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OPTIMIZATION-BASED TECHNO-ECONOMIC ASSESSMENT OF ONSHORE WIND TURBINES UNDER UNCERTAINTY IN SLOVENIA

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DAVID TIAN HREN, ZORKA NOVAK PINTARIČ,
ANDREJA NEMET

University of Maribor, Faculty of Chemistry and Chemical Engineering, Maribor,
Slovenia
david.hren@um.si, zorka.novak@um.si, andreja.nemet@um.si

CORRESPONDING AUTHOR
david.hren@um.si

Abstract Renewable energy systems require site-appropriate technology selection to ensure both high energy production and economic viability. This study developed a general optimization-based techno-economic framework for assessing onshore wind turbine configurations, and applied it to nine representative locations in Slovenia, optimizing hub height, rotor diameter, and rated power using annual energy production, net present value (NPV), levelized cost of energy (LCOE), and a weighted combined objective. The selected configurations were evaluated through deterministic sensitivity analysis and Monte Carlo simulation, to assess the uncertainty in the wind resource, technical, and economic parameters. Maximizing energy production alone produced oversized and economically inefficient configurations, whereas optimization based on the economic objectives (NPV and LCOE) yielded smaller turbines, and the combined-objective formulation provided a more balanced trade-off. Wind resource quality, electricity price, capital expenditure, and discount rate were the principal determinants of profitability, while favorable deterministic outcomes did not always remain economically robust under uncertainty.

Keywords
renewable energy,
onshore wind energy,
wind turbine
optimization,
techno-economic
assessment,
uncertainty analysis

1 Introduction

Renewable energy technologies have evolved from niche alternatives to central components of modern power systems, driven by concerns about energy security, fuel price volatility, and long-term environmental sustainability (Anderson, 2020). Renewable sources such as solar, wind, hydro, biomass, and geothermal energy offer long-term sustainability, because they are replenished naturally and have relatively low environmental impact during operation. However, integrating these sources into existing energy systems involves not only technical challenges, but also economic viability, spatial constraints, and societal acceptance (Biluš et al., 2025). Among these technologies, wind power has emerged as one of the most mature and economically competitive options, supported by rapid technological development and large-scale deployment (Anderson, 2020). By 2050, wind power is projected to supply over 30 % of global electricity, with the potential to reduce CO₂ emissions by up to 14,871 million tons annually, equivalent to China's total emissions in 2021 (Long et al., 2023). Unlike traditional energy systems, wind turbines depend directly on the available resource, resulting in inherently variable and non-dispatchable power output. Most contemporary designs are horizontal-axis turbines with three blades, optimized for efficiency and reliability (Manwell et al., 2009). Their design and operation involve complex interactions between aerodynamic forces, structural loading, control systems, and electrical integration (Anderson, 2020).

The development and widespread adoption of wind farms as a promising source of electrical energy worldwide require an appropriate balance between aerodynamic efficiency, structural integrity, economic viability, spatial limitations, and environmental restrictions (Tahtah et al., 2023). Numerous factors must be evaluated to achieve a design that provides an appropriate trade-off between performance and cost, while considering various other constraints that make the specific design solution viable from all the relevant perspectives (Bottasso et al., 2012). Structurally, turbine design is governed by the need to provide sufficient support for the rotor–nacelle assembly, while elevating the rotor to heights with stronger and more stable wind resources. The design must account for multiple load types, including aerodynamic thrust from the rotor, wind loads acting on the tower, and gravitational loads from the structure and equipment (Alves Ribeiro et al., 2025). Increasing the size of wind turbines introduces a fundamental trade-off between energy production and structural and economic limitations. While the energy

captured by a turbine increases approximately with the square of its characteristic size due to the larger swept area, structural loads, mass, and associated stresses tend to increase with the cube, or even higher powers of scale. This results in increasingly demanding design conditions, particularly because weight-induced stresses become dominant as turbines grow larger (Sieros et al., 2012).

Performance and economic viability are influenced strongly by a combination of technical and financial parameters, with uncertainty playing a central role in project assessment. The most critical factor is the average wind speed, which has a dominant impact on energy production due to its nonlinear relationship with the power output. Turbine-related parameters such as the power curve and air density also affect performance significantly, while the wake effects play a comparatively smaller role in this context. On the economic side, parameters such as electricity price, installation cost, and discount rate determine profitability largely, with the net present value (NPV) being highly sensitive, because it captures the difference between large cash inflows and outflows (Afanasyeva et al., 2016). Wind turbine optimization therefore requires careful selection of the objective functions, since different choices can lead to fundamentally different and often suboptimal designs. Maximizing the annual energy production (AEP) alone is insufficient, because many geometrically different turbines can achieve nearly identical energy output while having significantly different structural mass, leading to inefficient designs (Ning et al., 2014). A multidisciplinary design optimization framework that incorporates both energetic and economic criteria is needed for an accurate assessment (Ashuri et al., 2016).

In Slovenia, the development of wind energy is shaped by a relatively constrained spatial and environmental context. Although the country has several areas with favorable wind conditions, especially in elevated and topographically exposed regions, Slovenia is not among the most wind-rich European countries due to its sheltered position relative to the Alps (Biluš et al., 2025). The largest wind energy potential is concentrated in selected mountainous, hilly, and karst regions, including parts of the Julian Alps, Karavanke, Kamnik–Savinja Alps, Pohorje, Kočevski Rog, Snežnik–Javorniki–Hrušica, Podgorski Kras, Slavnik, Nanos, Trnovski gozd, and Banjšice (Biluš et al., 2025; Republika Slovenija, Ministrstvo za infrastrukturo, 2015). However, many wind-suitable areas overlap with Natura 2000 sites, protected landscapes, cultural heritage zones, forests, water protection areas, or settlement-

related restrictions, which limits the practical spatial availability for wind turbine deployment substantially. The Slovenian national spatial assessment therefore defines potential wind energy areas not only according to wind resource criteria, but also according to environmental protection, legal restrictions, and distances from settlements, including the exclusion of areas less than 800 m from settlements (Republika Slovenija, Ministrstvo za infrastrukturo, 2015). Consequently, despite the existence of technically promising locations, wind energy deployment in Slovenia remains limited, and requires careful site-specific assessment of the measured wind conditions, environmental acceptability, spatial feasibility, and economic justification (Biluš et al., 2025; Republika Slovenija, Ministrstvo za infrastrukturo, 2015). Accordingly, this study aims to evaluate the technical and economic performance of onshore wind turbine configurations at selected Slovenian locations under uncertainty, and to identify the most favorable locations and turbine configurations.

