Journal of Entrepreneurship, Business and Economics
ISSN 2345-4695
2023, 11(2), 1–28

ECONOMIC EVALUATION OF OFFSHORE WIND INVESTMENTS IN TAIWAN: AN UNCERTAINTY APPROACH

Thi Hong Nhung Nguyen [1], Chia-Hua Chang [2], Hsiao-Jung Chen [3]

[1] *College of Business, Southern Taiwan University of Science and Technology, Tainan 71005, Taiwan*
[2] *Department of Industrial Management and Information, Southern Taiwan University of Science and Technology, Tainan 71005, Taiwan*
[3] *Department of Finance, Southern Taiwan University of Science and Technology, Tainan 71005, Taiwan*
E-mail: chiahua@stust.edu.tw

Received March 2023; accepted July 2023

Abstract
The offshore wind technology in Taiwan's market is in its early stages and has many uncertainties, despite its high growth potential. The emerging market is facing the challenge of establishing a cost-competitive offshore wind industry. This paper aims to evaluate offshore wind power investments in Taiwan using the probability-based Levelized Cost of Electricity (LCOE) model in order to investigate ways to overcome this challenge. To capture the project's uncertainties, a probabilistic approach and the Monte Carlo technique are utilized, and their effects on project evaluation are portrayed through the probability distribution of LCOE and sensitivity analysis. Additionally, a simulation based on a chronological approach is developed to directly investigate the probability density function of the capacity factor for a specific wind farm site. The study concludes that the proposed approach provides better insights into projects and performs better in project evaluation, especially for projects located in high-frequency wind areas.

Research paper

Keywords: Offshore Wind; Energy; Investment Evaluation; Uncertainty; Monte Carlo

Reference to this paper should be made as follows: Nguyen, T. H. N., Chang, C., & Chen, H. (2023). Economic Evaluation of Offshore Wind Investments in Taiwan: An Uncertainty Approach. *Journal of Entrepreneurship, Business and Economics*, *11*(2), 1–28.

Introduction

In the last two decades, the world has observed a strong growth of wind energy in the energy sector. In 2020, the total installed capacity of wind energy reaches 733.3 GW (IRENA, 2020) accounting for about 5% of world electricity and 2% of the world's total energy (BP, 2020). In the wind energy sector, although offshore wind energy has made up a relatively small proportion, the installed capacity of this section has incredibly increased 10 times from 3.3 GW in 2011 to 32.5 GW in 2020 (GWEC, 2020).

From 2021 to 2026, the offshore market is projected to expand at a compound annual growth rate (CAGR) exceeding 10%, with the Asia Pacific market demonstrating the highest CAGR (GWEC, 2020; Dana et al., 2022). According to estimates (GWEC, 2020), Taiwan will likely become one of the top five offshore wind markets in the Asia Pacific region over the next decade. Since cost reduction can only be achieved by reaching a certain level of market volume, the emerging market is facing the challenge of establishing a cost-competitive offshore wind industry. To investigate the ways to overcome this challenge, a proper assessment indicator is necessary.

The Levelized Cost of Electricity (LCOE) has emerged as the most frequently utilized metric in the energy sector to evaluate and contrast the cost-effectiveness of various energy sources. The LCOE metric is a variant of the discounted cash flow (DCF) approach, which is utilized to determine the break-even price of electricity that would balance the present value of a project's revenue with the total discounted cost over its entire life cycle. Theoretically, LCOE is a single value. However, it is suggested to display LCOE as a range of values to reflect the uncertainty of input variables such as energy production, capital costs, operation cost, and financial expenses. Indeed, several studies have employed Monte Carlo Simulation to produce the range of LCOE values formed as a probability distribution. The studies provide evidence that the probability-based LCOE offers a much better understanding of renewable energy investments by capturing the relevant risks.

This study employed the probabilistic approach and the Monte Carlo technique to capture the project's uncertainties and then portray their effects on project evaluation. The probability distribution of LCOE and sensitivity analysis are generated to assess these effects, with a focus on three variables: operation and maintenance (O&M) costs, capacity factor (CF), and return on equity (ROE). The study also developed a simulation based on a chronological approach to investigate the probability density function of CF for a specific wind farm site. Results suggest that this approach provides improved insights and better project evaluation, particularly for high-frequency wind areas.

The study is predicted to enhance its probabilistic approach by adding location-based impact into the distribution estimation of the CF. The LCOE output distribution provides better insights into projects and performs better in project evaluation, enabling more informed decisions by project developers and policymakers. Especially, the proposed approach of directly calculating capacity factor allows us to obtain a more accurate LCOE distribution of new projects in immature markets like Taiwan where the energy generation data of offshore wind projects are unreadily available.

The next section provides a review of relevant literature and the research gap, while section three introduces the LCOE model and CF simulation model used in the research. In section four, a case study project is presented, including a discussion on the uncertain nature of input variables within the LCOE model. Section five reveals the calculated CF distribution, LCOE output results, and sensitivity analysis. Finally, section six provides the conclusions.

Literature review

To date, several studies have proved the importance of accounting for uncertainty in principal input variables to acquire ranges of LCOE values. Feretic and Tomsic (2005), Roques, Nuttall, and Newbery (2006) proposed the probabilistic approach to solving the uncertainty issue in LCOE modeling by considering all possible or available likelihoods of the input variables. Darling, You, Veselka, and Velosa (2011) imported the distribution of input variables into the Monte Carlo simulation to compute the LCOE for photovoltaics. For nuclear and gas power projects, Geissmann and Ponta (2017) used the same approach to calculate the LCOE considering the risks in power plant projects. Meanwhile, Lucheroni and Mari (2017) develop a similar approach but include the fluctuation in carbon price and installation duration.

In the wind energy section, Ioannou, Angus, and Brennan (2017) combine Monte Carlo simulation with the stochastic approach to deal with the unstable financial and technical parameters that influence capital and operating cost ranges. Recently, Tran and Smith (2018) adopted the probabilistic approach to evaluate several generation technologies such as nuclear, coal, natural gas, biomass, solar PV, and wind. The mentioned studies provide evidence that the probability-based LCOE offers a much better understanding of renewable energy investments by capturing the relevant risks. However, since the used model is aimed to represent industry-level range values of LCOE for each technology, it is inappropriate for analyzing a specific project, specifically from geographically dependent resources.

