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Selection optimization in small and medium-scale wind turbines: A review based on aerodynamic, mechanical, and economic criteria

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Abstract

This study presents a comprehensive review that systematically examines the technical, aerodynamic, mechanical, and economic criteria used in the selection of small and medium-scale wind turbines. Turbine performance is evaluated within the framework of the rotor diameter–swept area relationship, tip speed ratio (TSR)–power coefficient (Cp) aerodynamic curves, Weibull wind speed distribution, and power curve parameterization. The fundamental mathematical models employed in annual energy production (AEP) calculations are explained, and the decisive influence of the compatibility between the wind regime and turbine characteristics on overall performance is emphasized. Mechanical components (noise, vibration, generator type) and economic indicators (levelized cost of energy—LCOE, operation and maintenance costs, payback periods) are comparatively assessed with respect to turbine selection. In addition, the performance of multi-criteria decision-making methods (AHP, TOPSIS, VIKOR, CoCoSo) and artificial intelligence-based models (ANN, GRU, CEEMD–GRU) is compared based on findings reported in the literature. The results indicate that hybrid optimization approaches are more effective in reducing uncertainty. The study also identifies future research directions, including turbine classification specific to Türkiye, site validation, and artificial intelligence-assisted real-time optimization.

1. Introduction

Small and medium-scale wind turbines have gained increasing importance in distributed energy generation, rural electrification, agricultural activities, emergency power systems, and building-scale renewable energy applications [1–3]. Advances in wind energy technologies have not only focused on large-scale turbines but have also led to a rapid increase in studies examining the performance, reliability, and cost-effectiveness of turbines in the 1–1000 kW power range [4, 5]. Energy and exergy analyses conducted at this scale indicate that small wind turbines can provide a sustainable and efficient solution in regions with suitable wind conditions [6–8].

Wind turbine selection represents a complex engineering problem involving numerous technical and economic parameters, including aerodynamic design, structural requirements, power curve characteristics, cut-in/rated/cut-out wind speeds, rotor diameter and swept area, blade profile, generator type, noise level, and investment and operating costs [9–12]. The literature emphasizes that this decision-making process should be addressed not solely based on energy production but also as a holistic optimization problem encompassing economic feasibility, environmental impacts, and operational conditions [13, 14].

In this context, multi-criteria decision-making (MCDM) methods have been widely employed in wind turbine selection studies. Supciller and Toprak evaluated different turbine models using SWARA, TOPSIS, and EDAS methods, revealing the multidimensional nature of the decision-making process [11]. Rehman et al. [10] determined the optimum turbine type for different sites using a TOPSIS-based approach that simultaneously considered technical and economic variables. Emeksiz and Yüksel [14] systematically compared 35 turbine alternatives using a hybrid MCDM model incorporating technical, economic, and environmental criteria. Şahin and Deliktaş [15] quantitatively analyzed the effects of factors such as rotor diameter, rated power, cost, and noise emissions on turbine performance by integrating entropy–TOPSIS and CoCoSo methods. A comprehensive review conducted by Eroğlu et al. [16] demonstrates that MCDM techniques applied in wind energy applications have diversified over the years and reached a level of methodological maturity.

Nevertheless, the existing literature exhibits several notable limitations. First, a significant proportion of studies focus on large-scale wind turbines, while technical and economic assessments specific to small and medium-scale turbines remain limited [17, 18]. Second, there are relatively few studies in which aerodynamic design, reliability analysis, and energy–exergy performance of small wind turbines is integrated with MCDM models [19, 20]. Third, many studies are conducted based on a single site or a single turbine model, which reduces the generalizability of the obtained results [21–24].

In light of these limitations, the study aims to systematically classify the technical, economic, environmental, and aerodynamic criteria used in the selection of small and medium-scale wind turbines; to examine the MCDM and artificial intelligence-based methods proposed in the literature within an integrated framework; and to identify methodological gaps in existing research. In doing so, the study seeks to provide a comprehensive evaluation framework for appropriate turbine selection in distributed energy applications, thereby offering a more reliable analytical basis for engineers, investors, and decision-makers.

2. Materials and Methods

This section presents, within a systematic framework, the technical characteristics of small and medium-scale wind turbines, the criteria used in turbine selection, and the optimization methods highlighted in the literature. First, the fundamental physical parameters that determine aerodynamic performance and energy generation capacity, together with their corresponding mathematical formulations, are explained. Subsequently, the technical–economic criteria governing turbine selection—such as wind regime, capacity factor, annual energy production (AEP), cost indicators, and environmental impacts—are discussed. Finally, multi-criteria decision-making (MCDM) and artificial intelligence-based optimization approaches are summarized, providing a holistic basis for the computational and evaluation methods employed in wind turbine selection processes.

2.1. Technical Characteristics of Small and Medium-Scale Wind Turbines

The technical performance of small and medium-scale wind turbines is governed by physical parameters that define the aerodynamic characteristics of the turbine, its energy generation potential, and operational stability [25, 26]. In this context, the power curve constitutes the primary reference defining the amount of power that can be generated at different wind speeds and lies at the core of performance evaluations [27, 28]. Since the accuracy of power curve data directly affects the reliability of key indicators such as annual energy production (AEP) and capacity factor, compliance with standardized measurement and validation procedures is essential [29–32].

