A Monte Carlo Model of a Wind Power Generation Investment

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This paper conducts a Monte Carlo analysis of a wind power generation investment using EViews. The analysis is based on modeling of the electricity price and costs uncertainties as stochastic variables and simulating Net Present Values (NPV) of the project. A generated NPV distribution enables a much deeper investment assessment comparing to a single point estimate of NPV or a collection of scenarios outputs. It allows users to estimate several informative risk measures: standard deviation, skewness, behavior in the distribution tails, and probabilities of extreme NPV values. The described Monte Carlo analysis can be useful for assessment of alternative power generation technologies.

INTRODUCTION

This paper demonstrates an EViews application of a Monte Carlo method for evaluation of a wind power generation investment. The electricity generation projects require significant capital investments, cannot be reversed, and embody many uncertainties arising from liberalization of electricity markets, changing technologies, fluctuating demand, unstable fuel prices, and stricter environmental protection regulations. Common capital budgeting methods (Net Present Value and Internal Rate of Return[1]) do not address these uncertainties. To assess risks, utilities traditionally use the sensitivity and scenario analyses (Spinney and Watkins, 1996; de Joode and Boots, 2001; Vithayasrichareon and MacGill, 2012). In the sensitivity analysis, an output (for example, Net Present Value) is estimated for different levels of an input (for example, the discount rate). The sensitivity is measured by a ratio of nominal changes in the output with respect to nominal changes in the input.[2] The scenario analysis calculates the output values for a set of scenarios (for example, optimistic, most likely, and pessimistic scenarios), where each scenario represents a different combination of inputs' values. However, the sensitivity and scenario analyses are limited in scope: choices of changes in input variables and scenarios are arbitrary, there are no estimates of the scenarios probabilities, and it is difficult to concisely summarize outputs of many scenarios (Brealey, Myers, and Allen, 2011; Spinney and Watkins, 1996). A Monte Carlo Simulations (MCS) approach can take into account multiple sources of uncertainty and their interrelationship. It involves describing uncertainty of inputs with probability distributions, repeated generation of random values from the inputs distributions and simulations of the output. Thus, a probability distribution of the output is produced. The distribution facilitates a much deeper investment assessment comparing to a single point estimate of the output or a collection of scenarios results. Users can estimate not only a standard deviation but also additional risk measures (skewness and behavior in the distribution tails) and probabilities of extreme output values. MCS are a valuable tool for conducting a detailed risk analysis of electricity generation investments, what is becoming very important (Hertzmark, 2007).

The Monte Carlo analysis can be useful for evaluation of alternative power generation technologies or their mixed portfolios. Spinney and Watkins (1996) illustrated the MCS use for investment planning of a hypothetical electric utility. They compared three alternative technologies to meet the utility needs over the 10-year period: pulverized coal, gas fired combined cycle combustion turbines (CCCT), and a portfolio of a coal plant and a CCCT. Rode, Fischbeck, and Dean (2001) applied Monte Carlo methods for appraisal of a nuclear power plant. De Joode and Boots (2005) gave an example of NPV simulations by Energy Administration Information (EIA) of the U.S. Department of Energy. Feretic and Tomsic (2005) used MCS to analyze electricity production costs in Croatia. They examined coal-fired, gas-fired, and nuclear plants. Roques, Nuttall, and Newbery (2006) introduced a probabilistic model (based on MCS) to evaluate investments in three base-load technologies: combined cycle gas turbine, coal, and nuclear. Yang and Blyth (2007) presented a model developed by the International Energy Agency (IEA) to quantify climate change impacts on power investments. One of modules of the model uses MCS to calculate stochastic NPVs for real option optimization of the investment timings. Authors applied the model to 12 case studies. The case studies involved four technologies: coal, gas, adding carbon capture and storage (CCS) to a coal power plant, and adding CCS to a gas plant. Madlener and Wenk (2008) used MCS and the portfolio theory to investigate five power generation investments in Switzerland: nuclear power, natural gas combined cycle, hydro plants, photovoltaic, and wind. Zhu, Zang, and Fan (2011) employed MCS and the real options theory to evaluate overseas oil projects. Vithayasrichareon and MacGill (2012) developed a Monte Carlo based tool to evaluate generation portfolios. The tool incorporates MCS, optimization methods, and the portfolio theory to derive the optimal mix of power generation plants. In a case study, they examined combinations of the coal, Combined Cycle Gas Turbine, and Open Cycle Gas Turbine plants.

Although there is growing interest in renewable energy technologies, out of reviewed MCS analyses of the energy projects, only one study by Madlener and Wenk (2008) considered wind generation investments. This paper makes a contribution to the energy research by implementing a Monte Carlo analysis of a wind power generation investment using the EViews software package.

