Artificial Neural Network Based Evaluation of Wind Energy Potential for Small-Scale Renewable Power Generation in Wufeng, Taiwan

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Abstract

This study investigates the wind energy potential in the Wufeng area of Taichung, Taiwan, with the aim of supporting the development of small-scale renewable wind power generators. Specifically, it seeks to evaluate wind patterns and meteorological parameters over a three-year period and to identify the most accurate predictive model for wind speed and energy output. A quantitative research methodology was employed, analyzing weather data using multiple regression algorithms, including Linear Regression, Lasso Regression, Ridge Regression, Support Vector Regression (SVR), Dynamic Thermal Rating (DTR), and Artificial Neural Network (ANN). The performance of these models was compared through data training and testing, with the ANN demonstrating the highest predictive accuracy. Using this model, the maximum expected wind speed was determined to be 5.56 m/s, corresponding to a potential energy output of 992.57 watts over a one-week period, indicating that the region is suitable for small-scale wind power development. However, the study is limited by its reliance on short-term data, which may not capture seasonal variations, economic feasibility, or operational constraints of wind power systems. Therefore, future research should incorporate long-term wind monitoring, feasibility assessments, and pilot projects to evaluate the practical performance and reliability of small-scale wind turbines in the Wufeng region.

Keywords: Artificial Neural Network, Energy Conversion, Renewable Energy, Wind Turbine

I. INTRODUCTION

Taiwan is situated in the subtropical zone of East Asia, spanning approximately 36,000 square kilometers. The central mountain range stretches from north to south of Taiwan, with an average elevation of 1,500 meters. The wind patterns in Taiwan throughout the year are primarily influenced by various factors, including the Asian monsoon and tropical cyclones during the summer and fall seasons, the northeast trade winds during winter and spring, and local wind convergence caused by the presence of the Central Mountains. Taiwan is also in the western Pacific region, known for its strong and consistent monsoon winds. The monsoon is a weather and climate phenomenon resulting from the temperature differences between land and sea due to the sun's zenithal movement, as proposed by Edmund Halley in 1686 [1], [2].

Due to its advantageous geographical location, the Taiwan government has set a target for renewable energy to constitute 15.1% of its total power generation capacity by 2025. Wind energy alone is expected to contribute 5.3%, indicating that wind power is the fastest-growing and accounts for the most significant proportion of all renewable energy resources. These predictions are based on data compiled by the Bureau of Energy under the Ministry of Economic Affairs (BEMOEA) of Taiwan in 2014, which provides information on the geographical distribution of wind speed with an average of 50 m/s and an average wind power density of 100 W/m² for a year [3], [4].

Specifically, in the central plains of Taiwan, the Wufeng area, located in Taichung, stands out as one of the regions in Taiwan with substantial potential for harnessing wind energy as a renewable resource. The Taichung area boasts an average annual wind speed of approximately 5-6 meters per second, with peak speeds occurring during winter. Furthermore, Wufeng's topographical features are characterized by its surrounding mountainous terrain, which can create funneling effects that enhance wind speeds and make them more consistent. Several factors support these conditions, making the Wufeng region highly favorable for the development of wind energy power plants. Moreover, there is an abundance of available land that can be utilized for the construction of renewable energy power plants [1], [5], [6].

Renewable energy stands out as the most cutting-edge solution, harnessing the potential of wind energy to generate renewable electricity. Wind energy offers numerous advantages, including no fuel consumption, low operational costs, and abundant wind resources. It is a sustainable source because it is renewable, widely distributed, and plentiful. Furthermore, the potential of wind energy contributes significantly to reducing greenhouse gas emissions, as it is an alternative energy source to fossil fuels in the electricity generation system [7], [8]. Wind turbines are essential tools for harnessing wind energy as a renewable resource. Wind turbines can generate mechanical energy, which can be used directly or converted into the energy most people need today, namely, electrical energy. Wind speed prediction models are crucial for creating an effective energy prediction system to address this issue [9], [10].

The Artificial Neural Network (ANN) is an information processing system inspired by the human brain, consisting of an artificial network of interconnected neurons. It comprises many processing elements that work collaboratively to solve complex problems. The Artificial Neural Network is a critical modeling approach used in machine learning, as it can gauge the energy capacity of wind power plants. It incorporates various parameters, such as relative humidity, average wind speed, solar radiation, and hourly weather conditions, within the Artificial Neural Network model [11]–[13]. Thus, this study aims to evaluate the wind energy potential in the Wufeng area of Taichung, Taiwan, by analyzing meteorological parameters and wind patterns over a three-year period to support small-scale renewable wind power development. Additionally, it seeks to identify the most accurate predictive model, with the Artificial Neural Network (ANN) applied to forecast wind speed and potential energy output for optimal turbine placement.

