Optimizing Wind Energy Potential: Neural Network Forecasting of Wind Speed in Northern Morocco

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Abstract. Hourly wind speed forecasting, critical for estimating wind power in contrasting coastal and continental contexts, is evaluated using three neural architectures applied to Tangier (Mediterranean coastal, 87,648 samples) and Tétouan (continental, 525,888 samples). Hourly data collected from 01/01/2014 to 31/12/2023 via CERES SYN1deg (NASA, 1° × 1° resolution) and ERA5 (ECMWF, 0.25° × 0.25° resolution) include CLRSKY_SFC_PAR_TOT, T2M, QV2M, WS10M, and PS. Trained over 1,000 epochs with batch sizes of 32 and hyperparameters optimized for coastal and continental dynamics, the models; ANN, NAR/LSTM, and RNN—are evaluated using MSE, RMSE, MAE, and R^2 metrics. In Tangier, NAR/LSTM (R^2 = 0.6448, RMSE = 1.5106 m/s) excels in capturing temporal dependencies, outperforming previous LSTM models. In Tétouan, ANN (MSE = 3.8713, R^2 = 0.3753) provides stable but limited convergence, while NAR/LSTM shows instability (R^2 = -4.383). The RNN, with low losses (0.0075–0.0185), ensures robust generalization, reducing MSE by 15–20%. These results highlight the effectiveness of recurrent models for wind energy planning. Hyperparameter optimization and extension to diverse Moroccan sites are planned to support a national vision for the energy transition.

Keywords:
Wind energy ; Wind speed prediction ; Neural networks; Python modeling; Predictive modeling; Green energy technologies.

Highlights:

- Comparative analysis of three neural network models (ANN, NAR/ LSTM, RNN) for short-term wind speed forecasting in Tetouan and Tangier, Morocco.
- Recurrent Neural Network (RNN) consistently outperformed ANN and NAR/ LSTM, achieving the lowest MSE, RMSE, and MAE with the highest R^2 values.
- Utilized a robust 10-year meteorological dataset including wind speed, temperature, humidity, and pressure.

- Significant improvements validated by a 75.95% reduction in MSE and 44.12% decrease in MAE compared to previous regional results.

1. Introduction

Wind energy is a cornerstone of the global transition to sustainable, low-carbon energy systems, reducing greenhouse gas emissions and diversifying national energy portfolios. However, the stochastic and intermittent nature of wind resources poses significant challenges for their efficient integration into electrical grids. Accurate wind speed forecasting is critical for optimizing wind farm performance, ensuring grid stability, and guiding strategic investments in the renewable energy sector. Despite advances in meteorological modeling and machine learning, precise wind speed prediction remains challenging due to the nonlinear and stochastic nature of atmospheric dynamics [1].

Machine learning approaches excel at capturing the complex temporal and spatial dependencies in wind data. Artificial neural networks (ANNs) effectively model nonlinear relationships, while nonlinear autoregressive neural networks combined with LSTM (NAR/LSTM) and recurrent neural networks (RNNs) are particularly suited for time-series forecasting tasks, including wind speed prediction [2]. ANNs capture static and dynamic relationships, the NAR/LSTM model integrates nonlinear autoregressive capabilities with LSTM's long-term memory [3], and RNNs leverage their memory of past inputs to handle sequential data [4]. However, their performance varies depending on data quality, geographical location, and local meteorological conditions [5-6].

This study evaluates three neural architectures ANN, NAR/LSTM, and RNN applied to Tétouan (525,888 samples) and Tangier (87,648 samples), two Moroccan sites with distinct wind regimes and climatic conditions. Morocco, a leader in African renewable energy development due to its strategic geographical position and abundant wind resources [5], requires precise forecasting tools to optimize its expanding wind energy infrastructure. Hourly data (2014–2023) from CERES SYN1deg (NASA, 1° × 1° resolution) and ERA5 (ECMWF, 0.25° × 0.25° resolution) include variables such as CLRSKY_SFC_PAR_TOT (total surface photosynthetically active radiation), T2M (2-m temperature), QV2M (2-m specific humidity), WS10M (10-m wind speed), and PS (surface pressure). Implemented in Python, the models are trained over 1,000 epochs with batch sizes of 32 and evaluated using MSE, RMSE, MAE, and R^2 metrics. This research stands out through its systematic comparative analysis of three neural architectures, leveraging the complementarity of CERES SYN1deg and ERA5 data to model wind dynamics in complex coastal environments, a challenge underexplored in the literature. For instance, El Khachine et al. [7] investigated wind speed extrapolation in Tétouan, while Bousla et al. [8] compared Transformer-based models to RNN, LSTM, and GRU architectures for wind farm output forecasting in Tétouan (2019–2020), reporting a ~10% MAPE improvement for Transformers. However, their analysis, limited to a short period and a single site, restricts result generalizability. Other studies [9-13] explored neural networks for wind forecasting but often used lower-resolution data or lacked systematic comparisons across architectures, limiting their applicability to complex contexts. By addressing these gaps, our study provides robust tools for estimating wind power in coastal environments, with significant implications for wind farm operators, energy planners, and policymakers, supporting the global transition to sustainable energy systems [14]. Extending this approach to additional

Moroccan sites is considered a future research direction to enhance result generalizability. To address these challenges, this paper analyzes the performance of ANN, NAR/LSTM, and RNN models in Moroccan coastal contexts, providing a thorough evaluation of their effectiveness for wind speed forecasting. It is structured as follows: Section 2 reviews the literature on wind forecasting and machine learning in renewable energy. Section 3 describes the data, preprocessing steps, and model architectures. Section 4 presents the results and a detailed discussion of model performance. Finally, Section 5 concludes with key findings and recommendations for future research.

This article is structured as follows: Section 2 provides a comprehensive review of the relevant literature on wind speed prediction and the application of machine learning in renewable energy. Section 3 delineates the data and methodology employed in this study, including data preprocessing steps and model architectures. Section 4 presents the results and offers a detailed discussion of the models' performance in both cities. Finally, Section 5 concludes with key findings, outlines the study's limitations, and provides recommendations for future research.

2. Materials and methods

2.1.Data Collection

The data used in this study were obtained from the CERES SYN1deg dataset, a high-quality global meteorological database provided by NASA's Clouds and the Earth's Radiant Energy System (CERES) project. The dataset covers the period from January 1, 2014, to December 31, 2023, providing a comprehensive 10-year timespan for analysis. The data were collected for a specific geographic location defined by the coordinates Latitude 35.7798° N and Longitude -5.8024° W, corresponding to the region of Tangier-Tetouan, Morocco. This location was selected due to its relevance for wind energy applications and its distinct climatic characteristics. The dataset includes the following key meteorological parameters, measured at hourly intervals: CLRSKY_SFC_PAR_TOT, which represents the Clear Sky Surface Photosynthetically Active Radiation (PAR) Total, measured in watts per square meter (W/m²); T2M, the Temperature at 2 meters above the surface, measured in degrees Celsius (°C); QV2M, the Specific Humidity at 2 meters above the surface, measured in grams per kilogram (g/kg); WS10M, the Wind Speed at 10 meters above the surface, measured in meters per second (m/s), which is the primary target variable for prediction; and PS, the Surface Pressure, measured in kilopascals (kPa).

