IMPROVING DECISIONS IN WIND POWER SIMULATIONS USING MONTE CARLO ANALYSIS

Devin Hubbard[1] and Borinara Park[2]

[1] Graduate Student, College of Applied Science and Technology, Illinois State University, United States
[2] Associate Professor, College of Applied Science and Technology, Illinois State University, United States

ABSTRACT: Computer simulations designed to predict technical and financial returns of wind turbine installations are used to make informed investment decisions. These simulations used fixed values to represent real-world variables, while the actual projects can be highly uncertain, resulting in predictions that are less accurate and less useful. In this article, by modifying a popular wind power simulation sourced from the American Wind Energy Association to use Monte Carlo techniques in its calculations, the authors have proposed a way to improve simulation usability by producing probability distributions of likely outcomes, which can be used to draw broader, more useful conclusions about the simulated project.

Keywords: Monte Carlo; Wind power; Risk management

1. INTRODUCTION

As wind power continues to be installed nationwide, with over 1,417 turbines installed in 53 projects this year alone, demand has risen for realistic and representative simulations to guide economic and technical decisions for these systems' construction [1]. Simulations meant to model wind power installations are already available to the general public and specialized contractors (advanced physics simulations intended to model the actual wind turbine design are outside the scope of this discussion) [2]. Some simulations are designed to run as purpose-built programs, either dedicated to multiple renewable energy platforms or specifically designed for wind power. Other simulations, including some used by the leading American Wind Energy Association (AWEA), are single-purpose spreadsheets that do not rely on specialized software; they can be run on any compatible systems.

Wind simulations function the same regardless of design philosophy: taking system and weather parameters defined by either specific user input or a general template, applying calculations according to prewritten formula, and determining numerical values for several qualities influenced by the given parameters. These values include economic price, power output, efficiency, financial break-even periods, and maintenance costs. By studying these values, a simple wind power project can be tested for feasibility without any construction or equipment investment.

The value of these simulations is in their ability to advise and inform real-world wind projects. Not all users may have the technical expertise to interpret a simulation's results and draw the proper conclusions. In some cases they may be misled by oversimplification as simulations provide single values instead of a range of possibilities, as an industry expert would provide to cover all bases. That oversimplification is the main issue with these simulations, regardless of their design: by requiring fixed values for inputs, they return outputs as fixed values, despite the fact that real outcomes can vary widely based on tiny changes to the actual inputs. Overly predictable simulation outcomes may be less viable for industry usage, as the initial conditions for the actual project may not correspond to those in the simulation. The simulation studied in this article is supported by the American Wind Energy Association, dedicated solely to wind power, and running on a spreadsheet platform which the authors have modified to allow for Monte Carlo and sensitivity analysis. With these tools the simulation can account for uncertainty in its calculations and provide a more realistic outlook, studying the impact of small changes in source variables.

2 AWEA MODEL

2.1 AWEA Model Description

The AWEA simulation serves as an ideal platform- easy to use in uncertainty analysis, and representative of other popular wind simulations. The categories provided for user input, whether default or custom-entered, include financing plan and interest rates; wind speed, terrain factors, and electricity cost; and system details, including costs of maintenance and installation, percentage of downtime due to failure and maintenance, and rate of performance decay. In every category, the preset entries are meant to provide representative samples of wind power scenarios - for instance, the 'site properties' section describes the preset options based on wind speed, elevation, and terrain, and the user-defined inputs are in every case given annotations about the possible ranges and meanings of their values. Notably, this means the simulation will assume a hard and fast default value of 96% every time when the value is noted as ranging from 95 to 98 percent in typical projects.

