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Multivariate Lifetime Prediction Model for Energy Efficient Region-Based Wireless Sensor Network

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ABSTRACT

In wireless sensor networks (WSNs), optimising energy efficiency while maintaining coverage and managing resource constraints remains a critical challenge. This paper introduces a novel Region-Based Multilevel Energy Efficiency Protocol (RBMEEP), which innovatively partitions the network into regions and sub-regions to enhance energy utilisation through optimised clustering and communication with the base station (BS). Unlike conventional protocols, RBMEEP significantly extends network lifetime, outperforming the Stable Election Protocol (SEP). The novelty lies in the integration of a Regression Prediction Model (RPM), which accurately predicts network lifetime based on node density and packet size. Simulation results demonstrate the model's high prediction accuracy, with up to 99.94% in smaller network areas and 99.87% in larger areas. This predictive capability allows for adaptable and efficient WSN design, tailored to specific user requirements. The proposed approach presents a significant advancement in extending the operational life of WSNs, offering a robust solution for energy and coverage optimisation. This work not only improves the theoretical understanding of WSN energy efficiency but also provides a practical framework that can be deployed in real-world scenarios.

1 | Introduction

Wireless sensor networks (WSNs) have emerged as a cornerstone technology across a wide spectrum of applications, including industrial automation, environmental monitoring, healthcare, military operations, and public safety. These networks comprise numerous sensor nodes deployed across a geographic area to monitor physical and environmental conditions, such as temperature, humidity, pressure, and motion. The data collected by these sensors are transmitted to a central base station (BS) for processing and analysis, enabling real-time decision-making and response [1, 2]. The versatility of WSNs has made them indispensable in critical domains such as disaster management, smart cities, combat monitoring, and building control systems, where continuous and reliable monitoring is utmost. Despite their widespread use, WSNs face significant challenges, primarily due to their inherent resource constraints. One of the key issues is maintaining continuous connectivity among sensor nodes, especially in dynamic and harsh environments where fixed infrastructure is often absent [3]. The deployment of sensor

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nodes in these networks must account for factors such as network coverage, connectivity, and data transmission reliability, all while managing the limited energy resources available to each node [4]. As WSNs are typically powered by batteries with limited capacity, efficient energy management is crucial to prolonging network lifetime and ensuring consistent performance. Energy efficiency is a critical concern in WSNs, as the energy consumption of sensor nodes directly impacts the overall network's operational lifespan. Nodes deplete energy during sensing, data processing, and communication activities, with communication being the most energy-intensive operation [5]. To address this, various energy-saving strategies have been proposed, including duty cycling, energy-efficient routing protocols, and clustering techniques. Clustering, in particular, has proven effective in reducing energy consumption by minimising the number of direct communications between sensor nodes and the BS [6, 7]. Cluster Heads (CHs) are elected to aggregate data from surrounding nodes and transmit it to the BS, either directly or through multi-hop routes, thereby conserving energy at the node level. However, the effectiveness of these approaches depends on the ability to optimise cluster formation and maintain energy efficiency across varying network conditions.

One of the fundamental challenges in WSNs is achieving efficient energy management while maintaining adequate network coverage. Current approaches often struggle with balancing energy efficiency and connectivity, leading to suboptimal network performance. The research question addressed in this paper is: How can we design a protocol that optimises cluster formation and routing to significantly improve energy efficiency and network lifetime in WSNs? To tackle this question, this paper introduces a novel Region-Based Multilevel Energy Efficiency Protocol (RBMEEP), designed to enhance network lifetime by optimising cluster formation and routing strategies. Unlike conventional protocols, RBMEEP dynamically partitions the network into regions and sub-regions, allowing for more precise energy management and communication routing. Additionally, this paper integrates a Regression Prediction Model (RPM) that accurately predicts network lifetime based on key parameters such as node density and packet size.

The main contributions of this paper are as follows:

1. Development of RBMEEP: A novel protocol that optimises cluster formation and routing to enhance energy efficiency and extend network lifetime.
2. Integration of RPM: A predictive model that accurately estimates network lifetime based on node density and packet size, providing actionable insights for network design and management.
3. Comparative Analysis: Demonstration of RBMEEP's superior performance compared to existing protocols such as the Stable Election Protocol (SEP) in terms of network lifetime and energy efficiency.
4. Practical Framework: A comprehensive framework that addresses the limitations of current approaches and offers a practical solution adaptable to various WSN applications.

The contributions of this work are twofold: first, to propose RBMEEP as a robust clustering and routing protocol, and second, the integration of RPM for accurate lifetime prediction. Together, these contributions offer a comprehensive framework for enhancing energy efficiency in WSNs, ensuring that the network can operate effectively under varying conditions and application requirements. The rest of the paper is structured into distinct sections, each serving a specific purpose as follows:

Section 2—Design Issues and Related Work: this section addresses design challenges and presents an overview of related work. Section 3—Stable Election Protocol (SEP): here, the Stable Election Protocol is discussed in detail. Section 4—Proposed RBMEEP Protocol and Simulation Results: this section introduces the Region-Based Multilevel Energy Efficiency Protocol (RBMEEP) protocol and presents simulation results related to it. Section 5—Proposed RPM Model. The final section provides a conclusion to the paper's findings and offers insights into potential directions for future research.

2 | Design Issues and Related Work

WSN nodes have limited energy, computation, and communication facilities, and they are distributed randomly or deterministically in the network area. The network's performance relies on both deterministic and nondeterministic algorithms. Sensor network classification is based on the homogeneity or heterogeneity of sensor properties, enabling them to perform various tasks.

2.1 | Hierarchical Clustering Protocols

In ref. [5], the authors propose a protocol that categorises nodes by energy level. Some nodes transmit data directly, while others use clustering. Fuzzy logic in CH selection improves system performance.

In ref. [6], the authors introduced a novel hybrid algorithm, incorporating the SIC algorithm and a dual Cluster Head (CH) approach. The SIC algorithm mitigates energy loss during long-distance data transmission between clusters through multi-hop communication. The dual CH selection method is employed to distribute the network load, resulting in an enhanced stability period compared to existing protocols.

In ref. [7], the authors presented a solution for addressing hot spot issues. They employed an efficient cluster-based routing scheme that dynamically adjusts cluster size using fuzzy logic. This protocol operates in a two-phase, multi-hop routing scheme for data transmission to the base station (BS). It effectively prolongs the network's lifespan by optimising energy consumption throughout the network.

In ref. [8], the (LEACH-Imp) protocol was introduced for sensor networks. This protocol employs multiple paths for routing data within cluster nodes. The optimal existing path is dynamically elected based on criteria such as path energy consumption, Sensor Node (SN) Residual Energy (RE), and route hop count during the data transmission phase. This protocol significantly improves the system's survival rate and throughput.

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In ref. [9], the authors discussed the SPR (Sequential Path Routing) approach for data routing in a network. In this approach, sensor nodes are deployed across various zones from top to bottom. Zonal Cluster Heads (CHs) facilitate data transfer between adjacent zone CHs. Only a limited number of nodes participate in the data forwarding task resulting in reduced delay and improved system performance.

In ref. [10], the authors introduced the DMEERP (Dynamic Multi-Path Energy-Efficient Routing Protocol) to balance energy consumption within the network. The protocol's operation is as follows: In the first phase, the network is initialised and clusters are formed. The selection of Super Cluster Heads (SCH) involves requests from multiple nodes or cluster heads at a given level. SCHs use multi-path routing for data communication inside the network. In the second phase, path reliability is enhanced to ensure more reliable data delivery.

In ref. [11], the authors proposed the GRMRP (Grid-oriented Multi-hop-based Routing Protocol) via a multi-hop communication scheme to improve network stability and performance. The GRMRP protocol divides the network into different virtual grids, which are additionally subdivided into basic components. Only one node is active at any given time, and the switching mechanism prolongs the lifetime of sensor nodes, resulting in improved system performance.

In ref. [12], a protocol was introduced to address coverage and connectivity challenges by considering the effective radius of nodes and Sensor Node (SN) Residual Energy (RE) as parameters. When the active node's energy is completely depleted, nodes in a sleep state become active. This protocol mitigates the problem of node overlap, effectively utilising overlapping SNs to extend the network lifetime through a sleep and wake-up mechanism.

In ref. [13], a protocol was proposed with the aim of minimising unbalanced energy consumption within the network. Cluster Heads (CH) are elected using the Residual Energy of the SN. The use of a greedy algorithm aids in identifying the optimal route and data transfer tasks. This protocol minimises indirect transmissions through intermediate nodes, leading to enhanced system performance.

In ref. [14], the authors discussed the APTEEN Protocol, which shares architectural similarities with the TEEN protocol. APTEEN incorporates proactive and reactive network features to accomplish sensor network tasks. Sensor Nodes (SN) periodically transmit data and also report changes in attribute values. The CH election process in the TEEN protocol is determined by attribute values, threshold values, and count time parameters.

In ref. [15], a multi-tier cluster approach was proposed for monitoring wild animals in agricultural fields. The agricultural field is divided into sub-sections based on their distance from the BS. The number of CH nodes increases at each level, contributing to the overall network's improved performance. This method places emphasis on the correlation factor among variables that are highly correlated with each other.

2.2 | Predictive Lifetime Models

In ref. [16], a statistical theorem was discussed to evaluate the impact of the two-fold prediction technique in the network. This approach reduces the count of transmissions and data collection tasks, resulting in minimised transmissions and enhanced system performance.

In ref. [17], a fuzzy-based model for rainfall prediction was introduced. The model incorporates parameters such as temperature, humidity, and soil condition (a constant parameter). It predicts rainfall in the North East region, contributing to improved human and animal survival.