Since renewable resources are location-specific, the capacity factor of a power plant should be tailored to the site. Heck, Smith, and Hittinger (2016) noted that variations in location can impact LCOE values for renewable energy projects by up to 50%, and affect their uncertainty through capacity factor variability (Yakubu et al., 2022; Arasti & Salamzadeh, 2018; Salamzadeh & Markovic, 2018; Romanovich et al., 2022). However, in emerging markets, limited data on energy performance makes capacity factor assumptions less reliable. Hence, the capacity factor needs to be directly calculated instead of simply assumed. Despite this, the issue is seldom addressed in current wind energy studies (Shen et al., 2020).

This study aims to to fill that research gap by expanding the probabilistic approach to compute the probability density function (PDF) of a capacity factor in LCOE modeling for wind energy projects. In the research, the probabilistic approach in LCOE calculation is designed at the plant level by factoring in the location-specific impact to estimate the capacity factor distribution. In the process, we focus on the probability density function (PDF) of three variables: Capacity Factor (CF), Return on Equity (ROE), and Operation and Maintenance Expense (OpEx). To compute the PDF of monthly capacity factors, we directly use hourly wind speed time-series data.

Methodology

This section will describe the employed techniques and models. In short, the probability distributions of those parameters are imported into the

LCOE model by using Monte Carlo simulation, generating the output LCOE distribution (see Figure 1). At the same time, sensitivity analysis is carried out to investigate the relationship between project valuation and input factors. The output distribution and sensitivity analysis are expected to capture the project uncertainty, providing insights into the project.

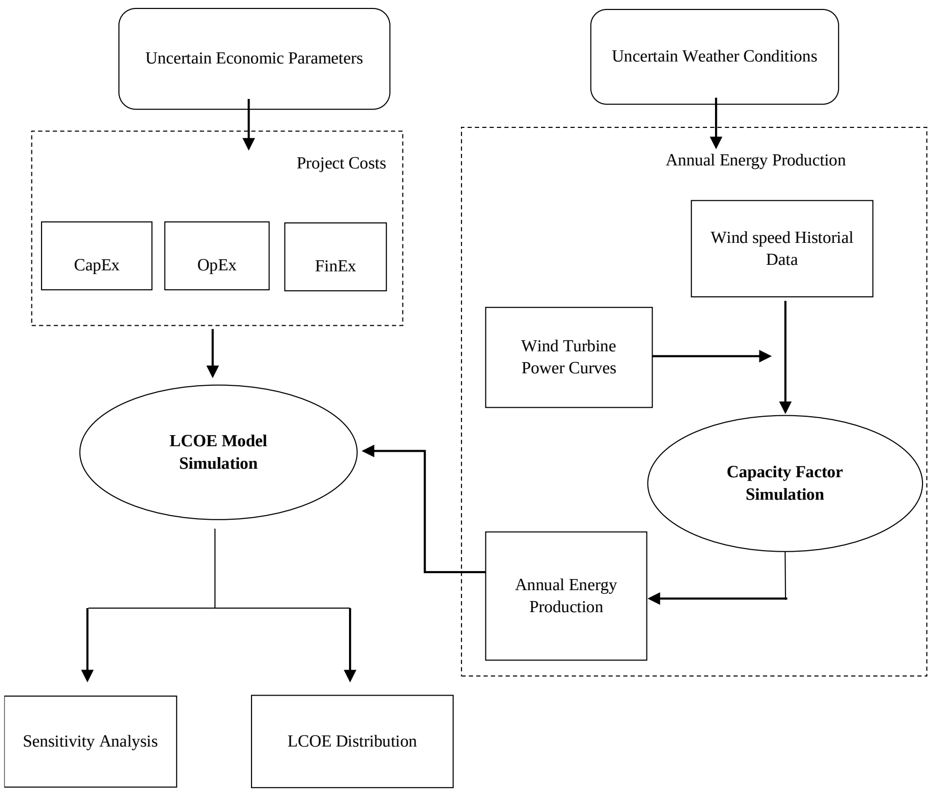

Figure 1. Flow chart of the proposed assessment model

LCOE Model Simulation

In this thesis, the LCOE calculation follows a manual of the economic assessment for energy conducted by Short, Packey, and Holt (1995), since the approach is compatible with Monte Carlo simulation and sensitivity analysis. The method relies on an evaluation of future cash flows using the discounted cash flow (DCF) approach. In this manner, the levelized cost of electricity (LCOE) can be defined as the price at which a project generates enough revenue to cover all discounted costs over its lifetime, resulting in a net present value (NPV) of zero. As the present value of project revenues equals the sum of the electricity price in year n multiplied by the annual energy production in year n (E_n) discounted with discount rate d, we get the equation:

$$\sum_{n=1}^{N} \frac{E_n \times LCOE_n}{(1+d)^n} = TLCC \tag{2.1}$$

where TLCC is the total discounted life-cycle cost of a wind power project. Assuming that the LCOE has a constant annual value, we can rearrange equation (2.1) as:

$$LCOE = \frac{TLCC}{\sum_{n=1}^{N} \frac{E_n}{(1+d)^n}} \tag{2.2}$$

The TLCC is composed of many different costs associated with owning an asset during its lifetime or the specific duration of interest to the investor (Short et al., 1995). TLCC can be calculated in different ways, depending on how taxes are treated (Batrancea et al., 2019, 2022). In the thesis context, we will take the effect of tax into account (Nguyen, Chang, & Tsai, 2022):

$$TLCC = CapEx - \sum_{n=1}^{N} \frac{Dep_n}{(1+d)^n} \times T_n + \sum_{n=1}^{N} \frac{OpEx_n}{(1+d)^n}(1-T_n) \tag{2.3}$$

where CapEx is the capital cost, while Dep_n, $OpEx_n$, and T_n are depreciation, operation and maintenance costs, and tax rate in year n, respectively.

