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Enhancing Energy Efficiency in IoT Wireless Sensor Networks: AI-Driven Clustering and Routing Protocols

Mohammed Younus Mohammed

Department of Electrical and Computer Engineering, Altinbas University, Istanbul, Turkey, m07813404000@gmail.com

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ABSTRACT

The Internet of Things (IoT) is now a disruptive technology that gives electronic devices the capacity for communication and cooperation in multiple fields. This research aims to enhance the efficiency of WSNs by including IoT and sophisticated energy-saving methods. The study is based on the "Modern Cluster Supervisor-Based Cluster Head (MCSBCH)" selection algorithm and Token Broker- Based Routing (TBBR), which applies Reinforcement Learning (RL) to improve energy management, clustering, and routing. The simulation results show that the RL-enhanced MCSBCH protocol has a packet delivery ratio of 66%, which outperforms ABR and 3LHHBTD protocols with PDRs of 42% and 22% respectively. The application of RL makes a significant improvement in the energy consumption as well, and saves energy for 25% more in MCSBCH + RL and prolongs network lifetime till 90%, while MCSBCH only consumes 50% of energy and has 55% network lifetime. It is shown that the proposed algorithms provide significant gains in network performance, energy consumption, and scalability, which are well-suited for many wireless applications such as disaster monitoring, health monitoring, and smart cities. In the future, integration of AI with developing technologies such as edge computing and blockchain may be investigated for improved scalability, security, and energy efficiency in WSNs with the IoT.

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1. Introduction

Wireless Sensor Networks (WSNs) are central to the Internet of Things (IoT), which enables things integration and efficient data sensing, monitoring, and processing. Examining the possibilities of WSNs on IoT, various issues must be overcome in practice to meet the potential of WSNs [1]. These problems are in terms of energy, network lifetime, and security. When solving these problems, this study aims to provide new algorithms and methods of improvement of the efficiency and security of the WSNs for the IoT [2]. WSNs consist of tiny sensor nodes that form their own network to perform tasks with minimal or no human assistance. These networks are employed in various uses, such as in environmental surveillance, medical as well and disaster management [3]. Energy conservation is a big factor

∗Corresponding author: Mohammed Younus Mohammed

Email addresses: *m07813404000@gmail.com*

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for WSNs to ensure their efficient and reliable working, because of sensor node batteries, which are not readily replenished or recharged. [4]. In addition, it is crucial to secure WSNs since the communication reliability can be affected by the presence of attacker nodes and other vulnerabilities. Cryptographic means to tackle security issues and hod been mainly cryptographic-based. Nevertheless, it is necessary to consider lightweight and energy-efficient security schemes fulfilling the particular needs of WSN embedded in the IoT [5]. In order to address these research areas and to cope with challenges of WSNs, this paper introduces the "Modern Cluster Supervisor-Based Cluster Head selection (MCSBCH)" scheme and Token Broker-Based Routing selection strategy (TBBR). The MCSBCH algorithm attempts to improve the efficiency of network operation by utilizing an improved cluster head selection mechanism together with a high-performance clustering-based routing protocol. TBBR, on the contrary, is designed to increase the lifetime of networked communication and provide a high level of secure access by suggesting an optimal route through which data can be transferred [6]. The importance of this study is to provide the basis for energy-efficient clustering protocols, routing techniques, and lightweight security mechanisms in the WSN of IoT. Through addressing energy consumption, network lifetime, and security issues, the proposed algorithms and schemes may enhance the performance as well as reliability of WSNs in various applications [7]. In this study, we assume application of the MCSBCH algorithm and TBBR strategy would contribute to better energy conservation, longer network lifetime, and improved security in WSNs-IoTs networks. The research further seeks to substantiate such a hypothesis with comparisons and performance measurements, as it can be seen to offer useful observations for WSN development in the IoT domain.

2. Literature review

Clustering, which is a well-known technique of topology control, is an essential part in reducing the power consumption of sensor networks. Selecting a CH is capable of evenly distributing load, controlling data transmission adaptively, and reducing energy consumption so as to prolong the life of the sensor network.

Energy-efficient routing and clustering in wireless sensor networks (WSNs) have been widely investigated because node batteries are typically non-rechargeable and difficult to replace. Early work focused on cluster-based routing built around the Low-Energy Adaptive Clustering Hierarchy (LEACH) and its descendants. Compared several clustering and routing strategies (PSO- and GSO-based schemes, FCM hybrids, and RSOM variants) against LEACH-WSN and EBC-S, showing that meta-heuristic optimization can significantly increase the number of alive nodes, reduce overall energy consumption, and improve throughput compared with the baseline LEACH family [8].

