Weibull-based Wind Cost Modeling in Dynamic Optimal Power Flow with Carbon Tax Considerations

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ABSTRACT

In the transition toward sustainable energy, economic optimization of power systems remains a critical challenge, particularly due to the variability of renewable energy sources, such as wind. By addressing the limitations of earlier research, which frequently make the assumption that wind speed is fixed, this article aims to determine a more realistic estimation of the Levelized Cost of Energy (LCOE) for wind power. In order to accomplish this, a Dynamic Optimal Power Flow (DOPF) framework is proposed, which incorporates carbon tax compensation and wind power cost modeling using a probabilistic Weibull distribution as its basis that represents wind speed variability. This approach leads to a more natural and representative estimation of annual wind energy production compared to conventional deterministic models. The DOPF problem is applied to a modified IEEE 30-bus system with integrated wind farms and is solved using the Improved Whale Optimization Algorithm (IWOA). According to the simulation results, the proposed Weibull-based LCOE formulation more accurately captures wind conditions in the real world. In comparison to the traditional LCOE approach, the introduced model lowers the overall generation cost by about 10,500 $/day under a carbon tax scenario of 50 $/MWh. This illustrates how enacting a carbon tax improves wind energy's economic competitiveness while simultaneously promoting emissions reduction. This study offers a fresh and thorough modeling framework that better captures wind energy costs in practical settings, assisting in the implementation of low-carbon policies and the development of optimal dispatch plans.

Keywords-dynamic optimal power flow; Weibull; levelized cost of energy; wind energy; improved whale optimization algorithm

I. INTRODUCTION

Electricity plays a vital role in achieving Sustainable Development Goal 7 (SDG 7), which emphasizes access to affordable, reliable, and sustainable energy. As a fundamental driver of economic growth and human development, electricity supports a wide range of sectors, including education, health, industry, and telecommunications. The transition toward renewable energy resources, particularly wind and solar, has become central to global decarbonization efforts due to their ability to reduce greenhouse gas emissions and lessen reliance on fossil fuels [1-3].

Among these, wind energy stands out for its cost-effectiveness and scalability. However, its inherent variability and intermittency pose challenges to system reliability, stability, and optimal dispatch. This situation calls for advanced optimization techniques that can accommodate the stochastic nature of renewable resources in power system operation [4-7].

DOPF is one such technique that extends the conventional Optimal Power Flow (OPF) by incorporating time-domain modeling of power generation and demand. It has been widely used to determine optimal generation schedules over multiple time periods while satisfying technical and economic constraints [8–11]. Despite its advantages, many existing DOPF models rely on deterministic assumptions for renewable generation, especially wind, which may not accurately reflect real-world conditions.

A key factor in assessing the competitiveness of renewable energy projects is the LCOE. This metric is widely used in both investment planning and policymaking, as it reflects the average cost of producing electricity over the lifetime of a project. However, traditional LCOE calculations often rely on fixed or average wind speeds, overlooking the inherently variable and unpredictable nature of wind. Authors in [12, 13] emphasized the importance of using probabilistic models to better capture this uncertainty and improve the accuracy of LCOE estimates. Furthermore, despite the increasing significance of carbon pricing in energy markets and environmental policy, many existing models still fail to incorporate mechanisms, like carbon taxes into LCOE evaluations and optimal dispatch strategies.

To address the existing gaps, this study proposes a novel DOPF that incorporates wind speed variability into LCOE estimation through a probabilistic Weibull distribution model. This approach enables a more accurate and realistic representation of wind power generation costs compared to traditional deterministic methods. Moreover, a carbon tax component is integrated into the economic assessment to internalize the external cost of carbon emissions and evaluate the impact of carbon pricing on the economic competitiveness of wind energy. The primary contributions of this work include the development of a stochastic LCOE estimation methodology that reflects real-world wind fluctuations, the incorporation of carbon pricing into the DOPF formulation to capture the environmental-economic trade-offs, and the implementation and validation of the proposed framework using a modified IEEE 30-bus system optimized with the IWOA.