The below equation is commonly used to compute the annual energy generated by a wind power system that has a capacity factor CF (Moné et al., 2017):

$$E = t \times Q \times CF \tag{2.4}$$

where t is the time length, typically measured in hours. Thus, t equals 8760 (hours) in the annual energy production calculation. Q denotes the installed capacity, which is determined by the number of turbines equipped as well as the turbine model.

By replacing two terms in equation (2) with equations (3 and (4) we obtain the equation as follows:

$$LCOE = \frac{CapEx - \sum_{n=1}^{N} \frac{Dep_n}{(1+d)^n} \times T + \sum_{n=1}^{N} \frac{OpEx_n}{(1+d)^n} (1-T)}{(1-T) \sum_{n=1}^{N} \frac{8760 \times Q \times CF_n}{(1+d)^n}} \tag{2.5}$$

In brief, four major input variables in the LCOE model of a power system are the capital expenses (CapEx), the annual operating and maintenance expenses ($OpEx_n$); the discount rate (d) presenting the financial expenses (FinEx) and the annual energy production (E_n) which mainly depends on the capacity factor (CF).

To apply Monte Carlo simulation to the LCOE calculation model, the uncertainty associated with each input variable will be well investigated. Based on the comprehensive understanding of their range of values, the probability distribution of these input variables will be defined (see Figure **1**). During the simulation, a set of sample values for all input variables is chosen at random by randomly selecting a value from each variable's distribution. The output value is obtained by importing iteration into the calculating model.

The resulting range of all possibilities generates a distribution that can capture the uncertainty of input variables. Each set of samples is referred to as an iteration. In the research, the simulation will have 100000 iterations.

Capacity Factor

The capacity factor (CF) is widely utilized as another measurement of energy production to evaluate the performance of wind systems (Nguyen et al., 2022). The CF of a wind turbine is defined as the ratio of power output produced by the turbine (E) to its full possible output (E_R) if it had been operating at rated capacity (P_R) over a duration period (H) (Ayodele, Jimoh, Munda, & Agee, 2012; Chang & Tu, 2007):

$$CF = \frac{E}{E_R} = \frac{E}{HP_R} \tag{3.7}$$

The power output produced by the turbine (E) is driven by wind turbine performance and wind speed. To deal with the unpredictable nature of wind speeds, many methods have been developed. Some studies adopt the parameter as well as non-parameter distributions to characterize wind speed distribution (Celik, 2004; Gass, Schmidt, Strauss, & Schmid, 2013; Ramírez & Carta, 2005), while some others employ the chronological approach treating wind speeds as time-series data (Chang, Wu, Hsu, Chu, & Liao, 2003; Nguyen et al., 2022). Chang and Tu (2007) suggested that the time-series approach can avoid errors in the parameter estimation process, giving a better prediction of energy production than other approaches. Thus, we also adopt the chronological approach in this thesis. Accordingly, the the energy output is computed by the below equation:

$$E = \sum_{i=1}^{H_\Delta} P_i(V)\Delta t_i \qquad (3.6)$$

where $P_i(V)$ is the energy generated at wind speed V of wind speed. Δt_i is the time interval and H_Δ is the number of Δt_i in examined duration. For the annual energy production, if the wind speed data used is hourly time-series, then Δt_i = 1 hour while H_Δ is 8670 (hours).

The value of $P_i(V)$ depends on the wind turbine effectivity presented as the power curve. Various models have been proposed for representing the wind turbine power curve (WTPC). However, many studies (Carrillo, Montaño, Cidrás, Díaz-Dorado, & Reviews, 2013; Teyabeen, Akkari, & Jwaid, 2017) indicate that the cubic model yields the lowest average relative error in capacity factor estimation. In the model, P(V) is calculated by air density ρ, is the swept area of the turbine A ($A=\pi r^2$), wind speed V and $C_{p,\,eq}$ constant equivalent to the power coefficient (Carrillo, Montaño, Cidrás, & Díaz-Dorado, 2013):

$$P(V) = \begin{cases} 0, & V \leq V_I \text{ or } V \geq V_O \\ \frac{1}{2}\rho A C_{p,eq} V^3, & V_I \leq V \leq V_R \\ P_R, & V_R \leq V \leq V_O \end{cases} \qquad (3.7)$$

where V_I, V_R, and V_O indicate the cut-in wind speed, the rated wind speed, and the cut-out wind speed, respectively. PR is the rated power output.

The CF in a time interval is a mean of the CF in smaller time intervals from time series (Nguyen et al., 2022):

$$daily\ CF = \frac{\sum_{i=1}^{24} P_i(V) \times 1}{24 \times P_R} = \frac{1}{24} \times \frac{\sum_{i=1}^{24} P_i(V)}{P_R}$$
$$= \frac{1}{24} \times \sum_{i=1}^{24} \frac{P_i(V) \times 1}{1 \times P_R} = \frac{1}{24} \times \sum_{i=1}^{24} hourly\ CF_i \qquad (3.8)$$

Capacity Factor Simulation

Since wind speeds are unpredictable, it is challenging to accurately determine the capacity factor of wind energy systems. In the study, we determine the CF's probability distribution from CF values generated based on historical wind speed data. Throughout the process, all values, including non-positive ones, are captured. As it is suggested to examine wind power at monthly intervals (Chang & Tu, 2007), the model will first estimate the monthly CF distributions, then generate the annual CF distribution by using MCS.

To obtain monthly CF (mCF) data, a method was employed where 10,000 random samples were chosen from historical time-series data of daily CF (dCF), each consisting of 30 observations. As daily CF values may exhibit autocorrelation due to the time-dependent nature of wind speed, moving block sampling was employed using a block size of three days. To ensure consistency, it was assumed that each month comprised 30 days, and therefore each sample consisted of 10 blocks or 30 daily CF values. The sampling process was carried out independently for each month of the year, from January to December.

Since the capacity factor will be directly calculated from wind speed data, the approach provides a more accurate estimation of the capacity factor of planned or under-construction wind projects. Moreover, the approach is appropriate for wind projects in immature markets where energy generation data are unreadily available.

