Volume 12, Issue 5
October 2023

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

Dynamic Energy-Aware Routing Protocols Using Reinforcement Learning in Large-Scale Sensor Networks

[1]Chandan Kumar, [2] Akrati Shrivastava, and [3]Vineeta Rathore

[1]School of Advanced Computing, Sanjeev Agrawal Global Educational University (SAGE), Bhopal, India

[2] InfoTech Education Society (IES) University, Bhopal, India

[3]Medi-Caps University, Indore, India

E-mail: [1]mckv.chandan@gmail.com, [2]aakratishrivastava93@gmail.com, [3]vineeta.rathore@medicaps.ac.in

ABSTRACT

Recent improvements in healthcare technology have led to significant progress in monitoring patient health using small wireless sensors. In the healthcare field, HealthCare has adopted cost-effective, tiny wireless sensors to send a lot of patient data through networks. One big challenge is efficiently managing data transfer while conserving energy in crowded and large Wireless Sensor Networks (WSN). This paper focuses on creating a smart and energy-efficient routing system using Reinforcement Learning, designed specifically for large sensor networks. To make IoT networks work well with many devices, the paper introduces a method to learn and choose the best energy-saving settings. This involves adjusting important network settings like transmission range, node density, and overall network area using Reinforcement Learning. In this method, the sink node stays in the central position to scale up the network density by three to four times while maintaining the same ratio as the original large network. By fine-tuning these design settings to improve energy efficiency and scalability, we can see how well the suggested protocol makes better routing decisions. This paper demonstrates the potential of modern Reinforcement Learning-based technology in making energy-efficient routing decisions to enhance network performance.

Keywords: Routing, WSN, Reinforcement Learning, Energy efficiency, Large area, Clustering, node density

1. INTRODUCTION

Recently, smart sensor networks have incorporated machine learning as a crucial component. Due to the limited memory and power of IoT devices, they constrain the computing potential of WSN. Collaborations in the Internet of Things (IoT) for healthcare have extensively utilized sensor-based monitoring and administration systems [1].

In summary, WSN finds predominant use in the HC sector, particularly in remote patient health monitoring system. The extensive network is segmented into compact clusters of sensor nodes. However, a significant obstacle lies in the effective transmission of data from sensors to the cluster head in WSN [2]. Consequently, the central challenge revolves around devising a low-energy routing protocol that enhances the overall network lifespan. The subsequent sections of this paper concentrate on the development of an Energy-Efficient (EE) routing protocol, emphasizing the selection of optimal design parameters.

Routing consumes maximum energy since it allows sensors to share information throughout an IoT network [3]. The main contribution of this work is to improve energy efficiency, which is based on the RL routing protocol. Energy efficiency is directly proportional to the network node's stability time. Because of an increasing density of nodes in large area networks, lifetime improvement of a node is a significant problem [4]. Energy efficiency is very critical for keeping a network operational for a longer time. The paper discusses several issues of IoT network routing protocols architecture. It also aims to explore the RL-based learning for improving the WSN routing challenges [5].

Figure 1 highlights the sensors most commonly used during the recent pandemic. The sensors depicted include oxygen sensors for monitoring breathing rate, temperature sensors for illness monitoring, pressure sensors on oxygen cylinders for level observation, pulse sensors for heart rate surveillance, gesture sensors for monitoring patient behavior, and sensors for tracking brain activity [6].

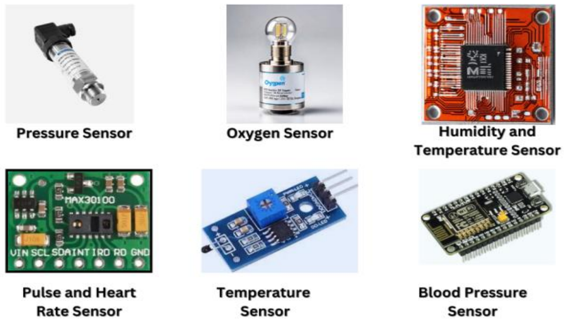


Fig.1: Health Care monitoring Sensors

Within the HC sector, WSN has deployed various sensors, and Figure 2 outlines their frequent applications. These sensors play a crucial role, especially during the recent pandemic [7]. Table 1 represents all the abbreviations used throughout the paper.

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

Table 1. Abbreviations Used in the Paper

Abbreviations	Full form
HC	HealthCare
IoT	Internet of Things
EE	Energy Efficient
RL	Reinforcement Learning
WSN	Wireless Sensor Network
CH	Cluster head
LA	Large Area
MIS	Mobile Information System
RLRP	Reinforcement Learning Routing Protocol
AI	Artificial Intelligence
BS	Base Station
PDR	Packet-delivery-Ration

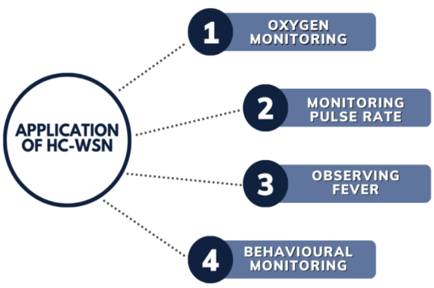


Fig.2: Applications of HC-WSN

By using the RL routing protocol, sensor devices are able to adjust according to dynamic changes in networks [8], such as the sink's location movement and the network's initial energy density as represented in figure 3. The planning and assessment of the larger life of routing protocol based on RL is offered in this paper. Reward signaling [9] is the only element of RL learning that does not include a supervisor. The RL is an aspect of ML and is intended to enhance effectiveness in an unknown network by using the trail-error technique to determine rewards as depicted in figure 3.

