Wind Power Prediction and Early Downtime Detection for Ireland

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ABSTRACT: Wind energy must be commercially competitive to be economically sustainable. Existing wind farms in Ireland must be more efficient to meet the 2009 EU Renewable Energy Directive target of 7% of total energy demand from onshore wind energy farms, which is 45% of the total national renewable energy target of 16%. WindPearl - a Sustainable Energy Authority of Ireland (SEAI) funded project is currently looking into improving Operations & Maintenance (O&M) of onshore wind turbine farms in Ireland. WindPearl uses bespoke data analytics, focusing on early and accurate downtime prediction with significantly improved wind turbine power curve forecasts. Both have real-time capabilities and adaptable to uncertain, imperfect, or poor data. The project, a combination of feasibility study and demonstration, uses real data from several wind farms in Ireland covering an entire range of manufacturers. Improved methodologies of wind power prediction are being developed, calibrated, and implemented for wind farms to demonstrate the improvement of operations and maintenance. The ability of replication, transferability and scalability are being established.

KEY WORDS: Wind Energy, Wind Farms, Analytics, Operations and Maintenance, Renewable Energy.

1 INTRODUCTION

Existing wind farms in Ireland should become more efficient to meet the 2009 EU Renewable Energy Directive target of 7% of total energy demand from onshore wind energy farms, which is 45% of the total national renewable energy target of 16%. The improvement of Operations and Maintenance (O&M) can be a key player in achieving this goal since this can contribute up to 35% of lifetime cost of a turbine and up to 49% if a major failure occurs.

Reducing O&M costs through better analytics and/or instrumentation can lead to greater returns in the long-term financial model of a wind farm portfolio. For onshore wind turbines, power curve warranties from the turbine manufacturer is typically available as an initial estimate around future performance, maintenance contracts are in place for turbine and substation servicing and operations management contract takes care of farm compliance and optimised performance. For example, for an availability warranty of generating power for 97% of the year, if 3% time is assigned to unscheduled downtime due to faults and for a 20MW wind farm, 1% downtime leads to more than €30,000 per year in revenue loss. O&M costs are often on average 1-2c€/kWh, and are double or triple than those originally estimated. Real behaviour of the turbines deviates from power curve warranties and both under and over-estimates have knock-on effects of estimated energy yield and related economic consequences or on decision-making. Consequently, simultaneous reduction of downtime through early and accurate detection of outage and reduction of uncertainties in operation power curves for wind turbines through improved forecasts can lead to significantly better O&M for wind farms. Figure 1 presents a situation where the challenges of power curve deviation and outage classification is illustrated. Such deviation can be sometimes difficult to model.

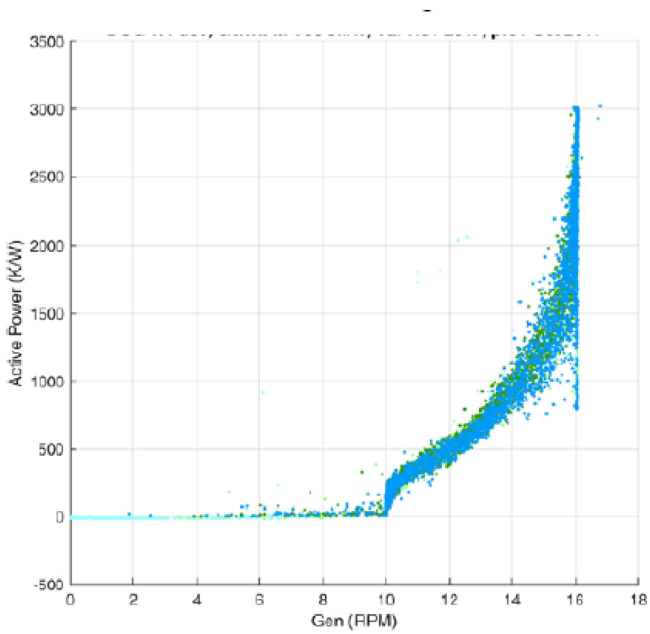

Figure 1. Challenges of Power Generation Forecasts for Real-Data.

Novel and additional instrumentation can be attractive for these purposes, the implementation and assimilation of these sensors and related hardware, along with communication issues provide a major hurdle to address the O&M issues in the short to medium term for operational onshore wind farms in Ireland. They also have the additional problem of replication, transferability and scalability. On the other hand, there has been exceptional advancements in various fields of signal processing, analytics, data mining, machine learning, time-series analysis, Bayesian updating, system identification and classification, anomaly detection and pattern recognition, but there has been inadequate adaptation of these advancement for O&M of wind farms. Advanced analytics with demonstrated applications on authentic, real data from wind farms along with an extensive evidence base around the performance of such O&M improvements can address the challenges in relation to replication, transferability, scalability and consequently around energy targets by improving efficiency through improved, data-driven information.

