Neural Network Models for Wind Power Forecasting in Smart Cities- A review

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Abstract: Urbanization's relentless advance intensifies the quest for sustainable energy sources, with smart cities leading the shift toward sustainability. In these innovative urban landscapes, wind power is pivotal in the clean energy paradigm. Efficient wind energy utilization hinges on accurate wind power forecasting, essential for energy management and grid stability. This review explores the use of neural network models for wind power forecasting in smart cities, driven by wind power's growing importance in urban energy strategies and the expanding role of artificial neural networks (ANNs) in wind power prediction. Wind power integration mitigates greenhouse gas emissions and enhances energy resilience in urban settings. However, wind's inherently variable nature necessitates precise forecasting. The surge in ANN use for wind power forecasting is another key driver of this review, as ANNs excel at modelling complex relationships in data. This review highlights the synergy between wind power forecasting and neural network models, emphasizing ANNs' vital role in enhancing the accuracy of wind power predictions in urban environments. It covers neural network fundamentals, data preprocessing, diverse neural network architectures, and their applicability in short-term and long-term wind power forecasting. It also delves into training, validation methods, performance assessment metrics, challenges, and prospects. As smart cities champion urban sustainability, neural network models for wind power forecasting are poised to revolutionize urban energy systems, making them cleaner, more efficient, and more resilient.

Keywords: Neural network, urban energy, Smart cities, ANNs, urban environments.

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1. Introduction

The inexorable urbanization of the world has made sustainable energy sources within cities a top priority. Smart cities, exemplifying innovation in infrastructure and services, are at the forefront of this transition toward sustainability. In such urban landscapes, renewable energy is vital, with wind power playing a significant role in the clean energy paradigm. Yet, the efficient use of wind energy relies heavily on accurate wind power forecasting, a cornerstone of energy management and grid stability in smart cities. This review delves into neural network models for wind power forecasting in smart cities, motivated by the escalating importance of wind power in urban energy strategies and the increasing prevalence of artificial neural networks (ANNs) in wind power prediction [1-3].

Wind power, integrated into smart cities' energy mix, lessens greenhouse gas emissions and bolsters energy resilience. Nevertheless, the variable nature of wind necessitates precise forecasting for efficient energy management. The second driving factor behind this review is the surge in ANN use for wind power forecasting. ANNs, a subset of artificial intelligence, excel at modelling intricate, dynamic relationships in data. This is invaluable for wind power forecasting due to the multitude of variables impacting wind speed and energy production.

This review aims to explore the convergence of wind power forecasting and neural network models. It elucidates the pivotal role of neural networks in improving the accuracy of wind power predictions in urban environments. We will cover neural network essentials, data preprocessing, various neural network architectures, and their applicability in short-term and long-term wind power forecasting. We will also delve into training, validation techniques, performance evaluation metrics, challenges, and future prospects. As smart cities lead the way in urban sustainability, neural network models for wind power forecasting are poised to transform urban energy systems into cleaner, more efficient, and more resilient ecosystems.

1.1. Importance of wind power forecasting in smart cities

In the context of rapidly urbanizing smart cities, the significance of wind power forecasting cannot be overstated. Smart cities are pioneering the integration of sustainable energy sources to reduce carbon emissions, enhance energy security, and foster economic growth. Wind power stands as a critical component of this transition towards clean and renewable energy. Wind energy offers numerous advantages in the smart city landscape. It's abundant, cost-effective, and produces minimal environmental impact. However, the inherent variability of wind poses a substantial challenge. Wind speed and direction can change rapidly, impacting energy production. This intermittency necessitates accurate wind power forecasting to ensure the stability and reliability of the energy grid. Accurate wind power forecasting allows smart cities to optimize energy generation and consumption. By knowing when and how much wind energy to expect, cities can make informed decisions about energy distribution, storage, and grid management. This, in turn, leads to improved energy efficiency, cost savings, and reduced greenhouse gas emissions [4].