II. MATERIALS

A. Weibull Distribution

It is often very difficult for wind power generators to predict and measure the level of speed and incoming wind power. Therefore, to solve this problem, researchers use the Weibull distribution function to map uncertain wind speeds with the Probability Distribution Function (PDF) $f_v(v)$ and Cumulative Distribution Function (CDF) $F(v)$ [14].

$$f_v(v) = \frac{k}{c^k} v^{v-1} \exp\left(-\left(\frac{v}{c}\right)^k\right) \tag{1}$$

$$F(v) = 1 - \exp\left(-\left(\frac{v}{c}\right)^k\right) \tag{2}$$

After mapping the unpredictable wind speed as a random variable from the Weibull distribution function, the equation for the power output of the wind power plant P_w can be calculated as:

$$P_w = 0 \; v < v_{ci} \; dan \; v > v_{co} \tag{3}$$

$$P_w = P_{rated} \left(\frac{v - v_{ci}}{v_r - v}\right)^3 \; v_{ci} \le v \le v_r \tag{4}$$

$$P_w = P_{rated} \quad v_r \le v \le v_{co} \tag{5}$$

The probability of wind power can be formulated and calculated as:

$$P_v = \int_0^v P_w f_v(v) dv \tag{6}$$

B. Dynamic Optimal Power Flow

The objective function in the DOPF problem is designed to minimize or optimize specific variables in the power system, such as generation cost as stated in (7):

$$\min F_G =$$

$$min \sum_{t=1}^{T} \sum_{i=1}^{N_G} (C_{G,i} \cdot P_{G,i}) + (C_{w,i} \cdot P_{w,i}) \tag{7}$$

$$P_w = \frac{1}{2} \rho A C p v^3 \tag{8}$$

The formula for thermal generation cost is:

$$C_{G,i} = \sum_{i=1}^{N_G} (\alpha_i + \beta_i P_{G,i} + \gamma_i P_{G,i}^2) \tag{9}$$

The following equations define the nonlinear power flow model used in this study:

$$P_{G,i} = \sum_{t=1}^{T} \sum_{j=1}^{N_B} |V_i| * |V_j| * |Y_{ij}| * cos(\theta_{ij} - \delta_i + \delta_j) \tag{10}$$

$$Q_{G,i} = -\sum_{t=1}^{T} \sum_{j=1}^{N_B} |V_i| * |V_j| * |Y_{ij}| * sin(\theta_{ij} - \delta_i + \delta_j) \tag{11}$$

$$P_{G,i}^{min} \le P_{G,i} \le P_{G,i}^{max} \tag{12}$$

$$Q_{G,i}^{min} \le Q_{G,i} \le Q_{G,i}^{max} \tag{13}$$

$$P_{w,i}^{min} \le P_{w,i} \le P_{w,i}^{max} \tag{14}$$

$$Q_{w,i}^{min} \le Q_{w,i} \le Q_{w,i}^{max} \tag{15}$$

$$-S_{ij}^{max} \le S_{ij} \le S_{ij}^{max} \tag{16}$$

$$V_i^{min} \le V_i \le V_i^{max} \tag{17}$$

$$\theta_i^{min} \le \theta_i \le \theta_i^{max} \tag{18}$$

$$R_i^{down} \le P_{G,i}^{t+1} - P_{G,i}^{t} \le R_i^{up} \tag{19}$$

Equations (10) and (11) represent the active and reactive power balances at the bus level. Equations (12-18) define the operational limits, including the upper and lower bounds for active and reactive power generation, transmission line capacity, voltage magnitude, and voltage angle. Additionally, Equation (19) imposes a ramp rate constraint, limiting the allowable change in generation output between time steps, as discussed in [15, 16].

