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An intelligent wind turbine with yaw mechanism using machine learning to reduce high-cost sensors quantity

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ABSTRACT

In this paper, with the assistance of some tools and a machine learning model, a smart wind turbine was formed that eliminates some expensive sensors and reduces sensor complexity. Squirrel cage induction generator (SCIG) and six rotor blades make up the proposed design, and depending on the wind's direction, the turbine itself can rotate the rotor hub to produce energy more effectively. Additionally, two stepper motors are coupled to the yaw mechanism with the aid of the rotor hub, and the entire controlling procedure will depend on the direction of the wind. The rotor hub must continuously revolve in the same direction as the wind to maximize wind energy utilization. Additionally, to correctly predict wind degrees, a machine learning model was deployed. Random forest regression was used to train and predict the wind direction. The model is deployed in Raspberry Pi, where the incoming sensor values are being stored. Using the generated data, machine learning model was trained and it can be concluded that the model can potentially replace some of the expensive sensors to reduce cost. The model can be used for similar weather conditions only based on machine learning model and fewer sensors.

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1. INTRODUCTION

A power generator generates electricity by converting mechanical energy to electrical energy. This technology produces power using renewable resources. The power generation capacity of a wind turbine is determined by several elements, such as the size of the power generator and the shape of the turbine blades [1]. Typically, wind turbines start producing electricity at wind speeds of approximately 4 m/s, achieve their maximum rated power output at around 13 m/s, and cease power generation at 25 m/s [1]. Due to the variability of the wind resource, the wind turbine operates at dynamic power levels that frequently fluctuate. Due to this fluctuation, the rotary engine at smart wind energy facilities operates at about one-third of its maximum practicable capacity on average over a year. The quantity of electricity generated by a turbine depends on two factors: wind speed and turbine availability. The power output provided by the wind is proportional to the cube of its speed, which means that if the wind speed doubles, its energy output can increase eightfold. Turbine availableness can be the aptitude to control once the wind is processing. But alternative factors like environmental issues and grid association necessities typically take precedence over the optimum wind capture layout [1], [2]. Although the system is very neatly designed, there are various sensors involved. Sensors are prone to error, meaning they generate null values, or even the sensors themselves can sometimes get damaged. So, using machine learning, the wind speed can be outputted with accuracy. After getting the training data set the dependency of the sensors is reduced by a machine learning model to correctly generate wind direction. Using the feature selection technique, the model can identify the absolutely necessary sensors to predict the wind direction [3]. Upon generating the machine learning model, it can be deployed in other turbines in that same area. But this time the model requires fewer sensors. Expensive sensors such as wind direction sensors can be avoided without reducing the performance of the system.

