Energy-efficient and reliable data transmission to enhance the performance of wireless sensor networks using artificial intelligence

Swapna Ch[1], Vijayashree R. Budyal[2]
[1]Department of Electronics and Communication Engineering, Sri Venkateshwara College of Engineering, Bengaluru, India
[2]Department of Information Science and Engineering, Sai Vidya Institute of Technology, Bengaluru, India

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ABSTRACT

For many years, the area of wireless sensor networks (WSN) has been popular for its wide range of time-critical and potential applications. However, it has many challenges that require more attention from the research communities to improve the network's operational efficiency. However, with consistently rising concerns for energy efficiency and optimized data transmission performance, most current research emphasises minimum power consumption and reliable data transmission aspects. The critical analysis and study of related works exhibit the shortcomings in existing data transmission schemes, which fail to cope with the dynamic conditions of WSNs on a larger scale and do not retain considerable energy performance. The study thereby introduces a unique approach to an energy-efficient and reliable data transmission framework that formulates machine learning-driven functional components to ensure effective data gathering, aggregation, and routing and dissemination strategies to properly balance energy and data transmission performance in WSN under dynamic conditions. The proposed framework's performance evaluation considers multiple metrics, such as analysis of network lifetime, Energy Consumption, Throughput, and Latency performance. The experimental outcome shows that the proposed system outperforms the existing baselines for the above performance metrics.

Corresponding Author:

Swapna Ch
Department of Electronics and Communication Engineering, Sri Venkateshwara College of Engineering
Kempegowda International Airport Road, Vidya Nagar, Central Telecom Society, Bengaluru
Karnataka 562157, India
Email: swapnaeng@gmail.com

1. INTRODUCTION

Wireless sensor networks (WSNs) generally consist of a large number of stationary and mobile sensor nodes, each with self-organizing capability and the ability to collaboratively sense, collect, process, and transmit data to the base station using either direct or multi-hop communication paradigm [1]. Many researchers have deeply studied WSNs, which have gained popularity due to their versatility and wide adoption in many applications, including agriculture and health monitoring, environmental monitoring, traffic monitoring, and many others. In these applications, WSNs are required to periodically transmit the sensed data to the remote central unit, also referred to as a base station, for processing, often through multi-hop paths. The sensor nodes' coverage within the network region relies on their limited energy capacity; once the nodes are deployed, they might get little or no maintenance. The primary challenge in WSNs is dealing with energy-efficient data gathering under varying circumstances, in which sensor nodes could be stationary or mobile, and the network can experience frequent topological updates. Another secondary challenge is to avoid the redundancy problem in sensed and gathered information for which the data aggregation approach is found suitable which also significantly influences the energy outcome by statistically summarizing the data collected by the sensors [2]. The tertiary challenge is to formulate a cost-effective data transmission modeling and energy-efficient multi-hop routing mechanism where the aggregator node should play a crucial role in dynamic and reliable route formation so that the optimal route could disseminate data from the source node to the destination [3]-[8].

There are studies which have significantly contributed to these problems of existing WSNs. Yang *et al.* [9] introduced an efficient compressive sparse data gathering approach based on compressive sparse sampling method and an efficient data recovery algorithm. Existing studies have also investigated cluster-based data gathering [10]. Yun and Yoo [11] explored reinforcement learning (RL)-based approaches to combine data aggregation and routing path selection. Guo *et al.* [12] focuses more on rechargeable WSNs and further talk about Deep-Q-Networks-based adaptive dual mode energy-aware routing strategy which follows the forward transmission principle. Raman *et al.* [13] presented a novel routing design to optimize the QoS aspects while improving the network lifetime of WSN. Liu *et al.* [14] presents a novel data dissemination framework for determining optimal storing probabilities and discarding probabilities to maximize the delivery ratio of data packets in WSN. Wang and Hsu [15] presented a two-tier data dissemination scheme which is designed based on Q-learning strategy to determine the most energy-efficient data dissemination path from source to base station. Further, there are various studies using energy efficient approach [16]-[20] while Artificial Intelligence-based approaches [21]-[27] have been witnessed to further optimize data delivery performance.