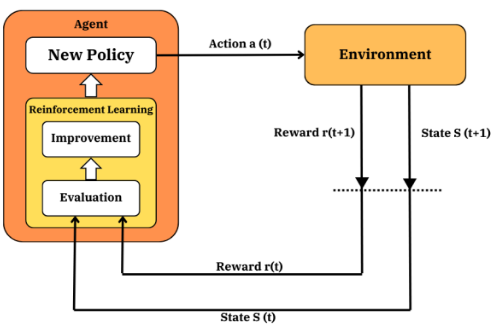


Fig.3: Basic RL-based model [14]

1.1 Health Care IoT-WSN Architecture

The sensor nodes network follows a heterogeneous nature and offers connectivity using the Internet for HC usage [10]. The extended HC-IoT-WSN architecture is represented in figure 4. The internet is the intermediate between servers and sensors of the network. The overall network is divided into multiple large area networks as can be observed from figure 4. There are numerous sensor node points in WSNs, and each of them is capable of sending data straight to a gateway or base station [11]. The individual large area networks may also be connected directly together through dedicated links in future WSNs [12]. Thus, it is needed to evaluate the performance of the large area networks, which is set as the goal of this research paper.

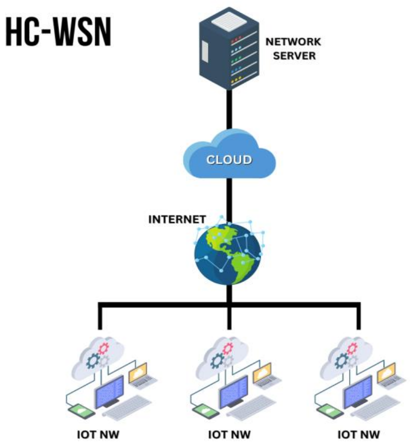


Fig.4: Extended architecture of HC-IoT-WSN

1.2 Classification of Energy Efficient WSN routing protocols

Classification of the various invented WSN routing techniques is shown in figure 5 for enabling EE interaction.

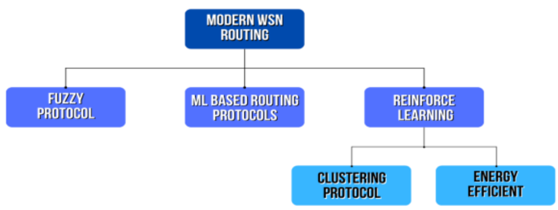


Fig.5: Various Energy efficient WSN routing protocols

The fuzzy based routing protocol [13], clustering based ML routing protocol [14], and RL-based energy efficient routing protocols [15] are different AI-based WSN routing protocols, which are also capable of adapting to dynamical modifications to the network. This section especially surveys the various studies related to the above protocols used in Large Area-WSN.

1.3 Issues of Existing WSN Routing Protocols

Current researchers face difficulties due to the flaws in the current routing systems, which are given below:

- There is a need to improve energy efficiency [16] in new routing protocols because the basic LEACH protocol is not very efficient.
- The main disadvantage of a stable election protocol (SEP) of a CH is that it cannot be selected dynamically across two distinct networks [17]. The nodes that were far away from the higher energy nodes perished quicker, which causes a crash of the entire network prematurely.
- The majority of current protocols has a short life span and is not adaptable to changing network dynamics [18].

Therefore, it is highly required to design an efficient prolonged lifetime routing protocol for large area WSN. The paper first reviews existing works of state of art routing protocols to further address these contributions.

Contribution of Work

This study focuses on the development of an RL-based routing protocol geared towards optimizing node clustering and the selection of CHs with the support of a Mobile Information System (MIS).

To thoroughly assess the performance of the proposed routing algorithm design, the network's geographical area and node density have been expanded by a factor of 2 to 5. This expansion serves as a critical evaluation criterion for the network's efficiency. To achieve the desired level of performance in densely populated, extensive networks, the study employs algorithms to facilitate learning and the selection of optimal parameters. One notable outcome of this research is the enhancement in the transmission range of sensors, achieved through RL methods, which demonstrates a threefold increase compared to conventional networks. This enhancement is accompanied by an initial boost in energy efficiency. The evaluation of performance is conducted through energy consumption comparisons and the monitoring of active node counts.

2. LITERATURE REVIEW

Zhang Meiyi et al. [1] used deep learning to create a WSN routing method. They have proposed an efficient routing approach. The nodes employ a traffic-flow-based method. This multi-hop architecture approach for altering network state enhances network manageability. The process depends on EE collection and on trafficking across multiple nodes.

Anju Arya et al. [2] suggested RL in WSN to suit the expectations of sensor network growth. Their Q-learning approach solves the prediction problem. The purpose of their investigation emphasizes QoS for increased network life time.

Anna Forster et al. [3] presented an RL-based approach for scattered web nodes. Their precise packet delivery ratio (PDR) statistics examine the effects on network efficiency. Experimental results show the effects of achieving better performance on routing costs.

In order to improve the high standard features and the effectiveness of WSNs, Arafat Habib et al. [4] provided RL-based protocols difficulties, along with deployment challenges. It follows through this research how the main focus would be on achieving a quicker convergence while addressing security concerns and multiple routing metrics.