C. Improved Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA) is a nature-inspired metaheuristic that simulates the hunting strategy of humpback whales, particularly their unique spiral bubble-net technique used to trap prey. Building on this concept, IWOA introduces a weight factor (w) to guide the movement of whale agents more effectively. This modification enhances the algorithm's performance by enabling faster convergence and improved accuracy, as noted in [16]. As a result of incorporating this weight factor, several equations in the original WOA are adjusted to reflect the enhanced search behavior.

1) Exploitation Phase

a) Mathematical Model of Prey Encirclement

$$Dis = |C * X_{Best} - Xi(t)| \quad (20)$$

$$X_i(t + 1) = X_{Best} - (w * A * Dis) \quad (21)$$

b) Mathematical Model of Maneuver from Spiral Bubble-net Feeding.

$$Dis' = |X_{Best} - X_i(t)| \quad (22)$$

$$X_i(t + 1) = w * Dis' * exp(l) * cos(2\pi l) + X_{Best} \quad (23)$$

2) Exploration Phase (Search for Prey)

$$Dis = |C * X_{rand}(t) - Xi(t)| \quad (24)$$

$$X_i(t + 1) = X_{rand}(t) - (w * A * Dis) \quad (25)$$

where Dis represents the distance between the current whale position and the best solution, C is the coefficient vector calculated as $C = 2$ *rand, with rand being a random number in (0-1), A is the coefficient vector calculated as A=2a*rand, with a decreasing linearly from 2 to 0 over iterations, while X_{Best} is the position of the best solution found so far. $X_i(t)$ is the current position of iteration. $X_i(t + 1)$ is the new position of the next iteration, and $X_{rand}(t)$ is a random position vector currently chosen.

III. PROPOSED APPROACH

A. Wind Generation Cost and Carbon Tax

Wind energy is now considered one of the cost-effective energy sources and technological advancements allow it to compete with conventional power generation technologies. The implementation of wind power into the electricity grid also raises new discussions related to the cost of electricity production. The cost of electricity is the cost of adding one unit of output (electrical energy), namely the change in total costs divided by the change in output [17]. The actual purpose of this objective function is to reduce the operational costs of wind generation *Cw* ($/*hr).*

$$Min\ Cw = C_w - C_{CT} \quad (26)$$

where C_w and C_{CT} are the wind cost function and carbon tax, respectively.

B. Levelized Cost of Energy (LCOE)

LCOE itself is a value index that shows the cost of energy production, which is the sum of all costs associated with a project, divided by electricity production over its lifetime. LCOE indicates the minimum price at which electricity can be sold so that the project can be built to be profitable [18]:

$$\text{LCOE} = \frac{(1+r)^{-i} \cdot \text{CAPEX} \cdot P_w + \text{OPEX} \cdot P_w}{\text{AEP}} \quad (27)$$

where CAPEX ($) represents the capital expenditures, OPEX ($/year) is the operational expenditure, AEP (MWh/year) is the annual energy production, P_w represent the amount of power generated by wind power, and r is the discount rate.

C. Capital Expenditures

Capital Expenditure (CAPEX) denotes the sum of all the values or costs spent before the operation of the wind farm. It covers the cost associated with development and consenting, turbines and substructure, electricity transmission, mooring, installation, and decommissioning [18].

D. Operational Expenditures

Operational Expenditure (OPEX) itself represents the value or cost associated with operations and maintenance. The cost is divided into two components, fixed components, which consider component repairs, staff, port facilities, equipment, and variable components that are associated with travel costs [19].

E. Annual Energy Production

Annual Energy Production (AEP) is the total annual energy that can be produced from a wind farm. This value depends on several factors, including the wind speed during the studied period, the chosen wind turbine model, and the number of turbines installed at the wind farm, which in turn depends on the installed power of the wind farm [11].

The current AEP formula can be calculated and seen as:

$$\text{AEP} = 8760 * \text{CF} * P_{wr} \quad (28)$$

where 8760 denotes the total hours in a year, CF is the capacity factor, and P is the rated power by the wind turbine. This research develops and proposes a new approach for the annual energy production equation by considering the probability density function of wind speed and the differential element of wind speed, as in:

$$AEP = 8760 * \int_0^{v_{max}} P_w\, f_v(v)\, dv \quad (29)$$

where $\int_0^{v_{max}} P_w$ are the integrals or sum amount power generated by the wind power, with various wind speeds, and $f_v(v)$ is the wind speed probability distribution function.

