FAULT DIAGNOSIS OF WIND TURBINE BEARING USING WIRELESS SENSOR NETWORKS

by

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Original scientific paper
https://doi.org/10.2298/TSCI17S2523R

This paper proposes wireless sensor networks to monitor the condition of wind turbines. It addresses lifetime maximization issue of sensor nodes using stable election protocol for a cluster of upto nine wind turbines. This paper presents results of both experimental and simulation studies of a wind turbine plant, in which the vibration signals from each wind turbine are taken and with the help of machine learning technique, the fault diagnosis is done for a plant with wireless sensor networks. An experimental case study is performed from a wireless sensor networks with a well reported wind turbine bearing fault diagnosis data set. The outcome of the study shows that if the number of wind turbines is five for one base station, then the lifetime of the sensor nodes are maximum using MATLAB.

Key words: *fault diagnosis, wind turbines, wireless sensor networks, life time maximization*

Introduction

In wind turbines fault diagnosis system is implemented using wireless sensor networks (WSN). Here, a major problem is the battery of the WSN. It is essential to conduct a study and find out the features and classifiers which will have least computational effort. In this paper, four commonly used features namely statistical features, histogram features, autoregressive moving average (ARMA) features and wavelet features were extracted from vibration signals. From the extracted signals, the features with least computational time were suggested. Similarly, 26 widely used machine learning classifiers were used and the one with good classification accuracy and least computational time was suggested. Another strategy to improve the battery life is by finding the optimum number of sensor nodes per base station to form a cluster. If the number of nodes is more, the radio distance to base station will be more; it reduces battery life. As wind turbines need to be installed at specific spacing, it cannot be installed closer. Hence, in this paper, a study was carried out by varying the number of sensor nodes for one base station. The network parameter and lifetime of battery were monitored to choose the optimum number of sensor nodes per base station. During the transmission of signals

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the energy of the sensor nodes is used as it uses a radio to transmit signals. There are four factors which consumes the energy for the sensor nodes. One is the quantity of data used for transmission, second is the frequency of transmission, third is the distance between the sensor node and the base station, and the last is the routing (the path travelled by the data). The first two factors are well reported area as there are many studies in those as reported in the literature. The last two factors were not taken into account in major studies. Hence, the last two features are chosen to find the energy dissipation and reduce energy consumption. In order to know the type of features and classifiers used in fault diagnosis of wind turbine as well as the WSN protocols a survey was carried out. They are briefly discussed here. There has been a lot of research and development on the fault diagnosis techniques and various features like statistical features [1], histogram features [2], ARMA features [3], and wavelet-discrete wavelet transform (DWT) features [4] have been reported to identify the faults. Also, different types of classifiers accuracies are found for every feature. Most fault diagnosis techniques used to concentrate only on the accuracy as it will detect the best classifier. Here the computational time is also taken for consideration as our concentration as the objective is to improve the lifetime of the WSN. A system is proposed for condition monitoring of wind turbines with the help of WSN [5]. New trends in condition monitoring of wind turbines and their strengths and weaknesses in the recent wind turbine condition monitoring industry is also reviewed. A fault diagnosis system with a two-stage neural network classifier using wireless sensor networks is proposed [6]. Wireless sensor network is used and the performance of wireless sensor network is evaluated. The sampling rate, channel bandwidth, number of channels, number of active sensors, and the power consumed by the sensor are analysed and the performance of the monitoring system is evaluated [7]. A multi-zonal approach is implemented for stable electron protocol (SEP) for heterogeneous WSN is proposed [8]. The following two contributions in fault diagnosis of a wind turbine using WSN are made in this paper: (1) the best feature and classifier combination is analysed for a fault diagnosis system with the help of the signals obtained from the bearing of the wind turbine and different machine learning techniques are used for different cluster combinations, and (2) the number of wind turbines per cluster is found by simulating the wireless sensor network using SEP protocol by changing four different combinations of clusters.

