RESEARCH ARTICLE

An Event-Triggered Energy-Efficient Wireless Routing Protocol for Fault Monitoring of Wind Turbines

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Abstract

Monitoring the health condition of wind turbines is crucial to ensure the safety and efficient operation of wind farms. Wireless sensor networks (WSNs) provide an economical and effective solution for such monitoring. However, when sensors detect faults in wind turbines, traditional WSN routing protocols often lead to redundant data transmission, resulting in energy waste. To address this issue, an event-triggered energy-efficient wireless routing protocol (EEWRP) is proposed specifically in this paper for wind turbine fault monitoring. The protocol improves the distributed energy-efficient clustering algorithm (DEEC) by first identifying the type of event and then using an adaptive dynamic sliding window method to determine the event-triggered combination threshold. The system only wakes up nodes and triggers data transmission in the case of abnormal conditions, effectively reducing data traffic and lowering network energy consumption. Simulation experiments show that the network lifetime of the EEWRP algorithm is increased by about 80% and 20% compared to the low-energy adaptive clustering hierarchy (LEACH) and DEEC algorithms, respectively, and the data transmission volume is about 8.74 times and 1.07 times that of the LEACH and DEEC algorithms, respectively. The EEWRP algorithm can effectively reduce the energy consumption, extend the network lifetime, and enhance the capability of data packet transmission.

Keywords: Wind turbine, Fault monitoring, Wireless sensor network, Event-triggered mechanism.

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1 Introduction

Wind turbines have been playing an increasingly important role in the global transition to renewable energy sources. Their efficient and reliable operation is crucial for maximizing energy production while minimizing environmental impact [1, 2]. However, operating in harsh dynamic environments, wind turbines are prone to various electrical, mechanical, and structural faults [3–5]. Early detection and diagnosis of these faults are crucial for preventing catastrophic failures, ensuring personnel safety, and optimizing maintenance plans. Wireless Sensor Networks (WSNs) provide an economical, efficient, and scalable solution for comprehensive health monitoring of wind turbines [6–8]. By deploying sensors at critical locations on the turbine, WSNs can collect real-time data on key parameters such as vibration, temperature, pressure, and current. This data can then be analyzed to identify anomalies and diagnose potential faults, enabling proactive maintenance and preventing downtime.

Although WSNs hold significant promise in wind turbine fault monitoring, traditional data routing protocols often face challenges in resource-constrained environments [9]. These protocols typically transmit data periodically without considering its significance, leading to redundant data traffic and excessive energy consumption. This is particularly crucial in wind turbine applications, as sensor nodes rely on limited battery power, and efficient communication is essential for the long-term sustainability of the network. To address these limitations, an event-triggered energy-efficient wireless routing protocol is proposed in this paper specifically for the fault monitoring of wind turbines. The proposed protocol does not transmit data periodically but triggers data transmission only after determining the type of event and when the decision variable exceeds a preset threshold, significantly reducing unnecessary data transmission, saving energy, and extending the network's lifespan.

An event-triggered routing protocol for wind turbine fault monitoring is proposed in this paper, aiming to optimize energy efficiency while maintaining reliable data transmission. The protocol first determines the type of event and then establishes an event-trigger threshold based on an adaptive threshold determination method using a sliding window. Data will only be transmitted when the monitored data exceeds a certain threshold and the rate of change exceeds the rate of change threshold, reducing energy consumption at the source of transmission to achieve energy saving. The structure of this paper is as follows: The second part introduces related work, the third part introduces the traditional DEEC algorithm, the fourth part elaborates in detail on the proposed event-triggered energy-efficient wireless monitoring routing protocol algorithm, the fifth part presents experimental results and analysis, and the final part is the conclusion.

2 Related Work

Some studies have explored the use of WSNs for fault monitoring in wind turbines. Z.Herrasti [10] designed a sensor for monitoring the condition of wind turbines. Various vibration signals were used in references [11–13] for anomaly detection in wind turbine bearings, gearboxes, and generators. Employed Acoustic emission signals were used in references [14, 15] for early fault monitoring of gearboxes and bearings. Janine [16] proposed a framework for fault detection and diagnosis in wind turbines using WSNs and machine learning. The application and development of machine learning in wireless monitoring of wind turbine faults were detailed in references [17, 18]. These works have demonstrated the effectiveness of wireless sensor networks in capturing crucial data for fault identification. However, most studies focus more on the collection and analysis of monitoring data, neglecting the energy efficiency of data transmission.

