Fault Diagnosis of Wind Turbine with SCADA Alarms Based Multidimensional Information Processing Method

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***Abstract*—This paper presents a first attempt to use Dempster-Shafer (D-S) evidence theory for the fault diagnosis of wind turbine (WT) on SCADA alarm data. As two important elements in D-S evidence theory, identification framework (IF) and Basic Probability Assignment (BPA) are derived from WT maintenance records and SCADA alarm data. A procedure of multi-dimensional information fusion for WT fault diagnosis is presented. The diagnosis accuracy using BPAs obtained from a sample WT and from the wind farm are compared and evaluated. The result shows that D-S evidence theory as a multidimensional information processing method is useful for WT fault diagnosis. Compared to previous SCADA alarms processing methods, the approach proposed predominates at aspects of simple calculation, superior capability on dealing with large volume of alarms through quantifying fault probabilities. It has the advantages of being easy to perform, low cost and explainable, which make it ideal for online application. A self-BPA-generating procedure for future online application with this approach is also provided in this paper. It is concluded that D-S evidence theory applied to SCADA alarm analysis is a valuable approach to intelligent wind farm management.**

***Index Terms*—Wind Turbine, SCADA Alarm, Fault Diagnosis, Multi-dimensional Information Processing, D-S Evidence Theory.**

I. INTRODUCTION

Wind farms are generally located in remote areas with a harsh operational environment. For current designs, wind turbine (WT) nacelles are typically located at 60 -120m height for wind farms installed both onshore and offshore. Limited accessibility leads to high costs for the operation and maintenance of wind farms. WTs are generally considered to have a 20 years working life; statistics shows that their operation and maintenance costs are estimated to account for 10%-15% of the total wind farm income[1,2]. For an offshore wind farm, the operation and maintenance costs are even higher; around 14%-30% of total wind farm project costs[3]. Maintenance costs strongly affect the net economic value of a wind farm[4]. Therefore, reducing this cost through optimization of wind turbine design and the construction of a sound operation and maintenance management strategy are essential to maintain wind power competitiveness[5,6].

Developing effective condition monitoring or online fault diagnosis is critical for efficient wind farm management[7]. This requires scientific methods to improve fault detection accuracy and to deliver realistic residual life predictions for machine and components. Currently, data driven fault detection and diagnosis methods are attracting intensive research attention. Such an approach can be classified into three main categories: model-based, signal-based and knowledge based methods[8-10]. Considerable progress has been made on model-based wind turbine fault detection[9,11], which has demonstrated its advantages for understanding system operational principles and then extracting fault features. But for a WT system, which is essentially a complex system, it needs significant further effort to construct comprehensive system models for quantitative and qualitative analysis. Process history and search strategy methods use advanced data processing methods or artificial intelligence techniques to diagnose WT faults. Although these approaches achieve automatic fault diagnosis, they face challenges of explaining the results, understanding the diagnosis process and then processing the outlier events[12]. Recently, evidence theory and vague evidence approaches have been applied to fault diagnosis/condition assessment for power systems and WTs[13-17]. Signals obtained from simulation or sensors are used. There is an increasing trend for using these types of methods for fault diagnosis of renewable power systems. However, the effectiveness of using such method for WTs remains unclear as the cases mentioned above are either based purely on simulation or are restricted in application to power systems.

Typically, data used for WT condition monitoring is high frequency data which requires a large storage volume. For high frequency data, such as vibration signals, common analysis approaches include Fourier Transform[18], Fast Fourier Transform[19], and wavelet transform[20]. These signal processing approaches require complex calculations that impact on real-time fault diagnosis performance. In addition, these approaches are applicable on limited failure modes. While, SCADA data, which is low frequency data, has attracted considerable research attention due to its in effect zero cost, and its potential for real-time WT condition monitoring and fault diagnosis[21-26]. Fuzzy inference theory and evidence theory have been successfully applied to SCADA signals (temperature, wind speed, output power etc.) for WT condition assessment[25]. New methodologies such as co-integration analysis of SCADA data for condition monitoring and fault diagnosis for WTs have also been used[26]. Most researchers have focused on using SCADA signals rather than SCADA alarms which are also recorded in WT SCADA system. The use of SCADA alarm signals for fault diagnosis was proposed 4 to 5 years ago. Methods using probability-based Venn diagrams and artificial neural networks have been investigated[27, 28]. Although the association of WT SCADA alarms with specific failures can be made the Venn diagram approach is not able to quantify failure probability. The use of artificial neural networks for alarm analysis is limited due to its exponential dependence on data volume. Recently, a classification method has been adopted to analyze WT SCADA alarms[29] however its fault prediction accuracy is in need of improvement.

Motivated by these shortcomings, this paper proposes a new method based on D-S evidence theory to quantify failure probability from SCADA alarms. This is a decision level and multidimensional information fusion method for fault diagnosis. The procedure for quantification of failure probability is presented. It provides useful information for wind farm operators to assist them in making decisions and to organize maintenance activities. In this study the historical maintenance records are taken as the identification framework and the associated basic probability assignment (BPA) is extracted from the SCADA alarm data. An improved D-S evidence theory approach is developed to diagnose faults. A verification case is presented to prove the effectiveness of this method.