II. Method

This paper presents an analysis of the accuracy of predicting renewable wind energy generation using the artificial neural network method to overcome the non-linear energy conversion system through appropriate variable and control input changes, thereby determining the maximum power. Based on this issue, the researcher utilizes a quantitative research approach because it states that quantitative data is a research method based on positivism (concrete data). The research data consists of numbers that will be measured using statistics as a tool for calculation and are related to the issue being studied to conclude. The quantitative research method is based on collecting actual data in the field, which is used to examine the quantity of specific data collected. The data gathered is then processed using research instruments and mathematical models. The quantitative research approach will analyze wind speed as a measure of energy potential for creating renewable wind power generators [14].

A. Wind Turbine

Wind turbines are devices used to harness wind energy and spin an electric generator, producing electrical energy. The operation principle of these wind turbines is based on energy conversion and utilizes a renewable natural resource, the wind. Small-scale wind turbines for residential areas typically have diameters ranging from 2 to 4 meters, producing energy from approximately 300 to 10,000 watts. The majority of wind turbines used are horizontal-axis wind turbines. The wind speed required to operate a small-scale wind turbine typically ranges from 3 to 5 meters per second (approximately 10 to 18 kilometers per hour) [15].

B. Conversion of Wind Energy into Energy

When converting wind energy into electrical energy, it is essential to accurately calculate the power that the wind turbine can generate. The term “power” in this context refers to a parameter used in engineering and energy science to measure the efficiency or performance of a system or device in generating electrical power or energy, with its size or capacity [16], [17].

$$E = \frac{1}{2}.Cp.p.D^2.V^3(watt) \tag{1}$$

E = Power generated by a wind turbine (W)
Cp = Power coefficient of the wind turbine,
p = Air density (kg/m³).
D = Diameter of the wind turbine (m).
V = Wind speed (m/s)

C. Artificial Neural Network

Inconsistent or erratic wind speeds present challenges in harnessing wind energy through turbines for conversion into renewable energy. Wind prediction models are required to create an effective energy prediction system. Artificial neural networks, based on the biological nervous system, are mathematical models that solve problems using algorithms for non-linear functions. Artificial neural networks are excellent tools known for their accuracy in conducting research across various fields. They can solve problems involving non-linear algorithm functions, data classification, load forecasting, and adjusting wave sizes as expected. Artificial neural networks have been widely used in various fields, including science and technology, to predict environmental parameters such as solar radiation, wind speed, power forecasting, and energy prediction [18]–[20].