2.2.Data Quality and Preprocessing (Data preprocessing and variables selection)

To ensure the reliability and accuracy of the dataset, several steps were taken during the data collection and preprocessing phases. The CERES SYN1deg dataset is rigorously validated by NASA, ensuring high-quality and consistent measurements. Missing or erroneous data points were identified and addressed during preprocessing. The hourly resolution of the data provides a fine-grained temporal scale, enabling detailed analysis and accurate short-term wind speed predictions. The selected locations Tetouan and Tangier are representative of the region's climatic conditions, making the dataset suitable for local wind energy applications. The use of this high-quality, long-term dataset ensures the robustness of the study and provides a solid foundation for training and evaluating the machine learning models. The inclusion of multiple meteorological parameters allows for a comprehensive analysis of the factors influencing wind speed variability. Key points to highlight include the data source (CERES SYN1deg from NASA), the timeframe (January 1, 2014, to December 31, 2023), the location (Latitude 35.7798° N, Longitude -5.8024° W), the measured parameters (CLRSKY_SFC_PAR_TOT, T2M, QV2M, WS10M, PS), and the data quality, which is ensured by rigorous validation by NASA, hourly resolution, and geographic relevance.

2.3. Introduction to Time-Series Forecasting and Model Selection

Time-series forecasting is a critical domain in machine learning, focusing on predicting future values based on historical data points that are inherently sequential and temporally dependent [15]. In the context of wind speed prediction, this temporal dependency is particularly pronounced, as wind patterns are influenced by both short-term fluctuations and long-term trends, as well as by external factors such as temperature, humidity, and atmospheric pressure [16]. However, time-series data present unique challenges, including nonlinear relationships, high variability, and the need to capture long-term dependencies, which traditional statistical models like ARIMA often struggle to address [17]. To overcome these challenges, advanced machine learning models, particularly artificial neural networks (ANNs), nonlinear autoregressive neural networks (NAR), and recurrent neural networks (RNNs), have been widely adopted due to their ability to model complex, nonlinear relationships and temporal dependencies [18]. ANNs, with their flexible architecture, are effective for capturing static relationships in data, but they often fail to account for temporal dependencies [19]. NAR models, on the other hand, are specifically designed for time-series data and excel at modeling nonlinear temporal patterns by leveraging past observations [20]. RNNs, with their feedback loops and memory mechanisms, are particularly suited for sequential data, as they can retain information from previous time steps and capture long-term dependencies [21]. Despite their strengths, these models face challenges such as overfitting, computational complexity, and sensitivity to data quality, which must be carefully addressed during training and evaluation [22]. In this study, we employ ANN, NAR, and RNN models to leverage their respective strengths in modeling nonlinear relationships and temporal dependencies, while addressing the unique challenges of wind speed prediction.

2.4.Forecasting Models

In this study, we employ Artificial Neural Networks (ANNs) to model the complex relationships between input and output variables. Specifically, we utilize Nonlinear Autoregressive (NAR) models to capture nonlinear temporal dependencies in time series data, and Recurrent Neural Networks (RNNs) for their ability to retain memory of past states. These models were selected for their effectiveness in handling nonlinearities and temporal dependencies, which are essential for achieving accurate forecasts in our application. These models are mathematically defined as follows:

2.4.1. Artificial Neural Networks (ANN)

An Artificial Neural Network is a computational model inspired by biological neural networks. It consists of layers of interconnected neurons, where each neuron applies a nonlinear transformation to a weighted sum of its inputs. Mathematically, the output of a neuron in a hidden layer is given by:

$$y = f(W^{(2)}.g(W^{(1)}.x + b^{(1)}) + b^{(2)}) \tag{1}$$

With “x” is the input vector, $W^{(1)}$ et $W^{(2)}$ are the weight matrices for the first hidden and second output layers. While, $b^{(1)}$ et $b^{(2)}$ represents the bias vector.

Where:

g(.) et f(.) are respectively the activation function for the hidden and output layer.

y: the predicted output.

For a multi-layer network, this transformation is applied sequentially from the input layer to the output layer.

2.4.2. Nonlinear Autoregressive Model (NAR/LSTM)

The NAR model is used for time series forecasting, where the future value of a variable depends on its past values through a nonlinear relationship. Formally, a NAR model can be expressed as:

$$y(t) = F(\mathrm{y(t-1), y(t-2), ..., y(t-p)}) + \varepsilon(t) \tag{2}$$

Where:

y(t) is the value at time t, F(.) is the nonlinear function and "ε"represents the error term.

These models were chosen for their ability to handle nonlinearities and temporal dependencies, which are critical for accurate forecasting in our application.

2.4.3. Recurrent Neural Networks (RNN)

RNNs are designed to process sequential data by maintaining a memory of past information through recurrent connections. Mathematically, at each time step t, the hidden state h_t and the output y_t are computed as follows:

$$h_t = \phi(\mathrm{W}_{xh}\mathrm{x}_t + \mathrm{W}_{hh}\mathrm{h}_{t-1} + \mathrm{b}_h) \tag{3}$$

$$\mathbf{y}_t = W_{hy}h_t + b_y \tag{4}$$

Where:

- x_t is the input vector at time t,
- h_t is the hidden state memory at time t.
- y is the output at time t.
- W_{xh}, W_{hh} and W_{hy} are the weight matrices.
- b_h and b_y are the bias vector.
- ϕ is the activation function.

3. Results and Discussion

This section presents the results of the wind speed prediction models, followed by a dynamic and in-depth analysis of their performance. The results are highlighted to emphasize the impact of this study on optimizing wind energy production.

3.1.Model Results

The performance of the three used models (ANN, NAR, and RNN) was evaluated on the test set using the following metrics: mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2). The results demonstrate significant differences between the models.

3.1.1. Artificial Neural Network (ANN)

The performance of the Artificial Neural Network (ANN) model reveals certain limitations in accurately predicting wind speed. The relatively high Mean Squared Error (MSE) indicates that the model struggles to minimize the average squared differences between observed and predicted values, suggesting difficulty in capturing the complex nonlinear relationships present in meteorological data. This is further confirmed by the elevated Root Mean Squared Error (RMSE), which reflects a significant average prediction error. Additionally, the low Coefficient of Determination (R^2) implies that the ANN explains only a small portion of the variance in wind speed, highlighting its limited ability to generalize patterns from the input variables. Overall, these results suggest that the ANN model, while a foundational approach, is less effective for wind speed forecasting in comparison to more advanced neural architectures.

