Assessing Wind Energy Potential in Markazi Province, Iran: A Data-Driven Approach with AI Algorithms

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Abstract: This paper investigates the wind energy potential in Markazi Province, Iran, focusing on three cities: Tafresh, Khomein, and Saveh. The primary objective of this study is to provide a comprehensive analysis of wind patterns using a combination of statistical approaches and artificial intelligence techniques. Wind data was collected from advanced meteorological stations in these cities over a two-year period (2018–2020), including detailed measurements of wind speed and direction at 10-minute intervals. This high-resolution dataset facilitated an in-depth examination of wind behavior and its suitability for energy production. Statistical analysis was conducted using the Weibull distribution and wind rose diagrams, which provided insights into the wind characteristics and their spatial variations. Additionally, Long Short-Term Memory (LSTM) networks were employed to predict wind speeds and temporal trends. These models effectively captured the complex relationships within the wind data and produced highly accurate forecasts. The comparison of actual and predicted wind rose diagrams demonstrated a strong alignment, validating the reliability of the LSTM-based predictions in reflecting real-world wind patterns. The results of this study demonstrate that combining traditional statistical methods with modern machine learning techniques provides a robust framework for analyzing wind energy potential. By leveraging these tools, the study offers valuable insights for sustainable energy planning and supports informed decision-making for renewable energy investments in Markazi Province.

Keyword: Wind Energy Potential, Wind rose , Weibull Function, Long Short-Term Memory (LSTM), Renewable energy

1. Introduction

The study of wind speed patterns and the assessment of wind energy potential are critical in renewable energy planning [1]. Numerous studies have employed various techniques to analyze wind characteristics and evaluate wind energy potential across diverse regions. For example, the variability of wind speeds and power potential has been frequently examined using the Weibull distribution [2]. However, while the Weibull distribution remains a popular tool for modeling wind speed, its limitations in capturing multimodal and highly variable wind speed distributions are often overlooked.

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In [3], the performance of three probability distributions—Weibull, Logistic, and Lognormal—was compared for wind speed modeling. The study highlighted that the Logistic distribution outperformed Weibull and Lognormal in certain cases, offering better accuracy for specific datasets. Nonetheless, these approaches heavily rely on static assumptions and often fail to adapt to rapidly changing meteorological conditions or seasonal variability.

The assessment of wind energy potential in Turkey, as discussed in [4], provides valuable insights into high-potential regions such as Marmara, Aegean, and Southeastern Anatolia, emphasizing favorable wind speeds and densities. Despite this, the study relies on historical averages and static probability distributions, which might not fully reflect short-term variations or long-term trends in wind speed data. Additionally, regional assessments often lack integration with predictive frameworks that could dynamically evaluate wind speed fluctuations for better resource planning.

The use of statistical tools like probability density functions (PDFs) for wind speed modeling is well-established. For instance, combining the Weibull function with wind rose diagrams allows a more comprehensive understanding of wind patterns throughout the year [3]. Wind rose diagrams provide critical information about wind direction and frequency, aiding in the assessment of wind regimes for energy projects [5]. However, these methods predominantly offer descriptive insights and do not inherently account for predictive or real-time applications.

Machine learning algorithms, such as support vector regression, random forests, and ensemble methods, have shown promise in predictive modeling of renewable energy systems [6,7]. Moreover, GIS-based multi-criteria decision-making has been explored for optimal site selection of renewable energy installations like solar power plants [8]. Despite these advancements, the application of machine learning models in wind energy often suffers from insufficient integration with statistical frameworks, leading to limited accuracy in capturing long-term wind speed trends.

In [9], the impact of wind direction on the power output and income of wind farms was explored. This research proposed a modified quadratic power curve to account for wind direction variability, offering a novel method for predicting wind turbine output. However, the study heavily relies on historical data to complete the wind datasets.