II. Wind Turbine Alarms and Maintenances

A. WT Alarm System

Alarm information is stored in the SCADA database. Alarms are triggered and recorded when key component signals exceed threshold limits[27]. In time domain, from a data storage perspective an alarm signal can be considered as a semi discrete signal. The occurrences of SCADA alarms can be recorded as binary signals. That is, the occurrences of an alarm are recorded as 1 while lack of alarm is recorded as 0. From this point of view, there are considerable savings in data storage space required compared to a conventional Condition Monitoring System (CMS).

WT SCADA alarms can be classified into four categories[27]: general alarms; system operation alarms; environmental alarms; and communication/software alarms to indicate component malfunction, an abnormal environment or system operational states. Normally, wind farm operators use SCADA alarms as emergency event indicators which assist them in mitigating risk. Alarms may also result in WT shut down. In this paper, alarms for monitoring the WT pitch system are considered. The alarms being considered are list in Table I. The alarm names indicate possible abnormal states of the system or the location where possible failure occurs. Some remarks are also provided. It can be seen that alarms a69, a72-a74, b54 are general alarms relating to the pitch system, whilst alarms a15, b67, b68, b69, b86-88 are associated with the communication system. Alarms b55, and b80-b82 occur when the three independent pitch positions are not coherent but these give no clear indication of the type of possible failures. Alarms a93-a95 and b56 provide warnings linked to the pitch system battery charger. Alarms b71-b73 related to the 24 volt supply. Some alarms, for example a72-a74, a93-a95, b71-b73, b80-b82, b86-b88, are grouped together because they correspond to the same signal from different blades.

TABLE I
LIST OF ALARMS IN THIS PAPER

Alarm ID	Alarm Name	Remarks
a15	Pitch don't answer	Pitch communication lost
a69	Pitch	Pitch warning
a72-a74	Blade 1-3 Emergency	Blade 1-3 are in emergency
a93-a95	Battery for blade 1 - 3	Pitch battery abnormal
b54	General Pitch Warning	General warning
b55	Pitch Incoherence	The pitch angle incoherence
b56	Battery Charger	Pitch blade battery charger abnormal
b67	Pitch 1-3 Can bus	Pitch 1-3 communication bus problem
b68	Pitch Can bus	Communication bus abnormal
b69	Pitch Device net	Pitch Device net warning
b70	Pitch position	Blade position abnormal
b71-b73	Pitch 24v	24 volts line abnormal
b80-b82	Pitch 1-3 Incoherence	The three pitch angles are incoherent
b86-b88	Pitch 1-3 Can	Communication signal abnormal

B. Maintenance Records

Although in online application maintenance record is not strictly necessary it is important for the development and testing stage of the fault diagnosis approach because it provides critical failure cases and reports. It further provides useful hints to researchers seeking to understand the origins of failures. The maintenance record (represented as M in the latter sections) collects together the repair activities carried out by the maintenance engineers. It records the specific date, the repair or component checking activities carried out. Such activities can be classified into three types: reactive maintenance (run to failure), preventive maintenance (time-based/scheduled), predictive maintenance (condition-based). In this paper, only instances of reactive maintenance are considered for fault diagnosis.

Due to the complex structure of a WT, large numbers of alarms are usually triggered once a specific fault occurs which may lead to a range of reactive maintenance interventions. From the maintenance records, the time and date of the fault and any specific component failures can be obtained. Using this information, SCADA alarms occurring at the moment or immediately prior to failure can be identified. Some fault events will trigger a single alarm while some will cause alarm storms. In this paper, D-S evidence theory takes SCADA alarms as the input evidence with maintenance decisions as the output. The ultimate fault diagnosis process is illustrated as Fig. 1, where the BPA is generated by D-S evidence theory as presented in the next section.

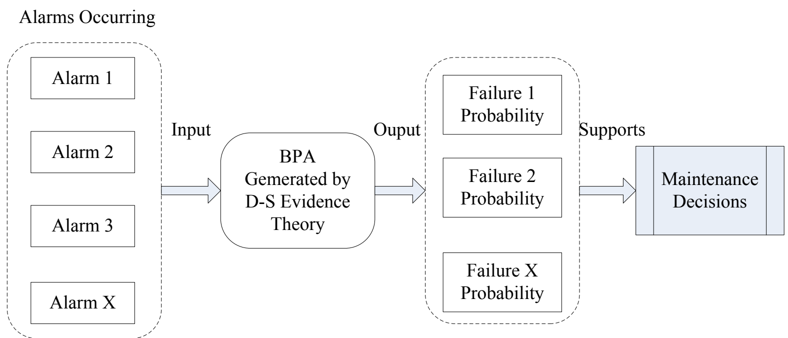

Fig. 1. Fault diagnosis process using alarms and D-S evidence theory generated BPA.