2. BACKGROUND STUDY

Abhi *et al*. [4] presents an intelligent wind turbine with a yaw mechanism consisting of six rotor blades and a squirrel cage induction generator. The yaw mechanism is controlled by two stepper motors which rotate the rotor hub towards the wind direction, allowing for the capture of maximum wind power. This design is beneficial in areas like Bangladesh, where wind direction can frequently change. Buaossa *et al*. [5] developed a micro wind turbine with three horizontal axis blade systems which includes a gearbox with a 10:1 ratio and a manual yaw mechanism driven by its tail vane towards the wind direction. Basta *et al*. [6] developed a wind turbine made with a three-blade horizontal axis system where they used an 8:1 gear train blade. Yıldız and Dandıl [7] built a three-blade horizontal air turbine and added a tailback side to the nacelle to allow it to spin in the direction of the wind. Fayeem *et al.* [8] created a miniature wind turbine with three plastic blades, a dc motor, and a switch-operated light-emitting diode (LED) light. Ostia *et al*. [9] on wind turbines has combined the spiral concepts of Archimedes and Savonius. Data from the sensors were stored and displayed statistically using an automatic data logger. Chandrashekhar *et al*. [10] used both the Savonius and Darrievs models to build a small-scale vertical axis wind turbine. Instead of employing a generator or alternator, a permanent magnet generator was created to use both kinds. Ahmed *et al*. [11] used the Savonius model to create a compact vertical axis wind turbine that utilized a 50:1 ratio gearbox. Chetan *et al*. [12] presented a wind turbine system that can be converted into a three- or six-blade wind turbine depending on the wind speed. The turbine has two identical systems, a star-connected three pins system with appropriate length, and a system of three springs connected sequentially between the pins and blades. The blade element momentum theory was employed by El-Okda *et al*. [13] to suggest a model, which made use of the chord length, optimum flow angle, and low Reynolds number airflow as well as the aerodynamic shape of the blades. El-Okda *et al*. [14], the authors examined the pitching of wind turbine blades and proposed a solution that could improve the efficiency of small horizontal axis wind turbines. A group of scholars Mohammadi *et al*. [15] developed a small wind turbine connected to the electrical grid, which was controlled by an electronic base stall and electronic yaw power. A conventional wind turbine was created by Putri *et al*. [16] using a power converter that combines a turbine emulator, buck converter, controller, and current detector. Instead of using an integral derivative controller, advanced control strategies like a fuzzy logic controller were used in research [17]. The contactless magnetic braking system is introduced in a study Anupa *et al*. [18]. That wind turbine controlled its DC motors rotation using a compulsive effect due to the eddy current on the brass plate connected to the generator. Cherif *et al.* [19], a hybrid excited flux switching generator was used to construct a turbine system. Koetket *et al.* [20], the wind speed is measured by measuring devices on wind turbines and rotating the nacelle in the direction of the wind. The turbine is trained to generate the most power possible based on the wind's direction and speed, according to the authors of [21], who presented two main aspects such as power electronics and smart systems to achieve maximum power using reinforcement learning. Different machine learning algorithms for data mining and forecasting were introduced in an article by Kunjumon *et al*. [22]. Singh *et al*. [23] presents some weather prediction tools to predict the weather. Extreme machine learning techniques have been employed by Study Rizvee *et al*. [24] to forecast the weather and assess the efficiency of their suggested model. Onal *et al*. [25], machine learning techniques were employed to accurately predict weather data while lowering sensor data inaccuracy. Rani *et al*. [26], which employed mathematical models to forecast weather such as rainfall, highest and lowest temperatures, humidity, and pressure.

3. RESULT AND DISCUSSION

3.1. Operational block diagram of wind turbine system

Due to the low wind speed (<25 m/s) in this approach, the turbines will spin at a low rpm. Therefore, in order to improve rotational speed, a gearbox has been developed, which speeds up the minimum synchronous rate. As a result, this turbine will operate in accordance with Figure 1 block diagram.

Due to an unstable wind flow, the rotor of the induction motor will rotate at an asynchronous rate (slip will be negative). Therefore, the motor will begin acting as a generator and generating power [27]. Since the squirrel case induction motor was utilized to create energy, an alternating-wave signal, also known as an alternating current (AC) signal, will be produced. In this model, the bridge rectifier is utilized to convert the AC signal to direct current (DC) signal since the generated power will be stored in a DC storage and the yaw mechanism controllers also operate in DC. The microcontroller and stepper motor that will drive the yaw mechanism is supplied by a DC-DC chopper circuit that regulates the DC voltage amplitude. Raspberry Pi 4 was used as system controller and the mentioned sensors in (Figure 1) will be stored for training the machine learning model. The model will initially save values of sensor data that can have an effect on wind direction as shown in Figure 1(a). After collecting data for a year, the unrequired sensors will be chosen based on data and eliminated. After eliminating these sensors, only the dependent sensor's input will be taken to predict the wind direction as shown in Figure 1(b).