Input data and case study

In this section, the proposal calculation model will be employed to generate the LCOE analysis for a case-studied offshore wind project. Since the data of installed cost, O&M cost and equity ratio are only available for the existing wind projects, we selected Formosa I project in Taiwan, which is the first offshore wind project at a commercial scale in the Asian-Pacific region as a case study. Table 1 presents input variables values from the profile of the project.

Table 1. Information of case studied wind farm

Input Parameters	**Value**	**Input Parameters**	**Value**
Location	24.711N; 120.814E	Capital Expense (CapEx)	626 Mil. USD
Turbine type	SWT-6.0-154	Annual Operation and Maintenance Expense (OpEx)	
Total Installed Capacity (Q)	120 MW	- *Range*	125-188 USD/kW-yr
Equity ratio	0.3*	- *Distribution - Log-normal*	μ = 5.05 σ = 0.1
Interest Rate ***	1.63%	Return of Equity (ROE)	
Tax rate (T) **	15.0%	- *Range*	12-16 %
Depreciation Period*	10 years	- *Distribution – Normal*	μ = 14 σ = 1
Project Lifetime (N)	20 years	Feed-in Tariff	17 USD cents/kWh

*Note: * We assume all projects imply the straight depreciation principle with a period of 10 years. Since the equity ratio is not available, we use the standard ratio of 0.3 (Kost et al., 2013).*

Source: innoVent.GmbH (2020), Shumkov (2018), thewindpower.net (2023), Taiwan (2018)

To estimate the distribution of LCOE for offshore wind farms, we will use Monte Carlo simulation (MCS). For each input variable in the LCOE equation (Eq. 3), a value will be randomly selected from its probability distribution to generate a set of input values, known as an iteration. The resulting

LCOE value will be recorded for each iteration. We will simulate 100,000 iterations in this study. We now consider the four main input variables in the LCOE calculation model.

Capacity Factor

Hourly time-series wind speed data for the wind farms between 2010 and 2019 are obtained from renewables.ninja database. Wind speeds in Taiwan are highly variable and occasionally reach extreme levels, with speeds over 25 m/s, while the average wind speed is 6.8 m/s and 6.7 m/s (

Table **2**).

Table 2. Descriptive Statistics for hourly wind speed

Minimum (m/s)	**Maximum (m/s)**	**Mean (m/s)**	**Standard Deviation**	**Count**	**P-value Jarque-Bera test**
0.2	38.2	6.8	3.6	87648	0.000

Table 3. Characteristics of the Offshore Wind Turbine

Characteristics	**Value**
Turbine Model	SWT-6.0-154
Cut-in wind speed V_I (m/s):	3
Rated wind speed V_R (m/s):	13
Cut-out wind speed V_O (m/s):	25
Rated power P_R (kW)	6000
a_1	-0.0026
a_2	0.0593
a_3	-0.2886
a_4	0.4573

Note: The cut-in, rated, and cut-off speeds are obtained directly from the power curve data of the turbine presented in Table A1. The values of a_1, a_2, a_3, and a_4 are obtained by running a regression between values of wind speed (V) and corresponding values of power output ($P_i(V)$) to fit the turbine power curve.

The results of the PDFs for monthly CFs are presented in this section.

Operation and Maintenance Expense

Typically, operation and maintenance expenses (OpEx) are categorized into fixed and variable costs (I. IRENA, 2012; Moné et al., 2017; Pereira et al., 2021). Fixed OpEx usually refers to known expenses related to operations, such as insurance, administration, and service contracts. Meanwhile, variable OpEx encompasses unforeseen maintenance and other expenses that are not covered by fixed contracts. However, since both aspects of OpEx are often mentioned as the total annual O&M costs in energy reports (I. IRENA, 2012; I. IRENA, 2019), in this study, we will present them as a single term – annual OpEx, measured in USD/kW/year.

The primary cause of uncertainty in OpEx arises from an unscheduled maintenance, which is determined by the wind turbine and component failure rate. The failure rate can be estimated using lognormal distribution or a two-parameter Weibull (Poore & Walford, 2008). For simplicity, we assume that the failure rate follows a lognormal distribution, leading to O&M costs being lognormally distributed as well. Table 1 illustrates the assumed distribution and range of OpEx, based on the Taiwan Ministry of Economic Affairs' demonstration model wind farm (BOE, 2014; Wen, Lin, Feng, Ko, & Lin, 2015; Salamzadeh et al., 2021, 2022). Thus, the annual OpEx for the studied project is estimated to be 3% of the capital expenditure.

Discount Rate

The discount rate (d) serves to discount costs and energy production while representing the project's financing expenses. To account for financing costs, the Weighted Average Cost of Capital (WACC) is commonly used (Ondraczek, Komendantova, & Patt, 2015). The study adopts the after-tax

WACC as the discount rate to also factor in the tax shield effect of debt, which can be calculated as follows (Nguyen et al., 2022):

$$WACC = \frac{E}{D+E} r_e + \frac{D}{D+E} r_d (1-T) \quad (9)$$

where T represents the average corporate tax rate; D and E are the debt and equity amounts utilized for project financing; r_e and r_d are the rate of return on equity and the interest rate, respectively. While the r_d and debt-to-equity ratio remains constant for a given wind project (Kost et al., 2013), the r_e can vary over the project's lifetime.

The return on equity is the expected return on investment for investors and is determined by the project's risk and the investor's risk aversion level (Nguyen et al., 2022). Hence, the r_e value may experience occasional fluctuations due to market volatility, policy uncertainty, and the impact of significant events (Shen et al., 2020). For the wind farms studied, we use a normal distribution that covers the range value for r_e to account for various financing scenarios (Table 1). Generally, the cost of equity for onshore wind projects ranges from 11% to 15% (Moné et al., 2015), and for offshore projects, we add a 1% premium due to their relatively high risk.

Capital Expense

The capital expense (CapEx) represents the total costs incurred by a wind farm project in the construction and installation. The CapEx is typically made up of three primary components: wind turbines (70-80% of total investment), system balance, and construction financing (Stehly & Beiter, 2020). Although CapEx values vary widely based on site and market (IRENA, 2019), for a specific project, CapEx depends on predicted factors such as installed turbine models, project size, and location, leading to minimal variation during construction. In our study, we use a single CapEx value based on the project profile (Table 1), but the net CapEx remains uncertain due to variations in the total discounted depreciation values caused by changes in the discount rate.

