 4: Solar PV uncertain variables [31, 32, 33, 39, 40].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	1,331 – 4,978	Normal	Mean (μ) = 3,685.42 & S.d. (σ) = 871.76
Fixed O&M cost ($/kW-yr)	7.56 – 39.49	Uniform	Min. (a) = 7.56 & Max. (b) = 39.49
Variable O&M cost ($/MWh)	–	–	–
Capacity factor (%)	15.5 – 35.0	Exponential	Mean (μ) = 21.33
Lifetime (years)	30 – 40	Uniform	Min. (a) = 30 & Max. (b) = 40
Fuel cost ($/MMBtu)	–	–	–
Heat rate (Btu/kWh)	–	–	–
Life-cycle GHG emissions (g CO_2eq/kWh)	38 - 50	Uniform	Min. (a) = 38 & Max. (b) = 50

small scales (such as residential applications). Uncertain variables for CSP are presented in Table 5.

Table 5: Solar thermal uncertain variables [31, 32, 33, 41].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	1,830 – 11,000	Normal	Mean (μ) = 6,433.64 & S.d. (σ) = 1,950.67
Fixed O&M cost ($/kW-yr)	49.50 – 115.00	Log-normal	Log mean (μ) = 4.21 & Log s.d. (σ) = 0.17
Variable O&M cost ($/MWh)	0.71 – 25.50	Log-normal	Log mean (μ) = 1.62 & Log s.d. (σ) = 0.96
Capacity factor (%)	6.8 – 46.9	Exponential	Mean (μ) = 30.86
Lifetime (years)	25 – 35	Uniform	Min. (a) = 25 & Max. (b) = 35
Fuel cost ($/MMBtu)	–	–	–
Heat rate (Btu/kWh)	–	–	–
Life-cycle GHG emissions (g CO_2eq/kWh)	10 - 29	Uniform	Min. (a) = 10 & Max. (b) = 29

3.6. Onshore Wind

Along with solar energy, wind energy resource in the U.S. is abundant [42, 43]. The number of wind projects, especially onshore wind projects, has increased significantly as wind energy technology matured over the years. In 2016, wind energy contributed 2,109 trillion Btu (618.1 million MWh) energy consumption to the electric power sector [30]. This number has steadily increased since the first large-scale wind farm was installed in the U.S. in the 1980s [44]. Table 6 details the uncertain variables used for onshore wind technology.

Table 6: Onshore wind uncertain variables [31, 32, 33, 45].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	1,200 – 4,000	Log-normal	Log mean (μ) = 7.62 & Log s.d. (σ) = 0.27
Fixed O&M cost ($/kW-yr)	10.28 – 60.00	Log-normal	Log mean (μ) = 3.33 & Log s.d. (σ) = 0.54
Variable O&M cost ($/MWh)	4.82 – 23.00	Exponential	Mean (μ) = 8.81
Capacity factor (%)	26.0 – 52.0	Uniform	Min. (a) = 26.0 & Max. (b) = 52.0
Lifetime (years)	15 – 20	Uniform	Min. (a) = 15 & Max. (b) = 20
Fuel cost ($/MMBtu)	–	–	–
Heat rate (Btu/kWh)	–	–	–
Life-cycle GHG emissions (g CO_2eq/kWh)	8.4 - 20	Uniform	Min. (a) = 8.4 & Max. (b) = 20

3.7. Offshore Wind

Despite the popularity of onshore wind in the U.S., offshore wind is fairly new and not widely implemented. The first commercial offshore wind farm (the Block Island Wind Farm) went online in late 2016 in the U.S [46]. Offshore wind also has significant potential in the U.S. due to the abundant availability [43]. Reducing the LCOE of offshore wind energy could boost the adoption of the technology. Table 7 details the uncertain variables used for offshore wind technology.

Table 7: Offshore wind uncertain variables [31, 32, 33, 45].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	3,100 – 8,000	Exponential	Mean (μ) = 4,667.97
Fixed O&M cost ($/kW-yr)	15.96 – 180.00	Log-normal	Log mean (μ) = 4.57 & Log s.d. (σ) = 0.54
Variable O&M cost ($/MWh)	13.00 – 40.00	Exponential	Mean (μ) = 21.11
Capacity factor (%)	31.52 – 45.00	Normal	Mean (μ) = 40.44 & S.d. (σ) = 4.02
Lifetime (years)	15 – 20	Uniform	Min. (a) = 15 & Max. (b) = 20
Fuel cost ($/MMBtu)	–	–	–
Heat rate (Btu/kWh)	–	–	–
Life-cycle GHG emissions (g CO_2eq/kWh)	10 - 15	Uniform	Min. (a) = 10 & Max. (b) = 15

3.8. Hydropower

Hydropower is the largest form of renewable energy in the U.S. in term of energy consumption in the electric power sector. In 2016, the amount of energy consumption in the electric power sector that came from hydropower was 2,465 trillion Btu (722.4 million MWh) [30]. This number was equivalent to about 45% (2,465 trillion Btu out of 5,582 trillion Btu or 722.4 million MWh out of 1,635 million MWh) of all renewable energy consumption in the U.S. in the electric power sector in 2016. Despite the fast growth of solar and wind power, hydropower is still positioned as an important renewable energy resource. Hydropower is more dispatchable than other renewable energy technologies. Table 8 details the uncertain variables used for hydroower technology.

Table 8: Hydropower uncertain variables [31, 32, 33, 47].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	500 – 11,070	Exponential	Mean (μ) = 3,064.60
Fixed O&M cost ($/kW-yr)	8.77 – 75.00	Exponential	Mean (μ) = 29.23
Variable O&M cost ($/MWh)	1.60 – 5.94	Exponential	Mean (μ) = 3.16
Capacity factor (%)	28.4 – 61.5	Normal	Mean (μ) = 43.12 & S.d. (σ) = 13.05
Lifetime (years)	50 – 100	Uniform	Min. (a) = 50 & Max. (b) = 100
Fuel cost ($/MMBtu)	–	–	–
Heat rate (Btu/kWh)	–	–	–
Life-cycle GHG emissions (g CO_2eq/kWh)	4.0 - 14	Uniform	Min. (a) = 4.0 & Max. (b) = 14

3.9. Biomass

Biomass is one of the oldest forms of renewable energy technologies. In 2016, 509 trillion Btu (149.2 million MWh) of energy consumption in the electric power sector came from biomass [30]. The advantage of biomass over many other renewable technologies is that biomass power plants are highly dispatchable. Unlike renewable energy technologies that depend on weather conditions, fuels for biomass power plants can be stored (similar to fossil fuels). Table 9 details the uncertain variables used for biomass power plants.