B	C	D	E
Site Characteristics			
	Site Properties		
		Average Wind Speed (m/s)	5.8
		Anemometer Ht (m)	10
		Wind Shear Exponent	0.143
		Weibull k	2
		Site Elevation (m)	0
	Avoided Energy Costs		
		Average Cost of Electricity ($/kWh)	0.07
		Nominal Electricity Escalation Rate (%/year)	0.02
System Characteristics			
	System Costs		
		Total Installed Cost ($/kW)	2665000
		Variable Costs ($/kWh)	0.015
		Nominal Variable Cost Escalation Rate (%/year	0.02
		Fixed Costs ($/kW)	0
		Nominal Fixed Cost Escalation Rate (%/year)	0.02
	Physical Characteristics		
		Rated Power (kW)	1500
		Rotor Hub Height (m)	64.7
		Availability (%)	0.98
		Performance Margin	0
		Performance Derating	0.1
		Hub Height Average Wind Speed (m/s)	7.58
		Air Density Factor	1.00
		Average Annual Power Output (kWh)	4398084
		Implied Capacity Factor	33%

Figure 1. Screenshot of AWEA simulation inputs

2.2 AWEA Model Limitations and Improvements

The main issue with these simulations is that real wind power has several unreliable factors. The speed of the wind is of course highly uncertain at any given moment, but on the simulation's scale of several years of operation, wind speeds can actually be charted on a Weibull probability distribution, the coefficient of which depends on the site's geography. Other values suffer from being deterministic; while wind turbine performance does degrade over time, it is unlikely that every turbine suffers the same percentage loss of performance every year, in the case of performance derating tracked by the simulation. The use of deterministic values in the model means that these key outputs are represented as stable values, despite the fact that a small variation of the simulation's inputs — most likely in the inputs selected above — can result in larger variations of the important financial outputs. Some of the values in the spreadsheet can vary from year to year in real life, and a 2% devaluation every year could jump between 1% to 3% at the least.

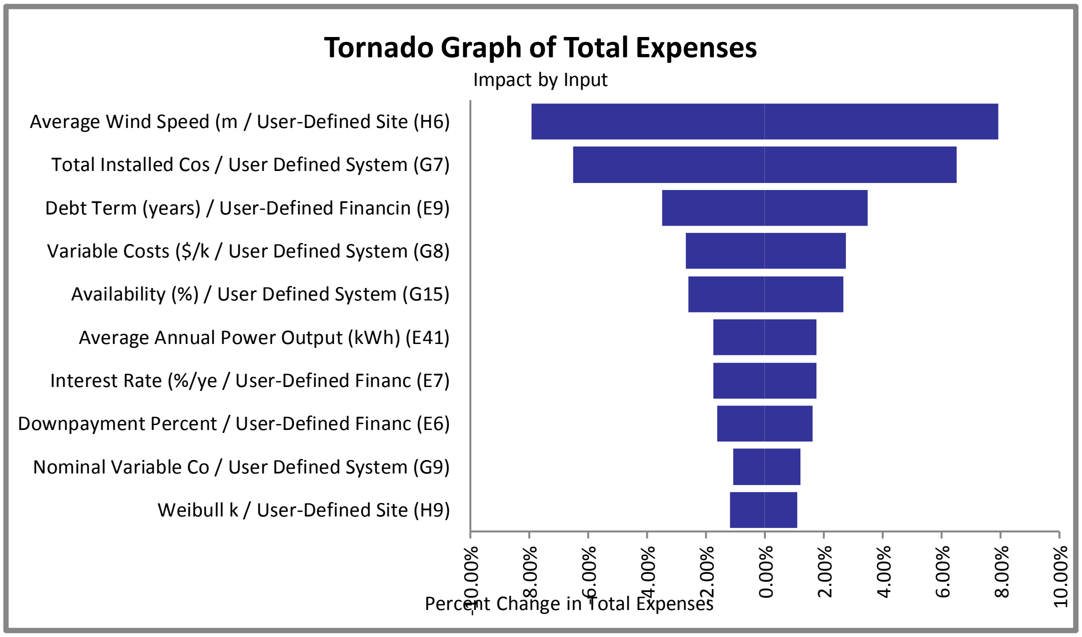

Figure 2. Screenshot of sensitivity analysis

In order to provide a broader range of simulation possibilities, several variables from the model have been represented by a spread of numerical values instead of single fixed values, as indicated by arrows added beside their entries in Figure 1. These inputs are variables most likely to be uncertain. The simulation also tracks key financial values, or outputs, generated by the simulation: the Net Present Value of the turbine at its moment of purchase; the Avoided Cost of Electricity, representing the value of all electricity generated; Total Expenses, or purchase, installation, and maintenance costs; Payback time in years; and Profit. The outputs have been taken from the simulation model directly, save for Profit which was constructed by subtracting expenses from avoided cost.

