كلية الهندسة بشبرا
FACULTY OF ENGINEERING AT SHOUBRA
ERJ
PRINT ISSN 3009-6049
ONLINE ISSN 3009-6022

ENGINEERING RESEARCH JOURNAL (ERJ)
Volume (53) Issue (4)
October. 2024, pp:13-19
https://erjsh.journals.ekb.eg

Taguchi optimization and ANOVA for wind speed measurements of wind turbine

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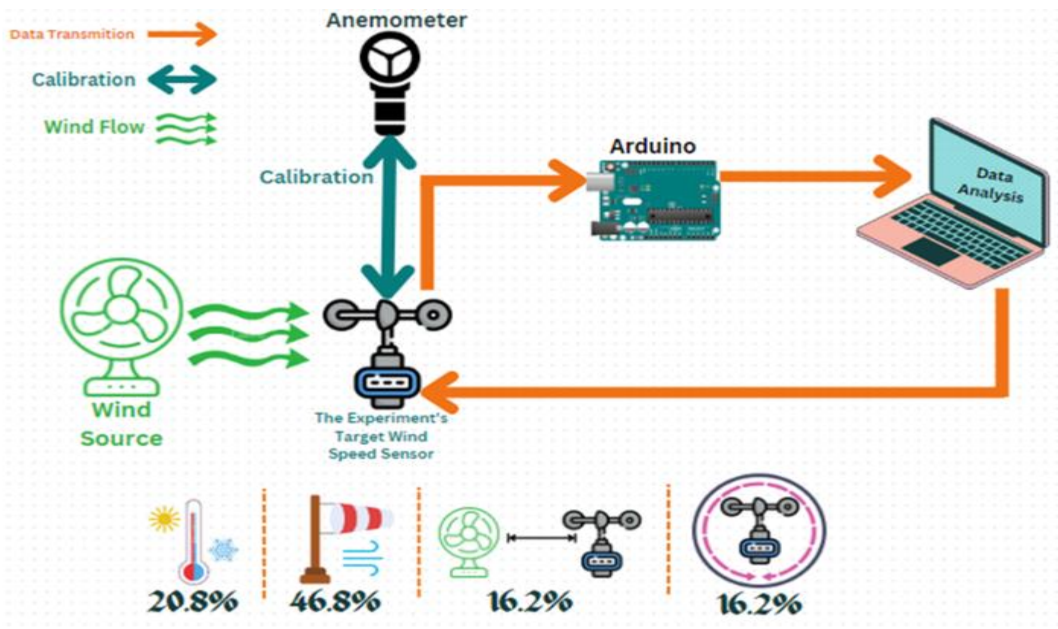
Abstract: Measuring wind speed is an important process in many applications, including measuring wind speed in wind turbines and making some vital actions based on wind speed, such as controlling the pitch angle of the blade and other important applications. The purpose of this work is to optimize the wind speed measurement technique by determining the effect of significant parameters throughout the wind speed measurement for a wind turbine. The findings of experimental wind speed measurement are provided using multiple Design of Experiments (DOE) tools, specifically the Taguchi technique and ANOVA.
The experimental studies take into account four parameters: ambient temperature, tilt angle (wind direction), distance from air source, and surrounding space. These parameters were chosen because they are frequently used in test cases. The results show that the tilt angle is the most significant element, accounting for 46.8% of the total contribution. As a result, Design of Experiment is deemed a reasonable method for determining essential parameters and their contributions to wind speed measurement.

Keywords: Wind Measurement Optimization; Cup Anemometer; Wind Turbine; Analysis of Variance (ANOVA); Taguchi Method; Design of Experiment (DOE).

Graphical Abstract:



1. INTRODUCTION

Measuring wind speeds is essential for a wide array of research and industrial purposes. It spans from basic assessments at construction sites to gauge surrounding air velocities [1], to intricate applications like signal-driven control operations in drone aircraft and wind turbine systems [2] [3]. Furthermore, wind speed measurements serve diverse functions, including weather monitoring, environmental research, and navigation in both aerial and maritime domains [4].