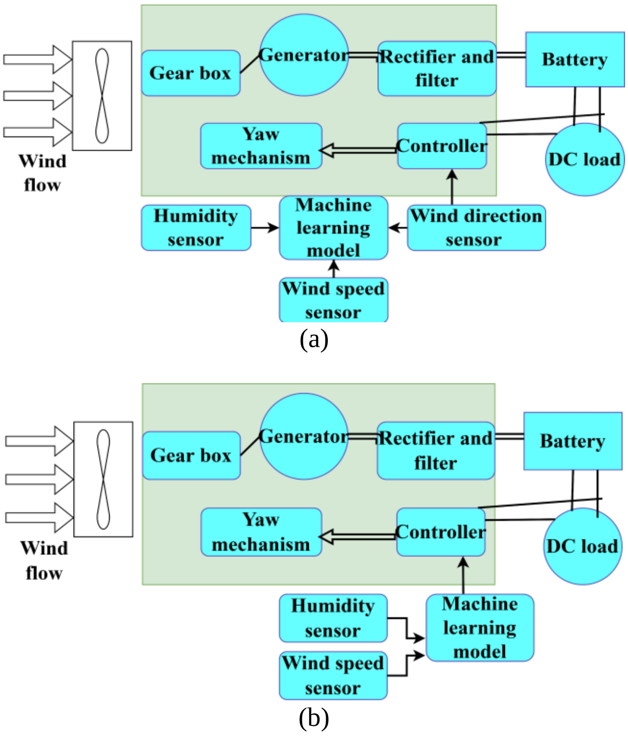
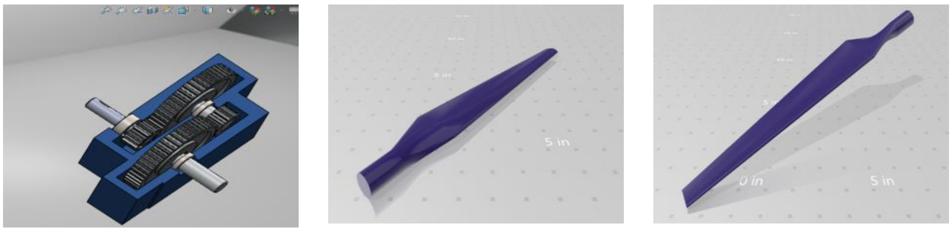


Figure 1. Diagram of wind turbine's operation (a) during training and (b) after training

3.2. 3D modeling

As wind speed in specific locations, such as Bangladesh, is low, the spin of the blade is relatively slow. Therefore, a gearbox has been installed between the wind turbine hub and the wind turbine's generation unit squirrel cage induction generator (SCIG) [28], [29]. The system's gearbox and blade design are illustrated in Figure 2. The design would benefit from a gearbox with a 1:64 proportion (Figure 2(a)). This gear ratio enhances the speed of the generator's rotating component. To achieve this gear ratio, four gear approaches were combined. As shown in Figures 2(b) and 2(c) depict the front and rear blades of a turbine in three dimensions, respectively.



(a) (b) (c)

Figure 2. Designed gearbox (a) 3D view, (b) blade's front side, and (c) blade's back side

3.3. Flow chart for code

This flowchart describes the yaw mechanism's control procedure. As the yaw mechanism starts, the stored energy will energize the microcontroller, motor drivers, wind direction sensor, and stepper motors. Figure 3 depicts the flow diagram for managing the spin (bidirectional) of the Yaw mechanism.