In their survey, Arafat Habib et al. [5] compared the key characteristics of various routing protocols, highlighting the positive impact of RL routing systems on network lifetime. They also addressed architectural challenges, emphasizing the need for data integrity to counter data redundancy issues. The analysis of routing protocols in WSNs, along with future plans, was driven by these considerations.

K. Anitha et al. [6] introduced a novel RL approach for routing optimization in their survey.

Khuram Khalida et al. [7] proposed an RL-based protocol for WSN using fuzzy logic, showcasing improvements in overhead ratio, delivery ratio, and average latency through experimental results.

Padmalaya et al. [8] tackled WSN routing challenges by incorporating ML approaches, leading to successful data exchange in data collection processes.

Ankit B. Patel et al. [9] presented a hierarchical routing method with a Q-routing algorithm, resolving issues and enhancing processing power, energy efficiency (EE), scalability, and information aggregation.

Navpreet Kaur et al. [10] devised a routing protocol selecting neighboring nodes and Cluster Heads (CHs) based on environmental conditions, minimizing energy consumption, and improving network lifetime.

S.E. Bouzid et al. [13] addressed energy consumption and WSN lifetime using an RL algorithm-based routing protocol, demonstrating high energy efficiency and extended network life through simulations and comparisons. Their future plans involve implementing the RL protocol in wireless network services.

Vially Kazadi et al. [14] introduced an EE routing protocol using RL, enabling devices to adapt energy levels, routing decisions, and mobility, reducing runtime, and minimizing energy consumption in comparison with other protocols.

SEP and DEC protocols were proposed in [15 and 16]. Wenjing Guo et al. [17] proposed an efficient RL-based routing algorithm for WSN, known as Energy Aware Routing (EAR), which employs a singular path to minimize energy consumption and enhance communication in forwarding nodes. The simulation incorporates a deep learning model and experimental parameters for WSNs.

In [18], D. Prabhu et al. introduced a reinforcement learning (RL) based routing algorithm for Wireless Sensor Networks (WSN). This algorithm constructs routes by considering the current network status, aiming to detect optimal routes that minimize transmission delay and enhance reliability through strategically chosen reward functions. This work places emphasis on the significance of reward functions and selects three reliable ones to compute the Q-value.

Zhibin Liu et al. proposed RLR-TET in [19], an RL approach that evaluates the shortest routing while achieving node energy balance. Their method is compared with five other algorithms, demonstrating quick responsiveness to network changes, improved energy balance of nodes, and successful extension of the network's lifetime.

In [20], Biradar Ashwini Vishwanathrao et al. presented an innovative solution named Reinforcement Machine

Volume 12, Issue 5
October 2023

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

Learning-enhanced Energy Efficient AODV (RML-EEAODV). This approach integrates reinforcement machine learning with the AODV routing protocol to create an energy-conserving routing mechanism. RML-EEAODV significantly enhances energy efficiency, reduces network overhead, and maintains a satisfactory packet delivery ratio.

Amin Nazari et al. introduced EQRSRL in [21], an efficient routing mechanism designed for various Internet of Medical Things (IoMT) applications. EQRSRL aims to provide a reasonable Quality of Service (QoS) for IoMT traffic by categorizing network traffic into three classes and treating them differently based on their QoS requirements. Simulation results demonstrate an 82% improvement in average energy consumption, 25% reduction in end-to-end delay, and a 7% increase in packet delivery ratio compared to state-of-the-art routing techniques.

Nilesh P. Sable et al. in [22] enhanced the RL-based routing path for Software-Defined Wireless Sensor Networks (SDWSNs). They recommended using a reward system that incorporates relevant network QoS and energy efficiency metrics. The SDWSN controller improves the routing path based on prior information when the agent receives the award and decides the next steps.

In [23], Zhao Zhao et al. proposed an improved RL framework and designed an energy-efficient multilevel routing strategy (MLRS-RL) for multiple transmission latency requirements. MLRS-RL introduces a method of model knowledge collection based on the time backoff principle to preliminarily learn network environment information before network operation.

Table 2 summarizes the recent works based on Energy-aware WSN Routing Protocols.

