Automated on-line Fault Prognosis for Wind Turbine Pitch Systems using SCADA data

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Abstract

Current wind turbine (WT) studies focus on improving their reliability and reducing the cost of energy, particularly when WTs are operated offshore. A SCADA system is a standard installation on larger WTs, monitoring all major WT sub-assemblies and providing important information. Ideally, a WT's health condition or state of the components can be deduced through rigorous analysis of SCADA data. Several programmes have been made for that purposes; however, the resulting cost savings are limited because of the data complexity and relatively low number of failures that can be easily detected in early stages. This paper proposes a new method for analysing WT SCADA data by using an a-priori knowledge-based ANFIS with the aim to achieve automated detection of significant pitch faults. The proposed approach has been applied to the pitch data of two different designs of 26 variable pitch, variable speed and 22 variable pitch, fixed speed WTs, with two different types of SCADA system, demonstrating the adaptability of the approach for application to variety of techniques. Results are evaluated using Confusion Matrix analysis and a comparison study of the two tests is addressed to draw conclusions.

Keywords: Wind Power, SCADA Systems, Fault Prognosis, Artificial Intelligence, ANFIS.

1. Introduction

Wind is currently the fastest growing renewable energy source for electrical generation around the world. It is expected that a large number of wind turbines (WTs), especially offshore, will be employed in the near future with the aim of achieving the desired carbon emission targets and providing alternative energy sources for customers [1]. WTs are designed to be operated around 20 years and their life-time reliability is the viable factor for the success of any wind farm (WF) project.

Following a rapid acceleration of wind energy development in the late 20^{th} & early 21^{st} century, current studies of WTs are beginning to focus on improving the cost of energy. The main reason is to ensure that wind generated electricity is competitive with other generation sources. Costs for wind generated electricity can be higher because O&M costs constitute a significant share of the annual cost of a WF and WT downtime. With the rapid growth of wind energy and more offshore WTs to be employed in the near future, there is a commercial interest in ensuring reduced O&M costs by increasing reliability and having more economical operations. The essence of improving WT reliability is to reduce the downtime and increase the availability by optimising both the WT design and its maintenance schedule [2]. Both these strategies require a full understanding of the WT system and a detailed analysis of its failure mechanisms. Most modern large WTs are now manufactured with some types of Supervisory Control and Data Acquisition (SCADA) and Condition Monitoring (CMS) systems that monitor the main components and it is possible for WT operators to analyse these data to identify WT's systematic performance.

Ideally, a WT's health condition or state of the WT's component can be deduced through rigorous analysis of SCADA and CMS data. This information would also be very useful to plan power outages and schedule effective maintenance schemes. However, many WF operators have been unable to make full use of these available, due to large unmanageable volumes of data and lack of domain knowledge impeding its analysis and interpretation.

2. Wind Turbine Reliability

WT reliability is largely dependent on the design of the machine, along with the quality of its sub-assemblies and the manufactured quality of its components [3]. WT technology has developed and matured in recent years, the design of large WTs has become fairly standardised, centring around the three-blade, horizontal, up-wind design of the original "Danish Concept".

2.1 Current Reliability Knowledge

Some studies have analysed publicly available data in an attempt to gain knowledge of overall WT reliability, whilst also ascertaining the reliability of particular sub-assemblies in relation to the whole system. Existing research has taken many different approaches to analyse the public available data. Some have looked at reliability based on WT rating [4] or weather & location [5]. Some studies have investigated the reliability of different WT sub-assemblies [4, 6].

A quantitative study of WT faults have been carried out by Tavner et al. [2, 4] on 25,322 WT-years of data. Fig 1 shows the comparison between failure rate and downtimes of different WT sub-assemblies, such as those described in [7], from three large EU surveys of onshore WTs.

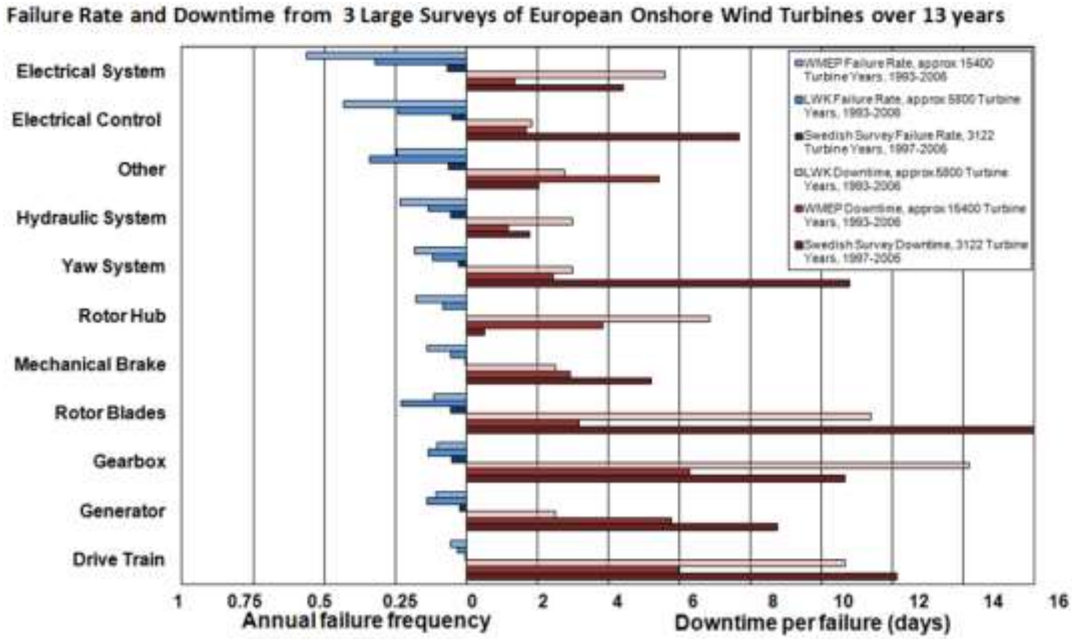
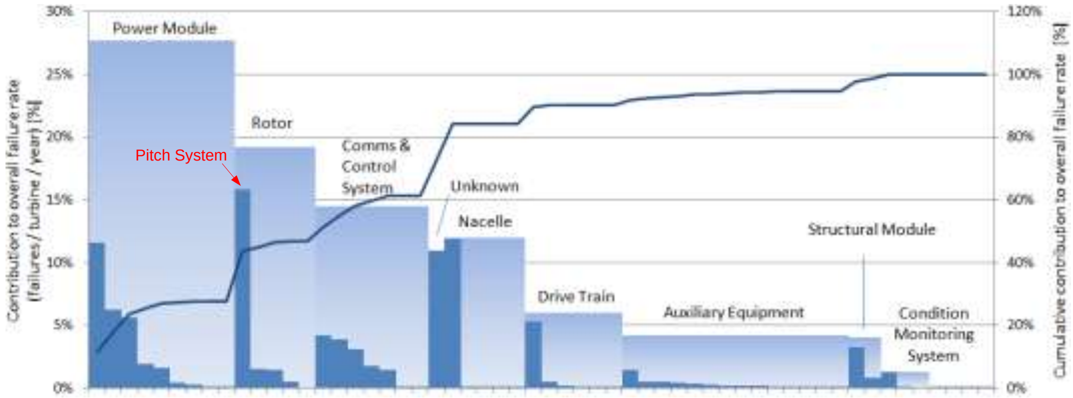