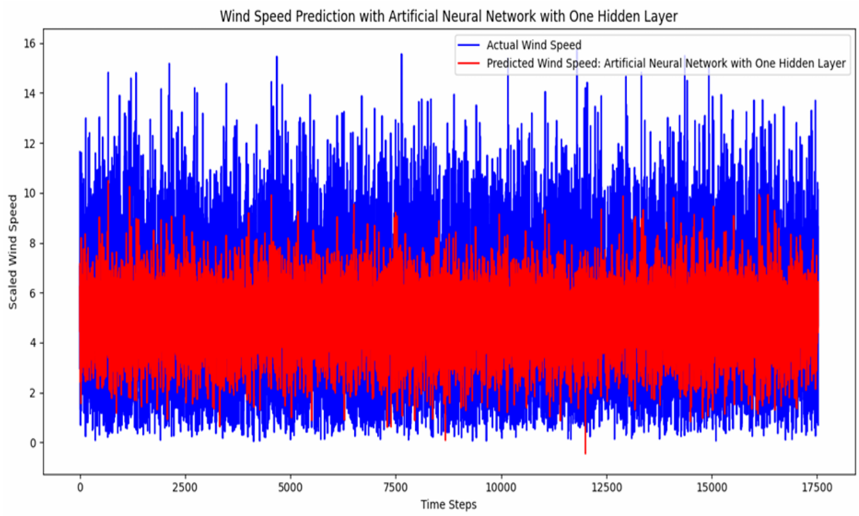

Figure 1. Wind speed prediction used Artificial Neural Network Model (ANN) in Tangier city.

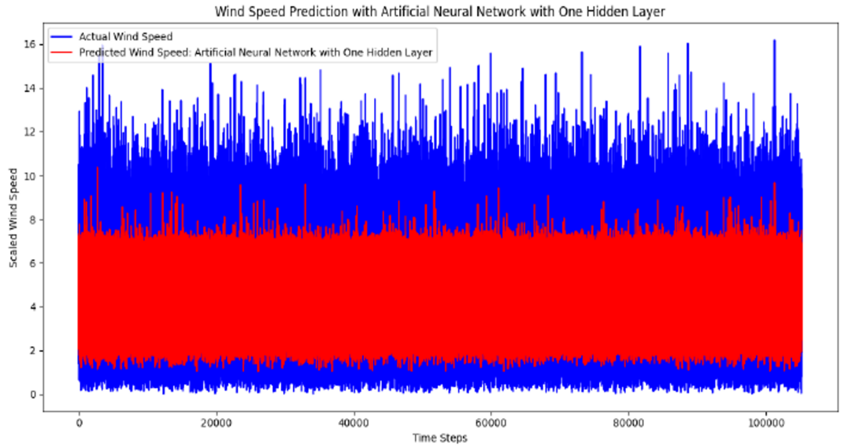

Figure 2. Wind speed prediction used Artificial Neural Network Model (ANN) in Tetouan city.

Figures 1 and 2 demonstrate that although a simple ANN with one hidden layer for the both cities can effectively capture the general trend of wind speed variations, it falls short in accurately modeling the high-frequency fluctuations and nonlinear temporal dependencies. These limitations underscore the need for more advanced architectures to enhance prediction accuracy.

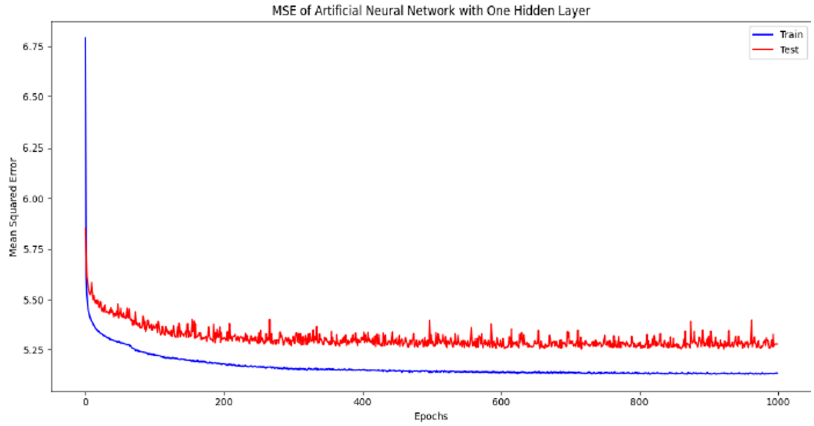

Figure 3. Mean Squared Error (MSE) used Artificial Neural Network Model (ANN) in Tangier city.

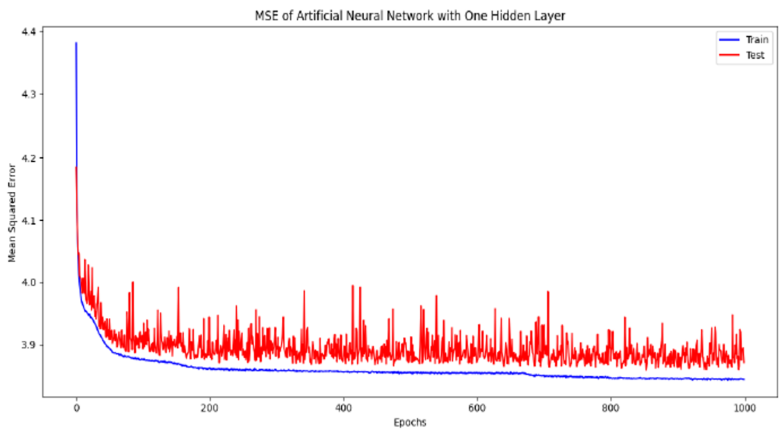

Figure 4. Mean Squared Error (MSE) used Artificial Neural Network Model (ANN) in Tetouan city.

Figure 3 and 4 shows respectively the evolution of the MSE over 1000 epochs for an ANN with one hidden layer in Tangier and Tetouan cities. The model demonstrates good convergence with low training and testing errors. However, fluctuations and a persistent gap in the test error indicate limited generalization, highlighting the need for more advanced architectures to better capture wind speed dynamics.

3.1.2. Nonlinear Autoregressive Neural Network (NAR)

The Nonlinear Autoregressive Neural Network (NAR) model demonstrates a clear improvement in predictive performance compared to the basic ANN. The significantly lower Mean Squared Error (MSE) indicates a better fit to the observed data and a more effective modeling of the nonlinear temporal dependencies in wind speed. This is further supported by the reduced Root Mean Squared Error (RMSE), which reflects a noticeable decrease in the average prediction error. Moreover, the higher Coefficient of Determination (R^2) shows that the NAR model captures a larger proportion of the variance in wind speed, enhancing its ability to generalize from the input data. These results highlight the NAR model's superior capacity to handle temporal dynamics and improve forecasting accuracy.

