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Fuzzy Inference Rule Based Fault Diagnosis Decision Algorithm for Wireless Sensor Network based Wind Turbine Power System

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Abstract: While the wind power system deployed in offshore with Wind Turbines (WT) have been considered as a significant sustainable energy source, its adverse operation conditions in offshore inevitably led operators to adopt a remote control management such as Wireless Sensor Network (WSN) technology for a reliable Condition Monitoring System (CMS). In general, the CMS with WSN has been considered as an efficient technique to improve WT availability and reduce the operation and maintenance costs. However, it still need a highly reliable monitoring and diagnosis technique to prevent the CMS from falling into a fault decision. Thus in this study, we propose an efficient Fuzzy inference rule based fault diagnosis algorithm to analyze and diagnose the acquired sensing data from monitoring sensors in CMS with WSN structure. We apply two parameters, i.e., the spectrum correlation calculation parameter of vibration frequency and the deviation range calculation parameter of fault mode sensor data as inputs of Fuzzy membership functions to diagnose the failure condition of WT. The computer simulation results showed that the proposed algorithm could be useful to lower the error probability of fault decision of WT's condition.

Key words: Wind power, wind turbine, wireless sensor network, condition monitoring system, intelligent algorithm, simulation

INTRODUCTION

The wind power has been considered as a significant sustainable energy source by a virtue of specific attractive points such as to improve energy structure and to protect the ecological environment. However, the wind power system deployed in offshore with Wind Turbines (WT) has adverse operation conditions such as capricious marine climate and location far from land. Moreover, since, larger WT fail more frequently and thus, require more maintenance cost, its maintenance costs has become increasingly important as wind turbine size becomes larger (Yang *et al*., 2010). These lead operators to consider a variety of method to handle these failure and maintenance problems. Therefore, the Supervisory Control And Data Acquisition (SCADA) and Condition Monitoring System (CMS) of WT are very essential to operators for guaranteeing reliable maintenance and increasing operating availability (Hameed *et al*., 2010).

Although, SCADA system is very essential to operators for measuring WT's energy production and delivering WT's operational data, CMS is optional for monitoring, analysis and reporting the conditions of components of WT. Thus, more effective and reliable CMS techniques are required for providing continuous indications of component condition based on signal processing techniques with sensors, including monitoring, analysis and reporting. Note that, CMS are used to monitor the status of operating components such as blades, rotors, gearbox, generator, main bearings and tower. One of promising ways to deliver data of various sensor nodes, attached to major components of WT in a remote place to the monitoring center is to apply Wireless Sensor Network (WSN) technology for reliable Operation and Maintenance (O&M). In the offshore WT system, the sensor nodes play role in collecting energy parameters of wind blades. Thus, CMS with WSN is considered as an efficient technique to improve WT availability and reduce the O&M costs.

However, the CMS with WSN has still fault decision problems because of various reasons such as sensor node's malfunction, weather, abrupt wind turbulence or high temperature, etc. Thus, in this study, we propose the fuzzy rule based fault diagnosis decision algorithm with

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the efficient and intelligent CMS structure with WSN for analyzing the acquired data from monitoring sensors. In the proposed algorithm, two major parameters are considered as inputs to fuzzy membership functions to analyze and diagnose the fault condition of WT. These two major parameters are the spectrum correlation calculation parameter of vibration frequency and the deviation range calculation parameter of fault mode sensor.

MATERIALS AND METHODS

Wsn based cms structure with wind turbine

Wind turbine and CMS structure: Most WT machines are three-blade units comprising the main components, i.e., blades, rotors, generator, gear box and computer system. The considered CMS structure with WT employing wireless sensors and its network is shown in Fig. 1 which is for acquisition and monitoring of wirelessly sensing data. Each wireless sensor node attached to those main components of WT machine (i.e., generator, gear box and computer system) sends its normal operation condition to the control center remotely. These sensing data are monitored and analyzed by CMS in the control center to monitor the normal operational condition of WT and detect/send the typical failure event (or fault mode) such as abnormal vibration in gearbox or rotors, electric short circuits in the generator and overheating of the gearbox (Hameed *et al*., 2010).

Among these failure events, vibration has been considered as a main maintenance factor to be analysed for a reliable condition monitoring of WT. Vibration analysis is the most popular technology employed in WT with different sensors for different frequencies, i.e., position transducer for the low frequency, velocity sensor for the middle frequency, accelerometer for the high frequency and (Verbruggen, 2003). Thus, in this study, the measured and sensed vibration frequency data is taken into account as a main input parameter to be utilized for a better reliable fault diagnosis decision (Feng *et al*., 2010; Meik and Ilmar; 2011).

The proposed fault diagnosis decision algorithm: The CMS with WSN has still need a highly reliable monitoring and diagnosis method to prevent the CMS from falling into a fault decision caused by sensor node's malfunction, weather, abrupt wind turbulence or high temperature, etc. Thus, in this study, we propose the fuzzy rule based efficient and intelligent fault diagnosis decision algorithm for helping to avoid a fault decision. The proposed fuzzy inference rule based fault diagnosis decision algorithm in CMS control center is shown in Fig. 2. In this algorithm, two major calculation data are used as input parameters in fuzzy decision algorithm to analyze and diagnose the condition of WT.