III. D-S Evidence Theory

D-S evidence theory distinguishes itself from traditional probability theory by its capability to deal with epistemic uncertainty. This makes it uniquely able to cope with the situations where it is difficult to evaluate probabilities[30]. WT SCADA alarms indicate operational risks. Their connections with WT failures are intrinsically probabilistic but calculation of the relevant probabilities is problematic. In addition, SCADA alarms are generated by multiple sensors which make the analysis even challenging. The capability of D-S evidence theory to combine evidence from multiple sources with different properties makes it an ideal approach for SCADA alarm analysis. In actual WT fault diagnosis, due to the variability of the WT operating environment and the nonlinear control, output data streams of a WT are often strongly random and this makes fault identification difficult. Misdiagnosis or missed detection of WT faults is unavoidable. Increasing the dimension of the input data can facilitate more comprehensive fault feature identification and can effectively reduce uncertainty in the diagnosis process. Moreover, diagnosis of possible system failure is essentially a process to quantify the likelihood of an event though it is always misunderstood as a process of affirming the conclusion. D-S evidence theory is a decision level information fusion method which is able to use multiple evidence streams to come up with probability of confidence/belief/decision[31]. It has the potential to provide a comprehensive diagnosis for WTs.

D-S evidence theory uses "belief" to measure the tendency of evidence to support specific propositions. Through the fusion of multiple sources of evidence, the probability of supporting proposition sets are calculated. The D-S analysis procedure is outlined below[30]:

(1) Identification framework (IF)

Definition 1: Evidence theory firstly defines a set of hypotheses M as the identification framework which can be described by equation (1). Set M is defined to be a set of mutually exclusive elements f_l to f_n.

$$M = \{f_1, f_2, f_3, \ldots f_n\} \tag{1}$$

At any time, an element f_i is taken from M where M is known as the identification framework (IF). In this paper, it represents the maintenance activities which essentially reflect a set of failures.

Definition 2: The set of all subsets of M is called the power set, as given in equation 2

$$2^M = \{\varnothing, \{f_1\}, \{f_2\}, \ldots \{f_n\}, \{f_1 \cup f_2\}, \{f_1 \cup f_3\}, \ldots \{f_1 \cup f_2 \cup f_3\}, \ldots M\} \tag{2}$$

where Ø is empty set.

(2) Basic probability assignment (BPA)

Definition 3: Once the IF is determined, the mass function m can be defined as a mapping of the power set P(M) to a number between 0 to 1. Mass function m is a mapping: $2^M \rightarrow [0,1]$. For any subset M_i of 2^M, all have $m \in [0,1]$. The mass function m is also called Basic Probability Assignment (BPA) of 2^M and P(M) is the basic probability number (BPN) of M. Its properties are given in equation 3

$$\begin{cases} m : P(M) \rightarrow [0,1] \\ \sum\limits_{M_i \subseteq 2^M} m(M_i) = 1 \\ m(\varnothing) = 0 \end{cases} \tag{3}$$

m( ) represents the proportion of all relevant and available evidence that supports the claim that a particular element of M belongs to the set M_i but not to a particular subset of M_i. Any subset M_i of P(M) satisfying $m(M_i)>0$ is called a focal element.

(3) Evidence fusion

Definition 4: $P_1(M_i)$ and $P_2(M_j)$ are two BPAs. D-S evidence fusion process of $P_1(M_i)$ and $P_2(M_j)$ is given by equations 4,5 and 6.

$$m_{12}(M) = \frac{\sum\limits_{M_i \cap} P_1(M_i) P_2(M_j)}{1-K} \qquad (M \neq \varnothing) \tag{4}$$

$$m_{12}(M) = 0 \qquad (M = \varnothing) \tag{5}$$

$$K = \sum_{M_i \cap} P_1(M_i) P_2(M_j) \tag{6}$$

where K represents basic probability mass associated with conflict.

(4) BPA properties

The D-S evidence fusion process can be regarded as an orthogonal computation. P_1 and P_2 are two BPAs that are used for evidence fusion expressed as $P_1 \oplus P_2 = P_{12}$.

BPA properties:

$$\begin{cases} P_1 \oplus P_2 = P_2 \oplus P_1 \\ (P_1 \oplus P_2) \oplus P_3 = P_1 \oplus (P_2 \oplus P_3) \end{cases} \tag{7}$$

Although D-S evidence theory can obtain fusion results from multiple information streams, there are still some deficiencies in its practical fault diagnosis application[32,33]:

①Conventional conflict problem: when serious conflict appears in the BPAs the fusion can produce unreasonable results.

②One vote veto problem: when one or more inconsistent instances of evidence appear there will be a veto after the combination.