LEACH-type protocols and optimization-based routing into conceptual taxonomies. Provided a conceptual framework and comparative study of energy-efficient routing protocols, classifying clustering schemes into "traditional" and "optimization-based" categories and highlighting the limitations of direct single-hop communication from cluster heads (CHs) to the sink in classical LEACH (unbalanced CH energy and routing holes). Specifically on LEACH-based hierarchical protocols, reviewing LEACH and several successors, and then introducing TLEACH, which combines the T-LEACH threshold rule for CH selection with sleep–awake scheduling. Simulation results showed improved lifetime over LEACH and T-LEACH, but decisions remained largely rule-based without explicit AI or learning [9]. To overcome the rigidity of purely rule- or threshold-based clustering, several authors have introduced AI-based cluster formation and CH selection. Prasad et al. proposed an Energy-Efficient Cluster-Based Artificial Intelligence Routing protocol in which a self-organizing map (SOM) neural network forms clusters by considering node position and residual energy, and then selects CHs accordingly. Their results showed lower energy consumption and longer network lifetime than traditional clustering methods, though the work was evaluated in a conventional WSN setting with limited consideration of IoT-specific traffic heterogeneity [10].

Hybrid bio-inspired and neural approaches have further extended the SOM-based design. Ahmed et al. developed a bio-inspired energy-efficient cluster-based protocol for IoT in disaster scenarios, where SOM is used for initial cluster formation, and an Artificial Bee Colony (ABC)–Firefly optimization adjusts cluster sizes based on CH energy and distance to the sink. The protocol supports multi-hop relaying and targets harsh emergency environments, demonstrating gains in lifetime and coverage compared with classical cluster-based schemes, but it is specialized for disaster-response use cases and does not explicitly address generic IoT application mixes. A cluster-based routing protocol that uses SOM in combination with Butterfly Optimization and Ant Colony Optimization for CH selection, reporting improved energy balance but still relying on offline meta-heuristic tuning rather than online learning [11].

Fuzzy-logic and swarm-intelligence driven clustering. Proposed CHHFO, an efficient cluster-based routing protocol that uses a fuzzy-logic system (remaining energy, distance to base station, and neighbour count) to select cluster heads, while a collaborative Harris Hawks Optimization algorithm chooses optimal relay CHs [12]. The scheme improved throughput and reduced energy consumption relative to several Harris-Hawk-based baselines, showing that combining fuzzy reasoning with advanced meta-heuristics can yield robust cluster-based routing. However, CHHFO still relies on a fixed rule base and offline optimization rather than adaptive learning that reacts to changing IoT workloads [13].

Neural networks have also been integrated directly into LEACH-style protocols. A neural-network-enhanced LEACH variant that incorporates an Energy-Hole Removing Mechanism (EHORM) together with a trained neural model to select CHs and mitigate the classical energy-hole problem [14]. Their simulations indicated significant gains in lifetime and energy balance compared with LEACH and ILEACH, but the work remained limited to a single-sink WSN scenario without explicit modelling of IoT traffic classes or quality of service requirements [15].

An AI-driven energy-aware data aggregation and routing protocol in which residual energy, node proximity, and local traffic load are used for adaptive CH selection, while a Deep Q-Network (DQN) learns energy-efficient multi-hop routes. Compared with LEACH, PEGASIS, and HEED, the DQN-based scheme achieved a longer network lifetime, better packet delivery ratio, and reduced latency, illustrating the potential of DRL for joint clustering and routing decisions [16].

In the specific context of IoT-based WSNs, researchers have begun to integrate AI not only for routing but also for resource allocation and cross-layer optimization. Alrabadi proposed an AI-powered resource allocation scheme using the Whale Optimization Algorithm (WOA) to minimize communication cost, balance load, and increase energy efficiency in IoT-centric WSNs. The study demonstrated improved lifetime, throughput, and spectral efficiency, confirming the benefits of AI-based optimization in heterogeneous IoT scenarios, although clustering and routing were treated at a coarse, resource-allocation level rather than as a tightly integrated protocol [17].

Classical LEACH-based clustering and fixed routing rules, through optimization-based and fuzzy/neural enhancements, to fully AI-driven clustering and RL/DRL-based routing that can adapt to dynamic conditions. However, many existing AI-enhanced protocols are still evaluated in relatively simple WSN scenarios, focus on either clustering or routing (rather than their joint optimization), or only partially account for the heterogeneity and quality of service demands of IoT applications. The present work on AI-driven clustering and routing for energy-efficient IoT-WSNs addresses these gaps by jointly optimizing cluster formation and multi-hop routing under IoT-relevant constraints, and by comparing classical and AI-based baselines within a unified experimental framework.

3. Problem Statement

Wireless Sensor Networks (WSNs) in tandem with the Internet of Things (IoT) are indispensable for various applications that include environmental monitoring, healthcare, agriculture, and smart cities. But WSNs suffer from great challenges in terms of energy, lifetime network, and secure issues that suppress their effectiveness and scalability in IoT settings.

Energy in WSNs is one of the most important issues. Because sensor nodes' batteries are battery-driven, which cannot be easily replaced or charged, the energy-saving protocol is very important for network lifetime improvement. With the growing number of things, in the IoT paradigm energy consumption issue has become more challenging. The traditional techniques for regulating energy consumption fail to adapt well to dynamic networks, leading to inefficient utilization of available resources and node death. Another important challenge is network lifetime, i.e., the time that a WSN can work maintaining adequate performance levels before nodes run out of energy. The larger and more complex the network is, the higher the probability of the same energy consumption rate at different nodes. If the distribution of energy is not properly controlled, an early retirement or a decrease in dependability of the network can be experienced, as well as high maintenance costs. The intelligence in the existing protocols may not be able to adapt to changing network/traffic conditions (e.g., traffic loads may vary, while energy is available in an increasing/decreasing order), resulting in haphazard selection for forming base stations or routing paths, thus leading to energy waste.

