The Promise of Causal Reasoning in Reliable Decision Support for Wind Turbines

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ABSTRACT

The global pursuit towards sustainable development is leading to increased adaptation of renewable energy sources. Wind turbines are promising sources of clean energy, but regularly suffer from failures and down-times, primarily due to the complex environments and unpredictable conditions wherein they are deployed. While various studies have earlier utilised machine learning techniques for fault prediction in turbines, their black-box nature hampers explainability and trust in decision making. We propose the application of causal reasoning in operations & maintenance of wind turbines using Supervisory Control & Acquisition (SCADA) data, and harness attention-based convolutional neural networks (CNNs) to identify hidden associations between different parameters contributing to failures in the form of temporal causal graphs. By interpreting these non-obvious relationships (many of which may have potentially been disregarded as noise), engineers can plan ahead for unforeseen failures, helping make wind power sources more reliable.

KEYWORDS

Wind energy, Explainable AI, Causal reasoning, Deep learning

1 INTRODUCTION

With the wind energy revolution flourishing, more turbines continue to be deployed in complex environments, especially offshore [1]. Thereby, the challenges in operations and maintenance (O&M) continue to proliferate, leading to significant costs. Wind turbines consist of sophisticated sensors, which regularly measure operational parameters from the turbine and its environment [1].[1] Additionally, the records of various faults which occur are logged into alarm logs and maintenance records. All this information is stored in the form of Supervisory Control & Acquisition (SCADA) data, which can be harnessed by AI models for decision support.

Many existing studies have focused on applying traditional machine learning models (such as support vector machines, decision trees, probabilistic models etc.) [3] for predictive maintenance with promising results. More recently, deep learning models (artificial neural networks, including recurrent neural nets) [4] have proven to be highly effective in predicting faults with high accuracy, given the largely non-linear nature of SCADA data with complex patterns of faults. However, this comes at the cost of interpretability and accountability as they are generally black boxes lacking rationale behind the decisions. Also, while conventional ML techniques like decision trees, Bayesian learning etc. can be easier to interpret and more transparent, they can be significantly outperformed by their deep learning counterparts for time-series data [9]. This makes most turbine operators prefer signal processing or numerical simulation-based approaches for O&M. To realise the full potential of data-driven decision making in the wind energy sector, trust and confidence has to be instilled into the prediction making of these conventionally opaque and non-intuitive models. Specifically, the reasons behind *why* and *how* a model makes certain predictions need to be analysed by the engineers & technicians.

Causal reasoning is an integral cognitive process in making predictions and explaining complex phenomena [5]. Given that the SCADA data from turbines is complex and non-linear with presence of multiple (often hundreds) of features, modelling relationships between these features during different types of faults can help discover novel insights in data-driven decision making. While causal inference has been successfully applied to other domains (such as medicine and finance) [8, 11], it has seen limited utility in the wind industry. To the best of our knowledge, the closest application of such techniques utilises Normal Behaviour Models to identify the effect of causal inference in improving fault-classification accuracy in turbines [10], but does not provide a solution to identify the complex hidden relationships in an intuitive manner (such as through temporal causal graphs). Additionally, it uses hypothetical simulations rather than real-world data for faults in turbines.

In this study, we propose the application of convolution neural nets (CNNs) with attention for inference in extracting these complex relationships in wind turbine SCADA data from an operational real-world turbine, and identifying the effect of such relations on the turbine's operational status. The proposed technique can help identify hidden relationships (called confounders) as well as the temporal delay between these causations via temporal causal graphs. This can contribute to reliable decision support for wind energy sector and beyond.

2 CASE STUDY

We utilise SCADA data from an operational turbine [2] rated at 7 MW, and use 102 time-series based features (such as active power, wind speed, operational parameters of gearbox, generator etc.) labelled with multiple categories of faults (e.g. in Gearbox, Yaw System,

[1]This contains a variety of parameters from both the turbine's environment (e.g. wind speed, air pressure, wind direction etc.) as well as its sub-components (e.g. gearbox oil temperature, generator converter speed etc.)

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[2]Acknowledgement: Platform for Operational Data (POD) from ORE Catapult: https://pod.ore.catapult.org.uk

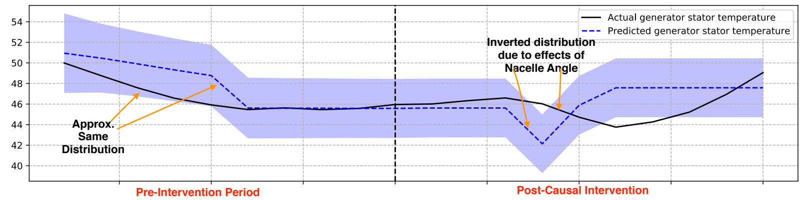

Figure 1: Causal effects (non-obvious) of nacelle angle (X) on generator stator temperature (y) during anomaly in Yaw system using BSTS Approach (Statistically Insignificant). Probability of random occurrence p = 24.88% and 95% interval of percentage change in X and y = [-3.44%, 1.73%].