It has been observed that conventional approaches are well-suited for static wireless sensor networks, but applying them directly to WSNs with node mobility introduces several challenges, such as instability in computing matrices required for accurate data recovery and synchronization issues. The existing hieratical and cluster-based data gathering approaches even though offers significant energy outcome but poses some common limitations in large-scale WSNs under varying circumstances of dynamic conditions. The selection of optimal cluster head (CH) becomes challenging during the data dissemination process when SNs move from one location to another and the network structure constantly varies. It has been also observed that majority of the in-network data aggregation methods even though significantly enhance the network lifetime of WSN but they incur high network overhead and lacks effective packet delivery ratio measures for energy-constraint dynamic WSNs. Also, few of the methods considers complex XOR mathematical calculations for which they introduce additional network overhead with increasing data sensing rate. Even though cluster-based data aggregation models are found emphasize more on energy problems of WSNs but mostly overlooked data transmission reliability performance. Thereby their adoption in WSNs with varying circumstances still remain questionable from energy and data transmission reliability perspective. The existing RL-based algorithms especially Deep RL-Models and Deep-Q-Networks involve frequent state evaluation functions and complex calculation of reward functions and Q-value updates leading to more energy consumption of mobile nodes.

The study introduces a combined cost-effective framework for energy-efficient and reliable data transmission (EERD), which covers all the above aspects of data gathering, aggregation, routing and dissemination. In this proposed work, the study conceptualizes the design framework based on efficient cluster-based approaches and applies effective machine learning (ML) models to ensure better energy and data transmission performance under varying conditions of WSN. The novelty of the EERD framework offers the following novel features as value-added contribution viz. i) it introduces a unique approach of higherachical data gathering where the strategy offers a unique proposition of unsupervised learning to effectively formulate dynamic clusters of mobile sensor nodes and select cluster heads under the varying circumstances of WSN. It also introduces a novel data compression modeling for captured sensor readings to reduce the transmission cost and also enhances the energy performance of WSN, ii) EERD also enables a novel adaptive Q-learning (QL)-based strategy to optimize the data aggregation performance of WSN under dynamic conditions. The approach applies two distinct data aggregation models to eliminate irrelevant and redundant data transmission and incorporate Q-learning model for effective CH selection which not only improves the energy but also data transmission reliability to a significant extent, iii) The framework of EERD also offers a unique-approach of energy-efficient routing solution which construct a novel reward function and Q-value updating model to suit and energy-requirements in dynamic conditions of WSN, the unique approach of Q-value computation ensures appropriate selection of CH based on RL-driven criteria through which reliable and cost-effective routes can be established to base station, iv) Finally EERD framework offers a novel solution for data dissemination where it explored the potential of RL strategy for optimizing the sensor node activation based on event occurrence probability and proximity considerations. Here the optimized sensor node activation and timely event detection has not only enhanced the energy consumption performance but also reduced the latency of the captured information dissemination.

2. METHOD

The prime aims of the study are to introduce a cost-effective, reliable and energy-efficient data transmission framework to enhance the performance of WSN under dynamic conditions where nodes could be either static or mobile. Figure 1 highlights the proposed architectural design of the EERD framework and its important components for data gathering, aggregation, routing and data dissemination. The study adopts analytical methodology to represents the working scenario of EERD. Different from the prior studies, the EERD offers energy-efficient and reliable data transmission in any scale and dynamic forms of sensor-based networks.