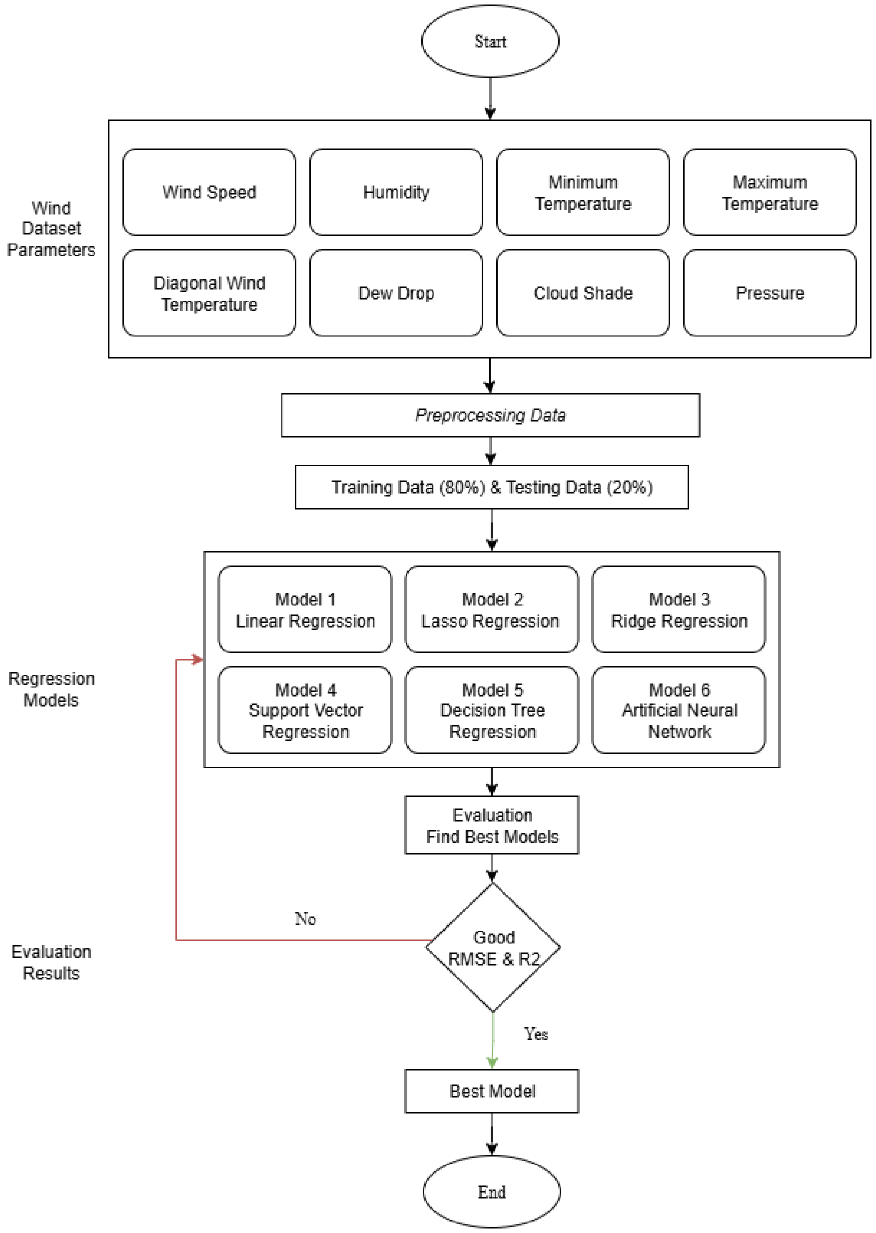

Figure 1 Research Procedures

The research procedure required to achieve the expected analysis is designed to follow the overall research development framework and is structured around a four-stage model consisting of monitoring, modeling, validation, and evaluation. In the monitoring stage, meteorological data such as wind speed, direction, temperature, and pressure are systematically collected to provide a reliable representation of the Wufeng area's wind patterns. The modeling stage uses these data to develop predictive models, particularly employing Artificial Neural Networks (ANNs), to estimate wind speed and potential energy output and identify trends essential for turbine placement and renewable energy planning. In the validation stage, model predictions are compared with actual measurements using statistical metrics to ensure accuracy and reliability. Finally, the evaluation stage integrates all findings to assess the wind energy potential and provide practical recommendations for small-scale wind power development. This structured approach ensures the study produces systematic, reliable, and actionable insights into the renewable energy capacity of the area. The following, each process is described in detail:

1. Monitoring

The initial step in this methodology's research procedure is monitoring, a critical phase that focuses on systematically gathering and documenting all relevant information necessary for the study. This process involves collecting a comprehensive range of data, including historical records, observational measurements, and any existing datasets that can provide insight into the variables under investigation. In addition, the monitoring stage requires a careful design of the data collection framework to ensure accuracy, consistency, and reliability, taking into account both temporal and spatial factors that may influence the results. Special attention is given to identifying and recording triggering factors, patterns, and anomalies that could affect the development of the analysis. The accumulation of a sufficient quantity of high-quality data at this stage forms the foundation for subsequent modeling, as it enables a detailed and precise evaluation of the potential for generating renewable wind power. By thoroughly executing this monitoring process, the research ensures that the subsequent analytical stages are built on a robust and empirically grounded understanding of the system under study.

2. Modelling

The second step in the research procedure involves the modeling process, which entails implementing various regression models, including linear regression, Lasso Regression, Ridge Regression, Support Vector Regression (SVR), Decision Tree Regression (DTR), and Artificial Neural Network (ANN). In this process, the input and output data for the model should be identified. Data preprocessing, error data removal, and splitting into training, validation, and evaluation sets must be carried out. Once the data is prepared, regression model approaches can be applied. The researcher then presents Figure 1, a flowchart of the proposed model, as a reference for determining the regression model used to analyze wind speed for generating renewable energy power [21], [22].