In [10], the feasibility of wind energy potential along the coastline of Pakistan is analyzed using predictive models and artificial neural networks (ANN) for forecasting wind data. While the study highlights Karachi as the most suitable location for wind farms, the ANN employed lacks sufficient precision in capturing long-term wind variability, limiting its reliability for accurate forecasting.

Long Short-Term Memory (LSTM) neural networks, in particular, have gained recognition for their effectiveness in time series analysis, making them ideal for wind speed prediction over extended periods [11]. However, past studies employing LSTM networks often overlook the incorporation of domain-specific statistical insights, such as Weibull or wind rose analysis, which could enhance model interpretability and robustness. This highlights the need for hybrid approaches that combine statistical methods with machine learning techniques to address gaps in adaptability, accuracy, and contextual understanding of wind speed variations.

Iran has made significant strides in the development of wind power plants, with notable projects scattered across the country. One of the earliest and most influential wind farms is the Manjil Wind Power Plant situated in Gilan. This pioneering onshore wind farm was commissioned in 1994 and boasts a capacity of around 90 MW. It played a pivotal role in jumpstarting wind energy production in Iran. Another remarkable wind farm in Iran is the Kahak Wind Farm located in Qazvin. It was commissioned in 2017 and has been inaugurated in two phases, ultimately reaching a final capacity of 100 MW. This sizable wind farm stands as one of the largest in the country. Similarly, in Qazvin, the Siahpoosh Wind Farm was commissioned in 2018 and has a capacity of 61.2 MW, contributing to the renewable energy landscape of the region. In addition to these larger wind farms, there are also smaller-scale installations that deserve recognition. One such example is the Khaf Wind Turbine in Khorasan Razavi, installed by Aria Razi Company. With a capacity of 2.5 MW, it was commissioned in 2015. Furthermore, the Aoun Ben Ali Wind Power Plant in Tabriz and the Safa Wind Power Plant in Isfahan each have capacities of 0.66 MW. Overall, wind power in Iran has made noteworthy progress, with a daily electricity generation capacity of approximately 600 MW from wind sources alone. However, considering the country's total electricity generation capacity of around 90,000 MW, there is ample scope for further growth and the establishment of new wind power plants in regions like Markazi Province in order to meet the growing demand for energy [2].

While wind power plants have been successfully developed in various regions of Iran, including Gilan, Qazvin, Neyshabur, Khorasan Razavi, and Isfahan, there remains ample potential for further expansion. One such region that could greatly benefit from the establishment of a wind power plant is Markazi Province. This province boasts favorable conditions for wind energy production due to its strong and consistent winds. Furthermore, its central location within Iran, close proximity to major population centers, and high electricity demand make it an ideal candidate for the development of a wind power plant. Such a project in Markazi Province could significantly contribute to Iran's overall electricity generation capacity. The efforts and dedication of Iran's Renewable Energy and Electricity Efficiency Organization have contributed to the acquisition of valuable insights through their website. By examining the map provided on the website, we observe the regions prone to wind, visualized through distinctive red dots. These areas signify immense potential for the harnessing of wind energy and serve as promising locations for future renewable energy projects in Markazi Province. Considering the rich data available from the meteorological stations and the continued efforts in renewable energy development, Markazi Province stands as a promising hub for advancing sustainable energy solutions within Iran's broader energy landscape [12].

This study offers an in-depth analysis of wind patterns in Markazi Province, Iran with a focus on three towns in the province- Tafresh, Khomein and Saveh, using a hybrid approach. This information is crucial for the assessment of wind power potential and the development of wind energy projects in the region. To facilitate the analysis of wind patterns in the region, comprehensive meteorological stations have been established in these cities. The Tafresh, Saveh, and Khomein meteorological stations, renowned for their cutting-edge technology and reliable data, serve as invaluable sources of information for wind energy enthusiasts and researchers alike. However, Weibull distribution and wind rose visualization are combined with LSTM networks for advanced wind resource assessment. The use of LSTM networks is expected to capture complex spatiotemporal dependencies in wind data for accurate forecasting of wind speeds at different altitudes. By leveraging the strengths of statistical tools and modern machine learning, the proposed approach provides superior insights into wind speed variability. The innovation of this study lies in its hybrid methodology, which combines traditional statistical techniques with state-of-the-art machine learning algorithms. This approach not only enhances the accuracy of wind energy potential assessments but also facilitates a deeper understanding of spatiotemporal wind behavior. Moreover, this research highlights the potential of Markazi Province as a hub for renewable energy development, addressing a critical gap in the literature. By demonstrating the utility of LSTM models in wind resource assessment, the study sets a precedent for future applications of AI-driven techniques in renewable energy planning.