Pitch System etc.) which have historically occurred in the turbine and have been logged into alarm records. The individual categories of faults are called Functional Groups. We utilise 21,392 samples for our study.

2.1 Applying traditional statistical methods

Before applying deep learning based causal inference methods, it is important to demonstrate the key drawbacks of more traditional approaches. Initially, we applied the commonly used statistical approach of Bayesian Structural Time-Series (BSTS) for causal inference [6] [3] to our data. We wanted to explore the role of causal inference in identifying the *hidden relationships* between the causing/intervening variable on the response/outcome variable. As an example, we demonstrate a relationship which is interpreted as random and spurious by traditional methods, but is identified as a hidden confounder by the deep learning-based causal inference model in Section 2.2. Figure 1 depicts the statistical effects of variation in the **turbine's nacelle angle (intervention)** on the **generator stator temperature (response)** during an actual anomaly in the Yaw system. Here, the pre-intervention period shows the predicted time-series of the response variable using the BSTS model which we would have expected without the causal event occurring, while the post-intervention period highlights how the variable changes as a result of the intervention caused by nacelle angle. Though we see that the intervention seems to have a negative effect on the predicted response variable (as the actual time-series distribution is approximately inverted after the intervention caused by nacelle angle), this is found to be very minor (a -3.44% change in nacelle angle causes a 1.73% change in generator stator temperature in the 95% confidence interval). We found that the BSTS technique found little significance in how these metrics are causally related, and interpreted the associations as statistically insignificant and possibly spurious. To confirm this inference, we calculated the auto-correlation for this metric as shown in Figure 2. The auto-correlation components are clearly non-zero for the variations of the lagged time-series, outlining that the variable is in fact not random, but has a temporal nature, motivating us to look for alternate causal inference models.

As an additional experiment with a recent state-of-art statistical algorithm for causal inference, we applied the deconfounder [11], which uses probability factor modelling to identify causal associations in time-series. We found that the model again ignores non-obvious relationships as those above. More importantly, both of the compared techniques can only identify cause-effect relationships between univariate causes and outcomes, but significantly suffer in cases with multiple latent relationships (e.g. during an anomaly in a turbine, wherein a group of multiple causes can lead to many possible outcomes). Importantly, we were unable to obtain an intuitive, e.g. graph-based causal reasoning approach through these techniques. Thereby, we were motivated to apply deep-learning based causal inference to our problem.

[3]https://github.com/dafiti/causalimpact

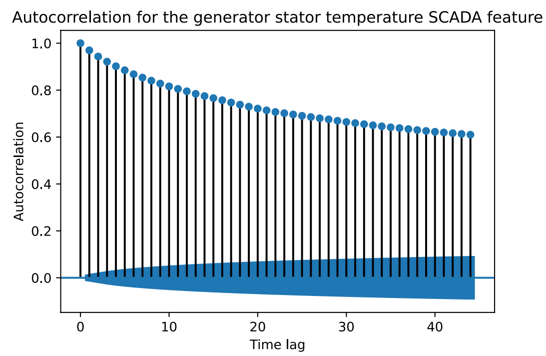

Figure 2: Auto-correlation for the generator stator temperature time-series. The components are significantly non-zero, signifying non-random nature of the metric.

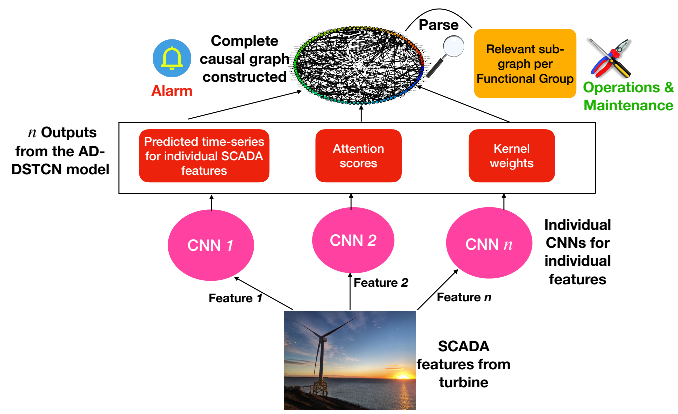

Figure 3: Proposed technique for identification of hidden causal confounders in SCADA data.

