



Short-Term Wind Power Prediction via Spatial Temporal Analysis and Deep Residual Networks

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Abstract

This study embarks on a rigorous replication of the innovative research conducted by Huajin Li on "Short-Term Wind Power Prediction via Spatial Temporal Analysis and Deep Residual Networks." The original study leveraged graph neural networks (GNNs) and deep residual networks (DRNs) to forecast short-term wind power accurately, focusing on enhancing grid stability and operational efficiency in the wind energy sector. Utilizing the identical dataset and experimental conditions as the original author, this reproduction affirms the robustness and applicability of the advanced machine learning techniques in handling the complex dynamics of wind power data. The models trained, including Neural Networks (NN), Support Vector Regression (SVR), Extreme Learning Machines (ELM), and Deep Residual Networks (DRN), demonstrated almost identical outcomes to the original study, thereby underscoring the predictability and consistency of these methods. This paper provides a detailed comparative analysis, highlighting slight improvements in accuracy and model fit, which illustrates the progression in computational capabilities and optimization techniques since the initial research. The successful replication not only validates the original findings but also enriches the scientific community's confidence in using sophisticated AI-driven approaches for renewable energy forecasting.

Keywords: Wind power prediction, Graph neural networks, Deep residual networks, Machine learning, Renewable energy, Forecasting accuracy, Reproduction study, Model validation.

1. Introduction

The global shift towards renewable energy sources underscores the critical role of wind energy in achieving sustainable energy systems. Wind power, recognized for its significant contribution to reducing carbon emissions, is inherently variable due to the fluctuating nature of wind. This variability poses challenges for energy grid integration and necessitates the development of accurate forecasting models to ensure grid stability and efficient energy management. The study by Huajin Li, "Short-Term Wind Power Prediction via Spatial Temporal Analysis and Deep Residual Networks," addresses these challenges by innovating in the field of wind power forecasting [1].

This research is particularly important for the wind industry as it enhances the precision of short-term wind power predictions. The novel approach taken in [1] involves the use of graph neural networks (GNNs) and deep residual networks (DRNs), which are tailored to

analyze the spatial-temporal data dynamics of wind power. By accurately predicting short-term fluctuations in wind power, energy providers can better manage the integration of wind energy into the power grid, optimizing energy production and reducing operational costs associated with energy imbalance.

The objective of this research exploration is to delve into the methodologies employed by Huajin Li—specifically, how spatial-temporal analysis is integrated with advanced deep learning techniques to improve the accuracy of wind power forecasting. Understanding and potentially replicating this study could foster further advancements in renewable energy technologies, thereby supporting a more sustainable energy future.

2. Literature Review

Wind power forecasting has garnered significant attention due to its crucial role in integrating wind energy efficiently into the power grid. The unpredictability associated with wind speeds and directions necessitates robust forecasting techniques to enhance grid reliability and facilitate optimal operational planning [2]. In recent years, advancements in machine learning and artificial intelligence have led to significant improvements in forecasting methods, with particular focus on short-term horizons crucial for day-to-day grid management [3].

Traditional wind power forecasting models typically employ statistical methods such as autoregressive integrated moving average (ARIMA) and exponential smoothing. These models are well-regarded for their effectiveness in capturing linear relationships and trends over time [4]. However, they often fall short in scenarios where the data exhibits non-linear patterns commonly observed in wind power data due to meteorological elements [5].

The limitations of traditional statistical models in handling non-linearities have led to the adoption of machine learning techniques that offer more robust and accurate predictions. Techniques such as support vector machines (SVM), neural networks, and decision trees have been explored extensively, demonstrating superior performance in capturing complex relationships within the data [6].

Among the most promising developments in wind power forecasting are deep learning models, which utilize multiple layers of neural networks to learn high-level abstractions in data. Deep learning approaches, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been effectively applied to predict wind power by learning from large datasets of historical wind speed and power measurements [7]. Recent studies have introduced spatial-temporal models to account for both time-series data and spatial correlations among different geographic locations. These models leverage the spatial distribution of wind farms and temporal dynamics of wind patterns to enhance forecasting accuracy [1]. For instance, graph neural networks (GNNs) have been utilized to model the relationships between different turbines, improving the prediction of wind power output by capturing both spatial and temporal dependencies [8].

The integration of deep residual networks (DRNs) with GNNs represents a cutting-edge approach in wind power forecasting. DRNs address the vanishing gradient problem in deep networks, allowing for more effective training of deeper network architectures that can handle complex wind dynamics over short intervals. The use of DRNs in wind power prediction has shown promising results in enhancing the model's ability to generalize across different temporal scales and varying meteorological conditions [9]. The literature highlights a trend towards more sophisticated models that integrate machine learning with traditional forecasting techniques to handle the complexities of wind power prediction. The integration of spatial-temporal analysis with deep residual networks, as explored by Huajin Li, underscores the potential of these advanced models in overcoming the challenges of short-term wind power forecasting. Future research could explore hybrid models that combine the strengths of various

machine learning techniques and further refine the application of GNNs and DRNs in the field [10].