Monte Carlo analysis can mean the model produces probability pictures instead of single solid figures that may not tell the whole story. These kinds of results can be used to help the customer make more informed decisions, without oversimplification of data that could produce frustration and confusion when real results fail to match up to a deterministic model's prediction. The simulation spreadsheet underwent both Monte Carlo and sensitivity analysis in order to generate information based on these uncertain values and consider how these conclusions affect real-world use of the simulation.

3. CASE STUDY

3.1 Case Study Description

The AWEA model was tested in a case study intended to evaluate the effect of introducing uncertainty to the model's calculations. The model was set up to simulate a 1.5 MW wind turbine, with 20% of the purchase price paid in cash, installed on a low-altitude smooth plain and with a relatively low maintenance availability of 95%. . This design is representative of a Midwestern turbine collocated with grazing or farming land. The farmer in this case study would represent an ideal simulation user: someone interested in investing in wind power, but lacking technical knowledge, using the simulation to make a decision based on financial return. Other simulation values were left as the defaults in the AWEA spreadsheet.

The initial setup for this case consisted of selecting the variables for the study. The spreadsheet was configured using user-defined variables intended to simulate a utility-scale wind turbine. The variables of uncertainty were added to the Monte Carlo software plug-in used for this article [3]: annual power output of the turbine; the wind shear exponent, or the disruption caused to wind flow by a lack of smooth terrain around the turbine; escalation rate of variable costs, due to business disruption or other factors; system availability, or percentage of time the system is operable and ready to generate power; and performance derating, the factor by which power generation lessens due to wear and age on turbine components. Once the variables of uncertainty seen in Figure 1 were added to the Monte Carlo software, they were programmed to vary within 5 percent of their base values in a uniform spread. The simulation then ran through 500 iterations, varying those selected inputs along the five-percent range, recording the values of the five financial outputs listed above at every iteration. The simulation results were then automatically displayed as histograms, showing the spread of values recorded.

3.2 Sensitivity Analysis

Figure 3. Financial outputs and their percentage changes based on five percent variations in selected inputs

These values were obtained through a sensitivity analysis suite. The mode of operation was the similar to the Monte Carlo program; the five financial outputs above were added to the software, which then ran calculations to determine which variables in the simulation had the greatest influence on the outputs' values. In Figure 2, the simulation shows the changes to the Total Expenses of the turbine caused by 5% changes to several input variables. Figure 3, below, collects the five most important variables to affect each output and shows the percentage change caused to an output by a 5% variation in input, as seen in Figure 2.

Based on Figures 2 and 3, it can be concluded that Average Wind Speed is the greatest driver for the five most important outputs: Total Expenses increase with annual power output, which is directly related to Average Wind Speed. The positive financial worth of the turbine is based on power production, which is again directly related to Average Wind Speed. The most important outputs here are the previously mentioned values that will influence the simulation user's decision to construct or not construct the wind turbine- financial profit, total cost of installation and upkeep, revenue in electricity production, net present value of the turbine over its life, and the number of years required for financial payback. Note that this is not one of the

Output	Input #1	Input #2	Input #3	Input #4	Input #5
Net Present Value	**Ave Wind Speed**	**Ave Cost Elec**	**Availability**	**Power Output**	**Installed Cost**
Value Changes	-25.44% | 25.43%	+/- 13.95%	+/- 11.16%	+/- 11.16%	+/- 8.42%
Avoided Cost Elec	**Ave Wind Speed**	**Availability**	**Power Output**	**Ave Cost Elec**	**Elec Escalation**
Value Changes	+/- 6.25%	+/- 2.74%	+/- 2.74%	+/- 2.74%	+/-0.91%
Total Expenses	**Ave Wind Speed**	**Installed Cost**	**Debt Term yrs**	**Variable Cost**	**Availability**
Value Changes	+/- 2.14%	+/- 1.8%	-3.27% | +0%	+/- 0.94%	+/- 0.94%
Payback Years	**Ave Wind Speed**	**Ave Cost Elec**	**Installed Cost**	**Availability**	**Power Output**
Value Changes	-20% | +33.3%	-6.67% | +13.33%	-6.67% | +13.33%	-6.67% | +13.33%	-6.67% | +13.33%
Profit	**Ave Wind Speed**	**Ave Cost Elec**	**Availability**	**Power Output**	**Installed Cost**
Value Changes	+/- 12%	+/- 6.58%	+/- 5.27%	+/- 5.27%	+/- 2.53%