This study has been folded as follows. In the next section, we will give some preliminaries. Section 3 analyse the wind data and LSTM is used to predict the wind speed in section 4. Finally the paper has been concluded in section 5.

2. Preliminaries

2.1. Dataset

In this study, we collected wind data from three meteorological stations Tafresh, Khomein, and Saveh for a period of two years, from 2018 to 2020. Tafresh, Khomein, and Saveh meteorological stations were chosen due to their strategic locations and availability of reliable wind data. These stations are equipped with advanced anemometers and meteorological instruments that accurately measure wind speed and direction. The data sampling was conducted at regular intervals of every 10 minutes, providing us with a comprehensive dataset to analyze wind patterns and assess wind power potential in the region. By collecting data at such high frequency, we were able to capture the fine-scale variations in wind behavior over a two-year period. This level of temporal resolution allows for a detailed analysis of wind patterns and the identification of important trends and variations throughout different seasons and years.

The wind data collected from these stations serves as a valuable resource for understanding the wind characteristics in the region and determining the wind energy potential. It provides insights into the prevailing wind directions, average wind speeds, and wind speed fluctuations at different times of the day.

Wind speed generally increases with height and in the boundary layer this increase is owing to less friction at higher elevations. For wind turbine engineering, the variation of wind speed with height can be defined relative to wind measured at a reference height of $10m$. By a power law profile, the amount of change in wind speed is as equation 1[13]:

$$V(h) = v(10)(\frac{h}{10})^{\alpha} \tag{1}$$

where $v(h)$ is the wind speed at height h, $v(10)$ is the wind speed at the anemometer measurement height of $10m$ and the exponent α varying parameter between 0.11 and 0.40 depending on the surface roughness and atmospheric stability. For neutral stability condition and smooth open country α is provided as 0.14. The result of using the power law profile was illustrated by Vallero with $\frac{1}{7}$ as the value of α which is approximately 0.14. This value is widely applicable to a low surface and well exposed site and thus has been used in many scientific studies to obtain the vertical profile of wind speed in the boundary layer. So, in this study we used 0.14 for a and calculated wind speeds at $50m$, $80m$, $100m$ and $120m$ altitudes by using the measured $10m$ anemometer level wind speeds [14].

2.1. Weibull parameters and probability assessment of wind power density

Generally, wind speed data well matches the Weibull shape, and many studies have used the Weibull distribution and the following equations to assess the properties of wind speed and the corresponding wind power densities at various places around the world [13]. The Weibull wind speed probability density function can be represented as equation 2:

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{2}$$

where $f(v)$ is the probability of observing wind speed v. Also, k is the dimensionless Weibull shape parameter and c is the Weibull scale parameter in m/s. The shape parameter determines the shape of the distribution curve, indicating whether the wind speed data is skewed or bell-shaped. On the other hand, the scale parameter represents the wind speed at which the distribution reaches its maximum value, also known as the most probable wind speed. The Weibull shape and scale parameters k and c are related with the mean wind speed v_m as equation 3:

$$v_m = c\Gamma\left(1+\frac{1}{k}\right) \tag{3}$$

where Γ is the gamma function. After estimating the mean and the variance of the wind speed data, Weibull parameters, k and c can be calculated as equation 4,5:

$$k = \left(\frac{\sigma}{v_m}\right)^{-1.086} \tag{4}$$

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

The most probable wind speed, $v_{mp}(m/s)$, defined as the most common wind speed for a given wind speed probability distribution function, can be expressed as equation 6:

$$v_{mp} = c\left(\frac{k-1}{k}\right)^{1/k} \tag{6}$$

Wind speed corresponding to the maximum energy $v_{max}(m/s)$ can be calculated by using the Weibull parameters k and c as equation 7:

$$v_{\max} = C\left(\frac{k+2}{k}\right)^{\frac{1}{k}} \tag{7}$$

Wind power density $P_d(W/m^2)$ can be determined as equation 8:

$$P_d = \frac{1}{2}\rho c^3\Gamma(1+\frac{3}{k}) \tag{8}$$

where ρ is the density of air in kg/m3 [14-15].

2.2. LSTM neural network

LSTM is a type of artificial recurrent neural network (RNN) architecture that has gained significant popularity in the field of deep learning. It is designed to effectively capture and process long-term dependencies in sequential data, making it particularly suitable for tasks such as natural language processing, speech recognition, and time series analysis. Traditional RNNs suffer from the "vanishing gradient" problem, where the gradients diminish exponentially over time, making it difficult for the network to learn long-term dependencies. LSTM addresses this issue by introducing a memory cell and several gates that regulate the flow of information within the network [16]. So, the key component of an LSTM cell is the memory cell, which stores information over long sequences, see Figure 1. The cell has an internal state that can be selectively updated or forgotten based on the inputs and the current state. This makes LSTMs capable of retaining relevant information over extended periods, enabling them to handle sequences with long gaps between important events.

In addition to the memory cell, LSTMs contain three types of gates: the input gate, the forget gate, and the output gate. These gates are responsible for controlling the flow of information into and out of the memory cell [16,17]. The input gate determines which values from the input should be stored in the memory cell. It takes into account the current input and the previous hidden state. By applying a sigmoid activation function, it outputs values between 0 and 1, indicating how much of each input component should be stored [18]. The forget gate decides which information should be erased from the memory cell. It considers the current input and the previous hidden state and applies a sigmoid function to determine which parts of the memory cell should be forgotten. The output gate regulates the output of the LSTM cell. It combines the current input and the previous hidden state, passes them through a sigmoid function, and then applies the hyperbolic tangent function to the cell's current state to produce the final output.

During the training process, the parameters of the LSTM network, including the weights and biases, are learned using backpropagation through time. This involves computing the gradients of the loss function with respect to the network's parameters and updating them using optimization algorithms such as stochastic gradient descent [17,19]. By incorporating memory cells and gating mechanisms, LSTMs excel at learning from and predicting sequences, making them valuable tools in a wide range of applications[17-20].

Based on the connections shown in Figure 1, the mathematical expressions can be expressed as follows:

Forget gate: $$f_t = \sigma(W_{fh}h_{t-1} + W_{fx}x_t + b_f) \tag{9}$$

Input gate: $$i_t = \sigma(W_{ih}h_{t-1} + W_{ix}x_t + b_i) \tag{10}$$

Candidate Cell State: $$\tilde{c}_t = tanh(W_{\tilde{c}h}h_{t-1} + W_{\tilde{c}x}x_t + b_{\tilde{c}}) \tag{11}$$