The paper is organized as follows. Section 2 presents the model formulation and optimization framework, including the definition of turbine design variables and constraints, Weibull-based wind resource characterization, hub height wind speed correction, turbine power estimation, annual energy production calculation, and economic evaluation. Section 3 describes the computational workflow used for the selected Slovenian wind energy areas, including area-specific wind resource parameters, deterministic optimization, sensitivity analysis, and a Monte Carlo uncertainty analysis. Section 4 presents the results of the deterministic optimization, sensitivity analysis, and uncertainty assessment, comparing the selected areas and turbine configurations in terms of energy production, economic performance, financial risk, and robustness under uncertain input parameters. Section 5 discusses the main findings and study limitations, while Section 6 summarizes the conclusions, identifies the most favorable locations and turbine configurations, and outlines directions for future work.

2 Model Formulation and Optimization Framework

This section presents the mathematical model used for the techno-economic assessment of wind turbine configurations. The model combines wind speed distribution modeling, hub height correction, turbine power estimation, annual energy production calculation, and economic evaluation.

2.1 Design Variables and Constraints

The wind turbine design is defined by three continuous variables: hub height, rotor diameter, and rated power. These variables determine the overall size of the turbine and affect the available wind resource, swept rotor area, maximum electrical output, investment cost, and economic performance directly. The limits of the design variables were selected based on the specifications of the existing commercial onshore wind turbines. Specifications from five major manufacturers were reviewed using their respective product documentation (ENERCON, 2026; GE Vernova, 2026; Nordex Group, 2026; Siemens Gamesa Renewable Energy, 2026; Vestas, 2026). The rated powers of the reviewed turbines range from approximately 2.4–7.2 MW. The reviewed commercial turbines also indicate typical rotor diameters of approximately 75–175 m and hub heights of approximately 75–175 m; these ranges were therefore used as the corresponding bounds for the design variables.

An additional ground clearance constraint was included to ensure physically feasible turbine geometries. The minimum distance between the lowest blade tip position and the ground was set to 20 m, preventing unrealistic combinations of low hub height and large rotor diameter. This constraint was calculated as the difference between hub height and rotor radius, so only configurations satisfying the minimum blade-tip clearance were considered feasible. Thus, the optimization design space was restricted to commercially representative and geometrically feasible onshore wind turbine configurations.

2.2 Wind Speed Characterization Using the Weibull Distribution

Wind resource characterization is necessary to estimate the expected energy production of a wind turbine at a selected location (Solari & Losada, 2016). Because wind speed is a stochastic variable, its frequency distribution must be described before the turbine output can be calculated (Loukatou et al., 2018). In this work, the wind resource is represented by a two-parameter Weibull distribution, which is used commonly for long-term wind speed modeling in renewable energy studies (Afanasyeva et al., 2016; Shi et al., 2021; Wais, 2017). The Weibull probability density function is given in Equation (1):

$$f(v) = \frac{k}{A} \left(\frac{v}{A} \right)^{k-1} \exp \left[- \left(\frac{v}{A} \right)^k \right], \quad v \geq 0 \quad (1)$$

where v is the wind speed, A is the Weibull scale parameter, and k is the Weibull shape parameter. The parameter A describes the characteristic wind speed level at the location, while k determines the form and spread of the distribution (Shi et al., 2021). Because wind resource data are usually available at a reference height, they must be adjusted to the selected turbine hub height. This adjustment is made using the power-law wind shear relation (Afanasyeva et al., 2016), shown in Equation (2),

$$A(h) = A_{\text{ref}} \left(\frac{h}{h_{\text{ref}}} \right)^a \quad (2)$$

where h is the turbine hub height, h_{ref} is the reference height, and a is the wind shear exponent. The value of a depends on the terrain roughness and atmospheric conditions, with lower values typical of open terrain and higher values typical of areas with more obstacles (Rasaq, A. K. et al., 2015). In the case study the reference height is 100 m, so A_{ref} corresponds to A_{100} . The parameter k is assumed to remain constant with the height.

The Weibull distribution is divided into discrete wind speed intervals. For each interval, the probability of occurrence is calculated and converted into annual operating hours. These hours are then combined with the turbine power output at the representative wind speed for each interval. This links the location-specific Weibull parameters with the turbine power model and the subsequent economic evaluation.

2.3 Turbine Power Model and Operational Constraints

After the wind speed distribution is adjusted to the hub height, the turbine power output is calculated for each wind speed interval. The model uses a system-level power formulation based on rotor diameter, rated power, power coefficient, drivetrain efficiency, and operational constraints. The aerodynamic power relation

used to estimate the power extracted from the wind passing through the rotor swept area is based on the standard wind turbine power formulation reported by (Castillo et al., 2023), as shown in Equation (3),

$$P_{\text{aero},i} = \eta C_{p,i} P_{\text{wind},i} = \eta C_{p,i} \frac{1}{2} \rho \pi R^2 v_i^3 \quad (3)$$

where $P_{\text{aero},i}$ is the turbine power obtained after accounting for the power coefficient and drivetrain efficiency in the wind speed interval i , $P_{\text{wind},i}$ is the power available in the wind passing through the rotor swept area, v_i is the representative wind speed of interval i , ρ is the air density, R is the rotor radius, $C_{p,i}$ is the power coefficient, and η is the drivetrain efficiency. In the implemented optimization model, this aerodynamic power term is not taken directly as the final turbine output, but is constrained further by the rated power, cut-in and cut-out wind speeds, maximum blade-tip speed, and rated-torque limitations.

The power coefficient $C_{p,i}$ represents the fraction of available wind power extracted by the turbine and is limited by the Betz limit (Bavanish & Thyagarajan, 2013). In the implemented model, $C_{p,i}$ is expressed as a polynomial function of the tip-speed ratio λ_i (González et al., 2010), as shown in Equation (4).

$$C_{p,i} = 0.0344 - 0.0864\lambda_i + 0.1168\lambda_i^2 - 0.0484\lambda_i^3 + 0.00832\lambda_i^4 - 0.00048\lambda_i^5 \quad (4)$$

The maximum value of this function is $C_{p,\text{max}}=0.4764$, which occurs at a tip-speed ratio of approximately 7.33 (González et al., 2010). In the implemented model, the actual value of λ_i is determined from the operating rotor speed, which is limited by the maximum allowable blade-tip speed. Therefore, the turbine is not assumed to operate at the optimal tip-speed ratio under all wind speed conditions. Equation (5) describes the final constrained turbine power output used for the AEP calculation,

$$P_i = \begin{cases} 0, & v_i < v_{\text{ci}} \\ \min(P_{\text{aero},i}, P_r, T_r \omega_i), & v_{\text{ci}} \leq v_i \leq v_{\text{co}} \\ 0, & v_{\text{co}} < v_i \end{cases} \quad (5)$$

where P_i is the final turbine power in the wind speed interval i , P_r is the rated power, T_r is the rated torque, ω_i is the operating rotor speed, v_{ci} and v_{co} are the cut-in and cut-out wind speeds, respectively. In the implemented model, the cut-in speed is 3 m/s and the cut-out speed is 25 m/s. The rotor operation is constrained further by a maximum blade-tip speed of 80 m/s, which prevents unrealistic rotor speeds and reflects the practical operational limitations (Resor et al., 2014). The final power model therefore represents a constrained operational power curve rather than a simple rated-power-limited curve.