Simulation study

The simulation methodology is given in fig. 1. A fault diagnosis system of a wind turbine using WSN uses IEEE 802.15.4 and ZigBee protocols to transmit the signals from wind turbine to base station [9]. The basic structure consists of a sensor node equipped in every wind turbine located in the field and one base station is kept for a certain group of wind turbines. The main objective is to maximize the life of the battery used for WSN . Every wind turbine is installed with a fault diagnosis system which acts as a sensor node. The simulation study was carried out in two phases: one is design of fault diagnosis system and simulation of WSN using SEP.

Design of fault diagnosis system

The fault diagnosis is carried out using the following steps: conditioning of the signal, data acquisition, extracting features, and classifying features. A Dytran make transducer which is of piezo electric type is taken to acquire the vibration signals from the bearing of the wind turbine (typically 4 to 12 bearings). The analyser has a charge amplifier and an analogue to digital convertor unit (ADC). The extracted signals from the analyser are stored in the memory of the sensor unit. The bearing is analysed for four different conditions, good, inner

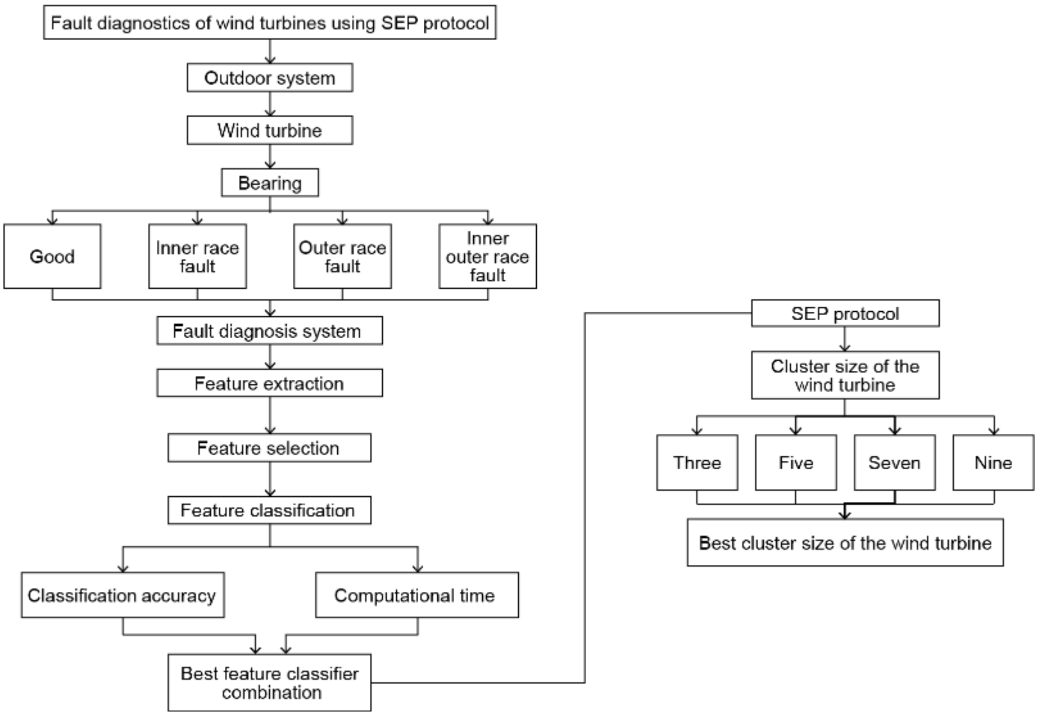


Figure 1. Flowchart of simulation methodology

race fault, outer race fault, and inner outer race fault. Vibration signals were extracted for each of the cases. The following four features were used for fault diagnosis: statistical features, histogram features, ARMA features, and wavelet features. With each set of features, the dimensionality reduction was carried out to reduce the number of features, as it will reduce the processing time for feature extraction which in turn will increase the lifetime of the battery. The 26 classifiers were used for feature classification and the classifier with highest classification accuracy and less processing time was chosen. Choosing effective parameters in each stage of fault diagnosis system will reduce the computational effort and will in turn maximise the lifetime of the nodes in the network.

