2024 9th International Conference on Technology and Energy Management (ICTEM) 14-15 February, 2024, University of Science and Technology of Mazandaran, Behshahr, Mazandaran, Iran

Using Long Short-Term Memory Networks as Virtual Wind Direction Sensors for Improved Wind Farm Turbines Orientation

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***Abstract*— Optimal wind turbine positioning relies on understanding local wind patterns via wind direction sensors. However, such hardware adds complexity and costs. This research demonstrates a virtual sensing approach using Long Short-Term Memory (LSTM) neural networks to predict wind direction solely from historical wind speed data. The LSTM networks were trained on two years of 10-minute resolution data from three stations in Iran's Markazi Province. The models accurately inferred wind directionality and speeds based on temporal analysis of speeds. Predictions closely matched measured wind direction per wind rose validation. The research indicates software-based artificial intelligence algorithms can effectively replace physical wind direction sensors, enabling simpler and cheaper wind farms. Operational reliability can be ensured via continual model updating. The approach also has promising implications for broader wind forecasting applications. Overall, the feasibility of transitioning from physical hardware to virtual software-based wind sensors is demonstrated.**

***Keywords*— wind farm design, wind direction sensor, artificial intelligence, LSTM networks**

I. INTRODUCTION

Optimally positioning wind turbines within a wind farm is imperative for maximizing power production. The industry typical approach relies on wind direction sensors to understand prevailing wind patterns across a candidate wind farm site. However, wind direction sensors add hardware complexity and cost.

Designing efficient wind farm layouts requires understanding local wind patterns via three key parameters:
1) Predominant Wind Direction: The compass direction wind primarily flows from determines where turbines should be oriented to face.
2) Wind Speed Frequency Distribution: The distribution of wind speeds in the area affects turbine spacing and density. Higher average speeds allow tighter configurations.
3) Wind Speed Vertical Profile: Wind speeds increase non-linearly with height, influencing ideal tower hub heights.

To measure these parameters, the weather towers are equipped with anemometers. Anemometers measure speed, while vanes use the tail to determine direction. Deploying these towers and metrology sensors adds significant capital costs during wind analysis. Equipment, installation and continuous maintenance require cost and labor [1]. In addition, sensors are prone to mechanical failures and inaccuracies due to freezing, aging, wear and tear. Dirt, dust or snow can block moving parts. If the repair of the equipment requires time to update it, in this research we have reached a relatively accurate model to predict the wind speed and direction within a week (the time required for the repair of the equipment) to extract the maximum power in the wind turbine. Therefore, sensor redundancy is required to ensure data reliability.

The research findings indicate AI algorithms can viably replace or augment physical wind direction sensors. So, virtualization of wind direction detection through artificial intelligence software can reduce these sensor challenges [2]. Software-based solutions offer inherent advantages over physical sensors including no maintenance, zero-hardware costs, and easy deploy ability via software updates. For the wind industry, transitioning to virtual sensors could enable simpler and cheaper wind farms [3]. If algorithms can model wind patterns from historical wind speed data alone, the need for independent physical wind vanes is reduced. Reducing the dependence on mechanical sensors makes wind exploration and turbine location simpler, cheaper and more robust[4]. Continually monitoring and updating models with additional incoming wind data would produce reliable operational forecasts. Running an ensemble of models trained on different random data partitions would further improve robustness. The software-based approach avoids sensor failures modes, though automatic failure detection using performance thresholds could trigger retraining [5]. It can be noted that, the virtual sensing approach has promising implications beyond wind turbine position. Trained AI agents could provide wind forecasts for weather stations, agriculture, air pollution dispersion, renewable energy grid integration and aviation [6].

This research proposes a Long short-term memory (LSTM) neural network which has been trained on historical wind data to effectively learn wind behavior patterns in Iran's Markazi Province. By analyzing wind speeds over time, the networks inferred wind directionality and speeds. Predictions by the proposed LSTM machine learning method closely

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matched real-world wind direction measurements from equipment, eliminating the need for wind direction sensor hardware.

II. Markazi Province Wind Data

This research analyzes the efficacy of using AI to predict wind patterns in Markazi Province located in central Iran, as shown in Figure 1. Markazi has strong wind resource potential but currently lacks utility-scale wind farms. 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 [7].