In ref. [18], a historical data reconstruction method was proposed, which relies on historical data and a data rebuilding process to forecast data. This data prediction model minimises transmission and control delays within the network by forecasting future values based on specific points, achieving greater efficiency and control over network delays.

In ref. [19], a hidden Markov method was proposed for optimising the sequence of node placement and prediction techniques to enhance target coverage within the network. The paper also incorporates the trust concept to determine the optimal sequence of Sensor Nodes (SN) and improve network lifetime.

In ref. [20], the LQP (Local Quadratic Programming) method is utilised to achieve LINQ quality features, but it does not fully attain network prediction result validity. To address these issues, the RVFL method is introduced. The RVFL method, in combination with the LQP method, enables prediction results in smart grid environments for real-life applications.

In ref. [21], an adaptive filtering technique was introduced for network data drop. It employs a dual forecast scheme to forecast future values, using a curved combination, two distinct adaptive filters, and distinct window sizes. This model reduces transmission error rates and maximises energy efficiency within the network.

In ref. [22], the authors contrast with various approaches, one optimum strategy to increase network lifespan in the intended coverage is to modify nodes' sensing and communication ranges based on their energy levels. At the network layer, energy-efficient routing and communication protocols are created, and the nodes are scheduled in an active/sleep mode. Nodes in a sensor network can be in any of three states: active, sleep, or idle. In the data transmission, a sensor node uses the maximum energy. The most effective way to increase network longevity is to schedule nodes to alternate between the active and sleep states. Regression models can be helpful for the prediction of SN's lifetime by predicting node states in efficient manner.

2.3 | Energy-Harvesting and Adaptive Techniques

In ref. [23], the authors proposed the Wireless Energy Harvesting (WEH) technique for IoT-based sensors. WEH technology

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enhances ease of implementation, increases data availability, and reduces development costs. The design of WEH for IoT-based sensor networks offers significant advantages in the realm of wireless energy harvesting systems.

In ref. [24], the authors explored both distributed and centralised techniques for wireless sensor networks, focussing on deployment considerations, node types, event detection methods, and essential components for building the network backbone. The centralised approach can lead to issues such as network collisions, message loss, and traffic congestion.

In ref. [25], the authors delved into the deployment of SNs within the network area, aligning with the specific application requirements and user specifications. For smaller network areas, a random topology is employed for SN deployment. Conversely, larger network areas benefit from uniform and circular topologies, which have been shown to enhance the lifetime of the network by 41%, and 38%.

In ref. [26], the MSRP (Mobility-Aware Sink-based Routing Protocol) technique was proposed, bearing similarities to the EEMSR protocol. In this approach, Cluster Heads (CH) exclusively perform data collection tasks when the sink is in proximity to the network. The proposed MSRP approach is primarily intended for applications with delay tolerance. The mobility of sink nodes is obtained by the average energy of clusters, contributing to the improved network lifespan.

In ref. [27], a protocol was proposed to improve node RE, stability, and lifetime. The protocol consists of two stages: in the first stage, a new CH selection process is based on a new formula. In the second stage, a trust function is employed to ensure accurate data. Concurrently, a data fusion process aggregates all data for transmission to the BS.

In ref. [28], the authors proposed the ARSH-FATI-CHS algorithm, a novel approach to enhancing the energy efficiency and enhancing the lifetime of WSNs. The proposed approach use clustering algorithm that dynamically balances exploration and exploitation during the cluster head (CH) selection process, considering factors such as residual energy, communication distance, and workload on CHs. By integrating the ARSH-FATI algorithm with a heuristic-based Novel Ranked Clustering (NRC) method, the approach significantly reduces transmission energy consumption and improves the overall network lifetime by up to 25% compared to existing techniques such as Particle Swarm Optimisation (PSO). The results show an average LT improvement of 60%, 40%, and 25% over LEACH, PSOC, and PSO-ECHS, respectively.

In ref. [29], the shuffled ARSH-FATI metaheuristic is proposed to address the problem of Lifetime Maximisation using Range-Adjustable Sensors (LM-RAS) in WSNs, which are crucial components of IoT systems. This approach optimises the lifetime of WSNs by generating energy-efficient coverage schemes and scheduling their activation using a Linear Programming (LP) model. By splitting the LM-RAS problem into two subproblems and employing a multi-population method that includes a merge, shuffle, and partition (MSP) algorithm, Shuffled ARSH-FATI ensures diversity and high-quality solutions.

Table 1 discusses each group's common strengths/limitations that will lays the foundation of the proposed work.

The approach [28], highlights the importance of CH selection criteria and network partitioning, which is also addressed in the proposed RBMEEP protocol. Although ARSH-FATI-CHS optimises CH selection through dynamic trade-offs, RBMEEP further advances the field by introducing a hierarchical multi-level clustering structure, which enhances scalability and energy efficiency in larger network deployments.

The use of adaptive routing protocols to further enhance energy efficiency and network performance is suggested by authors [29], the concept of relay nodes are proposed in RBMEEP to

TABLE 1 | Common strengths and limitations of existing works.

Thematic group	Common strengths	Common limitations
Hierarchical clustering protocols	– Efficient energy usage through clustering – Scalable structure for large networks – Reduced transmission overhead – Extended network lifetime	– Cluster head (CH) overload in high-traffic scenarios – Re-clustering overhead – Static or semi-adaptive CH selection lacks flexibility
Predictive lifetime models	– Reduced communication overhead via forecasting – Better resource utilisation through pre-emptive scheduling – Enhanced responsiveness to sensed data trends	– Requires historical or training data – Less effective in highly dynamic environments – Additional computational complexity
Energy-harvesting and adaptive techniques	– Enables long-term deployments – Adaptive to dynamic topology and energy levels – Improved sustainability in IoT contexts	– Requires specialised hardware (e.g., EH modules) – Higher protocol complexity – Sensitivity to parameter tuning

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facilitate data aggregation and forwarding, reducing the direct transmission load on primary nodes and thereby optimising energy consumption. Their inclusion enables a hybrid routing approach, which improves network reliability and fault tolerance by providing additional routing paths and ensuring uninterrupted data transmission even if some primary nodes fail.

Using these literature reviews, Table 2 summarises the literature gap and how the proposed RBMEEP protocol addresses these gaps.

3 | Stable Election Protocol

The SEP protocol employs a two-level hierarchy, employing both Advanced Nodes (AN) and Normal Nodes (NN) within the network area. The working of the SEP protocol is depicted in Figure 1. NNs are typically situated at a considerable distance from the BS and consequently demand additional energy for transmitting data to the base station. The preliminary energy level of ANs is 'E_α' times greater compared to the NNs. Let us assume that 'SN' represents the total number of nodes inside the network. The proportion of advanced nodes is denoted as 'SA', The amount of initial energy of normal nodes is 'E_0', while advanced nodes possess energy levels $1 + E_\alpha$ times higher.

Then, the total IE of heterogeneous WSN is represented as [31].

$$S_N E_0(1 + E_\alpha S_A) = S_{N\times}(1 - S_A)E_0 + S_N S_A E_0 \times (1 + E_\alpha) \quad (1)$$

In Equation (1), it is evident that the total energy of the new heterogeneous network is enhanced by a factor of $(1 + E_\alpha\ S_A)$. The probability assignments for the Cluster Head election process in the network depend on the energy levels of the sensor nodes (SN). Data transmission from the clusters to the sink is carried out using a Radio energy dissipation model. Initial Energy (IE) is used for CH election probability in the SEP protocol. The SEP protocol assigns weighted probabilities to each sensor node. The weighted probability for a normal sensor node is denoted as P_{normal}, and for an advanced sensor node, it is represented as P_{advance} in Equations (2) and (3):

$$P_{\text{normal}} = \frac{P}{1 + E_\alpha S_A} \quad (2)$$

$$P_{\text{advance}} = \frac{P}{1 + E_\alpha S_A} \times (1 + E_\alpha) \quad (3)$$

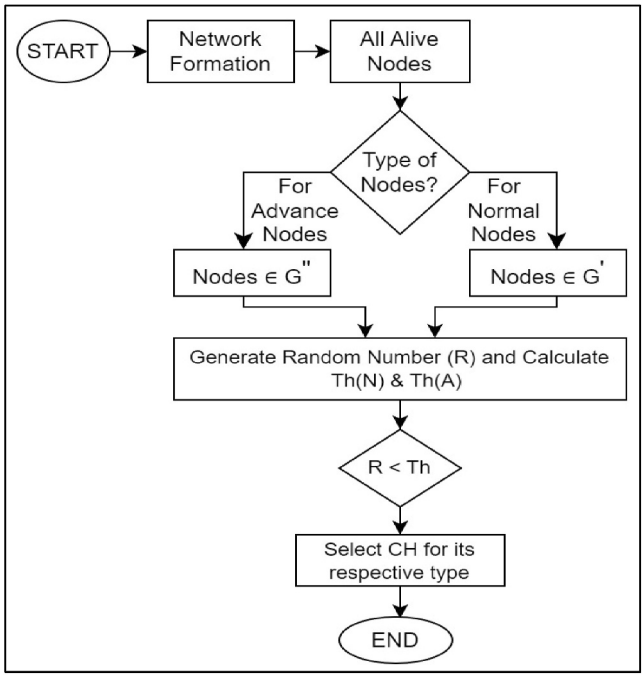


FIGURE 1 | Flowchart of SEP.

TABLE 2 | Challenges/gap in existing work.