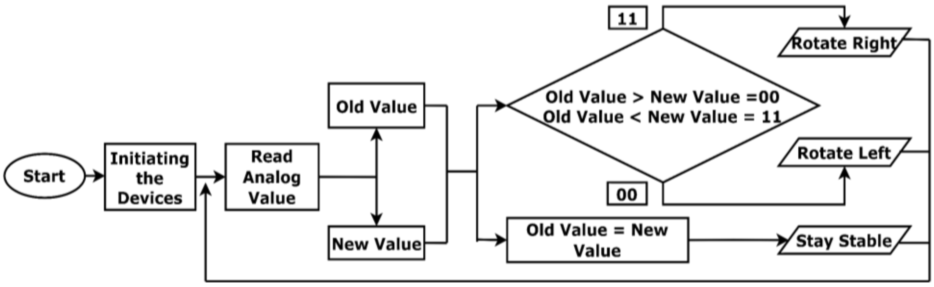


Figure 3. Flow chart for controller commanding code

After activating all equipment, the controller will begin reading the wind direction sensor's data. The controller will remember the previous data to determine whether the old value is higher than the new value. In this situation, the controller will generate "00" to direct the motor drivers to spin the motors to the left. If the controller determines that the new value is higher than the previous value, it will instruct the motor drivers to rotate the motors to the right by generating the number "11". However, when both numbers are equal, the controller will remain silent, and the motors will remain stable. After finishing each iteration, the controller will begin a new iteration by reading the analog data from the wind direction sensor. It should also be noted that the controller will not tell the drivers to rotate the motors with every degree of wind direction change. It will order the driver to spin the nacelle when the wind direction shift is sufficient (recommended as code).

3.4. Data processing

Data was collected from sensors. The gathered data included features such as temperature, wind direction, humidity, air pressure, and wind speed. The data had a total of 45,252 rows. On the humidity column, the lowest value is five and the highest value is 100%, the air pressure differs from 1,002 pa to 1,038 Pascale, the wind direction column’s value is from 0 to 360 degree, the wind speed differs from 0 to 5.10 NMPH, and the temperature value differs from 273.85 to 308.13 kelvin. For machine learning, data pre-processing and decision generation Jupyter notebook tool was used. Again, the collected data had several null values. The humidity column had 151, the air pressure column had 251, and the temperature had two null values. The null values were processed by replacing them with the median of that column values. After that, the data were divided into test and train datasets. Initially, for training the machine learning model, labeled data set is required. For preparing the labeled data set, various sensors, including wind direction sensor, is also required. But after attaining enough data set to train the machine learning model, some sensor’s data generation can be left out. Now from the left-out sensor, the wind direction sensor is no longer required. Using feature selection techniques, some other sensor data that are not related to the model are identified and removed.

3.5. Training machine learning model

The training and test data sets were partitioned to train and evaluate the prediction model. Specifically, seventy five percent of the data was allocated for training, while the remaining twenty five percent of the data was used for testing. Next, for training more accurate models, less relevant rows were removed. To identify the most related features for correctly predicting wind direction, python sklearn’s SelectKBest and f classif were used. After evaluation, we found that wind speed, temperature, and humidity were the most relevant features for identifying wind direction. Next, the model was trained using sklearn library’s ‘RandomForestClassifier’.

3.6. Sensor error value handling

Sensors are prone to getting error or damaged. So, a checking mechanism for learning if a sensor is producing unexpected value is denoted by the following Algorithm 1. The system takes 1,200 values as input per hour.

Algorithm 1. Checking mechanism
```
previousValues[1,200] : empty
while(previousValues.size() != 1,200 ):
previousValues.append(sesnorValue)
end
avgOfPreviousValue : avg(previousValues)
previousValues : empty
randomIndex[20] : empty
statusValues [20]: empty
for i in range (0.1200):
n: randNumber()
randomIndex.append(n)
for i in range(0,randomIndex.size()):
tempValue : abs(avgOfPreviousValue -previousValues[i])
if(tempValue > thresholdValue){
statusValues [i]= True
}
if(statusValues .count > 15 == true){
Warn("Problem with the sensor");
}
```