The security issues worsen the difficulties in IoT-based WSNs. The more these networks interconnect, the higher the risk of attacks like eavesdropping, data alteration, and denial of service. The traditional cryptographic algorithms are usually too much for power and processing resource constrained sensor nodes. lightweight and energy-efficient security mechanisms are necessary to protect the data confidentiality and integrity while not degrading the performance.

It is well-known that AI-based methodologies have great potential to tackle the above, important problems that cannot wait. Through machine learning and artificial intelligence, energy management of the nodes could be optimized, the network lifetime is extended by intelligent clustering and routing, and security is ingrained through real-time anomaly detection and adapting security protocols. AI-enabled algorithms through which the network can adaptively operate by considering instantaneous data to make decisions, such as cluster-head election, routing path identification, and energy utilization better. Further, AI models are capable of forecasting a network failure, security threat, proactive maintenance, and the welfare state of the network.

In this context, it is important to investigate the capability of AI-oriented techniques (in this work, we analyze the introduced Modern Cluster Head concept and the Model-Based Clustering Technique Enhanced with Token Broker Routing for Computational Engineering Networks) to promote higher energy efficiency and network lifetime extension, together with security issues in WSNs integrated with IoT.

4. Proposed work.

In this part, we describe the proposed strategies for improving the effectiveness and security of WSNs in the Internet of Things (IoT) based on AI. The major algorithms and strategies proposed here are as follows: The "Modern Cluster-Supervisor-Based Cluster Head" (MCSBCH) selection algorithm, Token Broker-Based-Routing (TBBR) strategy, AI-enabled energy management, and AI-based security optimization. These are AI-based approaches to solve the important issues of energy, network lifetime, and security in WSNs.

4.1 MCSBCH Algorithm

The selection of VCH proposed in this study is an MCSBCH-based approach aiming to enhance the energy efficiency and stability of IoT-integrated WSNs. The main idea of the MCSBCH algorithm is to present a dynamic shaping CS in order to manage more effectively the CH selection procedure based on real-time energy predictions and node conditions. In a typical clustering algorithm, the organizer may be chosen in accordance with static thresholding or is selected randomly, leading to unbalanced energy utilization and early death of the node. In response to these factors, the MCSBCH algorithm uses artificial intelligence (AI) to predict node energy levels in advance. The energy and status of all nodes are kept as records by the CS (Cluster Supervisor), and based on these remaining energy levels and the vicinity of other nodes, the CH (Cluster Head) is elected. The node having the maximum energy reservoir is selected as the cluster head. This guarantees that the cluster head node always has enough capacity to deal with data transmission without draining power too fast. Also, in the algorithm, another backup node is pre-determined to be a cluster head if the energy of the current cluster head node runs out. This smart selection mechanism, assisted by AI algorithms, minimizes the probability of single points of failure inside the network, which improves the overall stability of D2D communications, while extending the network's lifetime by effective balancing energy consumption between nodes. By the effect of predicting energy dying early, the system can make informed decisions for cluster head and backup node regarding more efficient utilization of energy and better network performance. The step-by-step procedure of the proposed MCSBCH with RL-assisted cluster-head selection is summarized in Algorithm 1.

Algorithm 1: MCSBCH with CS and RL-assisted CH switching

Input: set of sensor nodes $\boldsymbol{N}$, initial energy $\boldsymbol{E_i(0)}$for each node
Output: elected CH and backup CH for each round

1. Deploy nodes and initialize Cluster Supervisor (CS).
2. Initialize Q-table $\boldsymbol{Q(s,a)}$(or RL model parameters).
3. For each, round $\boldsymbol{r = 1, 2}, \ldots$do
   4. Each node $\boldsymbol{i}$sends its residual energy $\boldsymbol{E_i(r)}$And local statistics to CS.

5. CS computes $\boldsymbol{\hat{E}_i(r+1)}$For all nodes using the prediction model.
6. CS forms candidate set $\boldsymbol{C} = \{\boldsymbol{i} \mid \boldsymbol{\hat{E}_i(r+1)}$dy policy on $\boldsymbol{Q(s_r, a)}$.
9. Apply action $\boldsymbol{a_r}$: elect CH and backup CH accordingly.
10. Run intra-cluster communication and data forwarding for the round.
11. Compute reward $\boldsymbol{r_r}$From PDR, energy consumption, and delay.
12. Observe the new state $\boldsymbol{s_{r+1}}$and update $\boldsymbol{Q(s_r, a_r)}$Using Q-learning.