A study of electricity generating costs by IEA and the OECD Nuclear Energy Agency (Tanaka and Echavarri, 2010; IEA/NEA, 2010) points that the onshore wind plants are becoming competitive if local conditions are favorable. In North America, the median Levelised Costs of Electricity (LCOE)[3] per MWh for onshore wind are higher than that for nuclear but lower than for coal and gas plants at the 5% discount rate. While at the 10% discount rate, the North American onshore wind median LCOE are comparable to the coal and gas LCOE. The comparisons should be taken with a caution as the study did not include costs of integrating the renewable plants into the power systems. Unpredictability of wind plants can result in substantial systems costs. This weakness of wind technologies can be alleviated with geographical diversification and a combination with other technologies (IEA/NEA, 2010). The study predicts competitiveness of renewable technologies will continue to improve in the future. Consequently, there will be a greater interest in evaluation of wind power generation plants.

This work illustrates how MCS can be used in analysis of wind farm projects. The illustrations are based on a wind power generation plant from Brealey, Myers, and Allen, 2011, Chapter 6. Construction of the plant was completed in 2005, with costs totaling $386 million. The plant had an annual capacity of 360.5 megawatts (mW). It was expected to produce energy at the average load (capacity) factor of 35%. The operation and maintenance costs in the first year were estimated to be $18.9 million. The revenues and costs were projected to increase in the following years with inflation at an approximate rate of 3%. The project life was planned to be 20 years. The textbook suggests to use the 20-year MACRS (Modified Accelerated Cost Recovery System) depreciation, as for traditional power plants. The cost of capital is set at 12%, and the tax rate at 35%. For the given parameters and the electricity price of $55 per megawatt-hour (mWh), the point estimate of NPV is negative (-$87,271,670). Without the tax subsidies, the project would not have been undertaken.[4] The paper employs MCS to derive a probability distribution for NPV. Comparing to an analysis with the single point estimate, the distribution helps conduct a detailed assessment of the investment risks, tradeoffs, and necessary tax breaks.

The next section builds a deterministic model of the wind farm investment in EViews. Then paper conducts a sensitivity analysis of the project to determine inputs with greater impacts on the project NPV. The fourth section explains choices of probability distributions and corresponding parameters for the critical inputs. The fifth section describes the Monte Carlo simulations and examines generated distributions for NPV. The section calculates several risk measures and probabilities of extreme NPV values. It also investigates tradeoffs between risks and costs of the project. The concluding section summarizes results and outlines directions for future research.

DETERMINISTIC MODEL OF THE WIND FARM

MCS begin with deterministic modeling of a project – the wind farm. Wind power generation plants are characterized by shorter construction periods, relatively higher investment costs, and lower operation and maintenance (O&M) costs. There are no fuel and CO_2 costs. The 2010 edition of the IEA/NEA study "Projected Costs of Generating Electricity" estimates that the median lead time for wind plants is one year. The study reports that, at the 10% discount rate, investment costs constitute 84% and O&M costs – 16% of the total generation costs for wind technologies. After the construction, variable costs of wind farms do not change much.

Our model's objective is to determine NPV of the wind farm:

$$NPV = -Inv + PV(Cash\ Flows) = -Inv + \sum_{t=2006}^{2026} \frac{Cash\ Flow_t}{(1+r)^t}, \tag{1}$$

where *Inv* is construction costs[5], *r* is the discount rate (cost of capital), *Cash Flow* is the project cash flow.

$$Cash\ Flow_t = PAT_t + Depreciation_t\ , \tag{2}$$

where *PAT* is the Profit After Tax, *Depreciation* is the MACRS depreciation.

$$PAT_t = (Revenues_t - Costs_t - Depreciation_t) \cdot (1 - Tax\ Rate), \tag{3}$$

where *Costs* is Operation and Maintenance Costs.

$$Revenues_t = (Load\ factor) \cdot Capacity \cdot 8{,}760\ hours \cdot Price\_electr_t, \tag{4}$$

where *Price_electr* is the electricity price per mWh.

$$Price\_electr_t = Price\_electr_{t-1} \cdot (1 + Electricity\ price\ increase\ rate) \tag{5}$$