Table 2. Summary of recent works based on Energy-Aware WSN Routing Protocols

Authors	Approach/Protocol	Key Contributions/Findings
Zhang Meiyi et al. [1]	Deep learning-based WSN routing	Efficient routing using a traffic-flow-based method; Multi-hop architecture for enhanced network manageability; Reliance on EE collection and node trafficking.
Anju Arya et al. [2]	RL (Q-learning) for WSN growth	QoS-focused Q-learning approach for increased network lifetime.
Anna Forster et al. [3]	RL-based approach for scattered nodes	Precise packet delivery ratio (PDR) analysis; Better performance on routing costs with improved network efficiency.
Arafat Habib et al. [4]	RL-based protocols for WSN	Focus on quicker convergence, security concerns, and multiple routing metrics for improved WSN features and effectiveness.
Arafat Habib et al. [5]	Survey on RL-based routing protocols for WSN	Improved network lifetime through RL routing systems; Consideration of architecture difficulties and data redundancy.
K. Anitha et al. [6]	Survey on RL-based routing protocol optimization	Introduction of cutting-edge learning technique for routing optimization.
Khuram Khalida et al. [7]	RL-based protocol with fuzzy logic for WSN	Utilizing fuzzy logic in a protocol for Q-learning resulted in improvements in overhead ratio, delivery ratio, and average latency, as confirmed by experimental findings.
Padmalaya et al. [8]	ML-based routing protocol for WSN challenges	Achieving successful data exchange in data collection processes was realized by incorporating machine learning (ML) approaches.
Ankit B. Patel et al. [9]	Hierarchical routing with Q-routing algorithm for WSN	Enhanced routing strategies were implemented to address scalability, processing power, and energy efficiency, with experimental results demonstrating an increased network lifespan and improved energy efficiency
Navpreet Kaur et al. [10]	Routing protocol with CH selection based on environmental conditions	Cluster head nodes were strategically chosen to minimize energy consumption and enhance network lifetime, as corroborated by simulation results indicating a notable improvement in the overall lifetime span.
S.E. Bouzid et al. [13]	RL-based routing protocol for WSN energy efficiency	An RL algorithm was employed for dynamic path selection, incorporating two processes - discovery and continuous learning - to enhance energy efficiency and extend the network's lifespan.
Vially Kazadi et al. [14]	RL-based EE routing protocol for WSN	Adaptive energy levels, routing decisions, and mobility for different devices; Reduction in runtime and energy consumption compared to other protocols.
Wenjing Guo et al. [17]	RL-based routing algorithm for WSN	Energy-aware routing (EAR) method for minimum energy usage and maximum network efficiency; Simulation using deep learning model and experimental parameters.
D. Prabhu et al. [18]	RL-based routing algorithm for WSN	Constructs routes considering current network status; Emphasizes reward functions for optimal routes, selecting three reliable ones for Q-value computation.
Zhibin Liu et al.	RLR-TET - RL for shortest	Compares with five algorithms; Quick responsiveness to network

ITEE Journal
Information Technology & Electrical Engineering
ISSN: - 2306-708X

[19]	routing and node energy balance	changes; Improved energy balance and extended network lifetime.
Biradar Ashwini V. et al. [20]	RML-EEAODV - RL and ML for energy-efficient AODV routing	Integrates RL with AODV; Enhances energy efficiency, reduces network overhead; Maintains satisfactory packet delivery ratio.
Amin Nazari et al. [21]	EQRSRL - Efficient RL-based IoMT routing	Categorizes IoMT traffic, treats differently based on QoS; 82% improvement in energy consumption, 25% reduction in end-to-end delay, 7% increase in packet delivery.
Nilesh P. Sable et al. [22]	Enhanced RL-based routing for SDWSNs	Recommends reward system with relevant QoS and energy efficiency metrics; SDWSN controller improves routing based on prior information.
Zhao Zhao et al. [23]	MLRS-RL - ML-based RL for multilevel routing	Improved RL framework; Energy-efficient multilevel routing; Model knowledge collection based on time backoff principle; Simulation for multiple transmission latency.

3. PROPOSED METHOD

The research has proposed Reinforcement Learning Routing Protocol (RLRP), which is designed to achieve EE system for the dense large area wireless network using the RL routing Protocol. As it is expected that in the near future the size and density of WSN will increase, hence, this research has designed the system with LA consideration.

The density of nodes is adjusted to achieve the best network performance using a well-designed RL-based protocol. Figure 6 illustrates the step-by-step process of the proposed energy-efficient RLRP design methodology. In this study, we aim to assess how well RL performs in routing when the nodes in the network are evenly distributed. The RL system makes decisions about which nodes become Cluster Heads (CH) in the network.

It is clear from figure 6 that the paper has proposed to vary the node density with the ratio of size of the LA network. Simulation is carried out every time for selection of center sink location. Overall, the size of the network has been increased to 4 times and is considered as 40000 square meters. The flow chart of designed methodology is sequentially presented in the Figure 7. The parametric initialization is followed by the energy calculation based RL model for Cluster Head selection.