Cell State Update: $$c_t = f_t . c_{t-1} + i_t . \tilde{c}_t \tag{12}$$

Output Gate: $$o_t = \sigma(W_{oh}h_{t-1} + W_{ox}x_t + b_o) \tag{13}$$

Hidden State: $$h_t = o_t . tanh(c_t) \tag{14}$$

where W_{fh} , W_{fx}, W_{ih} , W_{ix} , $W_{\tilde{c}h}$, $W_{\tilde{c}x}$, W_{oh} and W_{ox} represent the weight matrices associated with different gates and transformations in the LSTM architecture. W_{fh} and W_{fx} are weights for the forget gate, W_{ih} and W_{ix} for the input gate, $W_{\tilde{c}h}$ and $W_{\tilde{c}x}$ for the candidate cell state, W_{oh} and W_{ox} for the output gate. They determine how much influence the previous hidden state h and current input x have on the computation of each gate or transformation. h_{t-1} represents the previous hidden state at time $(t-1)$ while x_t denotes the input at time t. These are the main sources of information that LSTM cells use to update their internal states and produce outputs. b_f, b_i,$b_{\tilde{c}}$, and b_o are bias terms associated with the forget gate b_f, input gate b_i, candidate cell state $b_{\tilde{c}}$

and output gate b_o. Bias terms allow the LSTM to introduce shifts in the activation functions, aiding in learning and capturing relevant patterns in the data. c_t represents the cell state at time t, capturing and preserving long-term information. h_t denotes the hidden state or output of the LSTM cell at time t, which may be passed to subsequent layers or used for further processing. o_t represents the output gate activation, determining which parts of the cell state should be transmitted to subsequent stages. $\tilde{c}(t)$ denotes the candidate cell state, offering potential updates to the cell state. i_t represents the input gate activation, controlling the flow of new information into the cell state. f_t denotes the forget gate activation, determining what information from the previous cell state should be retained or discarded. Finally, c_{t-1} is the previous cell state, providing context for the update of the current cell state [17].

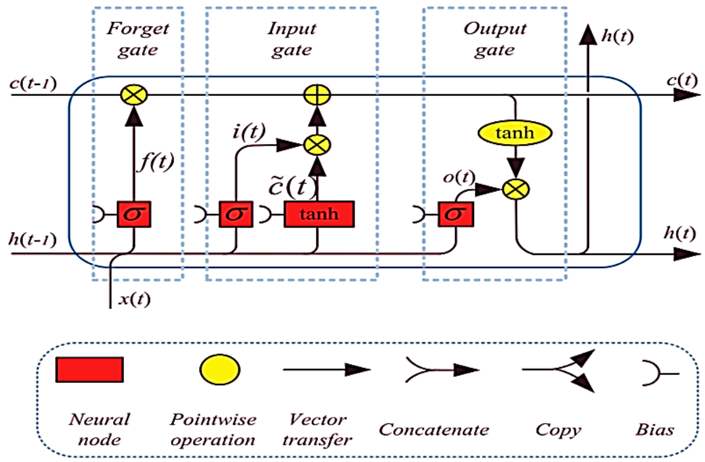

Figure 1: Architecture of LSTM with a forget gate [15]

3. Analysis of wind data

The distribution of wind speeds plays a crucial role in the assessment of wind power potential for the installation of a wind power plant. In this study, the Weibull distribution function was utilized to analyze the wind distribution characteristics at three different wind stations in Tafaresh, Khomein, and Saveh. To better visualize the wind distribution patterns, Figure 2 presents the Weibull distribution graphs for the three wind stations. The x-axis represents wind speed, while the y-axis represents the probability density function (PDF).