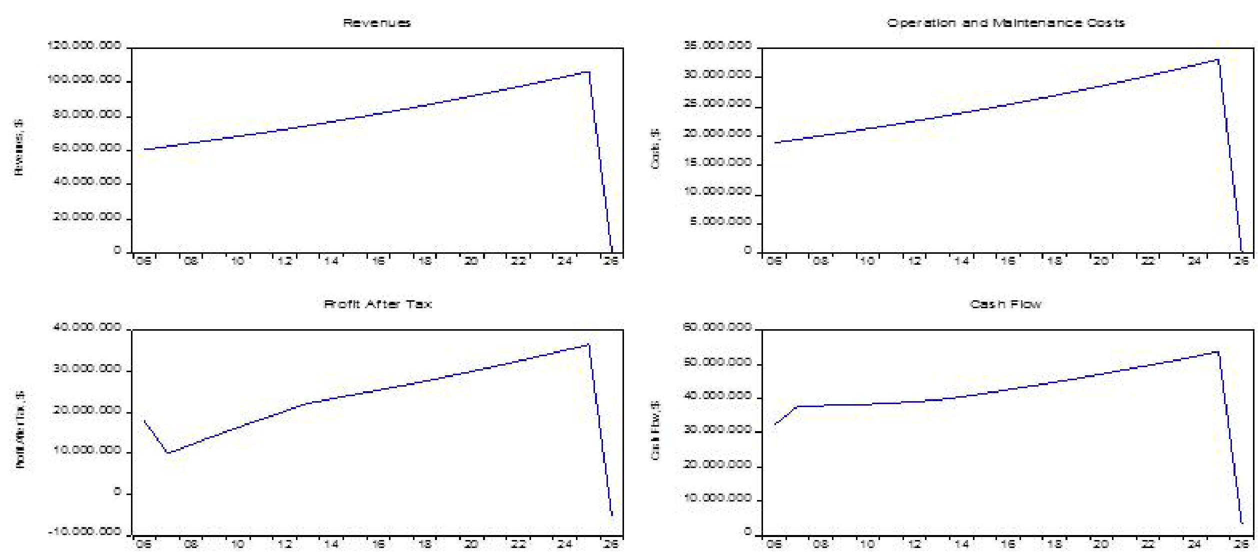
$$Costs_t = Costs_{t-1} \cdot (1 + Costs\ increase\ rate). \tag{6}$$

In equations (2) and (3), time t = 2006, … , 2026; while in equations (4) - (6), t = 2006, …, 2025. The project began to operate in 2006 and will end in 2025 (the project life is 20 years). In 2026, there will be no energy generation, only the MACRS depreciation. Thus, $Revenues_{2026} = 0$, $OM\ Costs_{2026} = 0$. The base case parameters of the deterministic model (1) - (6) are given in Table 1. The model was solved using EViews, the forecasting and analysis software package, over the 2006-2026 period. Time paths of the selected model variables are demonstrated in Figure 1. Since there is no energy production in 2026, there are abrupt declines of variables in that year. For the base case parameters, the NPV value is -$87,271,670. Without the tax breaks, the project would have been rejected.

TABLE 1
BASE CASE PARAMETERS

Parameter	Notation	Value
Construction costs	*Inv*	\$386 million
Discount rate	*r*	12%
Load factor	*Load factor*	35%
Annual capacity	*Capacity*	360.5 mW
Electricity price in 2006	$Price\_electr_{2006}$	\$55 per mWh
Operation and maintenance costs in 2006	$Costs_{2006}$	\$18.9 million
Price increase rate, t = 2007,…, 2025	*Electricity price increase rate*	3%
Operation and maintenance costs increase rate, t = 2007,…, 2025	*Costs increase rate*	3%
Tax rate	*Tax rate*	35%

FIGURE 1
BASE CASE VARIABLES OVER TIME



NPV SENSITIVITY

This section conducts a sensitivity analysis to identify inputs with greater impacts on the output (NPV). Uncertainties of those inputs will be crucial for the project economics. Five inputs are compared: construction cost, load factor, electricity price, operation and maintenance costs, and discount rate. As in a study by IEA/NEA (2010), input levels are varied 50% up and 50% down from the base case levels and the corresponding NPV values are calculated holding everything else constant.[6] Roques, Nuttal, and Newbery (2006) estimate sensitivity using input changes of 10%. The new NPV values and the NPV percentage changes (calculated with respect to the base case NPV = -\$87,271,670) are given in Table 2.