Moreover, wind power forecasting is essential for balancing the energy mix. As smart cities increasingly rely on renewable sources like wind power, integrating this energy effectively into the grid is crucial. Forecasting provides the insight needed to coordinate different energy sources, ensuring a consistent and reliable energy supply [1-3].

1.2. Significance of neural network models

The significance of neural network models in wind power forecasting for smart cities lies in their ability to harness the power of artificial intelligence. These models have revolutionized forecasting accuracy, providing smart cities with a robust tool to predict wind energy generation. Neural networks can analyze vast datasets, including historical weather patterns, wind turbine data, and environmental factors, to make precise forecasts [5-8]. This enhanced accuracy enables cities to optimize energy distribution and storage, reduce costs, and decrease reliance on fossil fuels. As smart cities strive to meet sustainability goals and ensure a stable energy supply, neural network models emerge as a critical technology for shaping the future of clean and efficient urban energy systems.

2. Wind Power Forecasting Efforts: Smart Cities

Across the globe, smart cities are embracing data-driven wind power forecasting as a linchpin of their sustainable energy strategies. These forward-thinking urban centers are leveraging data analytics, machine learning, and advanced sensors to predict wind power generation patterns accurately. From Barcelona to Singapore, these efforts are driving the integration of renewable energy sources into city grids, optimizing energy distribution, and reducing reliance on fossil fuels. Data-driven wind power forecasting is pivotal in promoting eco-friendly urban development and fostering a future where clean, renewable energy takes center stage in smart cities' energy portfolios. Table 1 shows the relevant literature from across the globe.

Table 1.

Method	Details	Literature
Spatio-temporal wind forecasting	The capability of various models to capture spatio-temporal characteristics of wind power forecast errors, accounting for factors like wind speed and direction. The models tested include linear ARX, regime-switching TARX, and regime-switching conditional parametric CP-TARX models. The evaluation measures involve R2 and RMSE for different wind regimes. Results show that while the linear ARX model explains 47.8% of forecast errors, TARX and CP-TARX models achieve higher R2 values of 49.9% and 54.2%, respectively. Cross-validation indicates that TARX models exhibit superior generalization ability, offering stable R2 values and slightly improved RMSE. The study acknowledges data limitations and the need for further evaluation in larger regions or complex terrains.	[8]
	This article applies Markov chain for spatio-temporal analysis. The analysis involved the utilization of historical records of both turbine power generation and wind speeds. This data was examined on an epoch-by-epoch and monthly basis to construct several Markov chains. These chains were created to encapsulate the statistical properties derived from the historical dataset. Importantly, it should be emphasized that the estimation of Weibull parameters constitutes an integral component of the spatio-temporal analysis	[9]

	process.	
	The study conducted a comprehensive analysis of wind data collected from October 2010 to September 2012, focusing on temporal variations of wind shear parameters. Statistically, Method 1, which accounted for these variations, exhibited the highest correlation coefficients (R2) of 0.996 at 100 meters and 0.981 at 150 meters, showcasing its superior performance in wind speed estimation. Moreover, Method 1 had the lowest Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), indicating minimal deviation from monitored wind speeds. Method 2 displayed the smallest normalized bias (NB = 0.1%) at 100 meters, while Method 1 slightly overestimated (NB = 0.3%) at 150 meters. These statistics underscore the importance of considering temporal variations for precise wind energy assessments, especially for taller wind turbines.	[10]
Support Vector Regression	The discusses the application of kernel-based learning methods in wind speed estimation for squirrel-cage induction generators. It uses Support Vector Regression (SVR) to estimate wind speed and optimize turbine performance. The SVR model is trained using turbine power data, rotor speed, and wind velocity samples. The paper emphasizes the importance of accurate power-speed curves and tip-speed ratio control to maximize wind energy extraction. Simulation results and experimental verification demonstrate the effectiveness of the SVR algorithm in estimating wind speed, with a slight delay due to execution time. The method is considered independent of generator constants or torque measurements and offers fast estimation, even with continuously varying wind speeds.	[11]
	The study assessed the performance of a Support Vector Machine (SVM)-based algorithm for very short-term and short-term Wind Power Forecasting (WPF). Comparisons were made with a persistence model and a Radial Basis Function (RBF) neural networks-based model using a dataset divided into training and testing data. Results revealed that the optimal training length for WPF was 100 days, showing diminishing returns with longer training data. For very short-term forecasting,	[12]