2.4 Economic Model

After calculating the AEP, the technical model is integrated with the economic model. The economic model estimates the capital expenditure (CAPEX), annual operating expenditure (OPEX), revenue from electricity sales, and the main economic indicators used to compare different turbine configurations. The capital expenditure is estimated using a component-based cost approach, following the National Renewable Energy Laboratory (NREL) wind turbine cost and scaling model (Fingersh et al., 2006), in which the main turbine and balance-of-system costs are related to the turbine size, rotor diameter, hub height, and rated power. Because the original cost equations are based on older cost data, escalation factors are applied using the producer price index data (Federal Reserve Bank of St. Louis, 2026). In the implemented model, this approach is used to estimate the total capital expenditure for each candidate turbine configuration, while the annual cash flows are evaluated using the electricity revenue, operation and maintenance costs, land lease costs, depreciation, profit tax, and discounted project cash flow. The annual revenue R from electricity sales is calculated using Equation (6),

$$R = p_{el} \cdot AEP \quad (6)$$

where p_{el} is the electricity selling price. The annual operating expenditure includes both operation and maintenance costs and land lease costs. The total annual operating expenditure C_{OPEX} is calculated using Equation (7),

$$C_{OPEX} = (c_{OM} + c_{lease}) \cdot AEP \quad (7)$$

where c_{OM} and c_{lease} are the specific operation and maintenance and land lease costs. The annual after-tax cash flow is calculated by accounting for the operating income, straight-line depreciation, taxable income, and profit tax. The depreciation is calculated over the project lifetime, and is used only for the tax calculation. Negative taxable income is not taxed. The annual after-tax cash flow CF is calculated using Equation (8),

$$CF = R - C_{OPEX} - \tau \cdot \max\left(R - C_{OPEX} - \frac{C_{CAPEX}}{N}, 0\right) \quad (8)$$

where τ is the profit tax rate, N is the project lifetime and C_{CAPEX} is the total capital expenditure. NPV is used to evaluate the lifetime profitability of each turbine configuration, by discounting the uniform annual after-tax cash flow over the project lifetime. It is calculated using Equation (9), where r is the discount rate.

$$NPV = -C_{CAPEX} + CF \cdot \frac{1 - (1 + r)^{-N}}{r} \quad (9)$$

This formulation assumes uniform annual cash flows occurring at the end of each year. The levelized cost of energy (LCOE) is calculated by annualizing the capital expenditure using the capital recovery factor, and adding the annual operating expenditure. It is given by Equation (10).

$$LCOE = \frac{C_{CAPEX} \cdot \frac{r}{1 - (1 + r)^{-N}} + C_{OPEX}}{AEP} \quad (10)$$

3 Model Implementation and Case Study Setup

This section defines the case study setup and computational implementation used to apply the previously described model to selected Slovenian wind energy areas.

3.1 Selected Slovenian Wind Areas and Input Data

Figure 1 shows the selected Slovenian study areas used in the case study, and indicates the wind speed zones above 5.5 m/s and above 7 m/s at 100 m above ground level.

Table 1: Wind resource input parameters for the selected Slovenian study areas

Area	A_{100} [m/s]	k [-]	α [-]
1	7.50	1.89	0.116
2	7.47	1.24	0.128
3	6.42	1.30	0.231
4	8.14	1.62	0.145
5	6.38	1.50	0.230
6	5.46	1.81	0.0566
7	6.65	1.52	0.158
8	7.41	1.50	0.0760
9	7.17	1.41	0.100

3.2 Optimization Module

The optimization was implemented in General Algebraic Modeling System (GAMS) as a nonlinear programming problem. The hub height, rotor diameter, and rated power were treated as continuous design variables within the admissible bounds, and subject to the geometric and operational constraints described in Section 2. The technical and economic equations were formulated directly in GAMS, linking the design variables and wind-resource parameters to the turbine power, AEP, CAPEX, OPEX, NPV, and LCOE. The resulting nonlinear programming problems were solved in GAMS using the CONOPT solver. The same mathematical model was applied to all nine study areas. MATLAB passed the area-specific parameters A_{100} , k , and a to GAMS, where an optimization run was performed for each area. Four optimization problems were considered: maximization of AEP (maxAEP), maximization of NPV (maxNPV), minimization of LCOE (minLCOE), and maximization of a weighted combined objective. Because AEP, NPV, and LCOE have different units and numerical ranges, each criterion was normalized separately for each area, using its corresponding minimum and maximum values before calculating the combined score. The LCOE criterion was inverted during normalization, so that a higher normalized value represented better performance for all three criteria. Weights of 0.15, 0.50, and 0.35 were assigned to AEP, NPV, and

LCOE, respectively, in the combined objective. The greater weight assigned to NPV reflects the emphasis placed on project profitability, while AEP and LCOE account for energy production and cost efficiency, respectively. The combined-objective configuration was obtained by maximizing the resulting weighted score, thereby providing a compromise between energy production, investment profitability, and cost of energy, rather than optimizing any individual indicator exclusively.

The optimization initially treated hub height, rotor diameter, and rated power as continuous variables. To obtain practically interpretable turbine configurations, nearby feasible rounded configurations were evaluated subsequently using the same technical and economic model. The best rounded candidate was selected separately for each optimization case, according to the corresponding objective criterion: highest AEP for maxAEP, highest NPV for maxNPV, lowest LCOE for minLCOE, and highest combined score for the combined objective. The resulting configurations were then used as the basis for the subsequent deterministic sensitivity analysis and Monte Carlo uncertainty analysis.

3.3 Deterministic Sensitivity Analysis

A deterministic sensitivity analysis was performed to evaluate the isolated influence of the selected input parameters on the main economic indicators. In this approach, one input parameter is varied, while all the other parameters remain fixed at their base values. This allows the individual effect of each parameter to be assessed without the interaction effects that occur when several uncertain inputs are varied simultaneously. The sensitivity analysis was conducted for the optimized turbine configuration obtained using the combined objective function.

The varied parameters included the Weibull scale parameter A_{100} , Weibull shape parameter k , electricity price p_{el} , discount rate r , CAPEX multiplier M_{CAPEX} , and OPEX multiplier M_{OPEX} . Each parameter was varied from -30 % to +30 % around its base value in 1 % increments. For each variation, the model recalculated the AEP, NPV, and LCOE.