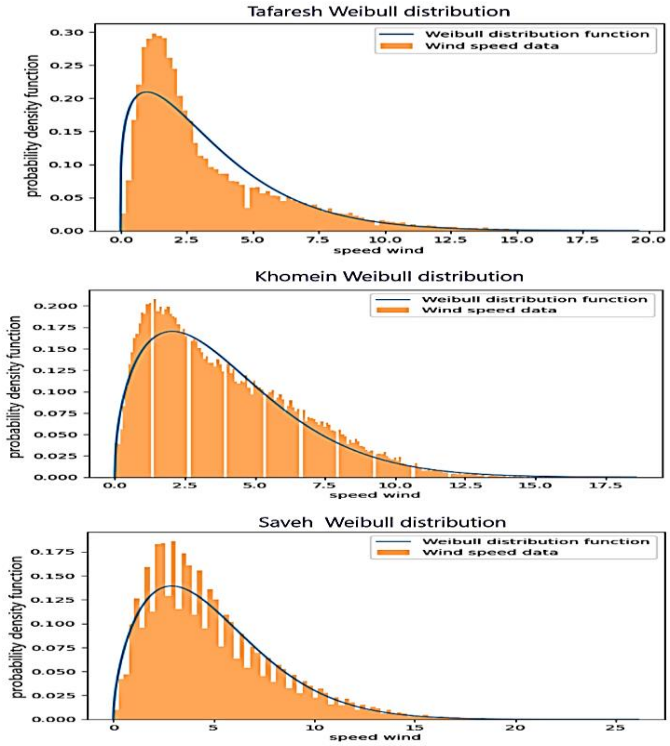

Figure 2: Weibull distribution graphs for the three wind stations

Table 1 displays the scale and shape parameters obtained for each of the three wind stations.This distribution effectively models the statistical characteristics and variability of wind speed using two main parameters:

- Shape parameter (k): Represents the concentration or uniformity of the wind speed distribution. Higher values of (k) indicate a more uniform and narrower distribution of wind speeds.

- Scale parameter (c): Reflects the average wind speed and has a significant impact on the amount of energy that can be extracted from the wind.

- Tafresh: Indicates low wind speeds and relatively wide variability.

- Khomein: Suggests higher wind speeds and more uniformity compared to Tafresh.

- Saveh: Represents the most uniform wind distribution and the highest average wind speed among the three regions.

Table1. shape parameters k (m/s) and scale parameters c (m/s) in the 2018-2020 period

Parameters	Tafresh	Khomein	Saveh
k	4.06	4.37	5.45
c	1.19	2.3	3.1

The wind power density (WPD) is the measure of the amount of energy available in the wind at a specific location[19,21]. It is calculated by multiplying the air density by the cube of the wind speed. WPD is usually expressed in watts per square meter (W/m^2). The higher the WPD, the more suitable the location is for wind energy generation. In this study, we calculated the WPD for three meteorological stations in Iran: Tafresh, Khomein and Saveh. We assumed a standard air density of 1.225 kg^3 and a wind turbine height of 80 m.

The calculation of wind power density at an altitude of 80 meters indicates that Saveh, with 38.85 W/m^2 has the highest potential for wind energy exploitation. This value highlights the favorable wind conditions in the region for installing high-performance wind turbines. Khomein, with a wind power density of 16.17 W/m^2 also shows considerable potential for developing wind energy projects, particularly for medium-scale applications. In contrast, the wind power density in Tafresh, at 2.27 W/m^2 is very low, indicating that the wind conditions in this region are not economically viable for wind energy exploitation. This analysis underscores the importance of selecting suitable locations based on local wind data for designing and operating wind farms.

3.1. Applications of the Data

- **Estimating Wind Uniformity:** Saveh, with the highest (k) value (5.45), has the most uniform wind distribution, meaning wind speeds in this region are concentrated within a specific range and are more stable. This can contribute to more consistent turbine performance.
- **Evaluating Energy Production Potential:** The (c) parameter in Saveh (3.1) and Khomein (2.3) indicates higher average wind speeds compared to Tafresh (1.19), suggesting greater potential for wind energy production in these regions.
- **Designing Suitable Turbines**: Using the Weibull distribution data, turbines can be selected to match the wind speed distribution of each region. For example, turbines for Khomein and Saveh should be designed for higher wind speeds.
- **Prediction with LSTM Models**: Weibull parameters are key inputs for LSTM models to predict the temporal trends and variations in wind speed over different time periods.
- **Economic and Engineering Analysis**: Weibull data indicates that Saveh, with higher uniformity and greater average wind speed, is a suitable option for wind energy investment. In contrast, Tafresh, due to its lower wind speeds, may not be economically viable for wind energy projects.

4. Wind Data Analysis Using LSTM

Modeling the wind data in the previous section and calculating the scale and shape parameters can help us in analyzing the wind speed in the area. Using these parameters obtained in artificial intelligence, which uses a two-layer LSTM network here, can predict the speed. And the generated power will help in the future, and in this way we achieved very good accuracy.

