The Offshore Wind Farms Investigations Using Machine Learning

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The offshore wind energy sector continues to make substantial progress, driven by the urgent need for renewable energy, climate change mitigation strategies, and the ambitious zero-emission objectives set by governments and local communities. Key drivers of this progress include scaling up offshore wind turbine dimensions to boost energy output, improving the efficiency of existing systems, addressing environmental concerns associated with these installations, exploring deeper waters for turbine deployment in areas with optimal wind conditions, and pursuing the innovation of floating offshore turbines. These challenges are at the forefront of efforts to advance the development, installation, operation, and maintenance of offshore wind energy systems.

Keywords: offshore wind ; offshore energy ; wind farm

1. Introduction

The progression of machine learning (ML) techniques and artificial intelligence has left an impact on various fields of science and engineering. It has influenced everything from the initial stages of discovery and ideation to the implementation of previously established methods and the presentation of results. The field of offshore renewable energy stands as no exception to these advancements. As governments and communities around the world drive for an increase in renewable energy generation, the challenges related to augmenting the capacity of current systems and constructing more efficient and environmentally friendly infrastructures have become more urgent. This “race” to achieve these objectives has elevated the significance of ML in this field. Particularly, ML techniques function as a set of tools that can render the processes of design, optimization, development, implementation, and maintenance more cost-effective and expedited.

2. Climatic Data Prediction and Environmental Effects

In the domain of wind speed prediction for optimized power generation, researchers have harnessed multilayer perceptron (MLP) neural networks to forecast wind speed values in hourly intervals, as demonstrated by Flores et al[1]. The published literature work not only involves predictive capabilities but also extends to the strategic guidance for siting wind energy conversion systems, as highlighted in the study by Marin et al[2]. Additionally, these networks have been employed to extract wind vector measurements from radar-image sequences, significantly enhancing the precision of ocean wind evaluation[3]. Moreover, researchers have successfully engineered MLP-based models capable of effectively predicting wind farm power by leveraging wind speed and direction data, as exemplified by the study led by Yan et al[4]. In a collective effort, these studies illuminate the potential of MLPs in elevating wind energy prediction, power optimization, and the comprehensive assessment of ocean wind dynamics.

The fusion of clustering techniques and neural networks has also been used in offshore wind energy and marine ecosystem studies. Within this landscape, certain investigations have embraced neural network-based clustering to precisely identify global offshore wind energy hotspots, yielding pivotal insights for strategic deployment[5]. In parallel, clustering algorithms and neural networks were used to forge a data-driven proxy model for predicting wind farm power[6]. Delving into image processing and deep learning, convolutional neural networks (CNNs) have been introduced to accurately identify bird species in close proximity to wind turbines[7],[8]. Furthermore, efforts have been made to detect sea breeze and low-level jet events using image-based techniques[9],[10],[11].

The domains of wave forecasting, wave-climate analysis, and climate impact assessment have witnessed the influence of machine learning as well. Researchers have used support vector regression (SVR) and the approximate Prony method for wave forecasting and the consequent development of strategies aimed at reducing the load on offshore wind turbines[12]. Furthermore, a framework for assessing the impact of climate change on offshore wind potentials has also been proposed to serve as an embodiment of ML's utility in wind simulation analysis and the projection of future wind power scenarios[13]. The random forest algorithm has also established its role in habitat analysis and species distribution modeling. This algorithm has been employed to evaluate the influence of offshore wind energy installations on marine species, as exemplified by the work of Friedland et al[14]. Expanding its application, the random forest regression technique has also been implemented to unravel the underlying factors influencing passive gear fisheries and to understand the effects of offshore wind farms on fishing activities, as showcased by Stelzenmüller et al[15]. Moreover, an amalgamation of hierarchical clustering and random forest has been implemented for the purpose of high-resolution habitat mapping[16]. Finally, Yu et al. employed an SVM optimized by the dragonfly algorithm for ultra-short-term offshore wind forecasting for power predictions[17].

ML's reach has also extended to some unique and innovative applications. Among these, an approach of reinforcement learning-based path planning for ship navigation within wind farm areas was introduced by Zha et al[18]. Another application involves the utilization of satellite remote monitoring to predict wave heights, showcasing the potential for ML to enhance wave forecasting, as highlighted by Tapoglou et al[19]. Furthermore, the fusion of machine learning and flight data has resulted in the creation of a collision risk map, demonstrating a potential safety measure enabled by these technologies, as showcased in the study by Mikami et al[20]. Machine learning techniques have also been used for mitigating noise in synthetic aperture radar images, attesting to their capability in enhancing image quality, as seen in the research by Xu et al[21]. Furthermore, Bayesian neural networks have been enlisted to predict offshore wind resources, underscoring the versatility of ML in varied contexts, as presented by Clare and Piggott[22].

