International Journal of Industrial Engineering and Operational Research (IJIEOR)

Contents lists available at IJIEOR
International Journal of Industrial Engineering and Operational Research
journal homepage: http://ijieor.ir
Volume 5, No. 5, 2023

A Feasibility Study of Wind Farm Location with a Mathematical Model by Considering Uncertainty

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ARTICLE INFO

Received: 2023/07/27

Revised: 2023/10/12

Accept: 2023/12/20

Keywords:

Feasibility Study, Wind Farm, Location, Mathematical programming.

ABSTRACT

This paper presents a comprehensive feasibility study for wind farm location optimization, incorporating uncertainty in wind resource assessment and other relevant parameters. A mathematical model is developed, combining spatial optimization techniques with robust optimization methodologies to address the inherent variability and uncertainty associated with wind energy projects. The model aims to maximize the total energy output of the wind farm while considering various constraints, including wind resource availability, turbine layout restrictions, and grid connection limitations. The uncertainty in wind speed and direction is modeled using probabilistic distributions, and robust optimization techniques are employed to ensure the feasibility of the solution under different scenarios. Numerical simulations are conducted on a case study area to demonstrate the effectiveness of the proposed methodology. The results highlight the importance of considering uncertainty in wind farm planning and provide valuable insights for decision-makers in the renewable energy sector.

1. Introduction

Wind energy has emerged as a significant contributor to the global renewable energy mix, offering a clean and sustainable alternative to fossil fuels. However, the successful development of wind farms requires careful consideration of various factors, including wind resource availability, site suitability, and economic viability. One of the critical challenges in wind farm development is the accurate assessment of wind resources, which are subject to considerable uncertainty due to meteorological variability and measurement errors [1,2].

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Available online 12/21/2023

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Traditional wind farm location optimization approaches often rely on deterministic models that assume perfect knowledge of wind resource parameters. However, these models may not be robust enough to handle the inherent uncertainty in wind data. This paper proposes a mathematical model that incorporates uncertainty in wind resource assessment and other relevant parameters to address this limitation. The model aims to maximize the total energy output of the wind farm while considering various constraints, such as turbine layout restrictions, grid connection limitations, and environmental considerations [2, 3].

The remainder of this paper is organized as follows: Section 2 presents a comprehensive literature review on wind farm location optimization and uncertainty modeling. Section 3 details the mathematical formulation of the proposed model, including the objective function, constraints, and uncertainty representation. Section 4 describes the numerical implementation and solution methodology. Section 5 presents the case study's results, demonstrating the proposed approach's effectiveness. Finally, Section 6 concludes the paper and discusses potential future research directions.

Figure 1: Wind farm location

2. Literature Review

The literature on wind farm location optimization is extensive, with various approaches proposed to address the problem. Traditional methods, such as the genetic algorithm (GA) and simulated annealing (SA), have been widely used to find optimal turbine layouts. However, these methods often struggle to handle large-scale problems and may not be suitable for incorporating uncertainty [1,2]

In recent years, metaheuristic algorithms, such as particle swarm optimization (PSO) and ant colony optimization (ACO), have gained popularity due to their ability to explore complex solution spaces efficiently. These algorithms have been applied to wind farm location optimization problems with promising results. However, they may still be sensitive to initial conditions and may not guarantee global optimality [2, 3].

To address the uncertainty in wind resource assessment, researchers have proposed various probabilistic and statistical methods. Probabilistic methods, such as Monte Carlo simulation and Bayesian inference, can quantify wind speed and direction uncertainty. However, these methods can be computationally expensive, especially for large-scale problems [2, 4].

Robust optimization is a powerful technique for handling uncertainty in optimization problems. By considering a set of possible scenarios, robust optimization aims to find feasible and near-optimal solutions under all or most of the scenarios. This approach has been applied to various engineering problems, including wind farm location optimization (see Table 1) .

