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An Exploration of State of Art Approaches on Machine Learning Based Energy-Efficient Routing Approaches for Wireless Sensor Networks

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Abstract. Wireless Sensor Networks (WSN) have increased reputation since its widespread applications and potential improvements in various fields. They have increased the enabling of IoT applications, due to easy accessibility and less cost. Data sensing is done through nodes in a wireless sensor network and processed the data, then sent to base station. The main design challenge in WSN is the efficient use of the limited energy and expansion of the network lifetime. It is attained by using an appropriate routing technique. Various routing protocols have been evolved for this regard. Also, the continuous improvements of IoT systems have leads to numerous novel protocols designed for wireless sensor networks, where energy saving is the highest importance. At another hand, the routing protocols have gained the greatest significance, because protocols may change depending on the application and design of networks. So, with the introduction of Machine Learning algorithms in WSN, they can become a self-oriented network. Machine Learning is an idea that machines can learn from the input data and provide correct and innovative decisions. This article reviews current WSNs routing protocols and proposes action plans for future approaches.

Keywords: Clustering · Energy Efficient · Machine Learning · Routing Algorithms · Wireless Sensor Networks

1 Introduction

Wireless Sensor Network (WSN) is a vital and significant technology owed to its efficient cost, high reliability, scope, low power and ease of deployment. WSN contains sensors as nodes and they are located in an area where sensing can be done and used to examine and record conservational data, including light, vibration, temperature, sound and motions and then sends that information to base station. [1]. The nodes' advantage is that they guarantee efficient wireless communication and sensing. WSNs are used

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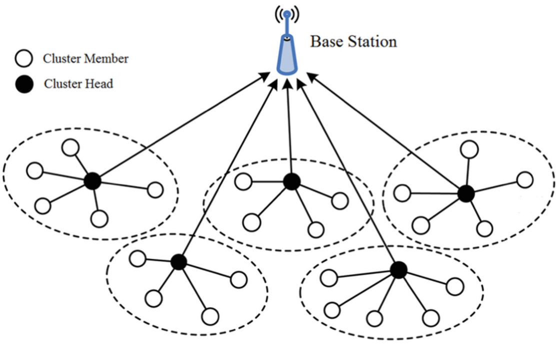

Fig. 1. Clustering based Wireless Sensor Network [Source: T Gui et al., 2016]

in many different applications, including healthcare, shipping systems, environmental monitoring, military, commercial and public security [2]. Every node interacts with base station (BS) during data distribution through a single hop or multiple hops [3]. This data transmission is a continuous process, so, it causes the more distant nodes significantly consume resources more rapidly than remaining nearby nodes. Since this problem may overcome when clustering method is employed in WSN. Figure 1 shows Clustering based Wireless Sensor Network.

Cluster Heads (CH) are recognized within each cluster as a result of the clustering process, which involves in the gathering of sensor nodes into clusters. The CH collects and transfers the data to BS using single or multiple hops in the network. A sink node closer to all the installed nodes is also used for data transmission [4]. CH directed the collected information to higher level CHs then finally sends data to BS in multiple hops data transmission. Moreover, the network reduces the need for centralization and encourages local decision-making, which improves scalability. Clustering methods decreases interference, cuts down on power usage and communication overhead and thereby extending the lifetime of the network.

Furthermore, external reasons and dynamic nature of the wireless sensor networks effects the CH selections, delay, routing, quality of service, localization, coverage, fault detections, security and reliability [5–7]. The traditional strategies of wireless sensor networks are specifically programmed. But consequently, this network might need to be redesigned, this impact causes the network may malfunction in a complex and dynamic environment. To solve this issue, numerous optimization techniques and machine learning (ML) are applied. Several evaluations based on various features of the clustering process in WSNs have so far been published by researchers [8–10]. The IoT applications have gained significant attention in many research fields [11].

Machine learning techniques have been used recently to deal with the limitations of traditional routing in Wireless Sensor Networks [12]. These techniques are known to provide significant improvements over traditional routing methods for enabling more energy-efficient routing algorithms in WSNs [13, 14].

This paper presents a number of recently-conducted research in the area of ML based routing algorithms. As it is hard to recharge sensor nodes, WSNs must be allocated effectively so that they maximize their usability and lifetime. For analysing complicated problems, Machine Learning techniques provide a generalized and flexible paradigm that fully matches the requirement for energy efficient routing in WSNs.

