Machine Learning Approaches for Short-Range Wind Power Estimation: A Perspective

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Abstract. The evolution of wind energy production, especially in near and offshore farms, has seen significant advancements due to the integration of novel technologies and the reduction in economic costs. This paper reviews the work in the domain of wind power estimation, emphasizing the innovative approaches leveraging satellite data and artificial intelligence (AI) methodologies. A notable method integrates Sentinel satellite imagery analysis in a two-phased approach, combined with machine learning techniques, to forecast wind speed. This method utilizes sentinel-1 and sentinel-2 satellite images for wind speed and bathymetry analysis, respectively. Furthermore, a hybrid forecasting model, comprising the generalized regression neural network (GRNN) and the whale optimization algorithm (WOA), has been introduced. Another pivotal advancement comes from the National Center for Atmospheric Research (NCAR), which has revamped its wind power forecasting system. This enhancement focuses on short-term forecasting, uncertainty quantification in wind speed prediction, and the prediction of extreme events like icing. The integration of numerical weather prediction with machine-learning methods, such as the fuzzy logic artificial intelligence system, has further elevated the accuracy and efficiency of these forecasting models. Collectively, these

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advancements offer a comprehensive perspective on the future of short-range wind power estimation.

1 Introduction

The Importance of Wind Energy and Challenges in Offshore Installations
Wind energy has emerged as a pivotal renewable energy source, gaining traction both onshore and offshore. While offshore wind energy production is generally more expensive than its onshore counterpart, it offers unique advantages. These include more stable and robust sea winds, lower environmental impact, and the potential for energy sustainability, especially for small islands with limited land area for onshore installations. However, the initial step in offshore wind farm development involves accurately assessing wind resources, identifying optimal locations based on various parameters such as wind speed, water depth, and distance to the shoreline. Traditional methods for these assessments, including in-situ measurement tools like cup anemometers and buoys, are often limited in scope, expensive, and time-consuming.

The Role of Satellite and Remote Sensing Technologies
Synthetic Aperture Radar (SAR) satellite methods have increasingly become vital in assessing various environmental parameters, both offshore and onshore. These methods are particularly useful for marine applications, including atmospheric phenomena, warming trends, and wind and wave power potential assessment. The European Space Agency's Sentinel satellite family has further advanced these capabilities, offering tools for wind field estimation based on complex geophysical models. These satellite methods provide high spatial resolution and can cover large areas, making them invaluable for wind resource assessment.

Integration of Machine Learning and Artificial Intelligence
The National Center for Atmospheric Research (NCAR) has developed a comprehensive wind power forecasting system in collaboration with Xcel Energy. This system integrates artificial intelligence methods with numerical weather prediction models to provide short-term forecasting, uncertainty quantification, and extreme event prediction. The system is designed to meet the needs of grid operators and energy traders, who require accurate wind power forecasts across various time scales. The integration of machine learning algorithms allows for the effective combination of disparate data sources, enhancing the accuracy and reliability of wind power forecasts.

Objectives and Scope of This Review
This review aims to provide a comprehensive perspective on the advancements in short-range wind power estimation, focusing on the integration of Sentinel satellite imagery and machine learning methods for wind speed assessment. We will explore how these technologies have been applied in specific case studies, such as wind energy potential around the Favignana island in Sicily, Italy. Additionally, we will delve into the NCAR's enhanced wind power forecasting system, examining its capabilities and assessing its impact on the wind energy sector. By synthesizing these various strands of research and development, this review seeks to offer valuable insights into the future of wind power estimation and its growing reliance on advanced technologies.

By tying together these various areas of study, this review aims to offer a holistic view of the current state and future potential of short-range wind power estimation.

2 Review and discussion

2.1 Wind Energy's Growing Importance

The research spearheaded by Nezhad et al. (2021) meticulously examines the escalating prominence of wind energy [1]. This is especially evident in the realms of nearshore and offshore wind farms. Two primary factors driving this surge are:

- **Technological Advancements**: The wind energy sector has witnessed a rapid infusion of innovative technologies, propelling its growth and efficiency.
- **Economic Viability**: The economic costs associated with wind energy have seen a significant decline, making it a more attractive and feasible energy source.

A Deep Dive into the Novel Forecasting Model [3-8]
At the heart of the study lies a groundbreaking forecasting model tailored for wind speed assessment. This model stands out due to its dual integration:

1. **Sentinel Satellite Imagery**: The study harnesses the power of Sentinel satellite imagery, specifically Sentinel-1 (S-1) and Sentinel-2 (S-2), to conduct a preliminary analysis of wind speed and bathymetry.
2. **Machine Learning Algorithms**: The research doesn't stop at satellite imagery. It further integrates a hybrid machine learning model, amalgamating the strengths of the Generalized Regression Neural Network (GRNN) with the innovative Whale Optimization Algorithm (WOA).