The operating range of a wind turbine is defined by the cut-in, rated, and cut-out wind speeds. The cut-in wind speed represents the minimum wind speed at which the turbine starts generating electricity [33], while the rated wind speed corresponds to the wind speed at which the turbine reaches its nominal power output [34]. The cut-out wind speed denotes the maximum safe wind speed at which the turbine is shut down to prevent overloading and structural damage [35]. Accurate determination of these characteristic wind speeds ensures that turbine performance is compatible with the targeted wind regime [36].

2.2. Technical Characteristics of Small and Medium-Scale Wind Turbines

The aerodynamic and statistical models employed in the performance analysis of small and medium-scale wind turbines are based on standardized mathematical formulations. The technical curves presented in Figure 1 and Figure 2 are constructed on the basis of the following fundamental expressions:

Swept Area, the effective area of the rotor exposed to the wind flow [37, 38]:

$$A = \pi * R^2 \tag{1}$$

where A is the rotor swept area (m^2), R is the rotor radius (m), and π=3.14159 is the circular constant. Tip Speed Ratio (TSR), defined as the ratio of the tangential speed of the blade tip to the wind speed [38]:

$$\lambda = \frac{\omega * R}{V} \tag{2}$$

where λ is the tip speed ratio, ω\omegaω is the angular speed of the rotor (rad/s), R is the rotor radius (m), and V is the wind speed (m/s). Power Coefficient (Cp), a dimensionless parameter representing aerodynamic efficiency [37, 38]:

$$p = \frac{Pout}{\frac{1}{2}\rho * A * V^3} \tag{3}$$

where Cp is the power coefficient (dimensionless), Pout is the power output of the turbine (W), ρ is the air density (kg/m^3), A is the rotor swept area (m^2), and V is the wind speed (m/s). Weibull Wind Speed Distribution, expressing the probability density of wind speed [39, 40]:

$$f(V) = \frac{k}{c} * \left(\frac{V}{c}\right)^{k-1} * e^{-\left(\frac{V}{c}\right)^k} \tag{4}$$

where f(V) is the probability density function of wind speed, k is the shape parameter, c is the scale parameter (m/s), V is the wind speed (m/s), and eee is the base of the natural logarithm. Mean Wind Speed [40, 41]:

$$\bar{v} = c * \Gamma\left(1 + \frac{1}{k}\right) \tag{5}$$

where $\bar{v}$ is the mean wind speed (m/s), ccc is the scale parameter (m/s), k is the shape parameter, and Γ(·) denotes the Gamma function. The integration of the turbine power curve P(V) and the probability density of wind speed. Annual Energy Production (AEP) [37, 38]:

$$AEP = \int_0^\infty P(V) * f(V) * dV \tag{6}$$

where AEP is the annual energy production (kWh or MWh), P(V) is the turbine power at a given wind speed (W), f(V)f(V)f(V) is the Weibull probability density function, and V is the wind speed (m/s). In digital applications [38, 42]:

$$AEP = \sum_{i=1}^{N} P(V_i) * h_i \tag{7}$$

where Vi is the iii-th wind speed bin, P(Vi) is the turbine power at that wind speed, hih_{i}hi is the annual number of hours corresponding to that wind speed bin, and N is the total number of wind speed bins. Capacity Factor (CF) [38, 43–45]:

$$CF = \frac{AEP}{Prated * 8760} \tag{8}$$

where CF is the capacity factor (dimensionless), AEP is the annual energy production (kWh or kW · h), Prated is the rated power of the turbine (W or kW), and 8760 represents the number of hours in one year.

This mathematical framework enables the consistent and comparable modeling of aerodynamic performance, wind statistics, and energy production projections. The rotor diameter and the corresponding swept area constitute the most fundamental geometric parameters determining the amount of energy that can be captured by the turbine, exerting a quadratic influence on energy production [46, 47]. Aerodynamic performance is evaluated through the relationship between the tip speed ratio (TSR) and the power coefficient (Cp), which plays a critical role in defining aerodynamic efficiency. The Weibull distribution, representing the long-term behavior of wind speed, is employed as the primary statistical tool in AEP calculations.

The joint consideration of these three parameters is crucial for accurately modeling wind turbine performance. Figure 1 illustrates the three fundamental technical curves commonly used in small-scale wind turbine analyses:

(a) the rotor diameter–swept area relationship,

(b) the TSR–Cp aerodynamic performance curve, and

(c) The Weibull wind speed distribution.

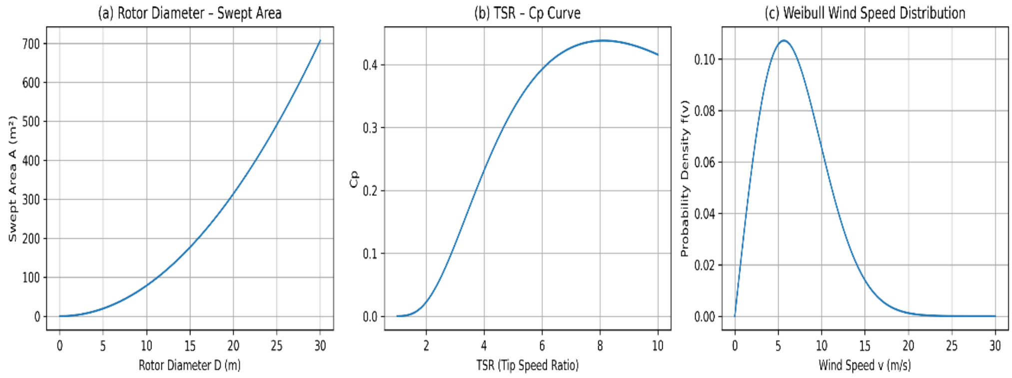

Figure 1. Fundamental technical curves of small-scale wind turbines.