Results

In this section, we present the results obtained for the capacity factor and LCOE distribution, along with a sensitivity analysis. We also elaborate on the benefits derived from using the proposed calculation model.

Capacity Factor

Table **4** displays the average monthly capacity factor (CF) for a studied wind farm, along with their respective standard deviations. Notably, the CFs of the Taiwan wind farm exhibit a higher degree of variability due to the volatile and occasionally forceful nature of the wind. Specifically, the months between October and February experience strong winds, resulting in monthly CFs that consistently exceed 50%. The annual CF distributions that are directly based on yearly averages might neglect the seasonal effect which creates significant variations of monthly average wind speed throughout a year. Therefore, we decided to calculate annual CF based on monthly CF distribution. In particular, we select a random CF value for each month from its distribution and then calculate the annual CF as the 12-month average.

Table 4. Monthly CF distribution parameters (%)

Month	Formosa I		
	Mean	**Standard Deviation**	***P-value***
Jan	58	5.7	*0.260*
Feb	50	6.3	*0.953*
Mar	37	5.4	*0.059*
Apr	29	4.6	*0.526*
May	28	4.7	*0.810*
Jun	36	5.5	*0.876*
Jul	34	5.7	*0.712*
Aug	27	5.1	*0.006*
Sep	37	6.4	*0.909*
Oct	64	6.0	*0.057*
Nov	56	6.4	*0.523*
Dec	68	5.7	*0.856*
Average Annual CF	**44**		

Note: To determine whether the monthly CF follows a normal distribution, the Anderson-Darling test is employed. Most of the tests gave a p-value > 0.005, there are some exceptions for some months in which the CF is low. As a result, the normal distribution of monthly CF values cannot be rejected and is considered a satisfactory approximation.

Table 5. Selected distribution of annual CF based on the traditional approach

Range	Distribution	Parameters	Sources
31.5-45	Normal	$\mu = 40$; $\sigma = 4$	Tran and Smith (2018)

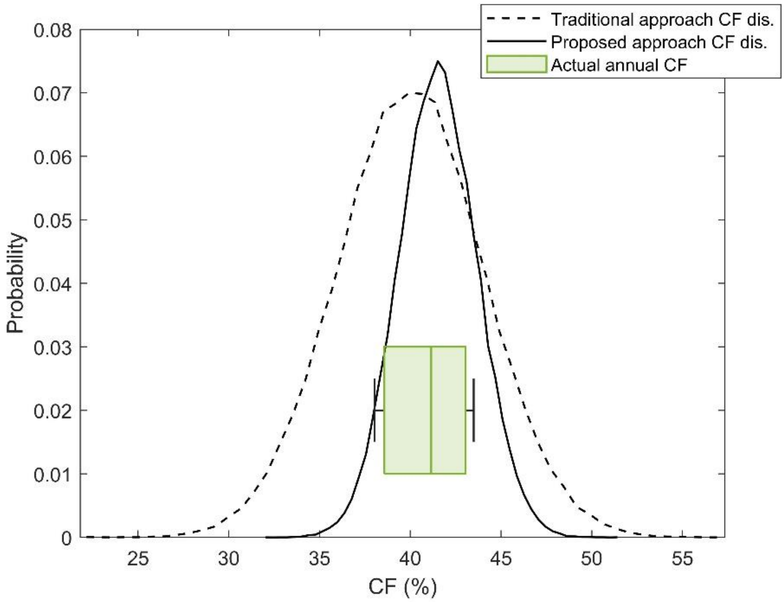

Figure 2. Comparing CF distribution using proposed and literature-based methods

To present the performance of the calculating method, we divided data from 10 year period into two groups: a training group of 6 years period from 2010 to 2016 and a testing group of 3 years period from 2017 to 2019. The training data was used to generate monthly and annual CF distributions, which were then compared to the historical annual CF values of 2017-2019. In addition, the CF values generated by the proposed method were compared to those assumed in previous studies.

Table **5** displays the assumptive distribution of annual CF based on Tran and Smith's approach (Tran & Smith, 2018), with the range of CF values adjusted based on a wind energy assessment report for Taiwan's offshore wind markets.

The proposed CF calculation method provides a more accurate estimation of CF values for a wind project, taking into account the unpredictable fluctuations in wind speed. As demonstrated in Figure **2**, The estimated CF distribution generated by the proposed method manages to encompass all actual CF values between 2016 and 2019, while the generated distribution is much narrower than the CF distribution suggested by the traditional approach.

LCOE distribution

Without Monte Carlo simulation (MCS), Formosa I's LCOE is 16.5 US$ cents per kWh. After fitting input variables to their range values and performing 100,000 iterations of MCS, we obtained the probability distributions of LCOE values for the case study project. Our analysis indicates that the normal distribution is the most appropriate for LCOE output.

By capturing the inherent unpredictability of wind energy projects, the LCOE range offers a deeper grasp of the anticipated costs for wind energy projects. Unlike single-point or scenario estimates, the probability-based method incorporates both the projected value and standard deviation to account for volatility in electricity prices. For instance, based on statistics from LCOE output (Table 6), one can state that the electricity cost of Formosa I is less than 18.4 US cents/kWh with a 95% confidence interval.

Table 6. Summary statistics of LCOE output (in US Cent/kWh)

Min	**Median**	**Mean**	**Max**	**Std Dev**	**Mean ± 2 Std Dev**
13.2	16.4	**16.5**	22.0	0.96	(14.6-18.4)

To compare the performance of our proposed CF simulation model to existing probabilistic models that assume a simple CF distribution, we conducted another MCS run while keeping all input variables constant except for the assumed CF. Two compared models show a difference of 0.63 USD cents/kWh in expected electricity cost values (Figure 3a), resulting in an increase of 28.3 USD mil. in expected NPV from -6.7 USD mil. to 21.6 USD mil. Figure 3b illustrates the correlation between LCOE output results and CF input values. By generating a more specific and accurate CF distribution, the proposed model provides a relatively thinner yet more precise LCOE distribution, leading to more well-informed decisions for both policymakers and project developers.