Challenge/gap in literature	Details	How RBMEEP addresses it
Energy management in static and dynamic environments	Existing protocols often use static approaches, inadequate for dynamic conditions such as node mobility and varying energy levels [4, 6, 7]	RBMEEP employs dynamic cluster head selection based on energy and proximity, adapting to changing network conditions
Scalability and network coverage	Methods such as GRMRP and SPR have limitations in ensuring performance as network size and complexity increase [9, 11]	RBMEEP's three-tiered architecture enhances scalability and coverage, overcoming the limitations of static methods
Predictive and adaptive mechanisms	Current approaches lack advanced integration of predictive models for real-time adaptation [18, 30]	RBMEEP integrates a regression prediction model (RPM) for accurate forecasting and real-time adaptation of network management
Dynamic adaptation	Future work in Shuffled ARSH-FATI involves integrating machine learning and adaptive routing for better efficiency	RBMEEP incorporates dynamic adaptation through its architecture and RPM, offering advanced real-time management and improved network performance
Energy-efficient clustering algorithms	ARSH-FATI-CHS optimises CH selection through dynamic trade-offs [28]	RBMEEP further advances the sensing field by introducing a hierarchical multi-level clustering structure, which enhances scalability

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A number is randomly created and the bigger threshold (T) value is selected as the Cluster Head (CH) for the current round. The CH is responsible for collecting the data and transmitting it to the BS. The threshold values for advanced sensors (T_{advance}) and normal sensors (T_{normal}) are defined in Equations (4) and (5):

$$T_{\text{normal}} = \begin{cases} \dfrac{P_{\text{normal}}}{1 - P_{\text{normal}}\left(r \bmod \dfrac{1}{P_{\text{normal}}}\right)}, & \text{if } N_{\text{normal}} \in G' \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

$$T_{\text{advance}} = \begin{cases} \dfrac{P_{\text{advance}}}{1 - P_{\text{advance}}\left(r \bmod \dfrac{1}{P_{\text{advance}}}\right)}, & \text{if } N_{\text{advance}} \in G'' \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

Here, G' and G'' refer to the sets of normal and advanced sensor nodes that were not selected as CHs for the existing round (r). The major drawbacks of the SEP include:

a. The successful deployment of Sensors in the network region is not guaranteed by the SEP protocol.

b. The network's CH election probability is solely determined by the SN's initial energy.

c. The network has an energy imbalance as a result of the heterogeneity features of SN.

The Region-Based Multilevel Energy Efficiency Protocol (RBMEEP) is proposed to tackle the limitations of the SEP. The RBMEEP approach is designed by incorporating multi-level-based clustering, which specifically considers the heterogeneity of nodes within the network.

4 | Proposed RBMEEP Protocol

The RBMEEP Protocol has been specifically developed for military applications. These applications are categorised into battlefield surveillance, intruder detection, combat monitoring, etc. In the context of battlefield observation, sensor nodes (SN) are strategically deployed on the battlefield, typically near enemy force routes. A key advantage is that these SNs can be positioned spontaneously and operate without requiring constant maintenance. Additionally, the RBMEEP contributes to energy conservation using monitoring factors such as enemy detection, environmental conditions, etc. The sensor nodes are deployed across a two-dimensional area with dimensions M × M, and the base station (BS) is centrally located within the network area.

The Region-Based Multilevel Energy Efficiency Protocol (RBMEEP) introduces several key innovations that set it apart from existing sensor network protocols, particularly in military applications. Unlike traditional approaches that often rely on static clustering or uniform node deployment, RBMEEP's methodology is distinguished by its hierarchical network architecture and dynamic clustering strategy.

4.1 | Distinctive Features and Significance

1. **Hierarchical Network Architecture:** RBMEEP's three-tier structure, comprising Zonal, Regional, and Auxiliary levels, represents a significant departure from conventional flat or single-tiered network designs. This hierarchical approach not only enhances network coverage and energy efficiency but also facilitates more effective data aggregation and transmission. Through breaking down the network into manageable zones and sub-regions, RBMEEP reduces the communication overhead and energy consumption typically associated with large-scale deployments.
2. **Dynamic Cluster Head Selection:** The protocol's innovative mechanism for selecting Cluster Heads based on their distance to the base station (BS) and residual energy introduces a level of adaptability not commonly found in traditional protocols. This dynamic selection process ensures that data is routed efficiently and that energy resources are utilised optimally, extending the network's operational lifetime and improving overall performance.
3. **Hybrid Routing with Relay Nodes:** RBMEEP incorporates a hybrid routing approach combined with relay nodes, a unique feature that enhances data transmission reliability and efficiency. This combination addresses the challenge of maintaining robust connectivity and data integrity across diverse network conditions, particularly in military environments where nodes may be randomly deployed and experience variable energy levels.
4. **Military-Optimised Design:** Specifically tailored for military applications, RBMEEP accommodates the spontaneous deployment and operational constraints of sensor nodes in battlefield scenarios. The protocol's ability to function effectively in such dynamic and high-stakes environments underscores its practical significance and potential impact.

4.2 | Assumptions for the Proposed RBMEEP Protocol

To cover the entire network area, a three-level architecture is introduced. The region is initially divided into zones, which are further subdivided into multiple regions, and these regions are then further divided into different sub-regions. These levels are respectively referred to as the Zonal, Regional, and Auxiliary levels (the lowest one). The selection of Cluster Heads (CH) is determined based on the criteria of minimising the node distance from the BS and maximising the node's remaining energy (RE).

a. SNs, including both advanced and normal nodes, are placed in a random deployment across the network area.

b. These nodes are static in nature, possessing heterogeneous characteristics.

c. Data transmission occurs through the multi-hop technique for routing among the Cluster Head nodes.

d. The system design does not account for noise factors and signal interference.

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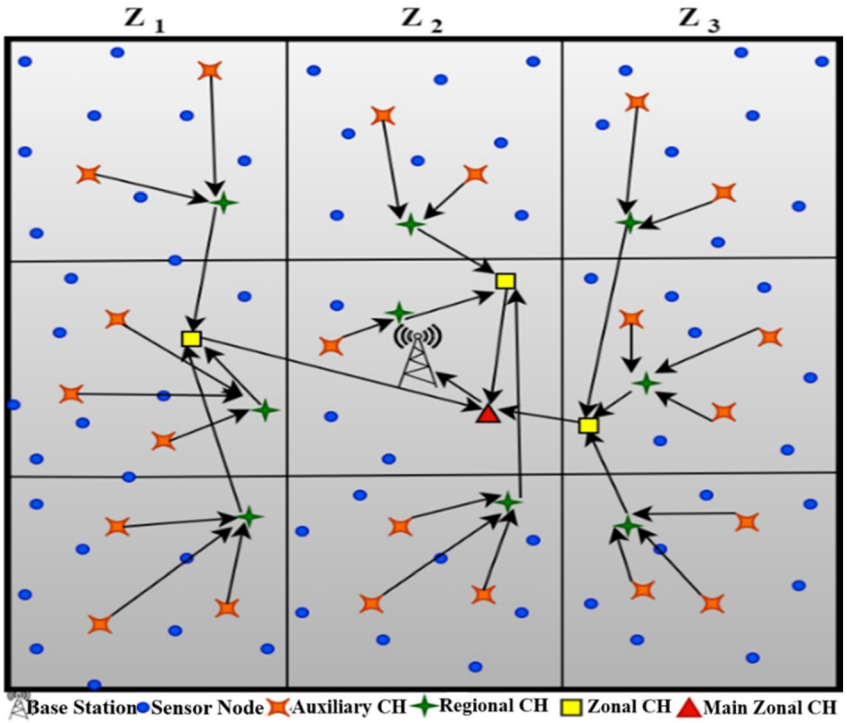


FIGURE 2 | Region division.

e. Approximately 10% of the SNs are regarded as being positioned outside the network region, possibly due to being inadvertently dropped after the upper.

f. The 5% Nodes are used as Relay nodes.

4.3 | Region Division Used in the Proposed RBMEEP Coverage and Connectivity

The network is partitioned into different zones. This zonal partition is further subdivided into various regions. These regions are then divided into various sub-regions labelled as {R1, R2,..... Rn}. These Rn sub-regions collectively form clusters referred to as Auxiliary Clusters (AC), each of which is overseen by an Auxiliary Cluster Head (ACH). The responsibility of ACH is to transmit the data to their Regional Cluster Head (RCH), from where it sends data to the Zonal Cluster Head (Algorithm 1).

If there are 'p' zones, each denoted as p1,... pn within the specified area, then there are 'p' Zonal Cluster Heads. Within zone p1, there exist 'q' regions, labelled as q1, q2, ... qm, and for each of these 'q' regions, there are 'q' Regional Cluster Heads. Furthermore, the 'qm' regional clusters are formed, each having varying sizes based on the number of nodes present in the region as illustrated in Figure 2.

The data are communicated to BS from ACH and the steps of the same are as follows [32].

a. ACH (Auxiliary Cluster Head) consolidates data from the set of Auxiliary Region Clusters $\{n_1, n_2, n_3, \ldots n_n\}$.

b. The collected data is then relayed by ACH to RCH (Regional Cluster Head), which further aggregates information from {ACH1, ... ACHn} within the respective region.

c. RCH subsequently transmits the aggregated data to ZCH (Zonal Cluster Head), which collects and merges data from {RCH1, ... RCHn}.

d. ZCH forwards the combined data to ZMainCH (Zonal Main Cluster Head), who accumulates information from {ZCH1, ... ZCHn}.

e. In the last, ZMainCH transmits the consolidated data to the BS utilising a hybrid routing approach.

f. The ZMainCH are used for data transmission to BS using Relay nodes.

4.4 | Proposed RBMEEP Algorithm

ALGORITHM 1 | Region Division Algorithm.