This sensitivity analysis provides a deterministic assessment of parameter importance, and helps identify which assumptions have the strongest effect on project profitability and production cost. It also supports the interpretation of the

broader uncertainty assessment, by showing which individual parameters are most influential when varied independently.

3.4 Monte Carlo Uncertainty Analysis

A Monte Carlo analysis was used to assess the robustness of the optimized turbine configurations under uncertainty in the wind resource, technical, and economic parameters. Instead of evaluating each configuration only once using nominal input values, the model sampled uncertain parameters from predefined triangular distributions repeatedly, and recalculated the technical and economic performance for each scenario. The uncertain input parameters used in each Monte Carlo realization were grouped into the input vector shown in Equation (11),

$$\theta^{(m)} = \left[A_{100}^{(m)}, k^{(m)}, \alpha^{(m)}, \rho^{(m)}, p_{el}^{(m)}, r^{(m)}, M_{CAPEX}^{(m)}, M_{OPEX}^{(m)}, N^{(m)} \right] \quad (11)$$

where the superscript (m) denotes the sampled value in Monte Carlo realization m , and $\theta^{(m)}$ is the corresponding input vector. The uncertainty ranges used in the Monte Carlo analysis are summarized in Table 2. The wind resource parameters were varied relative to the nominal values for each selected area, and the technical and economic parameters were varied around the base assumptions of the deterministic model. The base electricity selling price was set to 105 €/MWh by rounding the average baseload day-ahead electricity price of 104.64 €/MWh recorded in Slovenia in 2025 (Agencija za energijo, 2026). A base discount rate of 6 % was adopted, consistent with the values applied in previous economic assessments of wind energy projects (Mijakovski et al., 2018; Mikindani et al., 2025).

Table 2: Input parameters varied in the Monte Carlo analysis

Parameter	Base value	Range in analysis	Description
A_{100} [m/s]	Area-specific	± 20 %	Weibull scale parameter
k [-]	Area-specific	± 10 %	Weibull shape parameter
α [-]	Area-specific	± 20 %	Wind shear exponent
ρ [kg/m ³]	1.225	± 5 %	Air density
p_{el} [€/MWh]	105	± 20 %	Electricity selling price
r [-]	0.06	0.04-0.08	Discount rate
M_{CAPEX} [-]	unmodified (1)	0.8-1.2	CAPEX multiplier
M_{OPEX} [-]	unmodified (1)	0.8-1.2	OPEX multiplier
N [years]	20	15-25	Project lifetime

For each sampled input vector, the optimized turbine geometry and deterministic capital expenditure obtained from the GAMS optimization were retained as the basis for evaluation, while the sampled parameters were used to recalculate the technical and economic performance. The sampled multipliers M_{CAPEX} and M_{OPEX} were applied to their corresponding deterministic values. The turbine geometry was not reoptimized during the individual Monte Carlo realizations. The resulting distributions of AEP, NPV, LCOE, and related economic indicators were summarized using deterministic values, percentile ranges, and the probability of achieving a positive NPV.

4 Case Study Results

This section presents the deterministic optimization, sensitivity analysis, and Monte Carlo uncertainty analysis for the nine selected Slovenian study areas. The deterministic results first show how the selected objective function affects the turbine sizing and techno-economic performance. A deterministic sensitivity analysis is then used to identify the wind resource and economic parameters with the greatest influence on the selected configurations. Finally, the Monte Carlo analysis evaluates their robustness when the uncertain parameters vary simultaneously.

4.1 Deterministic Optimization Results

The deterministic optimization problem was solved separately for each of the nine sets of area-specific wind-resource parameters. Four optimization problems were solved for each set of area-specific input parameters: maxAEP, maxNPV, minLCOE, and the combined objective. The combined objective was selected as the main reference, because it accounts simultaneously for energy production, profitability, and electricity generation cost. The corresponding turbine dimensions are shown in Figure 2, with the dashed lines representing the lower and upper optimization bounds.

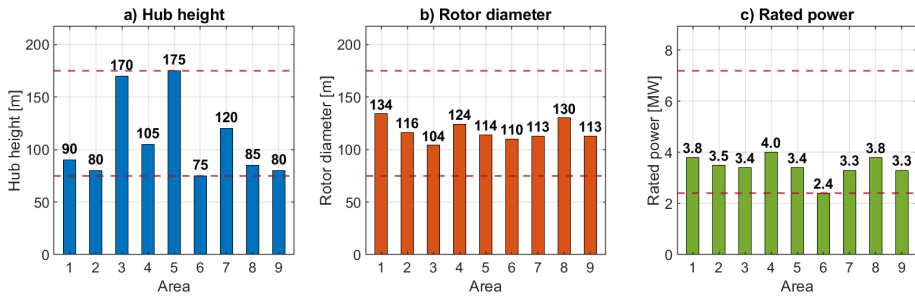


Figure 2: Rounded combined-objective turbine configurations for the nine study areas: a) hub height, b) rotor diameter, and c) rated power

The selected configurations differed substantially between the areas, particularly in hub height. The configurations obtained for Areas 3 and 5 had the greatest hub heights, at 170 and 175 m, whereas the configuration obtained for Area 6 had a hub height at the lower bound of 75 m. The rotor diameters ranged from 104 to 134 m and rated power from 2.4 to 4.0 MW. The results therefore showed that optimization using the combined objective did not yield the largest turbines systematically, but, instead, yielded configurations adapted to the local wind resource and the associated investment cost. The main technical and economic indicators of the selected configurations are presented in Figure 3.

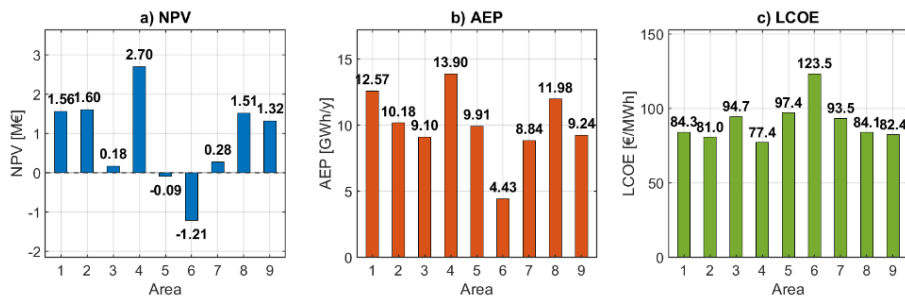


Figure 3: Deterministic performance of the rounded combined-objective configurations for the nine study areas: a) NPV, b) AEP, and c) LCOE

Under the combined objective, the most favorable overall results were obtained for Area 4, with an NPV of 2.70 M€, an AEP of 13.90 GWh/year, and the lowest LCOE of 77.4 €/MWh. Favorable results were also obtained for Areas 1, 2, 8, and 9, with

NPVs between 1.32 and 1.60 M€ and LCOE values between approximately 81 and 84 €/MWh. The configurations obtained for Areas 3 and 7 were only marginally profitable, with NPVs of 0.18 and 0.28 M€, respectively. The configuration obtained for Area 5 yielded an AEP of 9.91 GWh/year but had a slightly negative NPV of −0.09 M€. The least favorable results were obtained for Area 6, with an NPV of −1.21 M€, an AEP of 4.43 GWh/year, and an LCOE of 123.5 €/MWh. The optimization therefore yielded the minimum rated power of 2.4 MW for Area 6.

