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Classification and Detection of Electrical Control System Faults Through SCADA Data Analysis

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The development of electrical control system faults leads to increased mechanical component degradation, severe reduction of asset performance, and a direct increase in annual maintenance costs. This paper presents a highly accurate data driven classification system for the diagnosis of electrical control system faults, in particular, wind turbine pitch faults. Early diagnosis of these faults can enable operators to move from traditional corrective or time based maintenance towards a predictive maintenance strategy, whilst simultaneously mitigating risks and requiring no further capital expenditure. Our approach provides transparent, human-readable rules for maintenance operators which have been validated by an independent domain expert. Data from 8 wind turbines was collected every 10 min over a period of 28 months with 10 attributes utilised to diagnose pitch faults. Three fault classes are identified, each represented by 6,000 instances in each of the testing and training sets. Of the turbines, 4 are used to train the system with a further 4 for validation. Repeated random sampling of the majority fault class was used to reduce computational overheads whilst retaining information content and balancing the training and validation sets. A classification accuracy of 85.50 % was achieved with 14 human readable rules generated via the RIPPER inductive rule learner. Of these, 11 were described as “useful and intuitive” by an independent domain-expert. An expert system was developed utilising the model along with domain knowledge, resulting in a pitch fault diagnostic accuracy of 87.05 % along with a 42.12 % reduction in pitch fault alarms.

1. Introduction

Maintenance costs for wind energy represent between 20-25 % of total asset cost, of which, up to 75 % is due to unscheduled maintenance (WWEA, 2012). This deters future investment, increases the cost of wind energy and as such, reduces the long term economic viability of wind energy. As corrective maintenance can be up to 40 times more expensive than a proactive strategy (Hatch, 2004) there is the potential for significant cost savings on wind turbine operations and maintenance (O&M) costs. For this reason, maintenance is moving from a “fail and fix” reactive approach to maintenance, to a “predict and prevent” strategy for maintenance (Levrat et al., 2008).

Maintenance savings of 20-25 % can be achieved using condition based maintenance (CBM) (Djurdjanovic et al., 2003). This can be further increased with the correct application of methodologies such as reliability centred maintenance (RCM). However, uptake across all domains of prognostic technologies for the prediction of future failure modes has been slower than anticipated. It is believed that within the UK, CBM and prognostic technologies have only reached 10-20 % penetration into industry (Moore et al., 2006) This is believed to be due to many factors, such as: the lack of transparency of some expert systems, the capital outlay required for data collection and analysis, the uncertainty and inaccuracy present within some techniques, staff training costs and no proven track record in similar domains.

In this paper we present a new methodology for the development of a transparent expert system for the detection of wind turbine pitch faults utilising a data-intensive machine learning approach. This approach describes a classifier to determine the condition of the pitch system on a wind turbine, and if a fault is observed, the correct action to take depending upon its severity. Severe pitch faults requiring maintenance actions are then be presented to the maintenance operator whilst filtering out unnecessary information and

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reducing the cognitive load which is placed upon them. The data utilised for this methodology is from a pre-existing supervisory control and data acquisition (SCADA) system, meaning that no further sensors are required and no additional capital expenditure are incurred.

2. Wind Turbine Pitch Faults

Wind turbine pitch faults – a deviation of the blade pitch angle from a predefined optimum for a given wind speed – are the most common fault mode to occur. As can be seen in Table 1, pitch faults account for over one third of all faults which are present within the SCADA system which are then presented to the maintenance operator. It is not uncommon for over 2,000 SCADA pitch fault alarms to occur over a year. However, less than 5% of these directly correlate to a maintenance action within the maintenance log; wasting available maintenance resources with undue inspection and analysis. As such, there is a need to develop a data-driven expert system to allow the encapsulation of the behaviours both during and immediately preceding a pitch fault so that maintenance operators can further understand the extent of the fault, the causation of the fault and the maintenance action required.