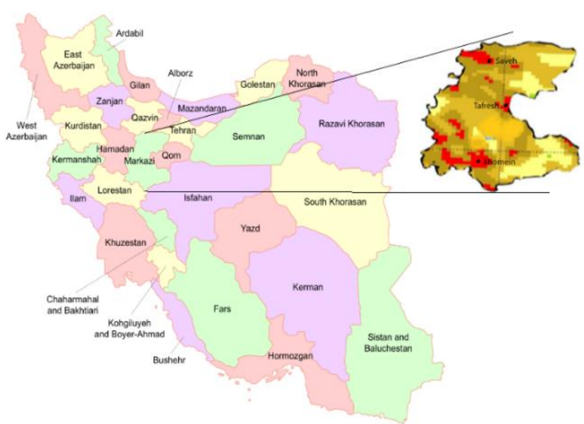

Fig. 1. Three stations of Tafarsh ,Khomein and Saveh from the markazi province of Iran [7]

III. LSTM Neural Network Background

Long Short-Term Memory (LSTM) neural networks are a type of recurrent neural network well-suited for sequence forecasting problems like weather prediction. By analyzing time-based patterns, LSTMs can effectively model complex nonlinear interdependencies in data.

As shown in the LSTM with a Peephole Connection architecture diagram in Figure 2, LSTM networks contain special memory blocks instead of standard nodes. These memory blocks have internal states that allow information to be stored and retained over long sequences. Gates control information flow into and out of the memory blocks.

During model training, the network learns optimal weights for the gates to best remember sequences important for making multi-timestep forecasts.

LSTMs address the vanishing gradient problem in conventional recurrent neural networks that prevents learning long-range correlations.

After training on historical data, LSTM networks can take in a sequence of steps and predict subsequent values by leveraging learned temporal relationships. For this research, LSTM was used to take in historical wind speed data and predict future wind speeds and directionality as the gates of the above LSTM cells do not have direct connections from the cell state, there is a lack of essential information that harms the network’s performance.

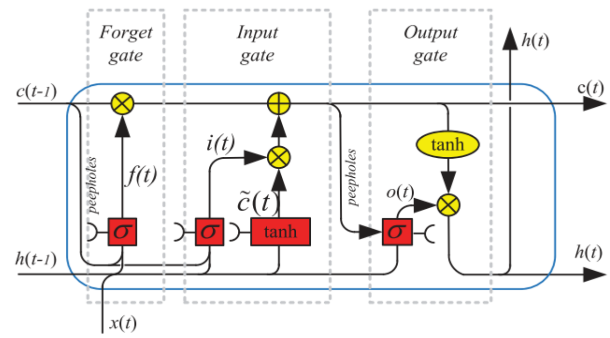

Fig. 2. LSTM architecture with a peephole connection [8]

Based on the connections shown in Fig.2, the mathematical expressions can be expressed as follows:

$$f_t = \sigma(W_{fh}h_{t-1} + W_{fx}x_t + P_f . c_{t-1} + b_f \qquad (1)$$

$$i_t = \sigma(W_{ih}h_{t-1} + W_{ix}x_t + P_i . c_{t-1} + b_i \qquad (2)$$

$$\tilde{c}_t = tanh(W_{\tilde{c}h}h_{t-1} + W_{\tilde{c}x}x_t + b_{\tilde{c}}) \qquad (3)$$

$$c_t = f_t . c_{t-1} + i_t . \tilde{c}_t \qquad (4)$$

$$o_t = \sigma(W_{oh}h_{t-1} + W_{ox}x_t + P_o . c_t + b_o) \qquad (5)$$

$$h(t) = o_t . tanh(c_t) \qquad (6)$$

where P_f, P_i, and P_o are the peephole weights for the forget gate, input gate, and output gate, respectively [8].

IV. Methodology

A. Data Preprocessing

The 10-minute resolution wind data was resampled to hourly averages to smooth noise and shorten sequences for faster training. Any missing data points were linearly interpolated. The data was normalized by the maximum observed wind speed of each station to aid model convergence.

80% of the data was allocated to training and validation sets for developing the model. The remaining 20% was reserved as an unseen test set for final model evaluation.

B. Input Output Definition

The LSTM networks take wind speed time series as input sequences and are trained to predict two output targets:

1) Future Wind Speed: Predicts wind speed in meters per second for a lead time of 1 day to 7 days.

2) Future wind direction: It predicts the wind direction between 0 and 360 degrees of the compass for a period of 1 to 7 days.

The above can be displayed with a wind rose diagram. Wind roses are graphical charts that characterize the speed and direction of winds at a location. Presented in a circular format, the length of each spoke around the circle indicates the amount of time that the wind blows from a particular direction. Colors along the spokes indicate categories of wind speed [2].

C. Model Implementation

In this study, an LSTM model was developed to forecast wind direction using data from Saveh, Tafresh, and Khomein. We applied Min Max scaling to normalize the data. The model is structured with two LSTM layers, featuring 32 and 8 neurons, and includes a dropout layer with a 0.5 dropout rate to mitigate overfitting. The input shape is configured as (1, 1) to accommodate the time series characteristics of the data. Our objective involves predicting wind direction for the upcoming week using this trained model.