For wireless sensor networks used for monitoring mechanical faults, obtaining useful information and ensuring low network power consumption are key constraints. Event triggering provides a good reference for reducing network power consumption. The Event-Triggered Mechanism (ETM) can effectively reduce the sampling rate and communication overhead while ensuring system performance [19]. Meisam [20] applied the ETM to WSNs, determining the trigger threshold based on historical information to decide whether to discard data packets, thereby achieving an efficient data aggregation method and extending the network life. The event-triggered threshold is set based on the chi-square distribution in references [21, 22], which was composed of the difference between the value measured at the current and that measured at the last sampling time. When the value of the event-triggered decision variable exceeded the threshold, an event would be triggered, and observation sampling would be performed. Wang [23] proposed an event-triggered routing protocol that determined whether to transmit data based on the severity of the event and the preset energy of the node. These three references have achieved certain results by reducing network power consumption and extending network life through methods such as historical data, chi-square distribution of monitoring data before and after, and setting event priorities. Fu [24] designed a high-frequency sensor, using the probability density of event occurrence to set the trigger threshold. When the monitoring value exceeded the threshold, the sensor is awakened for data transmission, effectively reducing the amount of transmitted data. Habibi [25] proposed a Bayesian inference-based fault detection method for the transmission chain sensor of wind turbines, obtaining the sensor fault probability through the Expectation-Maximization (EM) algorithm and particle filtering. The above methods either sort the monitoring data or use a single model to estimate the expected value or distribution of the target variable, and then determine the threshold to trigger transmission and reduce network power consumption. They don't fully consider the impact of threshold setting on network life. Obviously, the setting of the trigger threshold is very critical. A threshold that is too large may miss a lot of useful information, while a threshold that is too small will cause the system to be too sensitive to noise, resulting in more data transmission and increased network load. This paper uses the idea of a composite threshold, combining the change threshold and the rate of change threshold of wind turbine monitoring data. By considering the absolute size and change rate of the monitoring data, it identifies abnormal events. When it is a general event, and the monitoring data exceeds the threshold and the rate of change is also significant, the event is triggered, reducing false positives caused by noise or other non-event factors.

3 The distributed energy-efficient clustering Algorithm

The distributed energy-efficient clustering algorithm (DEEC) is a distributed energy-saving clustering routing protocol designed for heterogeneous WSN [23]. The protocol aims to enhance the network's energy efficiency and extend its lifespan through a clustering mechanism and the dynamic selection of cluster heads.

In the two-level heterogeneous network of the DEEC protocol, there are $(1-m)n$ common nodes and $m \times n$ advanced nodes. The initial energy of the common nodes is E_0, and the initial energy of the advanced nodes is $E_0(1+a)$, where a and m are preset percentage variables that determine whether a node functions as a common node or an advanced node. The total energy consumption within the network is expressed as:

$$\begin{aligned} E_{Total} &= n(1-m)E_0 + n \times mE_0(1+a) \\ &= nE_0(1+am) \end{aligned} \tag{1}$$

In the sensor network, nodes are divided into different clusters, with one node in each cluster elected as the cluster head (CH), responsible for collecting data from other nodes within the cluster and transmitting it to the base station. The selection of the CH is based on the energy level of the nodes to ensure balanced energy consumption. The probability of a common node becoming a CH is:

$$P(i) = \frac{E_i P_{opt}}{E_{avg}(1+am)} \tag{2}$$

Among them, $P(i)$ represents the probability of a node becoming a CH; P_{opt} is an optimization parameter that adjusts the selection probability of the CH; E_i is the remaining energy of the node; E_{avg} is the average energy of all nodes in the network; n is the total number of nodes in the network.

The probability of a node becoming a CH is related to the threshold as follows:

$$T(s_i) = \begin{cases} \frac{P(i)}{1-P(i)r \mod \frac{1}{P(i)}}, & s_i \in G \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where G represents the set of nodes qualified to become the CH in the r-th round, and s_i is a node in set G.

4 Proposed Method

4.1 Proposed Method

In a wind farm, each wind turbine is monitored by a certain number of sensor nodes placed on its key components. These sensor nodes obtain the parameters of the running states of components, and form a network through a specific network topology for data transmission.