These problems seriously affect the accuracy of fault diagnosis. Consequently a numbers of solutions have been proposed to deal with this. Yager[34] assigns conflict to uncertainty. Murphy[33] converts the evidence conflicts into arithmetic means. Yager's method classifies the conflict as uncertainty in the fault diagnosis problem which is too conservative to achieve the desired purpose. And Murphy's method did not consider the compatibility between evidence and conflict. In this paper the evidence distance method has been applied to the WT fault diagnosis problem[35]:

(1) Evidence distance calculation

In order to calculate the distance between evidences, the average BPA value of each group is required and calculated using equation 8:

$$\bar{P} = \frac{1}{n}(P_1 + P_2 + ... + P_n) \tag{8}$$

In order to determine weights, the distance d_i from the evidence to the average evidence is calculated:

$$d_i = e^{-|P_1(M_i) - \bar{P}(M_i)|} + e^{-|P_2(M_j) - \bar{P}(M_j)|} + ... + e^{-|P_i(M_n) - \bar{P}(M_n)|} \tag{9}$$

The smaller the distance between any two evidences, the greater the degree of similarity.

(2) Weight determination

The weights are calculated from the d_i according to equation 10.

$$c_i = \frac{d_i}{\sum\limits_{i=1,2,...,n} d_i} \tag{10}$$

Where the sum of weights, $\sum c_i$, are equal to unity.

(3) Weighted mean

The formula for evidence weighted fusion is given by equation 11:

$$P = c_1 P_1 + c_2 P_2 + ... + c_n P_n \tag{11}$$

IV. Applying D-S Evidence Theory on WTs Fault Diagnosis

In WT fault diagnosis, each alarm is treated as an item of evidence that supports different possible failures. Therefore, the BPA is essentially the conditional probability of maintenance/failure given the occurrence of certain alarm; this can be derived using Bayesian theory. Recall that Bayesian theorem describes the relationship between two conditional probabilities, and is expressed by equation 12:

$$P(B_i \mid A) = \frac{P(B_i)P(A \mid B_i)}{\sum_{j=1}^{n} P(B_j)P(A \mid B_j)} \tag{12}$$

Based on a Bayesian approach, alarms and maintenance/failure data are used to calculate the "belief"(or "support") for a set of maintenance activities M_i (linked to failures) if an alarm A_j occurs. This is calculated using equation 13:

$$P(M_i \mid A_j) = \frac{P(A_j \mid M_i)P(M_i)}{\sum_{i=1}^{n} P(M_i)P(A_j \mid M_i)} \tag{13}$$

where $P(M_i)$ is the probability of a specific repair activity, M_i . i is index of the associated fault. $P(A_j|M_i)$ is the probability that a specific alarm, A_j, occurs given the precondition of maintenance, M_i, with j the index of the alarm. $P(M_i|A_j)$ is the posterior probability and BPA obtained by D-S evidence theory.

In this process, the central role of D-S evidence theory is to extract the BPA by using a Bayesian network approach[36,37]. It is then possible to aggregate the evidence from multiple alarms using equations 4, 5 and 6 to estimate the failure probability. Although D-S evidence theory is able in theory to distinguish between "unknown" and "impossible", in this study the zero elements of BPA does not differentiate these two cases. Therefore, the calculation results obtained in this paper only evaluate the likelihood of the failure and cannot exclude the impossibility of the failure.

In this section, two years of wind farm SCADA alarms and maintenance records are used to perform the fault diagnosis. The analysis procedure outlined below.

Step1: Determination of Identification Framework (IF)

Using WT A339 as example, the IF can be obtained from its maintenance records. Four types of maintenance are recorded: "Screw"; "Pitch Failure"; "Bolt"; and "Others". These failures are related to the WT pitch system. “Screw” and “Bolt” are specific failed components in the pitch system, while the other two failures are general descriptions relating to pitch failure within the records. The dates when maintenance was undertaken for this WT are listed in Table II.

$P(M_1)$, $P(M_2)$, $P(M_3)$, and $P(M_4)$ are the probabilies each identified pitch failure as indexed by M_i. The probability is calculated from the frequency of occurence. From the occurences of Table II these probabilities are: $P(M_1)$=0.166, $P(M_2)$=0.5, $P(M_3)$=0.166, $P(M_4)$=0.166. The resulting power set 2^M ,excluding the empty set, is:

$$2^M = \{\{\text{Screw}\}, \{\text{Pitch Failure}\}, \{\text{Bolt}\}, \{\text{Others}\}\}$$

TABLE II
A339 Maintenance Records

WT	Maintenance	Date of Occurrence	ID
A339	Pitch Failure	2007/9/2	M2
A339	Pitch Failure	2008/1/25	M2
A339	Screw	2008/2/2	M1
A339	Others	2008/2/28	M4
A339	Pitch Failure	2008/6/6	M2
A339	Bolt	2008/6/26	M3

Step2: Extracting the BPA

(1) Alarm occurrence frequency analysis

Table III shows the frequency of alarms related to the four faults for WT A339. It shows the total number of occurrences of the alarms (with the IDs listed in the first column) for the different failures. For example, the first number 2 indicates that for identified Pitch Failure, alarm a15 has occurred twice.

TABLE III
A339 Maintenance Records

Alarm ID	Pitch Failure	Screw	Bolt	Others
a15	2	0	0	3
a69	13	5	3	10
a72-a74	9	3	3	12
b54	3	2	0	5
b55	0	1	0	0

b68	2	0	0	1
b69	0	1	0	0
b71-b72	2	0	0	1
b81	1	0	0	0
b86-b88	3	0	0	6

(2) Obtain P(A|M)

From the maintenance statistics and alarm frequencies, the probability of a specific alarm preconditioned by a specific maintenance activity can be obtained using equation 12. The results for WT A339 are given in Table IV.