This paper is planned as follows: Sect. 2 explains the machine learning methods for wireless sensor network in terms of supervised, unsupervised and reinforcement learning and their applications, advantages and limitations. The choice of Cluster Heads (CH) and Cluster formation in wireless sensor networks are covered in Sect. 3. A detailed review is presented related to routing protocols and reliability of wireless sensor networks in terms of machine learning methods in Sect. 4. Section 5 offers a study of unequal clustering for wireless sensor networks with machine learning methods. Lastly, Sect. 6 is the conclusion.

2 General Machine Learning Methods for WSN

Machine Learning is an analytical method that learns from experience. Its main advantage is the ability to provide generalized solutions. Machine Learning is an interdisciplinary area where it has a number of applications. It is used across different fields. Recently, it has been involved with solving issues in WSNs. Machine Learning is crucial in Wireless Sensor Networks as it helps in accessing vast amounts of data, streamlines computational procedures and automatically analyses complex data. Three sorts of learning are distinguished: supervised, unsupervised, and reinforced learning. Figure 2 below displays a classification of machine learning methods in WSN.

2.1 Supervised Learning

Supervised learning is a kind of machine learning where an algorithm is taught on a labelled dataset to predict output values based on input data. In the framework of

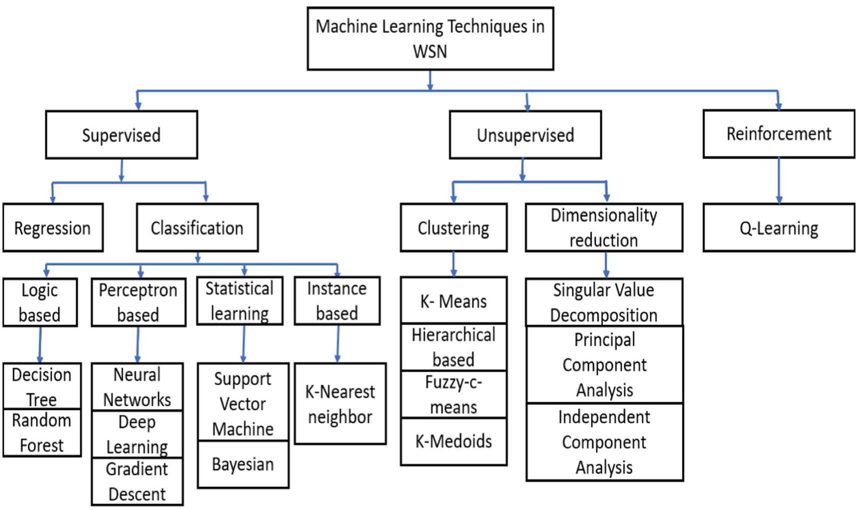

Fig. 2. Classification of Machine Learning Techniques in WSN

Wireless Sensor Network (WSN), supervised learning can be used to develop models that can accurately predict various sensor readings based on historical data. Supervised learning algorithms like decision trees, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) can be used in WSNs to develop models that can accurately predict various sensor readings [18]. However, developing accurate supervised learning models for WSNs can be challenging due to limited computational resources and power constraints of sensor nodes.

2.2 Unsupervised Learning

Unsupervised learning is the formation of associations without the use of input data by the produced model. This learning strategy, which is unsupervised, aids in resolving a number of WSN-specific difficulties, including routing, data aggregation, connectivity concerns, and anomaly detection. Clustering and dimensionality reduction are two more divisions of the process. Many algorithms make advantage of clustering. The Fuzzy-C-Means, K-Means, Hierarchical, and K-Medoids are among the most well-liked. Methods for reducing the number of dimensions include principal component analysis (PCA), independent component analysis (ICA) and singular value decomposition (SVD).

2.3 Reinforcement Learning

A type of machine learning called reinforcement learning teaches an algorithm to make judgements by making decisions in the real world. In the setting of wireless sensor networks (WSN), reinforcement learning can be used to develop intelligent decision-making algorithms for various applications such as energy management and routing. Reinforcement learning algorithms can be used to learn optimal routing strategies by receiving rewards or penalties based on the network's performance. Reinforcement learning algorithms such as Q-learning and deep reinforcement learning can be used in WSNs to develop intelligent decision-making algorithms that can optimize several network parameters such as energy consumption, routing, and data aggregation. However, developing effective reinforcement learning algorithms for WSNs can be challenging due to the limited computational resources and communication constraints of the sensor nodes.

