Applied Engineering Letters Vol.10, No.4, 211-221 (2025) e-ISSN: 2466-4847

A HYBRID STATISTICAL APPROACH FOR PERFORMANCE OPTIMIZATION OF MICRO-SCALE WIND ENERGY SYSTEMS

UDC:621.548

Original scientific paper https://doi.org/10.46793/aeletters.2025.10.4.3

Dattu Balu Ghane[1*], Vishnu D. Wakchaure[1]

[1]Amrutvahini College of Engineering, Sangamner- 422608, Dist. Ahilyanagar, India

Abstract:
Micro wind turbines (MWTs) are becoming a promising source of electricity generation for decentralised electricity generation, especially in rural areas. The efficiency of MWTs depends on some design and operational factors, including the number of blades, blade radius and wind speed. This paper seeks to establish the effects of these parameters on the performance of the turbine and determine the best configuration that will yield the highest power and efficiency. The experimental design was done systematically using the Taguchi method with an L16 orthogonal array to reduce the number of experiments required for the analysis. Two dependent variables, namely power output and coefficient of performance (Cp), were recorded for each configuration tested. The results of the experiments were analyzed using Analysis of Variance (ANOVA) to test the significance of each input factor and the Weighted Sum Model (WSM) for multi-objective optimization. As for the WSM method, unequal weights were assigned to power (0.35) and Cp (0.65), with efficiency taking precedence over other factors. The optimization studies revealed that the highest performing turbine was the three-bladed turbine with a radius of 0.26 m and a wind speed of 12 m/s. Confirmation experiments under these conditions also showed the same results with little variability, thus confirming the experimental results. The present work offers a systematic, quantitative approach to improve MWT performance, useful for the design and implementation of small-scale wind energy systems in distributed energy applications.

ARTICLE HISTORY
Received: 8 September 2025
Revised: 4 November 2025
Accepted: 21 November 2025
Published: 15 December 2025

KEYWORDS
Micro wind turbine, Performance evaluation, Taguchi method, ANOVA, WSM optimization

1. INTRODUCTION

The world energy map is changing, and countries are shifting from reliance on conventional sources of energy, such as fossil fuels, to clean energy. This is due to the rising global concern of greenhouse gas emissions, climate change, and energy security [1–4]. Wind energy is one of the most important renewable energy sources because of its ability to be scaled up, the reduction in costs and the availability of the resources in most parts of the world [5–8]. The growth of wind power is further enhanced by the advancements in the technology of turbines, resource assessment, and integration of the power grid [9–12]. Modern methods of wind energy extraction include onshore wind power, offshore wind power, floating wind power, and vertical axis wind turbines, depending on the area and conditions of the location, thus enhancing the use of the resource and speeding up the shift to clean energy [13–15].

MWTs are an effective solution for decentralized and small-scale electricity generation, particularly in areas where the centralized electricity

*CONTACT: Dattu Balu Ghane, e-mail: dattu.ghane@gmail.com

infrastructure is lacking or is underdeveloped. These compact systems are used to capture wind energy at low speed and can be installed in homes, farms or small communities to provide electricity for such facilities [16–19]. It is crucial in decentralizing electrification for energy democracy and minimizing dependence on diesel generators and providing energy in low-resource environments [20–23]. Besides the renewable benefits of generating clean electricity without any emissions, these turbines have associated economic benefits such as cheaper electricity prices, energy security, and possible employment for local engineers in the installation and maintenance of turbines. Due to these characteristics, Micro Wind Turbines (MWTs) are most suitable for rugged terrains and underdeveloped areas where the installation of conventional power systems is either impossible or financially unviable [24–27].

The optimization of MWTs also poses several challenges because of the interdependency of various design parameters that need to be fine-tuned for efficiency. Among these parameters, the number of blades, blade radius, and the wind speed that is available to the turbine are some of the most important parameters that determine the power produced as well as the aerodynamics of the turbine. The number of blades influences torque and rotational speed; it has been found that three to five blades may be the most effective under some conditions; adding more blades may decrease efficiency due to drag and costs [28–30]. Blade radius is also important since it affects the swept area and the capacity of the turbine to capture wind energy; nevertheless, the increase in the radius leads to an increase in the structure load and rotation inertia, which can decrease efficiency in low wind speed [16,31,32]. Another important factor is the availability of wind speed since power is directly proportional to the cube of the wind speed, and therefore, a slight increase in velocity leads to a huge increase in energy produced. However, MWTs operate primarily in low wind speed environments and hence, the design of the blade, pitch angle, and aerofoil has to be optimized to work in such conditions [33].

A number of research studies have been conducted in the recent past to determine how micro and small-scale wind turbines can be designed to be more efficient aerodynamically, structurally, and in terms of energy yield under low wind speeds. In research [34] Q-Blade and Boundary Element Method (BEM) theory were used to model and analyze NACA 4412 and SG6043 aerofoils for Horizontal Axis Wind Turbine (HAWT), and found that the maximum power output of 245.09 W at Tip Speed Ratio (TSR) of 6 with low cut-in velocity of 1.80 m/s and 1.70 m/s respectively, which could be very effective for low wind areas. In the same way in paper [35] used a genetic algorithm in conjunction with BEM to optimize chord length and twist angle and achieved a tremendous 140% improvement in the startup torque with a mere 1.5% decrease in the power coefficient, thus allowing the operation of the turbine at a low wind speed of 4 m/s. In research [36], the BEM modelling was enhanced by incorporating the Viterna-Corrigan stall model, and the optimised blade design was further verified by simulating in the MATLAB/Simulink environment, resulting in lower cut-in speed and higher power output than the experimental values.

