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A Study on Energy-Efficient Wireless Sensor Network based on Machine Learning Techniques

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Abstract
Wireless sensor networks (WSNs) are advantageous when there is no existing infrastructure (such as in military applications, emergency relief efforts, etc.) and it is necessary to develop a network at a low cost. A predetermined routing protocol or intrusion detection system is not available to Wireless Sensor Networks because they are dynamic by nature and need separating the network's nodes to do this. Because nodes in the majority of WSN applications are mobile and rely on battery capacity and the availability of restricted resources, energy consumption is an important research area for carrying out a variety of activities in WSNs. Self-learning algorithms that function without scripting or human involvement can be effectively used to report this problem depending on the applications need. This study investigated different ML-based WSN systems and exploring the ML techniques for energy efficiency along with some open issues.

Keywords: *WSN, Lifetime – Network, ML, Energy Efficiency, Clustering*

1. Introduction

Monitoring, domestic, and other uses are among the possibilities for wireless sensing networks (WSNs) [1] through [4] these networks have hundreds of connected nodes, they are constructed with low-energy technology. The Area of Interest, which is often a difficult location to enter, is covered by these nodes. The replacement of a node's energy sources once they run out may be difficult or perhaps impossible. It is desirable to develop an energy-efficient algorithm to save energy and extend network lifetime (LT). As a result, WSN must take energy efficiency into account both during the design process and now after deployment [5]. WSN nodes expend energy when processing, detecting, sending, or receiving packets. According to testing results, communication consumes the greatest energy.There are various ways to transmit a message to the targeted node in such a dense network. As a result, choosing the optimal one, or the routing method, is a crucial decision that can offer an effective way to save energy [6].This challenge of route optimization while upholding service quality is regarded as an NP-Hard one [7].

The development of routing protocols in WSNs has received a lot of attention. There are still a few issues to be fixed, Conventional routing techniques rely on uniform devices. The minimum hop route, highest available energy, and negligible energy path may all function effectively in this situation. They will also result in a short network lifetime and poor energy efficiency in heterogeneous networks. It is necessary to consider the variability of nodes' communication and energy capacity. Most of the protocols that have been suggested are either flat or hierarchical.The most often used LT definition in terms of optimization is the moment the first node goes down [8], [9]. In contrast, this period is not critical, as the network will continue to function even if a node fails. Consequently, it is desirable to develop a unique routing approach for LT optimization based on relevant feedback that takes into account these constraints.Nodes will self-configure and learn over time. There is no requirement for prior topological expertise.To choose a current and shrewd course of action, they will regularly acquire and refresh their knowledge. Our objective is to optimize LT in three areas and in energy efficiency terms to accommodate a variety of applications.

Following is the outline for the rest of this paper: Part II will provide an overview of the routing problem as well as our recommended strategy, Reinforcement Learning for LT Improvement (R2LTO).Performance evaluation is discussed in section 4, and the findings are compared to those of previous research. The article is concluded in Section 7, which also covers the next research.

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2. ML Algorithm for WSN

Machine learning has proven to be highly helpful for WSNs, since these algorithms can perform a more accurate analysis of shifts in external factors like as temperature, elevation, and other variable environmental circumstances. WSNs using machine learning techniques have potential applications for IoT technology, cyber security, and computer communication. For various applications, various types of WSNs are required, and if they are based on machine learning, they also require machine intelligence with human involvement [10]. The authors of [12] present an excellent detection strategy based on ML while considering a few particular challenges. Biologically influenced machine learning techniques include fuzzy, evolutionary, and artificial neural approaches [13]. There are three sorts of machine learning strategies discussed in [14]: supervised, unsupervised, and supervised learning techniques.

2.1 Supervised Machine Learning

In machine learning supervised learning, the computer model is constructed using a tagged training set consisting of the inputs and outputs with fixed values. Using a system model, the connection between input and output or other system variables can be determined. These WSN-based learning algorithms can be utilized to handle localization and target targeting [15], query parser and events detector [11] medium authentication and authorization [15], packet sniffing and privacy [9], [2], data integrity, service quality QoS, and error checking [2].

2.2 Unsupervised Machine Learning

In unsupervised learning, the system model is independent of input and output parameters. By examining the similarities between such a sample set and an unsupervised learning method, various groups can be formed from the sample set. Unsupervised learning methods may be employed in a variety of WSN applications, such as data collection at sink code situations or WSN node clustering [3]. The system model is found to be appropriate for issues with complicated variable connections since it is independent of labeled parameters. Exploratory factor analysis [5] and K-means clustering [4] are the two primary categories of this sort of learning method.

2.3 Reinforcement Machine Learning

The system model learns using the reinforcement learning method by interacting with its surroundings. This kind of machine learning incorporates a reward system for sensor nodes that improve their performance over time. The most popular kind of reinforcement learning algorithm, called Q-learning, has been shown to be successful in resolving routing problems [6].