The influence of the optimization criterion on turbine sizing is compared in Figure 4.

Maximization of the AEP yielded solutions at the upper bounds of all three design variables in every area, corresponding to a hub height and rotor diameter of 175 m and a rated power of 7.2 MW. This was expected, because the maxAEP objective accounts for increased energy capture without accounting for the associated investment cost directly. In contrast, the maximization of NPV and minimization of LCOE yielded substantially smaller configurations. The minimization of LCOE yielded the minimum rated power of 2.4 MW in every area, whereas the maximization of NPV yielded rated powers between 2.4 and 3.7 MW. The resulting differences in NPV, AEP, and LCOE are shown in Figure 5.

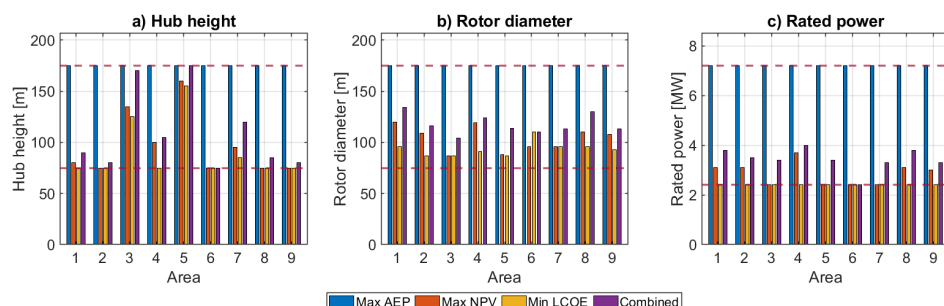


Figure 4: Comparison of the rounded turbine configurations obtained using the maxAEP, maxNPV, minLCOE, and combined objective functions: a) hub height, b) rotor diameter, and c) rated power

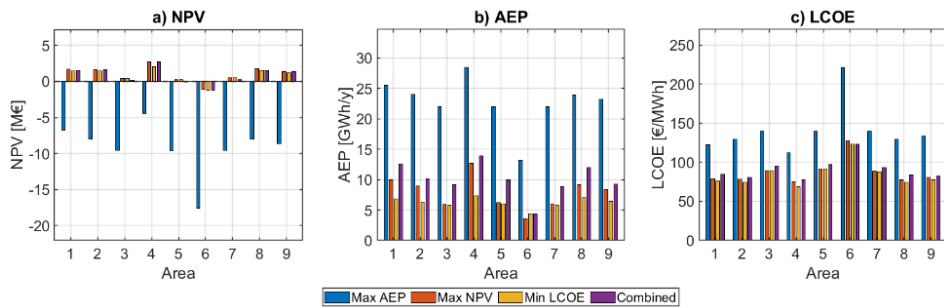


Figure 5: Comparison of the deterministic performance obtained using the rounded maxAEP, maxNPV, minLCOE, and combined objective configurations: a) NPV, b) AEP, and c) LCOE

The maxNPV and minLCOE solutions yielded similar economic outcomes, although the resulting turbine dimensions differed. The minLCOE solutions resulted in smaller turbines, whereas the maxNPV solutions tended to retain somewhat larger configurations. For the more favorable areas, the combined-objective solutions yielded higher AEP with only a limited reduction in NPV relative to the maxNPV solutions. For example, in Area 4, the AEP increased from 12.71 GWh/year for the maxNPV configuration to 13.90 GWh/year for the combined configuration, while NPV decreased only slightly from 2.74 to 2.70 M€. In Area 1, the AEP increased from 9.94 to 12.57 GWh/year, while NPV remained similar at 1.56 M€ for the combined configuration compared with 1.72 M€ for the maxNPV configuration. The trade-off was less favorable in the marginal areas. For Areas 3 and 7, the solutions obtained using the combined objective had substantially higher AEP but lower NPV than the corresponding maxNPV solutions. For Area 5, the configuration obtained using the combined objective increased AEP from 6.20 to 9.91 GWh/year, but shifted the NPV from a slightly positive 0.29 M€ to -0.09 M€. The economic penalty associated with increased energy production was therefore relatively small in the more favorable areas, but became more pronounced in the marginal areas.

Overall, the deterministic results showed that the optimization criterion affected both turbine sizing and project viability strongly. The solutions obtained by maximizing AEP were oversized and economically inefficient consistently, whereas those obtained by maximizing NPV and minimizing LCOE were smaller and

exhibited stronger financial performance. The combined-objective solutions yielded higher AEP than the purely economic solutions, with the associated NPV penalty depending on the site quality. The deterministic results identified Area 4 as the most favorable location, followed by Areas 1, 2, 8, and 9. The results for Areas 3 and 7 indicated only marginal economic attractiveness, the combined-objective configuration for Area 5 was slightly uneconomic, and the results for Area 6 indicated unfavorable economic feasibility under the deterministic assumptions. The combined-objective configurations were therefore retained as the reference designs for the subsequent uncertainty and sensitivity analyses.

4.2 Deterministic Sensitivity Analysis

A deterministic sensitivity analysis was performed for the rounded combined-objective configurations. The sensitivity trends were qualitatively similar across the nine study areas. To avoid presenting repetitive and visually congested figures, Area 4 was selected as an illustrative case for detailed discussion. It was chosen because the deterministic results obtained for this area indicated the strongest techno-economic performance, and provided a clear representation of the relative influence of the investigated parameters. The sensitivity of NPV for Area 4 is shown in Figure 6. The red dotted line represents the economic break-even point at which NPV equals zero.