F. Stocastic Wind Speed

This study analyzes wind speed data from the Sidrap region in South Sulawesi (latitude: -3.7958°, longitude: 119.8369°), home to Indonesia's largest wind power plant, with a total capacity of 75 MW. The dataset includes approximately 8,000 hourly wind speed measurements, collected over one year. To capture the wind characteristics of the region, Weibull distribution was applied from which the scale parameter (c) and shape parameter (k) were derived. The results show that the Weibull distribution provides a good fit to the measured data and offers a solid foundation for wind power system planning and performance assessment. Figure 1 presents the Weibull distribution curve for the Sidrap site, along with key turbine specifications. The wind farm operates 30 turbines, each with a rated power output of 2.5 MW, resulting in a total installed capacity of 75 MW. The turbines have a cut-in wind speed of 3 m/s and a cut-out wind speed of 25 m/s. The average wind speed recorded at the site is approximately 11 m/s, which indicates favourable conditions for wind energy generation.

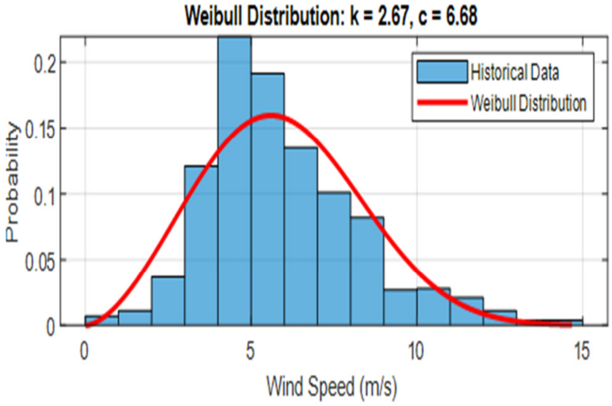

Fig. 1. Weibull distribution of Sidrap site.

TABLE I. SPECIFICATIONS AND QUANTITY OF OPERATED WIND TURBINES

No. of turbines	Wind turbine operating limits				Rated power, (MW)	Weibull PDF parameters
	Cut in (m/s)	Rated (m/s)	Cut out (m/s)	*P* rated (MW)		
30	3	11	25	2.5	75	c = 6.7 k = 2.7

G. *Wind Cost Function*

Using the proposed equation and the Weibull distribution data for the Sidrap site, the cost versus wind speed graph, presented in Figure 2, is derived. Figure 2 is obtained from:

$$\mathrm{LCOE} = \frac{(1+r)^{-i} \cdot \mathrm{CAPEX} \cdot P_{wr} + \mathrm{OPEX} \cdot P_{wr}}{\left(8760 \int_0^{v max} P_w \, f_v(v)\, dv\right) \cdot P_{wr}} \qquad (30)$$

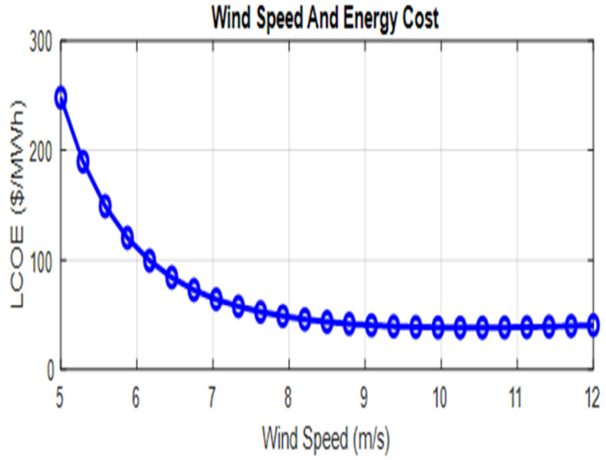

Fig. 2. LCOE and wind speed graph.