Figure 3. Sensitivity analysis results.

inputs chosen for Monte Carlo analysis; the wind is highly variable, but not on a year-to-year basis.

Availability and Power Output (two of the five chosen ‘uncertainty inputs’ that have been selected to be varied by Monte Carlo analysis) are also important, each of them important in four out of five financial outputs. This further emphasizes the variable, uncertain nature of the simulation’s findings. A tiny change from the base value can produce a great change in results not hinted at by the spreadsheet’s originally static values.

The Total Expenses entry suggests an unusual finding. Maintenance costs in the spreadsheet are directly related to the annual power output, which is in turn based on the wind speed. The fact that Average Wind Speed is the most important factor in Total Expenses suggests that maintenance costs are the biggest driver in total expenses! That is, the variable cost, which is directly related to power output, affects total expenses to a greater degree than changing the total cost of the hardware and installation.

3.3 Monte Carlo Analysis

The preceding figure shows the results of Monte Carlo analysis of financial payback time, calculated by the model. For non-technical investors using the simulation, the payback time is one of the most important figures in determining whether to invest in the wind project.

The value of this spreadsheet lies in the decisions based on its predictions. The oversimplification of data represented by deterministic values could lead to uninformed decisions. While a change of up to five percent may not be a large change for some variables, consider that the model supplies a base deterministic value of 15 years for financial payback. If the user does not see a guaranteed payback within 15 years, the simulation spreadsheet will be not be seen as worthwhile. Providing a graph of the possibilities for payback, and their likelihoods, gives the user greater confidence in the spreadsheet’s forecasting ability as well as informing the user of the variability inherent to this investment. Such a graph is shown below in Figure 4. An investor could use a graph like this to make strategic decisions about a wind power investment, as unlike the deterministic simulation results, the Monte Carle simulation provides both a potential list of outcomes and their respective probabilities.

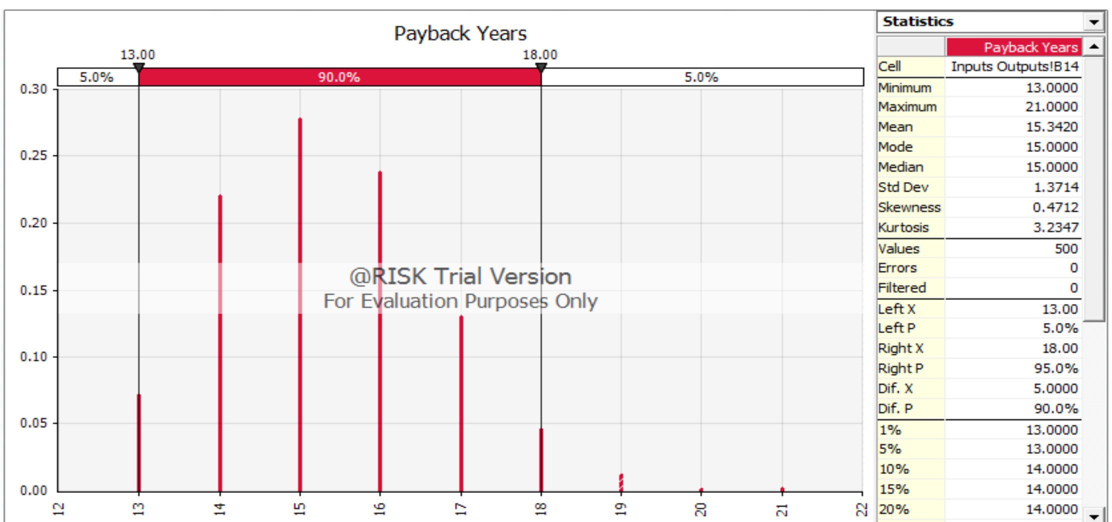

Figure 4. Screenshot of Payback Time distribution.