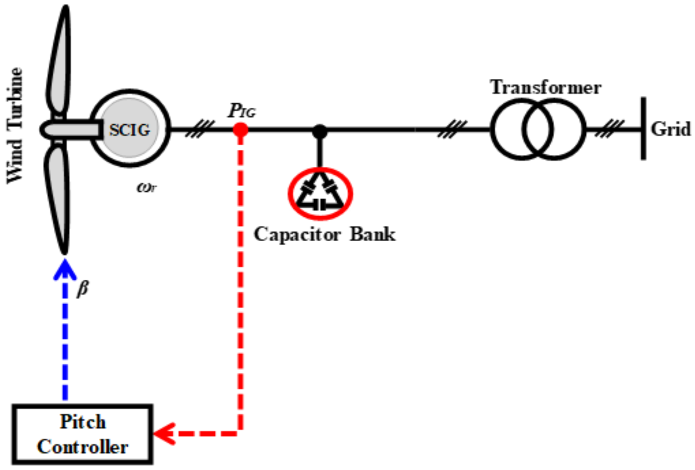
The threshold value from the above pseudocode can vary from sensor to sensor. For example, for the temperature sensor, the threshold value will be the average temperature value of that particular day until the threshold value is being compared. The following algorithm checks if the sensor is generating null value for a certain period to notify that it needs to be fixed or changed. The Algorithm 2 checks null value of a sensor data.

Algorithm 2. Checks null value of a sensor data
```
Boolean isNull : false
startTime = currentTime();
endTime = currentTime()+15 min
while(startTime != endTime ):
startTime = startTime + 1 second
if(geneatedValue!=null){
break
}else{
isNull = true; }
end
Return isNull;
```