Based on the updated AEP formula, a revised graph is obtained. To determine the wind cost function, the equation of the curve is derived, which facilitates the cost calculation during the optimization process. Through multiple exponential regression, the wind cost function is obtained by:

$$Cost\ Wind = P_w * (2.132 * 10^5\, e^{-1.42\, v} + 116.8\, e^{-0.1067\, v}) \qquad (31)$$

In (31), the wind cost function is obtained using a multiple exponential regression approach based on the data presented in Figure 2. Installing renewable energy systems can lead to financial benefits, such as cost reductions from carbon tax incentives. Taking this into account, the wind cost function that includes the carbon tax variable is given by:

$$Cost\ Wind = P_w * (2.132 * 10^5 * e^{-1.42\, v} + 116.8\, e^{-0.1067\, v}) - (P_w * C_{CT}) \qquad (32)$$

Equation (31) was first derived, followed by a validation process using MATLAB software. The results are illustrated in Figure 3, which presents a comparison between the graph generated from the data (shown as blue dots) and the curve corresponding to the analytical approximation given by (32) (represented by the red line).

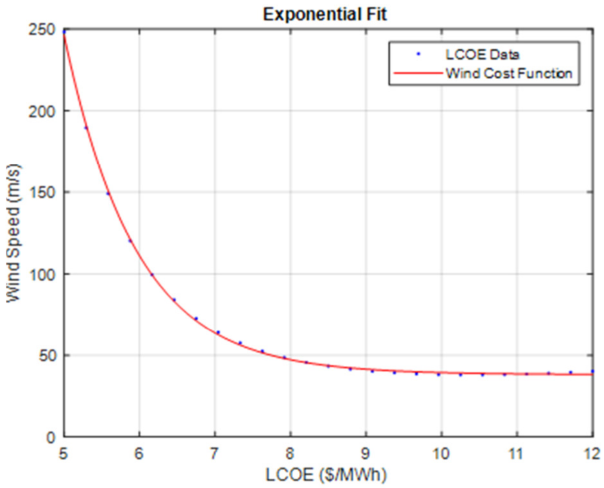

Fig. 3. Regression testing comparison graph.

IV. SIMULATION PARAMETER

The study was carried out in MATLAB using a modified IEEE 30-bus test system, where wind power was integrated at bus 30. The network includes 30 buses and seven generators—six thermal units located at buses 1, 2, 13, 22, 23, and 27, and one wind generator connected at bus 30. A 24-hour dynamic simulation was conducted, considering the fluctuations in both load demand and wind speed throughout the day. The main goal was to optimize power flow while keeping the system's operating cost as low as possible. Details of the simulation setup and parameters are provided in Tables II and V.

TABLE II. COST FUNCTIONS AND GENERATOR RATINGS

Bus No.	Unit	Fuel cost function			*Pmax* (MW)	*Pmin* (MW)	Ramp up and down (MW)
		a ($)	*b* ($/MWh)	*c* ($/MWh)			
1	1	0	2	0.00375	80	32	±16
2	2	0	1.75	0.0175	80	32	±16
13	3	0	1	0.0625	50	20	±10
22	4	0	3.25	0.00834	55	22	±11
23	5	0	3	0.025	30	12	±6
27	6	0	3	0.025	40	16	±8
30	7	(31)			75	0	±30

TABLE III. DAILY LOAD AND WIND SPEED VARIATION

Hours (a.m)	Load (MW)	*V* wind (m/s)	Hours (p.m)	Load (MW)	*V* wind (m/s)
1	189	9.3	1	204	11.4
2	184	10.1	2	206	11.7
3	173	10.9	3	202	11.8
4	170	9.7	4	200	11.1
5	173	8.9	5	205	10.9
6	183	8.7	6	216	9.8
7	168	8.5	7	235	9.4
8	171	7.9	8	261	9.3
9	183	7.3	9	247	9.7
10	199	7	10	235	8.7
11	201	8.9	11	212	10
12	203	10.4	12	196	10.1