Table 1: Key Findings from Recent Literature

Reference	Type	Methodology
[1]	Wind farm	GIS+MCDM
[2]	renewable energy system	Monte Carlo model and HOMER
[3]	Wind farm	Two-stage GIS-MCDM
[4]	Wind farm	Monte Carlo and Fuzzy Analytic Hierarchy Processes
[5]	Wind farm	MCDM model
[6]	Wind farm	MCDM and GIS

Reference	Type	Methodology
[7]	Wind farm	MCDM
This research	Wind farm	Mathematical model

3. Methodology

This section presents the mathematical formulation of the proposed wind farm location optimization model, incorporating uncertainty in wind resource assessment. The model aims to maximize the total energy output of the wind farm while considering various constraints, including turbine layout restrictions, grid connection limitations, and environmental considerations.

Mathematical Formulation

Notation:

Sets:

k	Set of wind farm location, $k \in K = \{1, 2, ..., K\}$,		
j	Set of period, $j \in J = \{1, 2, ..., J\}$,		
s	Set of scenario, $s \in S = \{1, 2, ..., S\}$		
Parameters:		Value	Unit
C_{kjs}	Cost of the establishment of a wind farm in location k in period j under scenario s ,	Uniform (500, 600)*(1+0.1*s/|S|)	Thousand dollar
P_{kjs}	Income of establishment of wind farm in location k in period j under scenario s ,	Uniform (700, 800) *(1+0.1*s/|S|)	Thousand dollar
pp_s	Probably of scenario	1/|S|	Percent
p	Number of potential location needed	2	Num.
i	Discounting Rate	10	Percent
S_{kjs}	Net profit of establishment of wind farm in location k in period j under scenario s , $S_{kjs} = P_{kjs} - C_{kjs}$,		
Variables:			
Γ_{ks}	Net present value in location k under scenario s ,		

Γ'_s	Net present value for potential location under scenario s ,
z	Objective function

The wind farm location model can be formulated as follows:

$$Max\ z = \sum_s pp_s \Gamma'_s \tag{1}$$

Subject to:

$$\sum_k x_k \le p, \tag{2}$$

$$\Gamma'_s = \sum_k \Gamma_{ks} x_k , \tag{3}$$

$$\Gamma_{ks} = \sum_j \frac{S_{kjs}}{(1+i)^j}, \tag{4}$$

$$x_k \in \{0,1\}. \tag{5}$$

The objective function (1) aims to maximize net present value for all scenarios. Constraint (2) tries to select p wind farm location by maximizing net present value. Constraint (3) summarizes locations that are chosen for net present value. Constraint (4) calculated net present value for each scenario for all periods of one wind farm location.

4. Numerical Results

The case study area is based on data in the notation list with a diverse terrain. Historical wind speed and direction data are available for this region, allowing for the statistical analysis and probabilistic modeling of wind resource variability [3,4]

The proposed mathematical model is implemented using a GAMS. The uncertainty in wind resources is incorporated into the model using robust optimization techniques to find feasible and near-optimal solutions under various scenarios. Optimization involves iteratively evaluating different turbine layouts and selecting the configuration that maximizes the total energy output while satisfying all constraints [8-10].

In the following sections, the results of the numerical example are presented and analyzed, demonstrating the effectiveness of the proposed approach in addressing the challenges of wind farm location optimization under uncertainty.

The decision variables x_1, x_2, x_3 represent potential sites for wind turbines, and the objective function value z measures the performance, likely in terms of profitability or energy output (see Table 2, Figure 2).