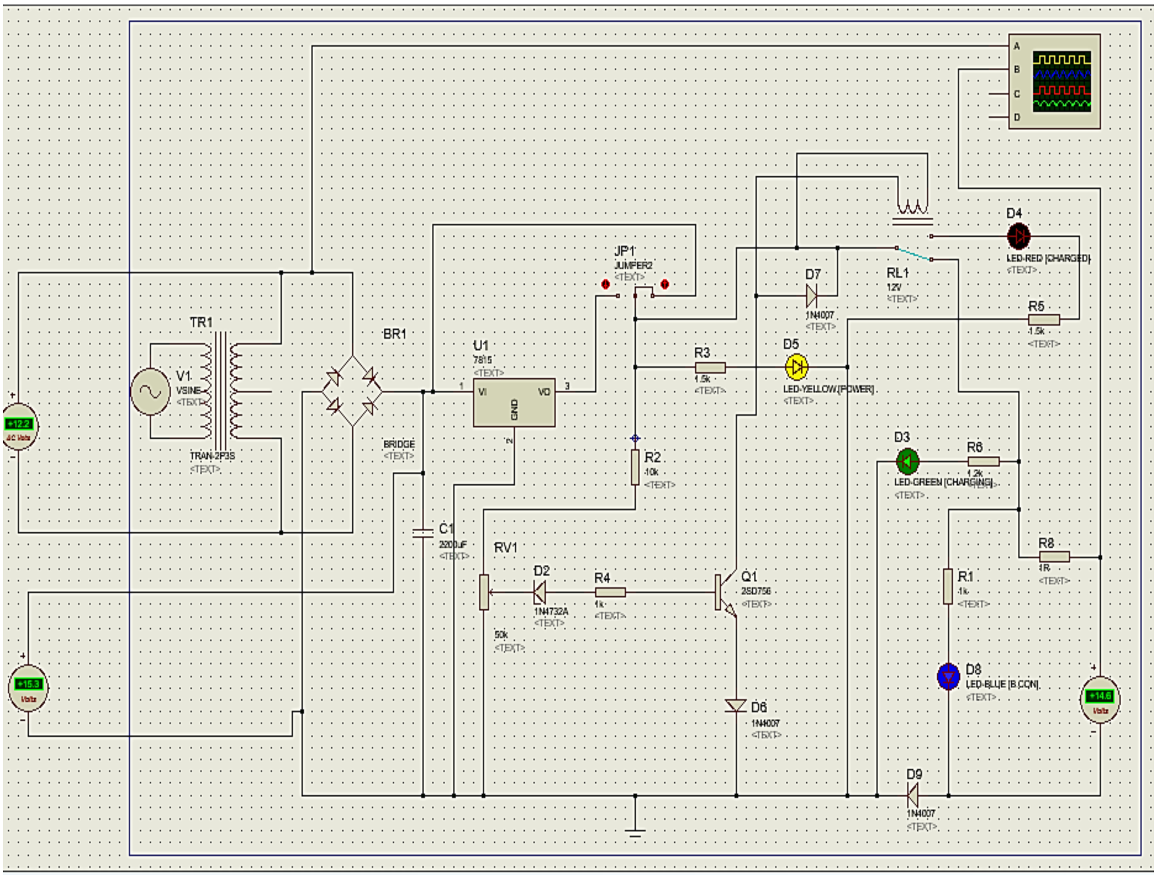
4. SIMULATION RESULT

To excite the stator coils of the SCIG generator with reactive power, the capacitor bank is connected in a delta configuration. Since SCIG is employed as a power generator, a critical rule of generated reactive power is essential to continue the electricity generation without the assistance of other sources [30]. Figure 4 shows the simulated diagram of the system. Power systems computer-aided design (PSCAD) or electromagnetic transient and DC (EMTDC) simulates the induction generator a shown in Figure 4(a) for the SCIG in 3 steps. After electricity has been generated, it must be stored in a DC battery. For a lead-acid battery to retain energy, a constant voltage charging circuit is necessary in Figure 4(b) [31]. Here, a bridge rectifier is used in conjunction with several more components, including a 12 volt relay, 7,815 regulator, Zener diode, and several resistors. Vin is connected to the battery-charging DC voltage that the relay supplies to the battery through the relay. Once the charging voltage hits the critical point, the Zener diode provides the transistor with sufficient base voltage.

As a result, when both the transistor and relay are active, the output riches its maximum level. Currently, the battery and energy source are being separated. When the battery is completely charged, the red LED will be replaced by an instant off-white LED, and the relay will be turned off, which is why the output voltage will be zero in a fully charged state. When the circuit's operational voltage exceeds 12 volts, the relay will be turned off, and the output will be zero. The induction generator produces an alternating current that cannot be stored in a battery as AC. Since it is known that lead-acid batteries require a constant voltage charger to charge themselves, this charging circuit is utilized. From the simulated input-output circuit as shown in Figure 4, it is evident that this charging circuit converts the AC signal to DC and that the DC output amplitude is constant. The output voltage of the charging circuit does not vary in amplitude, which is desired for lead-acid batteries.



(a)



(b)

Figure 4. Simulated diagram (a) layout of fixed speed wind turbine with SCIG (FSWT-SCIG) and (b) voltage charging circuit

5. PROJECT IMPLEMENTATION

The system prototype is depicted in Figure 5. The primary structural components are a 3 mm-thick stainless-steel sheet and a stainless-steel pipe, as shown in the first frame, as shown in Figure 5(a). The frame's overall height is around six feet, and both the base of the frame and the upper nacelle's base plate are constructed using metal sheets. The nacelle measures 20 inches in length, 13 inches in width, and 10 inches in height. In addition, Figure 5(b) illustrates a wind direction sensor. The yaw mechanism was implemented utilizing two stepper motors attached to the nacelle and powered by a stepper motor driver, as shown in Figure 5(c). The input for the stepper motor operators will come from the Raspberry Pi based on the direction of the wind output.

A gear is coupled to the shaft of the stepper motor, and also another gear is connected to the tower's frame, as shown in Figure 5(d). Then, these two gears are coupled such that the upper nacelle portion can rotate in the direction of the wind.

(a) (b) (c) (d)

Figure 5. Hardware implementation (a) side view, (b) wind direction sensor, (c) stepper motor attached with nacelle, and (d) pinions for yaw mechanism

6. RESULT ANALYSIS

6.1. Calculation of theoretical wind power

Wind power is determined by three distinct factors:

- Mass of air (density).
- Quantity of air (volume),
- Speed of air (Velocity), and

Now, it can be obtained from the definition of kinetic energy:

$$KE = \frac{1}{2}mv^2 \tag{1}$$

where, m=mass; v=velocity.