Generally, fault monitoring requires long-term, uninterrupted monitoring of equipment status, and a high sampling frequency is also necessary to capture early fault signals. However, these requirements conflict with the need for low power consumption. To overcome these challenges, an event-triggered mechanism is needed to operate the system in a low-power mode when no fault events occur, allowing for planned, longer intervals for data sampling. In the event of an anomaly, the system should demonstrate high performance and wireless communication capabilities.

For operating wind turbines, vibration signals are often rich and distributed over a wide frequency range due to the influence of environmental wind fields and component coupling. These noises may cause issues such as false alarms or high loads. To address these issues and ensure stable system operation, appropriate thresholds are needed to trigger data transmission when necessary. In light of this, an event-triggered energy-efficient wireless sensor network routing protocol is designed in this paper. The protocol is an improvement upon the DEEC protocol, incorporating an event-trigger mechanism that selectively forwards data that meets set conditions. Data aggregation is performed before forwarding, effectively reducing energy consumption during transmission, thereby achieving energy-saving goals. The system architecture is shown in Figure 1.

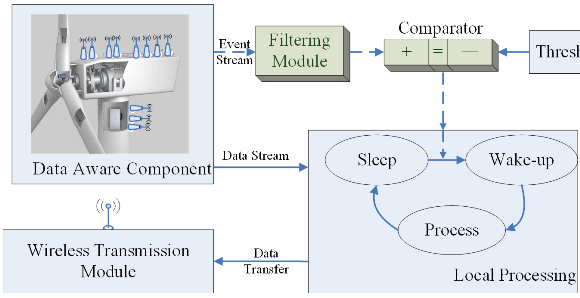

Figure 1. Schematic of an event-triggered energy-aware wireless sensing system.

As shown in Figure 1, sensors are installed or embedded at various locations such as the bearings, gearbox, turbine, and electrical circuits of the wind turbine to detect values like vibration, temperature, and current. After the event stream received by the sensors is filtered to reduce noise, it is compared with predefined thresholds to determine if there is any impact. When a fault occurs, the trigger signal from the comparator's output wakes up the processor to record signals from the data stream, extracting the required parameters. The processor then wakes up the wireless transmission module and wirelessly transmits the extracted parameters to the host for impact assessment. Afterwards, the processor and wireless transmission module enter a low-power mode, waiting for subsequent events.

4.2 The Event-Triggered Energy-Efficient Wireless Routing Protocol (EEWRP)

It is assumed that the sensors for fault monitoring of wind turbines mainly include types such as current, pressure, temperature, vibration, and torque, with event streams mainly includes current overload, excessive pressure, excessive temperature, excessive vibration, and excessive torque. Among these events, current overload and excessive pressure are defined as critical events, while the rest are defined as general events. The new protocol is based on the DEEC protocol, with an added event-trigger mechanism. When the system detects a critical event, it immediately transmits data to the base station. When the system detects a general event, the system triggers data transmission to the base station only when both the measured data and its rate of change exceed the corresponding thresholds. During data transmission, if the distance between the node and the base station is less than the distance threshold d_0, the node directly transmits the data to the base station. Otherwise, the data is sent to the cluster head through a clustering method, and then the cluster head forwards the information to the base station. If there are no event triggers in the system, it will periodically send data information to the base station at set intervals. The flowchart of this process is shown in Figure 2.

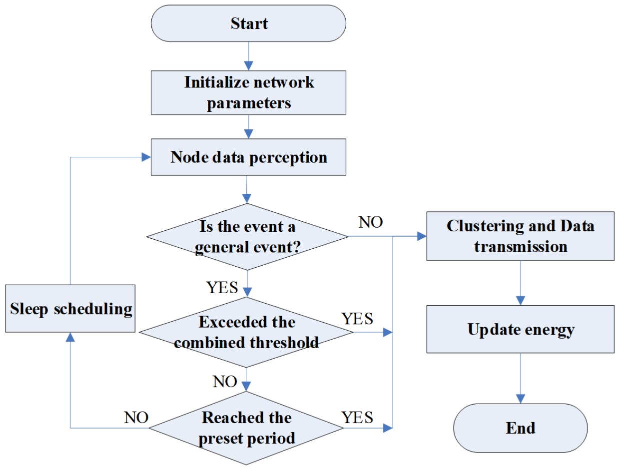

Figure 2. Algorithm flow chart.