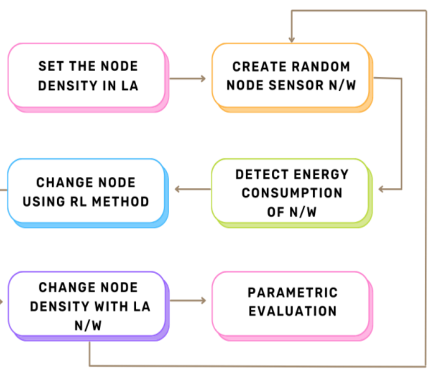


Fig.6: Workflow of processes of proposed Method

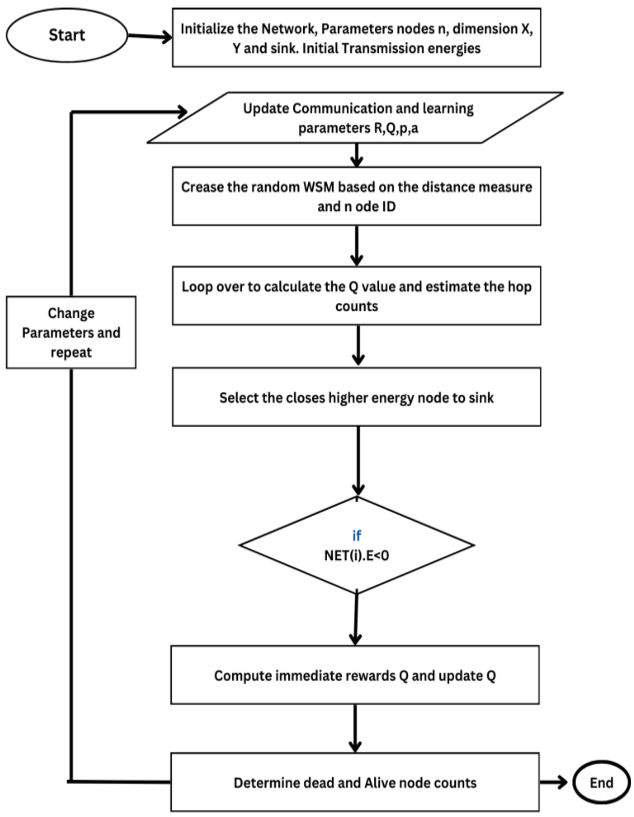


Fig.7: Flow chart of Proposed Methodology

Algorithm 1. Proposed Routing Protocol

1. Initialize the network parameters: →n, rounds, LA@ (X,Y), Sx, Sy and energies
2. Learning perimeter Declaration: learning rate , hop count probability Q=1-p
3. Network Creation: place the nodes at random distance and coordinates as
   for i=1:n
$x = rand(1,1) * xm;$ y$= rand(1,1) * ym;$
   end

ITEE Journal
Information Technology & Electrical Engineering
ISSN: - 2306-708X

4. Compute Q
   for i=1:n
   if(min_E ==max_E)
   Q(i) = 1 / S(i).hop
   S(i).Q = Q(i);
   else
   Q(i) = (p*(S(i).E - min_E)/(max_E-min_E)+(q1/S(i).hop));
   S(i).Q = Q(i);
   end
   end
5. CH election :
   for i=1:n
   $S(i).dist_{Euclidean}(S(i), sink)$
   $S(i).hop\ (S(i).dist_{Euclidean}\ /\ Range)$
   while length ($CHt_{tot} \leq CH_{max}$)
   if *(Qmax == max (S.Q))

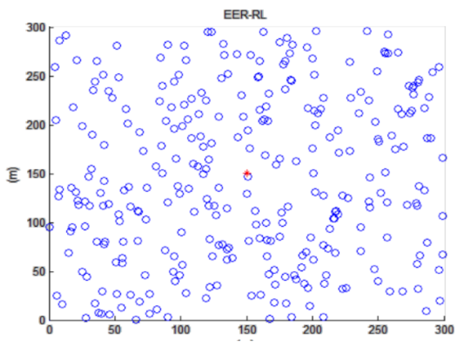
CH(tot) = CM(i);else calculate distance between C(i) and C(tot)
if dis<15 C=C+1
end
end
end

6. Cluster Formation
   for i=1:n
   Determine $S(i).dist_{Euclidean}$ for each CH(i) to nodes find the suitable Cluster.
   end
7. Evaluate the Aliv, Deadnodes and energy
   If (improvement met)
   end
   Else change area and learning rates and repeat (2-7)
8. end Algorithm

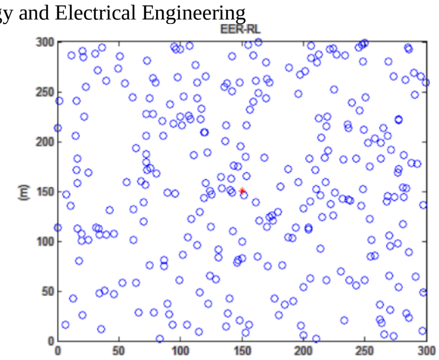
The node deployment for the two higher node densities across the 90000 m sq field of WSN with n=300 and n=400 are shown in figure 8.

It can be noted from figure 8 that it becomes more difficult to understand the network because whenever the node density increases, the distance between the nodes reduces. Thus, it becomes a difficult set of problems to cluster the nodes in this scenario.

Figure 9 shows the simulation for RL-based clustering of 100 nodes across a (200m x 200m) area for routing protocol. This paper considers the uniform distribution throughout the simulation cases.



(a) Network with n=400 nodes



(b) Network with n=300 nodes

Fig.8: Random node distribution over size of 300 square meter network

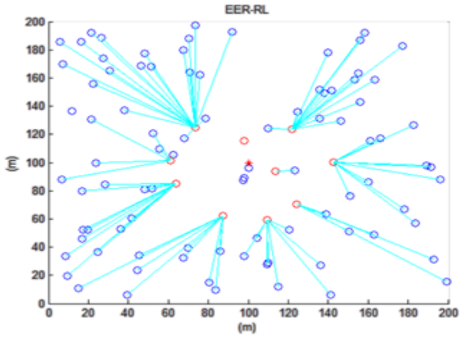


Fig.9: Node clustering for uniform probability distribution

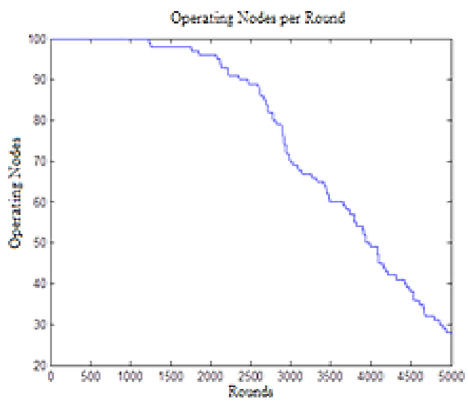
4. SIMULATION RESULTS & DISCUSSIONS

In this research, the fundamental simulation findings for current used RL-based WSN protocols are first validated. The usual field area of 100x100 with 100 nodes is taken into consideration for simulation during validation.

4.1 Validation of proposed method

Figure 10 illustrates the validation outcomes for proposed EE-RL [4] for the amount of operational alive nodes and the energy consumptions. A sink is located in the network's core and 100 nodes are used for the validation procedure.