TABLE IV
$P(A_j|M_i)$ OF A339

Alarm ID	Pitch Failure	Screw	Bolt	Others
a15	0.057	0	0	0.079
a69	0.371	0.417	0.5	0.263
a72-a74	0.257	0.250	0.5	0.316
b54	0.086	0.167	0	0.132
b55	0	0.083	0	0
b68	0.057	0	0	0.026
b69	0	0.083	0	0
b71-b72	0.057	0	0	0.026
b81	0.029	0	0	0
b86-b88	0.086	0	0	0.158

(3) Obtain P(M|A)/Extracting BPA

The BPA is calculated according to equation 13 and the results shown in Table V. This would seem to show that certain alarms, for example b55, b69 and b81, can give an unambiguous indication of the specific failure, ie Screw and Pitch Failure. But in fact, two different situations could give rise to these results:

①The alarm has strong correspondence to the failure. When this alarm occurs, a failure can be identified and then maintenance can be planned.

②The alarm seldom occurs. Within the time period of available data, its low occurrence leads to the result observed.

As the two situations cannot be distinguished, then these alarms are filtered out as special cases. The alarms and the required maintenance are written in the form of A- M as shown: b55→Screw, b69→Screw, b81→Pitch Failure. This essentially means $P(M_i|A_j)=1$.

TABLE V
$P(M_i|A_J)$ (OR BPA) FOR TURBINE A339

Alarm ID	Pitch Failure	Screw	Bolt	Others
a15	0.685	0	0	0.315
a69	0.26	0.097	0.582	0.062
a72-a74	0.201	0.065	0.652	0.083
b54	0.463	0.3	0	0.237
b55	0	1	0	0
b68	0.867	0	0	0.133
b69	0	1	0	0
b71-b72	0.867	0	0	0.133
b81	1	0	0	0
b86-b88	0.62	0	0	0.38

Step 3: D-S evidence fusion

Once alarms occur for a WT, the D-S evidence fusion procedure is carried out to provide fault diagnosis. The calculation undertaken uses equations 4 to 11. As there are numbers of alarms, which are treated as evidence to supoort specific faults/failures; the calculation is essentially a two dimentional procedure and the calculation results are shown in Table VI.

TABLE VI
FAULT DIAGNOSIS RESULT

BPA	M(Pitch Failure)	M(Screw)	M(Bolt)	M(Others)
a15	0.685	0	0	0.315
a69	0.26	0.097	0.582	0.061
a72-a74	0.201	0.065	0.652	0.082
b54	0.463	0.3	0	0.237
Fusion Result	0.43	0.111	0.266	0.193

The calculation procedure can be explained as follows. A BPA matrix of $P(M_i|A_j)$ is obtained as shown in Table V, where M_i are the different failures (as listed in the top row) and A_j are the alams (listed in the first column). When alarms occur (for example, a15, a69, a72-a74, b54) they are extracted from table V to calculate the associated probablity of failure. A BPA matrix is contructed as shown in the first five rows of Table V. Each element in the matrix is a BPN.

When the BPN has zero elements, conflicts appear. In this situation, alarms need to be classified in order to obtain reasonable fusion results. Alarms a69 and a72-a74 exhibit no conflicts and then they can fused firstly using the standard D-S evidence approach by referring to equations 4 to 6:

$$1-K=\sum_{i=1}^{y}\prod_{j=1}^{x}P(M_i \mid A_j) \qquad (x=2, y=4) \tag{14}$$

$$m(M_i)=\frac{\prod_{j=1}^{x}P(M_i \mid A_j)}{1-K} \qquad (x=2) \tag{15}$$

where x=2 in this application since there are two alarms (a69 and a72-a74) and y=4 because there are 4 kinds of failures. Values of x and y depend on the number of alarms and the failures respectively.

The fusion result of a69 and a72-a74 are listed in the last row of table VII. The remaining alarms (a15 and b54) exhibit conflicts. They are then fused with the fusion result obtained from a69, a72-a74 using the weighted mean approach given by equations 8 to 11. For this application these become:

$$\overline{P}(M_i)=\frac{1}{x}\sum_{j=1}^{x}P(M_i \mid A_j) \qquad (x=3) \tag{16}$$

$$d_j=\sum_{i=1}^{y}\exp[P(M_i \mid A_j)-\overline{P}(M_i)] \qquad (y=4) \tag{17}$$

$$c_j=\frac{d_j}{\sum_{j=1}^{x}d_j} \tag{18}$$

$$m(M_i)=\sum_{j=1}^{x}P(M_i \mid A_j)\times c_j \tag{19}$$

where c_j is consistent with definition in equation (10). And x=3 is due to the fact that currently the final fusion is made by considering a15, b54 and the result obtained from a69, a72-74. The fusion result $m(M_i)$ is also called the "belief" of failure M_i, which is used to quantify the supports for a given failure by these alarms. Then results are listed in the final row in Table VI. In this case, "belief" of "Pitch Failure" and "Bolt" are both high, which indicates a high likelihood of these two failures.