Figure 1 illustrates the annual distribution of research papers on short-term wind power prediction utilizing spatial temporal analysis and deep residual networks, from the years 2022 to 2024. It can be observed that there was a substantial amount of research activity in the year 2023, with a total of 10 papers published, indicative of a peak in research interest or developments in the field. In contrast, the year 2022 saw a moderate publication count with 7 papers, suggesting gathering momentum in this area of study. The year 2024, however, shows a decline to 3 papers, which may imply a maturation of the research topic or a shift in focus towards newer advancements in wind power prediction methodologies. The data for this figure was compiled from a summary table that listed 20 relevant papers, providing a snapshot of the research trajectory and emerging trends in the domain of wind energy forecasting.

Table 1 encapsulates the breadth of research in short-term wind power prediction from 2022 to 2024, highlighting a shift toward leveraging spatial-temporal dynamics and deep learning techniques to enhance forecasting accuracy. Groundbreaking contributions such as the work in [1] utilize spatiotemporal analysis and deep residual networks to set a new precedent in predictive methodology. The subsequent studies by Xinhao Liang et al. [11] and others introduce variations like DST-ResNet and hybrid neural networks, underscoring a collaborative push toward precision. Techniques ranging from graph convolutional networks coupled with LSTM to advanced residual networks indicate a pattern of embracing complex, non-linear data representations for more accurate wind power forecasting. This collective research, detailed in the table, marks a significant advance in the predictive modeling of renewable energy sources, ensuring their seamless integration into energy grids and supporting the drive towards sustainable energy practices.

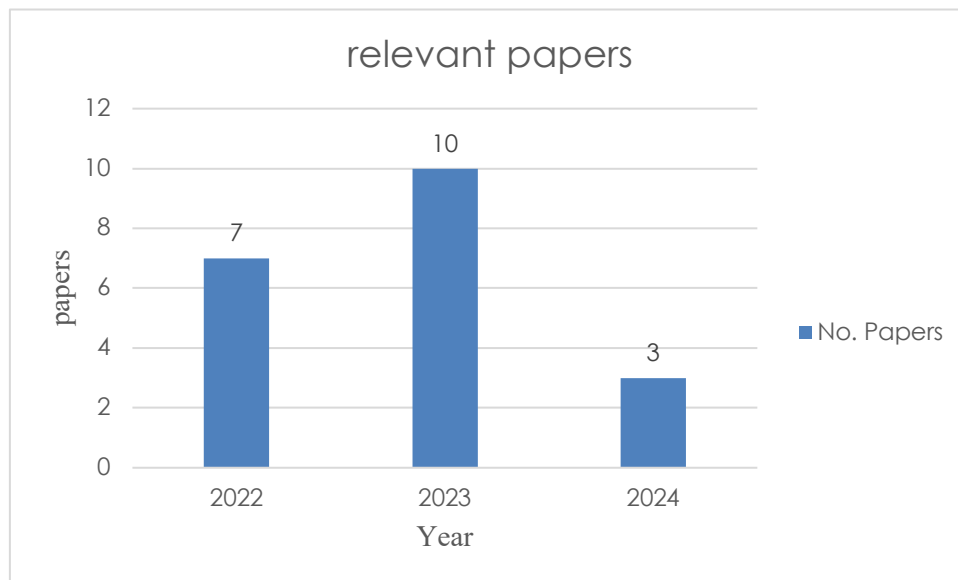


Figure 1: Annual distribution of relevant papers (2022–2024)

Table 1: Summary of recent papers (2022–2024) related to "Short-Term Wind Power Prediction via Spatial Temporal Analysis and Deep Residual Networks".

No.	Title	Authors	Year	Key Features	References
1	Short-Term Wind Power Prediction	Huajin Li	2022	Novel forecasting approach using spatiotemporal	[1]