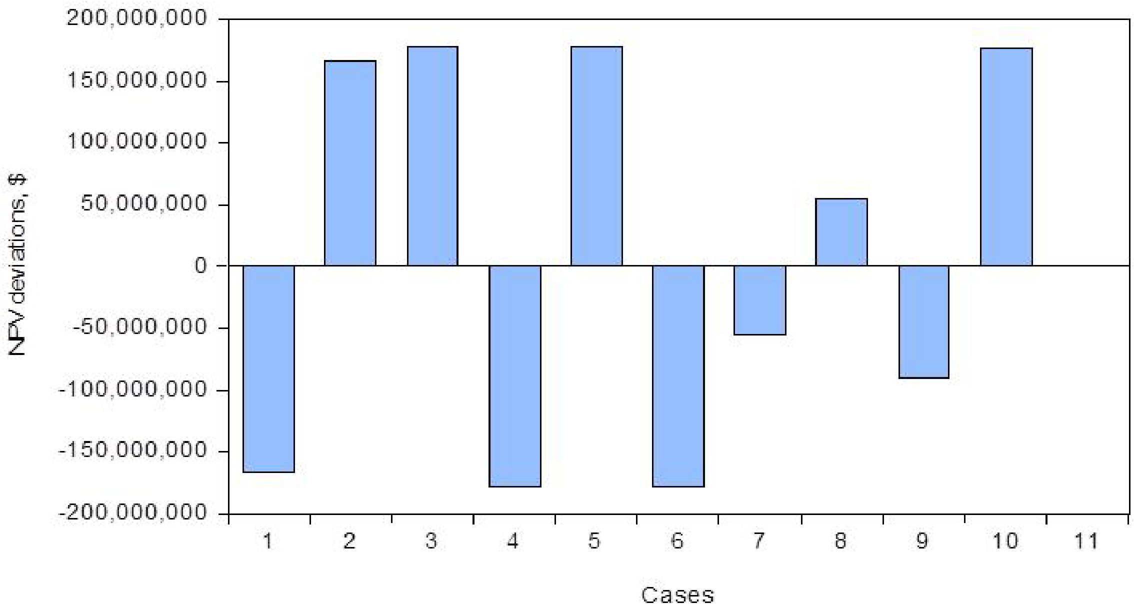
Since the initial NPV value is negative, a positive percentage change implies that NPV declined (became more negative), while a negative percentage means that NPV increased (became positive or less negative). Figure 2 illustrates deviations of the NPV values from the base case NPV. Table 2 and Figure 2 show three inputs with the strongest impacts on NPV: electricity price, load factor, and construction costs. In fact, the NPV variations are the same for variations in the initial electricity price and load factor. These two inputs affect NPV as the revenues product factors in equation (4). Percentage changes of the same magnitude in the initial electricity price and load factor have the same effect on revenues and, consequently, on NPV. Our sensitivity analysis results are similar to the IEA/NEA (2010) findings that load factor and construction costs have strongest impacts on LCOE of onshore wind technologies. Out of five inputs, O&M costs demonstrate the weakest impact on the wind farm NPV. High importance of construction costs and low importance of O&M costs could be explained by the cost structure of wind technologies: relatively high up-front costs and low operation costs.

TABLE 2
NPV SENSITIVITY

Case	Input change	NPV, $	% change in NPV
1	Construction costs up 50%	-253,857,500	191.05
2	Construction costs down 50%	79,314,140	-190.88
3	Load factor up 50%	91,149,600	-202.44
4	Load factor down 50%	-265,693,000	204.88
5	Initial electricity price up 50%	91,149,600	-202.44
6	Initial electricity price down 50%	-265,693,000	204.88
7	Operation & maintenance costs up 50%	-142,743,000	63.86
8	Operation & maintenance costs down 50%	-31,800,380	-63.56
9	Discount rate up 50%	-177,853,100	103.96
10	Discount rate down 50%	89,749,590	-202.84

The sensitivity analysis helped identify the critical inputs (uncertainties) for the project. However, the analysis is limited in scope: choices of the input changes are arbitrary, there are no estimates of the probabilities for variations in inputs, a change in each input is analyzed as stand-alone. In practice, changes in several inputs might occur simultaneously. A Monte Carlo Simulations approach can take into account multiple sources of uncertainty and their interrelationship. In order to run simulations, we need to describe the key uncertainties with probability distributions.

FIGURE 2
NPV DEVIATIONS FROM THE BASE CASE NPV



PROBABILITY DISTRIBUTIONS FOR KEY INPUTS

The paper assigns probability distributions for four inputs of the wind farm: electricity price, load factor, construction costs, and O&M costs. The previous section showed that the first three inputs have strongest effects on the project NPV, while O&M costs demonstrate weaker impact. The study does not define a probability distribution for the discount rate. It will be assumed to be constant during simulations.

Researchers use different models for the electricity price: Roques, Nuttall, and Newbery (2006) – normal distributions for the electricity price and the electricity price escalation; Yang and Blyth (2007) – Geometric Brownian Motion; Madlener and Wenk (2008) – lognormal distribution; Yun and Baker (2009) – mean reversion model. This paper uses a normal distribution for the electricity price percentage change with the mean = 3.0% (the base case value) and the standard deviation of 0.5%, as in Roques, Nuttall, and Newbery (2006). In the paper extensions we will use different models for the electricity price.

Spinney and Watkins (1996) employed the normal and beta distributions for the load growth of coal and gas CCCT plants. The beta distribution was used to take into account the leftward bias (overestimation) of load forecasts. Feretic and Tomsic (2005) used a triangular distribution for the load factor of nuclear, coal, and gas CCCT projects. Roques, Nuttall, and Newbery (2006) assumed a normal distribution for the load of nuclear, CCGT, and coal plants. Madlener and Wenk (2008) assigned minimum extreme value distributions for load of the nuclear and natural gas combines cycle (NGCC) technologies and lognormal distributions – for the hydro, wind, and solar technologies. Vithayasrichareon and MacGill (2012) did not make assumptions for a capacity factor. They calculated energy generation needed to meet the expected Load Duration Curve. This work employs the normal distribution for the annual load growth rate with the mean of 0% and the standard deviation of 1.50% similar to Spinney and Watkins (1996).