1: Input: Set of zones {p1, p2, ..., pn}, Set of regional clusters {q1, q2, ..., qm}
2: Output: Aggregated data transmitted to BS
3: Initialisation: Set ACH as the Auxiliary Cluster Head in each zone (ACH_1, ACH_2, ..., ACHn), Set RCH as the Regional Cluster Head in each regional cluster (RCH1, RCH2, ..., RCHm), Set ZCH as the Zonal Cluster Head in each zone (ZCH_1, ZCH_2, ..., ZCHn), Set ZMainCH as the Main Zone Cluster Head.
4: For each zone pi in {p1, p2, ..., pn}:
5: ACHi aggregates data from different Auxiliary Region Clusters set as $\{n_1, n_2, n_3, \ldots, n_n\}$.
6: ACHi transfers aggregated data to RCHi.
7: For each regional cluster qj in {q1, q2, ..., qm}:
8: RCHj aggregates data from {ACH_1 to ACH_n} in the defined region
9: RCHj transmits aggregated data to ZCHj.

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10: For each zone pi in {p1, p2, ..., pn}:
11: ZCHi aggregates data from {RCH_1, RCH_2, ..., RCHn} in the given zone.
12: ZCHi transmits aggregated data to ZMainCH.
13: ZMainCH collects data from {ZCH_1, ZCH_2, ..., ZCH_n}.
14: If (ResidualEnergy (ZMainCH) is *LOW*)
15: ZMainCH transfers collected data to Rely nodes.
16: Relay nodes transmitted data to BS.
17: Selection of new ZMainCH.
18: else
19: ZMainCH transmitted data to BS.

4.5 | Simulation Parameter

MATLAB was used to simulate the RBMEEP and SEP protocols in two different cases. The RBMEEP protocol is specifically developed to address the limitations observed in the SEP.

In Case 1 of the simulation, the study involved a network with an initial node count of 100, which was gradually increased to 1000 SNs in increments of 100 SNs. This network operated within a 100 × 100 square metre area and considered different packet sizes, namely 2000, 3000, and 4000 bits.

In Case 2 of the simulation, the network initially comprised 100 nodes, and this node count was progressively increased to 1000 SNs in increments of 100 SNs. The network operated within a 200 × 200 square metre area and considered various packet sizes, including 2000, 3000, and 4000 bits. Table 3 outlined the simulation parameters, and it was noted that 20% of the nodes within the network were selected as Advanced Nodes (AN), and the remaining 80% were Normal Nodes (NN).

Case 1. The Lifetime of RBMEEP and SEP for 100 × 100 m^2 region.

Figure 3a–c depicts the simulation outcomes for both the proposed RBMEEP protocol and SEP, with 100 SNs randomly deployed in a network spanning 100 × 100 square metres. The simulations cover various packets of 2000, 3000, and 4000 bits in size, correspondingly. Notably, the performance of the RBMEEP protocol demonstrates an extended network lifetime when compared with the SEP protocol.

Table 4 presents the results of the simulation analysis, where the node count ranges from 100 to 1000 nodes in increments of 100 nodes. These simulations are conducted in a network area measuring 100 × 100 m^2 and consider different packet sizes, namely 2000, 3000, and 4000 bits.

The analysis from Table 4 reveals that as the packet size increases within a specified network area, the network lifetime tends to decrease. However, there is an interesting observation: the network's lifetime improved around 400 in terms of nodes when using a packet of 4000 bits, 500 nodes for a packet of 3000 bits, and 2000-bit packet for the RBMEEP protocol. After reaching these points, the network lifetime experiences a rapid decline, primarily due to congestion or network delays.

Table 5 shows the comparison of SEP and RBMEEP Protocols in Terms of Network Lifetime (Mean ± Standard Deviation) Over 10 Runs with Statistical Significance (Mann–Whitney *U* Test).

Figure 4a–c shows energy dissipation at various points as first node dead (FND), half node dead (HND), and last node dead (LND) for 200 SNs in the simulation for 100 × 100 m^2 region.

The proposed approach outperforms the SEP protocol in energy dissipation at different points as shown in Table 6.

Table 6 compares the performance SEP and RBMEEP, across different data sizes (2000, 3000, and 4000 bits) based on node death metrics: first node dead, half node dead, and last node dead. The results indicate that RBMEEP consistently outperforms SEP in terms of node longevity across all data sizes. For instance, with 2000 bits, the first node in SEP dies at 820 rounds compared to 1295 rounds in RBMEEP, showing a significant improvement. As the data size increases, this thing continues. At 4000 bits, SEP's first node dies at 3093 rounds, while RBMEEP prolongs it to 3730 rounds. Similarly, for half node and last node dead metrics, RBMEEP consistently maintains a higher threshold, indicating better energy efficiency and overall performance, especially in larger data sets.

Case 2. The Lifetime of RBMEEP and SEP for 200 × 200 m^2 region.

TABLE 3 | Key parameters used in the simulation.

Parameter	Values for Case 1	Values for Case 2
Sensor area	(100 × 100) m^2	(200 × 200) m^2
Nodes	Varying from 100 to 1000	Varying from 100 to 1000
Size of packets	(2000, 3000, 4000) bits	(2000, 3000, 4000) bits
Initial energy of SN	0.5 J	0.5 J
Initial energy of AN	*E*0 (1 + *E*_α)	E0 (1 + *E*_α)
Energy factor (α)	1	1
Transmission, receival energy/bit (E_{elec})	50 nJ/bit	50 nJ/bit
Amplifier energy E_{fs}: $d < d_0$	10 pJ/bit/m^2	10 pJ/bit/m^2
Amplifier energy Emp: $d \geq d_0$	0.0013 pJ/bit/m^4	0.0013 pJ/bit/m^4
Node distribution	100% NN, 0% AN	80% NN, 20% AN

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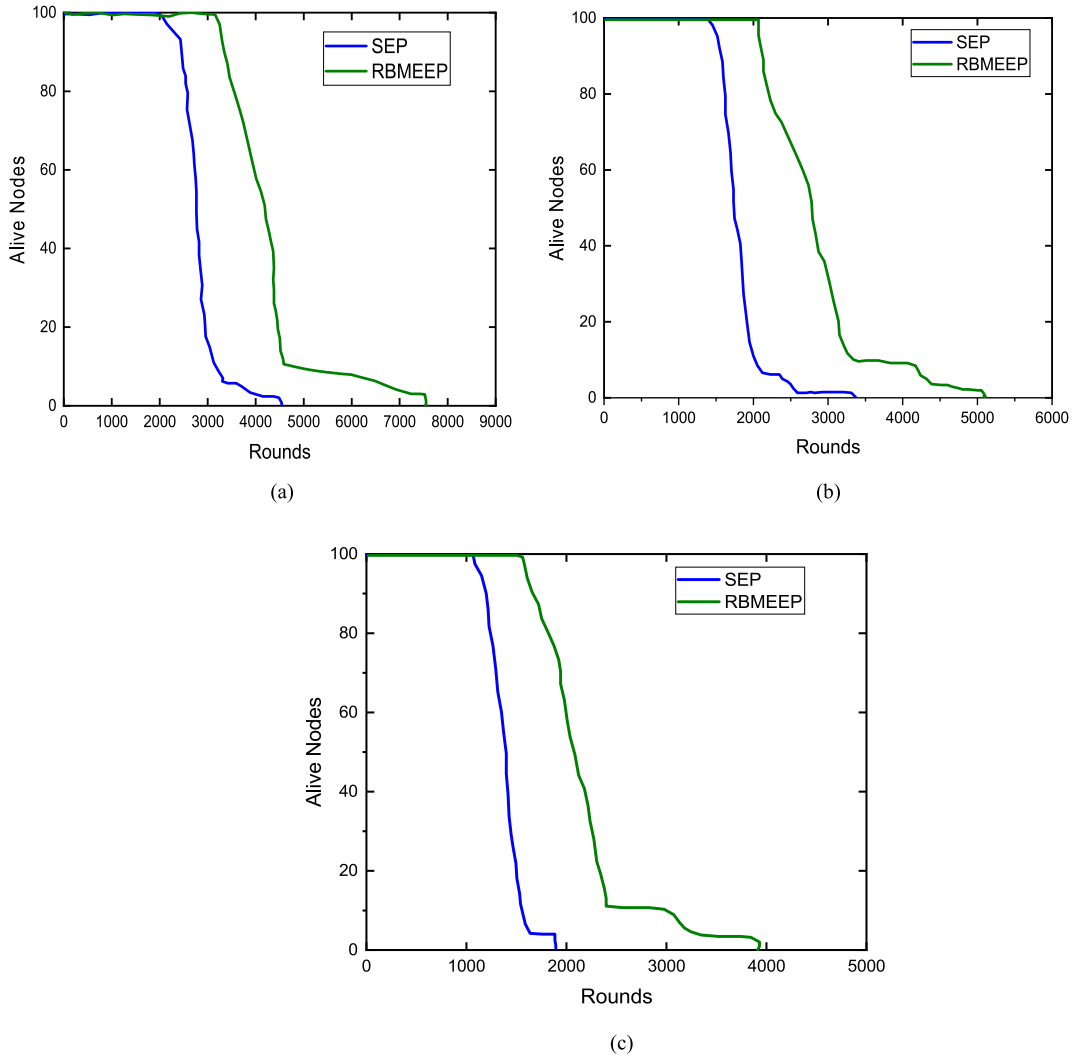


FIGURE 3 | (a) 2000 bits. (b) 3000 bits. (c) 4000 bits.

TABLE 4 | Proposed RBMEEP versus SEP protocol.