4.3 Adaptive Threshold Determination Method Based on Sliding Window

The adaptive threshold determination method based on sliding window is widely used in networked control systems, especially in scenarios where resources are limited or there is a high demand for real-time performance. In WSNs, this method can reduce unnecessary data transmission and extend the battery life of sensors. Its core principle is to dynamically set trigger conditions using historical information of the system state [26]. In this method, a sliding window is used to calculate the statistical parameters of the most recent C data points, and these parameters are then used to update the thresholds.

To obtain the threshold for event triggering, adaptive event triggering conditions based on two key factors are proposed in this paper. The first is the threshold for data change. Each sensor node monitors specific parameters related to potential faults. A predefined threshold is set for each parameter, and an event may be triggered when the measured value exceeds the corresponding threshold, indicating a potential anomaly. The second is the threshold for change rate. A sudden change in parameter values may also indicate the beginning of a fault. Statistical methods are used to monitor the rate of change over a specified time, in conjunction with the data change threshold. For general events, if the rate also exceeds the set threshold, an event will be triggered, which is beneficial for filtering out environmental noise.

The threshold for data change can be determined by the following formula:

$$V_t = \frac{1}{L}\sum_{i=1}^{L} v_i + k_1\sqrt{\frac{1}{L-1}\sum_{i=1}^{L}\left(v_i - \frac{1}{L}\sum_{i=1}^{L} v_i\right)^2} \quad (4)$$

The threshold for change rate can be expressed as:

$$R_t = \frac{1}{L-1}\sum_{i=1}^{L-1}|v_{i+1}-v_i| + k_2\sqrt{\frac{1}{L-2}\sum_{i=1}^{L-1}\left(|v_{i+1}-v_i| - \frac{1}{L-1}\sum_{i=1}^{L-1}|v_{i+1}-v_i|\right)^2} \quad (5)$$

In the formula, v_i represents the monitored value of a node within the sliding window, L is the size of the sliding window, and k_1 and k_2 are the adjustment factors for the numerical threshold and the threshold for change rate, respectively.

For each moment, every sensor parameter is compared with the predefined threshold that represents the normal operating range. For critical events, an event is triggered when the measured value exceeds the corresponding threshold:

$$ET_1 = I(), \text{ if } (v_i > V_t) \quad (6)$$

Using statistical methods to monitor the rate of change of v_i within a specified time period.

$$RC_i(t) = \frac{v_i(t) - v_i(t-\Delta t)}{\Delta t} \quad (7)$$

If the rate of change exceeds the predefined threshold for change rate, it may trigger an event:

$$ET_2 = I(), \text{ if } (RC_i(t) > R_t) \quad (8)$$

Let I be the indicator function, which takes the value of 1 if the condition is true, and 0 otherwise. From this, it can be concluded that for general events, an event is triggered when both the data change and the rate of change exceed their thresholds. That is, the combined threshold mathematical logic for monitoring data change and the rate of change is:

$$ET_2 = I(), \text{ if } (RC_i(t) > R_t) \quad (9)$$

This method ensures accurate fault detection, which in turn triggers data transmission, thereby maximizing the reduction of energy consumption.

5 Performance Evaluation

To demonstrate the effectiveness of the algorithm, the performance of the LEACH, DEEC, and the EEWRP protocol proposed in this paper are compared in terms of network lifetime, residual energy per round, and data transmission volume. The initial parameters of the network are shown in Table 1.

Table 1. Settings of simulation parameters.

The parameter name	The parameter value
The network area/(m×m)	100×100
Number of nodes	100
Node initial energy/J	0.5
Send energy consumption ETX/(nJ·bit^{-1})	50
Received energy consumption ERX/(nJ·bit^{-1})	50
ξ_{fs}/(pJ·bit^{-1}·m^{-2})	10
ξ_{mp}/(pJ·bit^{-1}·m^{-2})	0.0013
Number of routing execution rounds	6000

Figure 3 illustrates changes in the number of node deaths over time for the LEACH, DEEC, and EEWRP algorithm. Table 2 shows the time of the first node death (FND), the time when 50% of nodes have died (HNA), and the network lifetime of the three algorithms, respectively. It can be seen that the LEACH algorithm leads to the first node death occurring around 1000 rounds, with all nodes dying within approximately 2000 rounds; for the DEEC algorithm, the first node death occurs around 1400 rounds, with all nodes dying within about 3000 rounds; for the EEWRP algorithm, the first node death occurs around 1900 rounds, with all nodes dying within about 3600 rounds.