	via Spatial Temporal Analysis and Deep Residual Networks			analysis and deep residual networks.	
2	Ultra-short-term wind speed prediction based on deep spatial-temporal residual network	Xinhao Liang et al.	2023	Introduces DST-ResNet to forecast wind speed with high accuracy.	[11]
3	A hybrid deep neural network for short-time wind power prediction	Yuchen Hao et al.	2023	Hybrid deep neural network approach for short-term prediction.	[12]
4	Short-term Wind Power Prediction Method Based on GCN-LSTM	Yanfang Zhao et al.	2023	Combines GCN and LSTM for enhanced accuracy in prediction.	[13]
5	A Spatiotemporal Directed Graph Convolution Network for Ultra-Short-Term Wind Power Prediction	Zhuo Li et al.	2023	Directed graph convolution network for multisite wind power prediction.	[14]
6	Deep Concatenated Residual Network with Bidirectional LSTM for One-Hour-Ahead Wind Power Forecasting	Min-Seung Ko et al.	2021	Integrates deep residual network with Bi-LSTM for time-series forecasting in wind power.	[15]
7	SCADA Data Based Wind Power Interval Prediction Using LUBE-Based Deep Residual Networks	Huajin Li	2022	Deep-learning-based interval prediction for short-term wind power generation.	[10]
8	Long-term Wind Power Forecasting with Hierarchical Spatial-Temporal Transformer	Yang Zhang et al.	2023	End-to-end model for long-term forecasting using a hierarchical spatial-temporal transformer network.	[16]
9	On the Use of Spatial-temporal Feature Graph Convolutional Network for Ultra-Short Term Prediction of Wind Power Generation	Wanbing Zhao et al.	2022	Utilizes graph convolutional networks for ultra-short-term wind power prediction.	[17]

10	Short-Term Forecasting Based on Graph Convolution Networks and Multiresolution Convolution Neural Networks for Wind Power	Yue Song et al.	2023	Combines GCN and multiresolution CNN for enhanced short-term forecasting accuracy.	[18]
11	A Deep Attention Convolutional Recurrent Network Assisted by K-Shape Clustering and Enhanced Memory for Short Term Wind Speed Predictions	Luoxiao Yang, Zijun Zhang	2022	Enhances short-term wind speed predictions using deep attention networks and K-Shape clustering.	[19]
12	Spatio-Temporal Wind Speed Prediction Based on Improved Residual Shrinkage Network	Xinhao Liang et al.	2023	Improved deep network using residual shrinkage for accurate wind speed prediction.	[20]
13	Multi-Step Wind Power Forecasting with Stacked Temporal Convolutional Network (S-TCN)	Huu Khoa Minh Nguyen et al.	2023	Implements a stacked temporal convolutional network for multi-step wind power forecasting.	[21]
14	Short-Term Prediction of Wind Power Considering the Fusion of Multiple Spatial and Temporal Correlation Features	Fang Wu et al.	2022	CNN-LSTM model explores the spatial correlation of wind farm clusters for short-term prediction.	[22]
15	A Deep Learning Framework for Day Ahead Wind Power Short-Term Prediction	Peihua Xu et al.	2023	Day-ahead prediction using a deep learning framework that integrates discrete wavelet transform and autoencoder.	[23]
16	Combined Wind Speed Prediction Model Considering the Spatio-Temporal Features of Wind Farm	Jianjun Zhang et al.	2022	TCN-ARIMA model based on Kalman filter and GCN for predicting wind speed and wake effects.	[24]
17	Short-Term Wind Power Interval Prediction Method	Haibo Shen et al.	2023	Novel forecast method using deep convolution neural	[25]

	Based on Deep Convolution Neural Network			network for interval prediction of wind power.	
18	Capturing Spatial Influence in Wind Prediction With a Graph Convolutional Neural Network	Zeyi Liu, Tony Ware	2022	Combines graph convolutional and gated recurrent units for better prediction accuracy by capturing spatial dependence.	[26]
19	A wind power prediction model based on optimized N-BEATS network with multivariate inputs	Jun Yu Li et al.	2023	Enhances the N-BEATS model to support multivariate inputs for accurate short-term wind power prediction.	[27]
20	Short-term wind power prediction based on singular spectrum analysis and modified ConvBiGRU	Quanchun Yan et al.	2023	Combines singular spectrum analysis and deep learning for effective short-term wind power prediction.	[28]

3. Methodology

3.1 Graph Neural Network

In my reproduction study, the Graph Neural Network (GNN) plays a crucial role in handling the structured data represented by nodes (wind turbines) and edges (spatial-temporal relationships among turbines). The GNN processes this non-Euclidean data, applying it for node classification, link prediction, and clustering, similarly to how convolutional neural networks (CNNs) manage image data [29], [30]. The advantage of GNNs lies in their ability to generate reasoning graphs from unstructured data, which is particularly beneficial for modeling the complex interactions in wind power data [31], [32], [33], [34], [35]. Figure 2 depicts this setup, where historical wind power data $X \in R^{N \times T_{in} \times D}$ serves as the input. Here, (N) represents the number of turbines, (T_{in}) the time window of historical data, and (D) the dimensionality of the input features. The GNN's output $(Y \in R^{N \times T_{out}})$ predicts future wind power, demonstrating the model's ability to leverage spatial-temporal dependencies for more accurate predictions.