	2000		3000		4000	
Nodes	**SEP**	**RBMEEP**	**SEP**	**RBMEEP**	**SEP**	**RBMEEP**
100	4475	7508	3273	5135	1851	3959
200	4891	7681	2940	5246	2388	4049
300	5010	7897	2952	5581	3098	4240
400	4303	7968	3010	5692	2321	4420
500	4500	8054	3088	5826	2311	4333
600	4367	7840	3200	5549	2356	4078
700	4550	7666	3235	5298	2172	3862
800	4304	7611	2910	5295	2280	3767
900	4000	7336	2959	5093	2160	3508
1000	4306	7307	2908	4988	2275	3405

Figure 5a–c displays the simulation outcomes of both the proposed RBMEEP and SEP protocol. These simulations involve 100 SNs randomly deployed in a network spanning 200 × 200 square metres. Various packet sizes of 2000, 3000, and 4000 bits are considered. Notably, the performance of the RBMEEP exhibits improvement in the network lifetime when compared to the SEP.

Table 7 provides a comprehensive investigation of the simulation results. It encompasses scenarios ranging from 100 to 1000 SNs, with node increments of 100 SNs. The simulations occur in a network area measuring 200 × 200 square metres and consider different packet sizes, specifically 2000, 3000, and 4000 bits.

Analysis of Table 7 reveals a trend where, with increasing packet size in a fixed network, network lifetime tends to decrease. However, an interesting finding is that network lifespan with a packet of 4000 bits raises up to 600 nodes. Similarly, 500 nodes for 3000, and 2000 bits of packet size for the RBMEEP protocol. Beyond these thresholds, network lifetime decreases exponentially due to congestion. Most sensor network research is directed at battlefield surveillance, and the RBMEEP protocol optimises sensor node deployment to minimise network costs and maximise coverage. Table 8 shows comparison between SEP and RBMEEP for Mean ± SD and *p*-value (Mann–Whitney *U*) comparison.

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TABLE 5 | Comparison of SEP and RBMEEP protocols.

Nodes	SEP (mean ± SD)	RBMEEP (mean ± SD)	*p*-value (Mann–Whitney *U*)
2000	4470.6 ± 296.28	7686.8 ± 255.40	0.00018 (significant)
3000	3047.5 ± 141.10	5370.3 ± 277.34	0.00018 (significant)
4000	2321.2 ± 313.11	3962.1 ± 335.01	0.00018 (significant)

Note: The table clearly demonstrates that RBMEEP significantly outperforms SEP across all network sizes. RBMEEP consistently achieves higher mean values with lower variation, indicating both effectiveness and stability. Statistical validation using the Mann–Whitney *U* test confirms that the improvements are significant, highlighting RBMEEP's superior performance in prolonging network lifetime.

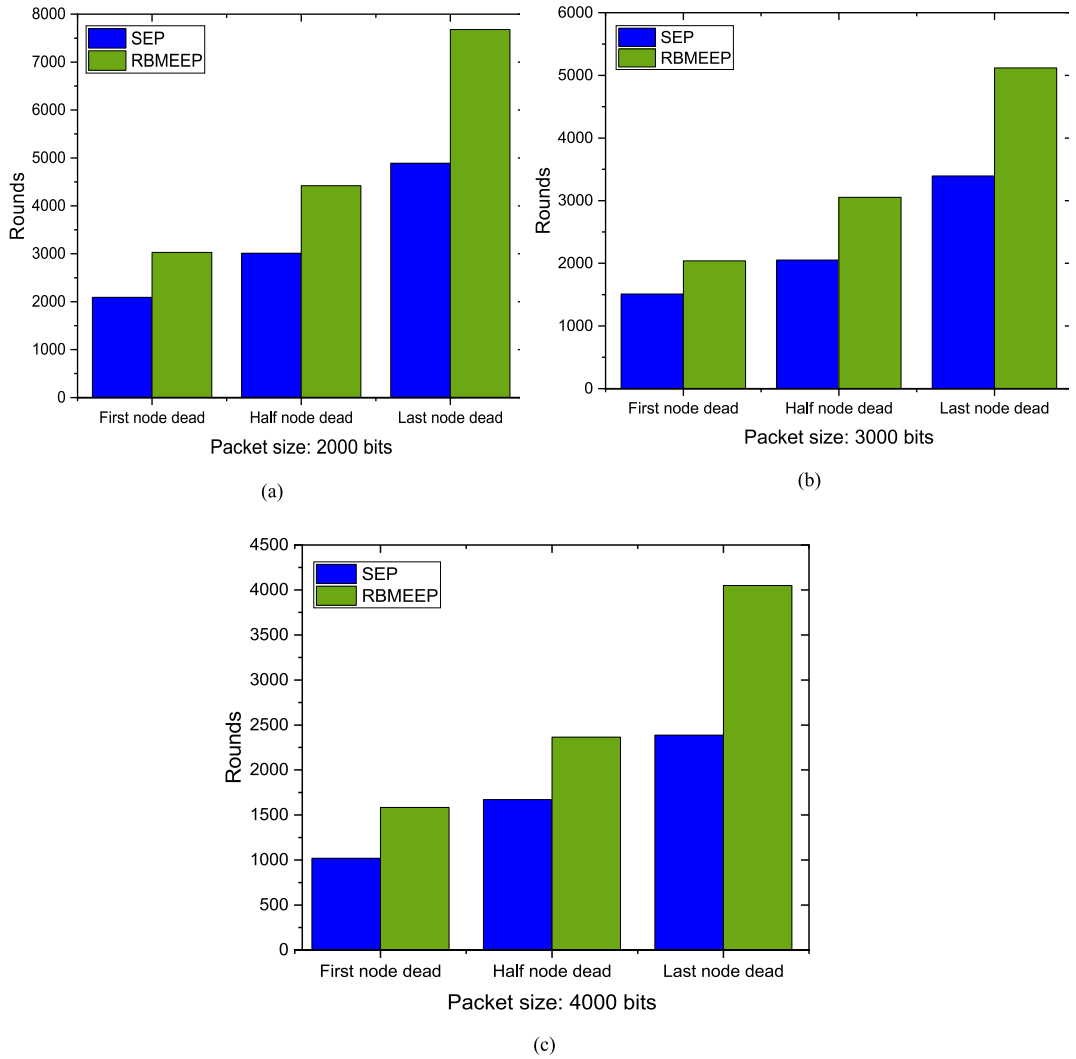


FIGURE 4 | (a) 2000 bits. (b) 3000 bits. (c) 4000 bits.

TABLE 6 | Energy dissipation at various points.

	SEP (4000 bits)	RBMEEP (4000 bits)	SEP (3000 bits)	RBMEEP (3000 bits)	SEP (2000 bits)	RBMEEP (2000 bits)
First node dead	1020	1585	1511	2040	2093	3030
Half node dead	1671	2365	2051	3053	3011	4421
Last node dead	2388	4049	3394	5119	4891	7681

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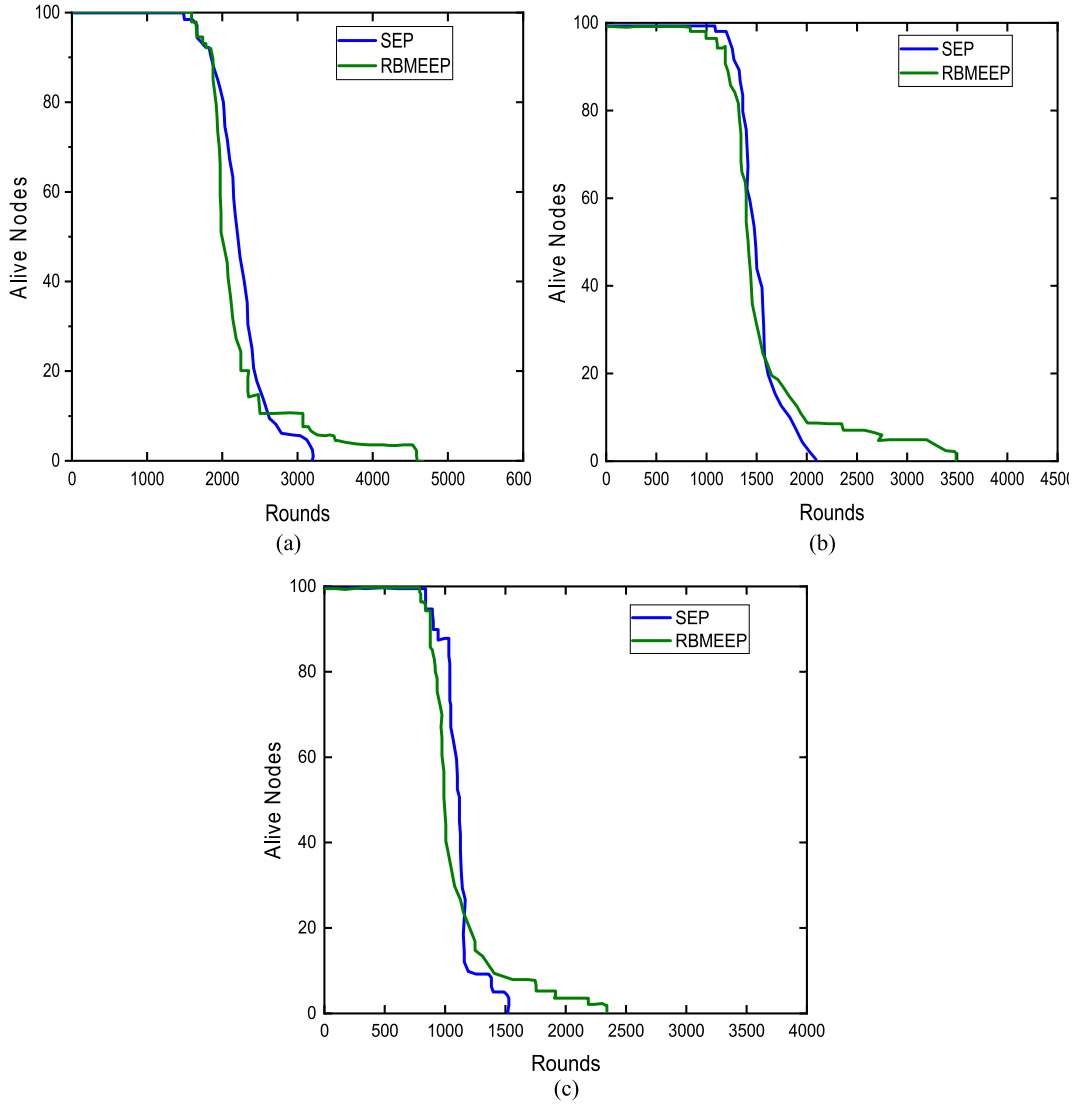


FIGURE 5 | (a) 2000 bits. (b) 3000 bits. (c) 4000 bits.