	the SVM model outperformed the RBF model and persistence model, achieving over 62% skill for one-hour predictions. However, skills decreased with longer prediction horizons due to less correlated data. The SVM model is more suitable for short-term WPF, but longer horizons may require additional variables or NWP integration for improved accuracy.	
	The research employed the Western Dataset to validate a Wind Power Prediction (WPP) model. This dataset reconstructed historical weather patterns in the western U.S. spanning 2004 to 2006, providing crucial data such as wind speed, power output, and more. Within this dataset, 68 specific grid points were designated for simulation studies. Three distinct prediction strategies were implemented, encompassing fixed-step, recursive, and multi-WSVM approaches. To identify the optimal training length for the model, experimentation was conducted, ultimately concluding that a 70-day training period yielded the best results. Notably, the fixed-step methodology demonstrated superior performance by striking a balance between accuracy and computational efficiency. This model showcased robust performance for 1- to 30-day predictions, surpassing the predictive capabilities of both persistence and RBF-SVM models. However, its effectiveness diminished as prediction horizons extended, underscoring the necessity for integrating additional meteorological variables for prolonged forecasting endeavours.	[13]
Random Forest	The study examined wind shear parameters using data from October 2010 to September 2011 and revealed significant seasonal and diurnal variations. Fixed wind shear parameters, commonly used in standards like ASCE7-05, led to substantial underestimations of wind speeds, especially at greater heights (up to 22%). An innovative approach involved on-site calibration of wind shear model parameters, accounting for their temporal variations. This method significantly improved wind resource assessment accuracy, particularly for wind farms with higher hub heights. Furthermore, it had the potential to enhance short-term wind energy forecasts, making them more reliable for grid integration, addressing the growing demand for wind energy.	[14]
XGBoost	The research introduced a prediction model	[15]

	implemented at the Hu-Si wind farm in Taiwan, which comprises six wind turbines each generating 0.9 MW. Employing XGBoost with data preprocessing and parameter tuning, the model delivered precise forecasts, resulting in a Root Mean Square Error (RMSE) of 0.177 MW for the training set and 0.352 MW for the forecasting set. Comparative assessments with alternative methodologies underscored the importance of integrating diverse Numerical Weather Prediction (NWP) models. The proposed model's probabilistic forecasting demonstrated its superiority by achieving valid Predicted Intervals (PIs), the smallest average Conditional Width Coverage (CWC), and greater forecasting stability in comparison to other techniques. The combined use of machine learning and deep learning techniques notably improved the accuracy of short-term wind power forecasting.	
Adaboost algorithm	The study conducted a comprehensive analysis of wind speed forecasting in the Hexi Corridor of China, employing various models. Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Mean Squared Error (MSE) were used to assess accuracy. Concept drift was identified, indicating decreasing accuracy with extended forecast steps. Parameters of the TW-FE-Adaboost-SVM model were determined via cross-validation, revealing α around 0.2 and β below 0.2. Support Vector Machines (SVMs) demonstrated suitability as weak learners, with fitting errors ranging from 20% to 30%. Jiuquan and Wuwei sites exhibited superior accuracy, especially with Adaboost-SVM for 1-step and 2-step forecasts. Site-specific variability was evident, impacting accuracy differently. The Adaboost-SVM method outperformed SVM, contingent on forecast steps and evaluation metrics. In summary, the TW-FE-Adaboost-SVM method holds potential for enhanced wind speed forecasting, especially for shorter horizons and specific Hexi Corridor sites, underscoring the need for adaptive models in the face of concept drift.	[16]

3. Challenges and Future Directions

3.1. Data scarcity and quality

Predicting wind forecasts for windmills poses substantial challenges stemming from data scarcity and data quality issues. Wind turbines, often situated in remote areas, encounter limited access to reliable wind data. A good case study was presented for offshore wind farms in the article here [17]. This paucity of data can severely hinder the creation of accurate forecasting models [17,18].