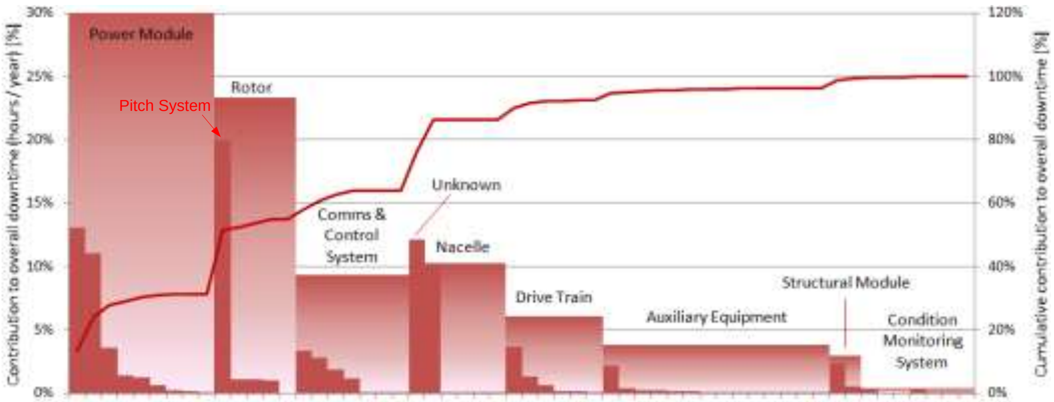
Figure 1: Failure/WT/year and downtime results, 25,322 WT-year LWK, WMEP and Swedish surveys, 1993-2006

It can be seen that Electrical System & Control had the highest failure rates, but the corresponding WT downtimes are not high. The major sources of downtimes have their root causes centred on the drive train, which refers to the large rotating components including the rotor, main bearing, main shaft, coupling, gearbox and generator. Although their failure rates are not high, their downtimes are the highest of all sub-assemblies as shown in Figure 1. This is because the repair procedures in drive train are complex and this will be aggravated particularly offshore, requiring not only special lifting equipment such as crane, but also vessels and the weather conditions will have to be considered.

Another study of WT sub-assembly reliability was carried out by more recent ReliaWind project [6]. Fig 2 shows more detailed breakdown results of WT sub-assemblies with data covering 1400 WT-year. The failure rate lessons from ReliaWind project are similar to the last study, but the downtime lessons are different showing greater emphasis on the power and rotor modules because it is believed these newer variable speed WTs have not yet experienced any major gearbox, generator or blade failure to date in service [8].



(a) Normalised failure rate of sub-systems and assemblies



(b) Normalised hours lost per turbine per year to faults in sub-systems and assemblies

Figure 2: WT sub-assembly reliability analysis, the 1,400 WT-year, 2004-2010

The recent ReliaWind project, shown in Fig 2, has shown that in that survey the pitch system was responsible for 15.5% of failures and 20% of total downtime and is the largest contributing assembly in both cases.

The current knowledge of WT sub-assemblies with the highest failure rate and downtime from public domain surveys are shown in Table 1, in descending order of significance:

	Failure Rate	**Downtime**
High	Pitch system	Gearbox
	Converter	Generator
	Electrical system	Rotor blades
	Rotor blades	Pitch system
	Generator	Converter
	Hydraulics	Electrical system
Low	Gearbox	Hydraulics

Table 1: Wind turbine sub-assemblies failure rate and downtime.

2.2 Current Research to Improve Turbine Reliability

Studies using SCADA and CMS data to detect WT faults have been researched during the past decade. One review [9] provided a detailed summary of new emerging techniques currently being researched. Some recent methods can be classified by the way process knowledge is incorporated into either model or signal-based methods. When a process is too complex to be modelled analytically and signal analysis does not yield an unambiguous diagnosis, a fault detection approach based on AI can be used.

In model-based techniques some modes of the systems were used to decide the occurrence of faults [10]. The system models can be mathematical or knowledge-based. A typical example was the WT Condition Monitoring Test Rig (WTCMTR) Matlab model developed at Durham University by Zaggout [11] to detect rotor and stator electrical asymmetries.

Signal or feature-based fault detections are based on analysis of measured output signals, which may derive from CMS or SCADA. Suitable signal features are then used to evaluate operating conditions. These features are usually studied in either the time or frequency domains. Some typical examples for detecting incipient WT gearbox failures have been developed using CMS signal analysis by Crabtree [12], SCADA signal variance analysis by Feng et al. [13] and an automatic CMS Sideband Power Factor (SBPF) algorithm by Zappala et al. [14].

Methods of fault detection based on artificial intelligence (AI) are designed to extract or infer knowledge from large volumes of sensor data. Many new researches have applied this method to WTs including a system called SIMAP based on artificial neural network (ANN) for detecting and diagnosing gearbox faults [15], a probability analysis of pitch performance curves for detecting pitch faults [16], an automated analysis system also based on ANN [17], a time-sequence and probability-based analysis to rationalise and reduce SCADA alarm data [18], a pattern recognition approach for identifying WT pitch faults [19], a further study of Venn Diagram analysis using a Bayesian Network for pitch faults [20], ANFIS normal behaviour model to detect abnormal behaviour of the captured signals [28] and data-driven approach for monitoring blade pitch faults [27].

It can be seen from above literatures that both CMS and SCADA data have ample information but are difficult to interpret for fault detection. In addition, the SCADA alarm information has been shown to be too ambiguous to indicate failure root cause. This highlights the need for more intelligent approaches that can use existing data to automatically provide accurate WT fault diagnosis and prognosis.

3. Research on Pitch System Reliability

3.1 Engineering Background

The pitch system controls the angle of attack of the WT blade to control the extraction of kinetic energy from the wind and avoid rotor over-speed in high winds. The pitch system is a vital part of modern fixed or variable speed WTs, whether it is for they use pitch-to-stall or pitch-to-feather control. This is because of the pitch system is not only responsible for regulating the WT’s power output, but also provides security braking in emergency situations and high wind speeds, requiring the WT to be stopped, with the rotor blades driven into their feathered positions, using power from a back-up system in the event of grid power failure [21].

In today’s wind industry, there are primarily two types of pitch actuation systems: hydraulic and electric. Most earlier WTs use hydraulic pitch systems [3], which has hydraulic actuators in the rotor hubs, applying torque to the blades either directly or via mechanical linkages. Its simplicity and high driving force are the main advantages; thus it has historically dominated WT pitch control. On the other hand, for newer WTs there has been considerable progress in the development of electrical pitch systems. In an electrical pitch system [3], each blade is controlled by an electric servo motor connected to a gearbox reducing the motor speed to apply a high torque to the blades. This kind of pitch system offers a number of benefits over hydraulic pitch system:

- There is no risk of oil leakage;
- It doesn't require a constant running hydraulic pump for actuation, it is therefore more power efficient;
- The major advantage of the electrical pitch system is its extended control possibilities and greater precision.

For these reasons, the electrical pitch system has become more frequently used in WTs in recent years.