TABLE IV. EXPERIMENT COST

	Experiment 1	**Experiment 2**
LCOE ($/MW)	56	Cost Function**
Tax Carbon ($/MW)	0 s.d 50 (step size 10)	

TABLE V. LCOE AND WOA PARAMETER

LCOE parameters		**WOA parameters**	
Parameter	**Value**	**Description**	**Value**
CAPEX ($/MW)	1.5×10^6	**Max Iterasi**	25
OPEX ($/MW/Years)	3×10^4	**Population size**	250
Discount Rate (*r*)	0.06	**Convernance factor (A)**	2 to 0
Lifetime (*n*)	25	**Coefficient (C)**	rand 0 up to 2

The flat LCOE is calculated using (27), while the dynamic LCOE is derived from (30).

V. RESULTS AND DISCUSSION

A. Fixed Cost Approach in Wind Power Generation

In the first scenario, the analysis was conducted using a static LCOE approach (27), where the cost of energy production from wind turbines was assumed to be constant and unaffected by fluctuations in wind speed at a specific location. The optimized system consisted of six thermal power plants and one wind power plant, with the objective of minimizing the total generation cost.

The optimization results indicate that, in all five test scenarios, the wind power plant did not contribute to the system's energy supply. This was primarily due to the relatively high LCOE of wind turbines under these conditions, which made wind power a less economical choice. In other words, wind energy was more expensive than the available thermal generation options, leading the optimization process to exclude it from the final dispatch solution. The first part of Table VI presents the results of five tests conducted without incorporating a carbon tax. These results indicate that relying on a fixed-cost approach for LCOE calculations may limit the integration of wind power into the system, particularly when its LCOE remains comparatively high. To address this limitation, a more dynamic representation of LCOE is required one that captures the inherent variability of wind resources and supports their more effective utilization within power systems.

TABLE VI. EXPERIMENT 1 LCOE FLAT MODE

Optimization costs without carbon tax						
Trial No.	**Thermal generation**		**Wind generation**		**Total**	
	Power (MW)	**Cost ($)**	**Power (MW)**	**Cost ($)**	**Power (MW)**	**Cost ($/day)**
1	4908.1	13345.8	0	0	4908.1	13355.8
2	4904.5	13684.2	0	0	4904.5	13684.2
3	4908.2	13308.4	0	0	4908.2	13358.4
4	4903.7	13366.1	0	0	4903.7	13366.1
5	4904.6	13330.6	0	0	4904.6	13350.6
Optimization costs with carbon tax 50 $/MW						
Trial No.	**Thermal generation**		**Wind generation**		**Total**	
	Power (MW)	**Cost ($)**	**Power (MW)**	**Cost ($)**	**Power (MW)**	**Cost ($/day)**
1	4895.9	13262.1	10.2	60.9	4906.1	13323.0
2	4894.6	13280.1	10.2	61.0	4904.6	13341.1
3	4885.1	13223.3	20.7	124.0	4905.7	13347.2
4	4897.3	13275.7	8.0	47.8	4905.2	13323.5
5	4897.1	13264.9	8.4	50.9	4905.5	13315.4

In the second part of Table VI, the total optimized generation cost is presented, which is lower than in the previous experimental scenarios. This cost reduction is mainly due to the inclusion of the carbon tax in the optimization process. The carbon tax acts as an incentive for increased wind power generation, as it encourages the shift toward cleaner energy sources and contributes to the reduction of carbon emissions.

In this experiment, carbon tax values were applied, that is $50 per unit of energy produced by wind power. Although the cost differences with and without a carbon tax were relatively small, they were enough to show that carbon taxes can lower overall generation costs, especially for wind power. Furthermore, the application of a carbon tax encourages the integration of wind energy into the system by making it more economically viable compared to fossil fuel-based generation.