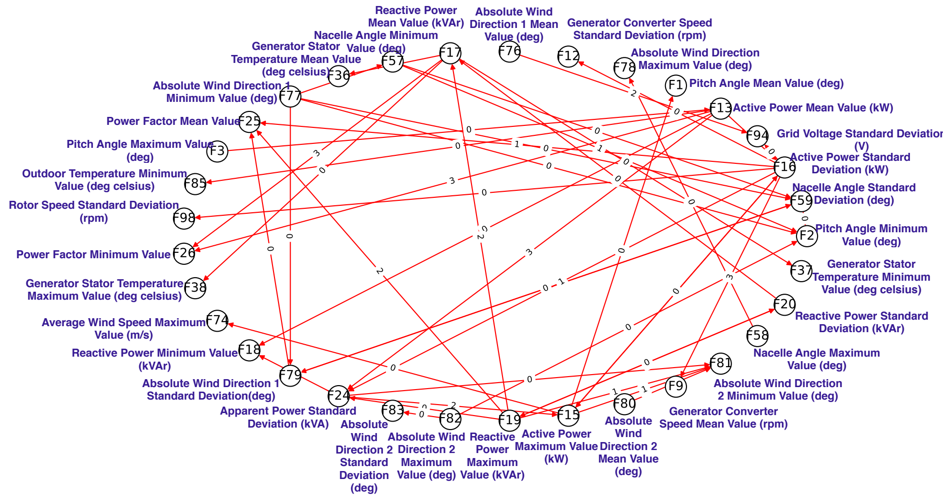

Figure 4: Identified temporal causal relationships in SCADA data during Yaw System anomaly using the proposed learning model. Here, the relation p → q would signify that p is causally affected by q.

2.2 Deep learning for causal reasoning

We apply Attention-based Dilated Depthwise Separable Temporal Convolutional Network (AD-DSTCN), first proposed by Nauta et al [8] for causal inference in the financial and neuroscientific domains. The data from wind turbines is extremely different from these domains, and can have multiple hidden confounders corresponding to specific classes of faults [2]. To realise the model for our domain, we modified the model architecture as explained below. Figure 3 depicts the methodology utilised briefly.

(a) Applying CNNs in time-series prediction of SCADA features. Initially, given the 102 SCADA features in our data, we use 102 individual CNNs (CNN 1 to CNN n) for predicting the corresponding time-series based feature i.e. each CNN predicts a univariate time-series. The predictions are made per the individual classes of anomalies in Functional Groups (sub-components) of the turbine.

(b) Attention mechanism for hidden confounders. To achieve causal inference and identify potentially significant relationships, we modified the original model's attention mechanism to generate an attention matrix containing the attention weights for each identified causal relation between different SCADA features in our dataset. The weights signify the importance of each SCADA feature causally affecting another, with a higher score signifying a greater contribution to the effect. Additionally, the model can identify the temporal delay between each causally significant time-series which the CNN predicts during the faults. We assume that attention weights can represent the SCADA features' distribution non-uniformly based on their contributions to causal effects, in line with Nauta et al.[8] who found that attention weights show strong connections with causal associations. We utilised the first 20 attention weights for each feature's causation to identify the most relevant relationships, as experimenting with different number of weights in multiples of 10 (i.e. 10, 20, 30 etc.) showed that 20 top-weights from SCADA features can help to identify most-reasonable causal associations for our problem in terms of number of hidden confounders identified and their relevance.

(c) Constructing the temporal causal graph. As the final step, we integrated the original CNNs with a dilation mechanism (which can help in identifying causal relationships during large temporal delays, commonly the case with SCADA data), and the attention mechanism in (2). This generates a complete causal graph (with every possible hidden confounder identified by the model) during different types of anomalies in the turbine. We extracted sub-graphs corresponding to multiple cases of these faults from the complete causal graph, and the temporal sub-graphs will only include those associations wherein the feature is important to the causation (i.e. any changes or variations in that feature affects another time-series feature during an anomaly).[4]

2.3 Evaluation of the learning model

To perform an evaluation on the performance of the proposed approach, initially, we compared the Mean Absolute Scaled Error (MASE) during the time-series prediction stage above against the state-of-art deconfounder [11] baseline from earlier. We observed that our model achieved a MASE of 1.066, outperforming the baseline (which achieved an MASE of 3.901) by up to 72.67%.