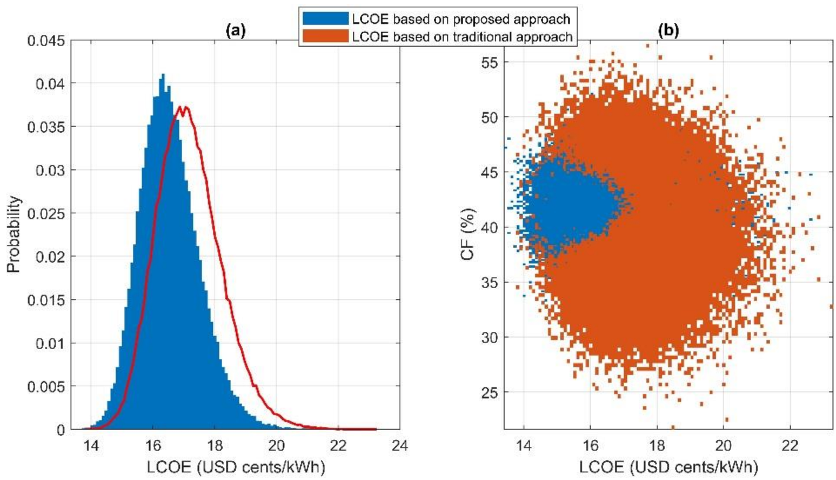

Figure 3. (a) Comparison of LCOE distribution generated by proposed and existing models; (b) The tiled histogram view of LCOE results with corresponding CF values

Sensitivity Analysis

Additional information can be obtained from an examination of the sensitivity of the LCOE to the various input variables. Sensitivity analyses were carried out by shifting a specific input variable by a range value of ±X% while holding all other input variables constant. To understand how real-world ranges influence LCOE, e is shifted in the range of 0.1 to 0.3, and the project´s lifetime, N is changed to a range of 20 to 25 years for both cases, and the tax rate T is shifted in the range of 10% to 20%. The figures below show us how each variable affects LCOE value.

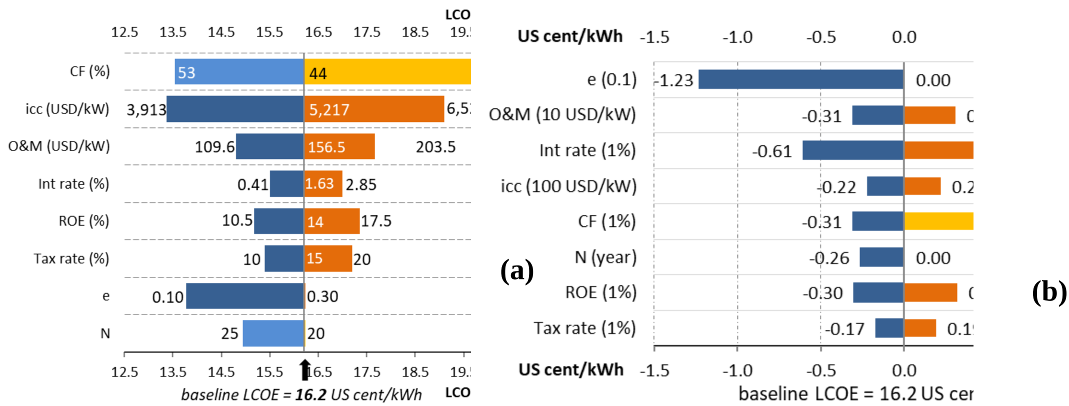

Figure 4. (a) Sensitivity of LCOE value to input variables (b) Margin effects of each input variable on LCOE (US cent/kWh)

Figure **4**a shows that the project's LCOE has a negative correlation with CF and N, but a positive correlation with other input variables. Increasing CF and N or decreasing CapEx, OpEx, or taxes can reduce LCOE, but these variables are usually not independent. For example, increasing CF with a more advanced turbine may raise ICC and LCOE, while extending the project lifetime may increase O&M and the expected return. Reducing the equity ratio of the project is also a good solution for project managers but a higher interest rate on loans is expected. By that, we introduce the concept of the margin effects of each input variable on LCOE (Figure **4**b). These margin effects can be used by the project developer can use to estimate the combined effect if more than one input variable changes its value. Nevertheless, every wind project possesses distinct features, and thus, the sensitivities depicted here are not universally applicable.

Conclusions

The utilization of Monte Carlo simulation in LCOE calculation is a well-established probabilistic technique that takes into account uncertainties within a wind project and creates a distribution of LCOE output. However, the existing studies typically rely on a simplistic assumption for energy production by utilizing the capacity factor value stated in the wind production assessment report of the industry.

The study concentrates on constructing an LCOE-calculation model and creates an LCOE output distribution for wind energy which captures the uncertainty elements associated with the input variables by conducting the Monte Carlo simulation. In particular, special attention has been paid to the PDF of three variables: operation and maintenance (O&M) costs, capacity factor (CF), and return on equity (ROE). In the paper, the key calculation is the time-series analysis of hourly wind speed data given wind turbine characteristics to directly investigate the probability function of the capacity factor. The study has completed the probabilistic approach in calculating LCOE at the plant level by adding the location-based impact on estimating the distribution of the capacity factor, allowing us to obtain a more accurate LCOE distribution of new projects in immature markets like Taiwan where the energy generation data of onshore and/or offshore wind projects are unreadily available.

Using real data from an offshore wind farm in Taiwan as a case study, we can draw the following conclusions:

(1) The normal distribution of monthly CF values cannot be rejected and is considered a satisfactory approximation. Although wind speed is unpredictable, the range of annual CF at a specific site is

smaller than expected and commonly assumed. Since the capacity factor will be directly calculated from wind speed data, the approach provides a more accurate estimation of the capacity factor distribution. The proposed approach is appropriate for planned or under-construction wind projects in immature markets where energy generation data are unreadily available.

(2) A probability distribution of LCOE values provides a better understanding of the cost of electricity generated by a wind energy project compared to a single value or scenario, as it considers the inherent uncertainty. The proposed model generates a narrow-downed but more precise LCOE distribution than existing probabilistic-oriented LCOE models by accounting for location-based impact on the uncertainty of a capacity factor. Using the proposed approach enables developers and policymakers to make practical decisions regarding price-based mechanisms like feed-in tariffs, green certificates, auctions, and feed-in premiums.