Table 9: Biomass uncertain variables [31, 32, 33, 48, 49].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	140 – 8,000	Normal	Mean (μ) = 3,390.28 & S.d. (σ) = 1,689.13
Fixed O&M cost ($/kW-yr)	12.00 – 487.20	Exponential	Mean (μ) = 135.29
Variable O&M cost ($/MWh)	0.01 – 17.00	Exponential	Mean (μ) = 6.08
Capacity factor (%)	36.4 – 76.3	Uniform	Min. (a) = 36.4 & Max. (b) = 76.3
Lifetime (years)	25 – 30	Uniform	Min. (a) = 25 & Max. (b) = 30
Fuel cost ($/MMBtu)	0 – 1.40 ($0 – 4.78/MWh)	Uniform	Min. (a) = 0 & Max. (b) = 1.40
Heat rate (Btu/kWh)	11,000 – 20,000 (3.22 – 5.86 kWh/kWh)	Uniform	Min. (a) = 11,000 & Max. (b) = 20,000
Life-cycle GHG emissions (g CO_2eq/kWh)	16 - 74	Uniform	Min. (a) = 16 & Max. (b) = 74

3.10. Geothermal

Compared to other developed renewable energy technologies listed above, geothermal was the smallest contributor (162 trillion Btu or 47.5 million MWh in 2016) to the energy consumption in the electric power sector in the U.S. [30]. Geothermal energy resources are often used for meeting heating demand, rather than meeting electricity demand. Nonetheless, geothermal power plants are an important of part of power generation, especially in the West where geothermal resources are densely populated. Table 10 details the uncertain variables used for geothermal power plants.

Table 10: Geothermal uncertain variables [31, 32, 33, 50].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	1,160 – 10,000	Log-normal	Log mean (μ) = 8.30 & Log s.d. (σ) = 0.53
Fixed O&M cost ($/kW-yr)	40.32 – 229.00	Uniform	Min. (a) = 40.32 & Max. (b) = 229.00
Variable O&M cost ($/MWh)	4.31 – 9.52	Exponential	Mean (μ) = 5.53
Capacity factor (%)	71.8 – 98.0	Exponential	Mean (μ) = 84.6
Lifetime (years)	35 – 40	Uniform	Min. (a) = 35 & Max. (b) = 40
Fuel cost ($/MMBtu)	–	–	–
Heat rate (Btu/kWh)	–	–	–
Life-cycle GHG emissions (g CO_2eq/kWh)	6.0 - 80	Uniform	Min. (a) = 6.0 & Max. (b) = 80

3.11. Pressure Retarded Osmosis

Pressure retarded osmosis (PRO) is an emerging renewable energy technology. PRO is a type of ocean energy that is based on salinity gradient between two bodies of water [51, 52]. PRO technology utilizes semipermeable membranes to convert osmotic energy into electrical energy. PRO is an emerging ocean energy that is suitable for locations with salty water sources nearby, including ocean water and inland high-salinity lakes. There are no commercial PRO power plants currently in operation in the U.S.. However, the potential for PRO in the U.S. is considerable, with an estimated 5,620 MW power production capacity [9, 53, 54]. The uncertain variables used for PRO power plants are listed in Table 11. These values are obtained from studies that investigated PRO system integration costs [9, 55].

3.12. Wave Energy

Wave energy converts kinetic energy from waves into electrical power. Wave energy potential has been estimated to be 2640 TWh/year in the U.S. [56]. Many methods for

Table 11: PRO uncertain variables [9, 53, 55].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	9,520 - 14,000	Uniform	Min. (a) = 9,520 & Max. (b) = 14,000
Fixed O&M cost ($/kW-yr)	240.00 - 260.00	Uniform	Min. (a) = 240.00 & Max. (b) = 260.00
Variable O&M cost ($/MWh)	–	–	
Capacity factor (%)	60.0 - 80.0	Uniform	Min. (a) = 60.0 & Max. (b) = 80.0
Lifetime (years)	20 - 30	Uniform	Min. (a) = 20 & Max. (b) = 30
Fuel cost ($/MMBtu)	–	–	
Heat rate (Btu/kWh)	–	–	
Life-cycle GHG emissions (g CO_2eq/kWh)	10 - 50	Uniform	Min. (a) = 10 & Max. (b) = 50

harvesting wave energy are under development [57]. As an emerging renewable energy technology, the publicly available data on wave energy power plants are sparse. As a result, the distribution of data is assumed to be uniformly distributed across the range of potential values. Table 12 details the uncertain variables used for wave energy.

Table 12: Wave uncertain variables [31, 32, 33, 58].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	6,200 - 16,100	Uniform	Min. (a) = 6,200 & Max. (b) = 16,100
Fixed O&M cost ($/kW-yr)	180.00 - 200.00	Uniform	Min. (a) = 180.00 & Max. (b) = 200.00
Variable O&M cost ($/MWh)	–	–	
Capacity factor (%)	25.0 - 40.0	Uniform	Min. (a) = 25.0 & Max. (b) = 40.0
Lifetime (years)	20 - 30	Uniform	Min. (a) = 20 & Max. (b) = 30
Fuel cost ($/MMBtu)	–	–	
Heat rate (Btu/kWh)	–	–	
Life-cycle GHG emissions (g CO_2eq/kWh)	8.0 - 11	Uniform	Min. (a) = 8.0 & Max. (b) = 11

3.13. Tidal Energy

Tidal energy harvests the energy from tides that is caused by the gravitational pulls of the moon and the sun along with the rotation of the earth [59]. Tidal energy systems are categorized into 3 types: tidal barrages, tidal turbines, and tidal fences. Tidal energy is popular around the world , but though there are no commercially operating tidal power plants in the U.S. The data on tidal energy is also limited. Due to the lack of data, the distribution of data is assumed to be uniform. Table 13 details the uncertain variables used for tidal energy.

Table 13: Tidal uncertain variables [31, 32, 33, 58].

Uncertain Inputs	Range	Distribution	Input Arguments
Overnight capital cost ($/kW)	5,400 - 14,300	Uniform	Min. (a) = 5,400 & Max. (b) = 14,300
Fixed O&M cost ($/kW-yr)	140.00 - 160.00	Uniform	Min. (a) = 140.00 & Max. (b) = 160.00
Variable O&M cost ($/MWh)	–	–	
Capacity factor (%)	26.0 - 40.0	Uniform	Min. (a) = 26.0 & Max. (b) = 40.0
Lifetime (years)	20 - 30	Uniform	Min. (a) = 20 & Max. (b) = 30
Fuel cost ($/MMBtu)	–	–	
Heat rate (Btu/kWh)	–	–	
Life-cycle GHG emissions (g CO_2eq/kWh)	2.0 - 6.0	Uniform	Min. (a) = 2.0 & Max. (b) = 6.0

4. Results and Discussion

4.1. Global Sensitivity Analysis of Power Generation Technologies

The following section illustrates the results from the global sensitivity analysis using the Monte Carlo method. Each simulation takes 10,000 possible combinations of uncertain variables. Results of energy technologies are presented to demonstrate the usefulness of assessing energy technologies from a system-wide viewpoint. The study incorporated uncertainties of input variables in the LCOE equation for the global sensitivity analysis. The case studies provide possible scenarios for estimating the LCOEs of energy technologies for commercial applications.