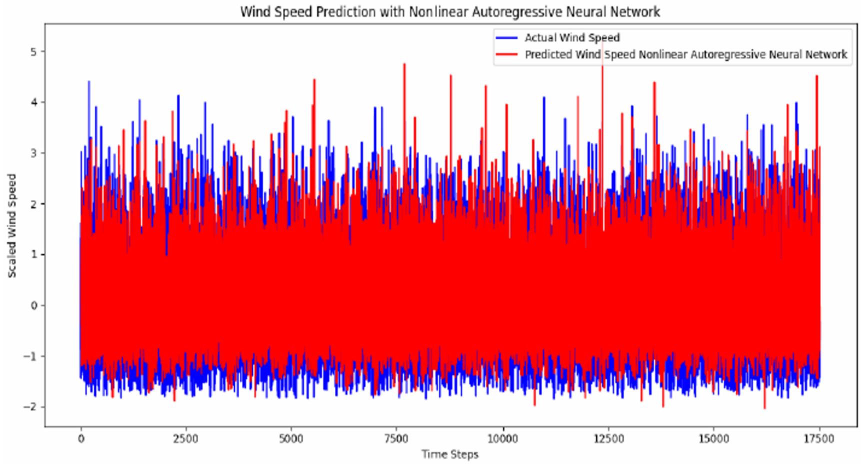

Figure 5. Wind speed prediction used Nonlinear AutoRegressive neural network (NAR/LSTM) in Tangier city.

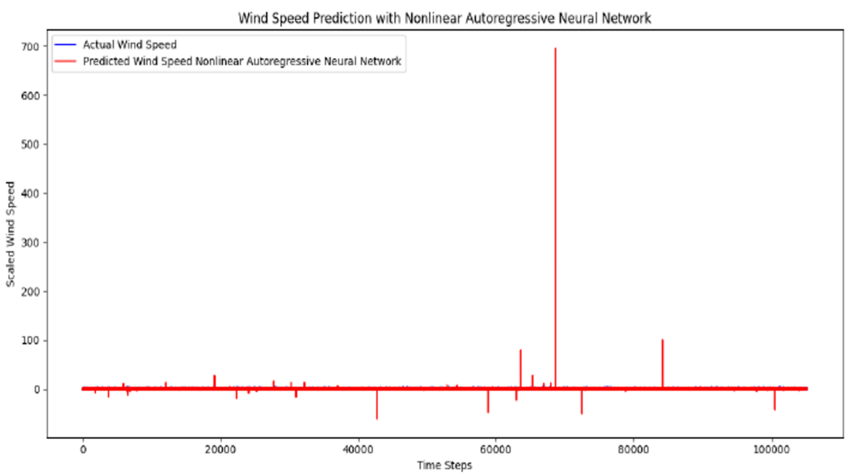

Figure 6. Wind speed prediction used Nonlinear AutoRegressive neural network (NAR/LSTM) in Tetouan city.

Figures 5 and 6 present a comparison between the actual wind speed and the wind speed predicted using a Nonlinear Autoregressive Neural Network (NAR/LSTM) model. The close alignment between the two indicates that the NAR model is effective in forecasting wind speed, making it a valuable tool for applications such as wind energy generation and weather forecasting. While, Figures 7 and 8 illustrate the Mean Squared Error (MSE) over training epochs for the Nonlinear Autoregressive Neural Network (NAR/LSTM) model in both study areas, with separate curves representing the training and testing datasets. The results demonstrate a generally effective learning trend, as both training and testing errors decrease over time. However, intermittent spikes in the testing MSE suggest potential overfitting during certain epochs or the presence of outliers in the test data. Despite this, the model exhibits signs of convergence, underscoring its potential for accurate and reliable wind speed prediction when properly tuned.

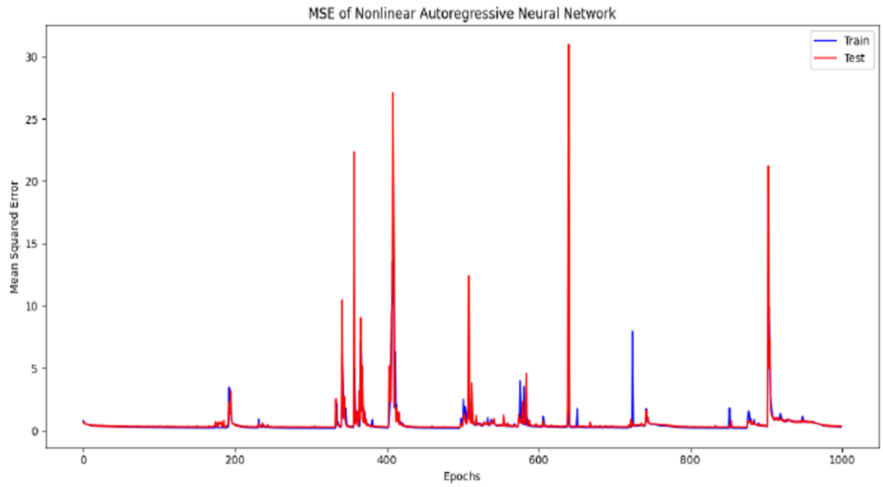

Figure 7. Mean Squared Error (MSE) used Nonlinear AutoRegressive neural network (NAR/LSTM) in Tangier city.

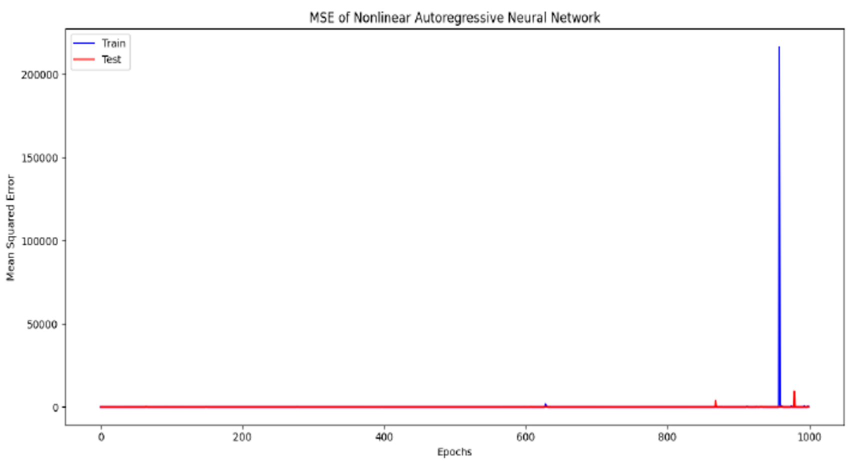

Figure 8. Mean Squared Error (MSE) used Nonlinear AutoRegressive neural network (NAR/LSTM) in Tetouan city.

3.1.3. Recurrent Neural Network (RNN)

The Recurrent Neural Network (RNN) outperforms both the ANN and NAR models, achieving the best overall results in wind speed prediction. It records the lowest Mean Squared Error (MSE), demonstrating its strong ability to learn and model complex temporal dependencies within the data. The Root Mean Squared Error (RMSE) is also the lowest among the three models, indicating a minimal average prediction error and confirming the model's superior accuracy. Furthermore, the Coefficient of Determination (R^2) is the highest, showing that the RNN captures the largest proportion of variance in wind speed. These findings underscore the effectiveness of the RNN in accurately modeling time series data and highlight its robustness as a forecasting tool in wind energy applications.