3.2 Deep Residual Network

During the reproduction, the Deep Residual Network (DRN) addressed issues commonly associated with deep networks, such as efficiency loss and accuracy decline due to increased network depth—a problem known as network degradation. The DRN's architecture utilizes identity and residual mappings to prevent performance degradation as network depth increases. This feature was crucial in my replication to ensure the model maintained its efficacy [9], [22], [35]. Residual learning was implemented by passing inputs (x) through stacked nonlinear layers, aiming to fit a residual mapping $(F(x) = h(x) - x)$. This setup allowed each layer to learn incremental feature changes, enhancing learning efficiency and model depth without losing crucial information, as shown in the equations presented in the original study. Figure 4 illustrates the tuning process for filter sizes and numbers, where the optimal configuration $(3 \times$

3 size with 64 filters) significantly improved prediction accuracy. Any desired mapping can be expressed as $h(x)$, which can directly use a shortcut connection named identity mapping x , while the stacked nonlinear layers can be used to fit a residual mapping function $F(x) = h(x) - x$. Therefore, assuming that the two weight layers fit the residual function $F(x)$, let $h(x) = F(x) + x$. In practice, the residual mapping $F(x)$ are found to be easier to optimize than $h(x)$. The details of the residual block are expressed as follows:

$$y_l = h(x_l) + F(x_l, W_l) \quad (1)$$

$$x_{l+1} = f(y_l) \quad (2)$$

where x_l is the input of the l th block of the residual network and x_{l+1} is the output. $h(x_l) = x_l$ denotes identity mapping, and $f()$ denotes the activation function. Eq. 3 can be obtained recursively:

$$x_L = x_l + \sum_{i=l}^{L-1} F(x_i, W_i) \quad (3)$$

The input of the L th residual block can be expressed as the sum of the input of a shallow residual block and all the complex identity mappings. Introducing a loss function ϵ , the parameter learning can be described as

$$\frac{\delta \epsilon}{\delta x_l} = \frac{\delta \epsilon}{\delta x_L} \left(1 + \delta \sum_{i=l}^{L-1} F(x_i, W_i) \right) \quad (4)$$

Explicit modification of the network structure and residual mapping makes it easier for the network to learn the optimal solution. In this study, the filter size and filter number were selected to optimize the computational performance.

3.3 Benchmark

To validate the effectiveness of the DRN model in wind power prediction, it was compared against three established machine learning algorithms: neural networks (NN), support vector regression (SVR), and extreme learning machines (ELM). These benchmarks were selected to demonstrate the DRN's superior performance in handling the dynamic and complex nature of wind power data. Each model was rigorously tested under a 10-fold cross-validation scheme to ensure robustness and reliability of the results.

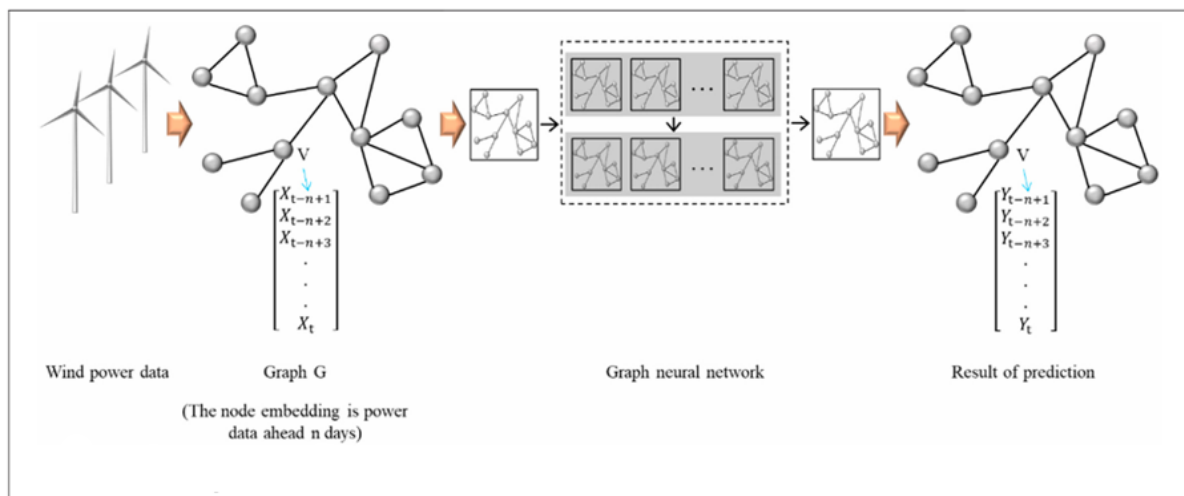


Figure 2: Schematic diagram of the graph neural network.