It can be observed from figure 10 that it is required to improve the stability period of the basic EE-RL protocol based on parametric optimization.



ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

Fig.10: Number of active or operational nodes validation of each round for the RL based routing protocol

4.2 Optimal Simulation Parameters

To evaluate the effectiveness of proposed routing method, it is suggested that the system randomly deploys 100 and 150 nodes across the LA-WSN field of (200m x 200m) while adhering to the uniform distribution with sink at (100m x 100m). Table 3 shows all of the best factors that were chosen and used in the simulation for proposed work to enhance greater effectiveness levels.

Table 3. Optimal Simulation Parameters

Parameter	Explanation	Choice
X, Y	WSN field area	200 m x 200 m
n	Nodes in the network	100 and 150
S_x, S_y	Sink coordinates	100, 100
E_{Tx}	Energy Transmitted	$50x10^{-9}$ in J
E_{Tr}	Receiver Energy	$50*10^{-9}$ in J
E_{amp}	Energy of the Amplifier	$100*10^{-12}$in J
E_{DA}	Aggregation Energy	$5*10^{-9}$in J
R	Range of transmission	[20, 40, 60]
α	Learning rate	[0.5, 1, 1.5, 2]
γ	Discount factor	0.95
p	Energy probability range	0.5
Q_{hc}	probability of hop counts	0.5

4.3 Outcome of Node Density on overall Performance

This experiment has been performed to evaluate the relationship between the node density and the LA of the network, considering the near future. The simulation comparison of performance of live nodes under operation for optimal 100 nodes and 150 nodes for 200 m x 200 m area (four times) is considered for the evaluation. The proposed method is considered and simulated for 5000 rounds for probability of transmission p=[0.5]. Figure 11 represents the comparison of the number of alive nodes for different node densities on the large area WSN. It is observed that by increasing the node density in a fixed area, it consumes the almost optimum energy of the nodes, although the node distance is changed. Similarly, in figure 12, energy consumption per round is compared with different node densities for large area WSN. It can be observed from the figure that increasing the density offers higher initial energy consumption and higher stabilized energy usage after half of rounds.

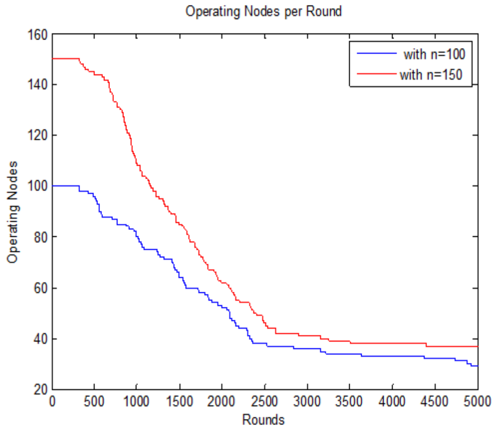


Fig.11: Comparison of operating nodes for two different node densities of proposed method

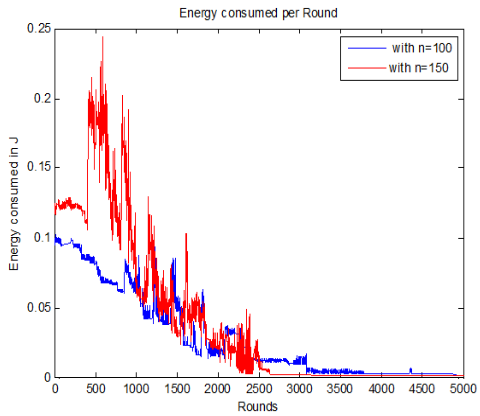


Fig.12: Comparison of energy consumption for two different node densities of proposed method

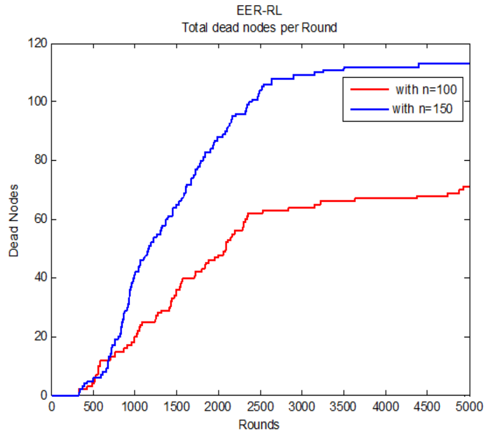


Fig.13: Result comparison of various dead nodes for two different node densities of proposed method

Volume 12, Issue 5
October 2023

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

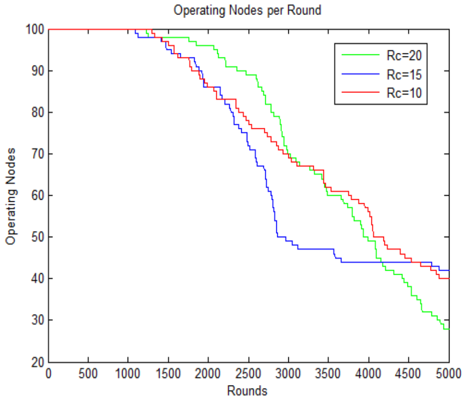


Fig.14: Impact of Variation of Transmission Range of proposed method

In figure 13, dead nodes per round are plotted for different node densities in large area WSN. It is observed by the graph that the proposed method gives a similar pattern and percentage of dead nodes compared to the normal standard case by increasing the node density.