3. Validation

The third step in the research procedure is the model validation process. This refers to the model's quality response upon completion of the testing process. The model must be validated using an input set consisting of wind parameter datasets that have been preprocessed with various regression models, and an output dataset comprising testing data. The testing data should consist of 80% of the data prepared earlier and 20% of the testing data for comparing the model's response to the data. The model's response based on the validation dataset must be evaluated both graphically and through the application of numerical quality metrics, which will be assessed according to specific numerical quality criteria. The model's numerical quality criteria may include using at least two numerical quality metrics, such as Root Mean Squared Error (RMSE) and Coefficient Determination (R^2):

$$\mathrm{RMSE} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(y_{est} - y)^2} \quad (2)$$

y = Actual observed value or data
y_{est} = Predicted value from the model or forecast
n = Number of observed data points

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - f(x_i))^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

R^2 = Coefficient of Determination
n = Number of Observations
y_i = Value in the sample
$\bar{y}$ = Sample Mean Value
$f(x_i)$ = Predicted value of yi

The performance of the regression model in predicting wind speed was evaluated using two key numerical metrics: Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2). RMSE measures the average magnitude of prediction errors, indicating how closely the predicted values match observed data, with lower values reflecting higher accuracy. R^2 quantifies the proportion of variance in the observed data explained by the model, reflecting its explanatory power. By considering both metrics together, the predictive quality of each regression model can be assessed. The results are then compared to determine which model most accurately predicts wind speed, providing a reliable basis for evaluating renewable wind energy potential [23]–[25].

4. Evaluation

According to the methodology, the final step in the research procedure involves the model evaluation process, which assesses the quality of the model's response on a dataset not used during the training or validation process. The model must be evaluated using an input and output dataset prepared to test data results and compare the model's response with measurable data. The model evaluation process is similar to the validation process, with the only difference being the number of numerical quality metrics used.

Predictions utilize wind turbine data, incorporating data from non-standardized error measurement methods, such as the Root Mean Square Error (RMSE). Therefore, evaluating these results across various locations might be statistically challenging. The coefficient of determination R^2 is used in this experiment to address this challenge. Accuracy can be calculated by the sum of the squares of the R^2 coefficient of determination, as given by the equation [26]-[27].

The experiment achieves an error distribution for all available data at this stage. This distribution is used in statistical analysis, and comparisons are made using RMSE. The values obtained for RMSE are also normalized, while R^2 is considered a measure of accuracy closer to 1, representing the most accurate result. Other error measurement methods, such as Root Mean Squared Error (RMSE), may be more commonly used. However, a large wind site and a wide wind range are required for statistical comparisons, and R^2 is measured as a more accurate measure.

III. Results and Discussion

A. Wind Energy Potential and Meteorological Analysis in Wufeng

This research obtained results on wind energy potential in the Wufeng area, Taichung, Taiwan. According to a study, the central plains of Taiwan, particularly in the Wufeng region, Taichung, have significant wind potential. This is due to the average wind speed of approximately 5-6 m/s with peaks in winter. Additionally, the topographical conditions of Wufeng are characterized by mountainous regions, creating a funneling effect that can increase wind speed and provide greater consistency, making it suitable for renewable wind energy electricity generation projects. Furthermore, the wind potential in the Wufeng region is analyzed, and the results of wind energy potential values are used to create renewable wind energy power generators. The existence of these wind energy power generators can be a solution to replace depleting non-renewable fossil energy sources. The research results utilize weather parameters, including wind speed, humidity, temperature, cloud cover, air mass, and dew point, with data from Taiwan's weather stations. The wind parameter data span a three-year time range, from 2020 to 2023.

Table 1 RMSE for Data Training and Testing with Coefficient Determination R^2

Machine Learning	Training	Testing	Fitting	Score R^2
Linear Regression	1.6940	1.6783	Good Fit	0.3360
Lasso Regression	1.7035	1.6779	Good Fit	0.3301
Ridge Regression	1.6940	1.6783	Good Fit	0.3360
SVR	1.7059	1.6651	Good Fit	0.3305
DTR	0.0007	1.6286	Over Fit	0.3646
ANN	1.4842	1.4521	Good Fit	0.4948

Based on all the testing results from various regression models used, as seen in Table 1, it is evident that in the subtest of RMSE for the training data, the trial values that come closest to the desired parameter values with good fitting results are obtained from the Artificial Neural Network (ANN) model, with a value of 1.4842. In the subtest of RMSE for the testing data, the best fitting result is also achieved with the Artificial Neural Network (ANN) model, with a value of 1.4521. Furthermore, the coefficient of determination (R^2) yields an excellent fitting result, with a relatively high value of 0.5372, which is higher than that of the other models.