The probability-normalized histogram of LCOE values for coal-fired power plants with uncertainty variables as shown in Table 1 is illustrated in the first plot in Figure 2. The LCOEs of coal-fired power plants range from \$0.02/kWh to \$0.20/kWh with a mean of \$0.0732/kWh and a variance of $9.45 \cdot 10^{-4}$ $(\$/\text{kWh})^2$. The small variance indicates that coal LCOEs are closely grouped. Furthermore, the LCOEs of coal-fired power plants exhibit a log-normal distribution. The maturity of coal-fired power plants helps reduce capital costs, resulting in low LCOEs. The second plot in Figure 2 illustrates the probability of obtaining given LCOE values for natural gas-fired power plants. In recent years, natural gas has become an important part of the power generation sector because of the significant reduction in price of natural gas. As a result, the LCOEs of natural gas-fired power plants are considerably low compared to LCOEs of other technologies. In this case, natural gas LCOEs range from \$0.02/kWh to \$0.12/kWh. The mean and variance of this distribution are \$0.0614/kWh and $1.68 \cdot 10^{-4}$ $(\$/\text{kWh})^2$, respectively. Furthermore, natural gas LCOEs obtained from the global sensitivity analysis exhibit a normal distribution. Similar to coal and natural gas LCOEs (as seen in Table 14), the LCOEs from nuclear power are also more predictable (tightly clustered) since the input data for this technology are well-established. Despite having a high initial capital cost, nuclear power plants are capable of generating a large amount of electricity over many years with high capacity factors. As seen in Figure 2, the LCOEs from nuclear power plants follow a log-normal distribution, which is similar to that of coal LCOEs. Overall, the LCOE distributions from coal-fired, natural gas-fired, and nuclear power plants demonstrate that established input data can generate more predictable results.

The probabilities of obtaining given LCOE values for solar PV and solar thermal power plants are presented in Figure 3. Unlike the plots in Figure 2, the plots in Figure 3 have wider ranges of potential values. The range of solar PV and solar thermal LCOEs extend to \$0.34/kWh and \$0.80/kWh, respectively. This is due to solar technologies having more uncertainties associated with them than the established power generation methods in Figure 2. Solar energy conversion, especially through solar PV, has been widely adopted as an alternate method for power generation. The sizes of solar PV generators range from utility to residential scales. Furthermore, the capacity factor for solar PV is low because of the nature of solar energy. The variability in capital costs and capacity factor results in the wider ranges obtained for LCOEs of solar PV. Even though solar thermal is not as widely adopted as solar PV for small scale, the addition of variable O&M costs adds complexity

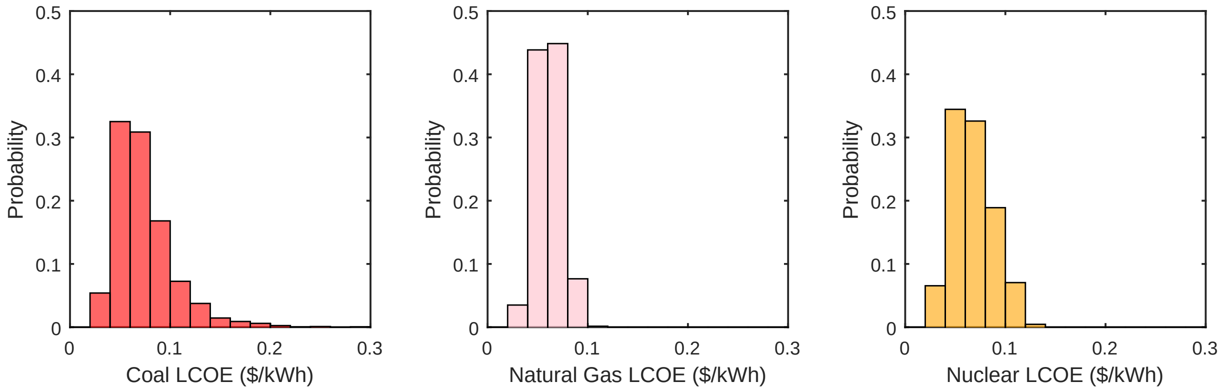

Figure 2: Probability-normalized histograms of coal-fired, natural gas-fired, and nuclear power plant LCOEs.

to the LCOEs. The capital costs of solar thermal are high while the capacity factor is low. Solar PV LCOE follows a normal distribution while solar thermal LCOE exhibits a log-normal distribution.

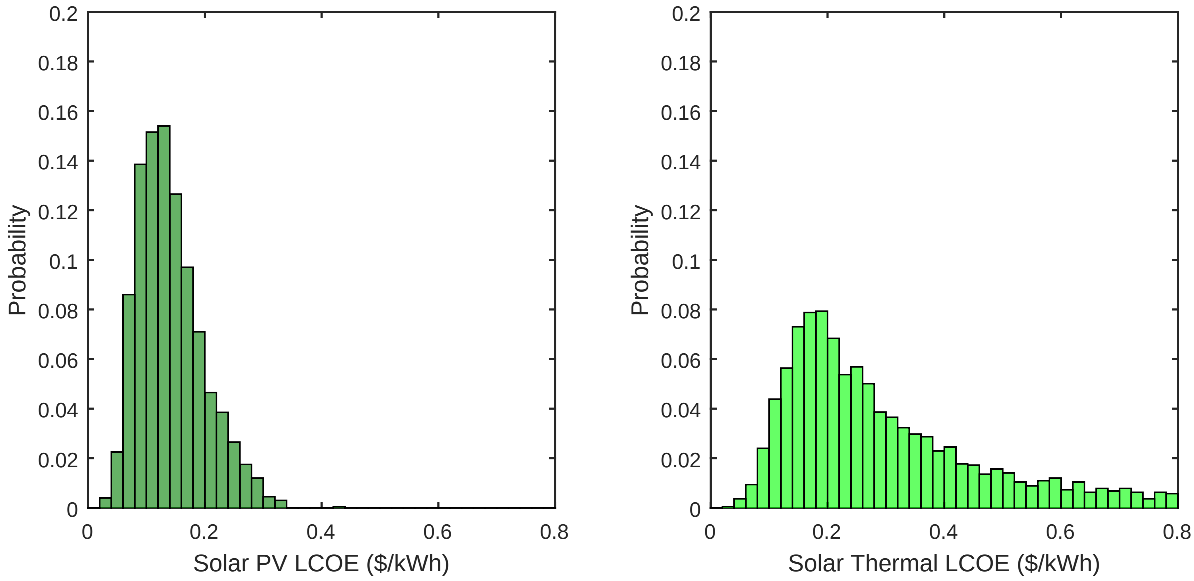

Figure 3: Probability-normalized histograms of solar PV and solar thermal power plant LCOEs.

The LCOEs of onshore wind and offshore wind obtained from the global sensitivity analysis suggest fundamental differences between the two of them (Figure 4). The mean LCOE of onshore wind is \$0.0817/kWh, while the mean LCOE of offshore wind is \$0.1822/kWh. Furthermore, the variance of onshore wind LCOEs is significantly smaller than the variance of offshore wind LCOEs ($0.7 \cdot 10^{-3}$ $(\$/\text{kWh})^2$ compared to $18.3 \cdot 10^{-3}$ $(\$/\text{kWh})^2$). Onshore wind is more widely implemented commercially, which helps reduce the cost. As a result, the distribution of LCOEs from onshore wind is more predictable and follows a normal distribution. Contrarily, offshore wind is not as mature as onshore wind. The capital costs of offshore wind energy are much higher than those of onshore wind energy. As the technology develops and commercialization efforts increase, the capital costs will eventually decrease. Considering the current state of development of wind technology, the LCOEs of offshore wind energy are currently considerably higher than the LCOEs of onshore wind energy.