The means from the Monte Carlo simulation of key variables do not vary greatly from the deterministic values, as might be expected; the comparisons are listed in Table 1. For this table, the statistical information compiled in Monte Carlo analysis, as seen in Figure 4, was used to determine a mean and standard deviation for each financial output (Payback Time, Total Expenses, etc.) The information was then compared to the deterministic output produced by using fixed values. The difference is that the standard deviations are not zero under Monte Carlo analysis: the spreadsheet no longer returns the same answers each time. Each output has its own level of variability, meaning that some graphs will produce a smaller range of potential outcomes, and therefore more reliable forecasting, than others.

Most apparent in the study of different variables is the effect of these small changes on payback time. In order to get a 95% confidence interval for financial payback time, as shown in the case study, the span must go from 13 to 19 years based on the data in Figure 4, showing a great variation in payback times that the user should be aware of before making such an investment. (Note that the simulation assumes a 30-year operational lifetime, so even very poorly returning turbines end up repaying the initial costs eventually.)

The Total Expenses field holds the smallest standard deviation despite a value in the millions. Users can take from this the lesson that avoided costs, not actual, are going to be much more difficult to predict. Of course this does not take into account the fact that $1,000 per year in a simulation could cost nothing for four years and then cost $5,000 in reality, but the graphs produced by Monte Carlo analysis suggest not only which paybacks are likeliest, but how far to expect the values to shift in practice. These graphs can then serve as risk profiles to evaluate the worth of potential investments and educate the investors as to the full spread of possibilities the investment can offer in costs and returns.

Table 1. Comparison of deterministic and Monte Carlo output values.

Output Variable	Monte Carlo Mean	Monte Carlo Std Dev	Deterministic
Net Present Value	$829,597.67	$79,891.52	$829,751.00
Avoided Cost of Electricity	$8,729,380.00	$205,880.34	$8,729,754.46
Total Expenses	$5,094,398.03	$42,004.59	$5,094,447.78
Payback Years	15.34	1.37	15.00
Profit	$3,634,982.69	$165,291.97	$3,635,306.68

4. IMPLICATIONS AND CONCLUSIONS

The AWEA simulation spreadsheet has shown several values important to users: its notations make it user-friendly, it uses a simple and familiar spreadsheet platform, and its model is very thorough in the number of variables it takes into account. Yet the study of the AWEA spreadsheet has shown several weaknesses in the model, most notably in the reliance on deterministic values in a notoriously variable field. Users both expert and non-expert may put too much faith in the predictions of the spreadsheet and set themselves up for disappointment or confusion when their investment's figures fail to match those forecasted by a professional simulation. By implementing the techniques of uncertainty analysis and stochastic methodology, such as sensitivity analysis and Monte Carlo simulations, the spreadsheet can be reworked to provide a portfolio of options instead of single values, allowing analysts and customers to make decisions knowing the relative likelihood of their outcomes.

The results from stochastic analysis show clearly that small changes in variables can produce great variability in the simulation's predicted results, costs, and returns on investment. By conducting this kind of analysis, the customer or client using this simulation will receive a more realistic view of project feasibilities, forewarned about risks, and make more informed decisions about their investment. The use of Monte Carlo analysis in project simulations like this is an adaptation that can be introduced into simulation models fairly easily, thanks to the flexibility of the software platforms being used. Wider deployment of these analyses promotes a more realistic and in-depth approach to decision making in forecasting simulations.

REFERENCES

[1] American Wind Energy Association, *U.S. Wind Industry Second Quarter 2012 Market Report*, AWEA Data Services, 2012.

[2] National Renewable Energy Laboratory, *System Advisor Model*, https://sam.nrel.gov/, 2012

[3] Palisade Corporation, *The DecisionTools Suite*, http://www.palisade.com/decisiontools_suite/, 2012