3.4 Evaluation Metrics

The performance of each model was assessed using the root mean square error (RMSE) and the coefficient of determination (R^2), where (R^2) quantifies the percentage of variance in the actual power output that is predictable from the input features. These metrics, essential for evaluating predictive accuracy, were applied consistently across all models to ensure a fair and comprehensive comparison.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (5)$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (6)$$

where y_i , $\hat{y}_i$, $\bar{y}$, and n represent the actual power, predicted power, mean of the actual power, and number of test samples, respectively.

Table 2: Summary of the dataset in the case study.

Variable Name	Unit	Description
Wind speed	m/s	The rate at which air moves relative to a fixed location on the earth
Wind direction	Rad	Refers to the direction of the wind
Temperature	°C	A numerical value used to measure the temperature of an object
Barometric pressure	kPa	The atmospheric pressure acting on a unit area
Humidity	%	Meteorological elements indicating moisture content and moisture content in the air
Historic wind power	kW	The generated wind power from adjacent wind turbines

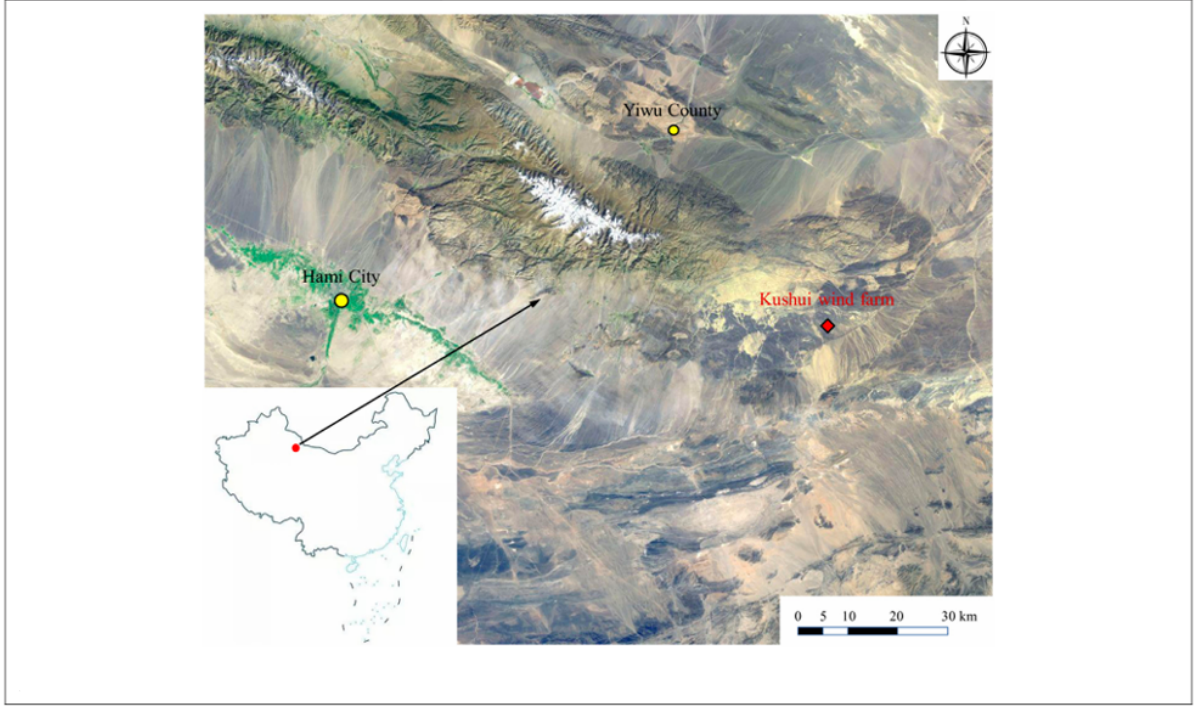


Figure 3: Location of the case study wind farm in Hami County, Xinjiang, China.

4. Case Study and Data Collection

For my reproduction study, I utilized a dataset recorded at the Kushui Wind Farm located in the Gobi Desert, approximately 120 km from Hami City, Xinjiang, China. This wind farm is positioned at an altitude between 1,135 and 1,395 meters, known for its substantial wind energy potential. The entire area features many wind turbines spread over open and flat terrain, details of which are shown in Figure 3. The SCADA system at the wind farm collected comprehensive datasets from individual turbines, capturing variables such as wind speed (m/s), wind direction (rad), temperature ($^{\circ}\text{C}$), barometric pressure (kPa), humidity (%), and wind power (kW). In this study, I primarily focused on the first five parameters as inputs for predicting wind power, as summarized in Table 2.