Figure 1(a) demonstrates that an increase in rotor diameter enlarges the swept area quadratically, highlighting the decisive influence of geometric design on the energy capture capability of the turbine [46, 47]. Figure 1(b) indicates that the power coefficient (Cp) reaches its maximum within a specific range of the tip speed ratio (TSR), and this behavior is consistent with the theoretical trends commonly accepted in aerodynamic optimization studies [48, 49]. Figure 1(c) illustrates the capability of the Weibull distribution to represent low-to-moderate wind regimes; the peak of the distribution identifies the wind speed range most frequently encountered by the turbine, providing critical information for power curve matching [50-53].

The combined evaluation of these subfigures establishes the integrated analysis approach required for performance prediction in small and medium-scale wind turbines. Other parameters influencing aerodynamic performance include the number of blades, blade profile coefficients (Cl, Cd), and stall behavior [48, 49]. In small wind turbines, two- or three-bladed configurations are generally preferred, and the selection of TSR is of critical importance to ensure sufficient torque generation at low wind speeds [54]. The generator type is another key factor determining the electrical performance of the turbine. In small and medium-scale applications, permanent magnet generators (PMGs) are widely used due to their ability to provide high torque at low rotational speeds. In larger systems, induction and synchronous generators offer advantages in terms of grid compatibility [55]. In addition, stall, active pitch, and electronic control-based speed control strategies have a decisive impact on energy production and load management [37].

2.3. Criteria Used in Wind Turbine Selection

Within the scope of this study, the criteria employed in wind turbine selection are classified in accordance with a systematic review methodology. While establishing the criterion sets, technical, economic, and environmental variables commonly adopted in the literature were considered, and design constraints specific to small and medium-scale wind turbines were also incorporated into the analysis. The primary determining parameter in turbine selection is the wind regime of the region. The long-term statistical behavior of wind speeds is most commonly modeled using Weibull and Rayleigh distributions, which are regarded as fundamental tools providing high accuracy in annual energy production (AEP) estimations [53, 56]. The compatibility between the wind regime and turbine characteristics directly influences the capacity factor and production efficiency [50-52].

The capacity factor represents the ratio of the actual energy generated by a turbine over a given period to its theoretical maximum production and is strongly affected, particularly in small-scale systems, by wind speed variability and power curve parameters [57]. Annual energy production (AEP) serves as a key indicator of both technical and economic feasibility in turbine selection and is calculated by integrating the power curve with the wind speed distribution [50, 58]. In this context, the accuracy of AEP calculations depends on the correct statistical modeling of wind speeds and the consistent integration of power curve data with the selected distribution. The high adaptability of the Weibull function, even under low and irregular wind regimes, constitutes the main reason for its widespread use in the literature [53, 56]. Characteristic power curve parameters such as cut-in, rated, and cut-out wind speeds represent the key components governing the capacity factor and energy production performance [50-52].

The analytical determination of AEP requires the integration of the turbine power curve P(v)P(v)P(v) with the wind speed probability density function f(v)f(v)f(v) over the entire wind speed range, thereby enabling a reliable estimation of the expected annual energy output of a turbine at a given site [38, 50, 58]. The flowchart presented in Figure 2 illustrates how the wind regime and turbine performance parameters are integrated in AEP calculations. Accurate modeling of wind speeds is particularly critical for small-scale wind turbines, as a substantial portion of energy generation occurs within low wind speed ranges. The integration of power curve data with the statistical distribution provides a quantitative representation of turbine performance under real operating conditions [42].

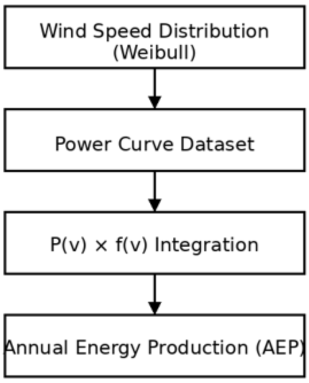

Figure 2. AEP calculation flowchart.

The accurate determination of AEP constitutes a fundamental input not only for the calculation of the capacity factor but also for economic analyses such as payback period, levelized cost of energy (LCOE), and overall investment feasibility. Consequently, errors in AEP estimations may lead to significant uncertainties in wind turbine selection from both technical and economic perspectives. In this regard, the methodology presented in Figure 2 contributes to establishing a robust analytical basis for the criteria employed in turbine selection.

Noise and vibration are critical evaluation criteria in terms of environmental compatibility, particularly for small wind turbines installed in proximity to residential areas. Aerodynamic noise originates from the interaction between the blade profile and the airflow, as well as from turbulence formation associated with rotor speed, and is therefore highly sensitive to blade geometry [59, 60]. Blade tip vortices and flow separation constitute the main components of aerodynamic noise [61]. Mechanical noise, on the other hand, is associated with internal components such as the generator, gearbox, and bearing systems. In turbines equipped with gearboxes, mechanical resonance, impulsive loads, and vibrations caused by misalignment are the primary factors contributing to increased noise levels [62, 63]. Within this framework, noise sources are classified into two main categories, and Figure 3 presents this distinction schematically [43].