Practical Application and Impressive Results
Nezhad and his team applied this comprehensive methodology to a real-world scenario: assessing the wind energy potential around the picturesque Favignana Island in Sicily, Italy. The findings from this application were enlightening:

- **Efficacy of Satellite Imagery**: The S-1 and S-2 satellite images proved to be instrumental in gauging wind speed and understanding the bathymetry around Favignana Island.
- **Accuracy Metrics**: The proposed model's performance was benchmarked against error metrics. The results were commendable with an RMSE of 0.0205, an MAE of 0.0159, and a MAPE of 6.8385.
- **Comparison with Existing Models**: When pitted against other established forecasting models, Nezhad's model showcased superior accuracy, underscoring its potential in real-world applications.

Broader Implications in the World of Wind Energy
Beyond the specifics of the study, it's essential to recognize the broader implications of such research. The integration of GRNN, with its adaptability and rapid learning capabilities, and WOA, inspired by the intriguing social behaviour of humpback whales, represents a paradigm shift in wind energy forecasting. This blend ensures optimized data processing, leading to more accurate and timely wind speed predictions. As the world grapples with the challenges of sustainable energy, studies like these pave the way for a brighter, greener future.

The study by Nezhad et al. (2021) underscores the transformative potential of machine learning in the realm of short-range wind power estimation. Delving deeper into the machine learning approaches, the integration of the generalized regression neural network (GRNN) with the whale optimization algorithm (WOA) emerges as a pioneering method. GRNN, known for its adaptability and rapid learning capability, combined with WOA, an algorithm inspired by the social behaviour and hunting mechanism of humpback whales, offers a robust and efficient model. This synergy allows for the accurate prediction of wind speeds by optimising the data processing and analysis. The machine learning model not only streamlines the forecasting process but also enhances the precision of predictions, making it invaluable for real-time decision-making in wind energy production. Such advancements in machine learning techniques, as highlighted in this study, pave the way for more sustainable and efficient utilisation of wind energy resources, especially in challenging terrains and conditions.

2.2 Wind Power Forecasting

In the ever-evolving landscape of renewable energy, wind power forecasting stands as a critical domain. The 2020 study by Kosovic et al. (2020), orchestrated in collaboration between the National Center for Atmospheric Research (NCAR) and Xcel Energy, offers a deep dive into this niche. The overarching aim of this research was to meticulously refine and expand the existing wind power forecasting system, ensuring it resonates with the dynamic needs of its user base [2].

Historical Context and System Evolution
The genesis of the system was rooted in a specific need: day-ahead power predictions, which were instrumental for power trading activities. However, as the energy landscape evolved and user requirements became more intricate, the system underwent a series of transformative enhancements:

- **From Day-Ahead to Short-Term**: Transitioning from its original purpose, the system now encompasses capabilities for short-term forecasting. This is pivotal for nuanced activities like unit commitment and economic dispatch, as highlighted by Kosovic et al. (2020).
- **Embracing Uncertainty**: Recognizing the inherent uncertainties in wind speed predictions, the system now integrates probabilistic forecasting. This approach offers stakeholders a spectrum of potential outcomes, aiding in informed decision-making.
- **Anticipating the Extremes**: In a world where extreme weather events are becoming commonplace, the system's ability to predict events like icing is invaluable. This is achieved through a harmonious blend of numerical weather prediction and a state-of-the-art fuzzy logic AI system.

Technological Innovations: The Heartbeat of the System [9-12]
Kosovic et al. (2020) illuminate several technological breakthroughs and integrations that serve as the backbone of the refined system:

- **Empirical Power Conversion Algorithms**:
  - These aren't your run-of-the-mill algorithms. They've been re-engineered to adopt a quantile approach for data quality control, ensuring unparalleled accuracy in predictions.
- **Analog Ensemble Approach**:

    - A novel approach, this has been seamlessly integrated to provide a granular quantification of forecast uncertainties, offering a multi-dimensional view of potential scenarios.
- **Short-Range Ramp Forecasts**:
    - A blend of the best: The system synergizes two distinct methodologies - the variational doppler radar analysis system and an observation-driven expert system. This fusion ensures robustness in short-range ramp forecasts.

The Pivotal Role of the WRF Model

The WRF model emerges as a cornerstone in the study by Kosovic et al. (2020). Tailored and fine-tuned for specific regions of interest, this model is continually enriched by a global community of dedicated researchers. When paired with local data assimilation, it promises optimized predictions for targeted sites. An intriguing discovery from the research was the pivotal role played by Nacelle anemometers. Installed on wind turbines, these devices:

- Record wind speeds with high temporal precision.
- Exhibit a robust correlation with inflow wind speeds.
- Enhance the efficacy of mesoscale NWP models through their data contributions.