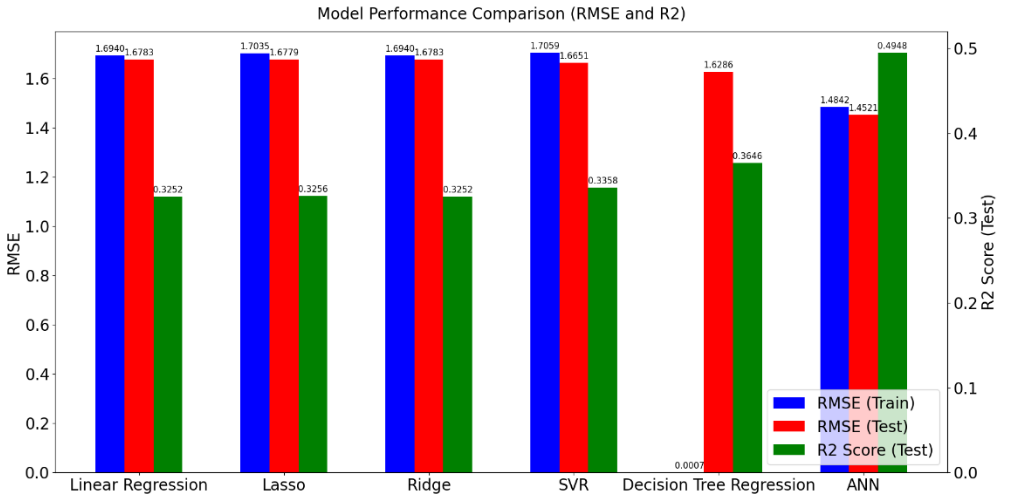

Figure 2 Machine Learning Performance Comparison

Therefore, among the various machine learning algorithmic models employed to predict renewable wind energy potential, the model utilizing the Artificial Neural Network (ANN) approach consistently exhibits superior performance, particularly in achieving the highest average values within the subtest parameters associated with a good fit. This consistent outperformance underscores the robustness and adaptability of the ANN framework in capturing complex, non-linear relationships inherent in wind energy datasets. Consequently, the evaluation outcomes affirm the ANN model's exceptional accuracy and reliability, thereby establishing it as the most effective analytical tool for modeling and forecasting in the context of renewable wind power generation.