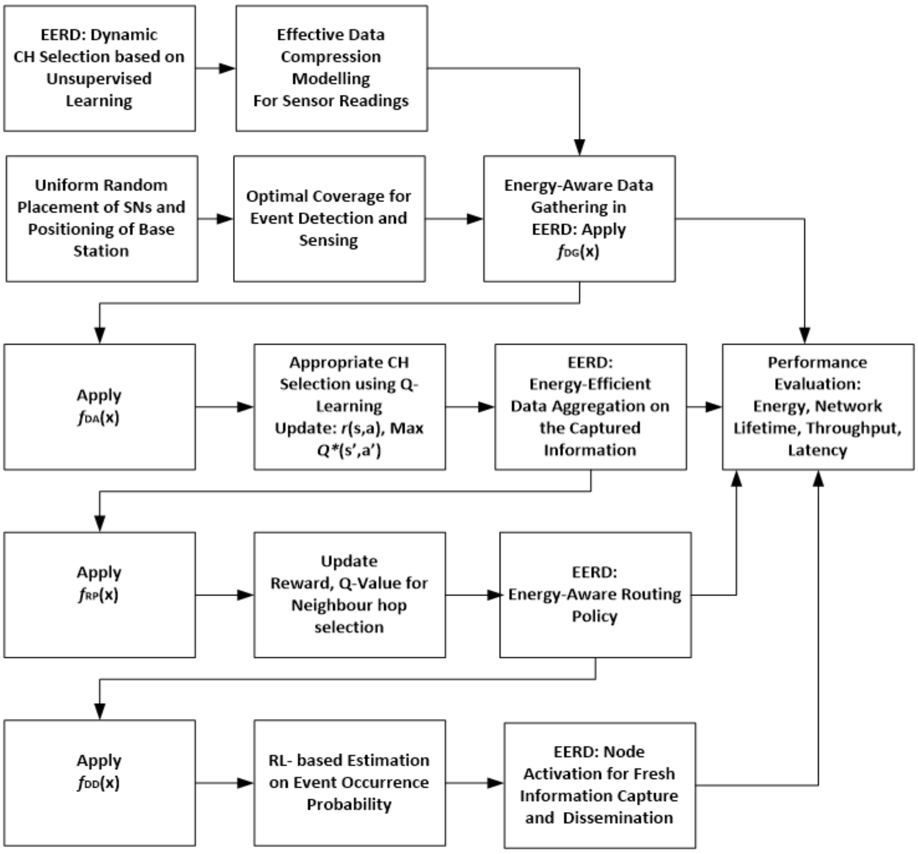

Figure 1. EERD architecture

The proposed study contributes towards four different aspects of WSNs under varying conditions which are data gathering, data aggregation, energy-efficient routing and data dissemination aspects. Here the entire research method is divided into four phases viz. formulation of energy-aware cluster-based data gathering strategy, a unique data aggregation framework solution using+ Q-Learning approach, (RL) based efficient routing strategy and RL-based optimized node activation and event detection strategy for effective data dissemination.

2.1. Data gathering strategy

In EERD the initial design and development considers effective data gathering (DG) which is modeled considering a function of $f_{DG}(x)$ that involves collection of sensor readings from the deployment region where the events occur and also further transmit the gathered data to the base-station considering either single-hop or multi-hop communication. Here the core objective of EERD is not only to minimize the number of sensed and transmitted data packets but also to maximize the number of rounds before the nodes die to enhance the longevity of the network. Here the design of data gathering in $f_{DG}(x)$ also employs effective cluster-formation paradigm and CH selection considering unsupervised learning so that reliable and energy-efficient data transmission could take place while balancing the overall-energy consumption. In EERD the cost of transmission is also reduced to a greater extent employing an efficient compression method over the captured sensor readings from the coverage of event. Initially the approach of $f_{DG}(x)$ employs an optimal sensor node deployment strategy which is designed based on connected graph and also it initially evaluates the number of nodes N and area of sensor node deployment$A \subset \mathbb{R}^2$. The proposed strategy further follows a uniform random distribution of nodes to compute x_i, y_i coordinates of each s_i. Once the sensor nodes are placed within the deployment region then it is assumed that each node can sense and detect event within its sensing range and respectively sensing range (s_R) is defined. Further the proposed $f_{DG}(x)$ also considers an optimal coverage model to suit the requirements of event detection while complying with the condition of distance evaluation for coverage point such as $d(p, s_i) \leq s_R$. The proposed $f_{DG}(x)$ performs the node deployment in such a way where all the node placement should comply with the optimal connectivity and coverage requirements within $A \subset \mathbb{R}^2$ that not only helps in better event capturing but also influences better clustering performance from both energy and data transmission point of view. The effective deployment of sensor nodes and base station in EEDG further result in $s_i(x_i, y_i) \cup x_{BS}, y_{BS}$. It has to be noted that in the EEDG all the sensor nodes are considered mobile whereas the base station placement is considered static within the deployment region.