TABLE 7 | The lifetime of RBMEEP versus SEP.

	2000 bits		3000 bits		4000 bits	
Nodes	**SEP**	**RBMEEP**	**SEP**	**RBMEEP**	**SEP**	**RBMEEP**
100	3180	4400	2090	3302	1490	2302
200	3290	4627	2520	3692	1523	2453
300	4030	4894	2868	3802	1747	2582
400	4460	5020	2538	3950	1901	2683
500	4083	5340	2950	4100	2153	2702
600	4166	5175	2554	3980	2193	2715
700	3710	5162	2535	3742	1925	2650
800	4042	5037	2550	3597	1923	2552
900	3516	5013	2522	3405	2010	2500
1000	4000	5062	2622	3254	1918	2400

Figure 6a–c shows energy dissipation at various points as first node dead (FND), half node dead (HND), and last node dead (LND) for 200 SNs in the simulation for 200 × 200 m^2 region.

The proposed approach outperforms the SEP protocol in energy dissipation at different points as shown in Table 9.

Table 10 presents a comparison of SEP and RBMEEP with data sizes (2000, 3000, and 4000 bits) based on node death metrics: first node dead, half node dead, and last node dead. Across all data sizes, RBMEEP exhibits superior performance compared to SEP. For example, with 2000 bits, the first node in SEP dies at 650 rounds, while RBMEEP extends this to 980 rounds. This advantage is even more pronounced at 4000 bits, where SEP's first node dies at 1650 rounds, but RBMEEP prolongs it to 2530 rounds. For half node and last node death, the trend continues with RBMEEP showing a clear edge. At 4000 bits, half of the nodes in SEP die at 4250 rounds, while in RBMEEP, it occurs at 4495 rounds. Similarly, the last node death in RBMEEP is delayed to 5160 rounds, compared to 4846 rounds in SEP. This highlights RBMEEP's overall enhanced efficiency and better energy management, particularly in larger data sizes.

Table 10 shows the statistical comparison of First, Half, and Last Node Death between SEP and RBMEEP under varying packet sizes. Each value represents the mean ± standard deviation over

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TABLE 8 | Delay comparison between SEP and RBMEEP at varying packet sizes.

Packet size	SEP (mean ± SD)	RBMEEP (mean ± SD)	*p*-value (Mann–Whitney *U*)
2000 bits	3847.7 ± 409.83	4973.0 ± 275.14	0.00025 (significant)
3000 bits	2574.9 ± 229.44	3682.4 ± 291.55	0.00018 (significant)
4000 bits	1878.3 ± 233.90	2553.9 ± 139.37	0.00018 (significant)

Note: RBMEEP demonstrates lower average delay across all packet sizes compared to SEP, indicating more efficient data delivery and reduced congestion. The improvements are statistically significant, as shown by the low *p*-values. These results confirm RBMEEP's capability to handle varying data loads with better stability and faster communication efficiency.

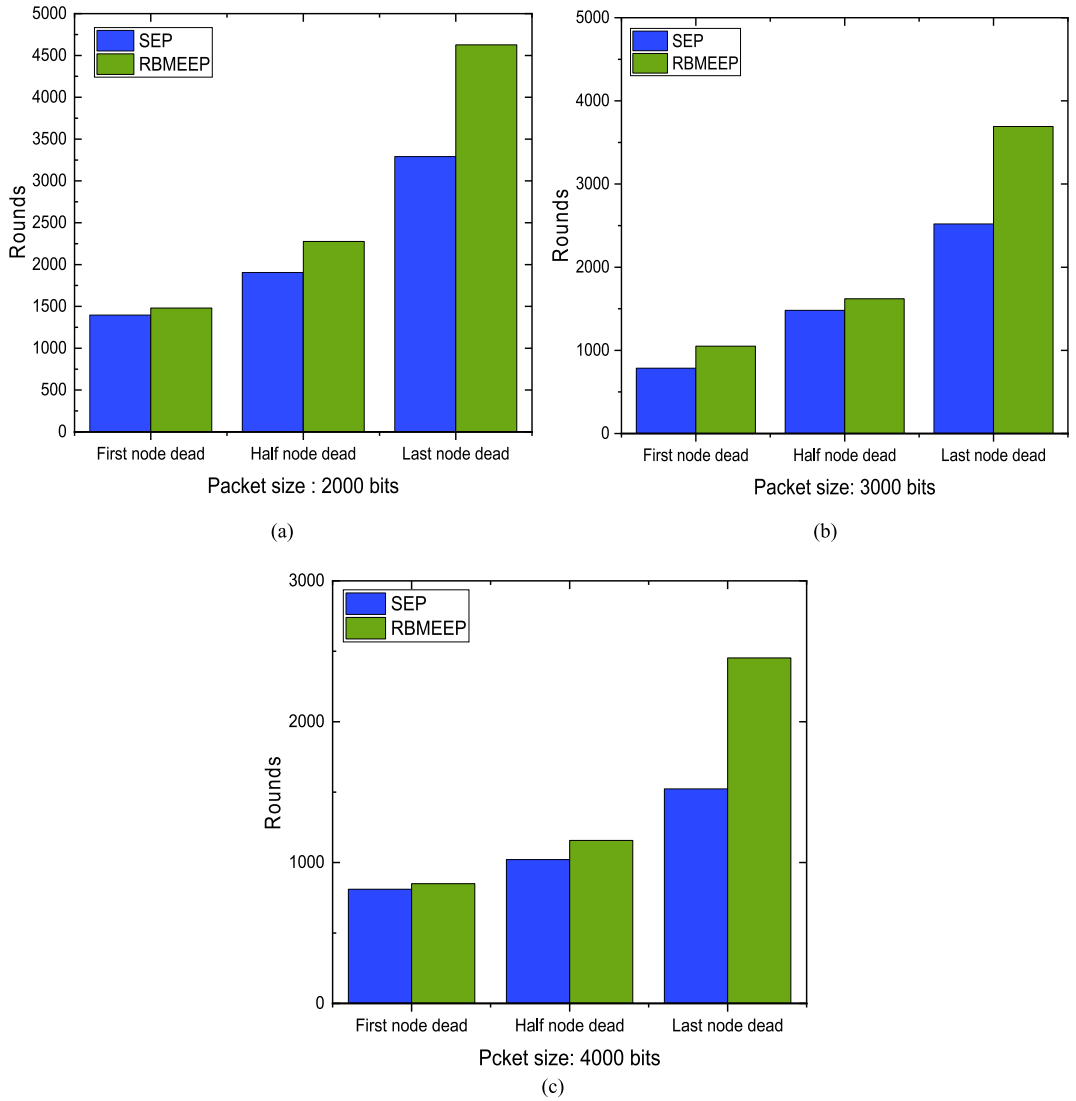


FIGURE 6 | (a) 2000 bits. (b) 3000 bits. (c) 4000 bits.

TABLE 9 | Energy dissipation at various points.

	SEP (2000 bits)	RBMEEP (2000 bits)	SEP (3000 bits)	RBMEEP (3000 bits)	SEP (4000 bits)	RBMEEP (4000 bits)
First node dead	1395	1480	785	1051	810	850
Half node dead	1905	2276	1480	1621	1021	1157
Last node dead	3290	4627	2520	3692	1523	2453

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TABLE 10 | Statistical comparison of first, half, and last node death between SEP and RBMEEP.

Event	Packet size	SEP (mean ± SD)	RBMEEP (mean ± SD)	*p*-value (Mann–Whitney *U*)
First node dead	2000 bits	1395.7 ± 45.9	1481.7 ± 44.7	0.00261 (significant)
First node dead	3000 bits	783.3 ± 18.3	1052.2 ± 27.1	0.00001 (significant)
First node dead	4000 bits	817.2 ± 21.6	849.6 ± 17.6	0.00066 (significant)
Half node dead	2000 bits	1924.2 ± 54.6	2252.2 ± 68.3	0.00039 (significant)
Half node dead	3000 bits	1459.9 ± 46.4	1635.0 ± 51.9	0.00065 (significant)
Half node dead	4000 bits	1022.1 ± 26.7	1156.6 ± 33.7	0.00041 (significant)
Last node dead	2000 bits	3264.2 ± 82.5	4621.5 ± 98.4	0.00001 (significant)
Last node dead	3000 bits	2507.8 ± 71.6	3686.2 ± 96.1	0.00001 (significant)
Last node dead	4000 bits	1523.2 ± 43.4	2444.1 ± 81.9	0.00001 (significant)

Note: RBMEEP consistently shows a statistically significant improvement in network longevity over SEP across all packet sizes and node death events. The improvements are backed by low *p*-values and clear increases in the mean death rounds. These results confirm RBMEEP's superior energy efficiency and balanced load distribution in dynamic WSN environments.

10 independent simulation runs. *p*-values were computed using the Mann–Whitney *U* test.