B. Cost Approach in Wind Power Generation βased on Wind Speed Weibull Distribution

In the second scenario, the generation cost is calculated using a dynamic LCOE model (30), where the wind energy cost depends on wind speed variability modeled via the Weibull distribution. This provides a more accurate cost representation based on site-specific conditions. As in the first experiment, five optimization runs were conducted under two cases: with and without a carbon tax. The first part of Table VII shows that without a carbon tax, wind power remains uncompetitive and is not utilized. In contrast, the second part shows that with a $50/MWh carbon tax, wind power is actively integrated in all runs, generating 750-950 MWh per day, up to 50% of the total capacity, highlighting the role of carbon pricing in promoting renewable energy.

This maximum contribution is primarily driven by the carbon tax, making wind power more cost competitive. A negative wind power cost is also demonstrated, indicating that producers receive incentives for reducing carbon emissions. The incentive depends on wind power generation and the carbon tax rate per megawatt, enhancing wind power's competitiveness. Additionally, integrating the carbon tax with a Weibull-based wind power cost function further strengthens wind power's role in the energy system.

TABLE VII. EXPERIMENT 2 DYNAMIC LCOE BASED ON WEIBULL DISTRIBUTION

Trial No.	Thermal generation		Wind generation		Total	
Optimization costs without carbon tax						
	Power (MW)	**Cost ($)**	**Power (MW)**	**Cost ($)**	**Power (MW)**	**Cost ($/day)**
1	4906.8	13318.9	0	0	4906.8	13318.9
2	4908.3	13301.0	0	0	4908.3	13301.0
3	4908.1	13345.8	0	0	4908.1	13345.8
4	4904.6	13330.6	0	0	4904.6	13330.6
5	4910.8	13329.5	0	0	4910.8	13329.5
Optimization costs with carbon tax 50 $/MW						
Trial No.	**Thermal Generation**		**Wind Generation**		**Total**	
	Power (MW)	**Cost ($)**	**Power (MW)**	**Cost ($)**	**Power (MW)**	**Cost ($/day)**
1	4008.7	10696.2	947.6	-8079.5	4956.3	2616.6
2	4186.2	11080.8	761.1	-6523.9	4947.3	4556.9
3	4159.8	11013.6	790.7	-6710.6	4950.4	4303.0
4	4046.3	10744.0	909.8	-8162.4	4956.1	2581.5
5	3995.3	10612.1	961.0	-8012.6	4956.3	2599.5

C. *Impact of Carbon Tax on Wind Power Generation Cost Function*

Experiments 1 and 2 demonstrate that without a carbon tax, whether using a flat LCOE model or a Weibull-based dynamic LCOE, wind power does not contribute to system optimization, confirming its relatively high cost compared to other energy sources. However, with a $50/MW carbon tax, wind generation significantly contributes, with the Weibull-based LCOE model outperforming the flat LCOE model.

Figure 4 portrays the relationship between generation cost and wind speed under a carbon tax. The blue line represents the flat LCOE scheme under tax rates from $0/MW to $50/MW, where the lowest wind generation cost at $50/MW tax is $6/MW—still uncompetitive against thermal generation at $3–$4/MW. In contrast, the red line, representing the Weibull-based LCOE scheme, shows a more competitive wind pricing structure. At $40/MW–$50/MW tax rates, wind producers receive incentives for carbon reduction, accelerating ROI and boosting wind power's market attractiveness.

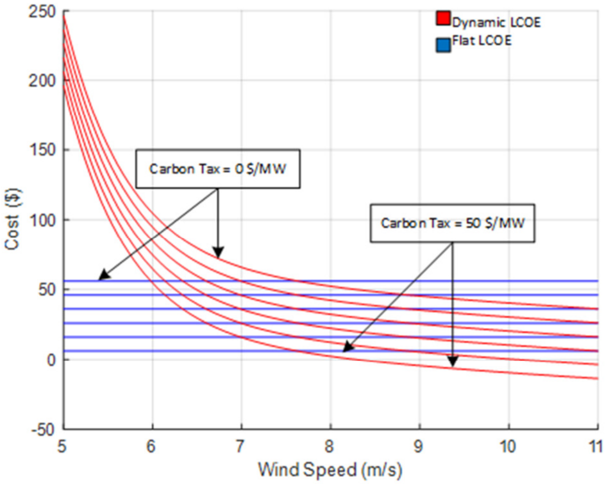

Fig. 4. Impact of variation carbon tax on wind power cost.