TABLE VII
FAULT DIAGNOSIS RESULT

BPA	M(Pitch Failure)	M(Screw)	M(Bolt)	M(Others)
a15	0.685	0	0	0.315
b54	0.463	0.3	0	0.237
Fusion result of a69,a72-a74	0.118	0.014	0.857	0.011

V. VALIDATION OF THE METHOD

In order to verify the D-S evidence fault diagnosis method described above SCADA alarm data and repair reports from13 WTs in a single wind farm are used and assessed.

Firstly, the maintenance activities in the wind farm and the number of WTs failed are statistically analyzed and shown in Fig.2. It shows that the top five failure modes for a WT pitch system are pitch failure (general description), battery failure, others (general/ambiguous description), pitch converter failure and pitch motor failure. Since the failures are recorded by different maintenance engineers, some general descriptions without a clear identification of faults are observed. Over 76% WTs have experienced pitch failures and nearly 40% turbines have experienced batteries failures.

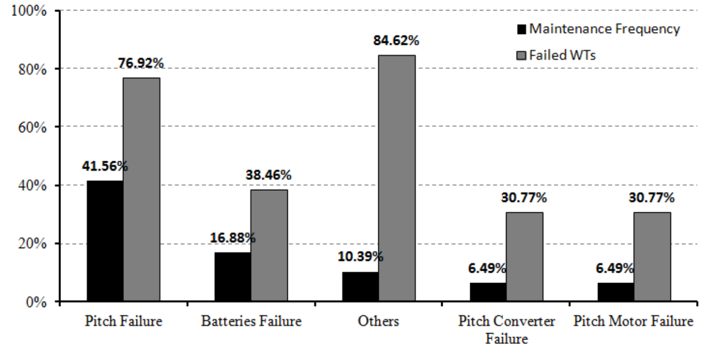

Fig. 2. Maintenance frequency % and number of WTs involved % in the wind farm

According to the description in the previous section, a BPA can be generated from a single WT or from all the WTs in the same wind farm. The two cases are defined as:

①"A representative WT's BPA": this is a BPA obtained from a specific WT in the wind farm.

②" All the WTs' BPA": this is a BPA obtained from all WTs in a wind farm (calculated from all 15 different maintenance actions and all 39 possible types of alarm from the different WTs in the wind farm).

A. Verification Test

"Batteries Failure" is chosen as a specific outcome for verification. The dates when the maintenance record indicated "Batteries Failure" occurred are selected and the alarms present on those days are used for evidence fusion. In addition, in the tables where there is a column of A-M, M is referring to "Batteries Failures". There are 9 WTs where "Batteries Failures" have occurred in this wind farm during the time for which data is available: A340, A341， A342, A343, A344, A345, A346, A348, A349. And for WT A343 "Batteries Failures" has occurred twice. The specific WT used to obtain the BPA is A342. Two testing BPAs are obtained and used to calculate the "Belief" in different failure modes. The results are obtained as outlined below.

(1) Using "A specific WT's BPA"

The maintenance record for A342 indicates that three types failure have occurred: "Pitch Failure", "Batteries Failure", "Pitch Motor Failure". The fusion result is as shown in Table VIII. In table VIII, there is a column with title 'A-M', which has been defined in section IV. The corresponding alarm ID of A_j is recorded in this column. In this test, Pitch Failure has the highest likelihood and Batteries Failure was ranked the second nearly for all the WTs except turbine A343.

TABLE VIII
FUSION RESULTS USING "A SPECIFIC WT'S BPA"

WT ID	Pitch Motor Failure	Pitch Failure	Batteries Failure	A-M
A340	0.0166	0.651	0.3324	none
A341	0.0916	0.735	0.1735	b87
A342	0.0025	0.7616	0.236	none
A343	0.244	0.6778	0.0782	none
A343	0.0724	0.7554	0.1722	none
A344	0.141	0.6998	0.1592	none
A345	0.005	0.6766	0.3184	none
A346	0.0166	0.651	0.3324	none
A348	0.0916	0.735	0.1735	none
A349	0.0724	0.7554	0.1722	none

(2) Using "BPA of All the WTs' in wind farm"

There are totally 15 types of failures in the whole wind farm. As "Batteries Failures" only are concerned in this verification study, the results are calculated and shown in Fig 3. Among the 15 types of failures, supports for "Batteries Failure" were ranked the second for 7 cases (The first rank is "Pitch Failure"). The remaining 3 cases ranked the third. Although there is some inconsistency due to ambiguous maintenance records the correct identification of the actual failure accounts for 70% of the cases.