Figure 3 showcases a comparison between the actual and predicted wind speeds at the Khomein, Tafaresh, and Saveh wind stations in the central province of Iran. The x-axis represents the sample index, while the y-axis represents the wind speed in meters per second. In the

Figure 3, the blue line represents the actual wind speeds recorded at the respective stations. These values serve as the ground truth for evaluating the accuracy of the wind forecasting model. The orange line, on the other hand, represents the predicted wind speeds generated by the two-layer algorithm of artificial intelligence. Upon visual inspection, it is evident that the predicted wind speeds closely align with the actual wind speeds. The model successfully captures the underlying patterns and trends in the wind data, resulting in accurate predictions. The closeness of the red line to the blue line indicates the model's ability to capture the dynamics of wind behavior in the central province of Iran. The figure provides valuable insights into the performance of the two-layer algorithm in wind forecasting. It demonstrates the algorithm's effectiveness in capturing the complex relationships and dependencies in the wind data, enabling accurate predictions.

Figure 3: Comparison between the actual and predicted wind speeds at the Khomein, Tafaresh, and Saveh

Figure 4 show The wind roses derived from the actual measured data and the LSTM-based predictions were compared and demonstrated a remarkably close resemblance. The wind direction distribution and wind speed frequencies exhibited a strong alignment, indicating the effectiveness of the LSTM algorithm in capturing the underlying patterns and characteristics of the wind behavior in the study areas. The level of approximation between the real and predicted wind roses suggests the reliability and potential utility of the LSTM model for wind forecasting in the Markazi Province of Iran.