Anemometers are the most common type of wind speed sensors, utilizing cups, vanes, or sonic methods to detect wind movement. Cup anemometers, employing rotating cups, and vane anemometers, utilizing a rotating vane, are traditional mechanical devices. Sonic anemometers, on the other hand, employ ultrasonic sound waves to measure wind speed [5] [6].

Additionally, hot-wire anemometers and windsocks are utilized in specific applications. Hot-wire anemometers measure wind speed based on the cooling effect of air passing over a heated wire, while windsocks provide a visual indication of wind direction and approximate speed [7].

Each type of sensor possesses its own set of advantages and limitations, influencing its suitability for particular applications.

The majority of onsite wind measurements on wind turbines, Fig. 1, are taken with classic cup anemometers. The cup anemometer consists of three cups, each positioned at the end of a horizontal arm and arranged in a star form on a vertical shaft. A cup anemometer rotates in the wind because the open cup has a higher drag coefficient than the smooth back of the cup. Any horizontal flow causes the anemometer to rotate in proportion to the wind speed. Therefore, the rotational speed during a defined period can be utilized to compute the average wind speed [8].

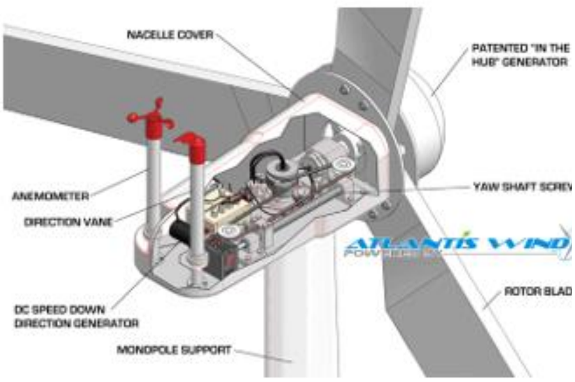


Fig 1 A schematic showing the parts of the wind turbine, including the cup anemometer [9].

Statistical methodologies are employed in identifying significant factors influencing data collection in engineering across diverse domains. One such tool is the Design of Experiment (DOE), which serves to pinpoint crucial, controllable variables affecting the outcome quality of a measurement process.

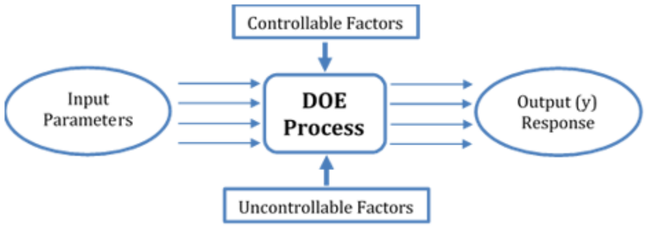


Fig 2 Process model

DOE is sometimes known as statistically designed experiments. The experiment and data analysis are designed to determine the cause-and-effect relationship between the output and experimental parameters in a process. Figure 2 illustrates the DOE process model [9].

In any DOE project, we will purposefully alter those experimental variables and examine the consequences on the output.

M. Moayyediana and A. Elkattan [10] demonstrated another utility of statistical techniques by assessing factors impacting temperature measurement. They examined the influence of the actuator, air speed, immersion level, and probe diameter, given their frequent involvement in test scenarios. Results underscored the thermistor probe diameter as the most impactful factor, contributing 41.87% to variations observed, highlighting the effectiveness of experimental design in perceptive crucial factors in temperature measurement.

In this research paper [11], the researchers applied L9 Taghuchi method of the DOE, as is the case in our current research, for designing a robust horizontal-axis wind turbine, but statistical methods were applied to other parameters, namely Reynolds number, aerofoil type, angle of attack, and Mach numberThe obtained signal/noise response for different wind turbine aerodynamic parameters leads to the following conclusions: The most and least influential variables for the drag coefficient are, respectively, the aerofoil type and Reynolds number; for the lift coefficient, the most and least influential parameters are, respectively, Mach number and Reynolds number; and for the power coefficient, the most and least influential parameters are, respectively, the aerofoil type and Mach number.

The primary influencing individual parameters that affect the wind turbine performance are the NACA 4712 Aerofoil at (L3), the input Mach number of 0.0146 at (L2), and the Re of

100000 for each of the three coefficients of lift, drag, and power, according to the main effects graphic. For the power and drag coefficients, the AOA is two degrees, respectively. Furthermore, 6 degrees is the most significant AOA for lift coefficient.