There are also at least two types of WT variable pitch control methods, whether electrical or hydraulic actuation is used. The first and older method uses blade pitch-to-stall to control the WT power output, known as variable pitch fixed speed, or stall-regulated, utilising one or two speeds of generator operation. More modern WTs generally use blade pitch-to-feather to control WT power output, known as variable pitch, variable speed with the generator speed varying over a range.

Nowadays, both hydraulic and electrical pitch systems are widely used in wind industry and in 2009 their market share was approximately 55% and 45% respectively in 2009 [22]. As mentioned in last Section, Tavner et al. [2] investigated WT subassembly reliability in three WT national populations during the period 1994-2006 showed that in those populations pitch systems generally had the highest failure rate. Another recent study [6], shown in Fig 2, showed that the pitch system was responsible for 15.5% of failures and 20% of the total downtime and was the largest contributing sub-assembly in both cases. In addition, the pitch system is vital part for the operation and protection of modern variable speed WTs and no successful WT pitch fault detection systems have been reported in the literature at the time of this research. Therefore, this research focuses on analysing WT pitch faults with the objective of developing an AI-based fault detection approach.

3.2 Research Data

There are about 2 Terabytes of real WT data available to the author, including both SCADA and CMS data. CMS data is not considered in this research as it only monitors the WT drive train and excludes pitch data.

For the SCADA data, 49GB from 5 different companies are available. However, by considering the number of WT and data availability, only two were considered suitable for this research. The information as listed in Table 2 as they included a significant number of WTs in different locations utilising two widely different sizes and designs of WTs:

Location	Data Size	WT & Data Description
Various	35.2 GB	• 1.67 MW variable pitch, variable speed indirect

locations, Spain		drive machine; • Onshore; • Electrical Pitch System, pitch-to-feather; • 6 WFs; • 153 WTs; • 10 minutes data contain alarms, maintenance log; • Available from Jun 2006 to Oct 2008;
Brazos, Texas, USA	13.0 GB	• 1 MW class variable pitch, fixed speed indirect drive machine; • Onshore; • Hydraulic Pitch System, pitch-to-stall; • 2 WFs; • 160 WTs; • 10 minutes data contain monthly report; • Available from Jun 2004 to Nov 2006;

Table 2: The two SCADA data sources

4. Proposed On-line Fault Prognosis System

As has been noted in the last Section, this study has decided to concentrate particularly on WT pitch faults because they are known to be significant in the industry. This Section aims to analyse the common pitch fault symptom and introduce the proposed fault prognosis procedure. The training procedure using variable pitch, variable speed SCADA data will also be introduced.

4.1 Pitch Fault Symptom Analysis

A statistical analysis of six known pitch faults from the Spanish data, Cases 1-6 in Table 3, have been made to find the common pitch fault symptoms, as shown in Fig 3, using the typical variable-speed pitch-to-feather [21] and pitch-torque-power curve [16].

WT	Case	Developing Fault	Maintenance	After Maintenance
A	Case 1	05/01/2008 ~ 15/02/2008	16/02/2008 ~ 21/02/2008	22/02/2008 ~ 03/03/2008
	Case 2	20/12/2006 ~ 14/01/2007	15/01/2007 ~ 25/01/2007	26/02/2007 ~ 10/02/2007
B	Case 3	22/08/2007 ~ 04/09/2007	05/09/2007 ~ 09/09/2007	10/09/2007 ~ 18/09/2007
	Case 4	17/10/2006 ~ 28/10/2006	29/10/2006 ~ 29/10/2006	30/10/2006 ~ 04/11/2006
	Case 5	10/08/2008 ~ 27/08/2008	28/08/2008 ~ 30/08/2008	31/08/2008 ~ 10/09/2008
	Case 6	20/09/2006 ~ 13/10/2006	14/10/2006 ~ 19/10/2006	19/10/2006 ~ 22/10/2006

Table 3: Six pitch fault cases from the same WF from Spanish data in Table 2.

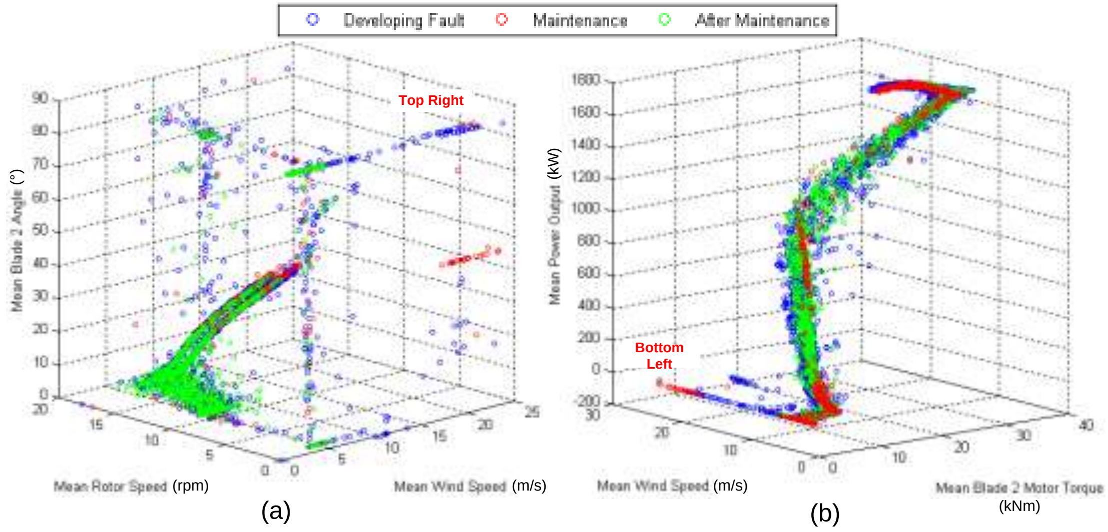


Figure 3: (a) Variable-speed pitch-to-feather curve for Case 1 in Table 3; (b) Pitch-torque-power curve for Case 1 in Table 3;

Fig 3(a) is the classic variable-speed pitch-to-feather curve, clearly showing the different phases of the WT blade control but also showing a considerable amount of noise due to blades being in the parked, 0°, or feathered, 87°, position. No After Maintenance data can be found on the top right corner of Fig 3(a), representing high wind speeds, high blade angle and low rotor speed. A normal running WT should not have feathered blades and zero rotor speed when the wind speed is greater than cut-in. Thus, any data appearing on top right corner of this 3D plot can be regarded as a possible pitch fault.

Fig 3(b) shows the less frequently seen pitch-torque-power curve. No After Maintenance data can be found on bottom left corner, representing high wind speeds, low motor torque and low power output. This is because a normal running WT should start generating power when the wind speed is greater than cut-in. Meanwhile, blade pitch motor torque is needed to change the blade angle to prevent rotor over-speed. Thus, any data appearing in the bottom left of this 3D plot could be caused by a pitch fault.

These graphs are presented in Fig 3 in 3D but analysis could be in one plane, simplifying any algorithm to two variables, so 2D views are shown in Fig 4. By comparing and analysing the difference between Developing Fault and After Maintenance periods, four 2D views in Fig 4, circled & numbered 1, 2, 4 & 5, can be identified as showing clearly abnormal SCADA data in the Developing Fault period. Therefore, these four 2D views, known as Critical Characteristic Features (CCF) shown in Table 4, will be used to identify WT pitch faults.