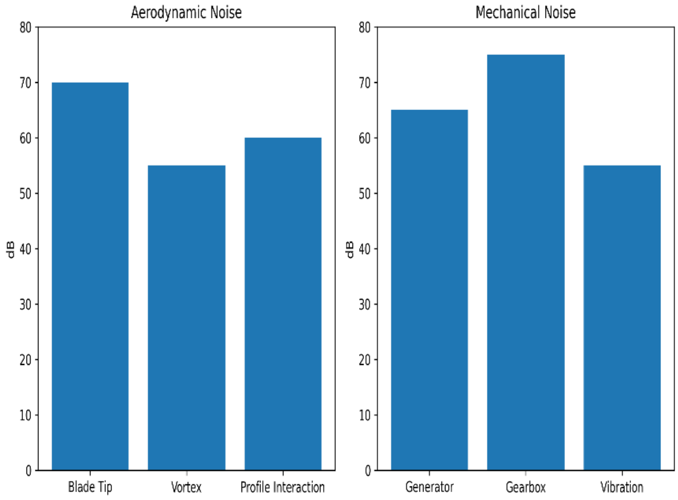

Figure 2. Noise classification in small wind turbines.

Figure 3 clearly illustrates the sources, magnitude, and generation mechanisms of aerodynamic and mechanical noise in small-scale wind turbines. Accordingly, the selection of blade profile, rotor speed, and generator type plays a directly decisive role for turbines to be installed in residential areas. Economic assessments constitute another fundamental component of wind turbine selection. Investment cost, operation and maintenance expenses, payback period, and the levelized cost of energy (LCOE) are the primary indicators used for an objective evaluation of economic feasibility [64-66]. In small-scale wind turbines, the relatively high proportion of maintenance costs compared to energy production necessitates reducing uncertainty in cost models and establishing reliable economic forecasts.

In addition, system reliability represents a critical parameter in long-term performance projections. Failure rates and component lifetimes are modeled in accordance with technical approaches proposed in the literature [67]. In this manner, technical performance, economic outputs, and environmental impacts are jointly evaluated to establish a holistic framework for optimal wind turbine selection.

2.4. Optimization Approaches Used in Wind Turbine Selection

The optimization methods employed in wind turbine selection are generally examined in the literature under two main categories: (i) mathematical and multi-criteria decision-making (MCDM) methods, and (ii) artificial intelligence-based optimization methods. These approaches enable the systematic evaluation of turbine performance within the framework of technical, economic, and environmental criteria. Mathematical optimization techniques include linear programming (LP), mixed-integer linear programming (MILP), and multi-objective optimization methods, which aim to determine the optimal set of turbine parameters under specified constraints [68-70]. Multi-criteria decision-making methods constitute one of the most widely used approaches in wind turbine selection studies; methods such as AHP, TOPSIS, VIKOR, and PROMETHEE are applied to weight different criteria and rank alternative turbine options [15, 71]. Considering the multidimensional nature of the wind turbine selection problem, the literature emphasizes that MCDM methods provide decision-makers with a consistent and systematic evaluation framework [72].

Artificial intelligence-based methods have emerged in recent years as another prominent group of optimization techniques for turbine selection, performance modeling, and energy production forecasting. Genetic algorithms (GA) and particle swarm optimization (PSO) are widely applied to optimize turbine geometry, control strategies, and aerodynamic parameters [73-75]. Artificial neural networks (ANNs), on the other hand, are preferred particularly for wind speed forecasting and annual energy production projections due to their high prediction accuracy [76-78]. In addition, hybrid optimization models combine MCDM and artificial intelligence techniques, enabling both criterion weighting and optimal turbine selection to be performed within a single methodological framework. The literature reports that hybrid models such as GA+ANN, AHP+TOPSIS, and entropy–fuzzy-based approaches have yielded successful results in small-scale wind turbine design and selection processes [61, 72, 76]. The integrated consideration of these methods allows the wind turbine selection process to be evaluated more comprehensively and with higher accuracy from both technical and economic perspectives.

3. Results and Discussion

In this section, the technical trends observed in the literature regarding comparisons of small and medium-scale wind turbines are first examined, and the effects of key performance-determining variables—such as rotor diameter, power curve characteristics, aerodynamic parameters, and wind regime—on turbine outputs are discussed. Subsequently, the performance of artificial intelligence-based models and MCDM-based methods used for energy forecasting and turbine selection is evaluated based on findings reported in the literature, and their contributions in terms of accuracy, decision support, and application domains are compared. Finally, the advantages and limitations of hybrid optimization approaches are summarized, and existing gaps in the literature are highlighted with respect to turbine comparisons specific to Türkiye, economic feasibility, environmental impacts, and site validation.

3.1. General Trends in Turbine Comparisons in the Literature

Existing studies on small and medium-scale wind turbines indicate that turbine performance is governed by multivariate interactions among wind regime, rotor geometry, and aerodynamic design parameters [2, 18]. The literature reveals that these turbines exhibit high sensitivity, particularly in low and moderate wind speed ranges, and that performance variations are more pronounced compared to large-scale wind turbines [1, 2, 7, 18].

Rotor diameter and swept area are the primary determinants of energy production. Tummala et al. [1] and Chagas et al. [3] report that the relationship between rotor diameter and AEP is nonlinear yet exhibits a strong increasing trend, while Bilir et al. [7] and Rodríguez-Hernández et al. [4] confirm these findings using field data. It is emphasized that the compatibility between the statistical distribution of wind speed and the turbine power curve is critical for the accuracy of AEP estimations; in particular, Weibull parameters are shown to accentuate performance differences in low wind speed regions [7, 18, 30]. The impact of rotor diameter on performance is not limited to energy harvesting alone. An increase in diameter also affects aerodynamic loads [79, 80], torque characteristics [81, 82], and structural stress distributions [80, 82]. Both early and recent studies indicate that this parameter plays a decisive role in design optimization [79, 81, 82].