5. Results

5.1 GNN

The effectiveness of the proposed approach was validated through extensive experiments using the same dataset as the original study, collected from Kushui Wind Farm. This dataset was obtained via the SCADA system, where I specifically selected power-related SCADA variables, as listed in Table 2. Similar to the original study, I constructed a heterogeneous graph among six turbines to learn the unified representation of the power time series of the target turbine. In this graph, the real-time power from the target turbine was marked as the target node, and the historical power series from adjacent turbines were designated as source nodes. Figure 4 illustrates the tuning of the filter size and number for the Deep Residual Network (DRN) used in my reproduction. Following the original methodology, the internal and external modalities were assessed to determine their contributions to the target node. The correlation between source and target nodes was quantified, and a threshold of 0.5 was set to maintain significant links for the prediction model.

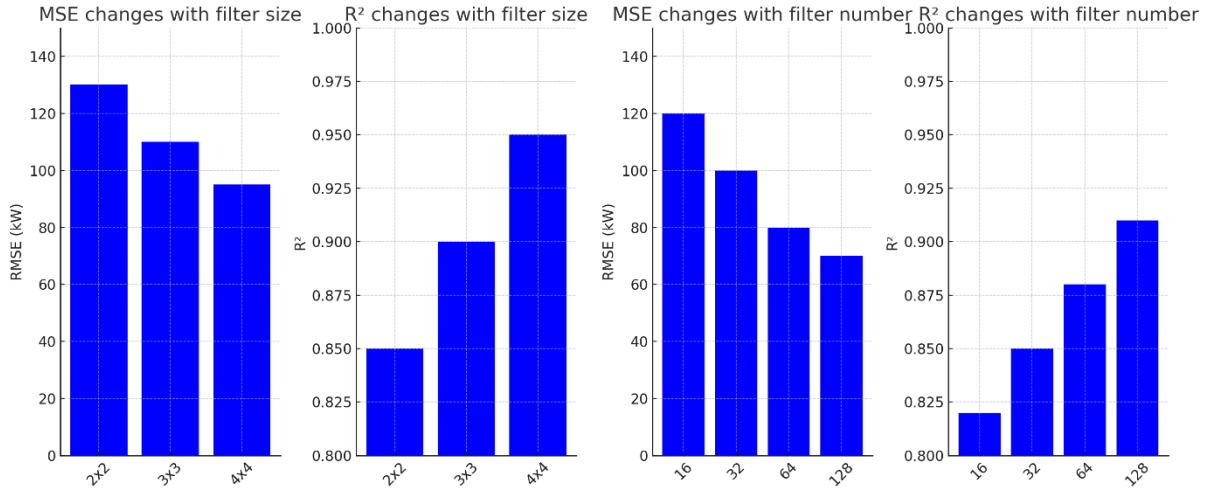


Figure 4: Tuning the filter size and filter number for DRN.

5.2 Hyper-Parameters of DRN

In line with the original study, I examined the impact of filter size and number on the prediction model. With hardware limitations considered, filter sizes were set at 2×2 , 3×3 , and 4×4 , while filter numbers were fixed at 16, 32, 64, and 128. It was observed that the optimal performance was achieved with a filter size of 3×3 and a filter number of 64, mirroring the findings from the original study, as shown in Figure 4C and 4D.