In research [37] BEM, Classical Lamination Theory and Particle Swarm Optimisation were used to study the effects of blade length and hub height, and it was found that hub height has a greater impact on reducing the cost of energy by 17.54% than the rotor diameter. In the structural design aspect, in research [38] BEM and Finite Element Analysis (FEA) were integrated to design a 5 kW HAWT blade using carbon fiber material, resulting in a 22% reduction in mass, an 11% reduction in deflection, and an expected 20-year operational lifespan. In research [39], a combination of Taguchi's L16 array and the Moth-Flame Optimization algorithm was used to design 3D-printed Polylactic Acid (PLA) blades and determine the infill and wind speed at which 100 W can be generated in low wind conditions with better structural strength than Acrylonitrile Butadiene Styrene (ABS).

In research [40], Computational Fluid Dynamics (CFD) and a genetic algorithm were used to design a wind turbine blade with a length of 5.244 m, achieving a better lift-to-drag ratio and maximum *Cp* of 0.4658 at TSR 6 compared to the conventional NACA 4412. Research [41] examined the aerodynamics and structure of wind turbines and found that proper blade designs can enhance power by 35% while the adjustment of the inclination angle can increase power by up to 66%. Additionally, the use of a confusor–diffuser configuration increased local wind speed by 21% and contributed to improved overall performance. In research [42], ANSYS was used for structural topology optimization and applied to make MWT components more lightweight, durable, reliable and suitable for urban and off-grid applications with reduced Levelized Cost of Energy (LCOE). All of these works collectively assert that micro wind turbine optimization is a multi-disciplinary problem which requires consideration of aerodynamics, materials science, structural mechanics and application of modern optimization algorithms to obtain the most appropriate solution that would enable micro wind turbines to work in different environments.

The above literature provides the direction that the designed model should generate (the highest) optimal Coefficient of Power (*Cp*) at the respective (lower) tip speed ratio. The power and torque generated by the designed model should be higher at low wind speeds.

Although many studies have been conducted to optimize wind turbines, few of them have been dedicated to the experimental and statistical optimization of micro wind turbines in low-wind environments, starting from 2 m/s with 0.4m blade length and high wind speed up to 22 m/s. This research fills this gap by adopting Taguchi design, Analysis of Variance (ANOVA), and Weighted Sum Model (WSM) for the multi-objective performance optimization. The goal was to find out the best combination of parameters that will give the highest power and efficiency. The research provides a clear and systematic method that can be easily replicated with the help of experimental confirmation tests.

2. MATERIAL AND METHODS

In this study, experimental design, statistical analysis and multi-criteria optimization are integrated to evaluate and improve the performance of MWT. A systematic approach based on Taguchi design of experiments, ANOVA and the WSM was used to systematically analyze the effect of the key design parameters and to identify the optimal configuration.

2.1 Experimental Design

The Taguchi method was used to study systematically the effect of key design parameters on the performance of an MWT. Using this method facilitates efficient experimental planning, in which it is possible to reduce the number of trials needed to a minimum while procuring statistically significant results. An investigation was carried out on three input parameters, namely the number of blades, the blade radius and the wind speed. Preliminary design considerations and practical applicability were used to assign four levels to each parameter.

The Taguchi L16 (4^3) orthogonal array, which accommodates three factors at four levels, allows only 16 experimental runs, and was used to structure the experimental design. Table 1 shows the parameters and their levels, and Table 2 shows the complete orthogonal array with factor assignments.

Table 1. Control parameters and their levels

Level	Number of Blades	Blade Radii (m)	Wind Speed (m/s)
1	3	0.20	3
2	4	0.22	6
3	5	0.24	9
4	6	0.26	12

Table 2. Taguchi L16 orthogonal array with assigned factor levels

Experiment	Number of Blades	Blade Radii (m)	Wind Speed (m/s)
1	3	0.20	3
2	3	0.22	6
3	3	0.24	9
4	3	0.26	12
5	4	0.20	6
6	4	0.22	3
7	4	0.24	12
8	4	0.26	9
9	5	0.20	9
10	5	0.22	12
11	5	0.24	3
12	5	0.26	6
13	6	0.20	12
14	6	0.22	9
15	6	0.24	6
16	6	0.26	3

This orthogonal array allows for the determination of the significant factors and their levels that would require fewer experiments to conduct, and forms the basis of the subsequent ANOVA and WSM optimization.

2.2 Statistical Analysis

In this research, ANOVA was used to determine the statistical significance of each input parameter, number of blades, blade radius, and wind speed, on the output responses of the micro wind turbine, power output and coefficient of performance. A linear model based on the experimental design generated through the Taguchi L16 orthogonal array was used in the ANOVA separately for both response variables. This method allowed decomposition of the total variation in the results into contributions from individual factors and experimental error. Each parameter was treated as a categorical variable with four levels, and the ANOVA was used to determine whether the levels of each parameter had statistically significant effects on the responses. The analysis of the results yielded the F values and p values, which were used to systematically evaluate the relative influence of input variables, which in turn supported the subsequent interpretation and optimization steps of the study.