The influence of aerodynamic design parameters has been extensively investigated in the literature. Blade profile, tip speed ratio (TSR), twist distribution, and stall behavior play a decisive role in small wind turbine performance. Alam and Jin [19] and Muhsen et al. [20] demonstrate that aerodynamic losses are more pronounced in small-scale turbines, particularly under turbulent flow conditions. More recent studies report that twist optimization can significantly enhance energy efficiency [48]. Overall, these findings demonstrate that evaluating the performance of small and medium-scale wind turbines solely based on nominal power ratings is insufficient, and that rotor geometry, aerodynamic design, and wind regime must be addressed through an integrated analysis approach.

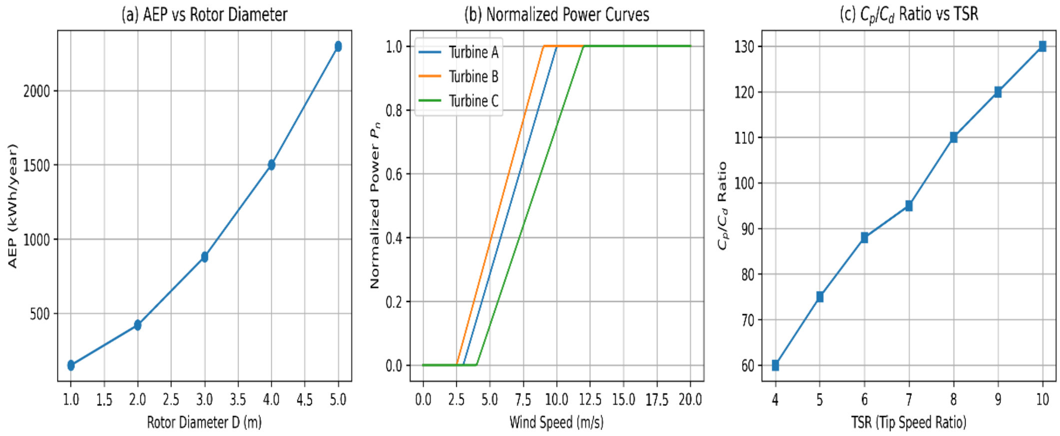

Figure 4. Comparison of rotor diameter, power curve, and aerodynamic performance in small-scale wind turbines.

Figure 4(a) shows that an increase in rotor diameter leads to a quadratic enlargement of the swept area, resulting in a pronounced improvement in AEP. This trend is supported by numerical and experimental data reported by Song et al. [30], Zhang et al. [31], and Mushtaq et al. [32], and has been further validated through long-term large eddy simulation (LES) analyses conducted by Postema et al. [50].

Figure 4(b) demonstrates that the normalized comparison of turbine power curves enables a more sensitive identification of performance differences in the cut-in, rated, and cut-out regions. The use of normalized power curve approaches has been reported to improve prediction accuracy in AEP calculations by Al-Khayat and Al-Rasheedi [58], Aldaoudeyeh [51], and Postema et al. [50].

Figure 4(c) indicates that increasing TSR values improve the aerodynamic performance represented by the lift-to-drag ratio (Cl/Cd). This increase is associated with the ability of thin-profile blades to generate higher lift at elevated TSR levels. Zhang et al. [31], Nugraha et al. [48], and Shakya et al. [64] have confirmed this relationship using both CFD and experimental methods. The interaction among rotor diameter, aerodynamic design parameters, and wind regime constitutes the dominant mechanism governing performance in small-scale wind turbines, and the literature underscores the necessity of addressing these systems through a multidimensional optimization approach.

3.2. Performance of optimization methods reported in the literature

Optimization methods employed in the design, selection, and performance prediction of small and medium-scale wind turbines have exhibited significant development in recent years. These methods are generally classified into artificial intelligence-based models, multi-criteria decision-making (MCDM) approaches, and hybrid optimization frameworks. The literature, particularly publications after 2023, provides detailed evidence of the effectiveness of these techniques in wind turbine performance prediction and optimal turbine selection.

3.2.1. Contributions of artificial intelligence methods to energy forecasting and optimal turbine selection

In recent years, machine learning and deep learning-based methods have offered substantial advantages in energy forecasting and turbine selection studies due to their ability to model the highly variable nature of wind speed. In particular, multilayer neural networks and hybrid models such as GRU/CEEMD significantly enhance prediction performance by decomposing wind speed fluctuations [56]. Bayesian networks enable high-accuracy prediction of multivariate performance outputs by explicitly defining causal relationships among parameters [83]. Deep learning–GIS (Geographic Information Systems) integrated models allow the optimization of HAWT/VAWT energy production by accounting for terrain and spatial variables [84]. Moreover, power optimization based on reinforcement learning, when combined with genetic algorithms, has demonstrated notable performance improvements in high-dimensional problems such as wind farm layout optimization [74]. These findings indicate that artificial intelligence-based models provide more flexible, faster, and higher-accuracy prediction capabilities compared to classical statistical approaches [85].