5 | Proposed Regression Prediction Model

The Regression Prediction Model is trained using three variables: ν_1, ν_2 and ν_3. In this model, ν_1 represents the packet size, ν_2 represents the number of nodes, and ν_3 represents the network lifetime. The model is characterised by six coefficients: C_1, C_2, C_3, C_4, C_5 and Δ. The purpose of the RPM model is to make predictions regarding the network lifetime depending on the taken value of independent variables, specifically for the RBMEEP protocol dataset simulation. These predictions are valuable as they facilitate the efficient replacement of sensor nodes with minimal human intervention and reduced maintenance costs.

At times, a linear model may fail to capture the characteristics of the data adequately, which is a phenomenon known as underfitting. In such situations, the model's simplicity is insufficient to represent the underlying patterns in the data. As a remedy, increasing the model's complexity may be necessary. This increased complexity often leads to the use of a quadratic equation, which can better capture nonlinear relationships in the data [22, 29].

The representation of Linear Regression is as follows:

$$f(\nu) = C_1 + C_2\nu + \Delta \tag{6}$$

where $f(\nu)$ represents the dependent variable, ν represents the independent variable, C_1 is the $f(\nu)$-intercept (the constant term), C_2 is the coefficient for the independent variable ν, Δ represents the error term.

The linear equation serves as the foundation for simple linear regression, which models a linear relationship between the independent variable (ν) and the dependent variable ($f(\nu)$). When the relations in the variable is more complex, as often seen in underfitting situations, a quadratic equation or higher-order polynomial regression model may be necessary to better capture the variable detail characteristics.

The Polynomial Regression Model is a flexible approach for modelling relationships between multiple independent variables and a dependent variable, allowing it to capture more complex and nonlinear relationships compared to simple linear regression. The degree '*d*' indicates the highest power to which 'ν' is raised, and it can be adjusted to better fit the data.

$$f(\nu) = C_1 + C_2\nu + C_3\nu^2 + C_4\nu^3 + \cdots + C_i\nu^d + \Delta \tag{7}$$

When dealing with two independent variables, the RPM can be expressed as follows:

$$f(\nu) = C_1 + C_2\nu_1 + C_3\nu_1^2 + C_4\nu_2 + C_5\nu_2^2 + C_6\nu_1\nu_2 + \Delta \tag{8}$$

where 'ν_1', 'ν_2' and '$f(\nu)$' are the 2 independent, and 1 dependent variables respectively. The intercept point of '$f(\nu)$' is C_1, C_2 is with the slope as 'ν_1', C_3 is with the slope as 'ν_1^2', C_4 is the respective slope for 'ν_2', C_5 is the respective slope of 'ν_2^2', C_6 is the respective slope for '$\nu_1\nu_2$', 'Δ' is termed as the model's error rate. The respective coefficients C_1, C_2, C_3, C_4 and C_5 are termed as RPM parameters and they collectively define the relationship between the independent variables and the dependent variable. The model's error rate is a measure of the deviation between the forecast values and the real observed values.

$$\Delta = f(\nu) - C_1 - C_2\nu_1 - C_3\nu_1^2 - C_4\nu_2 - C_5\nu_2^2 - C_6\nu_1\nu_2 \tag{9}$$

To determining the error degree for the given *i*th sample out of a total of '*k*' number of samples.

$$\sum_{i=1}^{k}\Delta_i = \sum_{i=1}^{k}\left(f(\nu)_i - C_1 - C_2\nu_{1i} - C_3\nu_{1i}^2 - C_4\nu_{2i} - C_5\nu_{2i}^2 - C_6\nu_{1i}\nu_{2i}\right) \tag{10}$$

The RPM parameters are determined through the minimisation of the equation, specifically, by minimising the Sum of Squares of Errors as outlined:

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$$\sum_{i=1}^{k} \Delta_i^2 = \sum_{i=1}^{k} \left(f(\nu)_i - C_1 - C_2\nu_{1i} - C_3\nu_{1i}^2 - C_4\nu_{2i} - C_5\nu_{2i}^2 - C_6\nu_{1i}\nu_{2i}\right)^2 \quad (11)$$

To minimise Equation (11), the partial derivatives of the equation with respect to each model parameter are calculated. These partial derivatives are then set to value zero. The subsequent linear equations are computed concurrently to determine the values of the RPM parameters as shown for the parameter C_1.

$$\frac{\partial \sum_{i=1}^{k} \Delta_i^2}{\partial C_1} = -2\sum_{i=1}^{k} \Delta_i = 0 \quad (12)$$

$$\frac{\partial \sum_{i=1}^{k} \Delta_i^2}{\partial C_2} = -2\sum_{i=1}^{k} \Delta_i\nu_{1i} = 0 \quad (13)$$

$$\frac{\partial \sum_{i=1}^{k} \Delta_i^2}{\partial C_3} = -2\sum_{i=1}^{k} \Delta_i\nu_{1i}^2 = 0 \quad (14)$$

$$\frac{\partial \sum_{i=1}^{k} \Delta_i^2}{\partial C_4} = -2\sum_{i=1}^{k} \Delta_i\nu_{2i} = 0 \quad (15)$$

$$\frac{\partial \sum_{i=1}^{k} \Delta_i^2}{\partial C_5} = -2\sum_{i=1}^{k} \Delta_i\nu_{2i}^2 = 0 \quad (16)$$

$$\frac{\partial \sum_{i=1}^{k} \Delta_i^2}{\partial C_5} = -2\sum_{i=1}^{k} \Delta_i\nu_{1i}\nu_{2i} = 0 \quad (17)$$

Thus, the partial derivatives are efficiently solved to get the coefficient value. The matrix-based approach simplifies the result of the required linear equations and provides an efficient means of determining the values of the model parameters. The solution to these equations for the coefficient values will provide the best-fit polynomial regression equation for your data with two independent variables. It captures both linear and quadratic relationships between the independent and the dependent variable.

Here is the pseudocode outline for polynomial regression with two independent variables 'ν_1', 'ν_2' and one dependent variable '$f(\nu)$' (Algorithm 2)

ALGORITHM 2 | RPM Model.

1. Import necessary libraries (scikit-learn v1.2.2, NumPy)
2. Set random seed to 42 for reproducibility
3. Load the dataset
4. Preprocess the dataset:
  a. Handle missing values
  b. Remove or correct outliers
5. Extract input features ν_1 and ν_2, and target output f(ν)
6. Generate polynomial features:
  a. Compute ν_1^2, ν_2^2, and $\nu_1{\cdot}\nu_2$
  b. Construct V_poly = [1, ν_1, ν_2, ν_1^2, ν_2^2, $\nu_1{\cdot}\nu_2$]
7. Split V_poly and f(ν) into training and testing sets using 80/20 ratio
  a. Use fixed random state for consistent partitioning
8. Initialise a second-degree polynomial regression model
9. Repeat the following for 10 independent runs:
  a. Train the model on the training set
  b. Predict output values on the test set
  c. Calculate and store Mean Squared Error (MSE)
10. Compute the average MSE across all runs
11. Retrieve and store the learnt model coefficients
12. For new input values (ν_1_new, ν_2_new), compute derived features:
  a. ν_1^2_new, ν_2^2_new, ν_1_new·ν_2_new
  b. Form input vector = [1, ν_1_new, ν_2_new, ν_1^2_new, ν_2^2_new, ν_1_new·ν_2_new]
13. Use the trained model to predict f(ν)_new from the input vector

The RPM model algorithm begins by importing essential libraries (e.g., scikit-learn v1.2.2) and setting a fixed random seed to ensure reproducibility. It loads the dataset and preprocesses it by handling missing values and removing outliers. From the cleaned data, it extracts the input features ν_1 and ν_2 along with the target output f(ν). Polynomial features are then generated by computing ν_1^2, ν_2^2, and the interaction term $\nu_1{\cdot}\nu_2$, forming the feature vector V_poly. The dataset is partitioned into training and testing sets using an 80:20 split with a fixed random state. A second-degree polynomial regression model is initialised and trained over 10 independent runs to account for variability. In each run, the model is trained on the training set and evaluated on the test set using Mean Squared Error (MSE). The average MSE is computed to assess model performance. Finally, the trained model predicts f(ν) for new input values using the derived polynomial terms.

5.1 | Experimental Results and Analysis

The proposed Regression Prediction Model (RPM) forecasts the lifetime of Sensor Nodes. In this forecast model, all SNs are trained based on data points. The values of the RBMEEP protocol and the RPM model are utilised to guess the lagging and leading delays, represented as the compensation factor.

5.1.1 | Case 1

The data provided in Table 3 is utilised for the training of the proposed Regression Prediction technique for a network area of 100×100 m^2.

Different independent variables are defined as:

$x1$ = packet size, $x2$ = sensor nodes, and dependent variable (y) = lifetime serve as the input parameters of the proposed RPM technique.

Likewise, simulations are conducted for a range of 100–1000 SNs in increments of 100 nodes, covering the 100×100 m^2 area. This is done for various packets having sizes of 2000, 3000, and 4000 bits. The simulation results are presented in Table 11, depicting the overall lifetime as predicted by the RPM in comparison to the RBMEEP.

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TABLE 11 | Performance assessment of the RBMEEP Versus RPM Model in a 100 × 100 m^2 network.