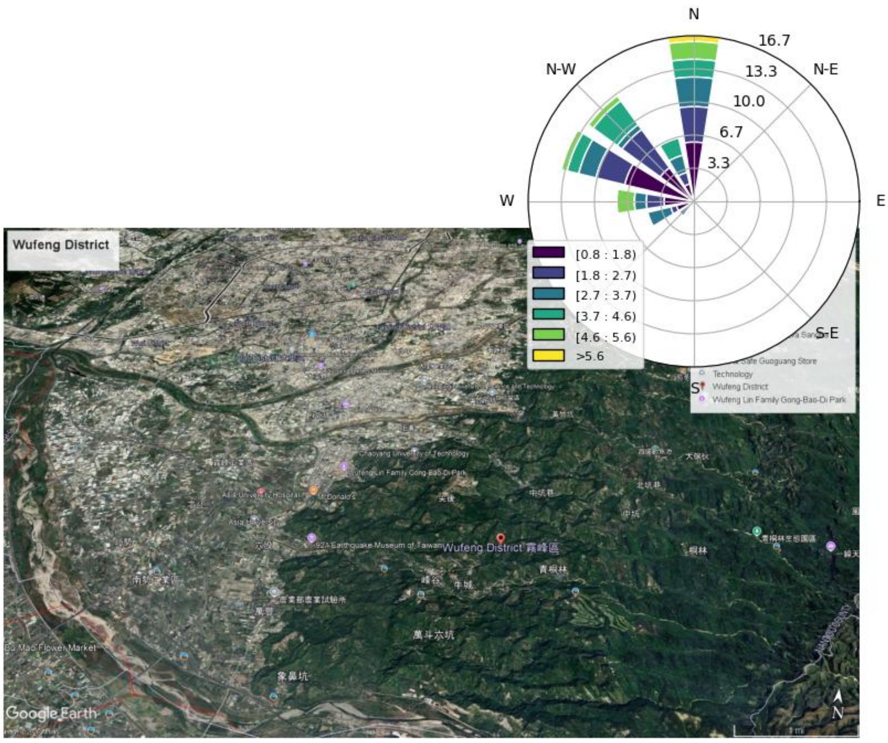

Figure 3 Map and Wind Rose of the Wufeng area in Taichung, Taiwan

The potential of wind energy in a region is influenced by its location and conditions. Changes in wind speed and direction vary from one location to another. Data on wind patterns over a minimum period of one year is required to assess wind energy potential. Wufeng is a strategically located area in Taiwan with relatively high wind potential. Researchers aimed to analyze wind direction and wind speed in the Wufeng region using wind rose methodology. This method helps identify prevailing wind directions with consistent speeds, which are crucial for wind turbine placement, and provides wind speed output for the region through wind rose diagrams. The researchers used latitude 24°02'29.87" N and longitude 120°43'32.968" E for the Wufeng region. This enabled the accurate prediction of wind speed and direction using maps and wind rose charts, as depicted in Figure 3.

Figures 3 present predictions of wind patterns in the Wufeng region, detailing both wind speed and wind direction across Taiwan. The analysis reveals the distribution of wind potential and the diagonal orientation of prevailing winds, highlighting the region's suitability for wind energy development. Winds in Wufeng are relatively strong, predominantly originating from the northern side, with measured speeds ranging from approximately 3 to 13.3 meters per second. This trend is clearly illustrated by the full bar petal wind rose oriented toward the north, indicating that north-facing installations would optimally harness the incoming winds. These winds, flowing from the sea and accelerating over the mountainous terrain, create favorable conditions for consistent energy generation. The data suggest that turbines strategically positioned to face the north could maximize energy capture, while also taking advantage of the natural topography that channels and intensifies wind flow in this region.

Beyond the wind patterns themselves, Wufeng offers considerable land resources that support the development of renewable energy projects. According to Chen and Wu (2015), more than 700 hectares of land in the region are suitable for wind power generation, providing ample space for the installation of multiple turbines. The green mountainous areas visible in Figures 3 represent open and accessible land that can be leveraged for energy infrastructure without significant environmental disruption. This combination of strong, consistent winds and available land makes Wufeng an ideal candidate for large-scale wind energy projects. Furthermore, the integration of wind turbines in these areas can contribute to Taiwan's renewable energy goals while optimizing land use in otherwise underutilized mountainous terrain, demonstrating both environmental and economic potential.

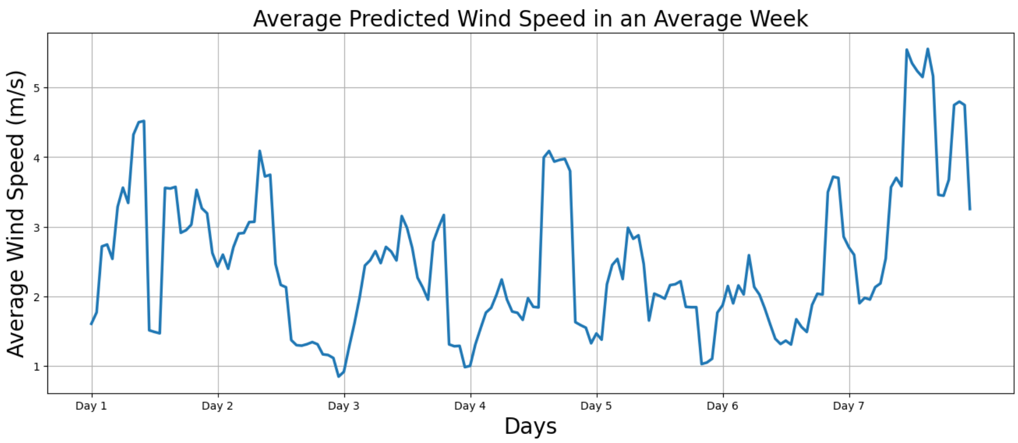

Figure 4 Weekly Average Predicted Wind Speed

Based on Figure 4, the wind speed in the study area exhibits noticeable fluctuations over the course of a week, with periods of both increase and decrease that reflect the dynamic nature of local wind conditions. Hourly measurements indicate a maximum wind speed of 5.56 m/s and a minimum of 0.84 m/s, highlighting the variability that must be considered when planning for wind energy utilization. These variations demonstrate that wind availability is not constant, emphasizing the importance of continuous monitoring and careful assessment of wind patterns to predict potential energy generation and ensure optimal operation of wind turbines. Understanding the temporal distribution of wind speeds is therefore critical for determining the most effective strategies for turbine placement, energy storage, and integration into the local power grid.