The success of machine learning-based methods is largely attributed to their ability to represent the nonlinear behavior of wind speed more effectively through artificial neural networks, temporal memory structures such as GRU/LSTM, and signal decomposition techniques such as CEEMD [86]. CEEMD-based models provide cleaner input signals by isolating noise components, while GRU architectures strongly capture temporal dependencies, yielding significant error reductions in short- and medium-term forecasts [87]. Bayesian networks offer additional advantages in uncertainty modeling and the identification of causal relationships [83]. On the other hand, deep learning–GIS integrated approaches have been reported to improve decision-support processes in turbine siting and site suitability analyses by efficiently processing high-dimensional datasets [84]. Reinforcement learning methods are increasingly being applied to optimization-oriented problems, particularly in turbine control and wind farm layout design [74].

In this context, Figure 5 presents a comparative evaluation of the RMSE performance of three artificial intelligence-based models (ANN, GRU, and CEEMD–GRU) across forecasting horizons of 1, 3, 6, and 12 hours.

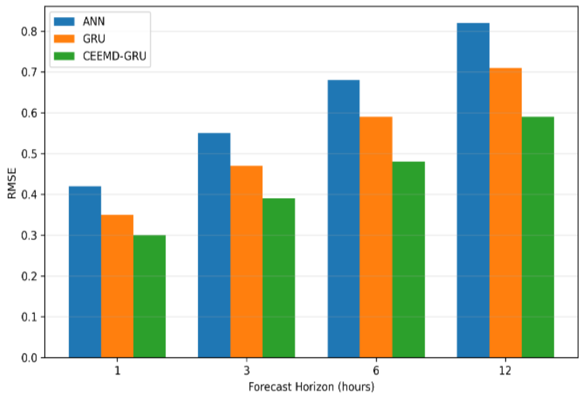

Figure 5. Wind power forecasting performance of artificial intelligence-based models.

As shown in Figure 5, the CEEMD–GRU model yields lower RMSE values than the other models across all forecasting horizons and represents fluctuating wind data more effectively. This outcome confirms that the combined use of signal decomposition techniques and memory-based learning algorithms significantly enhances forecasting accuracy. Although an increase in prediction error is observed for all models as the forecasting horizon extends, the relatively lower rate of error growth exhibited by the CEEMD–GRU model indicates that it maintains comparatively stable performance even in longer-term forecasts. In the ANN model, error growth becomes particularly pronounced for forecasting horizons of 6 hours and above, whereas the GRU model demonstrates a more balanced error trend. These findings reveal that wind power forecasting is highly sensitive to the temporal scale and that model selection plays a critical role in forecasting performance.

Overall, artificial intelligence-based methods are observed to provide lower errors and higher generalization capability compared to classical statistical models; consequently, they are increasingly preferred in optimal turbine selection, energy management, and wind energy planning. By improving the accuracy of decision-support systems, these methods make substantial contributions to both technical and economic evaluations.

3.2.2. Effectiveness of Multi-Criteria Decision-Making (MCDM) Methods in Wind Turbine Selection

Wind turbine selection is a multidimensional decision problem that requires the simultaneous evaluation of technical performance, economic feasibility, environmental impacts, and site conditions. In this context, multi-criteria decision-making (MCDM) methods are widely employed in the literature, as they enable systematic, objective, and repeatable comparisons of alternative turbines. Methods such as AHP, TOPSIS, VIKOR, PROMETHEE, and their fuzzy extensions stand out as reliable tools for determining criterion weights, handling uncertain data, and ranking alternatives.

Recent studies published during the 2023–2025 period demonstrate that MCDM methods provide successful and practical outcomes in site-based turbine selection, both in Türkiye and in international applications. For instance, Alkan and Kahraman showed that evaluation sensitivity under uncertainty can be enhanced in turbine selection by applying the interval-valued picture fuzzy TOPSIS method [88]. Şahin and Deliktaş compared Entropy–TOPSIS and CoCoSo methods and reported that different MCDM models exhibit similar ranking trends and deliver consistent results for site-specific decisions [15]. Yaman demonstrated that GIS-integrated MCDM models achieve high spatial accuracy in wind farm site selection [13]. In addition, earlier studies by Ermiş and Toklu support the conclusion that MCDM methods enhance decision reliability in small and medium-scale wind turbine applications [6].

In this context, Figure 6 presents the comparative distribution of scores obtained for turbine alternatives using different MCDM methods, visually illustrating the consistency of rankings across methods.

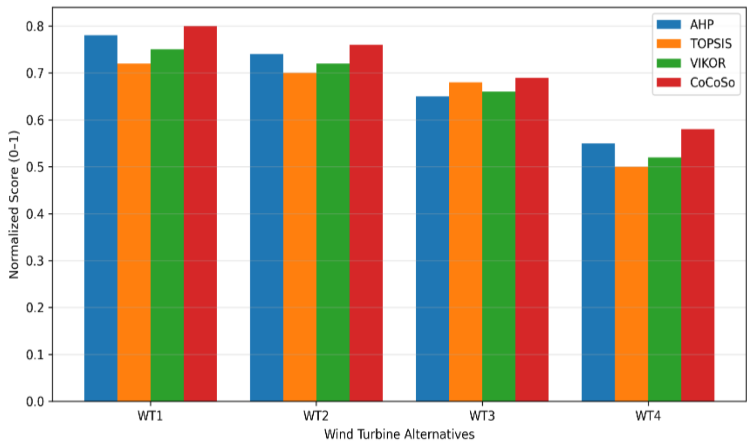

Figure 6. Comparative scores of wind turbine alternatives using different MCDM methods.