The WSN simulation using SEP protocol

The WSN has to be simulated to choose the parameters for the sensor node after setting up the fault diagnosis system. The parameters considered for simulation of WSN using SEP protocol is given in tab. 1.

Optimum number of nodes for each base station

As the radio present in the sensor node consumes more battery, the base station cannot be kept very far as it will drain the battery soon. On contrary base cannot be kept on every sensor node as it will increase the cost of the system. Hence, the idea is to keep a base station to a group of wind turbines called *clusters*. Hence, maximum number of nodes with maximum battery life has to be decided. Thus, the study was carried out by varying the number of sensor nodes in a cluster. The four combinations for which the simulation study was performed are

Table 1. The WSN simulation parameters

Parameter	Value
Cluster size	3, 5, 7, 9
Plant area [m]	200 × 200, 400 × 200, 600 × 200, 800 × 200, respectively
Number of base station	1
Initial energy of nodes	0.5 J
Energy for transferring a bit (ETX)	$5 \cdot 10^{-8}$ J
Energy for receiving a bit (ERX)	$5 \cdot 10^{-8}$ J
Free space energy (EFS)	$1 \cdot 10^{-11}$ J
Multipath energy (MPE)	$1.3 \cdot 10^{-15}$ J
Data aggregate energy (DAE)	$5 \cdot 10^{-9}$ J
Routing protocol	SEP
Maximum number of rounds	5000

as follows: three wind turbines with one base station, five wind turbines with one base station, seven wind turbines with one base station, and nine wind turbines with one base station. The field dimensions, the base station location, and the wind turbine locations are chosen for a 1.3 MW wind turbine in which radius of the blade is 30 m and it can be kept at a minimum of 3 to 10 times of its diameter is shown in fig. 2. The comparative analysis between four different