The recorded wind speeds fall within a range suitable for low-speed wind turbines, particularly those that operate at cut-in speeds between 3 and 5 m/s. This means that during periods when wind speeds reach or exceed the cut-in threshold, turbines can begin generating energy efficiently, while lower wind periods may require supplemental energy sources or storage solutions. By aligning turbine selection and operational strategies with these observed wind patterns, energy output can be maximized even under variable conditions. Moreover, this information can guide decisions about turbine design, height, and blade specifications, ensuring that the installed systems are optimized for the site-specific wind regime. Overall, understanding these wind speed fluctuations is essential for harnessing wind energy effectively, enhancing renewable energy potential, and contributing to sustainable energy development in the region.

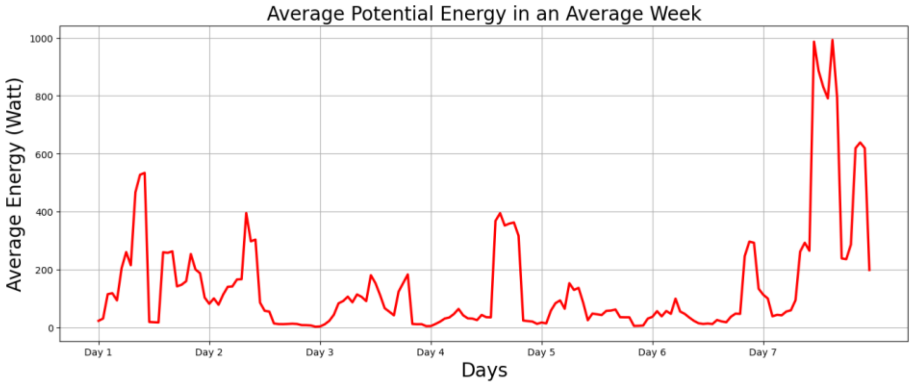

Figure 5 Weekly Average Potential Energy

The analysis results of the potential energy values, as illustrated in Figure 5, provide a comprehensive overview of the wind energy capacity in the Wufeng region over the course of a week, measured on an hourly basis. The data reveal that the maximum energy value recorded during this period reaches 992.57 watts, indicating the region experiences periods of strong wind that could be effectively harnessed for electricity generation. In contrast, the minimum energy value observed is 3.45 watts, reflecting moments of low wind activity and highlighting the natural fluctuations in wind availability throughout the week. This variation in energy values suggests that while the region does not experience constant high wind speeds, it demonstrates sufficient periods of wind activity that could support renewable energy generation. Based on these findings, the analysis strongly suggests that the Wufeng region possesses viable wind energy potential, making it a promising candidate for the development of a small-scale renewable wind energy power plant. The establishment of such a facility could contribute to sustainable energy production, reduce reliance on conventional fossil fuels, and support the broader goals of renewable energy integration within the region.

IV. Conclusion

An analysis using various modeling approaches and algorithms, including linear regression, Lasso Regression, Ridge Regression, Support Vector Regression (SVR), Dynamic Thermal Rating (DTR), and Artificial Neural Network (ANN), was conducted to obtain the best prediction results for wind energy. The results showed that the analysis method using Artificial Neural Network (ANN) demonstrated the most accurate relevance in analyzing the development of renewable wind power plants, as evidenced by the goodness-of-fit parameters. The analysis of wind speed potential revealed a maximum wind speed of 5.56 m/s and a minimum wind speed of 0.84 m/s. As a result, the wind potential in this area is suitable for constructing small-scale renewable wind power generators, as it meets the minimum wind speed standard of 3 - 5 m/s. The analysis of wind energy potential also indicated that the highest power output is 992.57 watts, while the lowest energy value obtained is 3.45 watts. The analysis is based on a short-term dataset and does not account for seasonal variations, economic feasibility, or operational constraints of wind power systems. Thus, future studies should use long-term wind data and conduct feasibility assessments, while pilot projects could help evaluate the practical performance of small-scale wind turbines in the Wufeng region.

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