3. Review of Routing Problem

Several routing protocol strategies have been proposed in the literature [10–12]. Q-routing was proposed by JA Boyan and ML Littman [13] as a hop-by-hop routing method based on Q-learning. Improving packet delivery rates while decreasing transit times is the focus of this effort. The lack of newness in this protocol is a problem. If a path hasn't been chosen in a while, the individual has no idea how things are right now. It has a narrow scope of understanding. Therefore, the learning process may become shaky. Routing protocols for delay-tolerant networks include Adaptive Reinforcement-Based Routing (ARBR) [14]. Each node contributes its own expertise, together with time and congestion information, to the decision of which node will forward packets. However, this method is reserved for exceptional circumstances. Multi-agent Reinforcement is a routing technique for WSNs that supports quality of service. Different QoS Routing Protocols (MRLQRP) are Learned [15-20]. In contrast to other approaches, in this one, the agents coordinate their calculations of the Q-values. According to [6], putting MRL-QRP into practicing be difficult. Some of the routing protocols now in use take networking LT into account.

Metrics show that the energy-aware routing (EAR) [7] protocol is an effective one. EAR stores many pathways that connect the sender and the destination in order to prevent utilizing the same minimal energy path twice. It uses a parabolic law to select one pathway from the ones recorded each time. Even while this methodology yields intriguing findings, it just considers energy use. In contrast to EAR, balance energy-efficient routing (BEER) takes into account both remaining energy and energy use[20-25]. The decision to follow the routing table that was originally created has an adverse effect on both EAR and BEER. The present condition of the network is not reflected in this table, though. A reinforcement learning-based routing framework (RLBR)has just [10] been presented. RLBR chooses based on distance, remaining energy, and hop count.

RLBR has various limitations even if it displays results more favorably than Q-routing and BEER. Nodes with more hops or more distances than the current node are not taken into consideration by RLBR when choosing the next forwarder. However, this restriction does not allow for the maximization of LT, just for the minimization of energy use. After looking at the aforementioned methods, this intends to

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offer a fresh methodology that overcomes these shortcomings.

Numerous definitions are used with the intention of optimizing LT in routing problems [9]. Depending on the application and the network topology, these definitions change. The LT definitions stated below are applied at work:

- The interval before the first dead node is discovered. If a node exhausts its energy supply, it is deemed to be dead.
- When the first isolated node will be revealed, if at all. A node is said to be isolated if it has energy but no path to a sink node.
- The period left before no more packets may be sent.

4. New Routing Algorithm

Wireless nodes operate as agents in our routing problem by selecting the subsequent forwarder node. When a sensor node in a WSN notices an event or gets a packet from one of its neighbors, it must select the subsequent forwarder from among itsneighbors. This activity is influenced by the neighboring states and the reward system.

The discovery process and the routing with continuous learning process are the two processes that make up our routing protocol.

4.1 Discovery Process

Reinforcement learning (RL) [10] is a solution to the problem that occurs when an organism must learn behavior through trial and error in a changing environment. The agent decideswhich of several possible actions to take based on his prior knowledge. The payoff comes after that point. The optimal policy is constructed by a learning procedure. These features make RL a good method for solving distributed real-time decision issues, such as routing difficulties.

A discovery technique is created to have a comprehensive strategy that improves the LT of WSN and energy use without any previous knowledge of the topology. Nodes will become self-configuring and learn over time through this process. The initialization of several nodes is the first phase. The sink begins by notifying his neighborsofthe notice package. The node's identifier plus information from the prior node make up a notification packet (node ID, location, remaining energy, and hop count). When a node receives a notice, it decodes the packet to determine who sent it. The Q-value of the sender's route and the hop count to the sink is calculated using equation 4.1 and equation 4.2, respectively. After encoding its data into the notification packet, the node sends it out to all of its neighbors.

$$P(Sender) = \frac{Energy(Sender)}{Hop(Sender)} \tag{4.1}$$

$$Hop(current) = Hope(sender) + 1 \tag{4.2}$$

Each node can initialize its neighboring table at this point. The following details are maintained for each neighbor in this table:

4.2Routing and Learning Process

After the initial phase of discovery, the data is sent along a path that is constantly updated based on new information. There was the potential for data packet transmission and reception at a network node. In addition to the characteristics of a notification packet, a data packet also has a Q-value, a next node ID, and data properties. As soon as a node receives a datagram containing a next ID value that does not match its own ID, it immediately drops the packet and changes its neighbor table.Each node has a current neighboring table thanks to this overhearing technique, which ensures that routing follows the network's actual conditions. If not, it selects the top contenders for the following position from the table across from it. The packet will be dispatched immediately if a sink node can be reached.

If not, it proposes the following forwarder. A dead or isolated node shouldn't be the next forwarder. The message will be discarded, and the present node will be regarded as an isolation node if none of its neighbors meet this requirement. Then, its Q-value and hop count are both set to 0. When there are several candidates, the next routing is selected using Q-values.