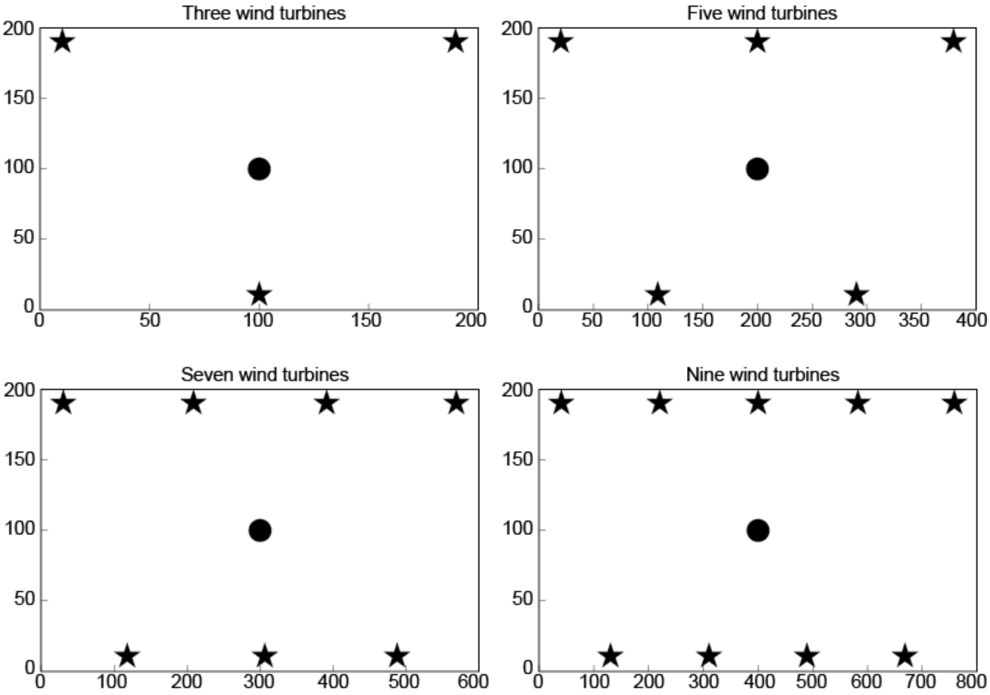


Figure 2. Four cluster combinations of wind turbines

combinations of clusters is done and the best cluster combination is found by simulating the results using WSN with SEP protocol. The energy consumption patterns are found. The SEP protocol used for simulation uses hopping technology if one node is battery drained it finds other way to transmit the data to the sink node. Even if few nodes are dead the data will reach the sink node. If the number of hops increases, the work load for every sensor node will also increase and it will in turn result in the battery drain of the sensor nodes. Hence the battery should be changed for the sensor nodes at appropriate time.

The simulated results are generated for all the cluster sizes and where the optimal size in which the energy of the sensor node is maximum is chosen and one base station is kept for that specific cluster size. The sensor node in the wind turbines acts as a wireless data acquisition system (DAQ). All the vibration signals extracted from the bearing are processed using machine learning techniques and the final result is sent to the base station. As all the processing is done in the sensor node location, all the extracted vibration signals need not be sent to the base station which reduces the work load for the sensor node, hence the battery is conserved. However, this increases the computational load of the sensor node which in turn increases the power consumption. Hence, the optimum feature selection and choosing right classifier is a crucial step (as explained in the section *Design of fault diagnosis system*). Keeping the maximum number of rounds allowed as 5000, the number of possible rounds was simulated using SEP protocol and the amount of data transmitted was also found. The primary concern of the study is to find the best cluster size for one base station (fig. 2). The results are presented in next section. The maximum number of rounds to which the nodes are alive represents the lifetime of the nodes indirectly.

Results and discussion

The wind turbines are fixed with a fault diagnosis system. In the fault diagnosis system the feature selection and classification is done with a perspective of reducing the computational time. Then, the number of nodes (cluster size), per base station is chosen by simulating the WSN using SEP protocol. The results are presented further in the paper.

Results of fault diagnosis system

In wind turbine, the vibration signals were collected from good bearing as well as the faulty ones (inner race fault, outer race fault, and inner and outer race fault). From vibration signals, four sets of features namely statistical features, histogram features, ARMA features and wavelet features were extracted. As discussed in the section *Design of fault diagnosis system*, not all extracted features in a particular set (*e. g.* statistical features) are important for classification. The feature selection process was carried out following the footsteps in [10] using decision tree and the feature selection is done. In statistical features among 13 features, the following 7 features are selected. In histogram features among the 15 features, five features are selected. In ARMA features among the nine features, five features are selected. Four out of 13 wavelet features are selected.

In tab. 2, *First 7* refers to all the seven features all features that appear in decision tree. Similarly, *First 6* refers to top 6 features that appear in decision tree. Referring to tab. 2, one can understand, *First 4* (*i. e.*, kurtosis, standard error, range, and minimum) is best suited for WSN application, as it gives high classification accuracy with less computational time. This exercise was carried using J48 decision tree algorithm. A similar study was carried out for other three features as well. Only the selected features were considered for the rest of the study. While choosing the classifier, usually, the concentration will be on classification