Fig Ref	Critical Characteristic Features
Fig. 4 (1)	Wind Speed (m/s) vs. Rotor Speed (rpm)
Fig. 4 (2)	Wind Speed (m/s) vs. Blade Angle (°)
Fig. 4 (4)	Wind Speed (m/s) vs. Motor Torque (kNm)
Fig. 4 (5)	Wind Speed (m/s) vs. Power Output (kW)

Table 4: four critical characteristic features

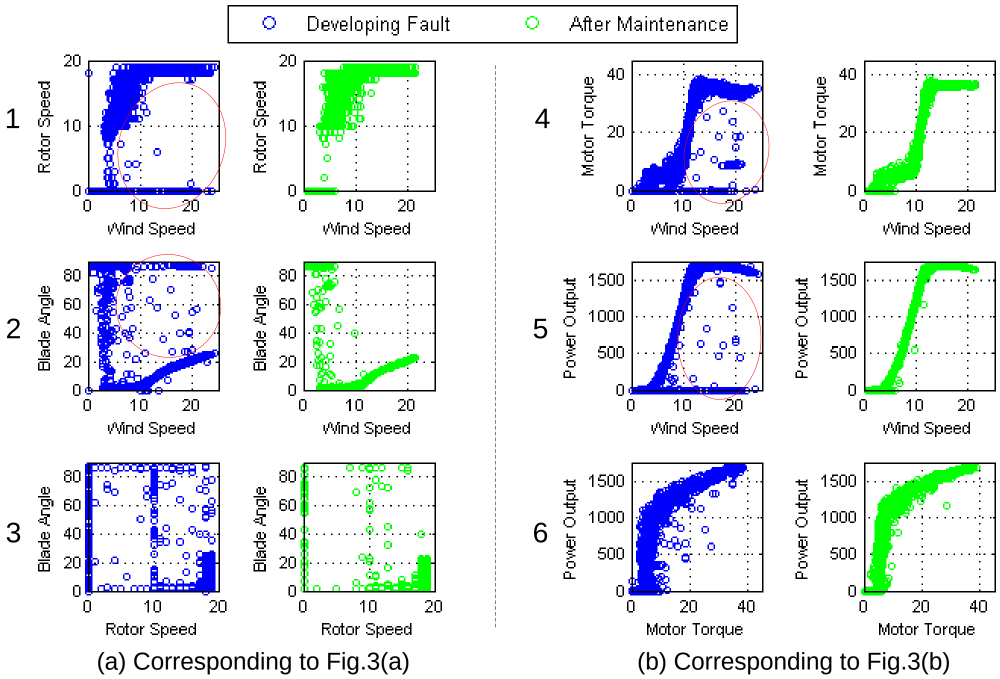


Figure 4: Subfigures 1-6 are corresponding 2D plots from Fig. 3 covering Developing Fault and After Maintenance periods.

An important engineering conclusion from Figs 3 & 4 is that generally the variable-speed pitch-to-feather curve, to the left, is more difficult to analyse than the pitch-torque-power curve, for the simple reason that the latter contains less noise caused by blade park and feather positions, which are clearly visible in Fig 3(a) and the corresponding graphs in Fig 4.

4.2 The Proposed Approach

In this work, the SCADA data described in Table 2 will be used to detect the incipient WT pitch faults by applying the four CCFs identified before. A number of different possible AI techniques, including Fuzzy Inference System (FIS), k-means clustering, Self-organizing Map, Artificial Neural Network (ANN), Naïve Bayes, Bayesian Network, Support Vector Machine and Adaptive Neuro-Fuzzy Inference System (ANFIS), were investigated. The criteria used to evaluate potential technique in this investigation are: interpretability of output, accuracy of diagnosis, and availability of necessary information. In the end, the a-priori knowledge-based ANFIS [23] was selected because it has been shown to have good interpretability and allows domain knowledge to be introduced into the conventional ANFIS model.

ANFIS is a fusion of two different systems that has combination of advantages from ANN, such as robustness, learning & training, and FIS, such as interpretability. ANFIS is a powerful approach for building complex non-linear relationships between sets of input and output data. An ANFIS system can be trained without the expert knowledge usually required by FIS. Both numerical and linguistic knowledge can be combined into a rule base by employing the fuzzy method. Fuzzy MFs can be optimally tuned by using optimisation algorithms. With the a-priori knowledge incorporation, the APK-ANFIS is able is to maintain the model consistency better under two conditions: data with noise and sparse input spaces.

The proposed APK-ANFIS fault prognosis procedure has 4 modules [26, 28], shown in Fig 5 as follows:

- **Data Acquisition:** This module will collect valid data from the SCADA system, ensuring no maintenance or manual stops in the collection period, and excluding any NULL data or any data not subject to factory supplied ranges, for example the wind speed range must be from 0m/s to 25m/s.
- **Feature Extraction:** Valid data are divided into signals and alarms. Data from the four CCFs described in last Section will be extracted from signals. Alarm distribution & showers will also be extracted to validate the final result [18].
- **Multiple Diagnosis:** Data from the four CCFs will then be passed to the corresponding APK-ANFIS to calculate fault degree. The overall result will be an aggregation of the 4 individual APK-ANFISs, defined as:
$$Result = \frac{\sum_{i=1}^{4} w_i * APKANFIS_i}{\sum_{i=1}^{4} w_i}$$
where w_i is the corresponding weight. All w_i were set to 1 for calculating the average in this case.
- **Fault Diagnosis Result:** Finally, the overall result will be checked against SCADA alarm distribution to provide a warning to the WF operator.

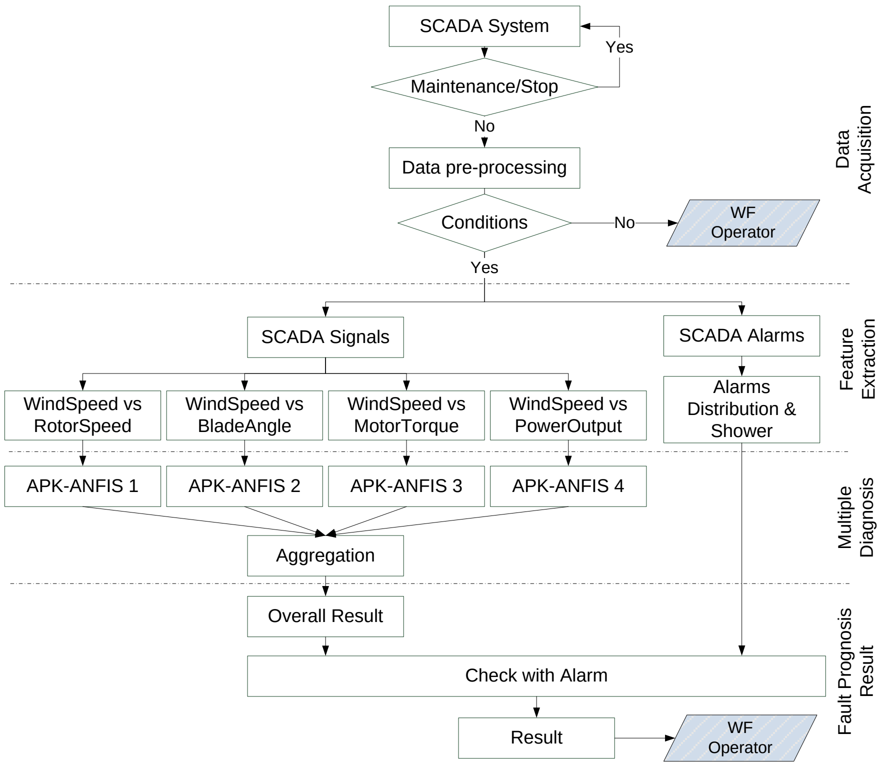


Figure 5: The proposed prognosis procedure

5. Test Results & Validation

This Section demonstrates the effectiveness of the proposed approach by applying it to data from two different designs of WTs of different technology with two different types of SCADA system, taken from Table 2, demonstrating the adaptability of APK-ANFIS for application to a variety of technologies.