Table 1: SCADA alarms aggregated by subsystem over a 28 month period for 2 wind turbines

Sub-system	Turbine 1	Turbine 2
Pitch	4,035	4,130
Weather	2,775	2,866
Inverter	1,438	1,751
Gearbox	504	374
Yaw	316	385
Communications	285	827
Total	9,353	10,333

3. Methodology

SCADA data from 8 wind turbines was collected over a period of 28 months and sampled every 10 minutes, across 190 channels. In total, 999,944 records were retrieved. This data was combined with SCADA alarm system data and maintenance log data to give a holistic overview of the condition of the turbine and so that pitch fault events of any cause could be analysed. Due to the inherent nature of the data acquisition, erroneous and missing values are common; these are manifested as implausible values, missing data and duplicate data. This is ascribed to malfunction of the sensors, mechanical systems, data collection systems and also imperfections within the SCADA system itself (Sainz et al., 2009).

Due to these problems, the data must be cleansed before processing can take place. Both missing and duplicate values were removed; missing values cannot accurately describe the current state of the wind turbine, and duplicate values provide no additional information whilst simultaneously increasing computational overhead. Once this is complete, attribute selection is performed. Based upon the work of Chen (2011) and Kusiak (2011), 8 attributes were selected for their consistently strong performance for wind turbine pitch fault diagnosis. Chen (2011) presents an artificial neural network (ANN) approach to pitch fault diagnosis, however, the diagnosis accuracy (M = 42.07 %, SD = 17.49 %) is relatively poor and black box nature of the approach is difficult to interpret by domain experts and maintenance operators. Whilst the work of Kusiak (2011) provides improved accuracy for the prediction of wind turbine pitch faults (M = 76.70 %, SD = 5.617 %), the genetic algorithm used provides human readable rules which are not necessarily transparent or easy to interpret by operators. As such, the attributes chosen for the model based upon the work in the literature were; average wind speed, maximum wind speed, blade 1 pitch motor torque maximum, blade 2 pitch motor torque maximum, average pitch motor torque, blade 1 pitch angle average, blade 2 angle average and SCADA alarm status. In conjunction with these attributes, 2 additional derived parameters were utilised based upon the work of Chen (2011). These are; the absolute difference in pitch motor torque and the absolute difference in blade angle.

Following this, the data was classified into three distinct groups; "No pitch fault", "Pitch fault developing" and "Pitch fault established". These represent the development of a fault over time within the wind turbine. By classifying the data in this way we can identify both the wind turbines which urgently require maintenance and also the turbines with a reduced remaining useful life (RUL). Maintenance logs were used to determine when pitch faults had been severe enough to warrant a maintenance action. The SCADA data from the 48 h preceding this maintenance action was used to describe the "Pitch fault established" class. The SCADA data prior to this where the SCADA-alarm for the pitch fault was active was used to describe the “Pitch fault developing” class. Finally, all other data was used to describe the “no pitch fault” class. Annual maintenance costs can then be reduced utilising this classification; either by scheduling further turbines into existing maintenance actions, or by pre-emptively scheduling those which require maintenance before they become inaccessible to external factors.

Repeated random sampling with 20 samples was utilised to remove the majority class bias inherent within the data. As “No pitch fault” was the dominant class and the turbine remains in this state for a prolonged period, a data-driven classifier will be stronger if it encapsulates this class well and ignores the pitch faults. However, as the aim of the system is the quality of the rules which describe the behaviour of the pitch faults, it is essential that this bias is removed so that the minority fault classes are encapsulated and characterised effectively. Within our data, the imbalance was typically between 125 to 380 instances per fault instance. Whilst other minority oversampling techniques could have been used – such as SMOTE, MSMOTE and FSMOTE (García et al., 2012) – no significant increase in rule accuracy was attained over using traditional repeated random sampling within our dataset. As such, the majority class was under sampled, and the minority class oversampled until the data was balanced.