The results presented in Figure 6 indicate that methods such as TOPSIS, VIKOR, and PROMETHEE evaluate turbine alternatives with largely similar ranking structures; therefore, the choice of method does not radically affect the final decision. In contrast, fuzzy extensions are observed to distinguish differences among alternatives more sensitively in situations characterized by high uncertainty.

Overall, these findings confirm that MCDM methods provide decision-makers with a systematic, data-driven, and repeatable evaluation framework in both technical turbine selection and site determination processes. Furthermore, the consistency of rankings across methods suggests that, when criterion weights are appropriately defined, turbine selection can be conducted in an objective manner. In this respect, MCDM models have become an indispensable component of modern decision-support systems.

3.2.3. Advantages and Limitations of Hybrid Optimization Methods

Hybrid optimization methods combine the high predictive capability of artificial intelligence algorithms with the systematic decision-support structure of Multi-Criteria Decision-Making (MCDM) models, enabling a more comprehensive treatment of multidimensional problems such as wind turbine selection, performance prediction, and design optimization. These methods provide decision-makers with a more balanced and holistic analytical framework, particularly in cases where heterogeneous data types and a large number of criteria must be evaluated simultaneously.

Hybrid applications reported in the literature have achieved significant performance improvements, especially in engineering problems that require optimization and decision support to be addressed concurrently. For example, GA + ANN models have demonstrated high accuracy in optimizing turbine blade geometry, control strategies, and aerodynamic parameters [48, 74]. Hybrid structures such as AHP + VIKOR have contributed to more effective uncertainty management during decision stages including material selection and subcomponent design [72]. In 2025, Şahin and Deliktaş proposed a triple hybrid model based on Entropy + TOPSIS + CoCoSo, which reduced uncertainty in turbine selection processes by enabling sensitive and robust computation of criterion weights [15]. Nevertheless, the literature also highlights certain limitations of hybrid optimization methods. As the number of parameters increases, model structures become more complex, and computational costs rise compared to both standalone MCDM and single artificial intelligence approaches. Moreover, the dependence of weighting stages on expert judgment may introduce a degree of subjectivity into the decision-making process. Consequently, the effectiveness of hybrid methods is directly related to the quality of the dataset employed and the accuracy of parameter optimization.

In this context, Table 1 provides a comparative summary of the advantages, limitations, and representative applications reported in the literature for artificial intelligence-based, MCDM-based, and hybrid optimization methods.

Table 1. Comparison of optimization approaches.

Method Type	Applied Methods	Advantages	Limitations	References
Artificial intelligence (ANN, GRU, CEEMD–GRU)	ANN, GRU, CEEMD–GRU	High accuracy; strong adaptability to nonlinear relationships; robust performance in short-term forecasting	Requires large datasets; risk of overfitting; limited model interpretability	[56, 75, 86]
MCDM (AHP, TOPSIS, VIKOR, CoCoSo)	AHP, TOPSIS, VIKOR, CoCoSo	Ability to evaluate multiple technical/economic criteria simultaneously; transparent ranking for decision-makers	Sensitive to expert judgment and weighting; may not fully capture criterion interdependencies	[9–11, 15]
Hybrid approaches (GA+ANN, AHP+VIKOR, etc.)	GA+ANN, AHP+TOPSIS, AHP+VIKOR, entropy–fuzzy hybrid models	Integration of criterion weighting and optimization within a single framework; stronger decision-support capability	Increased model complexity; higher computational cost; sensitive parameter tuning required	[72, 74, 75, 89]

The comparison presented in Table 1 indicates that optimization approaches play complementary roles in wind turbine selection and performance analysis processes. Artificial intelligence-based models demonstrate superior performance in representing nonlinear relationships and in short-term forecasting, whereas MCDM methods provide a transparent and systematic ranking structure for complex decision problems. By contrast, hybrid approaches integrate the advantages of both methodologies, offering a more sensitive decision framework in which technical, economic, and environmental criteria are jointly optimized. However, the higher computational cost of hybrid models and their sensitivity to data quality and parameter settings necessitate careful modeling practices during implementation. Despite these challenges, trends in the literature suggest that hybrid approaches are increasingly being adopted for multi-criteria decision support and performance optimization in wind energy systems, providing a methodologically robust solution.

3.3. Performance of optimization methods reported in the literature

Although the literature on small and medium-scale wind turbines has expanded considerably in recent years, existing studies still exhibit notable limitations from both methodological and application-oriented perspectives. These limitations constitute significant gaps for academic research as well as for decision-making processes in engineering practice.

Insufficiency of up-to-date and comprehensive turbine comparisons for Türkiye: Despite the availability of numerous regional analyses on Türkiye's wind energy potential, the number of holistic studies that comparatively evaluate small and medium-scale wind turbines based on technical, economic, and site suitability criteria remains limited. While Bilir et al. [7] and Yaman [13] provide valuable findings for specific turbine types, there is a clear lack of recent studies in which normalized power curves, wind regime modeling, and AEP estimations are compared within a unified methodological framework. Moreover, although Supçiller and Toprak [11] and Şahin and Deliktaş [15] present MCDM-based turbine selection examples for Türkiye, these studies do not include comprehensive comparisons grounded in long-term, site-scale production data. This shortcoming hampers the scientific support of turbine selection strategies and technology development policies tailored to Türkiye's specific conditions.