Through MLPs, clustering, deep learning, wave analysis, spatial modeling, and some other novel applications, researchers have addressed a spectrum of challenges, from predicting wind speed and ocean waves characteristics to modeling species distribution and analyzing habitats. This collective effort demonstrates ML's potential to reshape our comprehension of marine environments and to optimize the utilization of offshore wind energy systems.

3. Performance Modeling & Optimization

From Jeju Island in South Korea to current configurations, researchers have been striving to maximize the energy production of wind farms by implementing optimized layouts. MLP neural networks and genetic algorithms has been used to identify optimal locations for offshore wind farms, as exemplified by[23]. The forecasting of power production for these systems was studied through the development of linear regression and MLP[24]. Furthermore, Yang and Deng suggested a framework that integrates new turbines into existing setups, enhancing power output without additional land use[25].

ML methods were also employed to estimate power losses caused by wake effects within wind farms. For instance, Japar et al. used various ML models, including SVR and MLP, to accurately estimate power deficits attributed to wake effects in large wind farms[26]. Additionally, Yin and Zhao created predictive models for wind farm power output and turbine thrust using five different ML algorithms[27], while Nguyen et al.'s data-driven proxy models could predict aggregated wind farm power based on free flow wind conditions[6]. In another study, predicting wind turbine power output manifests through advanced MLPs[28]. Focusing on ultra-short-term prediction, Meng et al.'s attention-based ML model further refined wind power prediction[29].

ML's intelligence ushers in innovative control strategies for offshore wind farms. Deep reinforcement learning-based control system was implemented to optimize power generation in wind farms[30]. Further, Kheirabadi and Nagamune's Distributed Economic Model Predictive Control, combined with MLP networks, bolsters energy production in floating offshore wind farms[31], while Li et al.'s MLP-based sliding mode control could refine blade pitch control for wind turbines[32].

As the seas embrace wind turbines, ML models can be used to unmask their structural behaviors. Noppe et al. reconstructed thrust load history using neural networks[33], and Ahmad et al.'s MLP network could be used to simulate a hybrid floating wave energy-wind turbine platform's structural dynamics[34]. ML is used to model the structural behavior of wind turbine components as well. For instance, Penner et al. employed MLPs to model non-linear relationships between measurements in the context of structural behavior[35].

In the face of uncertainty, ML models are implemented to improve the clarity. Some studies focus on quantifying uncertainty in ML models, particularly in power curve modeling. For instance, Pandit and Kolios proposed methods to quantify the uncertainty of SVM-based power curve models using confidence intervals[36], while Keighobadi et al.'s adaptive controller counteracts uncertainty effects through radial-based functional MLP controllers[37]. Neural networks have also been used to interlace data and graphs. As an example, Yu et al. used graph neural networks to connect wind turbines within wind farms based on geographical locations[38]. Further, Chen et al.'s reinforcement learning optimizes dynamic response predictions of floating offshore wind turbines[39], while Lian et al.'s MLP-based regression model links loading conditions to offshore wind turbine performance[40]. Regarding power generation prediction, Mattsson et al. generated synthetic hourly electricity demand series via ML models[41]. Yin and Zhao's hybrid CNN-Long Short-Term Memory (LSTM) model optimizes offshore wind farm power generation[42], while Häfele et al. utilizes Gaussian process regression for optimizing offshore wind turbine jacket substructures[43].

Anagnostopoulos and Piggott's MLP-based wind farm flow field model could simulate wind turbine behavior[44]. Further, Zhang et al.'s multi-objective predictive control strategy harnesses gated recurrent neural networks for better power output performance[45]. Moreover, Dehghan Manshadi et al. melds vortex bladeless wind turbines and wave energy converters, predicting net power generation through ML[46], while Yonggao and Yi's neural network-based approach crafts an auxiliary toolbox to optimize reactive power compensation[47].

3. Health Monitoring & Maintenance

Researchers have been harnessing the power of ML to provide efficiency and reliability for wind farms. From predicting failures and maintenance requirements to making these systems more reliable in the harsh environment of the ocean, the ML techniques have been implemented in various capacities and forms. As one of the early attempts, Hameed et al. have combined a self-organizing map and an MLP neural network to predict turbine power output with a 95% accuracy at the Lillgrund wind farm[48]. But the ML implementation for maintenance purposes does not stop there. Wang and Infield have dived into historical data, using non-linear state estimation to detect gearbox failures[49]. Their adaptable model, applicable across similar turbines, is shedding light on the path to precision maintenance, where potential failures are identified before they become a problem.

Moreover, Pattison and colleagues have proposed an intelligent maintenance architecture that integrates fault detection, modeling, and scheduling[50]. As a result, downtime is minimized through predictive maintenance, making sure turbines are continuously up and running. While physics and data interact, Helsen et al. have explored big-data methods for predicting component failures[51]. Their approach provides some insights into a potential harmonious fusion between physics-based models and ML techniques. The effort continues with Li and Choung, who have looked into the fatigue damage prediction in mooring lines[52]. Their dynamic analyses and MLP networks are enhancing the reliability of offshore structures, ensuring they weather the storms of time. In another study, Kandukuri and the team proposed a bearing fault diagnosis with SVM-based classification, setting an approach for turbine health evaluation based on its bearing data[53].