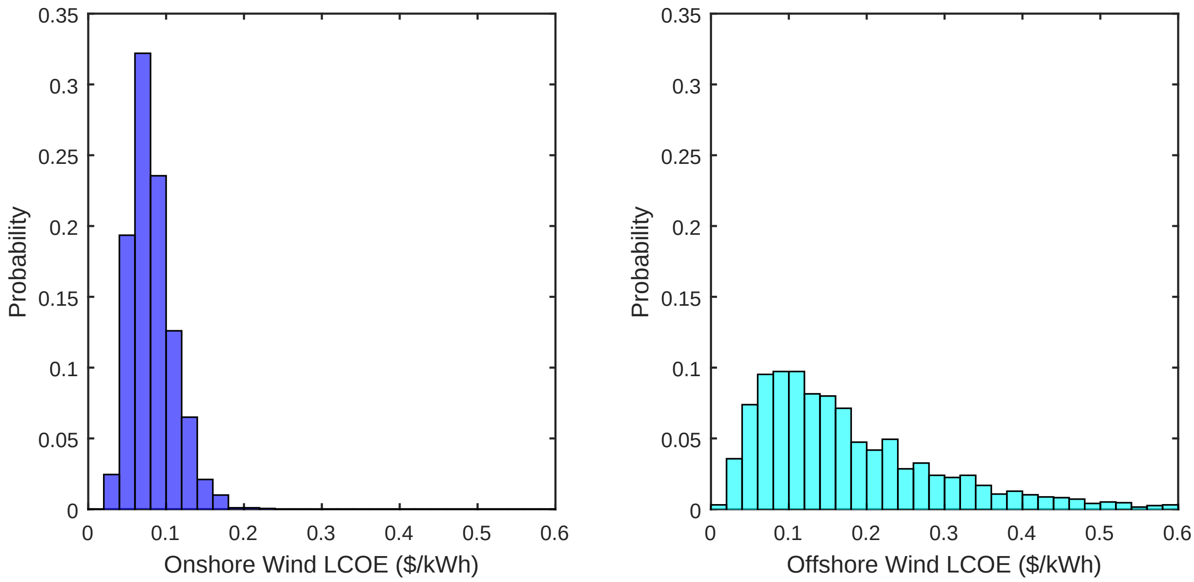

Figure 4: Probability-normalized histograms of onshore wind and offshore wind power plant LCOEs.

The results for the global sensitivity analysis studies of LCOEs for hydropower, biomass, and geothermal energy are shown in Figure 5. These three technologies are considered to be developed renewable energy technologies. The LCOEs from these technologies show that they are more predictable than those of offshore wind energy due to the maturity of these technologies. The capital costs from these technologies are well-defined. The means of hydropower, biomass, and geothermal LCOEs are \$0.0775/kWh, \$0.1025/kWh, and \$0.0693/kWh, respectively. These low values suggest the LCOEs are comparable to the average cost of electricity in the U.S. in multiple sectors [60].

The global sensitivity analysis of LCOE values for emerging ocean energy technologies are shown in Figure 6. Given the lack of data, the LCOEs of the three emerging renewable energy technologies are higher than the LCOEs of other technologies discussed. Ocean energy technologies are not widely implemented for power generation. Therefore, capital costs are considerably high for these technologies as well. The lack of commercial power plants also discourages the development of supply chains that provide systems and components for the technology.

The combined plot of probability-normalized histograms of LCOEs of different energy technologies (Figure 7) gives a comprehensive view of different methods of power generation and indicates the most probable LCOE values for each technology. Power generation technologies with lower LCOEs tend to be more popular and widely implemented. In this

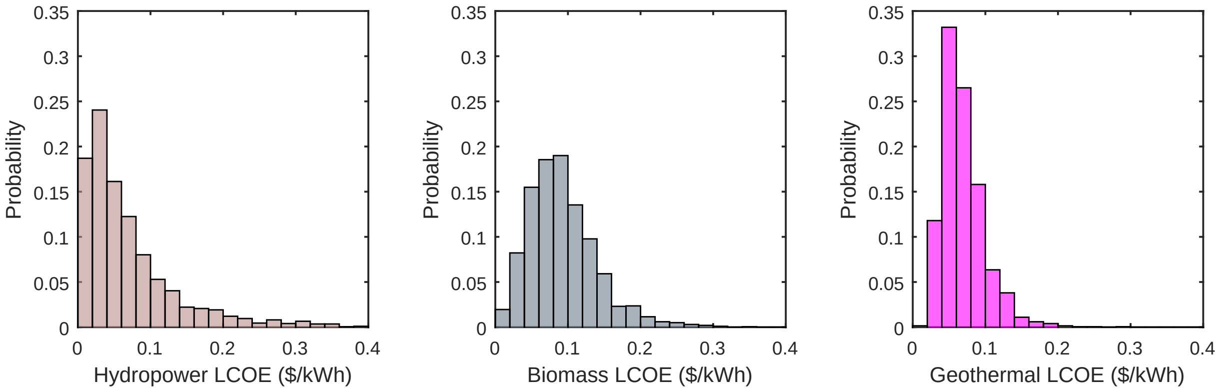

Figure 5: Probability-normalized histograms of hydropower, biomass, and geothermal power plant LCOEs.

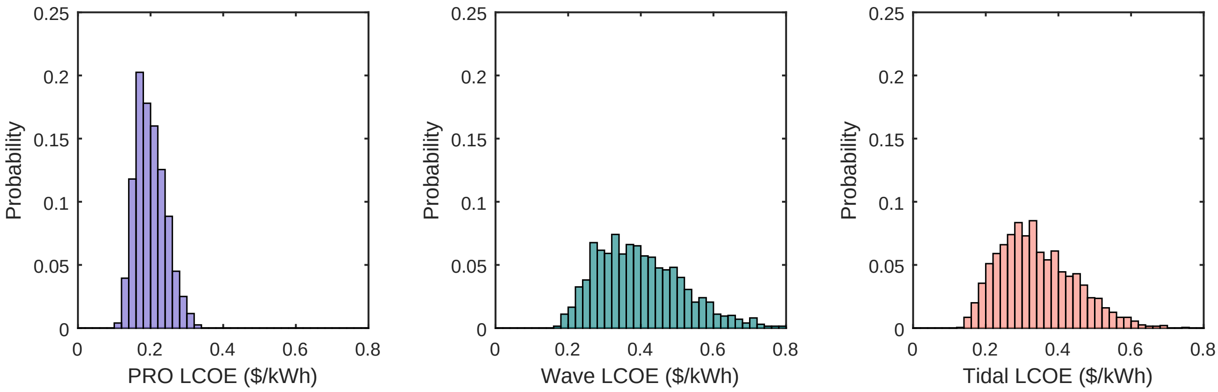

Figure 6: Probability-normalized histograms of PRO, wave, and tidal power plant LCOEs.

Table 14: Results of the global sensitivity analysis for LCOEs of energy technologies.