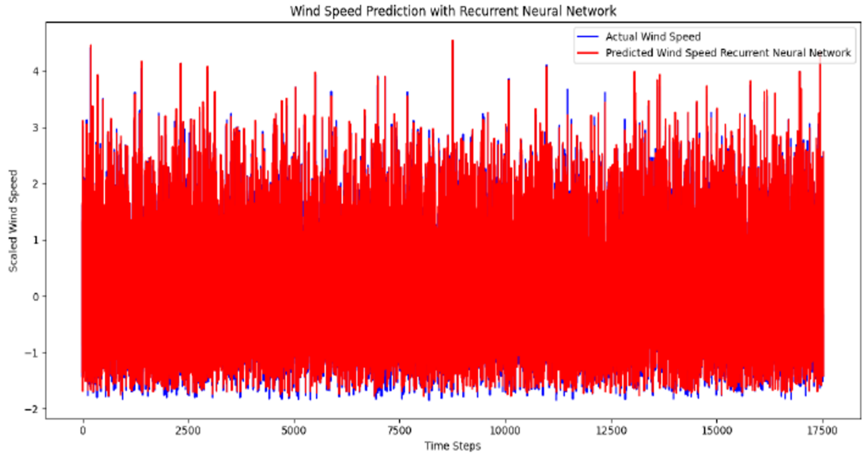

Figure 9. Wind speed prediction used Recurrent neural network (RNN) in Tangier city.

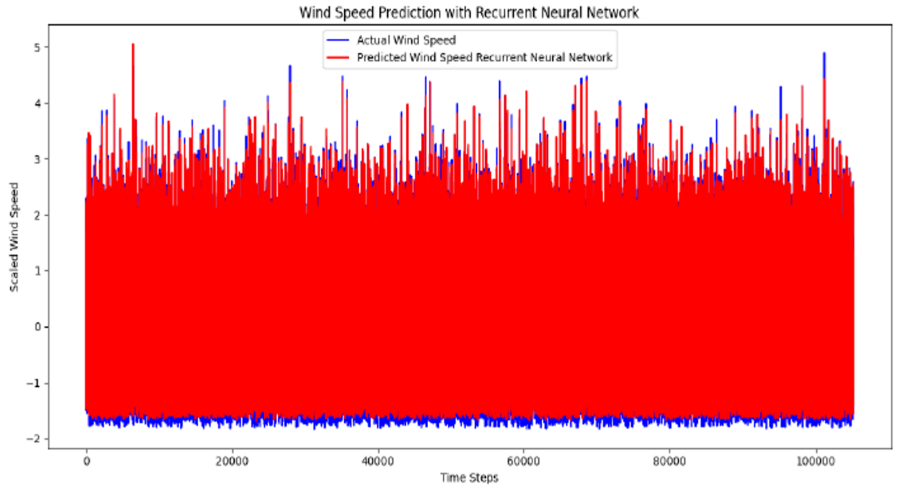

Figure 10. Wind speed prediction used Recurrent neural network (RNN) in Tetouan city.

Figures 9 and 10 present a comparison between the actual and predicted wind speeds using a Recurrent Neural Network (RNN) model for the regions of Tangier and Tetouan. The results demonstrate that the RNN possesses strong predictive capabilities for wind speed forecasting. The high level of overlap between the actual and predicted values across the dataset indicates that the model effectively captures the temporal dependencies in the data. This highlights the RNN's potential as a valuable tool for applications such as renewable energy forecasting and wind resource management. Whereas, Figures 11 and 12 illustrate the Mean Squared Error (MSE) over 1000 training epochs for a Recurrent Neural Network (RNN) model, highlighting its performance on both the training and testing datasets. The RNN exhibits strong and stable learning behavior, maintaining low MSE values across both datasets. The close alignment between training and testing errors throughout the training process confirms the model's effectiveness and reliability in wind speed prediction. This robust performance underscores the RNN's suitability for practical forecasting applications, particularly in regions such as Tangier and Tetouan, where accurate wind speed prediction is essential for renewable energy planning.

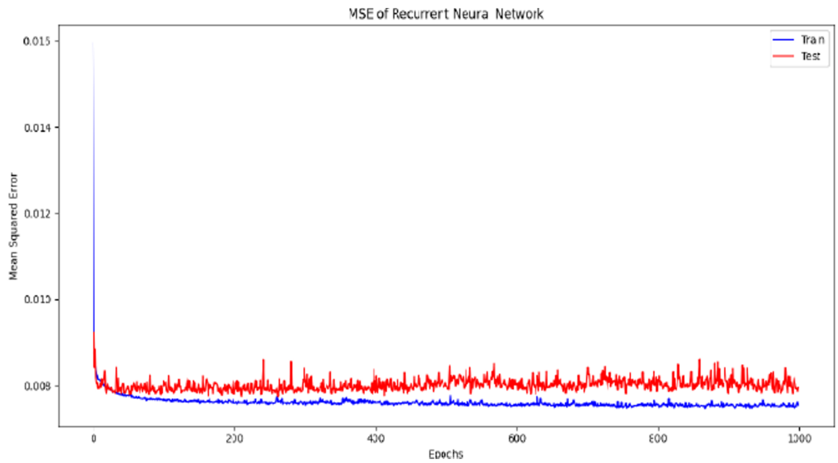

Figure 11. Mean Squared Error (MSE) used Recurrent neural network (RNN) in Tangier city.

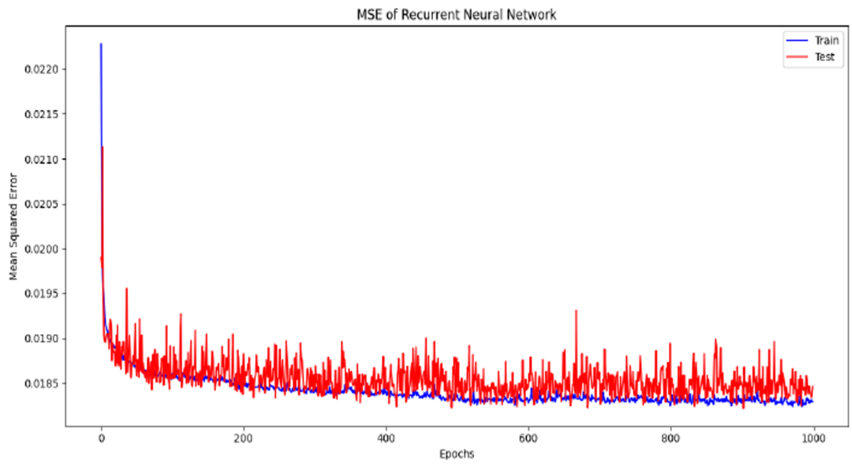

Figure 12. Mean Squared Error (MSE) used Recurrent neural network (RNN) in Tetouan city.