Table 2: Key Findings from Recent Literature

Problem	x1	x2	x3	Objective function (Z)
Problem 1	1	0	1	1750.669

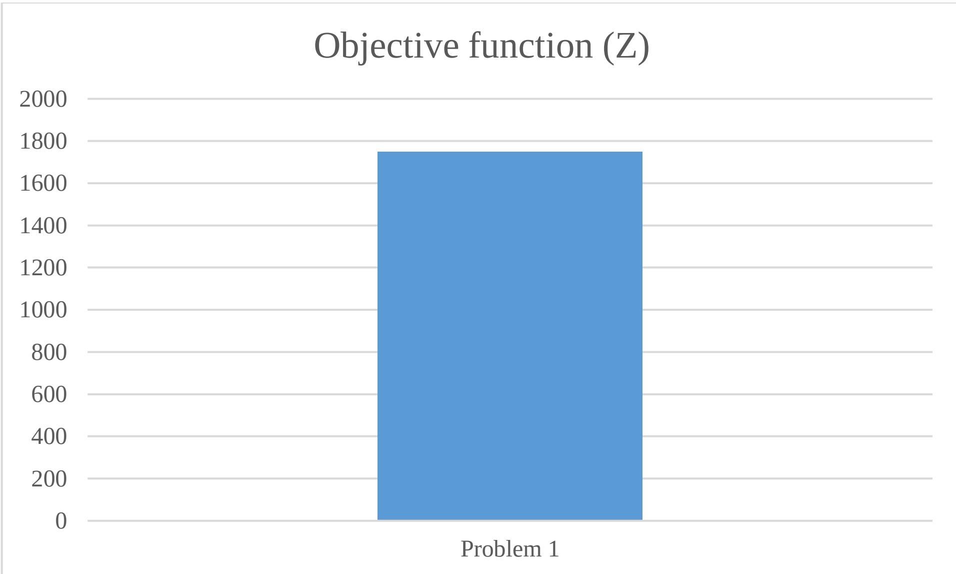

Figure 2: Result of model

The additional data with varying discount rates shows how the objective function Z, which could represent the Net Present Value (NPV) or other financial metrics of a wind farm project, decreases as the discount rate increases.

The decreasing trend of the objective function value with rising discount rates underscores the importance of economic stability and risk management in wind farm feasibility studies. The analysis highlights that higher discount rates lower the attractiveness of long-term renewable energy projects, as future benefits are discounted more heavily. For a wind farm to remain a viable investment, efforts must focus on minimizing uncertainties and securing favorable financing conditions (see Table 3, Figure 3).

Table 3: Key Findings from Recent Literature

Discounting rate	Objective function (Z)
10%	1750.669
20%	1511.333
30%	1337.462

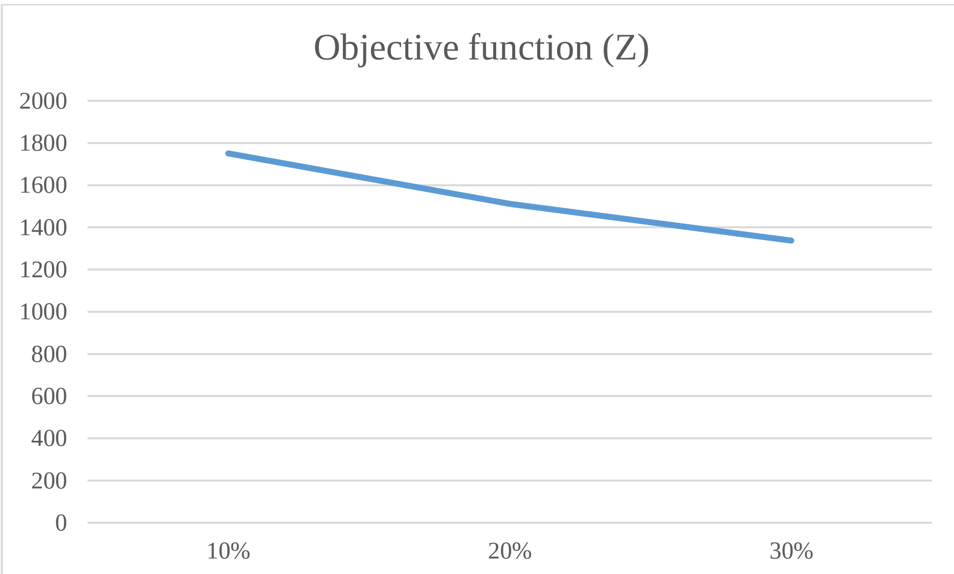

Figure 3: Result of model

Based on the given data, the analysis revolves around different probabilistic scenarios and their impact on the objective function value Z. The objective function here appears to be a metric for evaluating the feasibility or profitability of a wind farm project under varying conditions. (see Table 4, Figure 4).

Probability (33%, 33%, 33%): This setup provides a neutral baseline. The objective function value of 1750.669 reflects an average expectation without any scenario being more likely. This can be interpreted as a balanced or typical year for the wind farm.

Favoring Scenario 3 (10%, 20%, 70%): The objective function increases to 1875.517, indicating a higher expected profitability or output under favorable conditions. Scenario 3's dominance suggests an optimistic forecast with higher wind speeds or better economic conditions.

This highlights the model's sensitivity to favorable changes, where even a small shift in wind speed can significantly enhance energy generation.