The operations and maintenance (O&M) costs for wind assets is assumed to be 7.5€/MWh in this paper, which is a conservative figure when compared to other sources. The estimated service and spare parts are assumed to be 12% of O&M costs. Through optimization and more efficient asset management, such costs of O&M can decrease by more than 20% in the short term, leading to a service and spare parts cost in the short term around 0.7€/MWh. Installed wind capacity in Republic of Ireland for 2020 is forecast to be 4.0GW. Assuming a 30% capacity factor this will produce 10.1TWh in that year. EU wind energy production is forecast to be 581TWh in 2020. Increases in wind capacity means that cost of service and spare parts in ROI will be around 7€m in 2020, with the same cost in the EU at 407€m for 2020. The market therefore demands more effective monitoring and maintenance to ensure that these costs are minimised.

Improved and real-time power curve forecasts along with updating for site-specific and turbine specific information can lead to O&M improvements in line with renewable energy targets. Additionally, early and accurate detection of deficiencies leading to downtime along with classification of downtime signatures (e.g. pitching, underperformance, storm shutdown etc.) can further improve the efficiency of wind farms to a great extent. Quantitative estimates around the performance of these work can also indirectly influence availability warranties where accurate definitions and correct allocation of availability percentages can improve the current scenario where vague definition can often be present. A better power forecast and downtime estimate can also reduce epistemic uncertainties around availability data since turbines can be classified as available even when experiencing up to 30% efficiency reduction. It not only aids in effectively dealing with grid code compliance but also provides the closest estimate to the real yield scenario – which further influences the energy market. The Irish Transmission System Operator (TSO) provides a number of demands for short term wind power forecasting including: forecasts for site-specific and turbine-specific conditions, wind-power output based prediction as opposed to wind speed based predictions, hourly forecasts extending out to a forecast horizon of at least 48 hours, an accurate forecast with an associated confidence level and estimates of uncertainties, reliable forecasts of likely changes in wind power production and insights from meteorological conditions and use of historical data to improve accuracy of forecast over time.

Analytics driven O&M improvement of onshore wind farms are thus relevant in the energy market for not only wind asset owners but also wind energy traders. While the risk of the outages is pushed to the owners of the assets, the traders lose ability to trade about 2 hours before physical delivery. In reality, with the lack of liquidity that is been assumed in the last market closest to delivery a trader will probably lose the ability to trade almost 3-12 hours in advance of delivery. Improved real-time or short-term predictions will help significantly with persistence wind forecasting in the 1-3 hours before delivery and also influence the forecasting in the 3-12 hours before delivery. This will, as the market becomes more liquid around delivery, prove beneficial to trading. Forecast of outage and power curves is an area that is important for Ireland sustainable energy future for has not been developed well for this country. The maximum value in the industrial sector will be reaped by companies that both won wind assets and trades in wind power as well. A demonstrative evidence base for Ireland can shift the market towards a more analytics driven and efficient direction. These considerations will be more important now in the light of the Integrated Single Energy Market (I-SEM) and the proprietary modelling that is carried out in most companies.

While there has been no detailed project on this topic for Ireland, there exists some work with their constraints and limitations for Ireland. Overview papers for wind power generation forecasts provide some of the existing markers of performance [1] along with some initial cost estimates [2]. An existing works around downtime data for 11 turbines on the East on Ireland for 6 months' worth observations identify the need for classification of downtime and related alarms, along with the need for an algorithm as demonstrated through an example. The authors concluded that the performance in general were not high enough to warrant the system for a field trial, especially for recall scores. The same group approached the problem from the point of view of support vector machines and improved their results and obtained decent results for 24-hours ahead predictions for some downtime cases [3]. The lack of performance was attributed to inability to handle data complexity and related challenges around feature extraction and pattern recognition. A different group has prognostics assessment from standard SCADA data but only on bearing response [4]. However, this work highlights the power of using Bayesian updating for forecasts for wind farm data.

2 DESCRIPTION OF THE WINDPEARL PROJECT

The Sustainable Energy Authority Ireland (SEAI) funded WINDPEARL project (https://www.windpearl.net/) attempts to address some of these challenges with real data.

- It is observed from scanning the current research in Ireland, the importance of early, accurate downtime detection and improved power curve forecasting are globally felt but there is no dedicated project for Irish conditions and using data from Irish wind farms.
- There is inadequate benchmarking of methodologies for site-specific Irish conditions.
- While numerical algorithms in other fields have developed and evolved strongly, they have not been adapted for downtime detection and better power curve forecasting despite their potential.
- The impact of proposed methods on the energy market is an unexplored area and can only be investigated by applying and calibrating the methods directly on field data.
- There is inadequate work around working with uncertain, missing and poor data and their impact on detection/forecasting, although the importance and impact of data quality is well-acknowledged.