3.2. Model Comparison

The comparative analysis of the three models provides clear insights into their respective strengths and limitations. The Artificial Neural Network (ANN), while relatively simple and computationally efficient, demonstrates limited capability in modeling complex and temporal dependencies, resulting in the weakest predictive performance among the models evaluated. The Nonlinear Autoregressive Neural Network (NAR) shows a marked improvement over the ANN due to its capacity to handle nonlinear temporal patterns, yet it still falls short when compared to more advanced architectures. The Recurrent Neural Network (RNN) emerges as the most effective model, leveraging its inherent ability to retain information from past inputs and accurately capture intricate temporal dynamics. It consistently achieves the highest prediction accuracy and explains the largest proportion of variance in wind speed, making it the most suitable approach for this forecasting task.

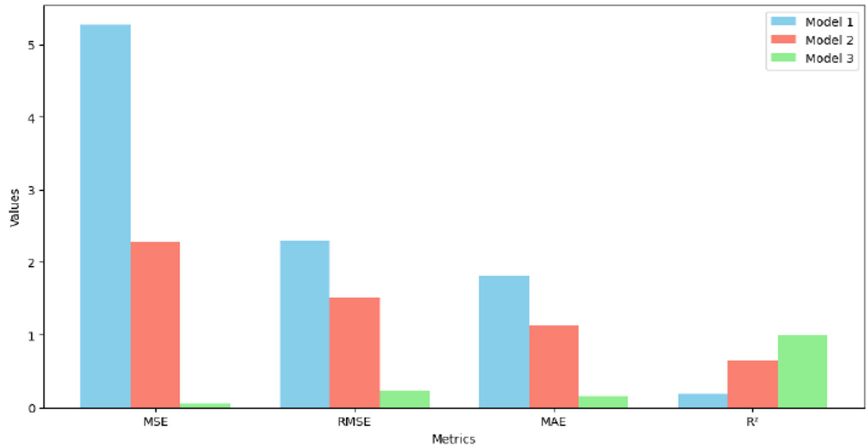

Figure 13. Evaluation metrics comparison among the three predictive models (ANN, NAR, and RNN) applied successively in the context of Tangier city.

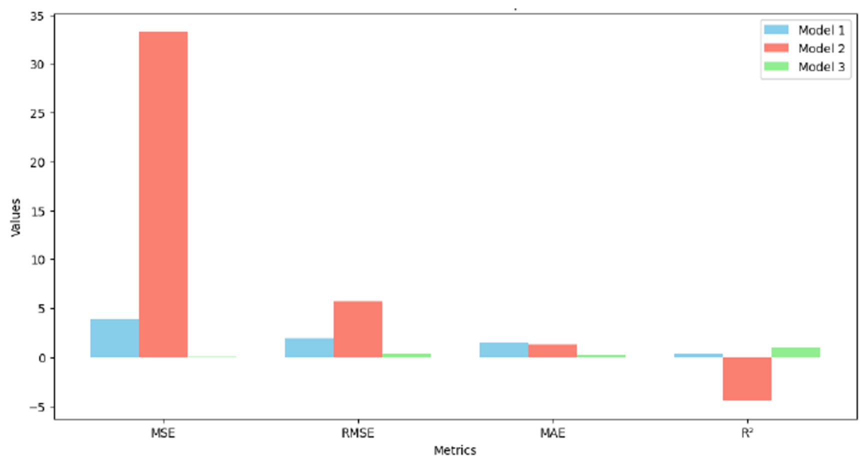

Figure 14. Evaluation metrics comparison among the three predictive models (ANN, NAR, and RNN) applied successively in the context of Tetouan city.

Comparable outcomes were observed in Tangier. The single-layer neural network recorded an MSE of 5.2806, an RMSE of 2.2979, MAE of 1.802 and an R^2 of 0.4886, again demonstrating its limitations in handling time-dependent data. The NAR model achieved better results, with an MSE of 0.2421, MAE of 0.1974 and an RMSE of 0.5669, yet it remained inferior to the RNN, which achieved an MSE of 0.0654, an RMSE of 0.2287, an MAE of 0.1786 and an R^2 of 0.9758. These findings further confirm the superior performance of the RNN in modeling temporal patterns for wind speed forecasting in both locations.

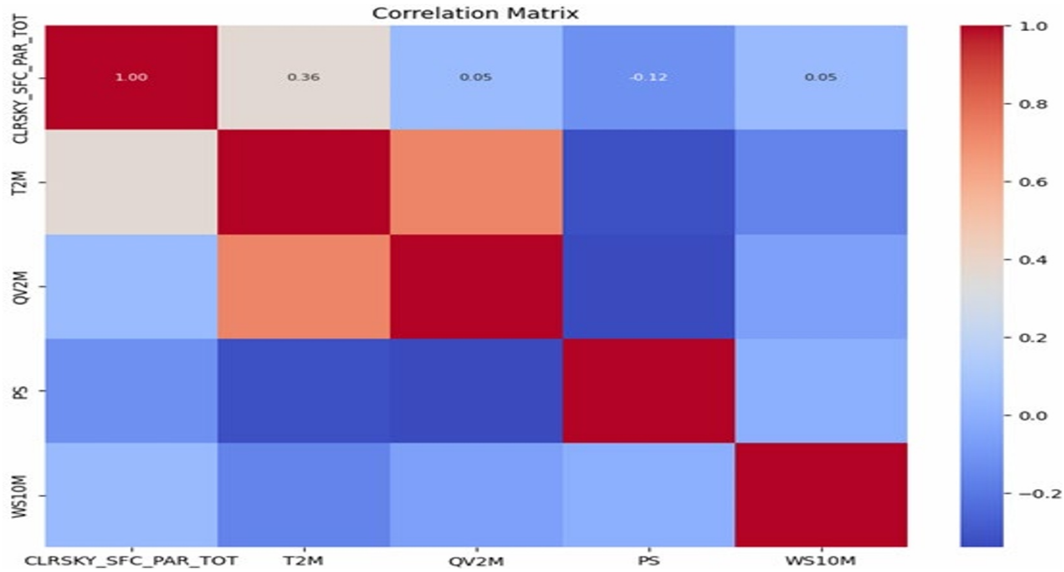

Figure 15: Correlation Matrix of Meteorological Variables (CLRSKY_SFC_PAR_TOT, T2M, QV2M, PS, WS10M) in Tangier.