2.3 Optimization Methodology

The WSM served as the multi-criteria decision-making (MCDM) tool in this research to find the best micro wind turbine system configuration through multiple performance indicator analysis. The study measured power output together with the coefficient of performance to serve as the main response variables for energy generation and aerodynamic efficiency assessment. The experimental data from the Taguchi L16 orthogonal array underwent normalization before WSM implementation to make criteria with varying units and magnitudes comparable. The benefit-type normalization formula served to normalize the data as follows:

$$X_{ij}^{norm} = \frac{X_{ij}}{X_j^{max}} \quad (1)$$

where X_{ij} - is the value of the *j*-th criterion for the *i*-th alternative, and X_j^{max} - is the maximum observed value of that criterion across all alternatives. The method transforms all values into a range from 0 to 1 while using 1 to indicate the most successful observed result.

The work assigned unequal weights to represent different response importance levels. The evaluation system assigned a 0.35 weight value to power output but gave a 0.65 weight value to *Cp* to reflect the higher importance of efficiency compared to power generation. The WSM score calculation for each configuration depended on this mathematical expression:

$$WSM_i = \omega_1 \cdot X_{i1}^{norm} + \omega_2 \cdot X_{i2}^{norm} \quad (2)$$

where WSM_i - is the overall score for the ith configuration, $\omega_1 = 0.35$ and $\omega_2 = 0.65$ are the weights for power and *Cp*, respectively, and X_{i1}^{norm}, X_{i2}^{norm} - are their corresponding normalized values. ω_1 and ω_2 values are decided based on the importance of each criterion relative to the others and experimental test results. The method generated a single composite score which combined the performance criteria with their specified priorities to enable comparison of experimental runs through ranking. The configuration achieving the highest WSM score became the optimal choice because it successfully balanced energy output with aerodynamic efficiency.

The optimization procedure being considered follows a methodical flow that begins with the clear formulation of the problem and the design of the experiment based on the Taguchi approach. The next stages are the systematic experimentation and the processing of the received data, which will be followed by the evaluation of normalized output variables through the WSM and, ultimately, the choice and validation of the best configuration. Fig. 1 illustrates this entire workflow in a schematic manner.

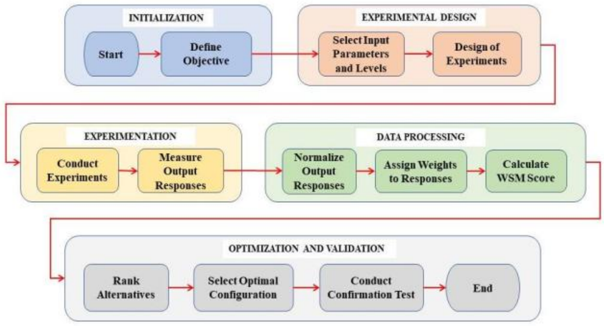


Fig. 1. Optimization process flowchart for performance enhancement of a micro wind turbine using Taguchi design and WSM

2.4 Experimental Setup

An experimental setup was designed to study the performance of an HAWT in a controlled wind environment. This setup, as shown in Fig. 2, consists of an axial-flow fan with a variable-frequency drive, a wind tunnel, the test turbine, and a set of real-time monitoring equipment. The fan was placed at the inlet of the tunnel, providing a steady airflow that was adjustable in velocity between 3 m/s and 12 m/s, thus providing uniform testing environments.

The HAWT was placed in the middle of the wind tunnel and oriented directly towards the air flowing in. The blade assemblies were 3D-printed in successive sets using thermoplastic polyurethane and with radii of 0.20 m, 0.22 m, 0.24 m, and 0.26 m and were installed alongside blade configurations of 3, 4, 5, and 6 rotors. A KE-856A digital anemometer mounted at blade height provided wind speed measurements with less than 3% error, and a DT-2234C non-contact rotational-speed sensor provided the rotations per minute (RPM) of the turbine without a mechanical connection. At the same time, the electrical power generated was recorded by a precision power meter connected to the turbine output terminals.

All instruments were connected to a data acquisition system to record wind speed, rotational speed and electrical power simultaneously. Such a combined architecture allowed accurate and repeatable measurement of turbine performance over a range of experimental conditions.

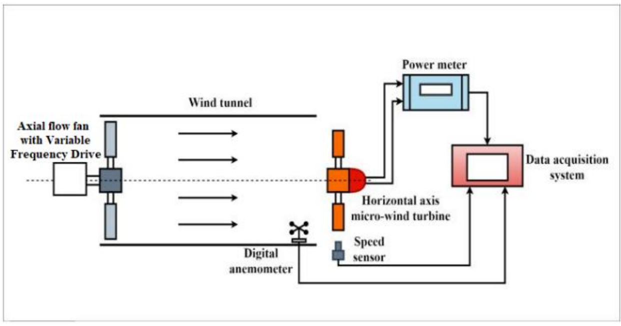


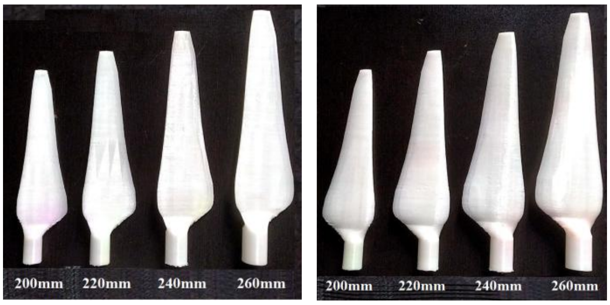
Fig. 2. Schematic diagram of the experimental test setup

2.5 3D Printed Blade Geometry

The blades used in this study were made of thermoplastic polyurethane, a polymer that is highly appreciated due to its combination of flexibility, impact resistance, strength, elasticity and fatigue properties-the latter being especially relevant to dynamic applications like wind turbines. The radius values tested included 0.20 m, 0.22 m, 0.24 m, and 0.26 m , which were a systematic sampling that was aimed at defining the effect of blade geometry on power and efficiency.