However, the framework EEDG gives the provision to place the base station anywhere within the deployment region during the evaluation of the framework. The uniqueness of the EEDG is that during data gathering it considers dynamic scenario of node movement and also adopts TDMA-radio resource scheduling within the clusters and the communication between CHs and base station considers CDMA access modeling to save significant amount of energy. Here the EEDG strategy employs an efficient approach for effective data compression based on conditional entropy to reduce the cost of transmission during the data gathering approach. Here the data refers to sensor readings which are gathered by the nodes within a cluster. Here the compression modeling basically exploit the predictability in data to reduce its size. Here the approach for compression exploits the prior state of sensor readings that significantly reduces the uncertainty about the current state and this reduction is exploited during the compression. Considering this approach sensor nodes only store the required information per readings. The EEDG further employs a cluster-based data gathering approach for event detection and information capture where it enables node mobility and further also formulates a unique functional module of $f_{cluster}(N, n_c\ )$ which is designed based on unsupervised ML approach. The functional module of unsupervised clustering basically returns the position of cluster center along with index of the cluster for each mobile node. Further the EEDG approach also generates CHs position $CH_i(pos)$ and further establishes radio-link between the mobile nodes within the clusters to the CH_i. The strategy further also establishes a connectivity model between the elected CH_i and base station and performs data gathering followed by optimized data transmission. The inclusion of unsupervised clustering approach is found light-weight in design and also well adaptive to the varying circumstances of WSN.

2.2. Data aggregation strategy

The EERD addresses the limitations in existing higherachical data gathering models and further also enables another functional module of data aggregation $f_{DA}(x)$ which is designed based on the concept of in-network data aggregation. The study finds the scope and suitability of RL towards optimizing the data aggregation scenario under varying conditions of WSNs and further introduces a unique approach of CH election based on RL-based policy. The EERD here employs RL-based methods to capture the network dynamics of WSNs during the data aggregation where due to node mobility network topology could change. The prime aim of this module is to ensure a proper balance between energy and data transmission reliability factors while electing appropriate CH for efficient data aggregation. Here the study introduces Q-learning based design which poses simplistic modeling and also found well-suited for dynamic conditions of WSN. The adaptive RL-based strategy here minimizes the energy consumption performance while optimizing the process of data aggregation and CH selection even when the network topology changes. The uniqueness of the model here is that it also introduces two different data aggregation models to reduce the transmission cost of aggregated data and effectively balance the overall energy consumption while establishing cost-effective transmission path of T_{path}. The functional module of $f_{DA}(x)$ initially follows optimal node deployment strategy for x_i, y_i and further define both state and actions. Here the formulation of state considers residual energy of each node within a cluster whereas the action enables appropriate CH selection and cost effective data transmission modeling. Based on the actions of the agent the EERD computes the reward function of $r(s, a)$ and updates the Q-Learning process in the form of $Q(s, a)$. This approach progressively updates the CH selection paradigm and converge to the optimal policy of CH selection. EERD further also enables an appropriate formulation of queue state while offers two data aggregation models A_{model1} and A_{model2}. Further EERD updates the energy levels and also further establishes the transmission path $T_{path}(v_i, v_{bs})$.

2.3. Routing strategy

In continuation the EERD framework also offers an efficient routing strategy which also exploits the strength factors associated with RL to enhance the operation time of WSN for longest period possible. The framework forms a cluster-based routing a basis for the work and further improvise the performance of routing considering RL approach. EERD aims to optimize the energy consumption with network scalability factors and also evaluates the reliability of data transmission aspect. The proposed routing protocol is presented with a function of $f_{RP}(x)$ which is mechanised to employ optimized route of data transmission considering efficient routing decision and route table update mechanism. Here $f_{RP}(x)$ also offers a better choice for hop selection during the process of route establishment. The reward function in the proposed work is modeled considering both the energy factor and average hop-count to the base station. The proposed framework initially considers a network deployment and setup phase and further employs an unique approach of efficient group-formation for $C_j(CH_i)$ and enables intra-cluster and inter-cluster communication. The EERD in this phase basically considers modeling of three distinct functions such as function for energy consumption modeling $f_E(\cdot)$, design of reward function $r(s,a)$ on the basis of hop count h_c and finally a function for Q-value update $f_Q(r(E_l(i),h_c))$. The optimal policy is obtained for selecting neighbour hop with $\max_a Q(s',a)$. EERD employs a unique approach of multi-hop routing so that significant energy during data transmission could be saved under dynamic conditions of WSN. Another uniqueness of the proposed $f_{RP}(x)$ design is that it offers more light-weight execution policy which significantly reduces the protocol run time and also enhances the throughput performance with increasing number of sensor activities. The inclusion of the RL strategy makes this framework adaptive to the network topological changes such as node mobility and energy levels and also helps improving the routing decisions. The novel approach of energy-threshold modeling also makes it more efficient when compared with the existing system.