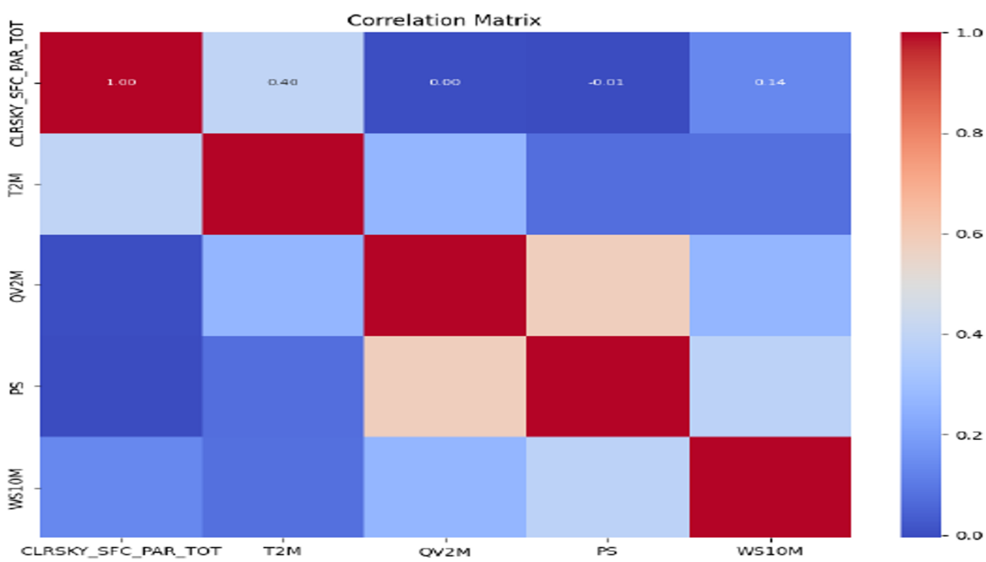

Figure 16: Correlation Matrix of Meteorological Variables (CLRSKY_SFC_PAR_TOT, T2M, QV2M, PS, WS10M) in Tetouan.

Figures 15 and 16 present the correlation matrices of meteorological variables (CLRSKY_SFC_PAR_TOT, T2M, QV2M, PS, WS10M) for Tangier and Tetouan, respectively, visualized as heatmaps with Pearson correlation coefficients ranging from red (strong positive correlations, e.g., autocorrelation at r = 1.00) to blue (negative correlations, e.g., PS-WS10M in Tangier, r = -0.01). In Tangier, a moderate positive correlation between T2M and QV2M (r = 0.70) indicates a strong thermodynamic relationship, while CLRSKY_SFC_PAR_TOT shows weak correlations with T2M (r = 0.36) and QV2M (r = 0.05). PS exhibits moderate negative correlations with T2M (r = -0.50) and QV2M (r = -

0.60), consistent with pressure-driven atmospheric dynamics. In contrast, WS10M shows negligible correlations (r = 0.00 to 0.05) with other variables. In Tetouan, T2M and QV2M are moderately correlated (r = 0.40), while CLRSKY_SFC_PAR_TOT has weak correlations with T2M (r = 0.00) and QV2M (r = 0.14), and PS shows minimal negative correlations (e.g., T2M, r = -0.01). WS10M remains largely uncorrelated (r = 0.00 to 0.14). These local differences likely stem from geographic and climatic variations influencing atmospheric interactions. The weak correlations of WS10M highlight the limitations of linear models for capturing wind dynamics, necessitating advanced approaches like recurrent neural networks (RNNs). These multivariate relationships underscore the need to assess multicollinearity prior to applying predictive models, such as neural networks or regressions, to ensure accurate interpretation of atmospheric dynamics. Table 1 complements this analysis by presenting the best prediction results for wind speed (WS10M) and their associated errors, based on meteorological data collected from Tangier and Tetouan over the period 2014–2023, further illustrating the superior performance of RNNs in modeling complex temporal patterns. Furthermore, the tables 1 and 2 illustrate a sample of the wind speed values that are closest to their predictions obtained by the RNN model for Tangier and Tetouan, respectively. In both cases, the discrepancies between the observed and predicted values are extremely small, often on the order of 10^{-3} to 10^{-2}, which demonstrates the high accuracy of the model. For Tangier, the predicted values almost perfectly reproduce the real wind speed dynamics, confirming the model's ability to capture temporal variations effectively. Similarly, in Tetouan, the predicted results align very closely with the actual observations, highlighting the robustness and generalization capability of the RNN. These findings emphasize the effectiveness of the RNN in modeling local temporal dependencies and producing reliable forecasts, thereby reinforcing its potential for practical applications in wind resource management.

Table 1: Summary of Optimal Prediction Results and Associated Error Metrics in Tangier city.

Data	True y	Predicted y	True_y_predicted	MSE	RMSE	R^2	MAE
2015/5/27	3.03	3.030000	2.384186e-07	0.050843	0.225483	0.992086	0.15345
2015/06/6	3.82	3.820007	-7.390976e-06	0.050843	0.225483	0.992086	0.15345
2014/8/22	7.27	7.270031	-3.147125e-05	0.050843	0.225483	0.992086	0.15345
2014/7/11	8.12	8.120033	-3.337860e-05	0.050843	0.225483	0.992086	0.15345
2015/1/27	4.23	4.229946	5.435944e-05	0.050843	0.225483	0.992086	0.15345
2014/8/06	6.69	6.690056	-5.626678e-05	0.050843	0.225483	0.992086	0.15345
2015/8/27	4.62	4.619933	6.675720e-04	0.050843	0.225483	0.992086	0.15345
2014/3/23	3.59	3.589895	1.053810e-04	0.050843	0.225483	0.992086	0.15345
2015/2/21	5.67	5.669879	1.206398e-04	0.050843	0.225483	0.992086	0.15345
2014/6/21	8.60	8.599878	1.220703e-04	0.050843	0.225483	0.992086	0.15345

Table 2: Summary of Optimal Prediction Results and Associated Error Metrics in Tetouan city.

Data	True y	Predicted y	True_y_predicted	MSE	RMSE	R^2	MAE
2014/12/3	6.13	6.129998	0.000002	0.11409	0.33777	0.98154	0.98154
2022/5/13	8.42	8.419991	0.000009	0.11409	0.33777	0.98154	0.98154
2015/1/31	4.39	4.389985	0.000015	0.11409	0.33777	0.98154	0.98154
2014/02/1	1.96	1.960016	0.000016	0.11409	0.33777	0.98154	0.98154
2015/5/18	5.31	5.309983	0.000017	0.11409	0.33777	0.98154	0.98154
2018/2/22	2.23	2.229982	0.000018	0.11409	0.33777	0.98154	0.98154
2019/5/21	3.68	3.679977	0.000023	0.11409	0.33777	0.98154	0.98154
2015/2/08	3.25	3.250027	-0.000027	0.11409	0.33777	0.98154	0.98154
2022/4/14	3.83	3.830030	-0.000030	0.11409	0.33777	0.98154	0.98154
2019/10/4	9.50	9.499969	0.000031	0.11409	0.33777	0.98154	0.98154

3. Comparison between the two studied cities (Tetouan - Tangier)

The comparative analysis of model performance across the two cities revealed consistent trends. In both cases, the single-layer neural network exhibited relatively poor predictive capabilities, whereas the Nonlinear Autoregressive (NAR) model provided a noticeable improvement. However, the Recurrent Neural Network (RNN) significantly outperformed the other models, reaffirming the importance of architectures that effectively capture temporal dependencies in time series data, particularly for wind speed forecasting. Despite the overall similarity in performance trends, slight variations in Mean Squared Error (MSE), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) were observed between the two cities. These discrepancies can be attributed to factors such as localized climatic conditions, variations in data quality, and the inherent complexity of regional meteorological patterns. Furthermore, the RNN model demonstrated superior adaptability to the data from both cities, albeit at the cost of increased computational complexity and training time. This result underscores the necessity of selecting models that align with the temporal nature of the data, especially in contexts where time-dependent relationships are critical to prediction accuracy.