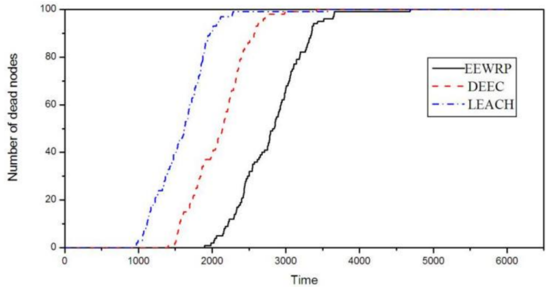

Figure 3. Graph of node death over time.

Table 2. Calculation results comparison of the three algorithms.

The r name of algorithm	FND	HNA	The life cycle	Data transmission
LEACH	962	1620	1000-2000	1.59×10^4
DEEC	1405	2136	1400-3000	1.30×10^5
EEWRP	1896	2818	1900-3600	1.39×10^5

Figure 4 shows a comparison of the residual energy of the networks for the three algorithms. It can be seen from the figure that compared to the DEEC and LEACH algorithms, the EEWRP algorithm can effectively extend the network lifetime and improve energy efficiency.

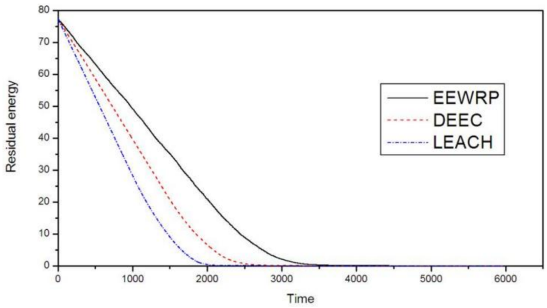

Figure 4. Graph of residual energy over time.

Figure 5 compares the data transmission volume of the three algorithms. It can be seen from the figure that when all nodes have died, the LEACH algorithm network has a data transmission volume of about 1.59×10^4 bits; the DEEC algorithm network has a data transmission volume of about 1.30×10^5 bits; and the EEWRP algorithm network has a data transmission on volume of about 1.39×10^5 bits. The total data transmission volume is the highest for EEWRP, followed by DEEC, and the least for LEACH. During the data transmission process, the data transmission volume of the EEWRP algorithm network is initially less than that of the DEEC algorithm but becomes more over time. This is because the EEWRP algorithm employs an event-triggered mechanism, where data is only transmitted to the base station when the event trigger conditions are met, thus reducing the transmission of redundant data. However, the EEWRP algorithm has higher network energy efficiency and a longer lifespan compared to the DEEC algorithm. As the network lifetime extends, the data transmission volume of the EEWRP algorithm will also increase.

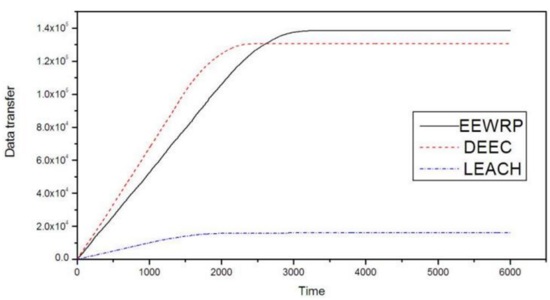

Figure 5. Graph of data transmission over time.

Based on the analysis above, compared to the LEACH algorithm, the EEWRP algorithm can improve the network lifetime by about 80% and increase the data transmission volume by about 8.74 times; compared to the DEEC algorithm, it has improved by about 20% and 1.07 times, respectively, as shown in Table 2. Therefore, compared to both the LEACH and DEEC algorithms, the EEWRP algorithm has significant improvements in terms of lifespan and data transmission volume.

6 Conclusion

This paper addresses the issues of redundant data transmission and high energy consumption often caused by traditional WSN routing protocols when used for fault monitoring of wind turbines, by proposing a new event-triggered energy-efficient wireless routing protocol (EEWRP). Its effectiveness has been validated by comparison with the LEACH and DEEC algorithms, showing significant improvements in aspects such as network lifetime, energy consumption, and data transmission. The newly proposed EEWRP algorithm increases the network lifetime by about 80% compared to LEACH and by about 20% compared to DEEC. Due to the improvement in network lifetime and energy efficiency, the data transmission volume of the EEWRP algorithm is also improved, which is about 8.74 times and about 1.07 times that of the LEACH and DEEC algorithm, respectively.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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