Construction costs modeling examples include: Spinney and Watkins (1996) – normal and beta distributions for the annual growth rate; Feretic and Tomsic (2005) – triangular distribution for nuclear, coal, and combined cycle gas plants; Roques, Nuttall, and Newbery (2006) – normal distribution with the mean values equal the base case values; Madlener and Wenk (2008) – gamma distribution to capture the right skewness of constructions costs (a possibility of cost overruns); Yun and Baker (2009) – Geometric Brownian Motion for the nuclear plant; Vithayasrichareon and MacGill (2012) – lognormal and gamma distributions. Our study applies a normal distribution for the wind farm construction costs (the mean value equals $386,000,000 – the base case value; the standard deviation equals $3,860,000 - 1% of the mean), following Spinney and Watkins (1996) and Roques, Nuttall, and Newbery (2006).

For conventional power generation plants, O&M costs mainly include fuel costs. Hence, uncertainty of their O&M costs crucially depends on volatility of fuel prices. For wind technologies, O&M costs are relatively stable when the construction is completed. Chosen probability distributions for O&M costs vary: Spinney and Watkins (1996) – normal and lognormal distributions for the growth rate, gas CCCT and coal plants; Feretic and Tomsic (2005) – two separate uniform distributions for fixed and variable O&M costs, nuclear, coal, and combined cycle gas technologies; Roques, Nuttall, and Newbery (2006) – normal distributions for fixed and variable O&M costs; Madlener and Wenk (2008) – normal distributions for fixed and variable O&M costs with the standard deviations equal to 10% of the mean values. The paper uses a normal distribution for the growth rate of O&M costs with the mean equal to the base case value (3%) and standard deviation equal 1% of the mean value (.03%), following Spinney and Watkins (1996), Roques, Nuttall, and Newbery (2006), and Madlener and Wenk (2008). The paper assigns lower standard deviation because O&M costs of wind technologies do not change much comparing to other power generation technologies. A summary of assigned distributions and their parameters for the wind farm is provided in Table 3.

TABLE 3
DISTRIBUTIONS AND PARAMETERS OF KEY INPUTS

Input	Distribution	Parameters
Electricity price acceleration	Normal	Mean = 3.0% (the base case value); standard deviation = 0.5%
Construction cost	Normal	Mean = $386,000,000 (the base case value); Standard deviation = $3,860,000 (1% of the mean value)
Load growth rate	Normal	Mean = 0% (the base case value); standard deviation = 1.5%
O&M costs increase rate	Normal	Mean = 3% (the base case value); Standard deviation = .03% (1% of the mean value)

The study describes uncertainties of the wind farm inputs with normal distributions as for now the goal is to explore the EViews implementation of MCS for wind power generation projects. In the following papers, more sophisticated distributions/models for the inputs and their dynamic relationships will be considered.

NPV MONTE CARLO SIMULATIONS

This section employs MCS to derive a probability distribution for the wind farm NPV taking into account four sources of uncertainty (electricity price, load, construction costs, and O&M costs). The simulations involve iterations of generating random values from the inputs distributions described in the previous section and calculating the corresponding NPV using a stochastic version of model (1) - (6):

$$NPV_i = -Inv_i + PV(Cash\ Flows_i) = -Inv_i + \sum_{t=2006}^{2026} \frac{Cash\ Flow_{it}}{(1+r)^t}, \tag{7}$$

where i is the iteration number, Inv_i is construction costs at iteration i, r is the discount rate, $Cash\ Flow_{it}$ is the project cash flow at iteration i in year t.

$$Inv_i = \$386{,}000{,}000 + NRND\_Inv_i \cdot \$3{,}860{,}000, \tag{8}$$

where $NRND\_Inv_i$ is a generated random value of the standard normal variable for constructions costs (Inv) at iteration i.

$$Cash\ Flow_{it} = PAT_{it} + Depreciation_{it}\ , \tag{9}$$

where PAT_{it} is the Profit After Tax at iteration i in year t, $Depreciation_{it}$ is the MACRS depreciation at iteration i in year t.

$$PAT_{it} = (Revenues_{it} - Costs_{it} - Depreciation_{it}) \cdot (1 - Tax\ Rate), \tag{10}$$

where $Costs_{it}$ is O&M Costs at iteration i in year t.

$$Revenues_{it} = (Load\ factor_{it}) \cdot Capacity \cdot 8{,}760\ hours \cdot Price\_electr_{it}, \tag{11}$$

where $Price\_electr$ is the electricity price per mWh at iteration i in year t.