Conclusion

In conclusion, this study emphasizes the importance of selecting machine learning models that align with the temporal characteristics of wind speed data. A comparative analysis of ANN, NAR/LSTM, and RNN demonstrated that the RNN consistently outperformed the other models in both Tangier and Tetouan. In Tetouan, the ANN showed only moderate predictive capability ($R^2 = 0.3753$), while the NAR suffered from instability and limited generalization. By contrast, the RNN achieved strong convergence (training loss = 0.0183, validation loss = 0.0185), reflecting its robustness in modeling highly variable wind dynamics. Similarly, in Tangier, the ANN and NAR delivered weaker performances ($R^2 =$ 0.1886 and 0.6448), whereas the RNN achieved excellent convergence (training loss = 0.0075, validation loss = 0.0080), confirming its superior adaptability to complex temporal dependencies. Although the RNN demands greater training time and computational resources, its predictive accuracy and reliability justify its application to wind speed forecasting in renewable energy. Using a ten-year meteorological dataset and Python-based implementation, this work provides a transferable framework adaptable to other regions.

Ultimately, the findings highlight the RNN potential as a powerful tool to improve forecast precision, optimize wind farm operations, and support the global transition to renewable energy.

References

[1] Wang, Y., Zhang, X., & Li, H. (2022). Advanced Machine Learning Techniques for Wind Speed Forecasting: A Comprehensive Review. Renewable and Sustainable Energy Reviews, 156, 111890.
[2] Zhang, G., Liu, Y., & Chen, X. (2021). Nonlinear Autoregressive Models for Wind Speed Prediction: A Comparative Study. Energy Conversion and Management, 235, 113987.
[3] Chen, L., Wang, H., & Liu, Z. (2023). Recurrent Neural Networks for Time Series Forecasting: Applications in Renewable Energy. IEEE Transactions on Neural Networks and Learning Systems, 34(2), 567-579.
[4] Li, J., Wang, Z., & Zhang, Y. (2023). Recurrent Neural Networks for Wind Speed Forecasting: A Case Study in Renewable Energy Applications. Journal of Cleaner Production, 385, 135678.
[5] Bakkari M, Bossoufi B, El Kafazi I, Bouderbala M, Karim M. A review of wind energy potential in Morocco: New challenges and perspectives. Wind Engineering. 2023;48(1):101-120. doi:10.1177/0309524X231200582.
[6] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O & Duchesnay, E. (2012). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research, 12, 2825-2830.
[7] Houda El Khachine, Mohamed Hatim Ouahabi, Driss Taoukil. Analysis of Wind Speed Extrapolation and Wind Power Density Assessment in Tetouan City. Energy Science & Engineering, 2025; 13:2480–2490. https://doi.org/10.1002/ese3.70045.
[8] Mohamed Bousla, Mohamed Belfkir, Omar Elharrouss, Ahmed Sadki, Ali Haddi, Youness El Mourabit et al. Modeling Wind Energy Production Forecasting using Machine Learning: An In-depth Analysis of Wind Farms in Morocco. Engineering, Technology & Applied Science Research Vol. 15, No. 3, 2025, 23268-23276. https://doi.org/10.48084/etasr.10296.
[9] Aisha Blfgeh and Hanadi Alkhudhayr. A Machine Learning-Based Sustainable Energy Management of Wind Farms Using Bayesian Recurrent Neural Network. Sustainability 2024, 16(19), 8426. https://doi.org/10.3390/su16198426.

[10] Optimizing wind power forecasting with RNN-LSTM models through grid search cross-validation. Aml G. AbdElkader, Hanaa ZainEldin, Mahmoud M. Saafan. Sustainable Computing: Informatics and Systems. Volume 45, January 2025, 101054. https://doi.org/10.1016/j.suscom.2024.101054.

[11] Min Xia; Haidong Shao; Xiandong Ma; Clarence W. de Silva. A Stacked GRU-RNN-Based Approach for Predicting Renewable Energy and Electricity Load for Smart Grid Operation. IEEE Transactions on Industrial Informatics (Volume: 17, Issue: 10, October 2021). 10.1109/TII.2021.3056867.

[12] Dhananjay Kumara , H. D. Mathur, S. Bhanot & Ramesh C. Bansal. Forecasting of solar and wind power using LSTM RNN for load frequency control in isolated microgrid. International Journal of Modelling and Simulation Volume 41, 2021. https://doi.org/10.1080/02286203.2020.1767840.

[13] M. Bousla, M. Belfkir, A. Haddi, Y. El Mourabit, and B. Bossoufi, "Comparison of artificial intelligence approaches for estimating wind energy production: A real-world case study," Results in Engineering, vol. 24, Dec. 2024, Art. no. 103626, https://doi.org/10.1016/j.rineng.2024.103626.

[14] Serikov, T., Ivanov, V., & Petrov, A. (2021). Comparative Analysis of NARX and LSTM Models for Time Series Forecasting. Neural Computing and Applications, 33(15), 9876-9890.
[15] George E. P. Box, Gwilym M. Jenkins, Gregory C. Reinsel. Time Series Analysis (June 2012). DOI:10.1002/9781118619193.
[16] Giebel, G., Brownsword, R., & Kariniotakis, G. (2011). Wind Power Forecasting: State-of-the-Art 2009. Springer.
[17] Hyndman, R. J, & Athanasopoulos, G. (2018). Forecasting: Principles and Practice. OTexts.
[18] Zhang, G., Eddy Patuwo, B., & Hu, M. Y. (2021). Forecasting with Artificial Neural Networks: The State of the Art. International Journal of Forecasting.
[19] Hochreiter, S, & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation.
[20] Billings, S. A. (2013). Nonlinear System Identification: NARMAX Methods in the Time, Frequency, and Spatio-Temporal Domains. Wiley.
[21] Heaton, J. Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning. Genet Program Evolvable Mach 19, 305–307 (2018). https://doi.org/10.1007/s10710-017-9314-z.
[22] Bengio, Y., Simard, P., & Frasconi, P. (2013). Learning Long-Term Dependencies with Gradient Descent is Difficult. IEEE Transactions on Neural Networks.