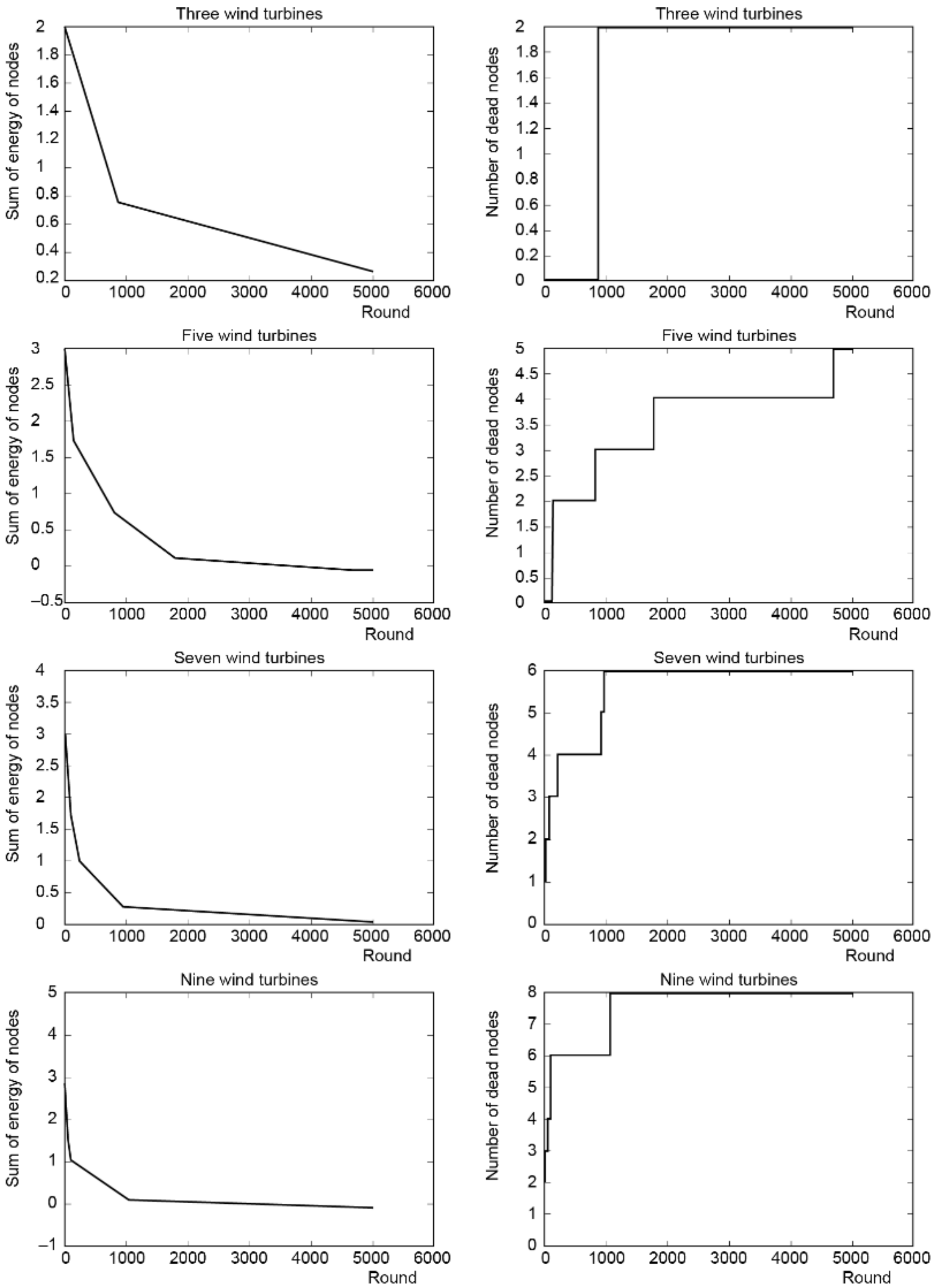
Table 2. Feature selection based on time and accuracy

Number of features	Statistical seatures		Histogram features		ARMA features		Wavelet features	
	CA [%]	Time [s]	CA [%]	Time [s]	CA [%]	Time [s]	CA [%]	Time [s]
First 7	90.50	0.02						
First 6	91.00	0.01						
First 5	91.25	0.01	90.25	0.02	95.75	0.02		
First 4	92.00	0.01	90.50	0.02	95.50	0.01	97.25	0.01
First 3	90.75	0.00*	89.25	0.02	95.50	0.01	96.75	0.01
First 2	91.00	0.02	90.25	0.01	95.50	0.01	96.50	0.01
First 1	87.25	0.00*	73.00	0.01	77.50	0.01	94.25	0.01