Overall, these limitations are directly linked to the operations and maintenance efficiency of wind turbines and the competitiveness of the wind energy market. WINDPEARL directly addresses all these limitations and provides solutions that can mark a paradigm shift for Ireland in terms of wind energy efficiency assessment methodologies, leading to significant improvement.

This includes,

- Dedicated use of data from Irish-owned farms from a range of manufacturers throughout the project and calibrating model parameters for output conditions for site-specific information from Ireland. This is ensured through access to data from several farms.
- Development of a comprehensive benchmarked repository for use in any Irish wind farm, leading to a national advantage in terms of improvement of Operations & Maintenance for the entire country. This will lead to an impact on the overall Levelised Cost of Electricity (LCOE).
- The flexibility of the use of the methods for various sites and for a wide range of input conditions, including the machine learning and subsequent pattern recognition advantage makes the final software robust and adaptable to changes in data. Consequently, re-calibration and adaptation to new conditions will have an automatic component.
- The project uses cutting-edge techniques from different fields of application to adapt to the wind turbine sector and transform them to most effective tools in this field. The combination of a) time-series forecasting b) machine learning and pattern recognition, c) multivariate statistical modelling, d) time-frequency analyses and e) system identification and f) anomaly detection methods form the most comprehensive set of tools for this topic.

The calibrated performance measures of the methods, along with the results of consequences for various scenarios expressed in monetary values or as utility curves will result in quantified estimate of such technical advancements and will create a model template for Ireland for any future techno-economic assessment for other developments in terms of demand, changed business scenarios or incorporation of novel or technologies.

The limitations around data quality will be addressed and quantified in terms of performance and solutions will be provided to handle them. Detailed solutions will be provided in the form of guidelines and numerical implementation to obtain maximum information with limited data quality. This will demonstrably reduce epistemic uncertainties in the wind energy market and will lead to lowering of cost.

The overall objectives of the project are as follows:

• Development of bespoke, robust, and demonstrable better methodology for accurate, early detection of wind farm downtime and accurate wind turbine power curve forecasts. [O1]

• Comprehensive calibration of the developed models using real wind-farm data. [O2]

• Direct use of authentic wind-farm data for development of methodologies and implementation of the sudden changes from signals through a recursive singular spectrum approach with integrated machine learning and pattern recognition [O3]

• Creation of a comprehensive evidence base for the developed methodologies with estimates of errors, inaccuracies and limitations of implementation. [O4]

• Creating guidelines, recommendations and solutions for transferability and scalability of developed methods for site-specific Irish conditions and for availability of data, including solutions for handling poor data, missing data and unknown patterns in data [O5]

• Developing insights of the impact of developed solutions on the business operations and maintenance of wind turbines, especially in an integrated single electricity market (I-SEM) [O6].

The overall project setup is presented in Figure 2.

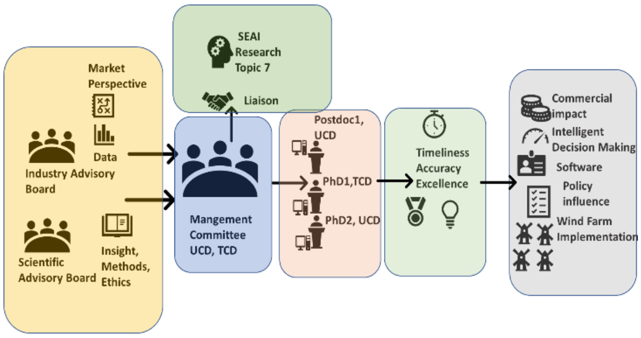

Figure 2. Project organisation of WINDPEARL project.

3 PROGRESS AND CHALLENGES

Progress in short-term forecasting has been carried out by integrating variational mode decomposition (VMD) and extreme learning machine (ELM) [5]. the VMD algorithm decomposes a signal into its principal modes concurrently by searching for a certain number of modes and their centre frequencies. ELM is a type of single hidden-layer feedforward neural network in which the input weight matrix is randomly assigned instead of using gradient-based learning methods. Figure 3 presents an example of the implemented VMD-ELM method for several days in an Irish wind farm using a single model and an ensemble composed by five VMD-ELM models that are trained independently and the final prediction is obtained as the average value of the forecasts provided by the models in the ensemble.