$$Load\ factor_{it} = Load\ factor_{i,t-1} \cdot (1 + NRND\_load_{it} \cdot 0.015), \tag{12}$$

where $NRND\_load_{it}$ is a generated random value of the standard normal variable for the load factor at iteration i in year t.

$$Price\_electr_{it} = Price\_electr_{i,t-1} \cdot (1 + Electricity\ price\ increase\ rate_{it}) \tag{13}$$

$$Electricity\ price\ increase\ rate_{it} = 0.03 + NRND\_Electr_{it} \cdot 0.005, \tag{14}$$

where $NRND\_Electr_{it}$ is a generated random value of the standard normal variable for the electricity acceleration at iteration i in year t.

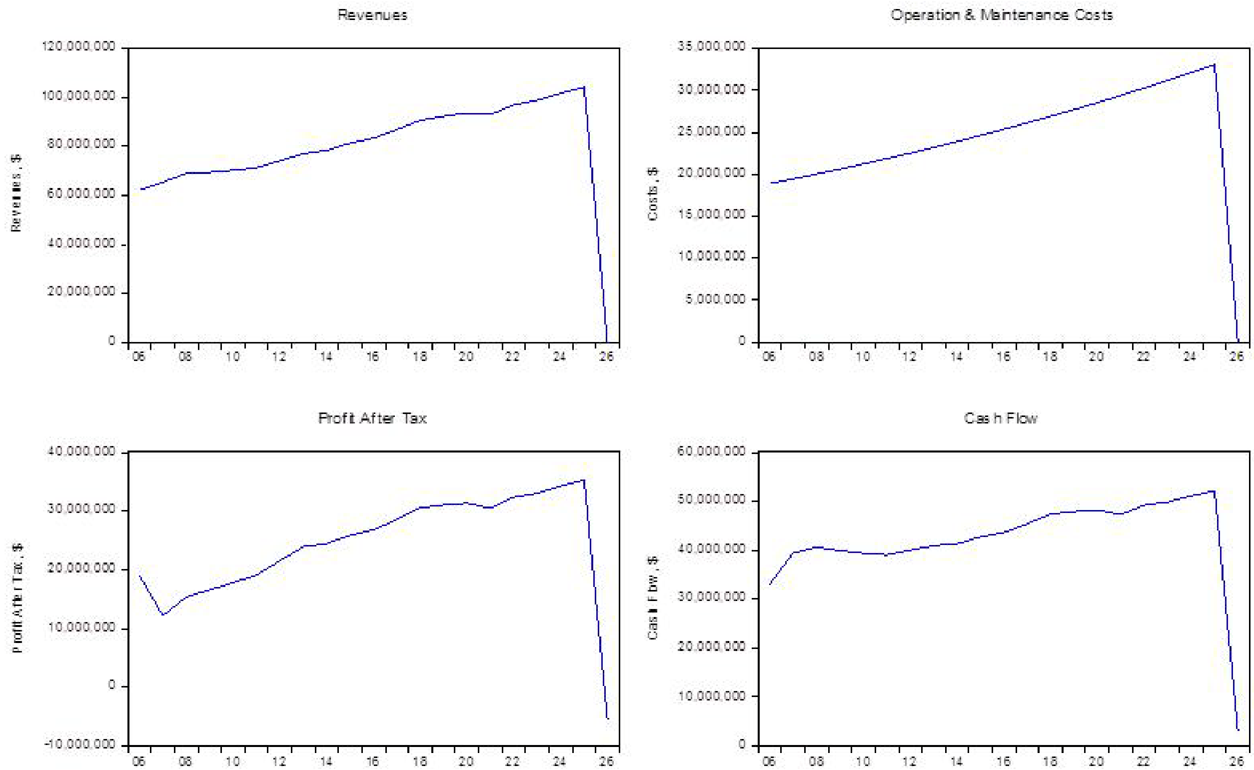
$$Costs_{it} = Costs_{i,t-1} \cdot (1 + Costs\ increase\ rate_{it}) \tag{15}$$

$$Costs\ increase\ rate_{it} = 0.03 + NRND\_Costs_{it} \cdot 0.0003, \tag{16}$$

where $NRND\_Costs_{it}$ is a generated random value of the standard normal variable for the O&M costs growth rate at iteration i in year t.

This study used EViews to run MCS for the wind farm. The stochastic model (7) - (16) was repetitively solved 5,000 times. At each iteration, project variables were generated for the 2006 – 2026 period and NPV was calculated. An example of the Revenues, O&M Costs, Profit After Tax, and Cash Flows paths is given in Figure 3. The stochastic trajectories in Figure 3 demonstrate some volatility comparing to the trajectories in Figure 1.