accuracy. Here, the classifier is chosen based on the computational time and the classification accuracy as less computational time will reduce the battery consumption of the sensor nodes. In feature classification, the classification accuracy given by multiclass classifier for wavelet feature is 98.5% and it is the highest among all others classifiers; however, the computational time it takes to build is 0.11 seconds. Whereas the classifiers, IBK and Kstar, give the classification accuracy of 98.25% in 0.01 seconds. If the classification accuracy of 0.25% is sacrificed, it will save 10 seconds which saves a lot of battery in multiple loops. Hence, little less classification accuracy is also accepted, if it increases the lifetime of the battery. There are few entries with '*' mark in feature selection and feature classification with computational time as 0.00 seconds. It does not mean that the computational time is 0 seconds. It only means that the computational time is lesser than 0.01 seconds.

Results of WSN simulation study

In a wind turbine field there will be a number of wind turbines. The number of wind turbines per base station is varied and the results are simulated using SEP. As discussed in the section *The WSN simulation using SEP protocol*, the four combinations of wind turbines simulation were performed and the results are discussed. The simulation parameters of SEP protocol based on WSN used for simulation study are, sum of energy of nodes , cumulative number of packets sent to base station, number of packets sent to base station, and number of dead nodes. Figure 3 shows the sum of energy of nodes *vs.* round for the four different cases. For three, seven, and nine wind turbine cases, the sum of the energy of nodes falls steeply. And the energy is maintained only up to 1000 rounds. Whereas the sum of energy of nodes is falling gradually in five turbine case and the energy is maintained up to 2000 rounds. In three wind turbine case, the energy is gradually reducing to zero till 5000 rounds; however, in seven and nine wind turbine cases, the energy becomes zero before 1000 rounds. Hence, from fig. 3, it is inferred that five wind turbine cluster combination makes a best cluster as it consumes less energy compared to other three cases. In fig. 3, the cumulative packet transfer rate is linear only upto 1000 rounds in three turbine, seven turbine, and nine turbine cases. Whereas, in five turbine case the cumulative number of packets transferred to base station is linear upto 2000 rounds. After the linear phase, the cumulative packet transfer rate is reduced. Thus, five turbine cases will have better cumulative number of packet transfer rate with respect to round. However, if the absolute value of the cumulative packets transferred to the base station is observed, it will give misleading interpretation. From fig. 4, for the three wind turbine cases the number of packets sent to the base station is consistently high only up to 1000 rounds. The



Sum of energy of nodes *vs.* round **Cumulative packets sent to base station *vs.* round**