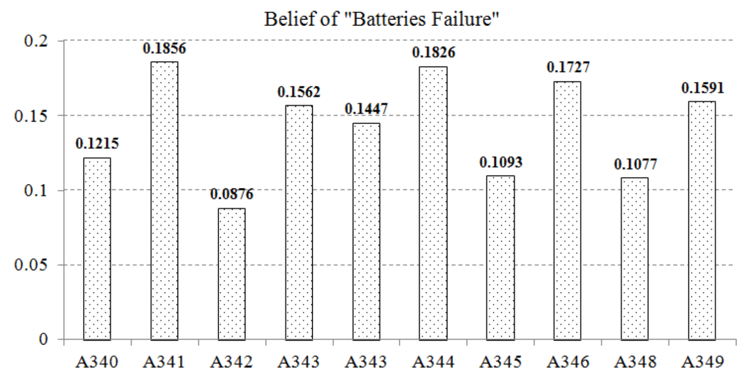

Fig. 3. Belief of "Batteries Failure" calculated using "BPA of All the WTs' in a wind farm"

(3) Performance evaluation

To evaluate the performance of using different BPAs for fault diagnosis, their false-positive and false-negative rates are calculated. As shown in table IX, "Batteries Failure" and all "non-Batteries Failures" of pitch system are assessed. The numbers list in the second row of table IX refer to the diagnosed "Positive" or "Negative" result for all the Batteries Failures. For all the non Batteries Failure cases, the same diagnosed result list in the third row. So the false positive rate, that is c/(c+d), is used to calculate the percentage of diagnosed Batteries Failures cases in all the actual non Batteries Failure Cases. It is essentially false diagnose rate. Fault negative rate, that is b/(a+b), is used to calculate the percentage of diagnosed non-Batteries Failures cases in all the actual Batteries Failure Cases. It is essentially miss diagnose rate.

The overall accuracy is defined as equation 20. It is used to evaluate the performance of thediagnosis results with BPAs derived from different data source.

$$\text{Accuracy} = (a+d)/(a+b+c+d)\times 100\% \qquad (20)$$

TABLE IX
DEFINITION OF FALSE-POSITIVE AND FALSE-NEGATIVE RATES

Category	Positive	Negative	Total
Batteries Failure Cases	a	b	a+b
Non Batteries Failure Cases	c	d	c+d
Total	a+c	b+d	a+b+c+d
False Positive	c/(c+d)	False Negative	b/(a+b)

For Table IX, some statistical rules apply as outlined below:

1) The beliefs resulting from fusion are ranked from high to low. Due to uncertainty resulting from the ambiguous maintenance terms, only the 2 failures with hight beliefs of failures are counted as positive.

2) When a strong correspondence alarms occur, that is whenever A-M appears, failure can be confirmed with confidence. This situation is also defined as postive.

Using these definitions, the calculation results are obtained and shown below.

a. Results using the WT A342 BPA are shown in table X below. Its overall accuracy is 76%.

TABLE X
FALSE-POSITIVE AND FALSE-NEGATIVE RATES OF USING A342 BPA FOR FUSION

Category	Positive	Negative	Total
Batteries Failure Cases	9	1	10
Non Batteries Failure Cases	8	20	28
Total	17	21	38
False Positive	0.286	False Negative	0.1

b. Using the entire wind farm BPA, the results are shown in table XI. Its overall accuracy is 86%.

TABLE XI
FALSE-POSITIVE AND FALSE-NEGATIVE RATES OF USING WIND FARM BPA FOR FUSION

Category	Positive	Negative	Total
Batteries Failure Cases	8	2	10
Non Batteries Failure Cases	3	25	28
Total	11	27	38
False Positive	0.107	False Negative	0.2

From the results shown in Tables X and XI, using a specific WT BPA to diagnose WT "Batteries Failures" generates about a 30% false positive rate and a 10% false negative rate. The false positive rate and the false negative rate obtained from using wind farm BPA is about 10% and 20% respectively. Fault diagnosis accuracy using BPA derived from wind farm is higher than using BPA derived from a sample WT.

B. Result Analysis

The tests above show the fusion results using BPAs obtained from different data. Good fusion results are obtained by using the BPAs extracted from all the WTs in a wind farm. In the test, it is found that the uncertainties come from the ambiguity in the failure records "Pitch Failure". BPAs derived from the wind farm deliver relatively higher diagnosis accuracy.

The tests reported above confirm that D-S evidence theory is capable of WT fault diagnosis. WT SCADA alarms provide multi-dimensional information for failure diagnosis. The results also show that the diagnosis accuracy using this approach is affected by the quality of the maintenance records. Improving the specificity of the maintenance records should improve BPA estimation. Suggestions for such improvement are given below:

①Maintenance data sheets should be standardized. Ambiguous (or general) descriptions of failure should be avoided. The records should be made according to a careful classification of failure modes.

②Maintenance data descriptions should be classified according to the type of maintenance: "Corrective maintenance" and "Routine maintenance" should use different data sheets. By doing so, the statistics will be easier to calculate and higher quality BPAs should result. Invalid calculation due to routine maintenance for which no alarms are observed can be avoided.

The merits of the current approach are summarized in the Table XII below by comparing it with the time-sequence and Venn diagram methods and neural network which have also been used for analyzing WT SCADA alarms. The method proposed in this paper shows that once alarms occur, the probability of failures (as indicated by specific maintenance activities) can be calculated with the BPA. The analysis effectively diagnoses the failures by showing the correlation between alarms and maintenance. This can be further used to review the redundancy of certain alarm installation. It potentially assists the system developer to understand and evaluation the system design, which distinguish this approach from model-based and artificial intelligent methods.