An equation can be formulated for power is the amount of energy per unit of time. [i], P = $\frac{1}{2} \times m' \times v^2$ where, $m' = \frac{dm}{dt}$. The mass flow rate (density multiplied by volume flux) is obtained through the principles of fluid mechanics: $\frac{dm}{dt} = \rho \times A \times v,$ therefore, the power generated by the wind can be stated as:

$$P = \frac{1}{2} \times \rho \times A \times v^3.$$

by factoring in the turbine power coefficient, the power in the wind can be calculated using (2):

$$P = \frac{1}{2} \times \rho \times A \times v^3 \times Cp \tag{2}$$

where,
P=Electrical power measured in watts.
ρ=The air density at sea level is around 1.2 kilograms per cubic meter.
A=The area of the turbine, measured in square meters, can be determined based on the length of the turbine blades = $\pi \times r^2$ = $\pi \times l^2$.
v^3=Wind speed is defined as the rate at which air moves, measured in meters per second.
Cp=The power coefficient, typically ranging from 0.05 to 0.45, varies depending on the design of the wind turbine.

Table 1 and Figure 6 present the theoretical power output at different wind speeds, with wind speed being the only variable in the equation. The calculations were based on a Cp value of 0.2836, which corresponds to a prototype blade angle of approximately 154°. This information can be utilized to estimate the power output of a wind turbine under different wind conditions.

Table 1. Values that were calculated theoretically

Density (ρ)	A=sweep area, (l=30 in) =0.76 m, A=$\pi \times l^2$	Wind speed (V)	Power coefficient (Cp)	Power P watt
		1		1.086
		2		8.688
		3		29.322
1.2	1.81	4	0.2836	69.504
		5		135.75
		6		234.576
		7		372.498

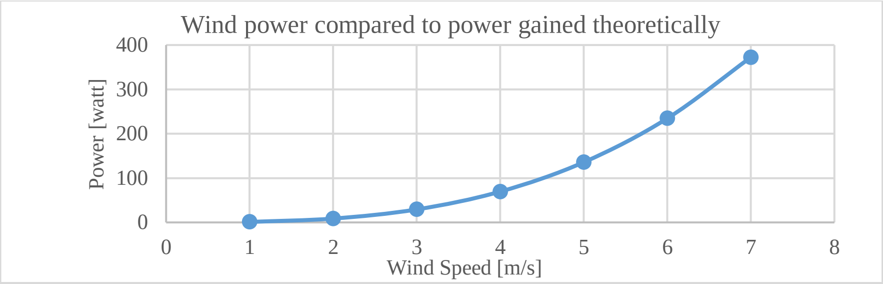


Figure 6. A graph comparing power gained theoretically to wind speed

6.2. Experimental readings

To assess the proposed design and construction of the wind turbine, an experimental setup was created to collect the necessary information for further analysis. Wind speeds were calculated for the corresponding RPMs and the outcomes were presented in Table 2 and Figure 7. The results were utilized to compute the output of the turbine blades and to evaluate the impact of vibrations on the stress and strain of the structure.

Now,

$$P = VI \tag{3}$$

where, V=voltage, I=current in amperes. Conversion of RPM to wind speed,

$$RPM = \frac{RPM \times 2\pi \times R}{Tsp \times 60} \tag{4}$$

here, RPM represents the revolutions per minute of the generator shaft, R=Radius of blade, Tsp=9.92.

Table 2. Experimentally gained data

No	RPM	Wind speed	No	RPM	Wind speed
1	1400	2.2	-	-	-
2	1450	2.29	10.34	0.86	9
3	1500	2.37	12	1.4	14.72
4	1550	2.45	14.89	1.9	19.3
5	1600	2.5	19	2.3	25.83