End

4.1.1 Real-time energy prediction at the Cluster Supervisor (CS)

The Cluster Supervisor (CS) operates in periodic rounds. At the end of each round r, every node iReports its current residual energy $E_i(r)$And the number of transmitted/received packets during that round. The CS then estimates the instantaneous energy consumption rate of the node. i As:

$$\Delta E_i(r) = E_i(r-1) - E_i(r) \tag{1}$$

Based on $\Delta E_i(r)$, the CS predicts the residual energy at the next round using an exponential smoothing model:

$$\hat{E}_i(r+1) = E_i(r) - \lambda_i(r) \tag{2}$$

were

$$\lambda_i(r) = \beta\, \Delta E_i(r) + (1-\beta)\, \lambda_i(r-1) \tag{3}$$

and $0 < \beta \leq 1$is a smoothing factor. Nodes whose predicted energy $\hat{E}_i(r+1)$falls below a threshold $\theta E_{\max}$They are excluded from the Cluster Head (CH) candidate set.
The final CH is selected among the remaining candidates by maximizing a joint metric that considers predicted energy and proximity to the CS/BS:

$$\mathrm{score}_i = w_1 \frac{\hat{E}_i(r+1)}{E_{\max}} - w_2 \frac{d_i}{d_{\max}} \tag{4}$$

where d_i is the distance of the node $i$to the CS (or BS), $d_{\max}$is the maximum distance, and w_1, w_2 are weighting parameters. The node with the highest score_i is elected as CH, while the second-best node is stored as a backup CH.

4.2 TBBR Strategy

The Token Broker-Based Routing (TBBR) technique is used to improve the routing of WSNs integrated with the Internet of Things (IoT) through route paths that are adaptively constructed based on the current network status.

The objective of TBBR is to maintain network stability and security by deploying a series of AI technologies combined with prediction on potential network failures and routing decisions.

Classical protocols often forward data along pre-computed paths or do not take into account current network information during path selection. On the contrary, TBBR uses AI to dynamically determine the state of the network, the energy level of its nodes, data flow, and possible areas of failure. According to these considerations, AI is able to suggest locations where network congestion and failure are most likely to occur, and re-plan route paths so as to avoid the forecasted issues. This data transmission, which is based on prediction, ensures that messages move via the best and stable paths; hence, lower latency and consumption of energy.

Moreover, TBBR involves the use of a token broker to mediate communication sessions and route packets with the aid of the predicted network performance. The token broker continuously, at any given moment, keeps track of the energy and network states and uses machine learning models to determine the most appropriate routing paths. This adaptive feature is added to the rate of transmission and transfer of data, but also to the strength of the network, which minimizes the probability of congestion or breakdown. The next-hop selection algorithm obtained by using the RL is the detailed TBBR routing process, which is shown in Algorithm 2.

Algorithm 2: TBBR with RL-based next-hop selection

Algorithm 2: Token Broker-Based Routing (TBBR) with RL
Input: set of active flows, neighbour tables for each node
Output: selected next-hop for each data packet

1. Initialize token broker and RL agent (Q-table or model).
2. For each routing decision epoch $\boldsymbol{t}$do
   3. Token broker collects: residual energy of candidate relays, link quality, queue length, and recent PDR.
   4. Construct state $\boldsymbol{s_t}$From these features.
   5. Action selection: choose next-hop relay $\boldsymbol{a_t}$using $\boldsymbol{\epsilon}$-greedy policy.
   6. Forward packets via selected next-hop.
   7. Measure energy consumed, successful deliveries, and delay; compute reward $\boldsymbol{r_t}$.
   8. Observe the new state $\boldsymbol{s_{t+1}}$And update the RL model (Q-learning update).
3. End for

4.3 AI-Driven Energy Management

The energy issue is a crucial issue in WSNs where sensor nodes are mostly powered by limited batteries. The AI-based energy predictor models give a massive benefit to the optimization of energy consumption as well as load balancing among the network nodes.

Through the inclusion of AI algorithms like Reinforcement Learning (RL), Deep Neural Networks (DNNs), and predictive modeling, the framework can process data from nodes in the network as it appears, and make decisions on-the-fly. This mechanism minimizes the energy consumption since it selects cluster heads and routing paths (and task scheduling) smartly according to the actual network's residual energies, traffic statuses, and predicted failure risk of all nodes. Energy management with AI-enabled edge computing further facilitates load balancing and manages the energy exhaust on any single node. By predicting energy consumption and assigning the workload dynamically, it can prolong network lifetime altogether. This proactive power management solution reduces the “energy holes” phenomenon, where some nodes deplete much sooner and leading to network partitions with deteriorated performance.