TABLE XII

MERITS OF CURRENT APPROACH ON WT FAULT DIAGNOSIS

Methods	On-line Fault Diagnosis	Fault Diagnosis Accuracy	Root Cause Analysis	Easy to perform
Time-sequences	Could be	Not proved	Not proved	No
Venn Diagram	No	Not proved	Yes	No
Neural Network	Yes	Low	No	Yes
D-S Evidence Theory	Yes	high	Yes	Yes

The approach presented in this paper can be further developed into a practical tool for on-line fault diagnosis. It is expected to support maintenance decision making for wind farm management. A flowchart of the implementation process for a future online system is shown in Fig. 4. Historical alarm data from the SCADA system and maintenance records are used to generate BPAs with Bayesian approach. BPAs obtained from historical data and online alarm data are fused based on D-S evidence theory to support maintenance decision making. After maintenance implementation, new maintenance records can be obtained and then used to update the historical data. Then a new BPA can be obtained which will be used for subsequent fault diagnosis. Therefore, a self-BPA-generating procedure and online fault diagnosis process is constructed. In this process, once the BPA is obtained/updated the time used on information fusion which is triggered by the occurring of alarms is short. This helps to improve the effectiveness of the diagnosis system.

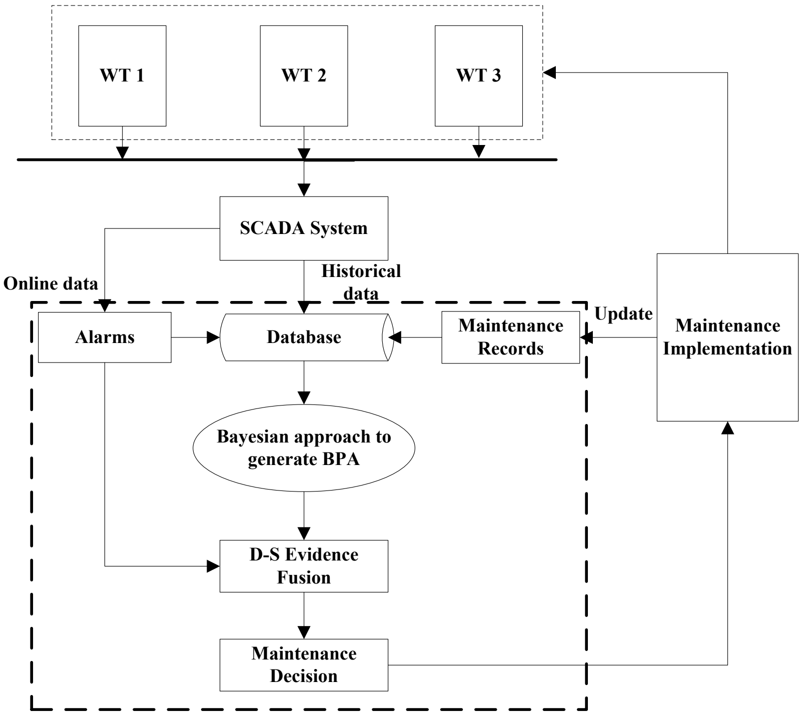

Fig. 4. Online application of D-S evidence theory for alarm analysis

VI. CONCLUSIONS

The fault diagnosis accuracy of using different data sets to generate BPAs are compared and evaluated, which proves the effectiveness of this approach. Although from a statistical point of view, using data from a larger sample size (wind farm level) is better than using data from a small sample size (a single WT), the comparable false positive and negative rate obtained shows the capability of this approach on dealing with relative small size data. The analysis also shows that this method is strong sensitive to the quality of maintenance records, which is reflected from the quantitative analysis of correlation between alarms and failures. It provides useful information for designers to understand the comprehensive system and perform corresponding optimization. This is the important advantage of the method proposed in this paper compared to current artificial intelligent approach on WT fault diagnosis which is still under the progress of using supervised learning method. The merits of the approach are then summarized and blueprint for future online application is also provided.

The applicability of D-S evidence theory for the analysis of SCADA alarms for WTs fault diagnosis has been demonstrated. The approach proposed in this paper essentially combined the merits of SCADA alarm data availability with straightforward data analysis that makes limited demands on data storage space and computational capability. Compared to traditional fault diagnosis approaches, the method proposed in this paper has the advantages of being easy to perform, low cost and explainable. Accurate fault diagnosis underpins efficient operation and maintenance. The approach presented here provides a new and effective method for WTs fault diagnosis.

ACKNOWLEDGMENT

This work was funded by National Natural Science Foundation of China under Grant No. 51505225, Open Fund of Jiangsu Wind Power Engineering Technology Center of China under Grant No. ZK18-03-01, Natural Science Foundation of Jiangsu Province under Grand No. BK20131350, Jiangsu Top Six Talent Summit Fund under Grand No.ZBZZ-045.

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