2.4 Applications

Machine learning-based energy-efficient routing approaches can be applied in various applications in wireless sensor networks (WSN), including - Environmental monitoring: WSNs can be used to monitor various environmental parameters, like air quality, water quality, and soil conditions. Precision agriculture: WSNs can be used for precision agriculture, where sensors can monitor crop conditions, soil moisture, and weather conditions. Smart cities: WSNs can be used for various smart city applications, for example traffic management, waste management, and public safety. Healthcare monitoring: WSNs can be used for healthcare monitoring, where sensors can monitor patient health conditions in real-time. Industrial automation: WSNs can be used for industrial automation applications, such as monitoring production processes, equipment status, and energy consumption. Overall, machine learning based energy efficient routing approaches can help to optimize data routing, reduce energy consumption, and extend network lifetime in a variety of WSN applications.

2.5 Advantages

Based on various requirements, machine learning algorithms offer significant advantages for WSNs, improving accuracy, efficiency, adaptability, security, cost-effectiveness, and predictive capabilities. These advantages make ML an attractive option for a wide range of Energy-Efficient Routing Approaches in WSN applications, from environmental monitoring to industrial automation and beyond.

2.6 Limitations

Although ML in WSNs has many benefits and a widespread of applications, it has several drawbacks. The FL method yields a non-optimal result and fuzzy rules must be used to relearn topological variations; The limited understanding of future information is the main problem with routing algorithms that emphasise reinforcement learning. As a result, the algorithms are inadequate for extremely dynamic circumstances since it takes them an extended time to find the best route [19]. Because, ML algorithms must learn from prior data and they cannot automatically generate accurate predictions. Functioning is depended on historical data and if the data is very high, processing will consume high energy.

3 Machine Learning Methods for Cluster Head Selection and Cluster Formation in WSN

WSNs consists of a huge number of small sensor nodes, they collect and transfer data to a central base station. Cluster formations and cluster head selections are critical tasks in WSNs that affect the network lifetime, energy efficiency, and overall performance. Machine learning methods can be used to form clusters and select cluster heads in WSNs. These machine learning methods can be used in WSNs to choose cluster heads and build clusters. K-means and fuzzy C-means clustering are unsupervised techniques that can be used for cluster formation, while PSO, ANNs, and Decision Trees are supervised techniques that can be used for cluster head selection. The application requirements and the data that are available determine the technique to use. Table 1 shows the CH selection and cluster formation using machine learning techniques according to various factors.

4 Routing Protocols for Clustering

Clustering-based routing protocols provide an efficient and scalable solution for transmitting data for WSNs. The selection of routing protocol is based upon a network topology, the application requirements and energy constraints of sensors. Below describes some Machine Learning Technique routing protocols for clustering.

Table 1. ML Techniques for Cluster Head (CH) Selection and Cluster Formation

Ref. No.	Year	Clustering Algorithm	Topology	CH selection criteria	Inference
[15]	2020	HQCA	Grid-based	Cluster quality, cluster density, mean distance and residual energy.	Greater scalability, reduced error rates, high reliability and effective performance.
[16]	2020	FCHA	Cluster-based	Relationship between residual energy and centrality.	The sink node dynamically creates CH.
[17]	2016	FBUC	Unequal clustering	Distance and node degree.	Enables CH nodes to live longer by being closer to the sink node.
[20]	2020	ANN	Hybrid	Residual energy, traffic load and distance.	In order to calculate the average energy and energy threshold, the chief node gathers data.
[21]	2017	Naive Bayes scheme	Tree	The sum of local distances and residual energy.	The CH node is identified using the Naive Bayes approach.
[23]	2018	EKMT	Hybrid	Energy remaining and distance.	Using the k-means method to identify the best CHs.
[24]	2020	IFPA and SVM	Tree	SVM Technique	Information collected by cluster head with SVM.
[25]	2019	Semi-supervised classification method	Hybrid	Centroid based method.	Depending on several zones, CH transmits data continuously or periodically.