After the data had been pre-processed, the RIPPER propositional rule learning algorithm (Cohen, 1995) was used to generate order independent, distinct encapsulations of explicit knowledge from the dataset. This technique was chosen due to its transparent, human-readable nature; ensuring trust was placed in the derived rules. An example of rules generated by the RIPPER algorithm can be seen in Figure 1. Although other techniques such as artificial neural networks can achieve high quality classifications, their “black box” nature makes them difficult to extract meaningful rules from. Similarly, although techniques such as clustering and instance-based classification seem intuitive, the high-dimensionality of the dataset and high levels of noise present means that decision regions are non-convex in nature and neither a high accuracy nor quality rules can be extracted from the system. Decision tree algorithms could have been utilised, however, each rule generated cannot be understood independently from the system, and as such, can be difficult to extract and encapsulate as a single unit of knowledge.

Blade 2 Angle ≤ 80.05 degrees, and
Blade 1 Angle ≥ 97.48 degrees, and
Wind speed ≥ 6.44 m/s, and
Average pitch motor torque ≤ 9.67 kN,
Then Pitch Fault Is Established.

Figure 1: A propositional rule generated by the RIPPER propositional rule learning algorithm

Of the 8 wind turbines, 4 were used for training with the remaining turbines used for validation. In order to ensure the robustness of the methodology against training turbine selection, all combinations of turbines for both training and validation were considered. In total, 70 combinations of varying training and validation turbines were created. These models created a Pareto surface compromising the trade-off between the number of rules and rule accuracy which were then presented to an independent domain expert, maintenance operator and decision maker. This allows for both a quantitative and qualitative analysis of these rules so that the causation and diagnosis of pitch faults could more effectively be understood. This enables operators to understand the underlying physical properties of pitch faults so that they can be trained to identify pitch faults before further damage occurs and the turbine needs to be shut down for expensive corrective maintenance.

4. Results

The RIPPER propositional rule learner was trained on 70 models so that the robustness of the methodology could be ensured. Pruning of the rule set was enabled to reduce the quantity of rules to prevent cognitive overload, and was utilized in conjunction with four optimization iterations with three fold partitioning of the data.

The accuracy of the classification for all models was in the range of 69.03 % - 87.41 % (*M* = 80.77 %, *SD* = 4.68 %), with the number of rules generated by each model being in the range of 6 – 38 (*M = 1*6, *SD = 5*.77). After removal of the models which were dominated by those with stronger classification accuracy but the same number of rules, 22 models were eligible to be presented to independent domain experts and maintenance operators for critical analysis of the rules generated. The 21 models developed had classification accuracy in the range of 69.99 % - 87.41 % (*M* = 82.70 %, *SD* = 4.26%). Similarly, the quantity of rules generated were in the range of 6 – 38 (*M* = 16.5, *SD* = 7.65).

A Pearson product-moment correlation was used to assess the relationship between classification accuracy and the number of rules generated by the model. Preliminary analyses showed the relationship to be linear with both variables normally distributed, as assessed by Shaprio-Wilk test ($p > .05$), and there were no outliers. There was little to no association between classification accuracy and the number of rules present, $r(21) = .056$, $p > .05$. This can clearly be seen in Figure 2. As such, it is beneficial to maintenance operators and decision makers that a smaller set of rules are analysed and understood. This enables a holistic understanding of the underlying behavior and development of wind turbine pitch faults whilst reducing cognitive load whilst providing comparable classification accuracy to the models with a larger rule base.

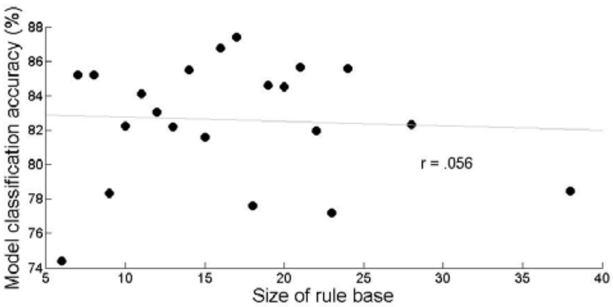

Figure 2: Dominant model classification accuracy plotted against the number of rules generated in each model. No strong correlation existed (r(21) = 0.056, p >.05)

Within the model selected, 14 rules were generated leading to an overall classification accuracy of 85.50 %. It is interesting to note that although a high classification accuracy has been attained in this model, it is still difficult to differentiate between no pitch fault existing and a pitch fault being present, with expert analysis required to certify classifications. As can be seen in Table 2, the Matthews correlation coefficient (MCC) (Matthews, 1975) for all classes is strong, showing high correlation between the learnt rules and the validation data. A substantial level of agreement was found between the developed model and the validation data (Cohen's $\kappa = 0.78$, $p < .05$).