In their concluding remarks, Kosovic et al. (2020) paint a vivid picture of the future. They emphasize the transformative potential of intertwining AI with numerical weather prediction. This symbiotic relationship not only amplifies the precision of wind power forecasting but also addresses the myriad challenges associated with it. As we stand on the cusp of a renewable energy revolution, the insights from this study serve as a beacon, guiding the seamless integration of wind power into modern power grids and shaping the future of sustainable energy[13-14].

3 Future Scope of Research

As the global demand for renewable energy sources, particularly wind energy, continues to rise, the need for advanced forecasting models and techniques becomes paramount. The integration of machine learning with traditional forecasting methods has shown promising results, but there remains a vast expanse of uncharted territory. The following are potential areas of research that could further revolutionise the field of short-range wind power estimation.

- **Deep Learning Integration:** While machine learning has been employed, the potential of deep learning, especially neural networks with multiple layers, remains largely untapped. These could offer more accurate and nuanced predictions.
- **Real-time Data Integration:** Incorporating real-time data from various sources, such as IoT devices, into forecasting models could enhance prediction accuracy, especially in rapidly changing weather conditions.
- **Cross-disciplinary Approaches:** Collaborating with experts from fields like marine biology and geology could provide insights into how other environmental factors might influence wind patterns, especially offshore.
- **Enhanced Satellite Technologies:** With advancements in satellite technology, there's potential for more detailed and frequent data collection, which could significantly improve forecasting models.

- **Adaptive Algorithms:** Algorithms that can adapt and learn from their prediction errors in real-time could be a game-changer, making forecasts more reliable over time.

4 Knowledge Gaps

While the strides in wind power estimation using machine learning are commendable, it's essential to acknowledge the existing gaps in our knowledge. Recognising these gaps not only provides direction for future research but ensures that current models and predictions are utilised judiciously.

- **Granular Data Collection:** Current models often work with aggregated data, which might miss out on micro-level changes in wind patterns. There's a need for more granular data collection and analysis.
- **Offshore vs Onshore Predictions:** Most studies focus on either offshore or onshore wind predictions. A comprehensive model that can seamlessly integrate both remains elusive.
- **Economic Implications:** While the technical aspects of wind power estimation are studied extensively, there's a gap in understanding its economic implications, especially concerning infrastructure costs and return on investment.
- **Long-term Predictions:** The focus has predominantly been on short-range forecasts. However, understanding long-term wind patterns, especially in the context of climate change, is crucial for sustainable energy planning.
- **Integration Challenges:** While machine learning models offer improved accuracy, integrating them into existing power grid systems and ensuring they work harmoniously with traditional models is still a challenge.

5 Conclusion

The evolution of wind power estimation techniques, especially in the realm of short-range forecasting, has been marked by significant advancements, particularly with the integration of machine learning and satellite imagery. Drawing from the comprehensive insights provided by the studies of Nezhad et al. (2021) and Kosovic et al. (2020), we conclude with the following key findings:

- **Satellite Imagery's Role:** The integration of Sentinel satellite imagery in wind speed assessment, especially in near and offshore areas, has emerged as a pivotal tool. This technology, when harmonised with machine learning, can revolutionise wind speed predictions, as highlighted in our abstract.
- **Machine Learning's Precision:** The studies accentuated the unparalleled accuracy achieved by blending machine learning with traditional forecasting methods. Techniques like the generalized regression neural network (GRNN) and the whale optimization algorithm (WOA) have set new benchmarks in prediction accuracy.
- **Short-term Forecasting Advancements:**Kosovic et al.'s emphasis on enhancing short-term forecasting, especially with the integration of AI, underscores the critical need for precise predictions in real-time energy grid management.
- **Offshore Wind Potential:** The potential of offshore wind energy, especially for regions with limited land area like islands, has been highlighted. Advanced forecasting models can significantly aid in harnessing this potential, as reiterated in our abstract.

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- **Challenges in Extreme Event Predictions:** The capability to forecast extreme events, such as high winds and icing conditions, remains a crucial area of focus. The integration of numerical weather prediction with AI techniques can offer valuable insights in this domain.
- **Future of Integrated Models:** The seamless integration of various data sources, including satellite imagery, real-time wind speed data, and machine learning algorithms, is the future of wind power estimation. As our abstract suggests, such integrated models not only streamline the forecasting process but also enhance the precision of predictions, making them indispensable for sustainable energy planning.

In essence, the future of wind power estimation lies in the confluence of advanced technologies, innovative algorithms, and a deep understanding of environmental dynamics. The reviewed studies provide a foundation upon which further research can build, driving the renewable energy sector towards a sustainable future.

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