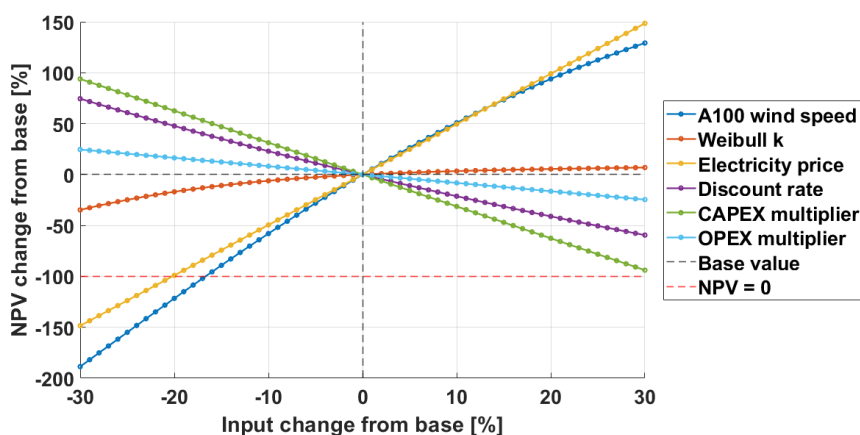


Figure 6: Deterministic sensitivity of NPV for the rounded combined-objective configuration in Area 4

The NPV was affected most strongly by $\mathcal{A}_{100}$, p_{el} , and CAPEX. The increased wind resource intensity or electricity price increased NPV, whereas a higher CAPEX or r reduced it. Relative to the base case, a 30 % increase in p_{el} increased NPV by 149 %, while a 30 % decrease reduced NPV by 146 %. Across the investigated ± 30 % range, the variation in $\mathcal{A}_{100}$ changed NPV by -188 % to $+129$ % relative to the base value. CAPEX also had a pronounced effect: a 30 % reduction increased NPV by 94 %, whereas a 30 % increase reduced it by 93 %. The influence of r was smaller, but still substantial, whereas variations in OPEX and k had comparatively limited impacts. The Area 4 configuration remained economically viable over most of the investigated range; NPV became negative only when $\mathcal{A}_{100}$ decreased by 17 % or p_{el} decreased by 20 %. Even with a 30 % increase in CAPEX NPV remained close to the economic break-even point, indicating comparatively robust deterministic performance for the evaluated configuration. The corresponding LCOE sensitivity is shown in Figure 7.

The parameter $\mathcal{A}_{100}$ had the strongest influence on LCOE. A 30 % decrease increased LCOE by 65 % relative to the base value, whereas a 30 % increase reduced it by 18 %. This asymmetric response results from the nonlinear influence of the wind speed on energy production. CAPEX was the second most influential parameter: a ± 30 % variation in CAPEX changed LCOE by ± 23 %. The parameter r changed LCOE by -11 % to $+12$ %, while OPEX caused a smaller variation of ± 7 %. The parameter k had only a limited effect. Electricity price p_{el} does not affect LCOE, because it influences project revenue rather than the cost or quantity of generated electricity.

Overall, the deterministic sensitivity analysis identified wind resource intensity, p_{el} , and CAPEX as the principal determinants of economic performance. The same general parameter ranking was observed across the study areas, although the magnitude of the responses and the distance from economic break-even differed. The results for Areas 3, 5, and 7 were more sensitive to relatively small adverse changes, while the configuration for Area 6 remained economically unfavorable over much of the investigated range. The configuration evaluated for Area 4, in contrast, remained comparatively robust under moderate deviations from the base assumptions. Because the deterministic sensitivity analysis varied each parameter independently, the combined effects of simultaneous uncertainty were evaluated subsequently using Monte Carlo analysis.

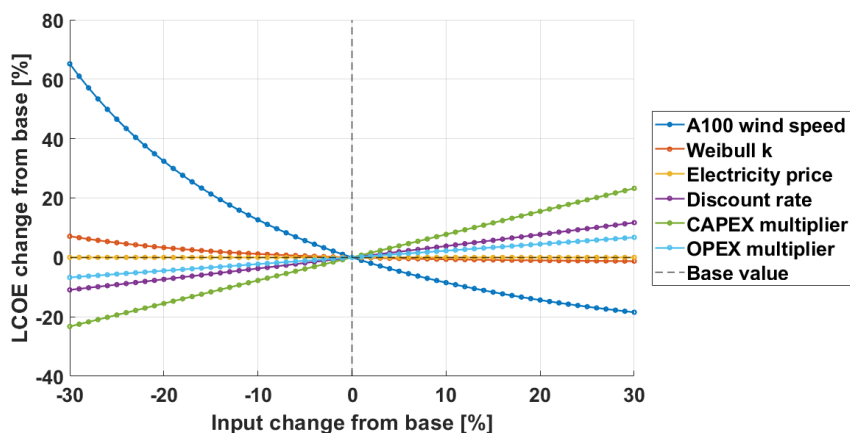


Figure 7: Deterministic sensitivity of LCOE for the rounded combined-objective configuration in Area 4

4.3 Monte Carlo Uncertainty Analysis

The Monte Carlo analysis was used to evaluate the robustness of the rounded combined-objective configurations when the wind resource and economic inputs varied simultaneously. For each study area 10,000 simulations were performed, using triangular distributions centered on the deterministic assumptions. Although AEP was calculated in every simulation, its uncertainty is not presented separately. Only the wind resource and technical parameters affect energy production directly, while p_{el} , r , CAPEX, OPEX, and N affect only the economic indicators. The deterministic AEP values also remained close to the center of the corresponding percentile intervals in all areas. The effect of the AEP uncertainty is therefore represented more meaningfully through its influence on NPV and LCOE.

The resulting uncertainty in NPV is presented in Figure 8. P05 and P95 denote the 5th and 95th percentiles, respectively, and therefore define the central 90 % range of the simulated results, while the base value represents the corresponding deterministic result.

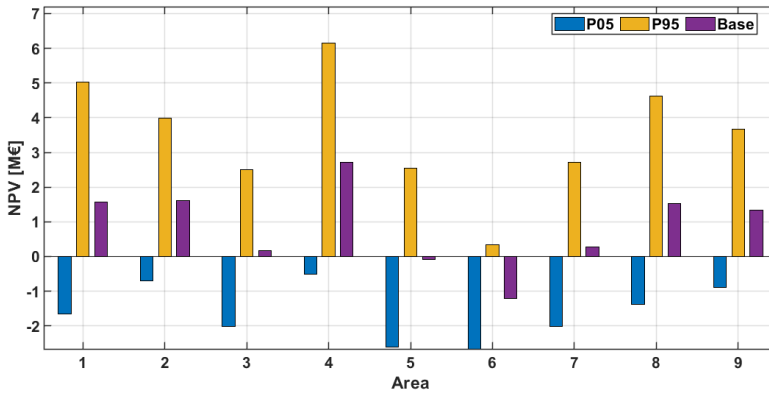


Figure 8: Base, P05, and P95 values of the NPV obtained from the Monte Carlo analysis

The strongest economic performance under uncertainty was obtained for Area 4. The NPV distribution for Area 4 ranged from -0.50 M€ at P05 to 6.14 M€ at P95, compared with a deterministic value of 2.71 M€. Comparatively favorable NPV results were also obtained for Area 2, with an NPV range from -0.70 to 3.98 M€. The NPV distributions for Areas 1, 8, and 9 were wider, but predominantly favorable, with P95 values of 5.02 , 4.62 , and 3.67 M€, respectively. Nevertheless, the P05 NPV was negative for every area, including the best performing configurations. This indicated that sufficiently unfavorable combinations of wind resource and economic conditions could make all the investigated projects uneconomic. The downside risk was particularly important for Areas 3, 5, 6, and 7, whose deterministic NPVs were already close to, or below zero. The least favorable NPV distribution was obtained for Area 6, with an NPV range from -2.68 to only 0.33 M€.