These two major data are the spectrum correlation calculation parameter of vibration frequency achieved from wireless sensor, $R_{spectrum}$ (n) and the deviation range calculation parameter of fault mode sensor, R^{s}_{sensor}. The former is used to diagnose the fault event and the latter is used to diagnose the degree of the fault condition. The spectrum correlation calculation parameter can be defined as the correlation between the measured (sensing) frequency (X(n)) and the typical fault (abnormal) mode frequency (Y(n)). We assume that the typical fault mode frequency data are saved in DB CMS Center. This can be expressed as:

$$R_{sepctrum}(n) = \sum\nolimits_{n=1}^{N} X(n)Y(n)(1) \quad (1)$$

where, N is the total number of spectrum resolution. This correlation value is used to decide the level of fault mode as an input to fuzzy membership function. The other parameter, R^{s}_{sensor} is defined as the averaged sum of each correlation of the measured (sensing) value ($x_S(n)$) and the typical known fault mode value ($y_S(n)$) of each sensors which can be written as:

$$R^{s}_{sensor}(n) = \frac{\sum\nolimits_{n=1}^{N} X_1(n)y_1(n)+x_2(n) \; y_2(n)+,\ldots,x_s(n)y_s(n)}{S} \quad (2)$$

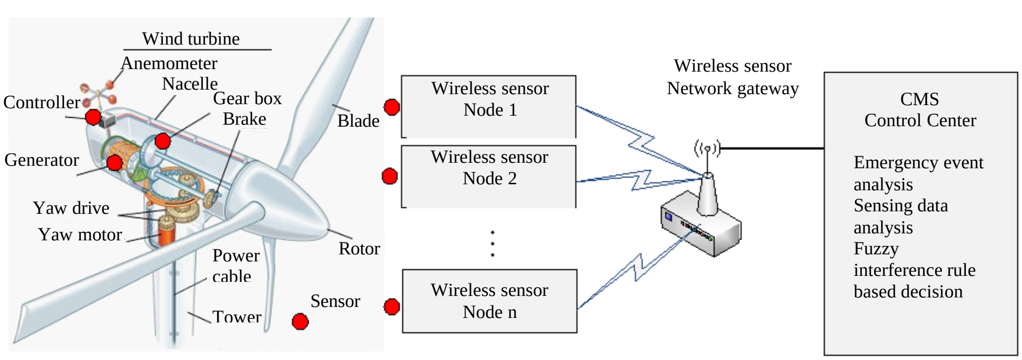

Fig. 1: The considered CMS structure with WSN for acquiring, monitoring and analyzing wireless sensor data

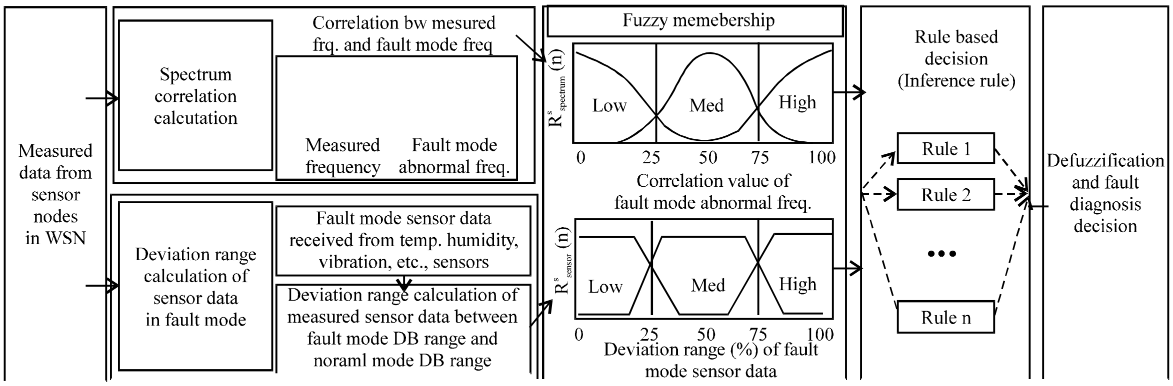

Fig. 2: The proposed fuzzy inference rule based fault diagnosis decision algorithm

where S is the total number of sensor nodes. This is also used as an input to fuzzy membership function for deciding the degree of the fault condition.

Fuzzy inference rule: For a better reliable diagnosis decision, these two parameters are utilized as inputs to fuzzy inference rule based decision algorithm as shown in Fig. 2. A fuzzy controller is based on three procedures such as fuzzification, rule-based control and decision and defuzzification (Feng *et al*., 2007).