(continued)

4.1 Machine Learning Techniques for Routing

Machine learning methods will be used to optimize several phases of routing protocols in clustering, leading to more efficient and reliable wireless communication. The selection of machine learning techniques and their implementation depends on specific

Table 1. (*continued*)

Ref. No.	Year	Clustering Algorithm	Topology	CH selection criteria	Inference
[26]	2016	K-means	Tree	Upgraded sensor node serves as CH.	Each cluster's BS node handles the offline phase, and the CH node handles the online phase.
[27]	2019	Adaptive SVM and ACSO classification	Hybrid	ACSO	Malicious nodes and selection of cluster head (CH) are reported.
[31]	2017	SVM	Hybrid	Decision function	Nonlinear classification and Hausdorff distance calculation.
[32]	2016	Bayesian based FDS	Tree	Decision rules and PJ	Locates the sensor nodes which are malfunctioning.

HQCA-High-Quality Clustering Algorithm, FCHA-Fuzzy based Cluster Head Amendment, FBUC - Fuzzy Based Unequal Clustering, ANN - Artificial Neural Network, EKMT – Energy-Efficient K Means Clustering Technique, IFPA - Improved Version for the Flower Pollination Algorithm, SVM - Support Vector Machine.

requirements of the WSN application, available sensor data and the energy constraints of the sensors (Table 2).

4.2 Machine Learning Techniques for Reliability

In clustering, reliability refers to the consistency of the clustering results obtained from multiple runs of the clustering algorithm on the same dataset or on similar datasets. Reliability can be accessed using various measures, such as the stability of the clustering solution, the reproducibility of the clustering results, or the robustness of the clustering algorithm to different initialization conditions [30]. A clustering algorithm is considered to be reliable if it produces stable, reproducible, and robust clustering results that are consistent with the underlying structure of the data and are interpretable by domain experts. Table 3 provides a study of reliability-based methodologies employing machine learning techniques.

5 Unequal Clustering for Wireless Sensor Networks

An unequal clustering method is used in wireless sensor networks to allocate the load across the cluster heads and avoid the energy-hole or hot-spot problems (Fig. 3).

Table 2. Routing protocols that employ machine learning methods

Ref. No.	Year	Protocol	Type	Cluster size	CH selection	Phases	Inference
[28]	2018	DFCR	Clustering based	Unequal	Depending on the energy and the sink node.	Data sharing, data routing, virtual backbone development, and cluster creation are the 4 phases.	Effective use of energy and energy balance.
[29]	2016	FAMA CROW	Hierarchical clustering based	Unequal	In accordance with the node's maximum level of proficiency.	Construction phase, identification phase and steady-state phase are the 3 phases.	Lowering energy use and addressing the hot spot issue.
[41]	2022	RLBEEP	Q-Learning	Unequal	Based on Q-learning reinforcement	Routing, sleep scheduling, and restrict data transfer are the 3 phases.	Improving the energy and transmission
[42]	2021	DBR, DEADs, RBCMIC	Un-Supervised K-Means ML algorithm	Unequal	Depending on factors like distance, remaining energy and mobility factor.	Cluster formation and choosing the cluster head are the two phases.	Better energy efficiency

DFCR – Distributed Fuzzy logic based unequal Clustering approach and Routing algorithm, FAMACROW – Fuzzy and Ant Colony Optimization Based Combined MAC, Routing and Unequal Clustering Cross-Layer Protocol for Wireless Sensor Networks, RLBEEP-Reinforcement-Learning-Based Energy-Efficient Control and Routing Protocol, DBR-Depth Based routing, DEADs-Depth and Energy Aware Dominating set, RBCMIC-Region Based Courier-nodes Mobility with Incremental Cooperative.

Uneven clustering boosts the size of the cluster far from BS and minimizes the size of the cluster closer to it. Since they have fewer Cluster Members (CMs) and generate less traffic, smaller clusters close to the BS require more inter-cluster traffic. Similar to this, larger clusters located further away from the BS have extra CMs and spend huge time interacting with one another. As a result, hot-spot issues are resolved by unequal clustering, which allows all CHs to have an equal quantity of energy. For an

Table 3. Analysis of reliability-based machine learning methods.