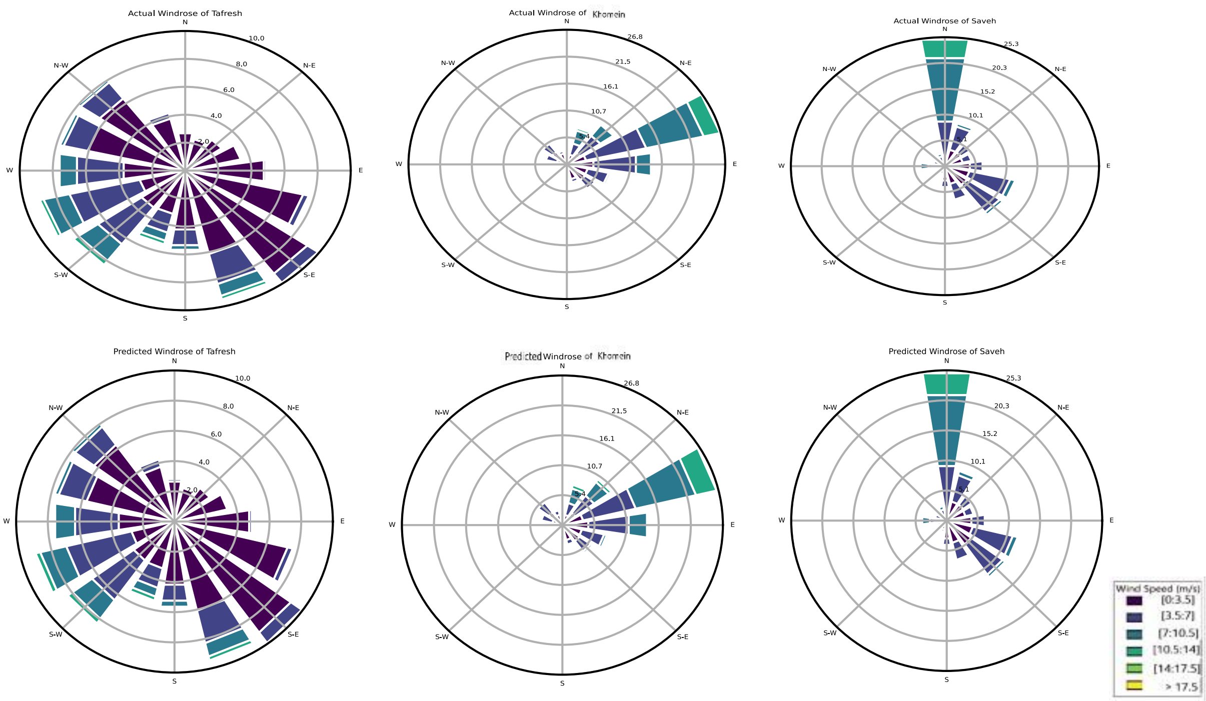

Figure 4: Comparison between actual and predicted Wind roses of three stations in the two-year period of 2018-2020

In this study, wind forecasting was performed in three stations, namely Tafarsh, Khomein, and Saveh, located in the Markazi province of Iran. The wind patterns observed at these stations were compared with the predictions generated by the double-layer LSTM (Long Short-Term Memory) algorithm. To evaluate the performance and accuracy of the algorithm, three important evaluation metrics were utilized: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared coefficient.

The MSE represents the average squared difference between the predicted wind values and the observed wind values at each station. It provides a measure of the model's ability to minimize prediction errors. Similarly, the MAE indicates the average absolute difference between the predicted and observed wind values, giving insights into the magnitude of errors.

Additionally, the R-squared coefficient, also known as the coefficient of determination, assesses the goodness-of-fit of the predicted wind values against the actual wind values. It represents the proportion of variance in the observed wind patterns that can be explained by the LSTM model. A higher R-squared value indicates a better fit and higher predictive accuracy.

To present a comprehensive analysis, these evaluation metrics were calculated for all three stations, and the results were tabulated in Table 2. The table provides a concise summary of the model's performance, allowing for a direct comparison of MSE, MAE, and R-squared values across the stations.

The inclusion of this table enhances the clarity and transparency of our findings, enabling readers to easily interpret and assess the predictive capabilities of the double-layer LSTM algorithm in wind forecasting.

Table2. Three parameters to measure the accuracy of the obtained model for three stations

	Tafresh	Khomein	Saveh
MSE	0.0017	0.0029	0.0012
MAE	0.0292	0.0377	0.0256
R-squared	0.8838	0.8719	0.9183

5. Conclusion

This study provides a detailed assessment of wind energy potential in Markazi Province, Iran, focusing on the cities of Tafresh, Khomein, and Saveh. Using a combination of statistical methods and artificial intelligence techniques, it evaluates wind patterns, temporal variations, and energy potential in these regions. Data collected over a two-year period from advanced meteorological stations formed the basis for analyzing wind speed and direction, enabling a comprehensive understanding of wind behavior.

The Weibull distribution and wind rose diagrams revealed significant variations in wind characteristics across the three locations. Saveh emerged as the most suitable area for wind energy development, given its consistent and higher wind speeds, while Khomein showed moderate potential for medium-scale projects. Conversely, Tafresh exhibited limited wind energy potential, making it economically unsuitable for large-scale wind farm investments.

The use of Long Short-Term Memory (LSTM) neural networks added value by predicting wind speeds and temporal patterns with high accuracy. The alignment between the actual and predicted data validated the model's reliability in capturing wind dynamics, including direction and frequency. This predictive capability is crucial for planning future wind energy projects and optimizing energy production strategies.

The calculation of wind power density (WPD) further supported these findings, with Saveh showing the highest potential for efficient wind energy exploitation. These insights underline the importance of site-specific data in designing wind farms and selecting appropriate technologies for maximum efficiency.

This research demonstrates the effectiveness of combining statistical and machine learning techniques in wind resource assessment. By leveraging these approaches, decision-makers can make informed choices about renewable energy investments, enhancing sustainability in energy production. Additionally, the study emphasizes the role of wind energy in reducing dependence on fossil fuels, mitigating environmental impacts, and supporting Iran’s goals for sustainable development.

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