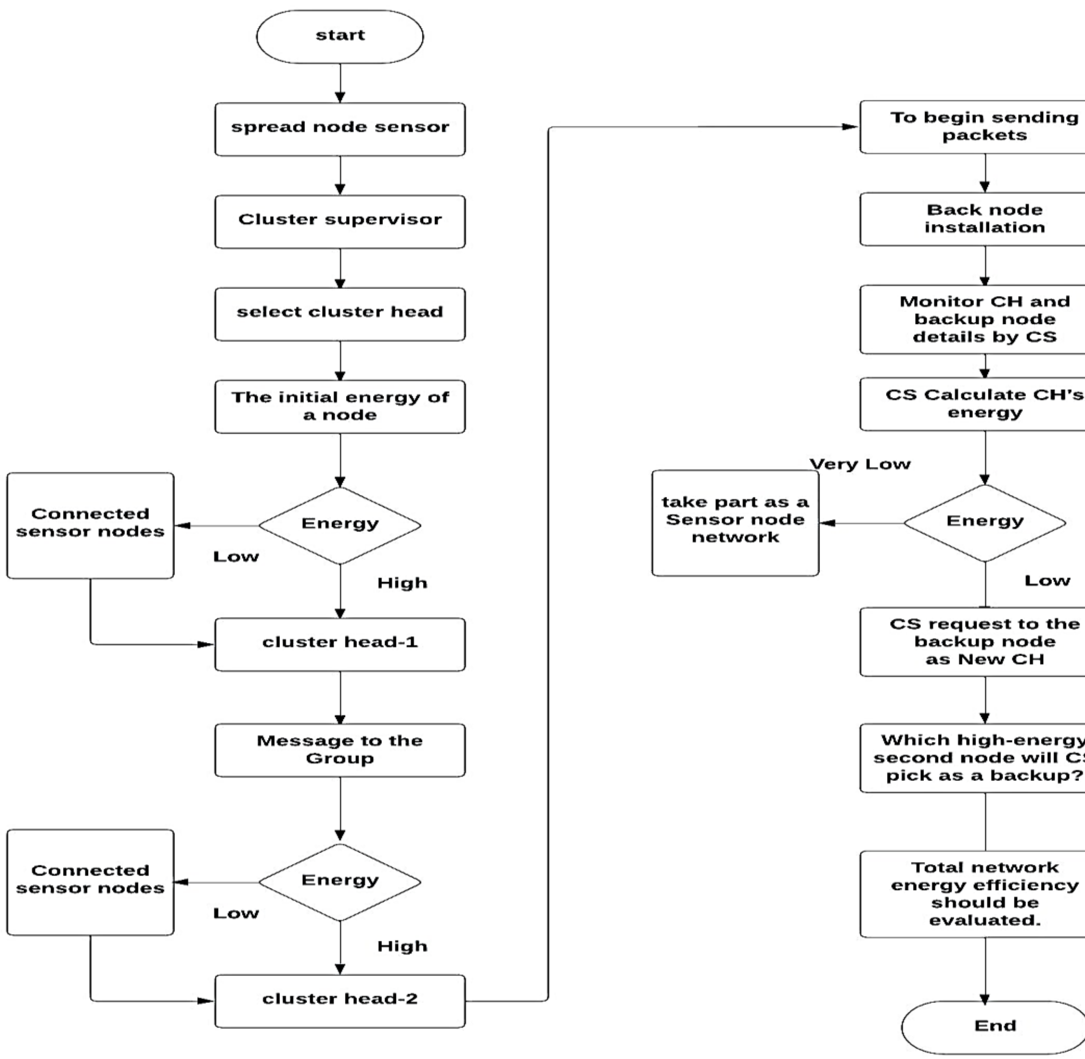

Fig. 1. Proposed mechanism workflow of cluster head selection in WSN.

The process of the MCSBCH algorithm developed for optimal energy utilization and prolonging the life of IoT-based Wireless Sensor Network (WSN) is shown in Fig 1. It starts with the deployment of sensor nodes and activation Cluster Supervisor (CS), which is handling cluster heads election according to the energy levels of the nodes. The initial energy of all the nodes is measured, and the node with the maximum energy is declared as a Cluster Head

(CH). In case the energy of the selected CH is high, it will be responsible for forwarding data in that group and make sure that all its connected sensor nodes are monitored, trying to maintain a load balance.

As the energy of CH1 decreases, if there is enough energy in another node to become Cluster head 2, then the system verifies. If CH energy becomes sufficiently low, a Cluster Supervisor sends an invitation to the backup node to become the new CH. The CS periodically listens to the active CH as well as the backup node to ensure that their remaining energy meets some constraint. The CS selects the standby node that has the largest amount of remaining energy to take on the CH tasks in the event there is a need. This dynamic process with AI enables the network to be stable in its energy dissipation, usage, and resource utilization. Afterward, system-wise energy efficiency is assessed to achieve the best performance. This energy expenditure illustrates the role of MCSBCH in enhancing intelligent decision-making, and thereby the efficient management of energy, extending the network's lifetime by appropriately selecting cluster heads and deploying backup node AI.

4.3.1 Reinforcement Learning model for routing and CH support

We employ a tabular Q-learning–based Reinforcement Learning (RL) agent to support both the MCSBCH cluster-head selection and the TBBR routing decisions. The agent runs at the CS/token broker and interacts with the network in discrete time steps (rounds).

State representation. At each decision step t, the agent observes a compact state vector summarizing current network conditions, including:

- average residual energy of cluster members $\bar{E}_{\text{cluster}}(t)$;
- residual energy of the current CH $E_{\text{CH}}(t)$;
- estimated hop count to the BS;
- local node density (number of neighbours);
- recent packet loss ratio and queue occupancy.
  These features are discretized into a finite set of state bins to enable tabular Q-learning.