Furthermore, the aforementioned statistical methodologies were employed to augment the precision of sound intensity measurements via practical experimentation. The investigation involved measuring sound intensity across varied scenarios and environments to clarify the role of critical parameters. Utilizing tools like the Taguchi method and Analysis of Variance (ANOVA) within the Design of Experiments framework, the study examined factors including temperature, distance, wind speed, and sensor angle. Remarkably, wind speed emerged as the major factor, accounting for 1.79626% of observed variations as per the ANOVA analysis [11].

Nevertheless, based on the authors' understanding, there remains a lack of comprehensive studies investigating the impact of various parameters on wind speed measurements. Furthermore, no research has been conducted to determine the pivotal parameters and their respective contributions to wind speed measurement through the implementation of the DOE methodology.

This paper presents a series of experimental trials employing a cup anemometer to explore the influential parameters and their respective contributions in wind speed measurement through the implementation of DOE. Data collection is facilitated by a Data Acquisition system. Following particular sensor calibration, the relative contribution percentage of each parameter is assessed by comparing their relative variances. The parameters under review in this investigation include temperature, tilt angle, distance from the air source, and surrounding space

2 METHODOLOGY & EXPERIMENTAL SETUP

This study looks into the significance of four parameters and their contributions, as indicated in Table 1. The temperature ($P1$), Tilt angle ($P2$), Distance from air source ($P3$), and surrounding space ($P4$) are analyzed at three levels. A range of real-world applications are used to determine which levels are appropriate. To attain the ideal configuration of controllable parameters and optimize the measurement process, the Taguchi orthogonal array approach is employed.

A. *Taguchi Optimization in the Design of Experiments*

Table 2 shows the L9 orthogonal array of Taguchi that was chosen based on the number of parameters selected and their levels. According to the chosen orthogonal array, the Taguchi technique reduces the number of tests, resulting in a savings in time and expense. This specific orthogonal array design translates the integers in the array columns into the actual parameter setting, assigns control parameters and design variables to array columns, and covers all parameters with a restricted number of tests [12] [13].

B. *Experimental Setup and Wind Speed Measurements*

After utilizing the Taguchi method to determine the most suitable number of experiments covering all possibilities of four factors and three levels for each factor, a total of 9 experiments were designed and their factors and levels were distributed based on the L9 orthogonal array, as outlined in Table 2. The Schematic of the experimental setup is depicted in Fig 3.

The wind speed sensor, depicted as a cup anemometer in Figure 4-a, designated for this study, underwent calibration using another anemometer sensor of established accuracy, as illustrated in Figure 4-b, which had been previously calibrated.

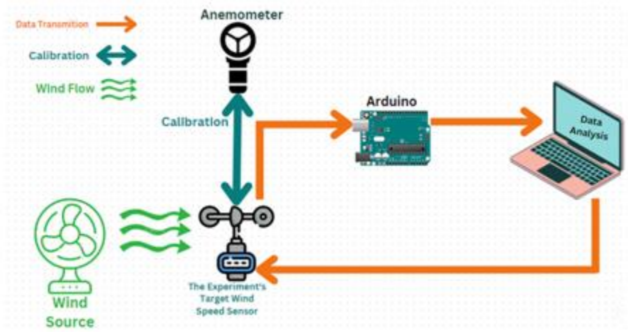


Fig 3 Schematic of the experimental setup, including a fan, standard anemometer, the experiment's target cup anemometer and data acquisition system

Table 1 Selected parameters and their levels

	$P1$:Temperature	$P2$:Tilt Angle	$P3$:Distance from air source	$P4$:Surrounding space
Level 1	Low (21 C°)	Pos 0	Near (90 cm)	**Small**
Level 2	Medium	Pos 1	Medium (120 cm)	**Big**
Level3	**High (35 C°)**	**Pos 2**	**Far (160 cm)**	**Open Air**

