AI-Driven Hierarchical Routing Protocol for Energy-Efficient Wireless Sensor Networks: Review

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Abstract: Wireless Sensor Networks (WSNs) are widely used in various fields including environmental monitoring, healthcare monitoring, industrial process monitoring, smart infrastructure and others. However, in spite of their popularity, the limited energy of the sensor nodes is still a significant challenge for sustainability and effectiveness of the networks. The main drawback of the conventional hierarchical routing approaches such as LEACH and HEED is the use of fixed or probability-based cluster-head selection solutions that result in the unbalanced energy consumption of the network nodes. To resolve this problem, this study proposes an Artificial Intelligence–Driven Hierarchical Routing Protocol (AI-HRP) which combines Deep Reinforcement Learning (DRL) for intelligent cluster-head selection and route management. The proposed framework is based on a Deep Q-Network (DQN) model which is used to select the optimal cluster heads based on different network parameters, such as, residual node energy, cluster density, link reliability, traffic condition etc. Moreover, a multi-level hierarchical structure is used to mitigate communications overhead while promoting scalability. The results of the simulations show that the proposed AI-HRP is superior to various existing hierarchical routing techniques in terms of network longevity, packet delivery performance, and overall energy utilization.

Keywords: Wireless Sensor Networks, Hierarchical Routing, Deep Reinforcement Learning, Energy Efficiency, Cluster Head Selection, Network Lifetime.

Introduction

Wireless Sensor Networks (WSNs) have considerable applications in unattended and dangerous environments such as disaster-prone regions with toxic gases, radioactive regions, structural health monitoring systems, battlefields, healthcare applications and smart agriculture [1], [2], [3]. However, the advent of Micro-Electro-Mechanical Systems (MEMS) and wireless communication technologies has spurred the popularity of WSNs in these applications [4].

As shown in Figure 1, a typical WSN is composed of sensor nodes, sink nodes and a sensor field (SF) [5], [6]. The sensor nodes are used to sense parameters like temperature, humidity, pressure etc. of the environment or physical parameters and send data to the user via sink nodes. These nodes sense events of interest and relay sensed data towards the sink node continuously [7].

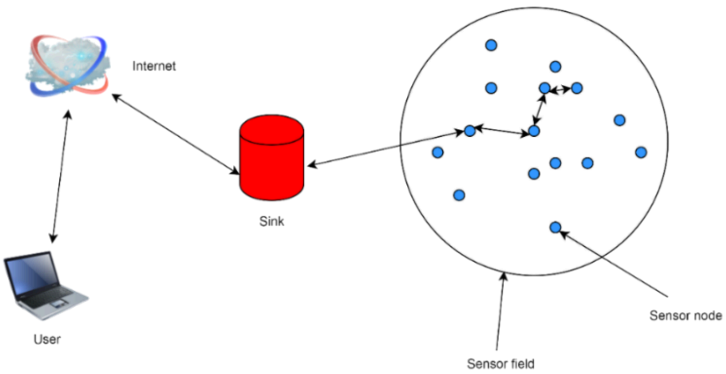

Figure 1: Architecture of WSNs

In static sink based networks, sensor nodes at the vicinity of sink are heavily responsible to forward data from far away nodes [8]. Because of this, these nodes burn out faster than the rest, causing premature node failure and degradation of the overall network performance. This effect is known as the energy hole problem, hotspot problem or crowded center effect (see Figure 2) [9].

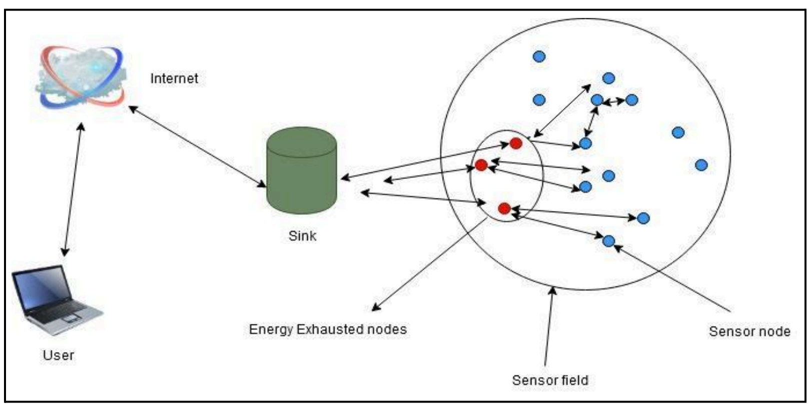

Figure 2: Energy hole Problem

To address this issue, mobile sinks have been introduced in WSNs. While mobile sinks offer some balance to energy use, they also bring added challenges such as sink location information maintenance and update [10]. One of the easiest ways to spread the information about the location of sinks is by flooding, but it causes too much network overhead and consumes more energy in resource-poor sensor networks [11].