Action space. For MCSBCH, actions correspond to: (i) keeping the current CH, or (ii) switching to one of the candidate backup CHs in the cluster. For TBBR, actions correspond to selecting one of the available next-hop relay nodes for each active flow.

Reward function. After each action, the agent receives a scalar reward that combines energy-efficiency and reliability:

$$r_t = \alpha \cdot \mathrm{PDR}_t - \beta \cdot \mathrm{EC}_t - \gamma \cdot \mathrm{Delay}_t,$$

where PDR_tIs the packet delivery ratio in the current interval? $\mathrm{EC}_t$is the normalized energy consumption, and Delay_tIs the average end-to-end delay. Positive rewards are given for high PDR and low energy consumption, and delay.

Learning rule. The Q-values are updated according to the standard Q-learning rule:

$$Q(s_t, a_t) \leftarrow (1-\eta)\, Q(s_t, a_t) + \eta[r_t + \gamma \max_{a'} Q(s_{t+1}, a')] \tag{5}$$

where ηIs the learning rate and γIs the discount factor.

The final input feature vector to the RL agent is:

$$s_t = [\bar{E}_{\text{cluster}}(t), E_{\text{CH}}(t), H_{\text{BS}}(t), N_{\text{neigh}}(t), \text{PDR}_{\text{local}}(t), Q_{\text{occupancy}}(t)] \tag{6}$$

In this way, the RL agent gradually learns to select CHs and routing paths that maximize long-term packet delivery while minimizing energy consumption and delay.

5. Results And Discussion

The MCSBCH algorithm performance is tested by means of MATLAB, which is indeed a well-known simulator among networking researchers. In this work, network simulation acts as a methodology to compute the interplays among different network segments. The elements that are simulated are routers, switches, nodes, access points, and links of communications, all serve to reflect the network behavior. MATLAB is a computer tool that simulates the quality of service and performance of the network. Supported network protocols include multicast, routing, and Transmission Control Protocol (TCP) for wired and wireless networks. Unless otherwise specified, the parameters in Table 1 were kept fixed.

Table 1. Network and Simulation Setup Parameters

Simulation	Parameters
Network area	100 m × 100 m
Number of sensor nodes	20, 40, 60, 80, 100
Node deployment	Uniform random
Initial energy per node	2 J
Radio electronics energy	50 nJ/bit
Data packet size	4000 bits
Channel data rate	2 Mbps
Simulation duration	500 rounds

MATLAB is used to simulate main network parameters like total number of nodes, area of the network, maximum distance for communication, data rate, channel bandwidth, and the IEEE 802.11 MAC protocol as the link layer protocol for this study. These parameters are essential for network modelling in a more realistic way and for fostering an objective estimation of the effectiveness of MCSBCH to improve energy efficiency and overall network performance, as exemplified in Figure 2.

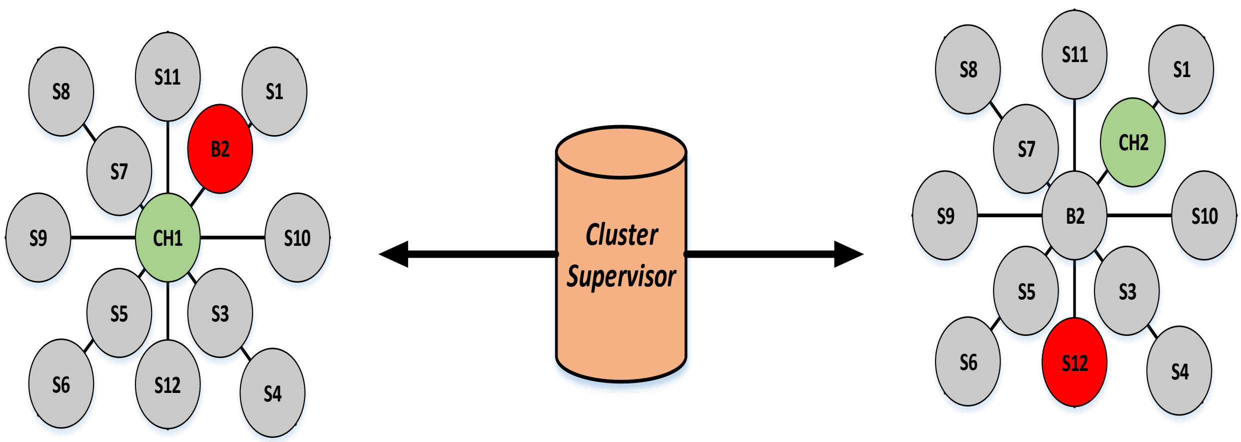

Figure 2. Cluster supervisor nodes distribution

The number of CH changes with the increasing density of node number in a network is plotted graphically in Figure 3. The value of the X-axis stands for the quantities of nodes (varied in 20 ~100), and that of the Y-axis represents the frequency of CH changes. The comparison is between three protocols: MCHBCS (red bars), LHHBTD (blue bars), and ABR (green bars). All three approaches demonstrate the growth of CH Changes with the number of nodes. But MCHBCS has the least number of changes, which is stability in terms of cluster head management. LHHBTD presents a slightly higher value of CH changes, and ABR contains the highest number of CH changes among all node counts. This indicates MCHBCS is capable of realizing more effective management on the cluster head, with increasing network size, whereas ABR may require additional optimizations to improve system stability and reduce frequent changes of CH.