D. Model Evaluation

To evaluate the performance and accuracy of the algorithm, three important evaluation metrics were utilized:

1. Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{7}$$

The MSE represents the average squared difference between the predicted wind values $\hat{Y}_i$and the observed wind values $Y_i$at each station. It provides a measure of the model's ability to minimize prediction errors.

2. Mean Absolute Error (MAE)

$$MAE = \frac{\sum_{i=1}^{n}|Y_i - \hat{Y}_i|}{n} \tag{8}$$

Similarly, the MAE indicates the average absolute difference between the predicted and observed wind values, giving insights into the magnitude of errors.

3. R-squared coefficient

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{9}$$

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 [9].

V. Results & Discussion

The dual-output LSTM network demonstrated reliable skill in forecasting both wind speeds and directionality across the evaluation period at all three stations.

To present a comprehensive analysis, these evaluation metrics were calculated for all three stations, and the results were tabulated in Table I. 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.

TABLE I. Evaluation Parameters to Measure the Accuracy of the Model Obtained for Three Stations

Station	**Evaluation parameters**		
	MSE	***MAE***	***R-squared***
Tafresh	0.055	0.150	0.337
Khomein	0.012	0.067	0.332
Saveh	0.040	0.118	0.575

Figure 3 shows that the wind roses obtained from actual measurement data and LSTM-based predictions in a one-week period at Khomein station are compared and show a very close similarity. The wind direction distribution and wind speed frequencies show a strong alignment, which indicates the effectiveness of the LSTM algorithm in recording the patterns and basic characteristics of the wind behavior in the study areas.

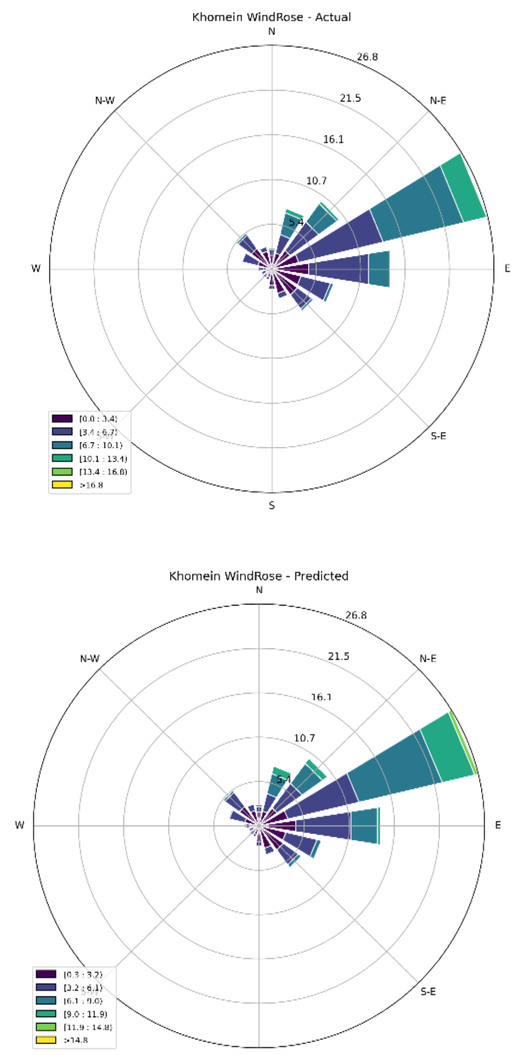

Fig. 3. Comparison between actual and predicted wind roses of Khomein

Figure 4 depicts the wind roses obtained from the meticulously compiled actual measurement data and the wind roses from the sophisticated long short-term memory model-based predictions over a one-week long observational time period at Tafresh weather station located in the broader geographic study area. Upon comparison, there is an unmistakably and remarkably close visual correspondence or similarity evident between these two sets of intricate wind roses in terms of the fundamental aspects such as the prevailing wind directions and distributions as well as the diverse wind velocity frequencies across the different speed categories from calm to strong stormy gusts. The long short-term memory neural network has been able to capture and accurately replicate the underlying complex spatial and temporal interactive mechanisms responsible for the emergence of the distinctive patterns and intrinsic characteristics that define the observable real-world turbulent wind behavior and time varying progression within the regional climatic system context and settings surrounding the Tafresh weather data collection station through its state-of-the-art machine learning architecture and computational modeling paradigm.