Technology	Mean ($/kWh)	Median ($/kWh)	Variance (($/kWh)^2)
Coal	0.0732	0.0672	$0.9 \cdot 10^{-3}$
Natural Gas	0.0614	0.0615	$0.2 \cdot 10^{-3}$
Nuclear	0.0671	0.0642	$0.4 \cdot 10^{-3}$
Solar PV	0.1410	0.1320	$3.1 \cdot 10^{-3}$
Solar Thermal	0.3207	0.2466	$48.8 \cdot 10^{-3}$
Onshore Wind	0.0817	0.0777	$0.7 \cdot 10^{-3}$
Offshore Wind	0.1833	0.1434	$18.3 \cdot 10^{-3}$
Hydropower	0.0775	0.0479	$23.8 \cdot 10^{-3}$
Biomass	0.1025	0.0951	$2.2 \cdot 10^{-3}$
Geothermal	0.0693	0.0635	$0.9 \cdot 10^{-3}$
PRO	0.1998	0.1957	$1.6 \cdot 10^{-3}$
Wave	0.3987	0.3842	$13.9 \cdot 10^{-3}$
Tidal	0.3400	0.3263	$10.6 \cdot 10^{-3}$

comparison, the LCOE values for fossil fuel-based power generation, nuclear power, and developed renewable energy technologies (hydropower, geothermal, biomass) are less than $0.10/kWh. Other renewable energy technologies such as solar PV and onshore wind are also quickly approaching affordability, or grid parity, in many areas. On the other hand, the

LCOEs of solar thermal, offshore wind, and ocean energy are still high and uncertain. The LCOE of natural gas in this study is the most well-defined among all technologies considered. The mean and variance of natural gas LCOEs are the lowest among all technologies (\$0.0614/kWh and $0.2 \cdot 10^{-3}$ $(\$/\mathrm{kWh})^2$, respectively).

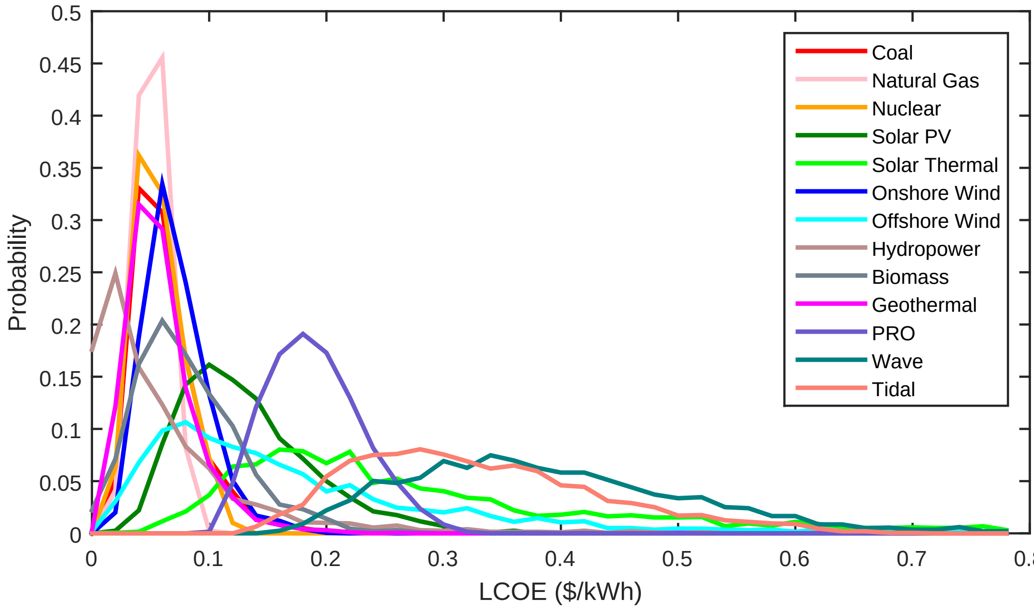

Figure 7: Probability-normalized histograms of LCOEs of different technologies without carbon pricing.

The statistical LCOEs of different technologies are also presented in a box-and-whisker plot in Figure 8. This type of plot reveals several important pieces of information. The shape of the distribution and its variability for each technology are illustrated, along with the median, first quartile, third quartile, and range (maximum and minimum) of values obtained. Moreover, Table 14 can be used as a complement to the box-and-whisker plot. This table details the mean and variance of LCOEs since these pieces of information are not shown on the plot. Solar thermal, offshore wind, and ocean energy have the widest ranges and variabilities. Since ocean energy technologies are not widely commercially implemented in the U.S., the input variables are sparse and uncertain, and these technologies show high variabilities in LCOEs. In the case of solar thermal, this technology still has high capital costs even though these costs are rapidly dropping as many solar thermal power plants in the U.S. are being developed. Contrarily, offshore wind in the U.S. is in the early stages of development. The first commercial offshore wind power plant was recently installed in the U.S. as mentioned earlier in the offshore wind section. In short, the learning rate is an important item to address for solar thermal and offshore wind to reduce capital and other associated costs. Future solar thermal and offshore wind projects can benefit from current ones in becoming more competitive in the electric power sector.

The results from the global sensitivity analysis (GSA) in this study are compared with LCOEs provided by the EIA in April 2017 and Lazard's Levelized Cost of Energy Analysis -

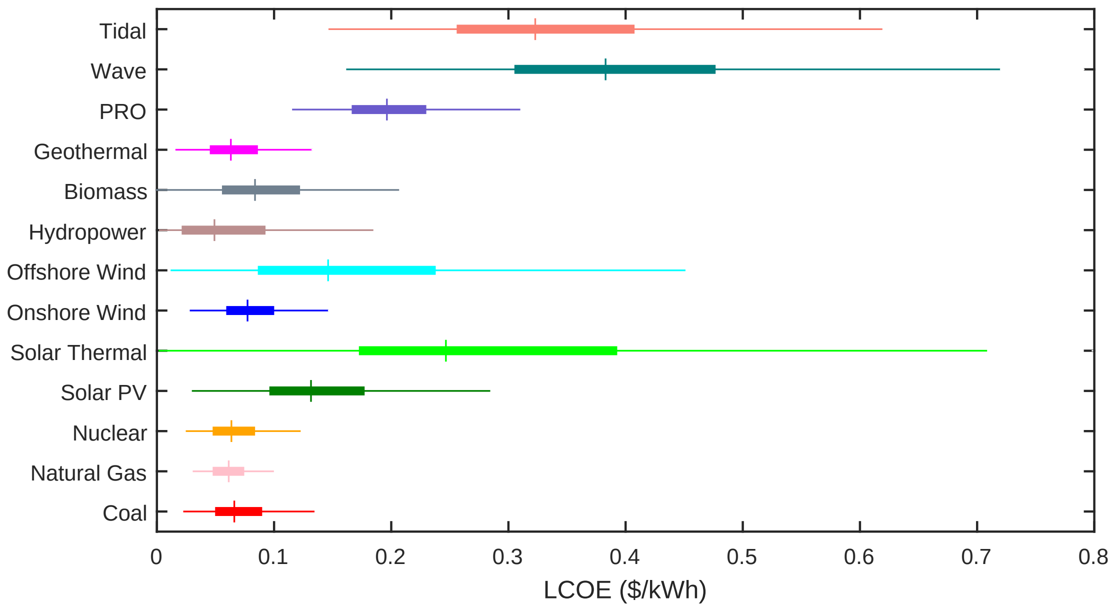

Figure 8: LCOEs of different technologies without carbon pricing.

Table 15: Comparison of LCOEs in the study (GSA) to LCOEs in EIA's and Lazard's recent reports [61, 62].