Fig. 3(a) and 3(b) show the front and back sides of the 3-D-printed blades, respectively, which are systematically lengthened and intentionally aerodynamically shaped in each of the configurations. The blades have a tapered profile, a smooth leading edge and a widening mid-section, all intended to maximise lift generation and minimise form drag. Close dimensional control during manufacture was adhered to in order to maintain consistency in structural integrity and surface finish. The mounting base was designed in such a way that it fits perfectly with the hub of the turbine, thus making it easier to perform consistent testing at all radii.

These geometrical decisions were specifically made to increase the capacity of the turbine to capture energy at low to moderate wind speeds and maintain mechanical reliability.



a) Front side b) Back side

Fig. 3. Front and back views of 3D-printed micro wind turbine blades with varying radii

3. RESULTS AND DISCUSSION

The results and discussion section provides detailed information about the experimental results using Taguchi design of experiments, ANOVA, and WSM optimization.

3.1 Experimental Test Results

Table 3 contains the experimental findings that provide a comprehensive analysis of the relationship between the number of blades, the blade radius, and wind speed on the output power and *Cp* of the micro wind turbine. The most significant factor affecting both the output responses is the wind speed. This is technically justified by the fundamental wind power equation as follows:

$$P = \left(\frac{1}{2}\right)\rho A V^3 \quad (3)$$

where are: *P* - is power, *ρ* - is air density, *A* - is the swept area, and *V* - is wind speed. This is because power varies with the cube of wind speed; as such, even minor improvements in wind velocity greatly improve power production. This is apparent from the comparison of Experiment 1, conducted at a low wind speed of 3 m/s with a power output of 0.40 W, and Experiment 4, conducted at a high wind speed of 12 m/s with a power output of 76.45 W, which shows a considerable increase in power as shown in Fig. 4.

Table 3. Experimental test results

Expt.	No. of Blades	Blade Radii (m)	Wind Speed (m/s)	Power (W)	Cp
1	3	0.20	3	0.40	0.19
2	3	0.22	6	6.64	0.33
3	3	0.24	9	32.33	0.40
4	3	0.26	12	76.45	0.34
5	4	0.20	6	4.63	0.28
6	4	0.22	3	0.59	0.24
7	4	0.24	12	55.87	0.29
8	4	0.26	9	41.61	0.44
9	5	0.20	9	19.73	0.35
10	5	0.22	12	47.45	0.29
11	5	0.24	3	0.98	0.33
12	5	0.26	6	13.00	0.46
13	6	0.20	12	39.60	0.30
14	6	0.22	9	28.56	0.42
15	6	0.24	6	9.51	0.40
16	6	0.26	3	1.31	0.37

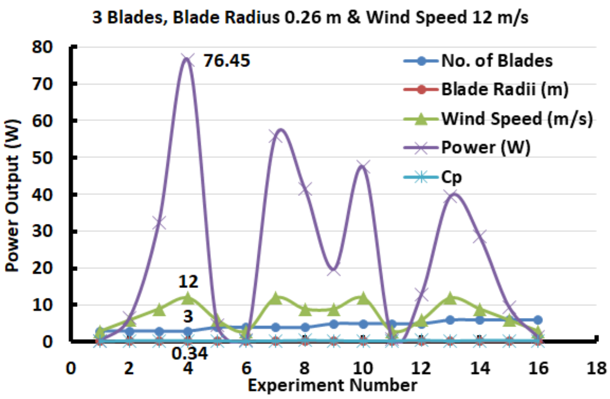


Fig. 4. Experimental Test Results

Blade radius is the second most significant factor since it impacts the swept area of the turbine, which is the third important factor in the wind power formula. With the increase in the radius, the area that can be used to harness wind power also increases, thus increasing the power output. For example, at 6 m/s wind speed, Experiment 2 (blade radius 0.22 m) yields 6.64 W while Experiment 12 (blade radius 0.26 m) yields 13.00 W; therefore, a slight increase in the radius results in a much higher energy yield. This also results in increased *Cp* values, which means improved aerodynamic performance of the turbine.

The number of blades influences the performance of the turbine by having to balance between the torque produced and the amount of drag force acting on the blades. More blades usually mean more torque, which is advantageous at low rotational speeds of the wind turbine. But if there are too many blades, it causes more drag and hence the rotational speed will be affected in a negative way. From the data, it can be observed that turbines with 5 blades yield the best *Cp* at medium wind speed, particularly Experiment 12 with 5 blades, 0.26 m radius, and 6 m/s wind speed, which has the highest *Cp* of 0.46. The 3-blade configurations, like in Experiment 4, on the other hand, produce high power at higher wind speeds, although the *Cp* values are slightly lower since the aerodynamics of the turbine are not fully optimal at such conditions.