Due to lack of ground-truth for the causal relationships identified (given that causal relations are generally hidden within the data, and define the key features which the model looks at during prediction making), we performed a qualitative evaluation on the temporal causal graphs generated by the model based on domain understanding. For this, one of the authors manually tagged the relevance of the relationships across 14 different types of Functional Groups in a binary fashion as either relevant or not. Based on this, our model identified relationships for different types of faults with an average

[4] We used 80% of 21,392 SCADA measurements for training the learning model, while remaining 20% was used for testing. A learning rate of 0.01, Adam optimisation and kernel dimensions 2x2 with dilation coefficient 2 were utilised in the CNN with single hidden layer in the depthwise kernel.

relevance score of 54.81%. In some cases, no hidden confounders were identified at all (e.g. Wind Condition Alarms, possibly due to the absence of multiple hidden confounding metrics, other than wind speed). The model achieved scores of up to 66.66% in some cases (e.g. Pitch System Fault) and higher than 60% relevance for various other categories (e.g. Yaw System, Pitch Alarms, Normal Operation etc). We discuss below an interesting case for the same Yaw system anomaly for which the causality task was discussed for the traditional statistical algorithms. Our goal here is to show that the deep-learning based causal inference approach has indeed real-world applicability and is promising for intelligent and reliable decision support. Figure 4 shows the sub-graph for the anomaly in Yaw system of the turbine (which has been our discussion case in Section 2.1). While the model picks up some obvious relationships (e.g. average wind speed being causally related to active power, nacelle angle to wind direction etc.), there are some relationships which are non-obvious. However, based on domain understanding and when viewing these relationships in a broader perspective, we find that many of these non-obvious relationships do indeed have a deeper meaning. These are the relationships which the traditional statistical approaches in 2.1 neglected, likely due to the lack of explicit declarative knowledge representation in these techniques. They assume that the response (outcome variable) can be effectively modelled using linear regression and would not be affected by intervention (changes) in the causing variable, which is very unlikely for SCADA data, with multiple, non-linear features.

Coming to one of the most notable identified relationship, we see that generator stator temperature mean value is causally related to the turbine's nacelle angle. Our deep learning-based causal reasoning approach identifies this non-obvious relationship. This is reasonable, considering that the nacelle angle of the turbine is also having causal associations with the turbine's pitch angle [5]. This indirectly affects the generator stator of the turbine, which can be affected during anomalies in the pitch system [7]. The anomaly in the pitch system here is likely caused due to error in the yaw system, leading to malfunctioning pitch during frequent start/stop of the turbine, thereby justifying the effect of yaw anomaly. Additionally, the model also identifies the time delay (1 time-step $\equiv$ 10 minutes for our data), after which the hidden confounding metrics take effect. There are several other hidden confounders identified by the model (e.g. reactive power to power factor), which are reasonable after thorough analysis but not obvious at first, and that our model can identify. The most problematic area for the causal learning task is that understanding the hidden relationships is often a difficult task at times, even for experts with extensive domain knowledge. Thereby, if engineers neglect the potentially important (but non-obvious) relationships as insignificant or noise, it may lead to a catastrophic failure. On the other hand, it is also possible that some relationships may be completely inaccurate, and are falsely interpreted as being potential causes for a particular category of fault. Thereby, we believe it is essential for the engineers to think out of the box in analysing the temporal causal graphs, and interpret the relationships with an open mind. The proposed approach can be a powerful tool, when the blessings of deep learning for causal inference are used in conjunction with human expertise for the most optimal maintenance strategies.

[5]The angle at which the blades are turned to ensure optimal power production

3 CONCLUSIONS AND FUTURE WORK

We have proposed a novel application of causal reasoning using attention-based convolutional neural nets to wind turbine SCADA data, which can play an integral role in making condition based monitoring more reliable and robust. Our study shows that deep-learning based causal reasoning is promising for the wind industry, and helps identify causal relationships which are generally neglected by traditional statistical causal inference algorithms, By providing a simple and intuitive way to visualise the causal relationships through temporal causal graphs, the approach brings more transparency to the predictive AI model, and can provide novel insights on unexpected significant parameters to continuously monitor during preventive maintenance, to avoid catastrophic failures. contributing to the goal of Explainable AI. This can be immensely helpful for maintenance engineers, who generally don't have sound understanding of AI. However, despite the advantages, the present approach fails to identify hidden confounders for some specific types of faults (e.g. wind condition alarms), and qualitative evaluation of some cases is difficult to establish due to the machine-oriented patterns discovered by the learning model. We believe that optimising the model through e.g. more useful data and human domain knowledge from the wind industry can help to improve the causal learning approach further. In future, we plan to perform a larger-scale human evaluation of this technique,and integrate it with other forms of knowledge (e.g. maintenance manuals and work orders) for reliable decision support in wind turbines.

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