Here the research alters the value of the node's transmission range (R) between 10, 15 and 20, and determines the impact of the transmission range R upon the proposed method. Figure 14 displays the outcomes of R assessments for both living and dead nodes. Here the value of Energy probability range (p) is set 0.5 and the size of the network is (100m x 100m), which is a normal size. The best outcome is obtained when R=20 is selected as the optimum range.

4.4 Comparative Study

Figure 15 compares the delay for various state-of-the-art routing methods of [15 and 16] with the proposed RL-based system. It is clear from the graph that suggested RL-based routing improves latency from previous works.

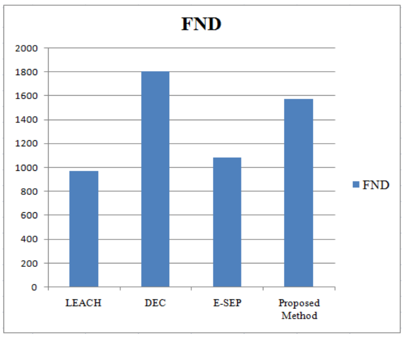


Fig.15: Comparison of FND with proposed method

5 CONCLUSIONS & FUTURE SCOPES

In this study, an energy-efficient RL routing protocol has been specifically designed for routing within a large scale WSN designed for applications in the HC sector. This protocol has been proposed to address the complexities of high densely populated nodes and leverages RL principles to optimize routing for networks covering areas four times larger than initial deployments. The primary goal of this routing approach is to identify the most efficient data transmission routes, thereby reducing energy consumption and extending the network's operational lifespan.

To initiate our investigation, we initially validated the number of active operational nodes for each round, employing an RL-based routing protocol within a 100-square-meter area. Notably, our findings demonstrated that RL-based routing significantly enhances the overall network lifespan. Building on these insights, we proceeded to explore the protocol's performance in more expansive network environments.

In our pursuit of finding the most effective network functionality using RL-based routing protocol architecture, we systematically adjusted node density to align with the specific network requirements. This involved deploying nodes in configurations characterized by higher node densities across a 900-square-meter WSN, encompassing scenarios with node counts of both n=300 and n=400.

Our observations revealed that as the area's node density increased, the network's energy consumption approached an optimal balance, even when accounting for potential variations in node distances. Furthermore, we conducted experiments varying the range parameter with the most favorable outcomes achieved when r=20, thereby designating it as the optimal range setting.

For large-scale network deployments, we conducted an in-depth analysis of energy utilization across various node densities per round. Our findings indicated that increasing node density initially led to higher energy consumption; however, this increase eventually stabilized after approximately 50 percent of the rounds.

Looking ahead, future advancements in energy efficiency and network longevity may be attainable through the implementation of an adaptive learning rate-based routing system. Additionally, optimization techniques could yield enhancements in network speed and overall performance in the times to come.

REFERENCES

[1] Aiqi Zhang, Meiyi Sun, Jiaqi Wang, Zhiyi Li, Yanbo Cheng and Cheng Wang, "Deep Reinforcement Learning-Based Multi-Hop State-Aware Routing Strategy for Wireless Sensor Networks", , Applied Sciences, MDPI, 2021, pp 1-12. https://doi.org/10.3390/app11104436

[2] Anju Arya, nisha Nehra, "Reinforcement Learning based Routing Protocols in WSNs: A Survey", 2018, International Journal for Research in Applied Science & Engineering Technology (IJRASET), Vol. 6, 2018, pp 3523-3529.

[3] Anna Forster, Amy L. Murphy, Jochen Schiller, Kirsten Terfloth, "An Efficient Implementation of Reinforcement Learning Based Routing on Real WSN Hardware", IEEE international Conference, 2008, , pp 1-6.

[4] Arafat Habib, Muhammad Yeasir Arafat, Sangman Moh, "Routing Protocol based on Reinforcement Learning for wireless sensor networks: A comparative study", Journal of Advanced Research in Dynamical and Control Systems, 2019, pp 1-10. https://www.researchgate.net/publication/331588735.