	GSA		EIA April 2017		Lazard's V11.0	
Technology	Range ($/kWh)	Mean ($/kWh)	Range ($/kWh)	Mean ($/kWh)	Range ($/kWh)	Mean ($/kWh)
Coal	0.0253 – 0.1356	0.0732	0.1027 – 0.1425	0.1232	0.0600 – 0.1430	NA
Natural Gas	0.0345 – 0.1020	0.0614	0.0524 – 0.0832	0.0573	0.0420 – 0.0780	NA
Nuclear	0.0284 – 0.1285	0.0671	0.0959 – 0.1043	0.0991	0.1120 – 0.1830	NA
Solar PV	0.0294 – 0.2854	0.1410	0.0584 – 0.1430	0.0850	0.0760 – 0.1940	NA
Solar Thermal	0.0352 – 0.7268	0.3207	0.1767 – 0.3730	0.2420	0.0980 – 0.2370	NA
Onshore Wind	0.2954 – 0.1564	0.0817	0.0434 – 0.0756	0.0637	0.0300 – 0.0600	NA
Offshore Wind	0.2589 – 0.4562	0.1833	0.1366 – 0.2129	0.1574	NA	NA
Hydropower	0.1200 – 0.2145	0.0775	0.0574 – 0.0698	0.0662	NA	NA
Biomass	0.1125 – 0.2260	0.1025	0.0848 – 0.1253	0.0637	0.0550 – 0.1140	NA
Geothermal	0.2356 – 0.1457	0.0693	0.0428 – 0.0534	0.0465	0.0770 – 0.1170	NA
PRO	0.1125 – 0.3146	0.1998	NA	NA	NA	NA
Wave	0.1456 – 0.7286	0.3987	NA	NA	NA	NA
Tidal	0.1347 – 0.6057	0.3400	NA	NA	NA	NA

Version 11.0 [61, 62]. All the LCOE values in Table 15 are unsubsidized. The LCOEs from the EIA represent the estimated LCOEs for plants entering service in 2022. As a result, their LCOEs , especially for renewables, exhibit lower values compared to the mean LCOEs from this GSA study. This results from their estimated cost reductions for prospective power plants built in the near future. Additionally, the LCOE ranges in the GSA study tend to be wider than those given by the EIA and Lazard since the GSA study results from carrying out a large number of possible combinations of input variables (i.e. 10,000 combinations). Furthermore, the reports from EIA and Lazard do not provide estimations for ocean energy technologies. This GSA study provides estimates for ocean energy technologies based on upscaling studies for these technologies.

4.2. Impacts of Carbon Pricing on LCOE

This section showcases the results from incorporating carbon pricing into the calculation of LCOE. The life-cycle GHG emissions data are used to quantify the amount of emissions over a system's lifetime. Every technology considered in this study produces a certain amount of GHG emissions over its lifetime, and all GHG emissions are converted to CO_2 equivalent emissions here. The following figures are selected to demonstrate the effect of carbon pricing on the LCOEs.

As seen in Figure 9, coal-fired power plants have the most substantial increase in LCOEs with carbon pricing included. This is due to coal having the highest emission coefficient among all considered technologies. The price of electricity from coal-fired power plants escalates from having one of the lowest LCOEs to having prohibitively large LCOE values when there is carbon pricing. A similar trend is observed with natural gas-fired power plants (Figure 10). There is a significant increase in LCOEs, even though the increase is less dramatic than that of coal. This is because natural gas has lower life-cycle GHG emissions compared to those of coal.

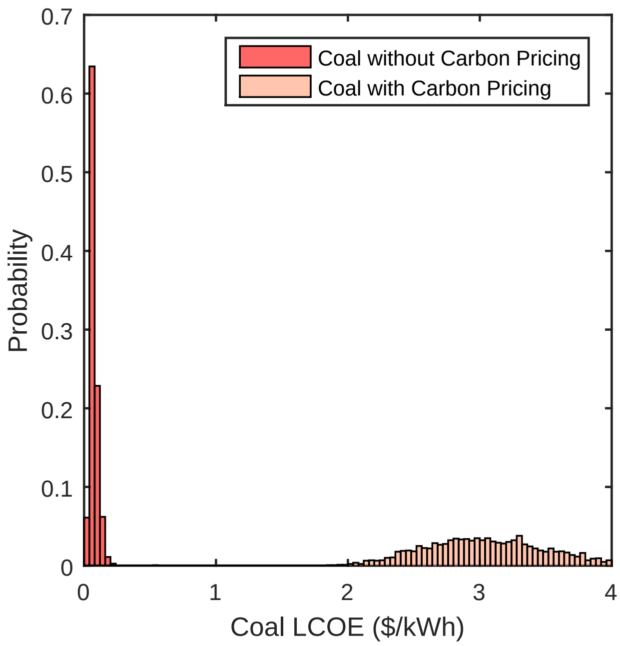

Figure 9: Probability-normalized histograms of coal LCOEs with and without carbon pricing.

Figure 11 and 12 show the results of carbon pricing on solar PV and onshore wind, respectively. Although renewable energy technologies are more environmentally friendly than fossil fuel-based technologies, in most cases the manufacturing process for renewable energy systems does emit GHGs. Since life-cycle GHG emissions coefficients are used, any GHG emissions for the technology 'from cradle to grave' are considered. Consequently, the LCOEs of renewable energy technologies also increase with carbon pricing. Both solar PV

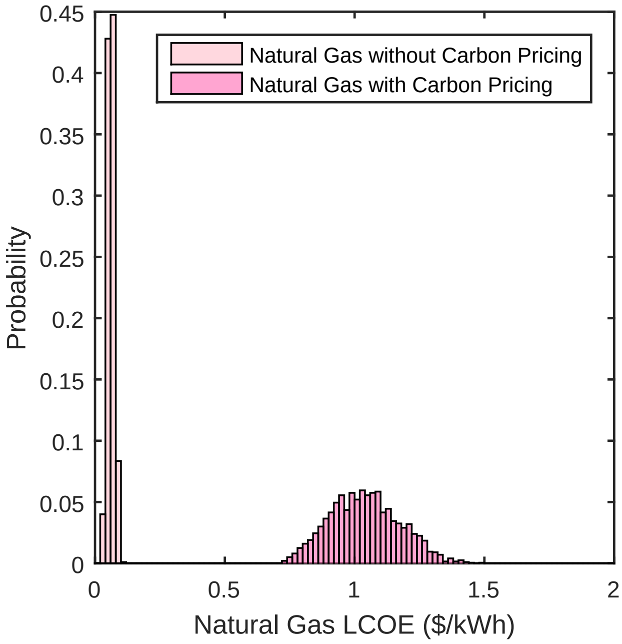

Figure 10: Probability-normalized histograms of natural gas LCOEs with and without carbon pricing.

and onshore wind LCOEs increase, although solar PV LCOEs escalate more rapidly. Solar panel production generally emits more GHGs than wind turbine production.

Table 16: Results of the global sensitivity analysis for LCOEs of energy technologies with carbon pricing.