5.1 Test on Spanish Wind Turbines

5.1.1. Training Procedure

The data of the six known pitch faults, as mentioned in Section 4.1, were used as a knowledge base for training and testing the individual APK-ANFIS. The four CCFs are represented using a vector as follows:

$$P_i = \left[I_{i,1}, I_{i,2}, O_i\right]^T, \quad i \in [1,2,3,4]$$

where P_i correspond to the four CCFs as mentioned in Figure 5 and the aggregation of them can be considered to characterise pitch fault. $I_{i,1}$ and $I_{i,2}$ are the inputs of the ith CCF. The O_i is the corresponding output and it takes one of the values 0 and 1, which indicate the *Absent* and *Present* state of the pitch fault. Thus, abnormal data, such as a possible pitch fault, were given value 1 and the remainders were given value 0, to represent *No* pitch fault. By putting six pitch faults' data together, 26,971 sets of data were collected, as shown in Figure 6. In addition, some a-priori domain knowledge was added. By using [23], to restrict the output in some specific input spaces, as encircled in Fig 6.

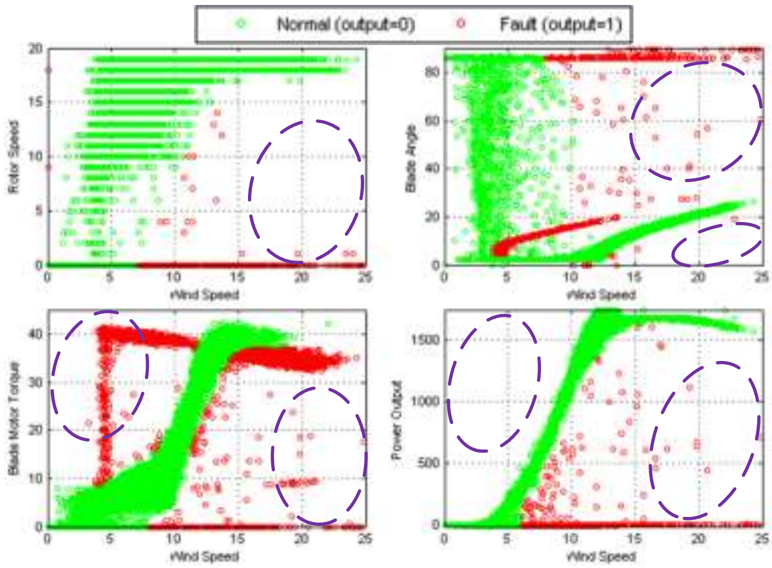


Figure 6: Training data from the six known pitch faults. Encircled areas have insufficient data and a-priori approach is required.

A hybrid learning algorithm [23, 26] was used in the APK-ANFIS, which used the quadratic programming for solving the constraint bound given by domain knowledge in the forward pass and the gradient decent method is used in the backward pass because of its ease of implementation. In order to find the optimal structure for each individual APK-ANFIS, batch testing using different numbers of membership function in each input were examined. These calculated the root mean square error of different structures and finally the optimal structures are chose, as shown in Table 5.

APK-ANFIS model	Optimal structure (The number of MFs in each input)
Wind Speed vs. Rotor Speed	5-by-5
Wind Speed vs. Blade Angle	5-by-5
Wind Speed vs. Blade Motor Torque	5-by-5
Wind Speed vs. Power Output	5-by-4

Table 5: The optimal structures

Finally, the output surfaces generated by individual trained APK-ANFIS models were shown in Figure 7. This clearly demonstrates that abnormal data will give a large output, close to 1 as shown in the "Hill", while normal data will give a small output, close to 0 and shown as the "Valley". A demonstration of the proposed diagnosis system with an arbitrary threshold 0.5 was made and shown in Figure 8, where Figure 8(a) demonstrates a normal running WT and Figure 8(b) demonstrates the detection of a possible pitch fault for which an "Alarm" has been triggered.

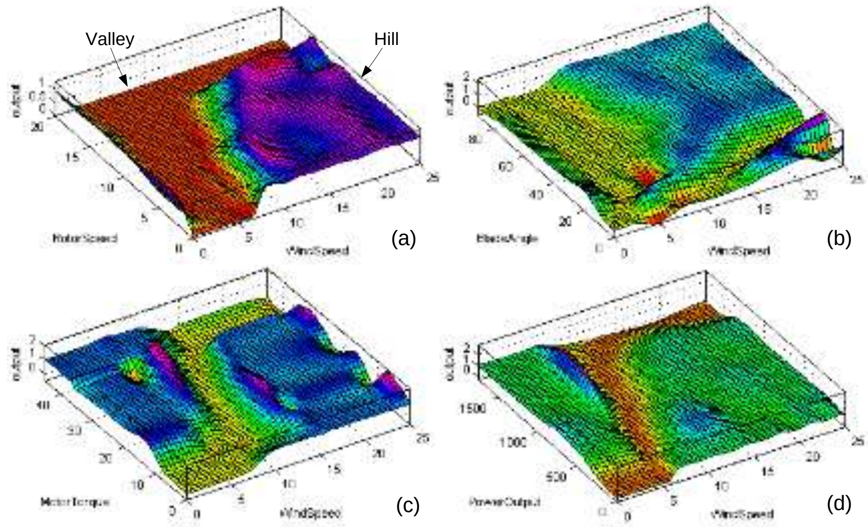
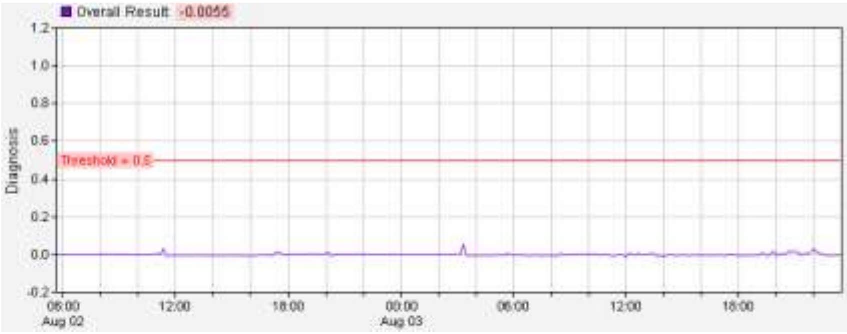
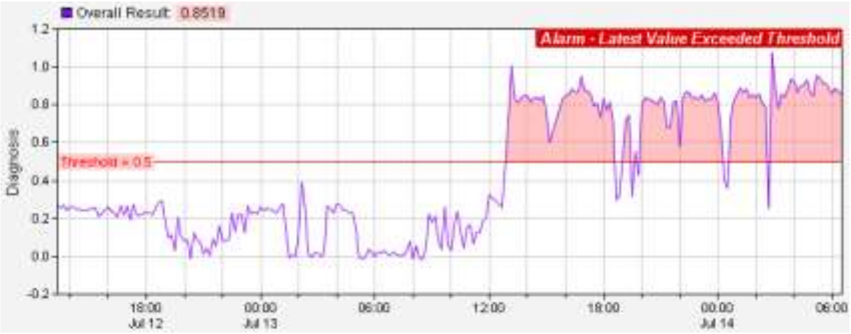