The resulting uncertainty in LCOE is shown in Figure 9.

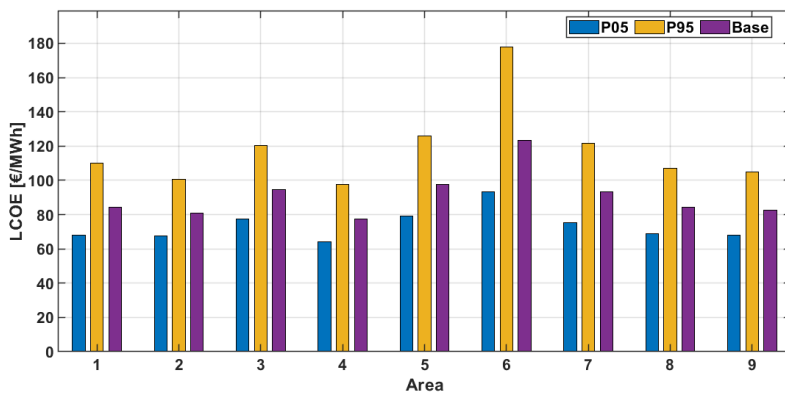


Figure 9: Base, P05, and P95 values of LCOE obtained from the Monte Carlo analysis

The lowest LCOE values under uncertainty were obtained for Area 4, with values ranging from 64.0 €/MWh at P05 to 97.7 €/MWh at P95. The LCOE distributions for Areas 1, 2, 8, and 9 were also comparatively favorable, although their upper percentiles generally exceeded 100 €/MWh. For example, the LCOE for Area 2 ranged from 67.6 to 100.5 €/MWh, while the corresponding LCOE for Area 8 ranged from 68.9 to 107.0 €/MWh. The results for the weaker locations were characterized by both higher deterministic values and less favorable upper tails. The highest LCOE values throughout the analysis were obtained for Area 6, ranging from 93.3 to 177.7 €/MWh. The P95 values obtained for Areas 3, 5, and 7 also exceeded 120 €/MWh. The larger upward deviation under unfavorable conditions was consistent with the deterministic sensitivity analysis, and resulted mainly from the nonlinear effect of reduced wind availability on electricity production.

A direct measure of economic robustness is provided by the probability of achieving a positive NPV, as presented in Figure 10.

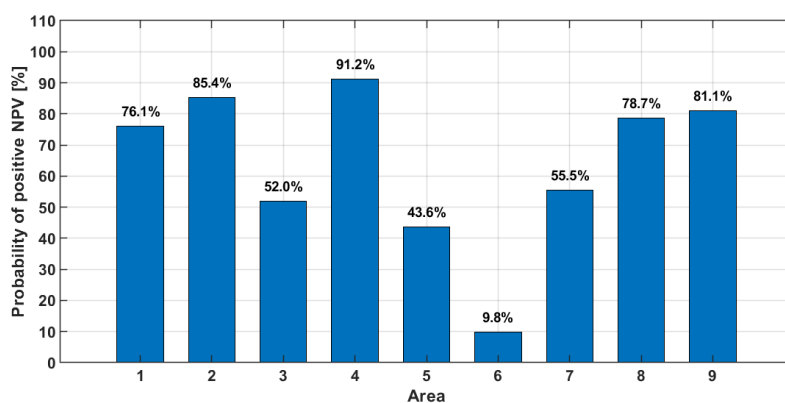


Figure 10: Probability of positive NPV for the rounded combined-objective configurations under the Monte Carlo analysis

The highest probability of a positive NPV was obtained for Area 4, at 91.2 %, indicating the greatest economic robustness among the evaluated locations. The second highest probability was obtained for Area 2, at 85.4 %, while the corresponding probabilities for Areas 9, 8, and 1 were 81.1 %, 78.7 %, and 76.1 %, respectively. The corresponding configurations therefore remained profitable in most simulated scenarios, although their negative P05 values showed that economic risk was not eliminated. The probabilities of a positive NPV for Areas 3 and 7 were 52.0 % and 55.5 %, respectively. Their outcomes were therefore approximately divided evenly between profitable and unprofitable scenarios, which were consistent with their marginal deterministic results. A positive NPV was obtained in only 43.6 % of the simulations for Area 5, indicating that unfavorable outcomes were more likely than favorable ones. The probability of a positive NPV for Area 6 was only 9.8 %. Although positive results occurred under a limited number of favorable scenarios, the configuration remained economically unattractive under most combinations of uncertain inputs.

Overall, the Monte Carlo analysis preserved the general ranking obtained from the deterministic optimization, but showed that deterministic values alone did not describe the project risk adequately. The Monte Carlo results identified Area 4 as the most favorable and robust location, followed by Areas 2, 9, 8, and 1. The results for Areas 3 and 7 indicated marginal economic feasibility, while those for Areas 5, and particularly 6, indicated substantial economic risk. These findings were consistent

with the deterministic sensitivity analysis, which identified wind resource intensity, p_{el} , and CAPEX as the principal drivers of project performance.

5 Discussion and Study Limitations

The results demonstrate that turbine selection cannot be based on energy production alone. Because the investment cost was not penalized, maximization of AEP resulted in hub height, rotor diameter, and rated power approaching their upper bounds, whereas the maximization of NPV and minimization of LCOE yielded smaller configurations. The combined-objective solution represented a compromise between production and economic performance, particularly in stronger-wind areas such as Areas 1 and 4. However, in marginal areas, increasing the turbine size could raise AEP while reducing NPV. The combined solution should therefore not be interpreted as universally optimal; a final selection should consider the individual values of AEP, NPV, and LCOE together with the associated uncertainty.

Across the investigated locations, the wind resource quality remained the principal technical determinant of feasibility. The sensitivity analysis identified the Weibull scale parameter, electricity price, CAPEX, and discount rate as the most influential inputs. The Monte Carlo results showed further that favorable deterministic values do not necessarily indicate robust profitability, emphasizing the importance of percentile ranges and the probability of positive NPV when evaluating marginal projects.