Technology	Mean ($/kWh)	Median ($/kWh)	Variance (($/kWh)^2)
Coal	3.0799	3.0496	0.2387
Natural Gas	1.0411	1.0344	0.0186
Nuclear	0.6092	0.5827	0.0348
Solar PV	0.6181	0.5782	0.0476
Solar Thermal	1.0908	0.8466	0.5814
Onshore Wind	0.1358	0.1290	0.0018
Offshore Wind	0.2959	0.2198	0.0612
Hydropower	0.5514	0.4265	0.2301
Biomass	0.4670	0.4562	0.0226
Geothermal	0.2557	0.2268	0.0179
PRO	0.5119	0.5043	0.0078
Wave	1.0528	1.0214	0.1017
Tidal	0.9065	0.8796	0.0739

The LCOEs of all considered technologies with carbon pricing (Figure 13) show a few significant differences when compared with the plot in Figure 7. The LCOEs of all technologies increase with carbon pricing, but the scale of that increase depends on the type of technology. Fossil fuel-based technologies experience much larger increases in LCOEs. For instance, the mean of coal LCOE values increases from $0.0732/kWh (without carbon pricing) to $3.0799/kWh (with carbon pricing). High GHG emissions during power generation contribute toward the extra cost of the system. The LCOEs of some renewable energy

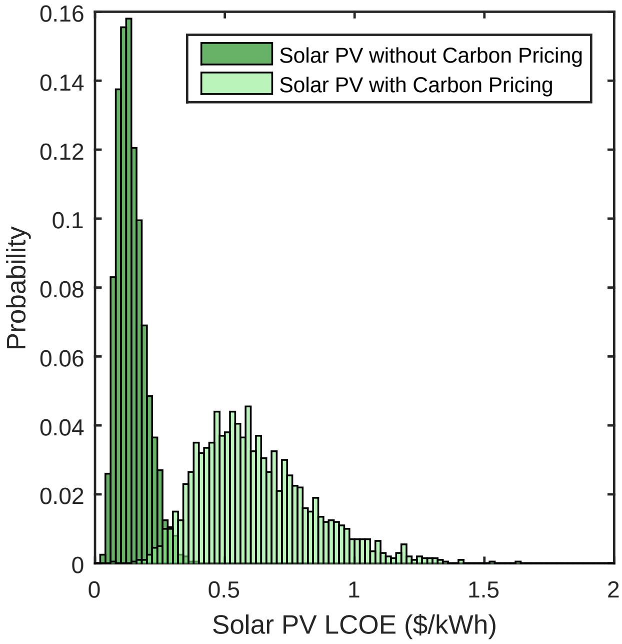

Figure 11: Probability-normalized histograms of solar PV LCOEs with and without carbon pricing.

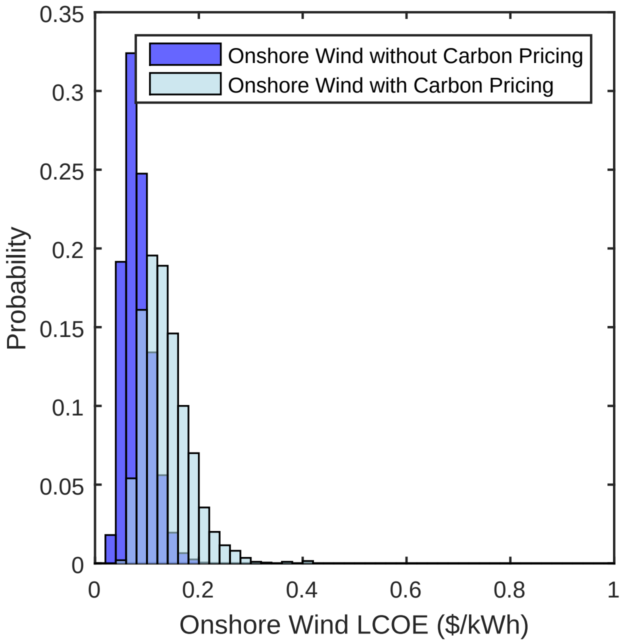

Figure 12: Probability-normalized histograms of onshore wind LCOEs with and without carbon pricing.

technologies also increase notably. Table 16 details the mean, median, and variance for LCOEs of all considered energy technologies. As an example, the mean of solar PV LCOEs jumps sharply from \$0.1410/kWh to \$0.6181/kWh. Figure 14 is a box-and-whisker plot for LCOE with carbon pricing. The trend in this plot is similar to the plot in Figure 13. Wider ranges and higher variabilities are observed for technologies with high life-cycle GHG emissions. In short, it is important to consider the system and component manufacturing GHG emissions when calculating LCOEs with carbon pricing. The use of life-cycle GHG emissions coefficients is more comprehensive than accounting for GHG emissions only during power generation.

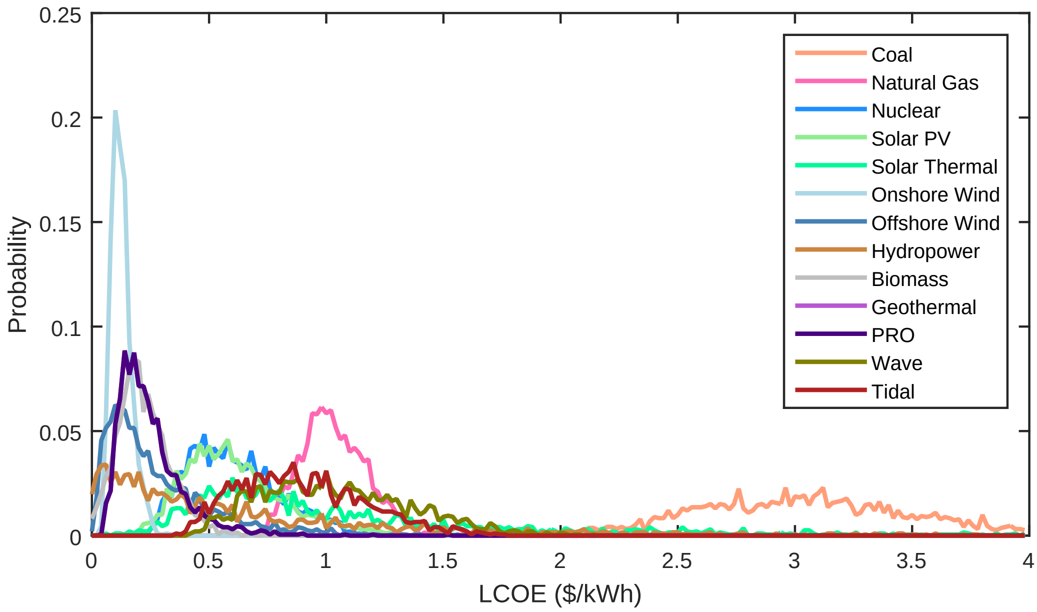

Figure 13: Probability-normalized histograms of LCOEs of technologies with carbon pricing.

4.3. LCOE Reduction Opportunities

The competitiveness of a given energy source for power generation, especially for emerging renewable energy technologies, can be significantly increased if the LCOE reduces and/or becomes more predictable. Observing the results of the global sensitivity analysis, there are multiple opportunities for LCOE reductions. This section provides guidelines for reducing the cost of generation. The following recommendations can be applied for all technologies, although some of them are more likely to affect emerging renewable energy technologies compared with developed energy technologies.