Figure 7: Output surfaces generated from the trained APK-ANFIS



(a) A normal running WT



(b) A possible pitch fault has been detected

Figure 8: Demonstration of the diagnosis system with an arbitrary threshold 0.5

5.1.2 Fault Prognosis using Proposed Approach

The trained system as described above was applied to a Spanish WF containing 34 variable pitch, variable speed WTs but 8 WTs in this WF had insufficient SCADA data, so were neglected and data from 26 WTs were used over a 28 month data period, from 01/Jun/2006 to 30/Sep/2008. For the selected WTs 910 pitch corrective maintenance records were found in this period, these were further reduced to 487 records according to the following criteria: A maintenance followed by another maintenance within an interval of not more than 2 days was considered as one effective maintenance record.

In order to test the trained system with new WF data, an algorithm was written to apply the trained diagnosis procedure to calculate the prognostic horizon for every pitch corrective maintenance activity. The Pseudo-code is shown in Table 6. Three potential prognostic horizons of 7, 14 or 21 days, were selected to avoid the false identifications. For example a half-year early warning probably has nothing to do with a corrective maintenance. In addition, to further reduce false identification, required Threshold and Window Sizes were defined as follows:

- Threshold (T) is the critical level for a WF operator to consider investigating a possible fault and is the aggregation of the four APK-ANFIS results with an output range from 0 to 1.
- Window Size (W) is the number of the consecutive data used to identify the incipient fault. The SCADA data used in this research was measured every 10 minutes; however a single measurement is insufficient to demonstrate a possible fault, thus this work chose a Window Size of 6, 18 and 48 10-min-interval, representing 1, 3 and 8 hours respectively, to avoid false identification.

```
Step 1:
Data Cleansing – remove data when it has maintenance;
Step 2:
Define H, W, T to represent Prognostic Horizon, Window Size, Threshold respectively
Declare H = 7, 14 or 21; W = 6, 48 or 18; T = 0.3, 0.5 or 0.8;
For each WT in the WF
    For each "pitch corrective maintenance record" in the selected WT
        Within the given Potential_Horizon = H days
            Find the earliest date when Window_Size = W and Threshold >= T
                Prognosis_Day = Maintenance_date – The_Earliest_date
End
```

Table 6: Pseudo-code for calculating the fault prognosis horizon.

The prognosis results for these different values of T & W with different potential prognostic horizons are shown in Fig 9. The x-axis is the prognostic horizon in days, the y-axis is the number of pitch corrective maintenance activities. *Undetected* items shown in graph are the number of undetected pitch corrective maintenance activities, out of 487. Fig 9 clearly shows that the proposed approach gives a significant warning of pitch faults with a long prognostic horizon up to 21 days, depending on the potential Prognostic Horizon, Window Size & Threshold.

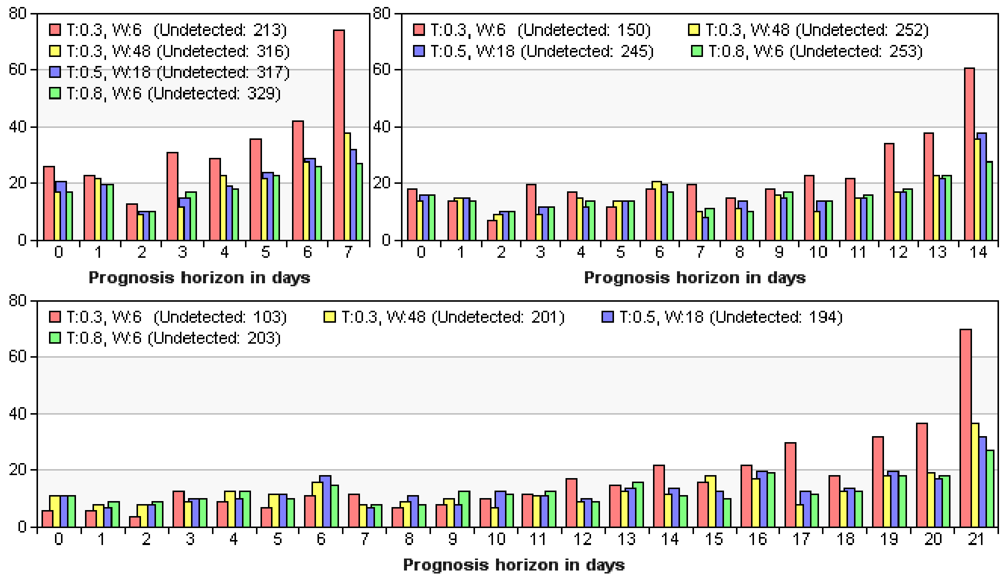


Figure 9: Plot of distribution of APK-ANFIS prognosis horizon in days with different potential prognostic horizon 7, 14 and 21 days. (T stands for Threshold and W stands for Window Size).

5.1.3 Confusion Matrix Analysis

In this section, a Confusion Matrix analysis was generated to demonstrate the accuracy of the proposed approach. The Confusion Matrix [24] contains information about the actual and predicted diagnosis performed by the proposed system defined as follows:

		Predicted	
		Needs Maintenance	No Maintenance
Actual	Had Maintenance	TP	FN
	No	FP	TN

	Maintenance		

- **True Positive (TP):** actual maintenance correctly predicted;
- **False Positive (FP):** incorrectly predicted as Needs Maintenance;
- **False Negative (FN):** incorrectly predicted as No Maintenance;
- **True Negative (TN):** correctly predicted as No Maintenance;

In addition, a further analysis of the data is performed utilising:

- Accuracy (ACC), the proportion of total predictions that are corrects, a key aspect determining the success of this approach;
- Error rate (ER), the proportion of total predictions that are wrong, $ER = 1 - ACC$;
- Recall (RC), the proportion of maintenance cases predicted as positive, needing to be high because an undetected failure might result in catastrophic failure;
- Precision (P), the proportion of predicted positive cases that are truly positive, needing to be as high as possible to avoid additional costs caused by false maintenance requests;
- F-measure (F), a trade-off between precision and recall, widely applied to identify the optimal setting of a classification system.

These are defined as follows:

$$ACC = \frac{TP + TN}{TP + FP + TN + FN}$$

$$ER = \frac{FP + FN}{TP + FP + TN + FN}$$

$$RC = \frac{TP}{TP + FN}$$

$$P = \frac{TP}{TP + FP}$$

$$F = \frac{2 * P * RC}{P + RC}$$

The Confusion Matrix analysis results of the proposed approach applied to the tested WF are shown in Table 7.