2.4. Data dissemination strategy

The study also further introduces another functional component of energy-efficient data dissemination strategy in the form of $f_{DD}(x)$ in EERD for effective future generation wireless sensor networks communications. The function of $f_{DD}(x)$ in EERD also employs an unique approach of RL to optimize the sensor node activations for appropriate event detection and timely information capture. The prime motive of this approach is to estimate event occurrence probabilities and optimize the sensor detection to enhance the energy performance and ensure reliability in data dissemination process. The EERD in this phase of the work also designs an intelligent computing paradigm which also estimate data freshness to perform timely data dissemination. The functional module of $f_{DD}(x)$ basically consists of two core functionalities which are custom WSN deployment using Open AI Gym functionalities considering $S_i \sim Po(\lambda)$ and $S_i = (x_i, y_i) \in \mathbb{R}^2$ and Intelligent node activation scheme based on RL-approach. The proposed modeling of $f_{DD}(x)$ considers event generation probabilities to generate random events within the sensing region and further computes final sensor positions, activation count, capture and non-captured events. The system also defines observation space during the modeling of event generation and network setup. Further the EERD framework defines a reward function $r(t)$ considering detected events and missed events and terminate the process of event generation. The RL-based node activation strategy further follows the observation space and takes the action in the form of $\arg\max_{a \in A} Q(s_t, a)$. The EERD in this phase also converges towards the optimal policy considering $Q^*(s,a)$ and updates the loss in the form of $Loss$. Eventually EERD enables an efficient strategy for rapid and fresh event capture which significantly influence the latency performance and also reduction in unnecessary sensor activations and estimation of information freshness also ensures reliability of data transmission from both energy and accuracy point of view.

3. RESULT AND DISCUSSION

This section discusses the numerical outcome obtained from simulating EERD in a computing environment. The implementation strategy of EERD follows the modelling and scripting of novel features, where a specific evaluation strategy is considered. The discussion of the outcome covers the simulation environment, quantitative results, and analysis of the core findings of the study.

3.1. Simulation environment

The EERD framework is analytically designed and modeled considering both MATLAB and Python scripting where the system design and development for the first three core functionalities such as $f_{DG}(x)$, $f_{DA}(x)$ and $f_{RP}(x)$ are modeled using MATLAB utilizing the i5-8250U CPU @1.60GHz and 1.80 GHz with x64-based processor, 64-bit operating system and 12 GB RAM. The simulation parameters considers 300-400 number of sensor nodes, 5-8 clusters, area size of 100 m2, and node speed of 1 m/s. Also, the node’s initial energy is considered between 0.5J /node to 10J /node. Also, the deployment strategy follows uniform random deployment pattern where data transmission energy for node is considered 50 nj/bit, data receiving energy is considered 50 nj/bit and data gathering energy is considered 50 nj/bit/signal. The system also considers maximum 1,400 rounds of simulation with packet size of 4k-5k bits and control packet size of 200 bits is considered. In the context of RL-based solution the value of discount factor varies between (0.4 - 0.9) with learning rate of 0.1 and exploration rate of 0.1 and aggregation factor of 0.7. The RL iterative rounds are considered to be 40-50 with a data rate of 100 bits/s. However, the functional module of $f_{DD}(x)$ in EERD is designed considering python scripting which is executed in Anaconda distribution installed in Windows 11, 64-bit machine. It also involves Open AI Gym functionalities. The system considers total 100 number of time steps for the evaluation of the model.