3.2 ANOVA Results

The outcomes of the ANOVA analysis of both output parameters, namely power and *Cp*, are shown in Tables 4 and 5, respectively. These tables show the level of significance of the three independent variables: number of blades, blade radius, and wind speed on the performance of the micro wind turbine.

Table 4. ANOVA Results for Power

Source	Sum of Squares	df	F-value	p-value
Blades	0.011380	3	15.97667	0.002884
Radius	0.033121	3	46.49726	0.000151
Wind Speed	0.037034	3	51.99128	0.000110
Residual	0.001425	6	–	–

In the case of power output, Table 4 indicates that out of all the independent variables, wind speed has the highest p-value of 0.000110 and F-value of 51.99. This is in line with the theory because wind speed determines the amount of kinetic energy that can be harnessed according to the wind power formula, which is the cube of the wind speed. The wind power is directly proportional to the cube of the wind speed, and this is well illustrated in the experimental data, where the increase of the wind speed from 3 m/s to 12 m/s leads to an exponential increase in the output power. The second most significant factor is blade radius, with the p-value of 0.000151 and F-value of 46.50, meaning that the bigger blade areas collect more wind energy to produce more power. The number of blades, though not as dominant as the other parameters, is also statistically significant (p = 0.002884, F = 15.98), which means that the number of blades does play a role in the torque and rotor performance, especially at low to moderate wind speeds.

Table 5. ANOVA Results for Coefficient of Performance (*Cp*)

Source	Sum of Squares	df	F-value	p-value
Blades	0.011380	3	15.97667	0.002884
Radius	0.033121	3	46.49726	0.000151
Wind Speed	0.037034	3	51.99128	0.000110
Residual	0.001425	6	–	–

As for the coefficient of performance, Table 5 shows the same trend as well. Again, the wind speed is found to be the most significant factor with the probability level of 0.000110 and F-statistic of 51.99, followed by blade radius with probability level of 0.000151 and F-statistic of 46.50, and the number of blades with probability level of 0.002884 and F-statistic of 15.98. The *Cp* is a non-dimensional parameter which indicates the ability of the turbine to transform the wind energy into mechanical power. The significantly higher F-values and lower p-values of wind speed and blade radius support their predominance in aerodynamic efficiency and the significance of blade count in the reduction of losses and achieving the blade-tip speed ratio.

3.3 Optimization Results

Table 6 shows the optimization of the MWTS by using WSM, which compares the power output and *Cp* to determine the best configuration of the 16 trials. The results indicate that Experiment 4 with the turbine having 3 blades, a blade radius of 0.26 m and a wind speed of 12 m/s has the highest WSM score and is ranked first. This configuration produces the maximum power of 76.45 W and *Cp* of 0.34 which is a good balance between mechanical power and aerodynamics as sown in Fig. 5. This configuration is dominant on the grounds of the wind power equation which states that power is a function of the cube of the wind velocity and square of the blade radius, meaning that high velocity of wind and larger swept area greatly improves performance.

Table 6. Optimization results using the Weighted Sum Method

Expt.	Power (W)	Cp	P norm	Cp norm	WSM score	Rank
1	0.40	0.19	0.19	0.32	0.27	16
2	6.64	0.33	0.33	0.56	0.48	11
3	32.33	0.40	0.40	0.67	0.58	6
4	76.45	0.34	0.34	0.57	0.49	1
5	4.63	0.28	0.28	0.47	0.40	12
6	0.59	0.24	0.24	0.40	0.34	15
7	55.87	0.29	0.29	0.49	0.42	2
8	41.61	0.44	0.44	0.74	0.63	4
9	19.73	0.35	0.35	0.59	0.51	8
10	47.45	0.29	0.29	0.50	0.43	3
11	0.98	0.33	0.33	0.55	0.47	14
12	13.00	0.46	0.46	0.78	0.67	9
13	39.60	0.30	0.30	0.50	0.43	5
14	28.56	0.42	0.42	0.71	0.61	7
15	9.51	0.40	0.40	0.67	0.57	10
16	1.31	0.37	0.37	0.63	0.54	13

Experiment 8 is the second-ranked experiment, which uses 4 blades with a 0.26 m radius at 9 m/s wind speed. Although the power output in this case is lower than in Experiment 4, its *Cp* of 0.44 is excellent for energy conversion efficiency under moderate wind conditions. Experiment 14, which is the third, uses 6 blades with a 0.22 m radius and a wind speed of 9 m/s to achieve both competitive power and *Cp* of 0.42. These results show that while high wind speed is an important driver of power output, the number of blades and blade geometry are important in maximizing efficiency.

The configurations ranked lower, like Experiments 1, 5, and 6, have a low wind speed and small blade radius, and therefore, low energy capture and *Cp*. For instance, Experiment 1 is ranked as the lowest with a 3-blade system at 0.2 m radius, 3m/s velocity and generating only 0.40 W of power with a *Cp* of 0.19. These results confirm the fact that there is a need for adequate wind power input and proper sizing of the rotor in order to achieve the best results in the performance of the turbine.