	ACC	*ER*	*RC*	*P*	*F*
T:0.3 W:6	88.3%	11.7%	37.0%	76.4%	49.9%
T:0.3 W:48	86.0%	14.0%	22.6%	66.1%	33.7%
T:0.5 W:18	86.4%	13.6%	21.2%	72.8%	32.8%
T:0.8 W:6	86.6%	13.4%	19.6%	79.3%	31.4%

Potential Prognostic Horizon = 7 days

	ACC	*ER*	*RC*	*P*	*F*
T:0.3 W:6	85.1%	14.9%	48.2%	89.2%	62.6%
T:0.3 W:48	80.6%	19.4%	30.7%	83.9%	45.0%
T:0.5 W:18	81.0%	19.0%	30.6%	88.5%	45.5%

T:0.8 W:6	81.0%	19.0%	29.0%	91.9%	44.1%

Potential Prognostic Horizon = 14 days

	ACC	*ER*	*RC*	*P*	*F*
T:0.3 W:6	85.9%	14.1%	62.2%	94.4%	75.0%
T:0.3 W:48	79.4%	20.6%	43.3%	92.1%	58.9%
T:0.5 W:18	79.3%	20.7%	41.8%	94.4%	58.0%
T:0.8 W:6	78.9%	21.1%	39.4%	96.2%	55.9%

Potential Prognostic Horizon = 21 days

Table 7: Confusion matrix analysis results with different potential prognosis horizons.

The table shows the high accuracy and precision of the proposed approach. It also can be seen that the precision is increase with the prognostic horizon out to 21 days, whilst the accuracy falls slightly. In addition, recall was improved greatly along with the increase of the potential prognostic horizon. Finally, the 21 days potential prognostic horizon is found reasonable as the error rate doesn't increase very much with the Recall, Precision and F-measure are improved greatly. The optimal Threshold and Window Size are 0.3 and 6 respectively in terms of Accuracy, Recall and F-measure. However, in terms of Precision, the optimal Threshold and Window Size are 0.8 and 6 respectively.

5.2 Test on Brazos Wind Turbines

5.2.1 Training Procedure

The proposed method has also been applied to WTs of different technology utilising different SCADA systems to collect data. The Brazos WF is located in Borden and Scurry counties in Texas, US [25]. It has 160 variable pitch, fixed speed WTs and each rated at 1MW with hydraulic pitch-to-stall control. The WF project was completed in December 2003 supplying approximately 30,000 homes. The Brazos SCADA System does not record blade torque or ram force, therefore only power curve, rotor speed curve and pitch angle curve can be used to provide 3 CCFs compared to the 4 CCFs for the Spanish WTs. The identification of pitch fault data in this research relies on maintenance logs; however Brazos WT maintenance logs are unclear. A different approach had to be developed, searching for keywords Event and Downtime, to identify the exact maintenance period for each individual maintenance activity.

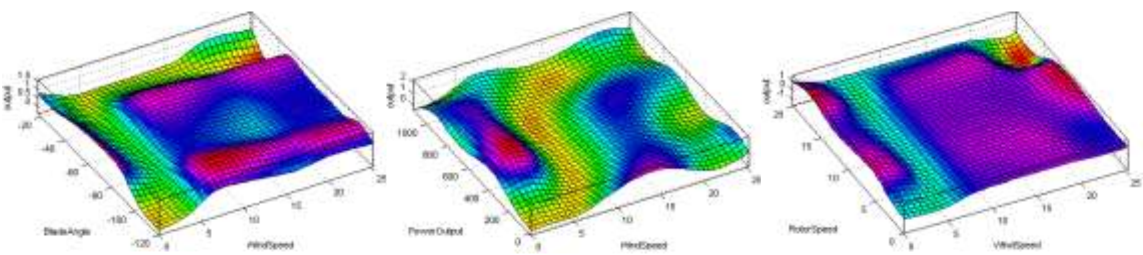


Figure 10: Output surfaces generated from the trained APK-ANFIS models

5 Typical pitch faults were then found and used to build a similar fault prognosis system and the output surfaces generated by individual APK-ANFIS models are shown in Fig 10. The surface chart clearly demonstrates the abnormal data will give a large output, close to 1 and

shown as “Hill”, while normal data will give a small output, close to 0 and shown as the “Valley”.

5.2.2 Fault Prognosis using Proposed Approach

The trained system was tested on the pitch data from the other 22 variable pitch, fixed speed WTs to test its fault prognosis ability. In the 22 WTs data selection procedure noise on SCADA signals was removed to avoid false identification. During the procedure, almost one sixth of data were found to be subject to an alarm entitled “Release to Run” and most of them with good wind speeds. We conjecture that this was due to high wind power availability but low grid demand, so the WF operator curtailed their WTs.

For simplicity, the potential Prognosis Horizon was given 21 days as it was likely to produce a better result. Window Sizes (W) 3 and 6, representing 0.5 and 1 hour intervals respectively, were chosen and the corresponding Threshold (T) were given as follows:

Window Size	Threshold
3	0.5
6	0.3

A similar algorithm to Table 5 was applied to the Brazos data for 22 WTs. Finally, the prognosis results are shown in Fig 10 showing that the proposed method does not give a significant pitch fault warning in this case. However, the result still demonstrates that the approach can be used for WT pitch fault detection, even on a WT of different technology and SCADA system.

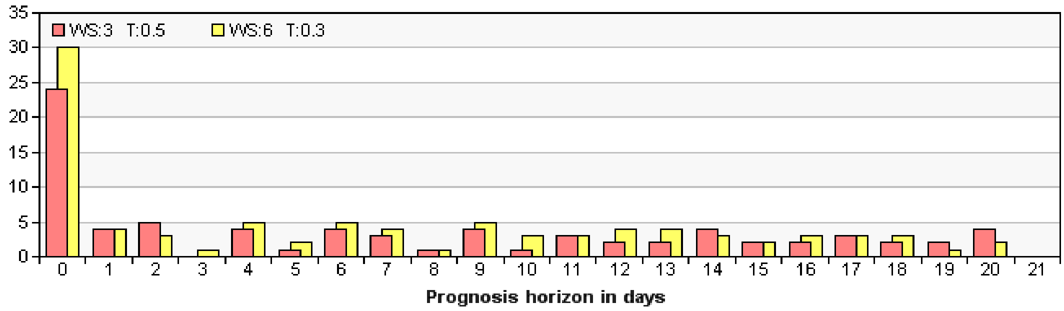


Figure 10: Plot of distribution of SCADA Signals prognosis horizon in days

5.2.3 Confusion Matrix Analysis

The Confusion Matrix analysis was used to evaluate the fault prognosis results using the method in Section 5.1.2 and results shown in Table 8. The results for the two conditions are very close, but the result from Window Size 3 and Threshold 0.5 is better as it has higher accuracy, recall and precision. In general, the Confusion Matrix analysis demonstrates the high accuracy and precision of the proposed approach. However, by checking against to the number of pitch faults, we found the high accuracy and precision is largely contributed by normal data as the Brazos WTs experienced less pitch faults.