The process of rule evaluation used in this study is a set of IF-THEN rules to determine the value of output variables. We used the spectrum correlation calculation parameter ($R_{spectrum}$ (n), "high", "medium", "low") as an indicator of fault event occurrence at each measurement and the deviation range calculation parameter of fault mode sensor (R^s_{sensor} (n), "high", "medium", "low") as an indicator of the degree of fault event. Then the inference rules are used to get information on fault mode. The inference rules can be expressed as follows:

$$\begin{aligned}&\text{Rule Rk: IF}\left(R_{spectrum}(n)\text{is cx}\right)\text{and}\left(R^{s}_{sensor}\text{ is cx}\right)\\&\text{then}\left(U(n,k)\text{ is }U(n)\right)\end{aligned} \tag{3}$$

where cx is fuzzy set and can be either "high", "medium" or "low". For example, the first inference rule is applied. The inference rule reads as "IF the spectrum correlation calculation is "high" and the deviation range calculation is "high" then the utility value of the nth measurement is U(n, 1). The proposed inference rule in this study is tabulated in Table 1.

In this study, we use fuzzy logic at each measurement of parameter to estimate the utility function which is defined by (U(n)). The utility function (U(n)) is defined as the normalized value of the weighted sum of the measured value based on each inference rule (M_k(n, k)). This can be expressed as:

Table 1: The proposed Fuzzy inference rule based fault diagnosis decision output with two parameters

Input/Rule k	$R^s_{spectrum}$ (n)	R^s_{sensor} (n)	Fault diagnosis decision
1	Low	Low	Quite low
2	Low	Med	Low
3	Low	High	Med
4	Med	Low	Low
5	Med	Med	Med
6	Med	High	Med
7	High	Low	Med
8	High	Med	Med
9	High	High	Quite high

$$U(n)=\frac{\sum_{k=1}^{k}M_k(n,k)\times U(n,k)}{\sum_{k=1}^{k}M_k(n,k)} \tag{4}$$

where, M_k(n, k) is the nth measured value of the kth inference rule from K rules. And it can be expressed as:

$$M_k(n,k)=w_{spectrum}\times R_{spectrum}(n,k)+w_{sensor}\times R^{s}_{sensor} \tag{5}$$

where each weighting value should be decided by operators considering the operational conditions of WT and their own system environment. Based on this utility function, the fault diagnosis is finally decided at each measurement.

RESULTS AND DISCUSSION

To evaluate the performance and its feasibility of the proposed fuzzy inference rule based fault diagnosis decision algorithm, we arbitrarily set the mean occurrence number of abnormal (typical fault mode) vibration frequency (high frequency with peak amplitude) of gearbox's sensor to 10 among total 1,000 measurement samples which is forced to be occurred randomly during the evaluation time. Moreover, to evaluate the effect of R^s_{sensor} (n), two kinds of sensors such as temperature, humidity are taken into account. Each mean number of

Table 2: The simulation results with/without the Fuzzy inference rule based fault diagnosis decision

Variable	Result without the proposed algorithm	Results with the proposed algorithm ($w_{spectrum}$, w_{sensor})				
		(0.0, 1.0)	(0.3, 0.7)	(0.5, 0.5)	(0.7, 0.3)	(1.0, 0.0)
Error probability of fault diagnosis decision	0.98	0.45	0.32	0.21	0.02	0.16

abnormal failure events (high temperature, humidity) is assumed as 20 among 1,000 samples. This algorithm test is carried out by a laboratory level computer simulation.

For evaluating the effect of weighting factor in Eq. 5 to the proposed algorithm, we assumed that these weighting factors ($w_{spectrum}$, w_{sensor} are set to (0.0, 1.0), (0.3, 0.7), (0.5, 0.5), (0.7, 0.3) and (1.0, 0.0). After 100 iteration with computer simulation tests for each cases, the error probabilities of fault diagnosis decision with/without the proposed algorithm is tabulated in Table 2. From these simulation results as shown in Table 2, it is concluded that the weighting factor of spectrum correlation calculation parameter ($w_{spectrum}$) is a very decisive parameter in lowering the occurrences of fault declaration. The lowest error probability is 0.02 when ($w_{spectrum}$, w_{sensor}) is set to (0.7, 0.3). However, it is noted that with $w_{spectrum}$ only, the lowest error probability could not be guaranteed. This indicates that the deviation range calculation parameter of fault mode sensor is still important to diagnose the true fault event. Moreover, it is noted that the decision of weighting factors and the selection of monitoring sensors should be mainly decided by the wind power system operators depending on the operational conditions of WT and their own system environment.

CONCLUSION

In this study, we proposed a fuzzy inference rule based fault diagnosis algorithm which is an efficiently feasible method to analyse and diagnose the wirelessly acquired data from monitoring sensors in CMS with WSN. It is shown that the proposed algorithm with two fuzzy membership input parameters, i.e., the spectrum correlation calculation and the deviation range calculation of sensor could guarantee the lower error probability of fault declaration of WT and thus, it could be a very feasible fault diagnose algorithm in wind turbine power system with WSN.

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