Ref. No.	Year	Protocol	CH selection	Cluster size	Approach	Inference
[33]	2020	Using an ensemble of fuzzy clusters.	Level of the fuzzy cluster based on weights.	Equal	ML	Each fuzzy cluster's unreliability is estimated to determine how reliable it is.
[34]	2019	RE-TOPSIS	Depends on threshold and index values.	Equal	ML	Careful choice of CH, reduced energy use, and reliability.
[35]	2020	Real-time reliability assessment.	Not stated.	Equal	ML k-means	The reliability result is calculated for each subsystem.

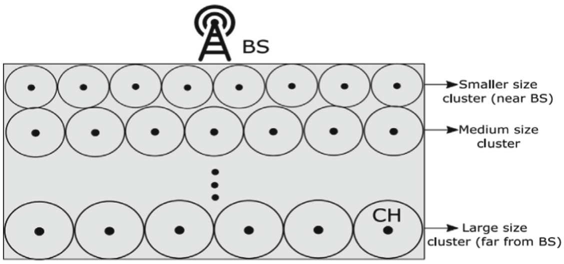

Fig. 3. Unequal clustering in WSNs [Source: Amutha, J et al., 2021]

energy-efficient WSN, many researchers provide various unequal clustering algorithms. To accomplish this effort, however, was inspired by the lack of study in unequal clustering techniques based on machine learning approaches. This section explores unequal clustering algorithms in depth and conducts an analysis based on the various cluster features.

5.1 Machine Learning Methods for Unequal Clustering

Distributed Unequal Clustering using Fuzzy logic (DUCF) modifies the allocation of nodes fairly among to clusters for prevent hotspot issues [22]. Many fuzzy based methods provide equal energy among CHs, prevent the hot-spot problem by considering additional input parameters and fuzzy rules, and extend the network life time [28, 38–40]. The input metrics to the fuzzy inference system (FIS) is the balancing energy, the distance to the sink node, and the degree of the nodes. The output measures are the size of the cluster and the choice to become CH. Table 4 displays the various machine learning methods-based uneven clustering methodologies.

6 Conclusion

In order to achieve efficient energy usage, this study concentrates on clustering and cluster-based algorithms. The effectiveness of clustering as a method of reducing energy consumption is considered in this review, along with the energy efficiency of WSN nodes. It uses machine learning methods to provide information on a range of topics, such as cluster head selection, cluster formation, unequal clustering, reliability and routing. The corresponding data is presented in their respective tables.

Table 4. Machine learning-based approaches for unequal clustering

Ref. No.	Year	Protocol	CH selection	Cluster size	Approach	Inference
[22]	2016	DUCF	Depends on the node degree, sink node distance, and residual energy.	Unequal	Fuzzy (ML)	Load balancing, improves network lifetime.
[28]	2018	DFCR	Higher energy sensor nodes close to the base station.	Unequal	Fuzzy (ML)	Effective use of energy and energy balance.
[36]	2019	EUDFC	According to turn based schedule.	Unequal	Fuzzy (ML)	Increase the lifetime.
[37]	2018	FUCA	Based on distance, node density and energy.	Unequal	Fuzzy (ML)	Energy efficiency is achieved.
[38]	2019	EAKDE	Energy remaining and distance to sink node.	Unequal	Fuzzy (ML)	Energy loss between CHs is balanced.
[39]	2022	GBK, GBK-R	Based on the nearest node to the grid cell in the cell grid.	Unequal	k-means algorithm-based grid-based routing.	Increased network lifespan and network stability.
[40]	2021	Fuzzy-based	Based on the simplifying the creation and upgrading of clusters	Unequal	sleep scheduling, fuzzy logic and machine learning	Extends the life of the sensor network by maximising the energy use of cluster heads and node members.

DUCF – Distributed Unequal Clustering using Fuzzy logic, DFCR – Distributed Fuzzy logic-based unequal Clustering approach and Routing algorithm, EUDFC – Enhanced Unequal Distributed Type-2 Fuzzy Clustering Algorithm, FUCA – Fuzzy based Unequal Clustering Algorithm, EAKDE – Energy-Aware adaptive Kernel Density Estimation, GBK – Grid-based K-Means Clustering Protocol, GBK-R – Enhanced grid-based k-means clustering protocol.

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