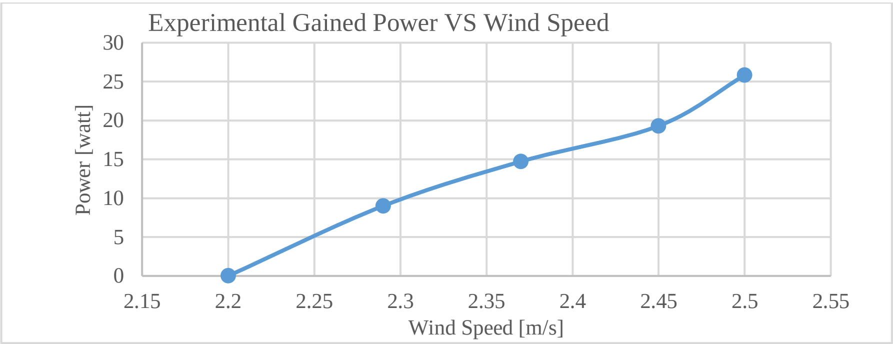


Figure 7. Graph of gained power vs wind flow

Figures 6 and 7 demonstrate the difference between theoretical and practical output Excel graphs. This difference can be explained by friction in the gearbox and bearings, which results in energy loss and a reduction in power output. Additionally, asynchronous wind speed can also impact the turbine's performance and cause deviations from the theoretical power output.

6.3. Machine learning model evaluation

Using Weka (machine learning and data mining tool), various algorithms were tested on the same data set. From all the classification and prediction models, an ensemble learning technique Random Forest gave the most optimum result. The evaluated values using the Weka tool are given in Figure 8 and Table 3. To detect the direction using the wind direction sensor can be very costly. The price can be ranged to 80 k BDT, which is very expensive for mass usage. Again, the relatively less costly models cannot generate very accurate results. Using machine learning, the sensor dependency and the cost can be reduced while ensuring very accurate outcome.

```
Classifier output

Time taken to build model: 0.11 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          83               83      %
Incorrectly Classified Instances        17               17      %
Kappa statistic                          0.6072
Mean absolute error                      0.2785
Root mean squared error                  0.3582
Relative absolute error                 61.8292 %
Root relative squared error             75.5279 %
Total Number of Instances              100

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Cla
                 0.909    0.324    0.845      0.909    0.876      0.611    0.897     0.950     c0
                 0.676    0.091    0.793      0.676    0.730      0.611    0.897     0.790     c1
Weighted Avg.    0.830    0.244    0.827      0.830    0.826      0.611    0.897     0.896

=== Confusion Matrix ===

  a  b   <-- classified as
 60  6 |  a = c0
 11 23 |  b = c1

                                                                        Activate Windows
```

Figure 8. Model evaluation using Weka

Table 3. Machine learning evaluation

Serial	Type	Value
1	Correctly classified instances	83%
2	Kappa statistics	61% (0.607)
3	Mean absolute error	27% (0.279)
4	Root mean square error	35% (0.358)
5	True positive rate	91% (0.909)
6	Precision	85% (0.845)

7. LIMITATION

The objective of this study is to determine an optimal method for rotating the wind turbine head to achieve the highest possible output from the wind turbine. The machine learning model depends on the sensor's data to train the model, but the sensor dependency will later be reduced after collecting enough training data. However, in order to maintain the model's accuracy, continual training is necessary. Otherwise, if the weather changes considerably over time, the model may become ineffective. With that in mind, automated data pipelining is necessary to further ensure continuous update of training data set feeding. This will let the system adapt to the continuous change and provide accurate wind direction for the turbine to rotate. Cloud platforms like Google Cloud, Amazon Web Services (AWS) can be used for data pipelining.

8. CONCLUSION

This paper focuses on designing and implementing an intelligent wind turbine that generates power and can also track the direction of wind flow to achieve greater power generation efficiency. This wind turbine is small in size, and it is possible to install this in any remote area where airflow is high, but the airflow tends to fluctuate a lot. In most cases, a tail vane is used to track the wind direction, which is not stable for structure, and it also causes the disturbance of continuous power generation. Upon collecting sensor data for a certain period, machine learning is implemented to determine the wind degree. Also, a mechanism for acknowledging sensor error was implemented. The project is developed in such a way that it can solve a very critical issue in developing countries and also improvises the project itself at various levels.

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