Energy efficient solution to this problem is hierarchical routing protocols. In such protocols, the higher levels (called cluster heads) are tasked with aggregating data from sensor nodes, updating sink location details and relaying aggregated data to the mobile sink, whereas the lower level nodes are responsible for sensing operations [12]. Most of the existing hierarchical routing strategies, however, use random or heuristic strategies to select the cluster heads that lead to unequal energy consumption and network lifetime [13].

Artificial Intelligence (AI) and more specifically Deep Reinforcement Learning (DRL) have recently given rise to adaptive and intelligent decision making in dynamic networks. Inspired by the developments, this paper suggests an AI-assisted hierarchical routing till DRL for better energy saving, optimal routing selection, and better lifetime of wireless sensor networks [14], [15].

Related work

Several, Mobile sink based hierarchical routing protocols have been proposed in last decades. In this section we revied theses routing protocols with different virtual infrastructure used for routing.

Wei et al. [16] proposed the Cluster-Based Energy Optimization Protocol with Mobile Sink (CEOMS) for wireless sensor networks. The protocol employs an energy-density metric to identify suitable cluster heads by considering factors such as the residual energy level of sensor nodes and the concentration of neighboring nodes. A mobile sink follows a two-dimensional movement pattern and collects data from all sensor nodes during a communication round. To improve network coverage, a mobility performance function increases the likelihood of distant nodes being selected as cluster heads. After cluster-head election, advertisement messages are broadcast to nearby sensor nodes, which associate with clusters based on the received signal strength. In the data-gathering stage, the sensed data from the member nodes is sent to the corresponding cluster head in the time series as defined. The cluster head aggregates the data, and then sends the aggregated information to the mobile sink. The complete communication cycle is when the mobile sink has finished collecting data from all the cluster heads.

Mirania et al. [17] proposed an energy-efficient routing scheme with Cluster Coordinator Nodes (CCNs) which uses mobile sink nodes. In this method, the sensing field is divided into five equal-sized clusters with a desired balance in the distribution of sensor nodes within each cluster. The selection criteria for the cluster-heads are residual node energy, proximity to the cluster and average distance to neighboring nodes. To alleviate the communication load on the cluster heads, a coordinator node is installed in the center of each cluster, which can be recharged. These coordinator nodes are intermediate relays between the cluster heads and the mobile sink. Data packets are sent straight to the cluster head if it is near the mobile sink. If not, the cluster head will send the aggregated data to the coordinator node which will then send the data to the sink. This mechanism reduces the amount of working energy utilization of regular sensor nodes and helps in the extension of network operation.

On wireless sensor networks with mobile sink, Jain et al. [18] proposed the Event-Driven Virtual Wheel-Based Data Dissemination (EDVWDD) scheme. The main objective of the protocol is to minimize the communication overhead required for the regular sink location advertisement and to achieve efficient dissemination of the sink position information. This approach to data transmission only occurs when an event happens, reducing the amount of unnecessary communication. To achieve efficient access to the sink location information, a virtual wheel topology is built over the sensing region. The rest of the nodes are called sensor nodes and the rest of the nodes that form the wheel are called wheel nodes. Only the wheel nodes have up-to-date sink location information; sink coordinates do not need to be broadcast through the network. When needed, regular sensor nodes ask for sink coordinates from wheel nodes in their vicinity. Once the location of a sink is detected, sensed data is passed on using a geographic routing strategy that chooses efficient forwarding paths, which decreases delay in passing data and enhances the routing efficiency.

Amutha et al. [19] designed an Energy-Efficient Cluster-Based Hybrid Routing Optimization Protocol for wireless sensor networks, which have two versions: HBACS (for static sinks) and HBCAM (for mobile sinks). The protocol includes two steps: firstly, cluster-head selection based on the butterfly optimization algorithm, and secondly, routing based on the Ant Colony Optimization algorithm, in which the energy efficiency is improved. There are five phases of HBCAM. At the network initialization stage, nodes are depicted as sensors, with their position and ID. During the cluster-head election phase, nodes are considered according to several parameters such as residual energy, intra-cluster communication distance, distance to sink, node degree and centrality measurement. Next, the formation of clusters based on energy and distance matrices is done to arrange nodes efficiently. The protocol also features a mobility-aware function that takes account of the mobility characteristics of a sink (e.g., speed and position) to improve energy management. At last, the routing stage identifies the energy efficient routes in consideration of the parameters such as residual energy, distance of communication and connectivity and increases the longevity of the network.