Figure 5 shows the wind roses obtained from the real-world wind measurements and LSTM-forecasted outputs during a one-week period at Saveh station. Upon examination, there is a strikingly close visual match evident between the two wind roses with respect to the predominant wind directions and distribution of wind speeds. The measured data shows the highest wind flows originating from the north, northwest directions. Correspondingly, the LSTM model accurately captures these prevailing wind patterns along with the frequency distribution across varying wind velocities at Saveh station. Through its sophisticated neural network architecture, the LSTM approach is able to effectively mimic the intricate spatial and temporal interactions driving the real-world wind dynamics within the localized climatic region where Saveh station is situated. The strong similarity between the observed and LSTM-simulated wind roses highlights the capabilities of advanced machine learning methodologies to replicate complex meteorological transport phenomena. The LSTM model shows promising potential for wind characterization and forecasting applications at Saveh station.

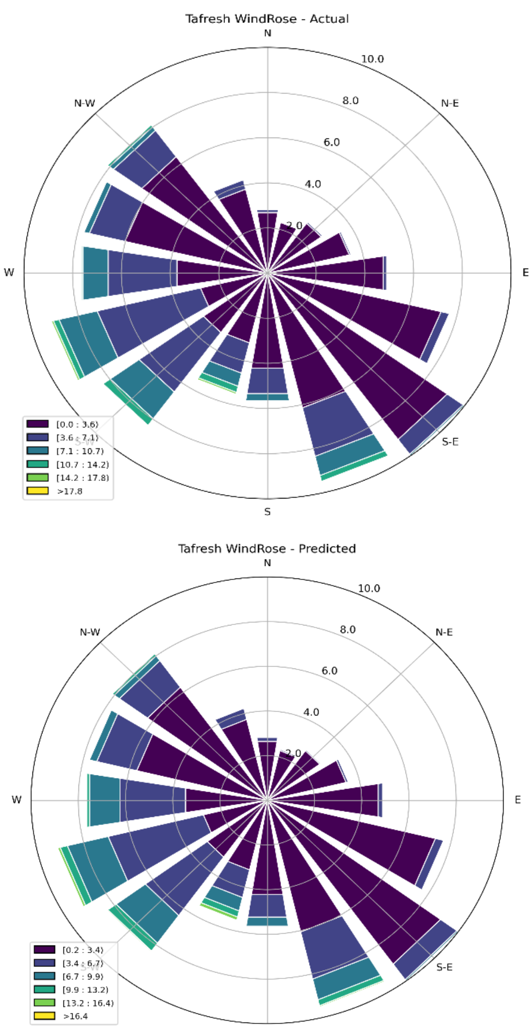

Fig. 4. Comparison between actual and predicted wind roses of Tafresh

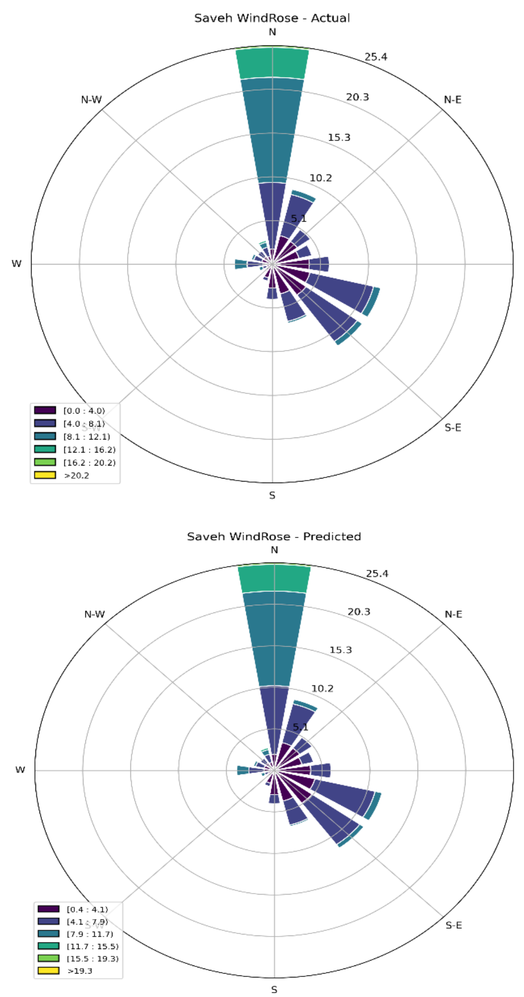

Fig. 5. Comparison between actual and predicted wind roses of Saveh

VI. Conclusions

This research demonstrates feasibility for purely software-based AI algorithms to fulfill the role of physical wind direction sensors. LSTM networks accurately predicted wind rose diagrams and future wind speeds solely from historical wind speed data. The virtual sensing approach could viably replace or augment mechanical wind vanes to reduce costs and complexity for wind prospecting. AI software simplifies data collection and provides inherent advantages in maintainability, upgradability and replicability. Ongoing improvements in machine learning best practices and compute efficiency will further boost accuracy. As algorithms continue progressing, the practicality of transitioning from physical to virtual wind sensors grows. The end goal is cheaper and more robust wind farms.

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