The present node, i, and its neighbor, j, are assumed to be these symbols. The strength of node i's connection to the sink through neighbor j is calculated using the equation. 4.3.

$$Q_{(t+1)}(i,j) = (1-\alpha)Q_t(i,j) + \alpha\left(R_{(i,j)} + Q_j\right) \tag{4.3}$$

Demonstrate that Q can be retrieved via the neighbor table (j). Specifically, R is the reward function (i, j). Since it has such a profound impact on the network's longevity and energy consumption, although this should be selected with great care. It needs to be inversely linked to the number of hops, proportionate to the amount of energy left, and proportional to the energy expended to transmit the packet (eventually distance). As such, the following is the hypothesized reward function using the equation 4.4

$$R(i,j) = \frac{Energy(j)}{hope(j)} \tag{4.4}$$

The energy(j) and hop(j) variables, respectively, reflect the node j's remaining energy and the number of hops to the sink via this node, respectively (j). These two pieces of information originate from the neighbor table of node i. Once the transmit energy is adjusted, the packet's estimated energy cost to go from node I to node j is denoted by T_x(i, j). When it comes to energy consumption, T_x is by far the most significant (rang).

5. Open Issue

A WSN ML-based algorithm should investigate several unresolved challenges, according to the literature review. Table I is an overview of the ML approaches that need to be determined as a problem in WSNs.

Table I - ML Techniques to Solve Diverse Issues in WSN

Energy Efficiency	SVM	These two are used for forecasting within a given time duration, a restricted amount of energy
	Deep Learning	It is utilized for calculating the quantity of harvested energy
	Evolutionary Computational	

Battery energy in sensor nodes in WSNs is limited. Due to the restricted quantity of energy available, a small, low-cost, and extremely energy-efficient wireless harvesting system is advised. It can accomplish this using efficient cross-layer wireless energy harvesting techniques for WSNs. As a result, machine learning is more essential in WSNs to improve network reliability. Large systems require cycles that can charge and discharge themselves in response to environmental changes. An efficient distribution of electricity is necessary for a network to last longer. Therefore, for energy allocation to be successful, the physical layer's energy control and the MAC layer's duty cycle adjustment should be synchronized.There are a number of potential operational and functional concerns that might develop when building WSNs, including but not limited to: sensor node energy and memory utilization, topology changes, communication link failures, and decentralized administration. An explanation of several the issues is provided below:

- Design challenges such energy consumption, data coverage, scaling, and fault tolerance must be considered while developing a wireless sensor network (WSN) because sensor nodes have limited memory, bandwidth, and computing capacity.
- Difficulties in determining a precise geographical location for a WSN are present due to the fact that its position is required by a variety of different applications. It follows that localization of the sensor network is an important issue to solve when constructing WSN.
- Difficulties in Event Recognizers and Query Processors: Broadly speaking, WSN monitoring can be either event-driven, continuous, or query-driven.

5.1 Genetic Algorithm

The concept of solutions for communities of applicants, such as chromosomes, is the backbone of genetic algorithms. To achieve optimal results, chromosomes communicate with one another through genetic operators [4]. Some of the defining moments in the evolution of the founding population are the processes of its production and evaluation. To make offspring, it uses this information to select the optimal chromosome and then carries out a crossover between the selected chromosomal pairs. Then mutation is used to determine the most advantageous solution to select.

6. Summary

WSNs rely on battery-operated, miniature sensor nodes to relay information or data back to a central hub. These sensor network may be permanently installed or moveable, depending on the scenario. The military can use them as first responders. Researchers from all around have proposed many solutions to the issue of the nodes' insufficient energy. Node clustering is a restricted version of the p-median problem. P-median problems are those that pertain to the localization algorithm. With this improvement, it is easier to find amenities at locations without having to worry about whether they are too far away from other users or how much money they will cost.

Even for simple setups, this problem has been deemed NP-hard [5]. It has been assumed that all nodes share the same transmit energy and that all stations have the same fixed amount of energy when disseminating and receiving to reduce the p-median problem in WSNs. It is crucial to have the correct relationship between the cluster radius and the node transmission range. To keep every node from turning into a sink node, it is important to fix sink nodes. If onewant to save energy while still transmitting data from sensor nodes and the cluster head, then determining where to put sink nodes is a good first step.

This study, which was published in more conventional academic journals, considered the case of fixed, permanent sensor nodes. Mobilizing nodes is another theoretical advancement that is unlikely to ever be implemented. Mobile nodes in WSNs provide for effective communication between and within clusters. Genetic algorithm has been successfully implemented in WSNs for machine learning, as evidenced by the aforementioned literature. The p-median problem could also be tackled using a different machine-learning technique, such as a complex neural network. To determine who deserves credit for a photograph, sophisticated neural networks are frequently employed. The input for a Convoluted Network might be a grid of data for each pixel in the image [3]. A grid of zeroes and ones rather than pixels, however, may be used as input for WSNs.

7. Conclusion

Some recent work on WSNs utilizing ML is reviewed, with short descriptions of each ML method for comprehension. Address various WSN-related concerns in this work, including routing, action recognition, data retrieval, and energy efficiency, that have never been covered in any other survey publications. The results of our tests between numerous ML-based techniques for use with WSNs were then collated. Some of the current unresolved challenges have been addressed using genetic algorithms in clustering approaches for learning algorithms for WSNs, which have been found to increase fuel efficiency.

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