Innovation in research and development plays an essential role in making the harvesting of energy resources possible. Innovative design and new methods for developing and operating energy systems can further enhance the system performance that is possible. For example, advancements in solar panel designs and materials (e.g. Perovskite cells, organic cells, and multijunction cells) have the potential to boost solar energy implementations [63]. Furthermore, improved wind energy technologies such as wind farm layout optimization and

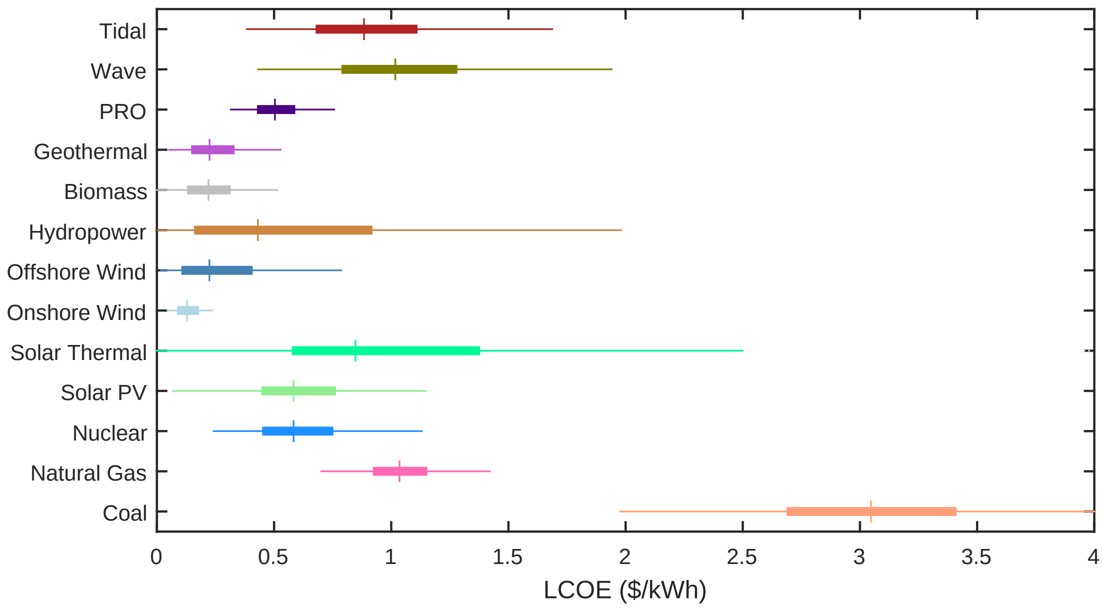

Figure 14: LCOEs of different technologies with carbon pricing.

wind blade design can increase the efficiency of wind energy [64]. Associated costs can be reduced from many types of technology advancement.

Another opportunity for LCOE reduction is present in the scaling effects of system sizes. As seen Tables 1-13, the capital costs of energy systems, especially emerging renewable energy systems, tend to exhibit a log-normal or exponential decay distribution. This observation indicates that the capital cost per kW decreases as the nameplate capacity increases (after the capacity passes the peak price). As a result, taking advantage of economies of scale can potentially reduce the marginal capital costs while increasing the power plant's capacity. However, power plant capacity is determined by a number of factors such as local energy demand, capital constraints, and availability of necessary resources. For developed energy technologies such as solar and wind energy, the risk related to scaling up system sizes is less than for emerging technologies (e.g. ocean energy).

Another opportunity for LCOE reduction comes from the effect of learning rate, particularly for emerging renewable energy technologies. Energy systems are often developed first at small scales and in laboratory settings. This research and development stage ensures the feasibility of the technology before any commercialization occurs. Learning rate for a certain technology is determined not only by laboratory scale results, but also by changes and advancements made once the technology is commercially available. The longer the technology is on the commercial market, the more manufacturers and operators can learn about the technology. Consequently, cost reductions can be achieved from manufacturing improvements and optimized operational methods. For example, the first commercial offshore wind facility in Rhode Island can serve as an example for other projects in the U.S. [46], contributing toward reducing costs for future projects.

Finally, the industrial supply chain network presents a potential opportunity for cost reduction. Having necessary components for systems or components available readily can help reduce costs. Timely schedules for construction and maintenance can be maintained, avoiding cost overruns. This area of improvement is most challenging for emerging energy technologies. Because they are new to market, and their technoeconomic performance is less certain, there may not be enough support from the appropriate manufacturers and vendors, or enough competition between vendors to keep costs down. The supply chain dilemma for emerging energy technologies can be described as 'the chicken or the egg' dilemma. For example, ocean energy technologies develop more slowly than other technologies. This is partly due to the lack of support from an established industrial supply chain. Pressure retarded osmosis technology, for instance, depends on the development of membranes that specifically target the PRO process to enhance the power generation [9]. However, the lack of an established industrial supply chain targeting these membrane requirements hinders the development of PRO. Ideally, simultaneous contributions from both technology developers and industry combine to advance the technology and reduce costs.

5. Conclusions and Policy Implications

This study contributes to performance-based global sensitivity analyses for energy technologies used in power generation considering uncertainties in capital costs, O&M costs, system reliability, and economic factors. The LCOEs for a variety of energy technologies, ranging from established to emerging ones, are computed. Moreover, carbon pricing using life-cycle GHG emissions is included for all technologies. Without carbon pricing, fossil fuel-based technologies (such as coal and natural gas) show advantages in terms of LCOE values for generating low-cost electricity. Other technologies such as nuclear power and developed renewable energy technologies (hydropower, biomass, and geothermal energy) are also very competitive. Furthermore, solar PV and onshore wind are quickly approaching affordability, and have even reached grid parity in some U.S. locations. On the other hand, the price of electricity from offshore wind, solar thermal, and ocean energy remains high enough to present a barrier to their implementation in many locations.

Electricity generating costs change significantly when carbon pricing is considered, especially for technologies that emit high quantities of GHGs. In particular, fossil fuel-based technologies are most impacted. Other technologies also experience increases in their LCOEs, although the levels of escalation are not as dramatic as those of fossil fuels. The addition of carbon pricing creates a dramatic shift in the competitiveness of energy technologies. Despite the fact that all LCOEs increase for all technologies, renewable energy technologies benefit the most from the presence of carbon pricing. Contrarily, fossil fuel-based technologies would transform from affordable to highly expensive.

Nonetheless, reducing LCOEs can increase the competitiveness of energy technologies. Opportunities for LCOE reductions can be found in many areas. Innovation in research and development, economies of scale, improved learning rates and industrial supply chains are a few examples. Decision makers who understand the implications of investments, given the state of the current market and the likely impact of those investments based on the uncertainties associated with the technoeconomics of the system, can further lower the cost of generating electricity and guide the most effective use of energy resources.

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Abbreviations

CSP	Concentrating solar power
EIA	Energy Information Administration
GHG	Greenhouse gas
GSA	Global sensitivity analysis
LCOE	Levelized cost of electricity
NREL	National Renewable Energy Laboratory
O&M	Operations and maintenance
PV	Photovoltaics
PRO	Pressure retarded osmosis
T&D	Transmission & Distribution

Nomenclature

C_{CO_2}	Annual CO_2 payment (\$/kW-yr)
CF	Capacity factor (%)
CP	Carbon price (\$/metric ton)
CRF	Capital recovery factor
EC	Emission coefficient (kg/MMBtu)
FC	Fuel cost (\$/Btu)
$FixedO\&M$	Fixed operations and maintenance costs (\$/kW-yr)
FV_{CO_2}	Future CO_2 payment (\$/kW-yr)
HR	Heat rate (Btu/kWh)

i	Interest rate (%)
n	Lifetime (year)
PV_{CO_2}	Present CO_2 payment ($/kW-yr)
OCC	Overnight capital cost ($/kW)
$VariableO\&M$	Variable operations and maintenance costs ($/kWh)

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