3.2. Quantitative results analysis

The performance of the EERD is evaluated with respect to four different evaluation parameters viz; i) average residual energy (J), ii) network lifetime (tu), average latency (time steps) and throughput (kbps). The performance evaluation also considers a comparison with the existing baseline approaches which are Exist1 and Exist2 respectively. Here Exist1 refers to popular RL-driven cluster-based data transmission modeling [10]-[12] and Exist2 refers to popular RL-driven data dissemination methods. The experimental assessment considers various instances during the simulation and also defines the standard criteria.

The following Figure 2 exhibits the outcome of the average residual energy in EERD. It has been observed that the EERD offers significant improvement in optimizing the energy usage when compared with Exist1 and Exist2 approaches. It has been observed that the EERD outperforms the existing approaches by approximately 23% in the measure of average residual energy. The analysis of network lifetime also exhibits that EERD significantly outperforms the Exist1 and Exist2 approaches with more time of simulation rounds in the measure of time as shown in Figure 3. It offers approximately 5-10% improvement in the measure of network lifetime when compared with Exist1 and Exist2. The analysis of the average latency is also exhibited in the following Figure 4. The analysis of latency outcome also shows that EERD offers significant improvement in the measure of Latency as well when compared with Exist1 and Exist2. In Exist2 approaches mostly cyclic and deterministic strategies are explored for node activation and event detection. The interpretation of latency outcome shows that the EERD offers approximately 18.9% improvement over the latency performance when compared with Exist1 and Exist2 approaches. The analysis of Throughput also shows that EERD ensures more successful transmissions when compared with Exist1 and Exist2 approaches as shown in Figure 5. The interpretation shows that EERD outperforms Exist1 and Exist2 approaches by approximately 9.84%.