Limited economic analyses for small-scale wind turbines: While the technical performance of small-scale wind turbines has been extensively examined, detailed analyses of economic indicators—such as investment costs, operation and maintenance (O&M) expenses, LCOE, and payback period—remain scarce. Although Yıldız et al. [66] and Donnelly et al. [67] present studies focusing on O&M costs, their analyses predominantly address large-scale or offshore turbines. Given that O&M costs constitute a higher proportion of total energy production costs in small turbines, economic assessments require a different methodological treatment; however, this proportion is rarely quantified in the existing literature. Rodríguez-Hernández et al. [4] contribute to economic evaluations, yet the geographical scope of their study is limited, and the lack of up-to-date cost analyses for regions with wind regimes similar to Türkiye persists. Consequently, LCOE-based comparisons for small-scale turbines remain a significant gap in the literature.

Insufficient consideration of environmental impacts (noise, bird collision, visual impact): The closer proximity of small-scale wind turbines to residential areas necessitates a comprehensive evaluation of environmental impacts. Nevertheless, studies addressing these impacts in an integrated manner are limited. Research on noise [61], including the work of Seevers et al. [63], provides technical insights into aerodynamic and mechanical noise sources; however, most studies are laboratory-based and lack sufficient field validation. Furthermore, very few studies simultaneously assess environmental criteria—such as bird collision risk, visual impact, and ecosystem compatibility—together with the technical parameters of small-scale turbines. Although Torres-Madroñero et al. [18] examine operational constraints, environmental dimensions are only marginally addressed. Therefore, the multidisciplinary evaluation of environmental impacts specific to small wind turbines represents a substantially underexplored research area.

Insufficient field validation in studies integrating wind regime modeling and turbine optimization: Significant progress has been made in recent years in wind regime modeling. Song et al. [30] proposed advanced methods for equivalent rotor wind speed estimation, while Aldaoudeyeh [51] and Kihel et al. [52] introduced improved versions of the Weibull function. However, studies that integrate these models with turbine performance optimization and validate them using field data are very limited. Although Mushtaq et al. [32] improved power curve modeling, field validation remains restricted. Similarly, artificial intelligence- and genetic algorithm-based optimization models developed by Dong et al. [74] and Mestari et al. [75] demonstrate high performance in simulation environments, yet have not been comprehensively tested using real turbine production data. This situation clearly indicates the need for studies that integrate wind regime modeling and turbine performance optimization with long-term field measurements.

Overall, these gaps highlight the necessity for future research that combines robust methodological frameworks with long-term, site-validated data, particularly for small and medium-scale wind turbines operating under region-specific conditions.

4. Conclusion

This study systematically consolidates the dispersed knowledge in the literature by examining the technical, aerodynamic, economic, and optimization-based criteria used in the selection of small and medium-scale wind turbines within a holistic framework. The findings yield important implications for both academic research and engineering-oriented decision-making processes.

Integrated analysis of technical criteria: The combined evaluation of the rotor diameter–swept area relationship, TSR–Cp aerodynamic curves, Weibull wind speed distribution, and power curve parameters together with AEP calculations clearly identifies the key factors governing small wind turbine performance. In particular, the dominant influence of rotor diameter on AEP and the critical role of TSR in aerodynamic efficiency confirm the decisive importance of technical criteria in turbine selection. The effect of the wind regime on performance sensitivity, as revealed through Weibull distribution analysis, normalized power curves, and capacity factor evaluations, demonstrates that small wind turbine performance is highly sensitive to regional wind conditions. Since energy production is predominantly concentrated in low-to-moderate wind speed ranges, these findings underscore the necessity of designing turbine power curves in close alignment with the statistical characteristics of the wind resource.

Evaluation of optimization approaches: A comparative assessment of artificial intelligence-based models (ANN, GRU, CEEMD–GRU), MCDM methods (AHP, TOPSIS, VIKOR, CoCoSo), and hybrid approaches indicates that hybrid methods, in particular, provide superior performance in reducing uncertainty and strengthening decision support. The classification presented in Table 1 offers an original contribution to the literature by integrating these approaches within a unified framework specifically for small and medium-scale wind turbine applications.

Literature gaps and future research needs: The analyses conducted in this study reveal several methodological gaps in the existing literature, including the limited number of small wind turbine comparisons specific to Türkiye, insufficient economic data, the restricted treatment of noise and environmental impacts, and the lack of studies validating the relationship between wind regime and turbine performance using field data. By systematically identifying these deficiencies, the present study provides a guiding foundation for future research.

In this context, the following research directions emerge as priorities:

• Development of artificial intelligence-based real-time turbine optimization systems,

• Establishment of small wind turbine classifications tailored to Türkiye's wind profiles,

• Implementation of AEP and performance analyses validated through long-term field measurements,

• Multidimensional environmental assessments linking noise, bird collision risk, and visual impact with technical design parameters,

• Support of economic indicators specific to small-scale turbines (LCOE, O&M costs, payback period) through comprehensive databases.

Overall, this study brings together technical performance parameters and optimization approaches within a common methodological framework, providing a comprehensive, applicable, and gap-filling reference for the selection of small and medium-scale wind turbines. In this respect, the work constitutes a significant contribution to both the academic literature and practical engineering applications.

Author contributions

Nesrin İlgin Beyazit: Conceptualization, Methodology, Data curation, Software, Writing-Reviewing and Editing.

Conflicts of interest

The author declares no conflicts of interest.

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