(3) The method also allows them to conduct a sensitivity analysis which presents the correlation between LCOE and input variables as well as their margin effects on LCOE. The margin effects of each input variable on LCOE might be a tool that helps the project developer to estimate the combined effect if more than one input variable changes its value.

The proposed approach can be used for real options analysis of project value by indicating the expected value and volatility of electricity cost for a specific offshore project. Additionally, this approach can serve as a strong foundation for future applications in project portfolio management. To increase the accuracy of the LCOE model, a future expansion of the model could pay interest to location-based factors that can affect the uncertainty of input variables, such as the effect of localization on the uncertainty of operation and maintenance expense.

References

1. Ayodele, T., Jimoh, A., Munda, J., & Agee, J. (2012). Wind distribution and capacity factor estimation for wind turbines in the coastal region of South Africa. Energy Conversion Management, 64, 614-625.
2. Arasti, Z., & Salamzadeh, A. (2018). A review of the status of social entrepreneurship research and education in Iran. Entrepreneurship Education and Research in the Middle East and North Africa (MENA) Perspectives on Trends, Policy and Educational Environment, 325-346.
3. Batrancea, L. M., Nichita, A., De Agostini, R., Batista Narcizo, F., Forte, D., de Paiva Neves Mamede, S., ... & Budak, T. (2022). A self-employed taxpayer experimental study on trust, power, and tax compliance in eleven countries. Financial Innovation, 8(1), 96.
4. Batrancea, L., Nichita, A., Olsen, J., Kogler, C., Kirchler, E., Hoelzl, E., ... & Zukauskas, S. (2019). Trust and power as determinants of tax compliance across 44 nations. Journal of Economic Psychology, 74, 102191.
5. BOE. (2014). Feed-in Tariffs of Renewable Energy. 2013. Bureau of Energy (BOE). Taipei, Taiwan. Retrieved from http:www.moeaboe.gov.tw.
6. BP. (2020). Statistical Review of World Energy. Retrieved from
7. Carrillo, C., Montaño, A. O., Cidrás, J., & Díaz-Dorado, E. (2013). Review of power curve modelling for wind turbines. Renewable Sustainable Energy Reviews, 21, 572-581.
8. Carrillo, C., Montaño, A. O., Cidrás, J., Díaz-Dorado, E. J. R., & Reviews, S. E. (2013). Review of power curve modelling for wind turbines. 21, 572-581.
9. Celik, A. N. (2004). A statistical analysis of wind power density based on the Weibull and Rayleigh models at the southern region of Turkey. Renewable energy, 29(4), 593-604.
10. Chang, T.-J., & Tu, Y.-L. (2007). Evaluation of monthly capacity factor of WECS using chronological and probabilistic wind speed data: A case study of Taiwan. Renewable energy, 32(12), 1999-2010.

11. Chang, T.-J., Wu, Y.-T., Hsu, H.-Y., Chu, C.-R., & Liao, C.-M. (2003). Assessment of wind characteristics and wind turbine characteristics in Taiwan. Renewable energy, 28(6), 851-871.
12. Dana, L. P., Salamzadeh, A., Mortazavi, S., & Hadizadeh, M. (2022). Investigating the impact of international markets and new digital technologies on business innovation in emerging markets. Sustainability, 14(2), 983.
13. Dana, L. P., Salamzadeh, A., Mortazavi, S., Hadizadeh, M., & Zolfaghari, M. (2022). Strategic futures studies and entrepreneurial resiliency: a focus on digital technology trends and emerging markets. Tec Empresarial, 16(1), 87-100.
14. Darling, S. B., You, F., Veselka, T., & Velosa, A. (2011). Assumptions and the levelized cost of energy for photovoltaics. Energy environmental science, 4(9), 3133-3139.
15. Feretic, D., & Tomsic, Z. (2005). Probabilistic analysis of electrical energy costs comparing: production costs for gas, coal and nuclear power plants. Energy Policy, 33(1), 5-13.
16. Gass, V., Schmidt, J., Strauss, F., & Schmid, E. (2013). Assessing the economic wind power potential in Austria. Energy Policy, 53, 323-330.
17. Geissmann, T., & Ponta, O. (2017). A probabilistic approach to the computation of the levelized cost of electricity. Energy Conversion Management, 124, 372-381.
18. GWEC. (2020). Global Offshore Wind Report 2020. Retrieved from
19. Heck, N., Smith, C., & Hittinger, E. (2016). A Monte Carlo approach to integrating uncertainty into the levelized cost of electricity. The Electricity Journal, 29(3), 21-30.
20. innoVent.GmbH. (2020). WINDFARM "MIAOLI". Retrieved from
21. Ioannou, A., Angus, A., & Brennan, F. (2017). Stochastic prediction of offshore wind farm LCOE through an integrated cost model. Energy Procedia, 107, 383-389.
22. IRENA, I. (2012). Renewable energy technologies: Cost analysis series. Retrieved from
23. IRENA, I. (2019). Renewable power generation costs in 2018. Report. Retrieved from Abu Dhabi:
24. IRENA. (2019). Renewable power generation costs in 2018. Report. Retrieved from Abu Dhabi:
25. IRENA. (2020). Renewable Capacity Statistics 2020. Retrieved from Abu Dhabi:
26. Kost, C., Mayer, J. N., Thomsen, J., Hartmann, N., Senkpiel, C., Philipps, S., . . . Schlegl, T. (2013). Levelized cost of electricity renewable energy technologies. Fraunhofer Institute for Solar Energy Systems ISE, 144.
27. Lucheroni, C., & Mari, C. (2017). CO2 volatility impact on energy portfolio choice: A fully stochastic LCOE theory analysis. Applied Energy, 190, 278-290.
28. Moné, C., Hand, M., Bolinger, M., Rand, J., Heimiller, D., & Ho, J. (2015). 2014 cost of wind energy review. Retrieved from