Several limitations must be considered. Each area was represented by modeled Weibull parameters at a representative point rather than long-term measurements at a confirmed turbine location, so local effects related to complex terrain, turbulence, wind direction, atmospheric stability, and icing were not captured in detail. The single-turbine model excludes manufacturer-specific power curves, dynamic control behavior, structural and fatigue loads, wake effects, wind farm layout, electrical losses, curtailment, and grid constraints. The economic assessment relies on escalated NREL cost-scaling relationships and simplified financial assumptions that omit project-specific transport, installation, financing, degradation, component replacement, decommissioning, and future electricity-price changes. The Monte Carlo analysis also assumes independent triangular distributions, although correlations may exist among the uncertain parameters. The framework should

therefore be regarded as a preliminary screening and configuration-selection tool, with detailed project development requiring site measurements, manufacturer-specific data, updated cost information, and wind-farm-level spatial, structural, environmental, and grid assessments.

6 Conclusion

The case study demonstrates that wind turbine size should not be selected independently of site quality and the chosen optimization objective. The maximization of AEP resulted consistently in hub height, rotor diameter, and rated power approaching their upper bounds, but the resulting increase in electricity generation was generally insufficient to compensate for the considerably higher CAPEX. The maximization of NPV and minimization of LCOE yielded smaller configurations. The weighted combined-objective solution was intermediate, retaining a substantial share of the achievable economic performance while increasing AEP. However, this compromise was most effective at locations with stronger wind resources, whereas larger configurations at marginal locations could increase production while reducing NPV.

Across the nine study areas, the strongest overall results were obtained for Area 4, with an AEP of approximately 13.90 GWh/year, an NPV of 2.70 M€, an LCOE of 77.4 €/MWh, and a 91.2 % probability of positive NPV. The second favorable group comprised Areas 1, 2, 8, and 9, for which positive deterministic NPVs were obtained and probabilities of positive NPV between 76.1 % and 85.4 %. The configurations evaluated for Areas 3 and 7 were only marginally profitable under the deterministic assumptions, and remained close to the economic threshold under uncertainty, with positive-NPV probabilities of 52.0 % and 55.5 %, respectively. The configuration evaluated for Area 5 was slightly uneconomic under the deterministic assumptions, and a positive NPV was achieved in only 43.6 % of the simulations. The least favorable results were obtained for Area 6, with an NPV of -1.21 M€, an LCOE of 123.5 €/MWh, and only a 9.8 % probability of positive NPV. The comparison demonstrates that turbine scaling alone cannot compensate for an insufficient wind resource, and that site quality remains fundamental to project feasibility.

The sensitivity analysis identified the Weibull scale parameter, electricity price, CAPEX, and discount rate as the most influential model inputs. The Monte Carlo analysis demonstrated further that favorable deterministic indicators do not necessarily represent robust investment performance, because negative outcomes remained possible, even at comparatively attractive locations. The probability of a positive NPV and the corresponding percentile ranges should therefore be considered together with deterministic NPV and LCOE, particularly when assessing marginal projects.

The developed framework provides a systematic basis for preliminary turbine-configuration and site screening, by linking energy production, economic performance, and uncertainty within a common assessment workflow. It also distinguishes between locations where the additional turbine scale creates sufficient value, and locations where it increases primarily investment exposure. Nevertheless, the results should be interpreted as screening-level estimates, because the analysis relies on modeled wind resource parameters, a simplified single-turbine representation, generalized cost-scaling relationships, and predefined uncertainty distributions.

Future work should focus on the following areas:

- **Dynamic turbine performance:** Evaluate the selected configurations using chronological wind speed data and dynamic models that account for variable-speed operation, pitch and torque control, start-up and shutdown behavior, curtailment, and operation near rated conditions.
- **Higher-fidelity technical modeling:** Compare the simplified power coefficient model with the manufacturer-specific power curves, blade element momentum models, and aeroelastic simulations that include turbulence, fatigue, extreme loading, blade deflection, and turbine class requirements.
- **Site-specific wind assessment:** Supplement the modeled Weibull parameters with long-term site-specific wind measurements, and account for complex terrain, wind direction, atmospheric stability, turbulence intensity, seasonal variability, and icing.
- **Wind-farm-level optimization:** Extend the framework to include wake interactions, turbine spacing, layout optimization, electrical losses, availability, access requirements, curtailment, and grid connection constraints.

- **Improved economic representation:** Incorporate updated turbine and balance-of-system costs, financing structures, degradation, component replacement, decommissioning, residual value, grid connection expenditure, and electricity price evolution.
- **Advanced optimization under uncertainty:** Consider correlations among uncertain parameters, and compare the weighted combined objective with Pareto-based multi-objective, stochastic, and robust optimization approaches.
- **Spatial and environmental integration:** Incorporate geographic information system data directly into the optimization, to represent protected areas, settlement distances, terrain accessibility, infrastructure, visual impact, and other practical siting constraints.

These extensions would allow the framework to progress from preliminary configuration screening toward a more comprehensive decision-support tool for site-specific wind energy planning and investment assessment.

Acknowledgment

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Povzetek s slovenskem jeziku

Optimizacijsko osnovana tehno-ekonomska ocena kopenskih vetrnih turbin v Sloveniji ob upoštevanju negotovosti. Sistemi za izrabo obnovljivih virov energije zahtevajo izbor tehnologije, ki ustreza posameznim lokacijam in zagotavlja visoko proizvodnjo energije ter ekonomsko upravičenost. V okviru raziskave je bil razvit splošen, na optimizaciji osnovan tehno-ekonomski okvir za ocenjevanje konfiguracij kopenskih vetrnih turbin, ki je bil uporabljen na devetih reprezentativnih lokacijah v Sloveniji. Spremenljivke optimizacije so bile višina pesta, premer rotorja in nazivna moč, ciljne funkcije pa letna proizvodnja energije, neto sedanja vrednost (NSV), izravnani stroški električne energije (ang. levelized cost of energy, krajše LCOE) ter utežen sestavljen cilj. Izbrane konfiguracije so bile ovrednotene z deterministično analizo občutljivosti in simulacijo Monte Carlo za oceno vpliva negotovosti vetrnega vira ter tehničnih in ekonomskih parametrov. Maksimiranje zgolj proizvodnje energije je privedlo do predimenzioniranih in ekonomsko neučinkovitih konfiguracij, medtem ko je optimiranje na podlagi ekonomskih ciljev (NSV in LCOE) privedlo do manjših vetrnih turbin, sestavljena ciljna funkcija pa je omogočila bolj uravnoteženo trženje. Kakovost vetrnega vira, cena električne energije, investicijski stroški in diskontna stopnja so se izkazali kot glavni dejavniki dobičkonosnosti, pri čemer ugodni deterministični rezultati ob upoštevanju negotovosti niso vedno izkazali ekonomske robustnosti.