Ziegler et al. have introduced robust load monitoring strategies that rely on strain measurements[54]. Their work guides the industry towards a more comprehensive understanding of load analysis. Moreover, Langenkamper et al. have crafted "virtual twins," a fusion of imaging and deep learning for offshore wind turbine health assessment[55], bringing the field closer to a general system where turbines are monitored with more precision. In this dynamic landscape, Hoxha et al. proposed a real-time monitoring for offshore wind turbine foundations, achieving a 97% accuracy in damage classification[56]. Additionally, Li and Zhang propose a system for fatigue detection in floating wind turbines, focused on optimizing operations for maximum efficiency[57]. And finally, Schröder and colleagues delve into the complex relationship between loads and turbine reliability[58].

As an attempt to unlock a paradigm of optimal condition monitoring, Baboli et al., proposed foreseeing failures and taking preventive actions through continuous temperature data and advanced ML networks[59]. Moreover, Cho et al. have devised a fault diagnosis approach in hydraulic systems, achieving a 97.5% accuracy across various fault types[60]. In this set of innovation, Eze et al. put forward an approach for deep subsea cable fault detection[61]. Their algorithms offers a high accuracy and paves the way for a more reliable energy transmission. Furthermore, Encalada-Davila et al. proposed a model adorned with an exponential weighted moving average technique to anticipate faults with a better accuracy[62].

4. Prospective

The application of ML techniques in the implementation of offshore wind turbines has opened up a new era of possibilities. Researchers have made significant efforts in harnessing the power of ML to enhance various aspects of offshore wind energy systems. Structural health monitoring and maintenance have been greatly improved through the predictive capabilities of ML, allowing for accurate identification of potential failures and enabling precision maintenance strategies. Moreover, ML has played a pivotal role in optimizing wind farm layouts, power production forecasting, and wake effects mitigation, leading to increased energy generation efficiency. The integration of ML-driven control systems has shown a great potential for improving the operational strategies of offshore wind farms, further enhancing their overall performance and energy output. Climatic data prediction and environmental studies have benefited from ML's predictive capabilities, aiding in the optimization of power generation and the assessment of environmental impacts.

As we look ahead, several promising research directions emerge in the domain of implementing ML techniques for offshore wind turbines:

Advanced Predictive Maintenance: Further advancements can be made in the realm of predictive maintenance by integrating real-time data from various sensors and sources. Research could focus on developing comprehensive models that not only predict failures but also recommend optimal maintenance schedules and strategies.

Intelligent Control Systems: ML's potential in control strategies is vast. Future research might delve into developing more intricate control algorithms that optimize the entire wind farm's operation, considering multiple variables such as weather conditions, power demand, and energy storage.

Multi-Physics & Hybrid ML Modeling: Integrating ML with multi-physics modeling could enhance the accuracy of predictions related to structural behavior, fatigue, and performance. Combining ML's data-driven insights with physics-based models can provide a more holistic understanding of turbine dynamics. Further, combining the strengths of ML with physics-based models can lead to hybrid models that capture both empirical data and underlying physical principles. This can lead to more accurate and adaptable models that evolve with changing operational conditions.

Enhanced Environmental Impact Assessment: ML can contribute significantly to environmental impact assessments, not just for marine ecosystems but also for interactions with other industries such as fishing. Future research might focus on developing more precise models that predict and mitigate the ecological consequences of offshore wind farms.

Fusion of Data Types: The fusion of various data types, such as satellite imagery, weather forecasts, and oceanographic data, can lead to more accurate predictions. Future research could explore innovative techniques for combining these data sources effectively.

Uncertainty Quantification: Addressing uncertainties in ML models, especially in power curve modeling and wake effects prediction, is crucial. Future studies could focus on developing methods to quantify and manage uncertainties, leading to more robust and reliable predictions.

Explainability and Interpretability: As ML models become more complex, ensuring their interpretability and explainability becomes essential. Research could be directed towards developing techniques that provide insights into how these models arrive at their predictions, enhancing trust and adoption.

Real-Time Decision Support: ML can play a pivotal role in providing real-time decision support for offshore operations. Future research might focus on developing systems that analyze vast amounts of data in real-time and provide actionable insights for operators to optimize performance.

Socio-Economic Impact Analysis: The expansion of offshore wind energy systems impacts not only the environment but also local economies and societies. Future research could delve into comprehensive socio-economic impact assessments, considering job creation, community development, and energy affordability. ML-based models can be implemented for the analysis and prediction of these potential impacts, specially resulting in the provision of insights for taking mitigating steps in the case of negative effects.

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