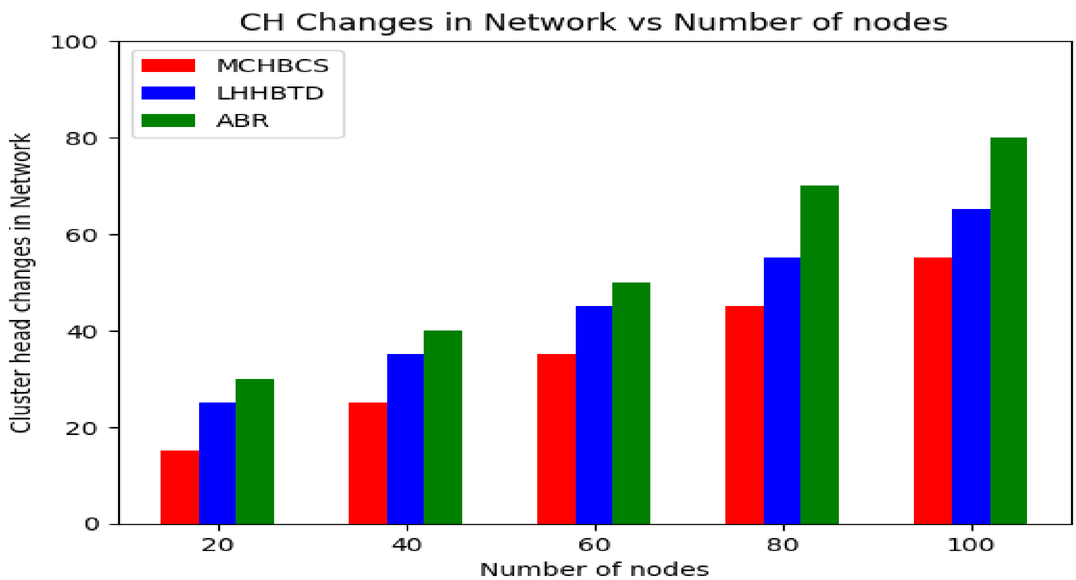

Fig. 3. Nodes Number vs. Cluster Head changes in the network.

In Figure 4, we show the trade-off between the number of collaborating nodes in transmission and its performance according to packet delivery ratio (PDR). In this graph, the X-axis indicates the number of nodes communicating, and the Y-axis is for the packet delivery ratio normalized to each algorithm. Analysis: The proposed MCSBCH algorithm yields a packet delivery ratio of 66% in the simulation results. As a comparison, the delivery ratio of the ABR protocol is 42%, and that of the 3LHHBTD one is 22%. It is observed from the comparison figure, MCSBCH has a better packet delivery ratio than 3LHHBTD and ABR, indicating that it achieves better efficiency in terms of transmission performance.

$$\mathrm{PDR} = \frac{\text{No of Received Packets}}{\text{No of Packets Sent}} \times 100.$$