	Packet size (bits)								
	2000			3000			4000		
No. of nodes	RBMEEP	RPM	LD (%)	RBMEEP	RPM	LD (%)	RBMEEP	RPM	LD (%)
100	7508	7525	0.19	5135	5262	2.49	3959	3965	0.47
200	7681	7686	0.06	5246	5436	3.62	4049	4094	1.11
300	7897	7822	0.95	5581	5553	0.50	4240	4193	1.12
400	7968	7902	0.83	5692	5615	1.36	4420	4235	4.20
500	8054	7927	1.58	5826	5620	3.54	4333	4221	2.57
600	7840	7895	0.70	5549	5569	0.36	4078	4151	1.80
700	7666	7807	1.84	5298	5462	3.09	3862	4025	4.23
800	7611	7664	0.69	5295	5299	0.08	3767	3844	2.04
900	7336	7464	1.74	5093	5081	0.25	3508	3606	2.79
1000	7307	7208	1.36	4988	4806	3.65	3405	3312	2.73

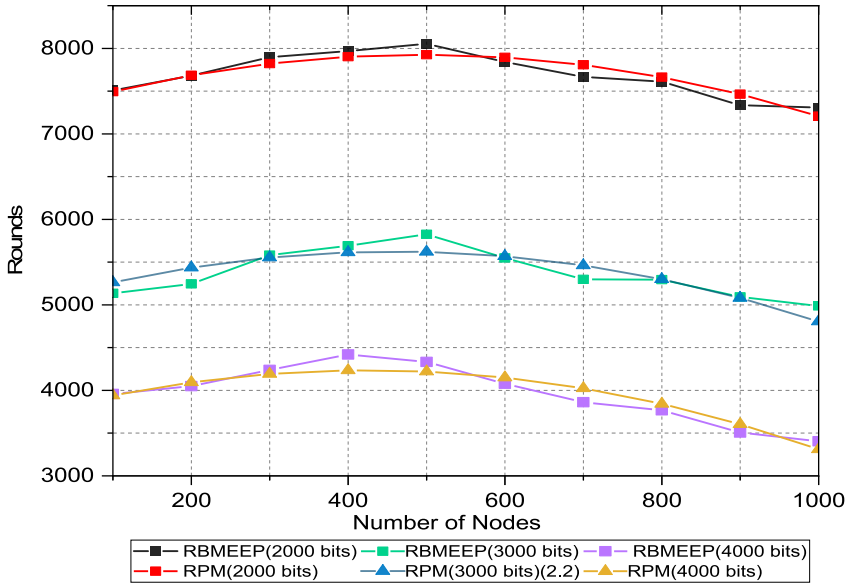


FIGURE 7 | RBMEEP versus RPM for 100 × 100 m^2 network.

Figure 7 displays the achieved simulation results of the proposed RPM model and the RBMEEP for '100' SNs within a 100 × 100 m^2 area, considering packets of 2000, 3000, and 4000 bits.

The simulation results indicate that for a packet of 2000 bits with 100 SNs deployed in a 100 × 100 m^2 area, the RBMEEP protocol achieves 7508 rounds of network lifetime, while the RPM model achieves 7525 rounds. Likewise, for a packet of size 3000, and 4000 bits, the RBMEEP results in 5135 rounds and 3959 rounds of network lifetime, while the RPM achieves 5262, and 3965 rounds.

The simulation results of the RPM model indicate a maximum relativity of 99.94%, and a minimum relativity of 98.16% for a packet with a size of 2000 bits. Moreover, for a packet with a size of 3000 bits, the maximum relativity is 99.92%, and the minimum relativity is 96.35%. In the case of a 4000-bit packet, the maximum relativity is 99.53%, and the minimum relativity is 95.77%. These values are in comparison to the performance of the RBMEEP.

5.1.2 | Case 2

The data provided in the given Table 3 is utilised for the training of the proposed RPM model for a network region of 200 × 200 m^2. The simulation results are presented in Table 12, providing insights into the performance of the RPM model under these conditions.

Assuming packet sizes of 2000, 3000, and 4000 bits, Figure 8 shows the simulation results of the suggested RPM approach and the RBMEEP protocol for 100 SNs deployed in a 200 × 200 m^2 network space.

RBMEEP produces 4622 rounds for a transmission packet of 2000 bits when 100 SNs are deployed in a 200 × 200 m^2 network, but RPM produces 4720 rounds for the same packet size. Similarly, when it comes to network lifespan, the RBMEEP protocol achieves 3466, 2415 rounds for 3000 and 4000 bits packets, while the RPM model achieves 3485, and 2420 transmission rounds.

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TABLE 12 | Performance assessment of the RBMEEP versus RPM for 200 × 200 m^2 network area.

	Packet Size (bits)								
	2000			3000			4000		
No. of nodes	RBMEEP	RPM	LD (%)	RBMEEP	RPM	LD (%)	RBMEEP	RPM	LD (%)
100	4622	4720	2.12	3466	3485	0.54	2415	2420	0.20
200	4837	4979	2.92	3856	3716	3.64	2561	2623	2.41
300	5190	5183	0.13	4028	3892	3.36	2735	2772	1.37
400	5297	5333	0.68	4168	4015	3.67	2828	2868	1.38
500	5648	5430	3.86	4334	4084	5.76	2854	2909	1.93
600	5420	5472	0.95	4169	4099	1.69	2837	2896	2.07
700	5386	5460	1.38	3905	4060	3.96	2765	2829	2.33
800	5336	5395	1.09	3811	3966	4.07	2705	2708	0.14
900	5252	5275	0.44	3569	3819	6.99	2621	2534	3.33
1000	5359	5101	4.81	3448	3618	4.92	2543	2305	9.35

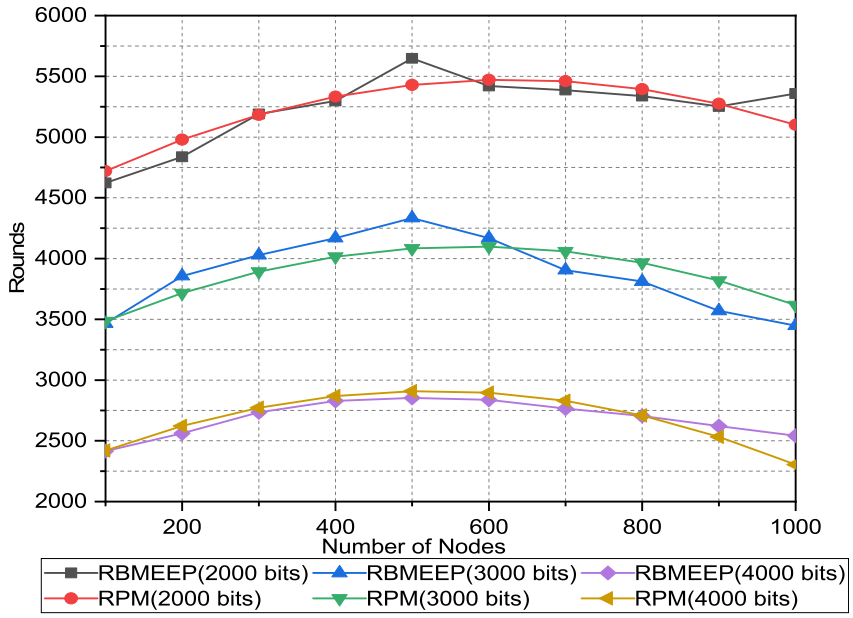


FIGURE 8 | A comparison of network lifetime between the RBMEEP versus RPM in a 200 × 200 m^2 network area.

According to the findings of the RPM during the simulation process, the maximum and minimal closeness values for the 2000-bit size packet are 99.87% and 95.19%, respectively. The greatest closeness is around 99.46%, and the minimal closeness is around 93.01% for a packet of 3000 bits. According to the RBMEEP protocol, the maximum closeness for a packet of 4000 bits is 99.86%, and the minimal closeness is 90.65%.

6 | Conclusion and Future Work

The predicted RPM model closely aligns with the performance of the proposed RBMEEP protocol and demonstrates high similarity to real data values. For packet sizes of 2000, 3000, and 4000 bits inside a 100 × 100 m^2 area, the closeness is 99.94%, 99.92%, and 99.53%, respectively. In a 200 × 200 m^2 area, the closeness values are 99.87%, 99.46%, and 99.86%. This underscores the model's effectiveness in capturing design constraints. The computed results in the simulation highlight the significant influence of data packet size and coverage region on network lifetime. Despite these promising outcomes, there are several limitations to the current approach. Firstly, RBMEEP has been evaluated primarily in static network scenarios, where nodes do not exhibit mobility. This limits the protocol's applicability in dynamic environments where node movement can significantly affect network performance and energy consumption. Additionally, the study focused on specific packet sizes and coverage areas; thus, the model's performance in varying network conditions and larger, more complex environments remains to be explored. In future work, we plan to implement RBMEEP on an IEEE 802.15.4-compliant testbed comprising 100 sensor motes to evaluate its performance under real-world RF interference and mobility conditions. We also intend to examine RBMEEP's adaptability across varying packet sizes and node densities by simulating dense and sparse deployments. To test its scalability, we will extend simulations to

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larger networks exceeding 1000 nodes. Furthermore, we aim to integrate RBMEEP with IoT-enabled platforms and include ambient temperature as an additional context-aware parameter to assess its impact on energy efficiency and routing decisions in practical WSN applications.

Author Contributions

Vipul Narayan: conceptualization, data curation, formal analysis, investigation, methodology, resources, software, validation, visualization, writing – original draft, writing – review and editing. **Swapnita Srivastava:** conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources. **Vikash Kumar Mishra:** formal analysis, supervision, validation, visualization, writing – original draft, writing – review and editing. **Mohammad Faiz:** supervision, validation, visualization, writing – original draft, writing – review and editing. **Shilpi Sharma:** supervision, validation, visualization, writing – original draft, writing – review and editing. **Vipin Balyan:** investigation, supervision, validation, visualization, writing – original draft, writing – review and editing. **Gunjan Gupta:** data curation, formal analysis, supervision, validation, visualization, writing – original draft, writing – review and editing.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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