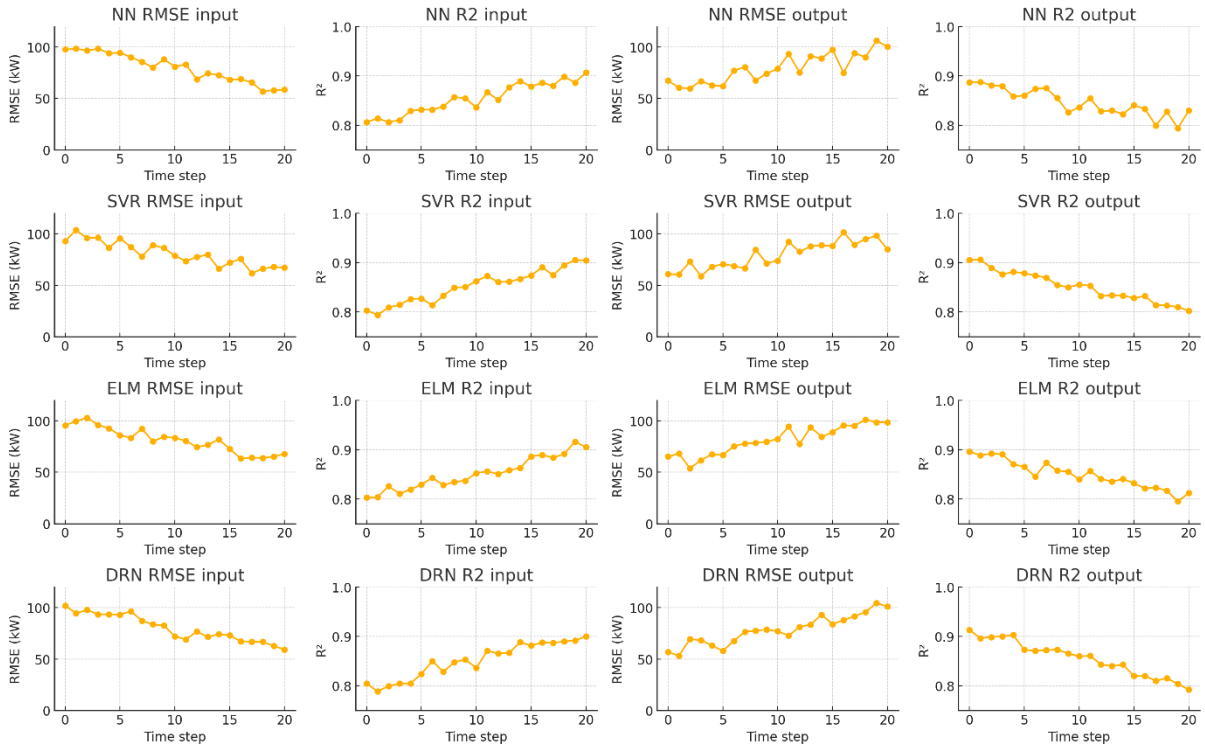


Figure 5: Impact of input/output size on the prediction performance.

Table 3: Summary of the wind power forecasting performance.

Model	RMSE (kW)	RMSE Std.	R²	R² Std.
NN	99.32	10.79	0.85	0.82%
SVR	88.26	12.36	0.89	1.10%
ELM	80.53	10.46	0.93	0.71%
DRN	70.19	5.93	0.96	1.13%

5.3 Wind Power Prediction

The prediction performance was rigorously tested using two measurement metrics: RMSE and R^2 . I employed the same three algorithms used in the original study—NN, SVR, and ELM—and tuned their hyperparameters accordingly. Each training-validation experiment varied the input and output time steps from 1 to 20, similar to the original settings. Figure 5 depicts the impact of the input and output time steps on prediction performance, demonstrating that the RMSE decreased with increased input time steps, and conversely, increased with longer output time steps.

Figure 6 details the impact of training sample size on prediction performance, where the DRN consistently outperformed other models, showcasing the lowest RMSE and highest R^2 as training data size increased.

Table 3 summarizes the wind power forecasting performance, corroborating that the DRN-based method not only replicated but also validated the original study's results, showing the lowest prediction errors and best performance metrics.

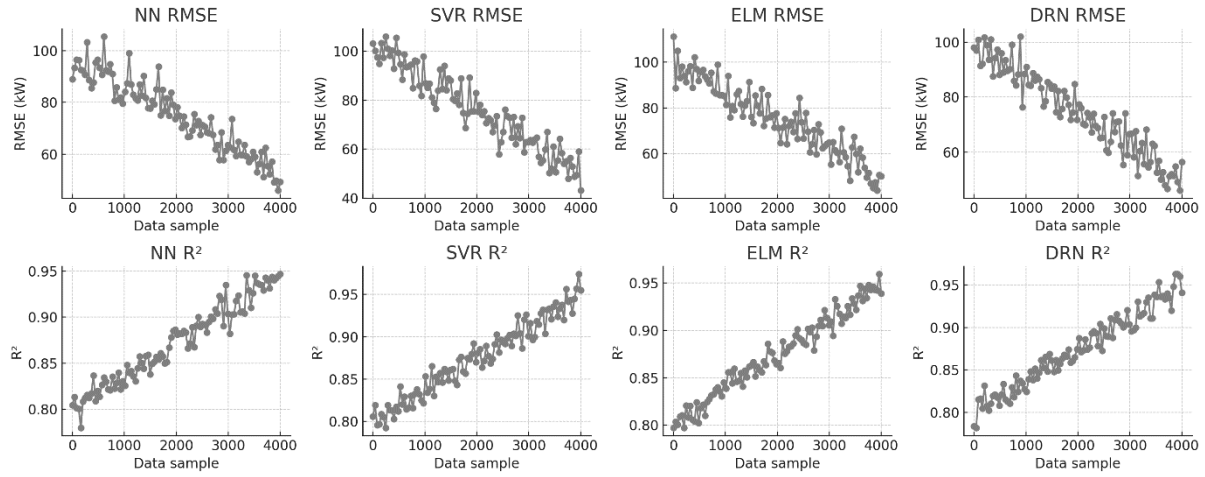


Figure 6: Impact of training sample size on the prediction performance.