Table 2: Descriptive statistics of the developed model

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC	PRC
No Pitch Fault	81 %	12 %	77 %	81 %	79 %	68 %	91 %	74 %
Pitch Fault Developing	100 %	0 %	100 %	100 %	100 %	100 %	100 %	100 %
Pitch Fault Established	75 %	1 %	80 %	75 %	78 %	67 %	91 %	79 %
Weighted Average	85 %	7 %	86 %	86 %	78 %	78 %	85 %	85 %

After deriving the classification, the 14 rules were presented to independent domain experts so that qualitative and quantitative analysis could be performed. Due to the min-max normalization process during pre-processing, values had to be converted back to ensure they were human readable. Once this had been done, a full analysis was performed.

5. Evaluation and exploitation of generated rules

Due to the size of the knowledge base, it was practical to have the domain expert evaluate each rule individually. This is done as the expert can provide a context sensitive ground truth to the analysis, along with experience of situations and conditions which may not have been present within the training data.

As domain experts have subjective opinions' with regards to what constitutes interesting, novel and important, it is difficult to quantify these characteristics. However, various artifacts are present within the rule-base which is expected given the nature of the classification. To assess the quality of the rules, a 56-item questionnaire was presented to an independent domain expert who has over 6 years wind turbine diagnostic and prognostic experience within academia. This questionnaire contained a 5-point Likert response scale ranging from 1 (*Not intuitive, useful, clear or interesting*) to 5 (*Highly intuitive, useful, clear or interesting*). There were 4 questions presented per rule generated from the model, assessing whether or not the rule was intuitive, useful, clear and interesting. The results of this analysis can be seen in Table 3.

Table 3: Independent domain expert evaluation

Question category	Number of questions	Mean response (1-5)	Standard Deviation of response
Intuitive	14	2.71	1.09
Useful	14	2.79	0.93
Clear	14	3.00	1.00
Interesting	14	3.07	0.96

As can be seen in Table 3, an average response of 2.89 was recorded; indicating that the rules are typically not particularly intuitive, clear, useful or interesting. This was unexpected. Rules were often regarded as just as useful (*M* = 2.79) as intuitive (*M* = 2.71). This is likely due to the nature of the complex nature of the underlying pitch faults. By having the independent domain expert drive the discussion it was found that of the 14 rules, 11 of the rules were deemed “interesting” and warranted further analysis. After performing this analysis, the independent domain expert was then presented with a further 13 rules, taken from the work of Kusiak (2011). To remove bias, the expert was not informed of the origin of either set of rules. A 52-item questionnaire was used containing a 5-point Likert scale from 1 (*Not intuitive, useful, clear or interesting*) to 5 (*Highly intuitive, useful, clear or interesting)*. This was to provide an objective analysis of the intuitiveness, usefulness, clearness and interestingness. Initially, the expert could not understand the rules due to their format and abstract nature, however, after some time, analysis could be performed. The comparative analysis showed that whilst the rules were found to not be less intuitive (*M* = 1.53, *SD* = 0.63) and clear (*M* = 1.46, *SD* = 0.49), they were still regarded as somewhat useful (*M* = 2.23, *SD* = 0.79) and interesting (*M* = 2.07, *SD* = 0.61). When questioned regarding this, the expert responded that as long as the rules were accurate and accountable, they could be disseminated at a later date. As such, it was determined that an expert system should be developed to aid maintenance operators with enquiries and to handle the large quantities of data present within the system.