Verma et al. [20] suggested an energy and delay efficient data acquisition mechanism for virtual-grid based wireless sensor networks with mobile sinks. The sensing area is divided into a virtual grid structure, with the chosen grid cells as virtual points (VPs) for data collection. The mobile sinks move in a pre-defined trajectory which starts and ends at the base station and visits all the VPs. While data is being gathered, the sink will temporarily halt in each VP to gather data from nearby grid regions. Each cell in the grid elects a Grid Cluster Head (GCH) to gather data coming from Grid Cell Members (GCMs). When the mobile sink reaches a VP, the GCHs that are in the VP directly communicate their aggregated data to a stationary sink by single hop communication. This will lead to more efficient data collection and less transmission delay.

The Quadrangle-Based Clustering Routing (QBCR) protocol is proposed by Bagga et al. [21] that partitions the sensing field into clusters with the shape of a quadrilateral based on the energy node characteristics. The protocol is specifically designed for heterogeneous wireless sensor networks, and classifies nodes into three energy classes: normal nodes, intermediate nodes and advanced nodes. These energy characteristics are then used to determine the cluster formation and deployment strategies, in order to have an energy balanced network consumption throughout. Furthermore, the number of cluster head differs from region to region which makes better utilization of resources and more stability of network.

For large scale wireless sensor networks, Wang et al. suggested an Adaptive Cluster Radius Multihop Routing Protocol with Direction Awareness (ACRM) [22]. The protocol uses the energy disparity metric based on the Gini coefficient for cluster-head selection and for dynamically changing the competition radius of individual nodes. This is done by creating an auction-like process to assign cluster-heads, and the nodes with the highest bids will obtain leadership. To prevent excessive energy depletion of weaker nodes, a price-decay mechanism is incorporated into the selection procedure. For intra-cluster communication, a hierarchical decision-making approach identifies suitable relay nodes to reduce overall energy consumption. Inter-cluster communication relies on a direction-aware scoring mechanism that evaluates both residual energy and forwarding direction to establish multihop routes. This strategy minimizes routing detours and prevents inefficient reverse-direction transmissions, thereby improving overall routing performance and energy efficiency.

The proposal “Hybrid Deep Reinforcement Learning and Bio-Inspired Optimization for Adaptive Routing and Clustering in Wireless Sensor Networks” by Basim Jamil Ali received approval [23]. The proposed routing method develops a new Hybrid Approach that combines two methods: Whale Optimization Algorithm WOA to find energy aware cluster heads, Deep Reinforcement Learning DRL to provide an adaptive multi-hop routing protocol. The proposed hybrid DRL-WOA will allow optimizing the cluster heads and routing nodes for optimized routes in order to reduce energy consumption and optimize energy efficiency by optimizing hop distance to make long-lasting and reliable communication processes.

The table 1 shows the comparative study of the various hierarchical routing protocol with related work.

Table 1. Comparison of various Hierarchical routing protocols

Routing Protocol	Methodology	Advantages	Limitations
CEOMS	Use energy density function for electing cluster head, according to residual energy and density of nearby sensor node.	Selection of cluster head in each round balance the cluster head load.	Large Size of cluster increase energy consumption.
CCO	Network is divided in equal number of clusters with equal SENNs. Data is transmitted through cluster coordinator nodes.	Cluster coordinator node introduced in every cluster for CH load distribution in data transmission to sink.	Number of clusters are fixed (five), which increase energy consumption.
EDVWDD	Multiple virtual wheel infrastructures is created according to the length of SF and communication range of SF. Wheel node created backbone structure for data transmission.	Reduce the overhead of mobile sink location advertise by wheel nodes.	Frequent re-construction of virtual wheel structure. Not suitable for periodic-event application.
HBAC	The HBAC protocol operates through five sequential stages: network representation and initialization, identification of the most suitable cluster heads, cluster construction, evaluation of the mobile sink's mobility characteristics, and energy-efficient data delivery through optimized routing paths.	Can be used for both Static sink and mobile sink.	Static sink introduce energy hole problem. Single layer cluster formation.
EDEDA	Subset of grid cells are considered as VPs where mobile sink travels for data acquisition.	Optimal VPs selection for data transmission.	Fixed trajectory path for mobile sink. VPs susceptible for hotspot problem.

ACRM	CH selection done by an energy disparity factor quantified based on the Gini coefficient.	Suitable for large scale WSNs	Its complex clustering and routing mechanisms may increase computational overhead and scalability challenges.
DRL-WOA	The framework combines Whale Optimization Algorithm and Deep Reinforcement Learning, where WOA facilitates intelligent cluster-head election and DRL enables adaptive multi-hop routing, thereby achieving efficient energy management and extending the lifespan of the wireless sensor network.	Coordinated clustering and adaptive routing decisions improve the network lifetime.	DRL–WOA assumes stationary sensor nodes, relies on computationally intensive offline DRL training, and lacks validation on very large-scale or real-world deployments.

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