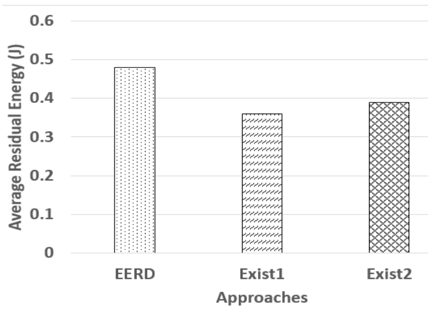

Figure 2. Average residual energy

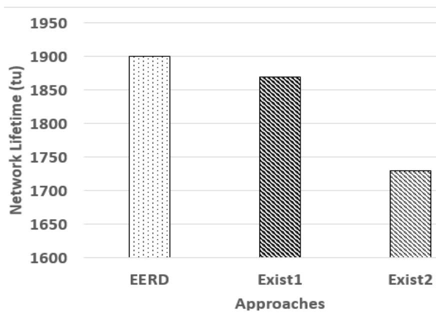

Figure 3. Network lifetime

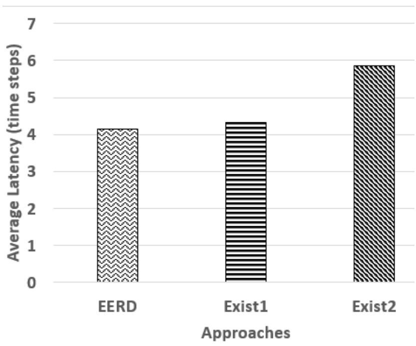

Figure 4. Average latency in time steps

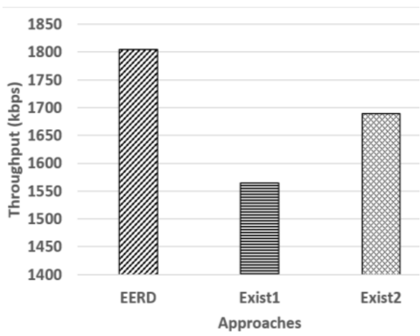

Figure 5. Average throughput measure

3.3. Discussion

The results of the EERD modeling and simulation demonstrate substantial improvements in energy efficiency, network lifetime, average latency, and throughput. Unlike traditional cluster-based data gathering models, EERD dynamically adapts to changing WSN conditions while incorporating a lightweight ML-driven approach for CH selection. A key advantage of this approach is its ability to reduce unnecessary data transmission through a unique information capture phase, minimizing transmission costs and optimizing data gathering efficiency. Additionally, the integration of a simplified Q-value updation strategy and reward function formulation enhances data aggregation and decision-making, contributing to a more energy-efficient and balanced WSN operation. Compared to existing deep RL (DRL)-based methods such as Deep Q-Networks, EERD offers faster CH selection convergence and reduced state evaluation complexity, leading to improved energy balancing among mobile nodes. While conventional DRL models involve high computational overhead, EERD optimizes RL processes to maintain efficiency without sacrificing accuracy. Additionally, its energy-aware routing mechanism, based on a lightweight RL strategy, significantly reduces hop count and network latency, outperforming traditional routing solutions. However, despite these advantages, the study has some limitations, such as the need for extensive real-world deployment and scalability testing under extreme network conditions. Unexpected results, such as the potential variability in convergence time under different network densities, suggest areas for further optimization. This study highlights the significance of EERD in addressing the challenges of data gathering, aggregation, routing, and dissemination in WSNs under dynamic conditions. The proposed framework successfully balances energy efficiency and data transmission performance, making it a promising approach for large-scale WSN applications. Future research should explore enhanced RL models to refine event occurrence probability estimation and further optimize real-time adaptability. Additionally, evaluating EERD across diverse real-world scenarios and heterogeneous sensor deployments could provide deeper insights into its practical applicability and long-term efficiency.

4. CONCLUSION

WSNs are critical for modern data communication, enabling efficient data gathering, aggregation, routing, and dissemination. However, challenges such as energy consumption, latency, and network lifetime require innovative solutions to enhance performance. This study introduces the EERD framework, which optimizes energy efficiency and network adaptability through a strategic analytical approach. By incorporating functional modules that balance energy usage under varying conditions, EERD provides an effective solution for both stationary and mobile nodes, making it a valuable advancement in the field of WSNs. The findings demonstrate that EERD significantly improves network performance, achieving 23% enhancement in residual energy, 5–10% increase in network lifetime, 18.9% reduction in latency, and 9.84% improvement in throughput compared to existing data dissemination strategies. While some may argue that traditional cluster-based models or DRL approaches offer similar benefits, these methods often come with higher computational costs and lack adaptability to dynamic WSN conditions. In contrast, EERD provides a more efficient and scalable alternative, making it a preferable choice for real-world deployments. Future research should focus on extending the EERD framework to more complex and dynamic WSN environments, such as networks with mobile base stations for enhanced energy-efficient data transmission. Additionally, exploring sparse and low-rank characteristics of WSNs could further improve data recovery accuracy. Researchers and industry professionals should consider building upon EERD's methodology to develop even more adaptive and intelligent WSN solutions, ensuring sustainable and high-performance communication networks for future applications.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Swapna Ch	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Vijayashree R. Budyal		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Swapna Ch currently pursuing her PhD in Visvesvaraya technological university Belagavi, Karnataka, India and received M.Tech. Degree in Systems and Signal Processing from Jawaharlal Nehru Technological University, Hyderabad, Andhra Pradesh. She is currently working as an Assistant Professor in Department of Electronics and Communication Engineering at Sri Venkateshwara College of Engineering, Bengaluru, Karnataka, India. She has experience of around 15 years in teaching and 4 years in Research. She has published papers in reputed International Journals and Conferences. Her area of research includes soft computing, wireless sensor networks, vehicular ad-hoc networks, network security. She can be contacted at email: swapnaeng@gmail.com.

Dr. Vijayashree R. Budyal received Ph. D degree in Electrical and Electronics from Visvesvaraya technological university Belagavi, Karnataka, India. She is currently working as Professor at Sai Vidya Institute of Technology, Bengaluru, Karnataka, India. She has vast experience of more than 27 years in teaching. She received best research publication award from VGST, Karnataka in 2014. She has received a research grant by VGST Govt. of Karnataka, Bengaluru under Technology Related Innovative Project in the year 2015-16. To her credit she has published papers in reputed International Journals like Elsevier, Springer and IEEE conferences, about 50 papers in international. She can be contacted at email: vijayashreerb@gmail.com.