Historical data, a fundamental component in forecasting, might be insufficient due to either short recording periods or inaccuracies. Moreover, the quality of available data can be compromised by sensor errors or external environmental factors, leading to unreliable measurements[19].

Another issue is the amalgamation of data from diverse sources, which can introduce inconsistencies and discrepancies, further complicating the task of predicting wind conditions [20]. To mitigate these challenges and enhance wind forecasts, an integrated approach is necessary [21]. This involves implementing advanced data collection methods, rigorous data quality control procedures, and the incorporation of state-of-the-art machine learning techniques [21,22].

Overcoming data limitations is paramount for optimizing wind farm operations, as it directly influences energy production and efficiency. Accurate wind forecasts enable better resource allocation, improved grid stability, and cost savings for wind energy producers. Therefore, addressing data scarcity and quality challenges is fundamental in ensuring a reliable and consistent energy supply from wind turbines.

3.2. Handling non-linear wind patterns

Wind availability in wind power generation exhibits a non-linear nature due to its dependence on varying wind speeds and turbulence. Small changes in wind speed can lead to significant fluctuations in power output. This non-linearity requires sophisticated modeling and forecasting techniques to optimize energy production and grid integration [23].

3.3 Incorporating external factors

Incorporating external factors in wind energy predictions involves considering variables like weather patterns, topography, and climate change. These factors significantly impact wind conditions and energy generation, making their inclusion crucial for more accurate and reliable wind energy forecasts [24].

3.4. Future Directions: Advancements in deep learning

Advancements in deep learning for wind energy prediction models hold significant potential for improving the efficiency and reliability of wind power generation. One key avenue of progress is the application of more advanced deep learning techniques, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), to wind forecasting. These models can capture intricate spatiotemporal patterns in wind behavior, enhancing the accuracy of predictions [5,25].

Another exciting development involves the integration of diverse data sources, including meteorological data, satellite imagery, and climate models. These additional data streams help create a more comprehensive picture of wind conditions, contributing to more precise forecasts [11-15].

Explainable AI (XAI) is becoming increasingly important in the wind energy sector. Understanding why a model makes a specific prediction is crucial for decision-making and model refinement. This interpretability aspect can lead to more trust in AI-driven predictions.

Furthermore, advancements in edge computing and the proliferation of Internet of Things (IoT) technologies enable real-time data processing, making it possible to adapt to rapidly changing wind conditions effectively.
In the future, there's potential to combine deep learning with reinforcement learning to optimize wind farm operations, helping in the strategic deployment of turbines and the integration of wind energy into the power grid. These developments collectively promise a more sustainable and efficient wind energy production landscape, contributing to a greener energy future.

4. Conclusion

In conclusion, this review has shed light on the critical role of neural network models in wind power forecasting, particularly within the context of smart cities. As smart cities continue to lead the way in urban sustainability, wind power is poised to play a pivotal role in clean energy strategies, offering an abundant and environmentally friendly energy source. However, the variable and intermittent nature of wind requires precise forecasting, which is where neural network models, a subset of artificial intelligence, come into play.
These models have the capacity to revolutionize the accuracy of wind power predictions by analyzing complex data relationships. With the support of advanced data analytics, machine learning, and sensor technologies, smart cities can harness the power of neural networks to optimize energy distribution, reduce costs, and reduce reliance on fossil fuels. This integration of neural network models represents a fundamental technological advancement in the transition towards clean and efficient urban energy systems.
Nevertheless, challenges persist, such as data scarcity and quality issues, the non-linear nature of wind patterns, and the necessity to incorporate external factors into predictions. Addressing these challenges is critical for advancing wind power forecasting further. Furthermore, emerging trends in deep learning and the integration of diverse data sources, combined with the application of Explainable AI (XAI), and the adoption of IoT technologies, are poised to shape the future of wind energy forecasting and contribute to a greener energy future in smart cities.

5. References

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