VI. DISCUSSION

The simulation results underscore the importance of incorporating both stochastic wind modeling and carbon pricing into the DOPF framework. In the first scenario, the use of static LCOE values led to the exclusion of wind power from the optimal dispatch due to its relatively high estimated cost. This outcome confirms a key limitation of conventional deterministic approaches, as previously noted in [12, 13].

In contrast, the second scenario employs a dynamic LCOE model based on the Weibull distribution, offering a more accurate and context-sensitive representation of wind energy costs. Despite this improvement, wind power remained economically unviable in the absence of a carbon pricing mechanism. These finding highlights that even advanced modeling techniques may not be sufficient to increase renewable energy adoption without supportive policy instruments.

The introduction of a carbon tax of $50/MWh significantly altered the system's economic landscape, rendering wind energy highly competitive. Under this scenario, wind power contributed up to 950 MWh per day, accounting for nearly 50% of the total energy demand. These results are consistent with previous findings in [13], which emphasize the critical role of carbon pricing in promoting renewable energy integration.

Compared to previous studies, such as [8, 10], which explore renewable integration through OPF without incorporating stochastic cost modeling, the proposed approach offers a more comprehensive perspective by combining probabilistic wind behavior with economic policy considerations. Moreover, while works like [15, 16] have demonstrated the effectiveness of metaheuristic algorithms in solving DOPF problems, this study extends their application by embedding environmental and economic components into the optimization process.

In summary, the findings validate the effectiveness of jointly applying Weibull-based LCOE estimation and carbon tax mechanisms in renewable-oriented power system optimization. This integrated strategy enables more accurate cost modeling while supporting the transition to cleaner energy within a policy- and market-driven context.

VII. CONCLUSION

This study proposed a DOPF model that incorporates a probabilistic wind energy cost function based on the Weibull distribution, along with the integration of carbon tax into the economic dispatch process. The model was applied to a modified IEEE 30-bus system and optimized using the IWOA, allowing for a more realistic and flexible representation of wind power in system operation.

The results demonstrate that using the Weibull distribution provides a more dynamic and accurate estimation of wind energy costs by capturing the natural variability of wind speed over time. This approach outperforms traditional flat LCOE models, enhancing the quality of decision-making in power system planning and resource allocation. Moreover, the integration of carbon pricing significantly improves the economic viability of wind energy. At carbon tax rates between

$40 and $50 MW/hr, wind power becomes not only competitive with conventional generation, but also capable of supplying up to half of the system's daily energy demand.

Additionally, under typical investment conditions, such as $1.5 million for a 2.5 MW wind turbine, a carbon tax of at least $40/MWh is shown to be a critical threshold for making wind energy financially competitive with fossil-based alternatives. These findings reinforce the importance of combining accurate stochastic modeling with supportive policy mechanisms to accelerate the transition toward sustainable energy systems.

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NOMENCLATURE

$f_v(v)$	Probability Distribution Function (PDF)
$F(v)$	Cumulative Distribution Function (CDF)
v	Current wind speed
c	Scale parameter in m/s
k	Dimension less shape parameter
P_w	Wind power output
P_{rated}	Rated wind power
v_r	Rated wind speed
v_{ci}	Cut-in wind speed
v_{co}	Cut-out wind speed
P_v	Probability of wind power
$f_v(v)$	Probability density function of wind speed
dv	Differential element of wind speed
F_G	Total generation cost to be minimized
N_G	Number of conventional thermal generators
C_G:	Cost function of the *i*-th conventional generator
P_{Gi}	Active power output of the *i*-th conventional generator

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