5.1 Expert System development

Due to the strong classification gained from the model, an expert system was developed to aid maintenance managers and decision makers so that available resources could be optimized. Due to the often inaccessible nature of offshore wind turbines, predicting failures can significantly reduce operations and maintenance (OM) costs, thereby increasing the competitive nature of wind energy.

The model developed in Section 3 was combined with domain knowledge (meta-data) elicited from the independent domain expert to autonomously filter SCADA data so that the maintenance operator did not have to analyse 190 channels of data coming from over 40 wind turbines. The expert stated that typically, SCADA-alarms for pitch fault are noisy, and only when constant irregularities are noticed over an extended period, is maintenance considered on the turbine. As such, based upon the expert-knowledge, a threshold was set that should either a “Pitch fault developing” or “Pitch fault established” classification be active for over 90 min, an alert would be sent to the maintenance operator. This would allow maintenance operators to reduce the time spent checking false-positive alarms and ensure that potential pitch faults with a higher likelihood of developing were checked first.

5.2 Evaluation of Expert system

In order to assess the validity of the expert system developed, historical SCADA-data from 4 wind turbines was used to determine the number of maintenance alerts issued in comparison to the onboard SCADA-alarm system. The validation turbines were independent of those used within the training model.

As can be seen in Table 4, in each of the 4 wind turbines analysed, a reduction in the number of alarms generated was observed. This was between 35.80 % - 52.26 % (*M* = 44.69 %, *SD* = 6.62 %), effectively reducing the workload of the maintenance operator when analyzing data to diagnose pitch faults. Similarly, this was the case for active alarm time; the reduction was between 28.06 % - 49.90 % (*M* = 35.68 %, *SD* = 8.60 %). This, again, reduces the quantity of information the maintenance operator has to manage.

It is worth noting that although 85 pitch maintenance actions were undertaken over the 28 month period in which this historical data was analysed, 11 of these maintenance actions were not detected by the expert system. This is mainly due to malfunction of the sensors, mechanical systems, and the data collection systems; Of the 11 instances, 7 occurred when data acquisition failed for an extended period. Due to the design of the expert system, missing data does not fully encapsulate the correct turbine condition, and as such, the accuracy is significantly reduced. It is believed that the remaining 4 cases are partly due to time-based preventive maintenance which may not have had sufficient basis for action based upon the observed SCADA-data.

Table 4: Comparison of expert system against SCADA-alarm system

Turbine	Pitch Fault alarm time	Number of pitch alarms	Number of pitch maintenance jobs	Expert system alarms	Expert system time active
01	15.46 days	193	25	97	10.06 days
02	17.68 days	222	25	106	12.72 days
03	12.04 days	127	26	75	8.45 days
04	19.64 days	215	9	138	9.84 days

6. Conclusions

In this paper we have presented a robust, accurate expert system for the classification and detection of wind turbine pitch faults, as validated by the 85.50% classification accuracy achieved. Transparent, human readable rules were extracted, analysed and verified by an independent domain expert – enabling trust in the expert system – one of the key barriers to wide scale adoption of CBM technology. These rules were found to be more intuitive than other rules within the literature, and provided the basis for an expert system to aid maintenance operators and decision makers. The number of SCADA alarms was reduced by an average of 44.68 %, with a mean reduction of active alarm time by 35.68 %. The developed expert system reduced the potential cognitive load on maintenance operators and decision makers by significantly reducing the number of alarms presented to them. This freed maintenance resources, enabling a reduction in annual maintenance costs whilst retaining quality of service. Additionally, no further capital expenditure was necessary due to using pre-existing technological capability. A diagnostic accuracy of 87.05 % is achieved in the system, although it is believed that this could be further increased should more reliable sensor technology become available. Our methodology provided a robust strategy to classify SCADA data as having no pitch fault, an established pitch fault or a developing pitch fault. This provides a means to both condition based maintenance and predictive maintenance strategies. Future work will aim to quantify the uncertainty of developing faults using robust multivariate statistical techniques so that the rate of fault development, fault severity and time until failure can be established.

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