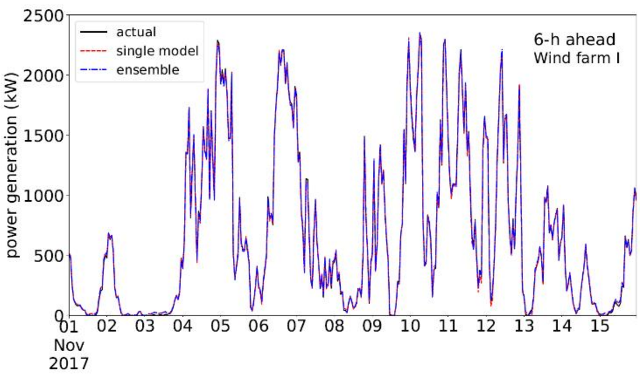

Figure 3. A combined VMD-ELM model application for a 6-h ahead wind energy forecast for a wind farm over a few days.

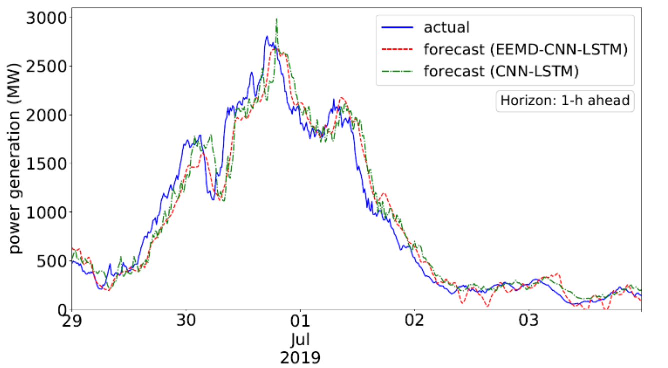

Figure 4. An example of a deep-learning based 1-hour ahead forecast of wind power in a wind farm over a few days.

Other decomposition-based techniques have been also explored such as ensemble empirical mode decomposition (EEMD) and some deep learning models such as convolutional and recurrent neural networks have been used to compute forecasts. Figure 4 shows an example of a deep-learning based 1-hour ahead forecast.

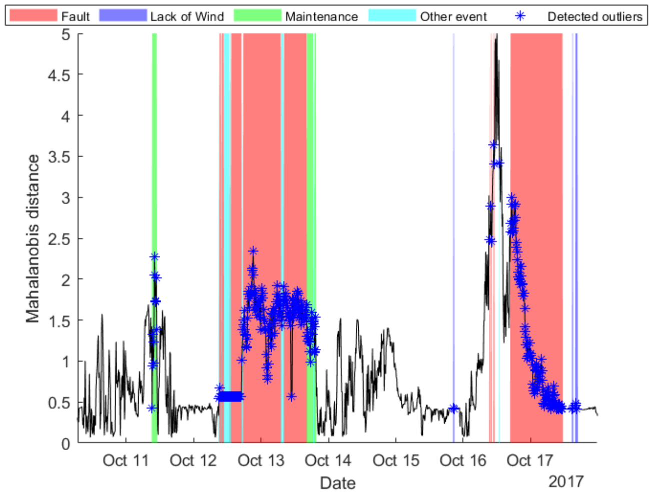

Figure 5. Mahalanobis distance for a 2-channel signal (power and wind speed) between the 10^{th} and 22^{nd} of October. Coloured areas show time periods with notable events for this turbine.

Advances in downtime detection have been carried out in terms of development of a novel method. This involves first the estimation of principal components (PCA) using recursive eigen-perturbation [6] for a wind farm or wind turbine using power and wind speed data. Wind turbine events were discriminated into four distinct categories based on turbine alarm data: Fault (causing the stopping of the turbine due to damage), lack of wind (causing the stopping of the turbine due insufficient wind), maintenance, and all other events (that did not cause turbine stopping). The consequent computation of a covariance matrix from the data integrated with damage markers (Mahalanobis Distance (MD), mean, standard deviation, skewness, kurtosis, higher order moments, autoregressive (AR) coefficient tracking) that have shown their capabilities in signal event detection [7] and other signal features eventually leads to early downtime detection with good computational efficiency. Figure 5 illustrates our findings so far. Our detection technique could detect most of the points (blue stars) contained in the event time periods and has so far been able to detect up to 89,5 % of them.

4 CONCLUSIONS

Statistical and deep learning models together with decomposition-based techniques have been applied to real data from Irish wind farms to predict and improve short-term wind power forecasts in Ireland. A combination of VMD and ELM provides promising results for short-term forecasts. Additionally, progress in downtime detection has shown encouraging results in a data-driven approach with an accurate discrimination of the flagged time periods.

ACKNOWLEDGMENTS

The authors would like to acknowledge the funding support from SEAI WindPearl Project 18/RDD/263. Vikram Pakrashi would also like to acknowledge the support of SFI MaREI centre and UCD Energy Institute.

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