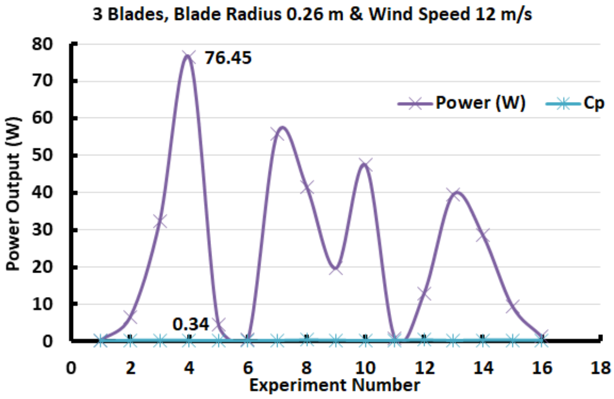


Fig. 5. Optimization of the MWTS by using WSM

3.4 Confirmation of Optimal Configuration

The confirmation test results provided in Table 7 confirm the optimal configuration obtained during the Taguchi-WSM optimization, which includes the number of blades of 3, blade radius of 0.26 m and blade speed of 12 m/s. These three consecutive trials under these conditions were 76.12 W, 75.88 W, and 76.45 W for the power output, and 0.342, 0.339, and 0.345 for *Cp*, respectively. The average power output of the trials was 76.15 W with a standard deviation of 0.29 W, which shows that the energy produced is quite consistent across the trials. Likewise, the mean coefficient of performance was calculated to be 0.342 with the standard deviation of 0.003, which further ensured the consistency and reliability of the aerodynamic efficiency at these settings.

Table 7. Confirmation Test Results for Optimal Configuration

Expt.	No. of Blades	Blade Radii (m)	Wind Speed (m/s)	Power Output (W)	Cp
1	3	0.26	12	76.12	0.342
2	3	0.26	12	75.88	0.339
3	3	0.26	12	76.45	0.345

Compared to the results obtained in Experiment 4 of the initial experimental design, where the power output was recorded to be 76.38447 W and the *Cp* of 0.34, the confirmation test results are similar. The variations in the output values are quite small, which is in the range of variability that is expected from experiments, thus supporting the validity of the optimization process. The minimal deviations also imply that the experimental setup is reliable and the identified configuration yields similar results when the experiment is repeated.

4. CONCLUSION

This research provided a comprehensive analysis of the performance evaluation and optimization of MWT through experimental techniques and tools in statistics and decision-making. The goal of this study was to establish the effect of the number of blades, the radius of the blades and the wind speed on the power output of the turbine and its coefficient of performance and to identify the most effective configuration of the turbine in terms of energy capture and aerodynamic efficiency. The experimental design adopted was the Taguchi L16 orthogonal array, and the results were analyzed using ANOVA to test the parameters for significance and WSM for the multi-objective optimization.
The key conclusions drawn from this study are:

- Wind speed was considered the most critical factor influencing both the power and *Cp* because of its cubed impact on energy production.
- Blade radius was the second most significant factor that affected the swept area and consequently the amount of energy that can be harnessed from the wind.
- The number of blades was also found to have a statistically significant but relatively less impact, which impacted the torque and rotational speed due to the wind speed.
- Accordingly, it was found from WSM analysis with non-equal weights (power: 0.35, *Cp*: 0.65) that the optimum configuration is 3 blades, 0.26 m blade radius, and 12 m/s wind speed.
- The confirmation test carried out in an optimal environment proved to have a high level of consistency, thereby confirming the reliability of the identified configuration.

Wind speed determines how much energy is available in the wind; even a small increase in wind speed gives a huge rise in energy output, while the number of blades only determines how efficiently that energy is captured. Therefore, wind speed is the most significant factor, and the number of blades is the least.

Further research should be done to incorporate other factors, such as the pitch angle of the blade, the shape of the blade, and the yaw angle, into the optimization model. The integration of computational fluid dynamics modelling could help in understanding the aerodynamics and the flow field in a much better way. Besides, the assessment under the real wind conditions and considering the synergies of a hybrid optimization approach might improve the applicability of MWTs in decentralised systems, especially for rural and off-grid areas.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest to report regarding the present study.

REFERENCES

[1] Q. Hassan, P. Viktor, T.J. Al-Musawi, B.M. Ali, S. Algburi, H.M. Alzoubi, A.K. Al-Jiboory, A. Zuhair Sameen, H.M. Salman, M. Jaszczur, The renewable energy role in the global energy Transformations. *Renewable Energy Focus*, 48 2024: 100545. https://doi.org/10.1016/j.ref.2024.100545

[2] P. Sadorsky, Wind energy for sustainable development: Driving factors and future outlook. *Journal of Cleaner Production*, 289 2021: 125779. https://doi.org/10.1016/j.jclepro.2020.125779

[3] A.R. Varne, S. Blouin, B.L.M. Williams, D. Denkenberger, The Impact of Abrupt Sunlight Reduction Scenarios on Renewable Energy Production. *Energies*, 17(20), 2024: 5147. https://doi.org/10.3390/en17205147

[4] K. Nam, S. Hwangbo, C. Yoo, A deep learning-based forecasting model for renewable energy scenarios to guide sustainable energy policy: A case study of Korea. Renewable and Sustainable *Energy Reviews*, 122, 2020: 109725. https://doi.org/10.1016/j.rser.2020.109725

[5] M. Xiao, T. Junne, J. Haas, M. Klein, Plummeting costs of renewables - Are energy scenarios lagging?. *Energy Strategy Review*, 35, 2021: 100636. https://doi.org/10.1016/j.esr.2021.100636