29. Moné, C., Hand, M., Bolinger, M., Rand, J., Heimiller, D., & Ho, J. (2017). 2015 cost of wind energy review. Retrieved from
30. Nguyen, T. H. N., Chang, C. H., & Tsai, P. C. (2022). Probability-based capacity factor in uncertainty analysis of electricity cost for individual wind projects: A novel approach. International Journal of Energy Research, 46(2), 980-994.
31. Ondraczek, J., Komendantova, N., & Patt, A. (2015). WACC the dog: The effect of financing costs on the levelized cost of solar PV power. Renewable energy, 75, 888-898.
32. Pereira, J., Braga, V., Correia, A., & Salamzadeh, A. (2021). Unboxing organisational complexity: how does it affect business performance during the COVID-19 pandemic?. Journal of Entrepreneurship and Public Policy, 10(3), 424-444.
33. Poore, R. Z., & Walford, C. (2008). Development of an Operations and Maintenance Cost Model to Identify Cost of Energy Savings for Low Wind Speed Turbines, July 20, 2004-June 30, 2008: National Renewable Energy Laboratory.
34. Ramírez, P., & Carta, J. A. (2005). Influence of the data sampling interval in the estimation of the parameters of the Weibull wind speed probability density distribution: a case study. Energy Conversion Management, 46(15-16), 2419-2438.
35. Romanovich, A. A., Dukhanin, S. A., Romanovich, M. A., & Salamzadeh, A. (2022, March). Modernization of the Mill's Working Bodies for the Production of Fine Building Materials. In International Scientific Conference on Innovations and Technologies in Construction (pp. 9-16). Cham: Springer International Publishing.
36. Roques, F. A., Nuttall, W. J., & Newbery, D. M. (2006). Using probabilistic analysis to value power generation investments under uncertainty: University of Cambridge, Electricity Policy Research Group.
37. Salamzadeh, A., & Markovic, M. R. (2018). Shortening the learning curve of media start-ups in accelerators: Case of a developing country. In Evaluating media richness in organizational learning (pp. 36-48). IGI Global.
38. Salamzadeh, A., Hadizadeh, M., & Mortazavi, S. S. (2021). Realization of online entrepreneurship education based on new digital technologies in Iran: A scenario planning approach. Journal of Entrepreneurship Development, 14(3), 481-500.
39. Salamzadeh, A., Hadizadeh, M., Rastgoo, N., Rahman, M. M., & Radfard, S. (2022). Sustainability-oriented innovation foresight in international new technology based firms. Sustainability, 14(20), 13501.
40. Shen, W., Chen, X., Qiu, J., Hayward, J. A., Sayeef, S., Osman, P., . . . Dong, Z. Y. (2020). A comprehensive review of variable renewable energy levelized cost of electricity. Renewable Sustainable Energy Reviews, 133, 110301.

41. Short, W., Packey, D. J., & Holt, T. (1995). A manual for the economic evaluation of energy efficiency and renewable energy technologies. Retrieved from
42. Shumkov, I. (2018). Taiwan's Formosa 1 Phase 2 offshore wind project achieves fin close. Retrieved from https://renewablesnow.com/news/taiwans-formosa-1-phase-2-offshore-wind-project-achieves-fin-close-615680/
43. Stehly, T. J., & Beiter, P. C. (2020). 2018 Cost of Wind Energy Review. Retrieved from
44. Taiwan, Ø. (2018). Financial close achieved for Taiwan's Formosa 1 offshore wind farm. Retrieved from https://orsted.tw/en/news/2018/06/fow1-financial-close
45. Teyabeen, A. A., Akkari, F. R., & Jwaid, A. E. (2017). Power curve modelling for wind turbines. Paper presented at the 2017 UKSim-AMSS 19th International Conference on Computer Modelling & Simulation (UKSim).
46. thewindpower.net. (2023). Retrieved from https://www.thewindpower.net/windfarms_list_en.php. Retrieved 10-01-2023 https://www.thewindpower.net/windfarms_list_en.php
47. Tran, T. T., & Smith, A. D. (2018). Incorporating performance-based global sensitivity and uncertainty analysis into LCOE calculations for emerging renewable energy technologies. Applied Energy, 216, 157-171.
48. Yakubu, B. N., Salamzadeh, A., Bouzari, P., Ebrahimi, P., & Fekete-Farkas, M. (2022). Identifying the key factors of sustainable entrepreneurship in the Nigerian food industry: The role of media availability. Entrepreneurial Business & Economics Review, 10(2), 1-17.
49. Wen, P.-L., Lin, J.-X., Feng, C.-C., Ko, F.-K., & Lin, S.-M. (2015). Feasibility of Taiwan's Offshore Wind Power Development

Appendix

Table A1. Data for power curves of the studied wind turbines

Wind speed V (m/s)	Power Pi (kW)	Wind speed V (m/s)	Power Pi (kW)
1	0	**11**	5850
2	0	**11.5**	5905
2.5	0	**12**	5960
3	170	**12.5**	5980
3.5	380	**13**	6000
4	590	**13.5**	6000
4.5	845	**14**	6000
5	1100	**15**	6000
5.5	1450	**16**	6000
6	1800	**17**	6000
6.5	2175	**18**	6000
7	2550	**19**	6000
7.5	3000	**20**	6000
8	3450	**21**	6000
8.5	3975	**22**	6000
9	4500	**23**	6000
9.5	5025	**24**	6000
10	5550	**25**	6000
10.5	5700	**26**	0

Source: https://www.thewindpower.net/turbines_manufacturers_en.php

Thi Hong Nhung Nguyen is a young reseacher driven by a passion for renewable energy. Her primary area of focus is on wind power energy. She possess a strong understanding of project management principles, recognizing their critical role in the successful implementation of green energy projects. By combining her expertise in wind power energy with her project management skills, she aims to contribute to the development and efficient execution of sustainable energy projects. Furthermore, she has a profound interest in green financing and continuously explore innovative approaches and financing models that facilitate the transition to a greener economy. Her goal is to attract investments in wind power and other renewable energy sources, ensuring their growth and sustainability. Through her research and work, she aspire to make significant contributions to the field of renewable energy, specifically in the areas of wind power energy, project management, and green financing.