ITEE Journal
Information Technology & Electrical Engineering
ISSN: - 2306-708X

[5] Arafat Habib, Yeasir Arafat and Sangman Moh, "A Survey on Reinforcement-Learning-Based Routing Protocols in Wireless Sensor Networks", The 8th International Conference on Convergence Technology, 2018, pp 359-360. https://www.researchgate.net/publication/325617283.
[6] K. Anitha, "A survey of optimization of routing protocol in wireless sensor network using reinforcement learning technique", IJARIIE, Vol-8 Issue-3, 2022, pp 5254-5256.
[7] Khuram Khalid, Isaac Woungang, Sanjay K. Dhurandher, Jagdeep Singh, "Reinforcement learning-based fuzzy geocast routing protocol for opportunistic networks", 2021, Elsevier Internet of Things, 2021, pp 1-12. https://doi.org/10.1016/j.iot.2021.100384.
[8] Padmalaya Nayak, G.K. Swetha, Surbhi Gupta, K. Madhavi, "Routing in wireless sensor networks using machine learning techniques: Challenges and opportunities", Measurement, Elsevier, Volume 178, 2021, pp 1-15. https://doi.org/10.1016/j.measurement.2021.108974.
[9] Ankit B. Patel, Hitesh B. Shah, "Reinforcement Learning Framework for Energy Efficient Wireless Sensor Networks", International Research Journal of Engineering and Technology (IRJET),Volume: 02 Issue: 02, 2015, pp 128-134.
[10] Navpreet Kaur, Inderdeep Kaur Aulakh, "An energy efficient reinforcement learning based clustering approach for wireless sensor network", 2021, EAI Endorsed Transactions, Scalable Information systems, 2021, pp 1-17. doi: 10.4108/eai.25-2-2021.168808.
[11] Petteri Nurmi, "Reinforcement learning for routing in ad-hoc networks", International Symposium on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks and Workshops, 2007, pp 1-8.
[12] Qianao Ding, Rongbo Zhu, Hao Liu and MaodeMa, "An Overview of Machine Learning-Based Energy-Efficient Routing Algorithms in Wireless Sensor Networks", Electronics, MDPI, 2021, pp 1-24.. https://doi.org/10.3390/electronics10131539
[13] S.E. Bouzid, Y. Serrestou, K.Raoof, M.N.Omri, "Efficient Routing Protocol for Wireless Sensor Network based on Reinforcement Learning", International Conference on Advanced Technologies, 2020, pp 1-6. DOI: 978-1-7281-7513-3/20.
[14] Vially Kazadi Mutombo , Seungyeon Lee, Jusuk Lee, and Jiman Hong, "EER-RL: Energy-Efficient Routing Based on Reinforcement Learning", Mobile Information Systems, Hindawi, 2021, pp 1-12. https://doi.org/10.1155/2021/5589145
[15] M. M. Islam, M. A. Matin and T. K. Mondol, "Extended Stable Election Protocol (SEP) for three-level hierarchical clustered heterogeneous WSN", *IET Conference on Wireless Sensor Systems*, 2012, pp 1-4. doi: 10.1049/cp.2012.0595.
[16] Ali Chamam, Samuel Pierre, "A distributed energy-efficient clustering protocol for wireless sensor networks", Computers & Electrical Engineering, Volume 36, Issue 2, 2010, pp 303-312. https://doi.org/10.1016/j.compeleceng.2009.03.008.
[17] Wenjing Guo, Cairong Yan, Ting Lu, "Optimizing the lifetime of wireless sensor networks via reinforcement learning-based routing", International Journal of Distributed Sensor Networks, 2019, pp 1-20
[18] Prabhu, D., R. Alageswaran, and S. Miruna Joe Amali. "Multiple agent based reinforcement learning for energy efficient routing in WSN." Wireless Networks (2023): 1-11.
[19] Liu, Zhibin, and Xinshui Wang. "Energy-balanced routing in wireless sensor networks with reinforcement learning using greedy action chains." Soft Computing (2023): 1-21.
[20] Vishwanathrao, Biradar Ashwini, and Pradnya Ashish Vikhar. "Reinforcement Machine Learning-based Improved Protocol for Energy Efficiency on Mobile Ad-Hoc Networks." International Journal of Intelligent Systems and Applications in Engineering 12.8s (2024): 654-670.
[21] Nazari, Amin, et al. "EQRSRL: an energy-aware and QoS-based routing schema using reinforcement learning in IoMT." Wireless Networks (2023): 1-15.
[22] Sable, Nilesh P., et al. "Enhancing Routing Performance in Software-Defined Wireless Sensor Networks through Reinforcement Learning." International Journal of Intelligent Systems and Applications in Engineering 11.10s (2023): 73-83.
[23] Zhao, Zhao, et al. "MLRS-RL: An Energy Efficient Multi-Level Routing Strategy Based on Reinforcement Learning in Multimodal UWSNs." IEEE Internet of Things Journal (2023).

AUTHOR PROFILES

Mr. Chandan Kumar is currently working in Sanjeev Agrawal Global Educational (SAGE) University, Bhopal as an Assistant Professor. He is having more than 12 years of teaching experience in the field of Computer Science. He has completed his B.Tech. from West Bengal University & Technology. He has completed M. Tech. from RGPV University, Bhopal. He is pursuing Ph.D. from NITTTR, Bhopal affiliated with RGPV in the field of IoT generated Video surveillance data. His area of research is IoT security, Wireless Sensor Network, Image processing and Data science. He has published two research paper in SCI Indexed journals, three papers in International journal, four research papers in Scopus indexed conferences, three paper in international conference and one book chapter in Scopus indexed Book Series. He has also published one patent. He is also an author of a book based on IoT. Apart from research, he is NPTEL certified in more than five subjects. He has also qualified GATE three times. He is the reviewer of many prestigious journals. He is a life time member of Soft Computing Research Society (SCRS) and Academic Research and Education Scientific Society (ARESS).

Ms. Akrati Shrivastava is currently working in InfoTech Education Society (IES) University, Bhopal as an Assistant Professor. She is having more than 7 years of teaching experience in the field of Computer Science. She has completed his B.Tech. from RGPV. She has also completed M. Tech. from SATI Vidisha, affiliated to RGPV University, Bhopal. Her area of research is Data mining & Machine learning. She has published one paper in International journal. Apart from research, she is CRISP certified trainer in Machine Learning.

Ms. Vineeta Rathore is currently working in Medi-Caps University as an Assistant Professor. She is having more than 14 years of teaching experience in the field of Computer Science Engineering. She has completed her B.Tech. from Truba College of Engineering and Technology. She has completed M. Tech. from IES-IPS Academy, Indore. She is pursuing Ph.D. from Medi-Caps University, Indore. His area of research is IoT security, Wireless Sensor Network, Artificial Intelligence, Machine Learning. She has published two research paper in International journals, one research papers in Scopus indexed conferences, She has also published two patent. Apart from research, she is certified FORTINET trainer.