[6] R.J. Barthelmie, S.C. Pryor, Climate Change Mitigation Potential of Wind Energy. *Climate*, 9(9), 2021: 136. https://doi.org/10.3390/cli9090136

[7] A. Kudelin, V. Kutcherov, Wind ENERGY in Russia: The current state and development trends. *Energy Strategy Reviews*, 34, 2021: 100627. https://doi.org/10.1016/j.esr.2021.100627

[8] D.X. He, Y. Li, Overview of Worldwide Wind Power Industry, in: Strategies of Sustainable Development in China's Wind Power Industry. Springer, Singapore, 2020: 29-60. https://doi.org/10.1007/978-981-13-9516-1_2

[9] A. Martinez, G. Iglesias, Global wind energy resources decline under climate change. *Energy*, 288, 2024: 129765. https://doi.org/10.1016/j.energy.2023.129765

[10] S.H. Li, Impact of climate change on wind energy across North America under climate change scenario RCP8.5. *Atmospheric Research*, 288, 2023: 106722. https://doi.org/10.1016/j.atmosres.2023.106722

[11] D.L. Woodard, A. Snyder, J.R. Lamontagne, C. Tebaldi, J. Morris, K.V. Calvin, M. Binsted, P. Patel, Scenario Discovery Analysis of Drivers of Solar and Wind Energy Transitions Through 2050. *Earth's Future*, 11(8), 2023: e2022EF003442. https://doi.org/10.1029/2022EF003442

[12] B. Rachunok, A. Staid, J.-P. Watson, D.L. Woodruff, Assessment of wind power scenario creation methods for stochastic power systems operations. *Applied Energy*, 268, 2020: 114986. https://doi.org/10.1016/j.apenergy.2020.114986

[13] S. Baur, B.M. Sanderson, R. Séférian, L. Terray, Change in Wind Renewable Energy Potential Under Stratospheric Aerosol Injections. *Earth's Future*, 12(10), 2024: e2024EF004575. https://doi.org/10.1029/2024EF004575

[14] K. Abhishek, Scenario of Wind Energy in India - A Review. *i-Manager's Journal of Future Engineering and Technology*, 18(2), 2023: 40-47. https://doi.org/10.26634/jfet.18.2.19017

[15] M. Glowik, W.A. Bhatti, A. Chwialkowska, A cluster analysis of the global wind power industry: Insights for renewable energy business stakeholders and environmental policy decision makers. *Business Strategy and the Environment*, 32(6), 2023: 2755–2766. https://doi.org/10.1002/bse.3268

[16] D. Ghane, V. Wakchaure, Parametric Analysis and Design Considerations for Micro Wind Turbines: A Comprehensive Review. *Energy Engineering*, 121(11), 2024: 3199–3220. https://doi.org/10.32604/ee.2024.050952

[17] P. Arumugam, V. Ramalingam, K. Bhaganagar, A pathway towards sustainable development of small capacity horizontal axis wind turbines – Identification of influencing design parameters & their role on performance analysis. *Sustainable Energy Technologies and Assessments*, 44, 2021: 101019. https://doi.org/10.1016/j.seta.2021.101019

[18] R.M. Yonk, C. Clark, J. Rood, Regulatory Impediments to Micro-Wind Generation, in: Microgrids and Local Energy Systems. IntechOpen, 2021. https://doi.org/10.5772/intechopen.99688

[19] P. Chauhan, S. Pandey, Meeting future energy demands sustainably: assessing small wind turbine installations in urban built environments. ShodhKosh: *Journal of Visual and Performing Arts*, 5, 2024: 197-210. https://doi.org/10.29121/shodhkosh.v5.iICETDA24.2024.1305

[20] H.E.V. Donnou, G.K. N'Gobi, H. Kougbéagbédè, G. Hounmenou, A.B. Akpo, B.B. Kounouhewa, Study of the Decentralized Electrification by a Micro-Wind Power Plant: Case of Ahouandji Locality in Southern Benin. TH Wildau Engineering and Natural Sciences Proceedings, 1, 2021. https://doi.org/10.52825/thwildauensp.v1i.7

[21] M.A. Qasim, V.I. Velkin, Experimental investigation of power generation in a microgrid hybrid network. *Journal of Physics: Conference Series*, 1706, 2020: 012065. https://doi.org/10.1088/1742-6596/1706/1/012065

[22] C. Veeramani, G. Mohan, Design of Fuzzy Gain Scheduled PI Controller for an Isolated Wind Energy Conversion System. International *Journal of Simulation: Systems, Science and Technology*, 2020: 64-71. https://doi.org/10.5013/IJSSST.a.15.01.09

[23] B. Maheswaran, A. Abd Aziz, E. Alexander, L. Brigandi, C. Branagan, Power Generation Through Small-scale Wind Turbine. 2020 ASEE Virtual Annual Conference Content Access, Virtual Online, 22 June 2020. https://doi.org/10.18260/1-2--35064

[24] S. Vickram, S. Kaviya, H. Dhamodharan, M. Sivasubramanian, Micro-Hydro Systems: Empowering Rural Communities with Small-Scale Solutions. *Nanotechnology Perceptions*, 20, 2024: 108-138. https://doi.org/10.62441/nano-ntp.v20iS6.10

[25] M. Pellegrini, A. Guzzini, C. Saccani, Experimental measurements of the performance of a micro-wind turbine located in an urban area. *Energy Reports*, 7, 2021: 3922–3934. https://doi.org/10.1016/j.egyr.2021.05.081