Table 2 Taguchi's L9 orthogonal array used to collect data

Experiment #	P_1:Temperature	P_2:Tilt Angle	P_3:Distance from air source	**P_4:Surrounding space**
1	Low	Pos 0	Near	**Small**
2	Low	Pos 1	Medium	**Big**
3	Low	Pos 2	Far	**Open Air**
4	Medium	Pos 0	Medium	**Open Air**
5	Medium	Pos 1	Far	**Small**
6	Medium	Pos 2	Near	**Big**
7	High	Pos 0	Far	**Big**
8	High	Pos 1	Near	**Open Air**
9	**High**	**Pos 2**	**Medium**	**Small**

Fig 4 (a) The cup anemometer is designated for this study , (b) An Anemometer sensor is used in the calibration process

3RESULTS & ANALYSIS

During the implementation of the experiments, the wind speed was measured using an anemometer sensor, taking 5 readings under the same conditions to ensure the consistency of the wind speed measurements as shown in Table 3 and calculating their average later in Table 4.

Signal to Noise (S/N) ratio

Taguchi using the S/N ratio to define the quality attributes that should be addressed for any engineering design challenges. The S/N ratio is divided into three categories: lower is better, nominal is best, and higher is better [15]. The S/N ratio uses average values to translate experimental data into values that are suitable for the evaluation of an optimum parameter analysis [16]. Because the goal of this study is to keep the measured value as close to the target value as possible using optimum parameters, the notional best quality feature has been chosen for the computation of the S/N ratio, as defined in Eq. 1 [10].

$$\frac{S}{N} = 20 * \log\frac{\bar{y}}{s} \qquad (1)$$

Where $\bar{y}$ is the average of the readings at each experiment and s is the noise power. The calculation for $\bar{y}$ and s are shown in equations 2 and 3, respectively [17]

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{i=n} y_i \qquad (2)$$

$$s = \frac{1}{n-1}\sum_{i=1}^{i=n}(\bar{y} - y_i)^2 \qquad (3)$$

Where y_i is each reading and n is the number of readings at each experiment.

Table 4 illustrates the calculation method of S/N using the "Nominal the best" approach, by computing the average of the five readings measured for each experiment using Equation 1, as well as calculating the noise, "Standard Deviation", for each experiment using Equation 2. Utilizing the average and s values, S/N was calculated using Equation 3.

Based on the data gathered in Table 4, the average of S/N ratio will have computed at each level separately for the response table, as presented in Table 5, in order to ascertain the ideal levels of the chosen parameters.

Table 3 Wind measurement of the test cases based on L9 orthogonal array, taking five readings at each experiment.

No. of Experiment	Temperature	Tilt Angle	Distance from air source	Surrounding Space	Wind Speed Readings [m/s] WS1	WS2	WS3	WS4	WS5
1	Low	Pos 0	Near	Small	3.82	3.82	3.06	3.06	3.82
2	Low	Pos 1	Medium	Big	0.76	0.76	0.76	1.53	1.53
3	Low	Pos 2	Far	Open Air	0.76	0	0	0	0.76
4	Middle	Pos 0	Medium	Open Air	3.82	3.06	3.06	3.82	3.06
5	Middle	Pos 1	Far	Small	0.76	0.76	0.76	1.53	0.76
6	Middle	Pos 2	Near	Big	0	0	0	0.76	0
7	High	Pos 0	Far	Big	3.06	3.06	2.3	3.06	3.82
8	High	Pos 1	Near	Open Air	6.12	5.36	5.36	5.36	5.36
9	High	Pos 2	Medium	Small	0.76	1.53	0.76	0.76	1.53

Table 4 Average, noise and S/N ratio Calculations for all experiments.

Experiment #	WS_{ave}[°C]	s²	s	*S/N* ratio
1	3.52	0.17	0.42	**18.53**
2	1.07	0.18	0.42	**8.07**
3	0.30	0.17	0.42	**-2.73**
4	3.36	0.17	0.42	**18.15**
5	0.91	0.12	0.34	**8.48**
6	0.15	0.12	0.34	**-6.99**
7	3.06	0.29	0.54	**15.11**
8	5.51	0.12	0.34	**24.20**
9	**1.07**	**0.18**	**0.42**	**8.07**

Table 5 The response Table of S/N ratio.