Figure 3. Wireless sensor networks simulation results – 1

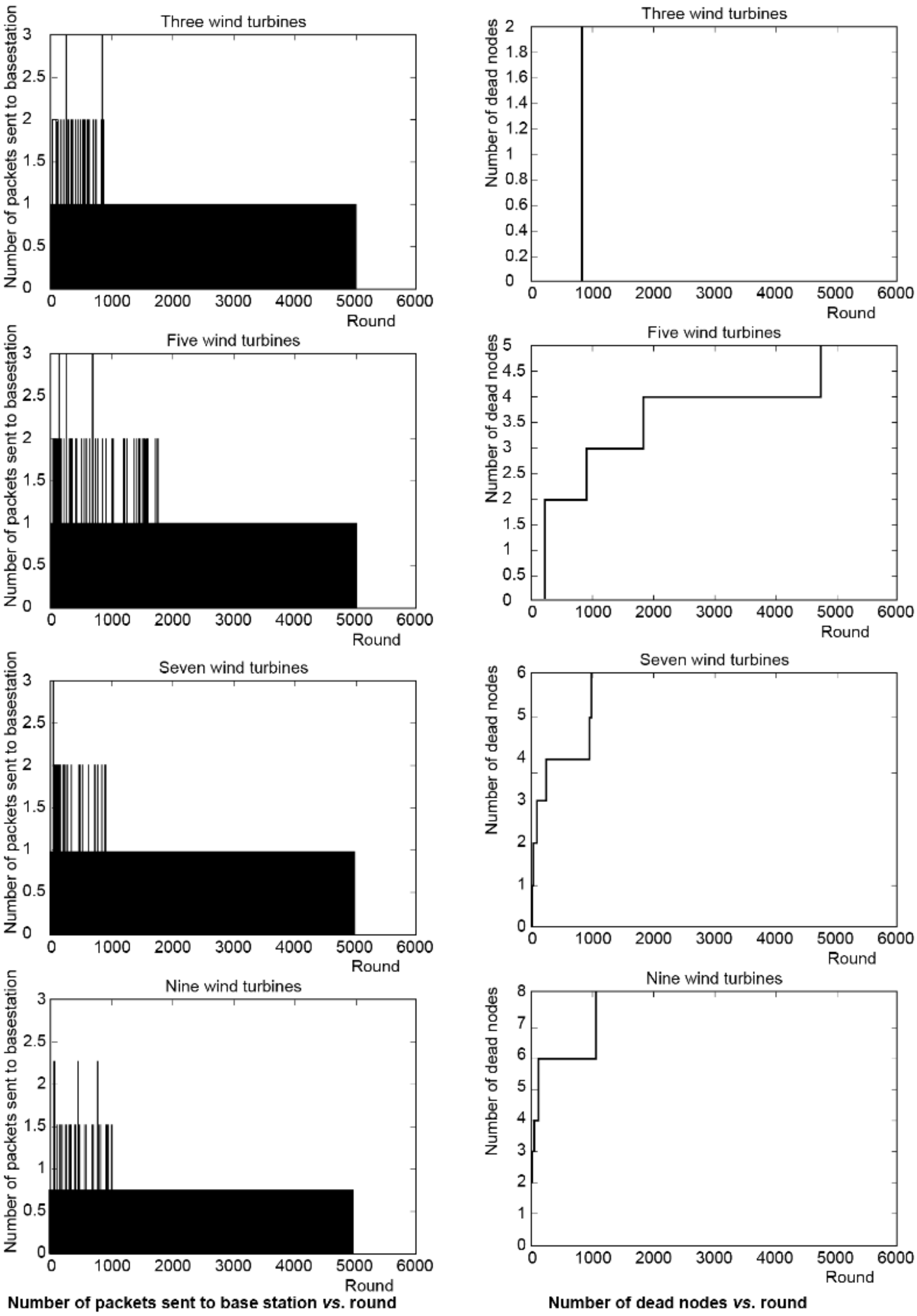


Figure 4. Wireless sensor networks simulation results – 2

same is true for seven and nine wind turbine cases. However, the five wind turbine case sent packets consistently high till its 2000 rounds. Hence, five wind turbines with one base station were found to be the best among the four combinations. From fig. 4, in three, seven, and nine wind turbine cases, except the last node the remaining nodes were dead in 1000 rounds. Whereas in five wind turbine case 2 nodes died initially, the third node died at 1000 rounds, the fourth node died at 2000 rounds and the last node is alive till 5000 rounds. As many nodes are alive beyond 1000 rounds, compared to other cases, the five wind turbine case is found to be the best.

Conclusions

This paper presents the simulated results of a WSN and the experimental results of a fault diagnosis system used in wind turbines. The objective of the experiment was to increase the battery life of every sensor node in the WSN as a result the overall lifetime of the WSN is increased. MATLAB is used to simulate the factory set-up in which SEP protocol is implemented for simulation. The lifetime of the sensor node is increased by designing fault diagnosis system with less computational time and choosing optimum number of wind turbines per base stations. From the results and discussion wavelet features (DWT – bior 3.1) with Kstar or IBK classifier gives less computational time and more sensor lifetime (battery life). From the simulation studies of WSN, one can conclude that the five wind turbines with one base station case are a best choice for lifetime maximization of the sensor networks. The fault diagnosis system designed using the above recommendations will have high classification accuracy as well as long lifetime for sensor nodes in WSN set-up.

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Paper submitted: March 20, 2017
Paper revised: May 25, 2017
Paper accepted: June 13, 2017