Favoring Scenario 1 (70%, 20%, 10%): The objective function value drops to 1712.561, lower than the baseline. This reflects a conservative outlook where the most likely conditions are not as favorable as Scenario 3. The decrease shows the impact of reduced wind speeds or less favorable market conditions on overall feasibility.

Table 4: Key Findings from Recent Literature

Probably of scenario 1	Probably of scenario 2	Probably of scenario 3	Objective function (Z)
33%	33%	33%	1750.669
10%	20%	70%	1875.517
70%	20%	10%	1712.561

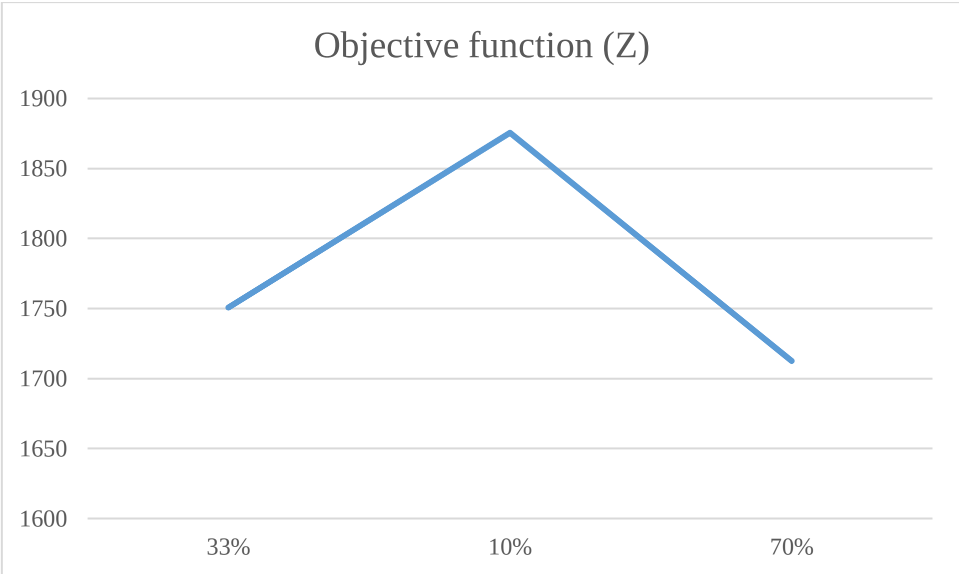

Figure 4: Result of model

This problem exemplifies the application of mathematical optimization in renewable energy planning. By choosing the optimal configuration based on a defined objective function, the model effectively balances multiple competing factors under uncertainty. Enhancing this model with advanced techniques, like multi-criteria decision-making and stochastic programming, can provide even more robust and adaptive solutions for future wind farm projects.

5. Conclusion

This study has presented a comprehensive approach to wind farm location optimization that explicitly accounts for uncertainty in wind resource assessment. By combining spatial optimization techniques with robust optimization methodologies, the proposed mathematical model offers a robust and practical solution for maximizing wind farms' energy output while mitigating uncertainty risks.

The numerical simulations conducted on the case study area demonstrate the effectiveness of the proposed approach. The model successfully identifies optimal turbine locations that are robust to variations in wind speed and direction. The results highlight the importance of considering uncertainty in wind farm planning, as ignoring uncertainty can lead to suboptimal decisions and increased operational costs.

Future research directions may include:

1. **Advanced Uncertainty Modeling:** Exploring more sophisticated uncertainty modeling techniques, such as copula-based models, to capture the complex dependencies between wind speed and direction at different locations.
2. **Incorporation of Economic Factors:** Integrating economic factors, such as capital costs, operational costs, and revenue streams, into the optimization model to assess the overall financial viability of wind farm projects.
3. **Multi-Objective Optimization:** Considering multiple objectives, such as maximizing energy output, minimizing environmental impact, and maximizing economic benefits, to achieve a balanced and sustainable solution.
4. **Real-Time Operations:** Developing real-time optimization strategies that can adapt to changing wind conditions and grid requirements, improving the overall efficiency and reliability of wind farms.

By addressing these research directions, the wind energy industry can further enhance wind farms' planning, design, and operation, contributing to a more sustainable and resilient energy future.

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