	$P1$:Temperature	$P2$:Tilt Angle	$P3$:Distance from air source	$P4$:Surrounding space
Level 1	7.96	**17.26**	**11.91**	**11.69**
Level 2	6.55	13.58	11.43	**5.40**
Level 3	**15.79**	-0.55	6.95	**13.21**
Difference	**9.25**	**17.81**	**4.48**	**7.81**

B Analysis of S/N Results

Observations from Table 5 reveal that the disparity between the smallest and largest average S/N values for each factor is referred to as the "difference". Notably, the factor "Tilt Angle" exhibits the greatest "difference" value, indicating it is the most significant parameter on wind speed measurement outcomes using the Cup Anemometer.

Furthermore, Table 5 highlights that the optimal parameter combination for maximizing Cup Anemometer performance involves high temperature, a tilt angle of 0, the sensor to be near an air source, and conducting measurements in open air conditions. This preference is attributed to these specific levels yielding the highest average S/N values in the table compared to other parameter levels.

C Analysis of Variance (ANOVA)

After establishing the optimal parameter set, the relative percentage of contribution is determined by comparing the relative variances of temperature averages for each parameter. ANOVA calculates several quantities, including degrees of freedom, sum of squares, pure sum of squares, and percentage of contribution. The computation of the sum of squares for each parameter and the total sum of squares is expressed as follows [10]:

$$\mathbf{SS_{Pi}} = \sum_{i=1}^{K_A}\left(\frac{A_i^2}{n_{A_i}}\right) - \frac{(\sum_{i=1}^{N} x_i)^2}{N} \qquad 4$$

$$\mathbf{SS_T} = \sum_{i=1}^{K_A} x_i^2 - \frac{(\sum_{i=1}^{N} x_i)^2}{N} \qquad 5$$

$$\mathbf{SS_E} = \left(SS_T - \sum_{i=1}^{K_A} SS_{Pi}\right) \qquad 6$$

where A_i is the average wind speed for each level, n_{A_i}stands for the number of levels, $x_i$is the wind speed value in each experiment, $N$is the number of experiments and $k_A$represents the number of parameters. For the calculation of the total degree of freedom (F_t) and the degree of freedom of each level (F_i) following equations were used, respectively [10]:

$$\mathbf{F_i = x_i - 1} \qquad 7$$

$$\mathbf{F_t = N - 1} \qquad 8$$

To determine the degree of freedom error, Eq. 10 is applied as follow:

$$\mathbf{F_e = F_t - \sum_{i=1}^{K_A} F_i} \qquad 9$$

Finally, the percentage of contribution pf each parameter () is calculated as:

$$\mathbf{P_{P_i} = \frac{SS_{Pi}}{SS_T}} \qquad 10$$

Analysis of ANOVA Results

By using Eq.5 – Eq.11 the weight or percentage of contribution of each parameter is calculated as shown in Table 6. The results indicate that the tilt angle with 46.8% has the highest contribution, followed by the temperature with 20.8 %, Distance from air source with and Surrounding Space with 16.2 % for each of them.

4.CONCLUSION

The focus of this research paper was on investigating four controllable parameters, Temperature (P1), Tilt angle (P2), Distance from air source (P3), and surrounding space (P4), on measuring wind speeds using the cup anemometer. To mitigate noise from controllable parameters, Design of Experiment (DOE) and associated methodologies such as the Taguchi method, Signal to Noise (S/N) ratio, and Analysis of Variance (ANOVA) were employed. Consequently, optimal levels of the selected parameters were determined, along with their respective contributions to enhancing measurement quality. The findings reveal that P2 holds the greatest significance, followed by P1, P4, and P3. The optimal parameter configuration comprises P1 at level 3, P2 at level 1, P3 at level 1, and P4 at level 3. Additionally, according to ANOVA, the tilt angle (P2) exhibits the highest contribution percentage (46.8%), trailed by temperature (P1) at 20.8%, and Distance from air source (P3) and Surrounding Space (P4) at 16.2% each.

Table 6 Analysis of Variance (ANOVA) of parameters, including the percentage of contribution of the parameters.

	F	S	P %
P1: Temperature	2	5.55	20.8
P2: Tilt Angle	2	12.49	46.8
P3: Distance from air source	2	4.34	16.2
P4: Surrounding Space	2	4.34	16.2
Error	0	0.00	0.0
Total	**8**	**26.72**	**100.0**

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