	ACC	*ER*	*RC*	*P*	*F*
T:0.5 WS:3	91.5%	8.5%	34.0%	96.0%	50.2%
T:0.3 WS:6	91.2%	8.8%	32.0%	91.0%	47.3%

Table 8: Confusion Matrix analysis results with Potential Prognostic Horizon = 21 days.

5.3 Comparison of Different Wind Turbine Results

5.3.1 Prognostic Horizon Results

The APK-ANFIS approach has been applied to pitch data from both Spanish & Brazos WTs with results plotted in Fig 12, where the effective prognostic horizons of the two methods can be seen.

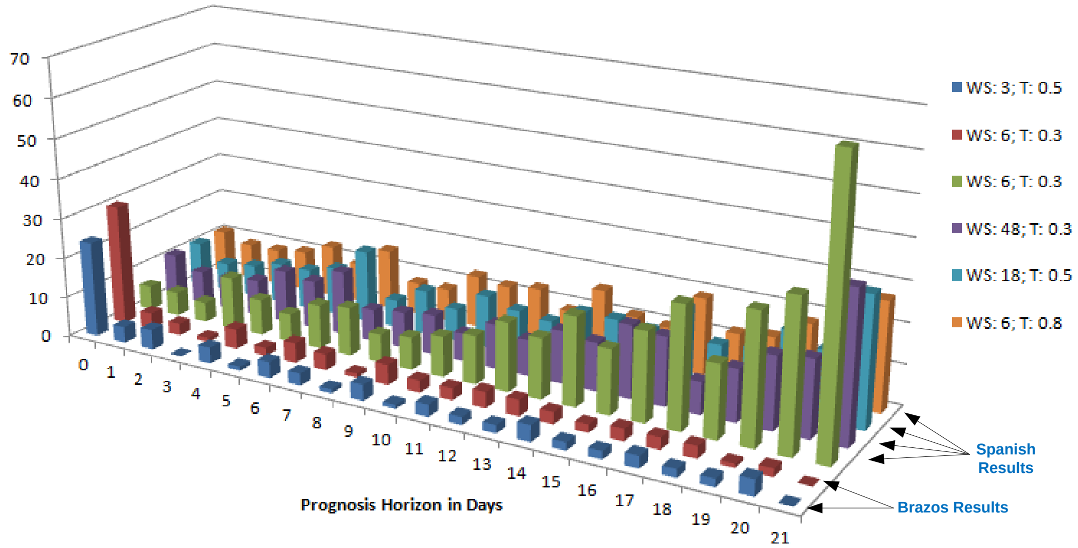


Figure 12: Prognostic Horizon Comparison

Fig 12 shows that APK-ANFIS gives a good fault prognosis horizon from the Spanish data but not from Braozs data. By reviewing this study, we believe the Brazos data has the following difficulties, which have an impact to the prognosis results:

- Brazos Maintenance Log was less clear having a big impact on data selection as Monthly Reports did not give exact start and end dates for each corrective maintenance;
- Brazos SCADA System does not record blade torque or ram force signal, which give most valuable WT pitch system signals;
- About one sixth of the Brazos WT data used for Fault Prognosis testing shows "Release to Run" with good wind speeds but WTs not operating due to curtailment at times of low grid demand.
- However, APK-ANFIS worked satisfactorily on an entirely different WT pitch technology.

5.3.2 Confusion Matrix Results

		ACC (%)	ER (%)	RC (%)	P (%)	F (%)
Brazos WT	T:0.5; W: 3	91.5	8.5	34.0	96.0	50.2
	T:0.3; W: 6	91.2	8.8	32.0	91.0	47.3
Spanish	T:0.3; W: 6	85.9	14.1	62.2	94.4	75.0
	T:0.3; W:48	79.4	20.6	43.3	92.1	58.9

WT	T:0.5; W:18	79.3	20.7	41.8	94.4	57.9
	T:0.8; W:6	78.9	21.1	39.4	96.2	55.9

Table 9: Confusion Matrix analysis results

The Confusion Matrix analysis results in Table 9 show that the Brazos data has higher accuracy because the Brazos WTs experienced less pitch faults and therefore accuracy is contributed primarily by normal data.

6. Discussion & Conclusion

The aim of this research was to develop an automated on-line fault prognosis system for WT monitoring using SCADA data. This objective has been achieved in two areas:

- First by the development of mechanisms to interpret appropriate raw SCADA data. This was achieved by using APK-ANFIS applied to the four CCFs. The use of the APK-ANFIS enabled the system to inherit the interpretability presented in FIS. Therefore, any observed numerical data can be transformed into linguistic and heuristic terms, which are normally expressed in a form of an if-then rule.
- Second by on-line fault identification automation. The proposed procedure consists of 4 modules: *Data Acquisition*, *Feature Extraction*, *Multiple Diagnosis* and *Fault Prognosis Result*. Each module was arranged to work automatically so that the whole procedure should work automatically. The training procedure was lengthy, but once trained, each module did not need much computational cost. In other words, the variable inputs to the trained system could be applied in real-time and a prognosis output is obtained in real-time.

SIMAP [15], the Venn diagram [18], Alarm Pattern Recognition [19], data-driven [27] and normal behaviour models [28] approaches were found to be similar to the proposed approach, however this new approach has shown the following advantages:

- **Better interpretability:** The APK-ANFIS is also a hybrid system containing the advantages of both ANN and FIS, thereby inherit the interpretability present in FIS.
- **Better rationalisation of the data:** The use of CCFs, see Fig 4, reflect the physical properties of a running WT and can be interpreted by WF Operators.
- **Incorporation of domain knowledge:** The latest developments of ANFIS allow experts to introduce domain knowledge into the ANFIS training procedure giving better interpretability for unseen input conditions.
- **More convincing prognosis result:** The prognosis result is convincing because this approach has been applied successfully to data from two datasets of WT of different designs and SCADA systems.
- **More feasible online fault prognosis:** The input variables for this proposed approach could be taken and applied to the model in real-time and a prognosis output is obtained in real-time too, as shown in Fig 5 & 8.

In summary, the novel contributions delivered by the research are:

- This research has introduced a fault diagnosis model using AI technique and demonstrated that the proposed approach gives prognostic warning of pitch faults up to 21 days.

- The robust and effective of this approach have been demonstrated by:
  - Applying the proposed approach to pitch data from two different designs and locations of WTs.
  - Results were evaluated using Confusion Matrix analysis to show the validity.
- Considerable large size of WT data were used in this research. There were 26 Alstom WTs, 63 WT-year data and 22 Mitsubishi WTs, 53 WT-year data.
- Online fault diagnosis is possible as the input variables of this proposed approach are taken in real-time and a diagnosis output is obtained in real-time too.
- In addition, the robust of the system was improved by the strong interpretability of the fault diagnosis model from two aspects:
  - Domain knowledge incorporation: APK-ANFIS allows expert to introduce domain knowledge to the system model.
  - Rationalisation of the Data: four CCFs, as mentioned in Section 4.2.1, reflect the physical properties of the running WT.

In conclusion, this research has presented a new fault prognosis model using APK-ANFIS and demonstrated it to detect pitch faults on two SCADA datasets from WTs of electric and hydraulic pitch systems and different SCADA systems, giving a pitch fault prognostic warning up to 21 days. SCADA signal analysis using APK-ANFIS has strong potential to provide automated online WT pitch fault detection and prognosis.

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