FIGURE 3
SIMULATED VARIABLES OVER TIME



The NPV simulations were performed at three different discount rates: (i) 5% and 10%, as in Roques, Nuttall, and Newbery (2006), IEA/NEA (2010); (ii) 12%, the project discount rate given in Brealey, Myers, and Allen (2011). The simulated NPV distributions are shown in Figure 4 and the statistics are provided in Table 4. The NPV distributions for all three discount rates are close to normal. Their skewnesses are close to 0 and kurtoses are close to 3 (Table 4). The approximate normality of NPVs is a result of the normality assumptions for four inputs of the wind farm (electricity price, load, construction costs, and O&M costs).

Figure 4 and Table 4 show that the mean NPV value is positive ($136,113,156) at the 5% discount rate and negative for two other discount rates. At the 12% discount rate, the mean NPV (-$89,533,139) is close to the base case NPV (-$87,271,670). At the 5% discount rate, the wind farm NPV is positive in all iterations (the minimum NPV = $42,000,750 > 0). At the 10% discount rate, the NPV values are mainly negative. Probability(NPV ≤ 0) = .9919, or Probability(NPV>0) = .81%. At the 12% discount rate, all NPV values are negative (the maximum NPV = -$43,491,180 < 0). Or, there is no chance of getting positive NPV unless the parameters of the project change or the government provides tax breaks. The standard deviation is higher at the 5% discount rate. The numbers illustrate that reducing the cost of capital for wind technologies will help make their economics acceptable.

FIGURE 4
NPV DISTRIBUTIONS

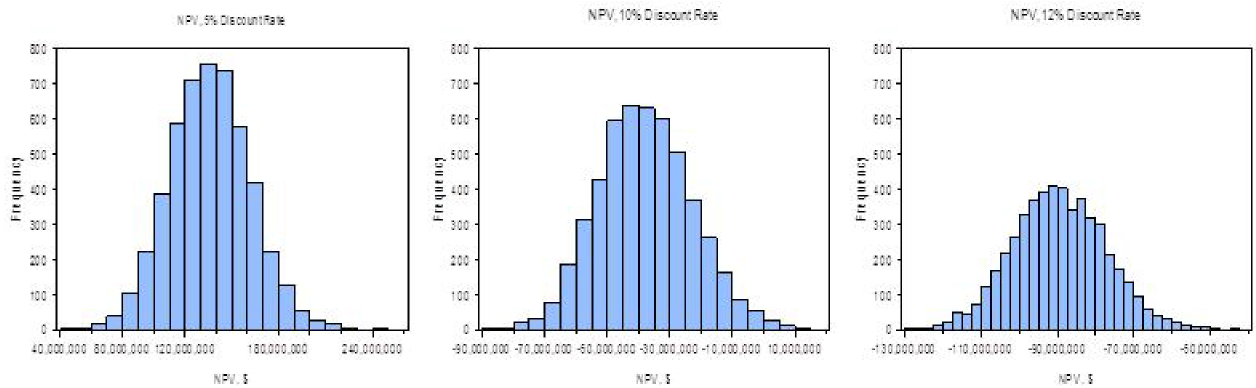


TABLE 4
NPV STATISTICS

Statistics	Discount Rate		
	5%	10%	12%
Mean	$136,113,156	-$37,906,779	-$89,533,139
Median	$135,834,850	-$38,354,980	-$89,790,975
Maximum	$241,552,600	$13,724,390	-$43,491,180
Minimum	$42,000,750	-$88,994,600	-$128,439,500
Standard Deviation	$25,627,607	$15,002,385	$12,214,835
Skewness	0.11	0.13	0.09
Kurtosis	3.11	2.94	3.01

With continuing investments in wind power generation technologies, there will be learning experience. It is quite plausible that over time the load factor will improve despite randomness of the wind availability. In order to investigate how the load increase will affect the NPV, this study run another series of NPV simulations assuming that the load factor growth rate follows the normal distribution with the mean of 2% and the standard deviation of 1.5% as in Spinney and Watkins (1996). The generated NPV distributions are depicted in Figure 5 and the statistics are given in Table 5.

Similarly to the first series of NPV simulations, the NPV distributions with load growth are close to normal. Their skewnesses are close to 0 and kurtoses are close to 3 (Table 5). Figure 5 and Table 5 display that, at the 5% discount rate, the NPV is always positive (the minimum NPV = $160,221,800). At the 10% discount rate, probability of getting positive NPV is 96.51%. At the 12% discount rate, probability of getting positive NPV is only 5.29%. The mean NPV value is positive for the 5% and 10% discount rates ($274,935,759 and $31,984,133, respectively) and still negative for the 12% discount rate (-$24,384,589). The standard deviation is again higher at the 5% discount rate. The load-growth mean NPV values (Table 5) are larger than in the no-load growth cases (Table 4). The project economics improve significantly with load growth: the probability of getting positive NPV in the no load growth case, discount rate of 10%, was negligible (.81%), while it is much larger in the load growth case (96.51%). At the 5% discount rate, the mean NPV doubled with the load growth comparing to the mean NPV with no load growth.