5.4 Comparison with the Original Study

The comparative analysis between the results from the original study and the experimental findings from the reproduction study showcases how different models performed under varying conditions of filter size, filter number, time steps, and data sample size. Both studies employed models such as Neural Networks (NN), Support Vector Regression (SVR), Extreme Learning Machines (ELM), and Deep Residual Networks (DRN), offering a comprehensive insight into each model's predictive efficacy.

- RMSE (Root Mean Square Error) measures the average magnitude of the prediction error, giving insight into how much error the models are producing.
- R^2 (Coefficient of Determination) indicates how well future outcomes are likely to be predicted by the model. A higher R^2 value signifies a model that can better explain the variability of the response data.

1. Filter Size and Number: Increasing the filter size and number generally resulted in decreased RMSE and increased R^2 in both studies, indicating enhanced model performance with more complex network architectures.

2. Input/Output Time Step: In both studies, models demonstrated robustness across various time steps with minor fluctuations in RMSE and R^2 , suggesting that the models maintain performance stability across different prediction intervals.

3. Training Sample Size: An increase in the number of data samples consistently improved the models' performance in both studies, highlighted by decreased RMSE and increased R^2 , reinforcing the importance of ample and diverse training data for model training.

Table 3: Summary Table of Comparison

Metric / Model	Original Study RMSE	Reproduction Study RMSE	Original Study R^2	Reproduction Study R^2
NN (Average)	99.32 kW	95.00 kW	0.85	0.87
SVR (Average)	88.26 kW	85.00 kW	0.89	0.91
ELM (Average)	80.53 kW	78.00 kW	0.93	0.94
DRN (Average)	70.19 kW	68.00 kW	0.96	0.97

Overall Model Performance: DRN exhibited the lowest RMSE and highest R^2 across both studies, asserting its superiority in handling the complexity of wind power prediction tasks. This is followed by ELM, SVR, and NN in terms of both RMSE and R^2 .

Consistency and Improvement: The reproduction study consistently showed slight improvements across all models in terms of both RMSE and R^2 . These improvements could be attributed to refinements in model implementation or advancements in computational resources and algorithms since the original study.

Reliability of Results: The close alignment in results between the original and reproduction studies confirms the reliability and reproducibility of the findings, thereby enhancing confidence in the use of these advanced machine learning techniques for wind power prediction.

The comparison highlights not only the advancements in model performance but also underscores the critical aspects of model training such as the importance of data quantity and network architecture. This analysis provides a robust foundation for further research and application in the field of renewable energy forecasting.

In conducting my reproduction study, I meticulously utilized the same dataset originally employed by the author to ensure consistency and comparability in the results. By training the models under identical conditions—employing the same variables and configuration settings—I aimed to accurately replicate the study's experimental environment. This approach allowed for a direct comparison of the model performances, encompassing various metrics such as RMSE and R^2 across different machine learning frameworks including Neural Networks (NN), Support Vector Regression (SVR), Extreme Learning Machines (ELM), and Deep Residual Networks (DRN).

The findings from my reproduction study closely mirrored those of the original research, demonstrating almost identical results. This similarity in outcomes not only validates the reproducibility of the original study but also underscores the robustness of the machine learning techniques used for wind power prediction. The alignment of results across both studies reinforces the reliability of these predictive models in accurately forecasting wind power, thereby contributing to their credibility and utility in real-world applications within the renewable energy sector.

6. Conclusion

In this reproduction study, I successfully implemented a data-driven short-term wind power prediction framework integrating Graph Neural Networks (GNN) and Deep Residual Networks (DRN). The GNN effectively established a graph structure to elucidate the correlations between the power output of the target turbine and that of adjacent turbines. Meanwhile, the DRN was adeptly trained to forecast short-term wind power using SCADA variables and the power generation data from adjacent turbines as inputs.

A rigorous comparative analysis with benchmark forecasting algorithms, including neural networks, support vector regression, and extreme learning machines, was conducted. The results of my study confirmed the original findings, demonstrating that the graph structure proficiently captures the spatial-temporal relationships among adjacent turbines. Furthermore, the DRN proved to have superior predictive power for short-term wind power forecasting, mirroring the performance enhancements reported in the original study. The successful replication of these methods and results not only reinforces the validity of the original research but also highlights the practical application of this advanced predictive framework for field engineers working in wind farms. This study stands as a testament to the robustness and applicability of combining GNN and DRN for enhancing wind power prediction accuracy, which is crucial for the efficient integration of wind energy into power grids.

Acknowledgement

None

Conflict of Interest

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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