[26] R. Banihabib, M. Assadi, The Role of Micro Gas Turbines in Energy Transition. *Energies*, 15(21), 2022: 8084. https://doi.org/10.3390/en15218084

[27] J. Vilà, N. Luo, L. Pacheco, T. Pujol, J.R. Gonzalez, I. Ferrer, A. Massaguer, E. Massaguer, Design of an active pitch control for small horizontal-axis wind turbine. *Renewable Energy and Power Quality Journal*, 19(2), 2021: 195-198. https://doi.org/10.24084/repqj19.253

[28] H. Muhsen, W. Al-Kouz, W. Khan, Small Wind Turbine Blade Design and Optimization. *Symmetry*, 12(1), 2019, 18. https://doi.org/10.3390/sym12010018

[29] A. Ashraf, I. Goda, M. M. Abdalla, A Simple Optimization Technique Using Matlab for Small Wind Turbine Blades. 2020 6th IEEE International Energy Conference (ENERGYCon), IEEE, Gammarth, Tunisia, 2020: pp.423–428.

[30] R.K. Gupta, V. Warudkar, R. Purohit, S.S. Rajpurohit, Modeling and Aerodynamic Analysis of Small Scale, Mixed Airfoil Horizontal Axis Wind Turbine Blade. *Materials Today: Proceedings*, 4(4), 2017: 5370–5384. https://doi.org/10.1016/j.matpr.2017.05.049

[31] L.T.T. Nhung, N. Van Y., D. Cong Truong, V. Dinh Quy, CFD analysis of key factors impacting the aerodynamic performance of the S830 wind turbine airfoil. *International Journal of Renewable Energy Development*, 13(6), 2024: 1068-1077. https://doi.org/10.61435/ijred.2024.60249

[32] S. Raut, S. Shrivas, R. Sanas, N. Sinnarkar, M.K. Chaudhar, Simulation of Micro Wind Turbine Blade in Q-Blade. *International Journal For Applied Science and Engineering Technology*, 5(IV), 2017: 256-262. https://doi.org/10.22214/ijraset.2017.4048

[33] E. Tengs, F. Charrassier, M.R. Jordal, I. Iliev, Fully automated multidisciplinary design optimization of a variable speed turbine. *IOP Conference Series: Earth and Environmental Science*, 774, 2021: 012031. https://doi.org/10.1088/1755-1315/774/1/012031

[34] D.A. Umar, C.T. Yaw, S.P. Koh, S.K. Tiong, A.A. Alkahtani, T. Yusaf, Design and Optimization of a Small-Scale Horizontal Axis Wind Turbine Blade for Energy Harvesting at Low Wind Profile Areas. *Energies*, 15(9), 2022: 3033. https://doi.org/10.3390/en15093033

[35] V. Akbari, M. Naghashzadegan, R. Kouhikamali, F. Afsharpanah, W. Yaïci, Multi-Objective Optimization of a Small Horizontal-Axis Wind Turbine Blade for Generating the Maximum Startup Torque at Low Wind Speeds. *Machines*, 10(9), 2022: 785. https://doi.org/10.3390/machines10090785

[36] A. Tahir, M. Elgabaili, Z. Rajab, N. Buaossa, A. Khalil, F. Mohamed, Optimization of small wind turbine blades using improved blade element momentum theory. *Wind Engineering*, 43(3), 2019: 299–310. https://doi.org/10.1177/0309524X18791395

[37] H. Yang, J. Chen, X. Pang, Wind Turbine Optimization for Minimum Cost of Energy in Low Wind Speed Areas Considering Blade Length and Hub Height. *Applied Sciences*, 8(7), 2018: 1202. https://doi.org/10.3390/app8071202

[38] K. Deghoum, M.T. Gherbi, M.J. Jweeg, H.S. Sultan, A.M. Abed, O.I. Abdullah, N. Djilani, Design optimization of small wind turbine blade based on structural and fatigue life analyses. *International Journal of Energy for a Clean Environment*, 24(5), 2023: 53–66. https://doi.org/10.1615/InterJEnerCleanEnv.2022045867

[39] S. Arivalagan, R. Sappani, R. Čep, M.S. Kumar, Optimization and Experimental Investigation of 3D Printed Micro Wind Turbine Blade Made of PLA Material. *Materials*, 16(6), 2023: 2508. https://doi.org/10.3390/ma16062508

[40] C.V. Rodriguez, C. Celis, Design optimization methodology of small horizontal axis wind turbine blades using a hybrid CFD/BEM/GA approach. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 44, 2022: 254. https://doi.org/10.1007/s40430-022-03561-4

[41] M. Jaszczur, M. Borowski, J. Halibart, K. Zwolińska-Glądys, P. Marczak, Optimization of the Small Wind Turbine Design—Performance Analysis. *Computation*, 12(11), 2024: 215. https://doi.org/10.3390/computation12110215

[42] S.C. Vetal, D. Kamble, V. Deulgaonkar, T. Gadekar, S. Mahadik, Structural Topology Optimization of Micro Wind Turbine Components: Integrating Mass and Material Strength Criteria for Realistic Results. SSRN, 2025. https://doi.org/10.2139/ssrn.5118414

© 2025 by the authors. This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License (CC BY-NC 4.0).