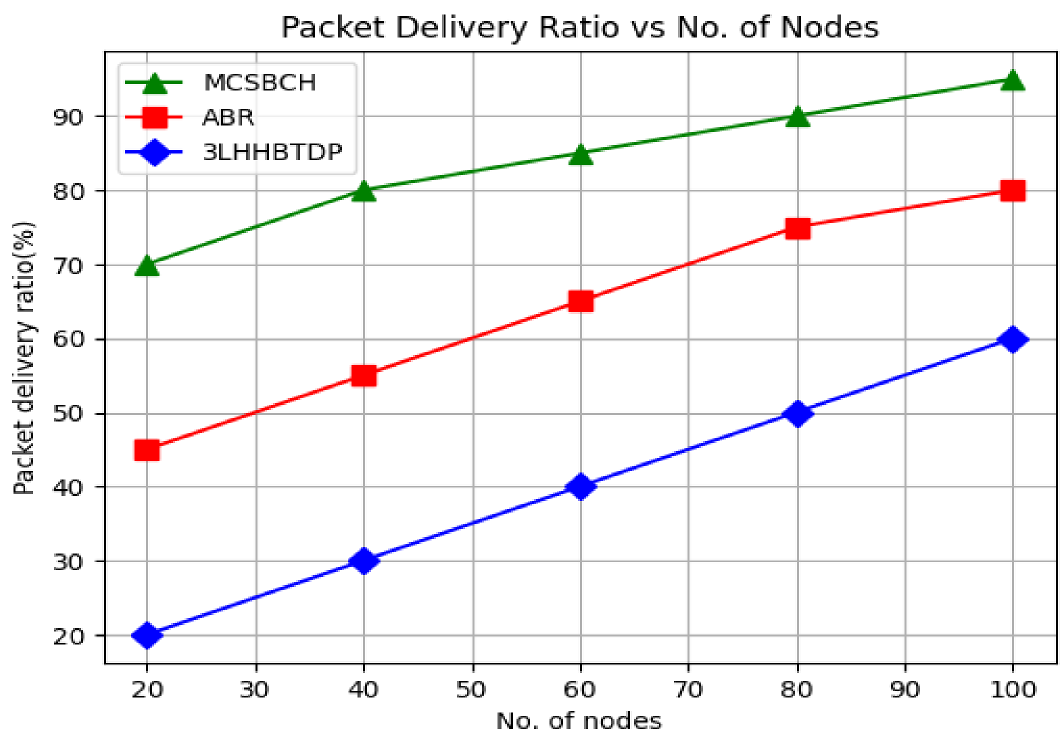

Fig. 4. Ratio of delivery packets vs. No of nodes

The efficiency of protocols is compared in the table and chart tabs, with the energy consumption and network lifetime of each protocol depicted with and without reinforcement learning (RL). The results show that the energy consumption and network lifetime of the MCSBCH (Traditional) protocol are 50% and 55%, respectively. RL simply adds to the energy saving of 25% when added to MCSBCH + RL, the network lifetime also increases as high as 90%. For the TBBR (Traditional) protocol, energy consumption accounts for 70% and network lifetime is reduced to 45%, while when integrating RL in TBBR + RL and energy consumption increases up to 75% of the total energy cost without providing a significant improvement on network lifetime, which slightly improves up to 50%. These differences are graphically depicted in the chart, where blue color stands for energy consumption and red color represents network lifetime. Second, it also indicates that RL has a great effect on the network lifetime, especially in the MCSBCH RL protocol, even though it leads to more energy consumption, as demonstrated with TBBR + RL. This study emphasizes trade-offs between the energy consumption and network lifetime when employing RL, where in some of the protocols an increase in network lifetime results in higher energy consumption.

Table 2. Energy consumption and network lifetime of the evaluated protocols.

Protocols	Energy Consumption (%)	Network Lifetime (%)
MCSBCH (Traditional)	50	55
MCSBCH + RL	25	90
TBBR (Traditional)	70	45

TBBR + RL	75	50

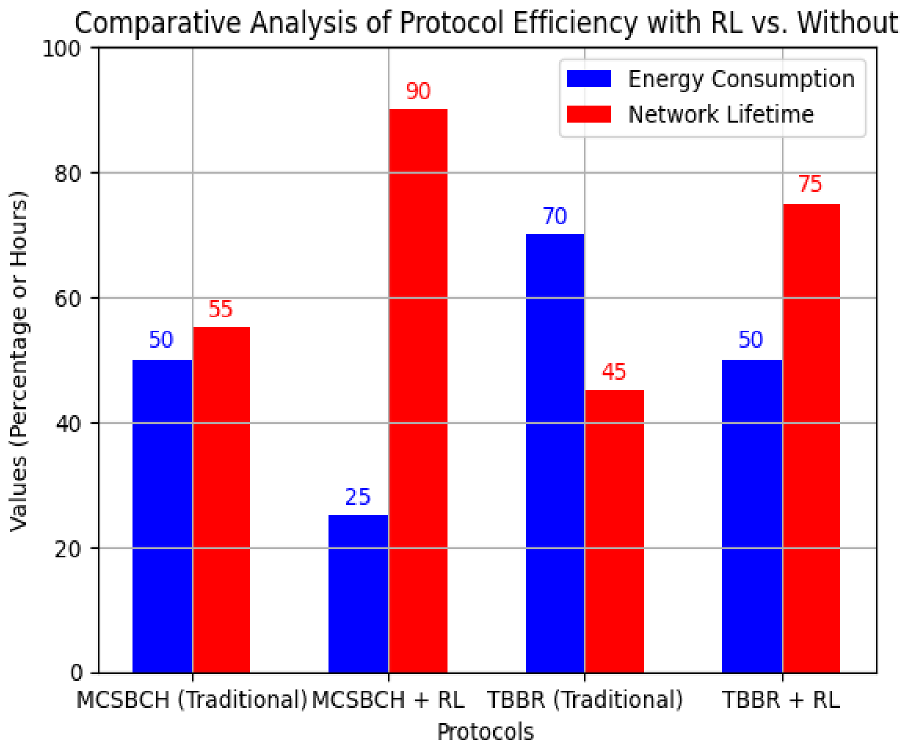

Figure 5. Comparative analysis with and without Reinforcement Learning

Conclusion

This paper deals with the energy consumption and network lifetime problems in IoT-integrated Wireless Sensor Networks (WSNs) via AI solutions. The MCSBCH selection algorithm and the TBBR strategy use an RL approach for optimizing CH selection, route, and energy management. The simulation results show that the MCSBCH algorithm with RL effectively recovers packet delivery ratio and decreases energy consumption, and obtains a 66% arrival rate than ABR of 42% and that of 3LHHBTD with only 22%. This further prolongs network life and makes the operation more stable and efficient. In the future, possibilities can be explored for combining AI with other evolving technologies, such as edge computing and blockchain, to potentially scale out even more, securing in nature presence and resource-efficiency of IoT-based WSNs.

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