FIGURE 5
NPV DISTRIBUTIONS, LOAD GROWTH

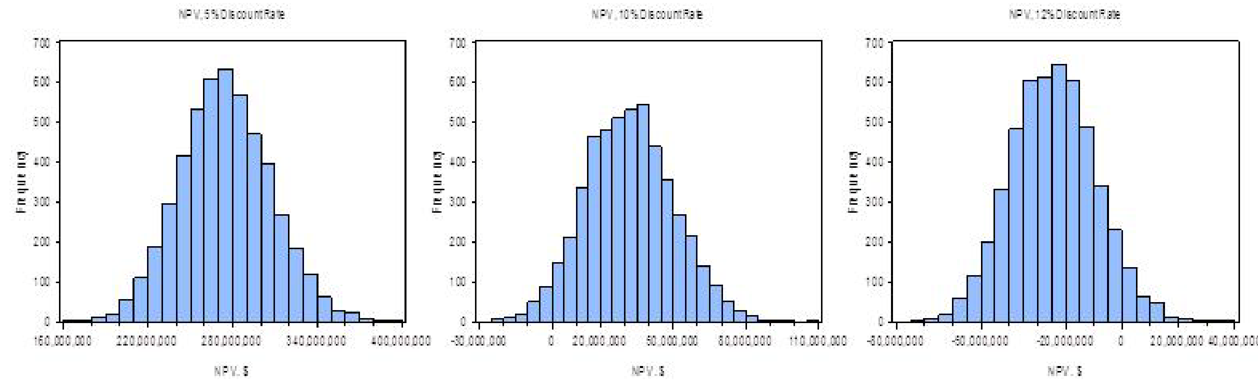


TABLE 5
NPV STATISTICS, LOAD GROWTH

Statistics	Discount Rate		
	5%	10%	12%
Mean	$274,935,759	$31,984,133	-$24,384,589
Median	$274,197,850	$31,436,525	-$24,422,340
Maximum	$397,630,000	$108,548,400	$35,165,830
Minimum	$160,221,800	-$24,080,830	-$71,6661,280
Standard Deviation	$32,342,913	$18,110,269	$14,882,308
Skewness	0.13	0.13	0.10
Kurtosis	3.06	2.96	2.91

These two series of the NPV simulations illustrate how MCS can be used for an analysis of a wind power generation project.

CONCLUSIONS

Economics of the power generation investments depend on many uncertain factors. A Monte Carlo Simulations framework can take into account multiple sources of uncertainty and their interrelationship. This paper demonstrates an EViews application of a Monte Carlo method for evaluation of a wind farm investment. It generates the NPV probability distributions. Comparing to a single point estimate of NPV, the probability distributions enable to assess a range of possible values and to estimate probabilities of certain NPV levels. MCS allow users to calculate different risk measures: standard deviation, skewness, and kurtosis. An illustrated MCS approach can be used for an analysis of alternative power generation technologies and their portfolios.

The paper describes uncertainties of the wind farm inputs with normal distributions. In the following paper, non-normal distributions/models for the inputs will be considered. One of the MCS shortcomings is inability to consider changes in relationships among variables over time (Spinney and Watkins, 1996; Roques, Nuttal, and Newbery, 2006). The extension of this paper will combine MCS and the EViews features to take into account dynamic relationships.

The study considers a stand-alone wind farm. Analysts (IEA/NEA, 2010; Hertzmark, 2007) point that the benefits of wind technologies can be strengthened with geographical diversification, the use of wind plants as supplements to other technologies, and the integration of wind forecasts into the power systems load decisions. It will be interesting to examine a wind power generation plant in a portfolio with other wind farms and/or other technologies.

ENDNOTES

1. Graham and Harvey (2002) report that the most popular capital budgeting methods are Internal Rate of Return and Net Present Value.
2. The sensitivity value depends on measurement units (Spinney and Watkins, 1996). In order to avoid dependence on measurement units, elasticity might be calculated. Elasticity is a ratio of a relative change in the output with respect to a relative change in the input. A relative change is a ratio of a nominal change with respect to the initial value of the variable.
3. LCOE equals the ratio of the present value of costs divided by the present value of produced energy.
4. To promote renewable energy technologies, governments implement special policies and offer tax and financial incentives (Bird et al, 2005; Komor and Bazilian, 2005).
5. For simplicity, we assume that the construction costs occur at the end of 2005. Given the estimated median lead time of one year for wind technologies, this assumption is plausible.
6. In the IEA/NEA study (2010), the output is LCOE.

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