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Energy efficient reliable data transmission for optimizing IoT data transmission in smart city

Ruchita Ashwin Desai[1], Raj Bhimashankar Kulkarni[2]
[1]Department of Technology, Shivaji University, Kolhapur, India
[2]Department of Information Technology, Government College of Engineering, Karad, India

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ABSTRACT

The rapid proliferation of the internet of things (IoT) technology has significantly transformed urban landscapes, giving rise to smart city frameworks that leverage interconnected devices for enhanced efficiency and functionality. In these environments, vast amounts of data are generated by diverse sensors and devices, necessitating advanced strategies for effective data collection and transmission. This paper introduces a novel approach to address data collection and transmission challenges in IoT-enabled smart city frameworks. The proposed design integrates IoT-Cloud for efficient data collection and employs the energy efficient reliable data transmission (EERDT) model, optimizing IoT data transmission. The enhanced dragonfly routing algorithm, incorporating the firefly algorithm, enhances data routing efficiency. Experimental results demonstrate EERDT's superiority over energy-aware iot-routing (EAIR) and location-centric energy-harvesting aware-routing (LCEHAR), revealing significant improvements in communication overhead, data processing latency, and network lifetime. The EERDT exhibits substantial reductions in communication overhead, enhancing overall network performance. The EERDT model showcases lower data processing latency and energy consumption, highlighting its potential for resource-efficient IoT data transmission. This work contributes an innovative solution for smart city IoT networks, emphasizing performance enhancements and resource efficiency.

Corresponding Author:

Ruchita Ashwin Desai
Department of Technology, Shivaji University
Kohlapur, Maharashtra, India
Email: ruchitaadresearch@gmail.com

1. INTRODUCTION

In recent years, the integration of the internet of things (IoT) with cloud computing has played a pivotal role in the development of smart cities, offering innovative solutions to urban challenges through the interconnection of various devices and systems [1]. The IoT-Cloud paradigm in smart cities involves the deployment of numerous sensors and devices across the urban landscape, generating vast amounts of data for real-time monitoring, analysis, and decision-making [2]. The advantages of leveraging IoT-Cloud in smart cities are numerous [3]. Cloud computing provides scalable and flexible resources for handling the massive volume of data generated by IoT devices [4]. It offers centralized storage, processing power, and data analytics capabilities, enabling efficient management and utilization of data for urban planning and governance [5]. However, this integration also poses challenges, such as concerns related to data privacy and latency issues, necessitating careful consideration in the design and implementation of smart city frameworks [6]. The success of a smart city depends significantly on its ability to harness the potential of the data generated by IoT sensor nodes [7]. Efficient data collection and analysis are crucial for obtaining actionable insights into urban processes, optimizing resource utilization, and enhancing the overall quality of life for citizens [8]. Rapid and accurate data analysis enables timely decision-making by city administrators, leading to improved services, better infrastructure planning, and enhanced public safety [9].

In smart cities, the IoT ecosystem is inherently heterogeneous, comprising diverse sensor nodes with varying capabilities and energy constraints [10]. Efficient data transmission is paramount, considering the resource limitations of many IoT devices [11]. Energy-efficient data transmission models are vital to extend the operational life of battery-powered devices, ensuring a sustainable and reliable smart city infrastructure [12]. Despite the transformative potential of IoT-Cloud integration in smart cities, challenges persist in achieving optimal data collection, analysis, and transmission [13]. Existing frameworks may fall short in addressing the specific needs of heterogeneous IoT environments, leading to inefficiencies, increased energy consumption, and compromised reliability [14]. Therefore, there is a pressing need for innovative solutions that can holistically tackle the challenges of data collection and transmission in smart cities [15]. This paper addresses the identified challenges by proposing a comprehensive solution. The primary contributions of this work are as:

- Designing IoT-Cloud-enabled smart city framework, specifically tailored for efficient data collection and analysis.
- Presents an energy-efficient and reliable data transmission (EERDT) model, acknowledging the heterogeneous nature of the IoT environment.
- To optimize data management in smart cities, enhancing overall system performance, energy efficiency, and reliability.

The manuscript is organized into distinct sections to systematically present the research findings. In Section 2, an in-depth exploration of various routing methods, with a particular focus on energy-efficient routing techniques, is provided. This section lays the foundation by reviewing existing methodologies, setting the stage for the introduction of the proposed EERDT model. Section 3 introduces the EERDT model and the enhanced dragonfly algorithm (EDA). Section 4 is dedicated to the presentation and analysis of the experimental results. This section critically evaluates the performance of the proposed EERDT model and EDA against existing routing methods. In section 5, the manuscript is concluded with a comprehensive conclusion.

2. LITERATURE SURVEY

Wang *et al.* [16] introduced a novel data-oriented routing-protocol for low-power and lossy-networks (RPL) approach. The approach laid out in their research aimed to partition information based on its contents throughout the process of routing. The efficacy associated with the RPL was enhanced through the application of the binary-gray wolf-optimization (BGWO) algorithm for route selection. The experimental evaluation conducted in OMNET and MATLAB 2022 a demonstrated the enhanced efficacy of the suggested approach in terms of energy usage effectiveness, instabilities time reduction, and total delay. Specifically, the amount of instability time percentage observed within the suggested approach is significantly lower in comparison with three similar approaches. For instance, within the quality-of service (QoS) and opportunity-routing-protocol for low-power and lossy-networks (ORPL) approaches, the instabilities time percentage was 57% for suggested approach, while it was 80% for both of these approaches. Moreover, in the case of the RPL approach, the instabilities time percentage was 89%. Further, a grid cell-based energy-efficient grid-routing approach (EEGT) was introduced in [17] to extend wireless-sensor-network (WSN)-based IoT application lifespan. EEGT divides the network's components across virtualized grid units (clusters) with equal sensor-nodes. Based on remaining energy alongside cell sink-node location, a cluster-head-node (CHN) is selected. A minimal-spanning-tree (MST) is created using the Kruskal technique that links nodes within every unit along is corresponding CHN to establish energy-efficient transmission routes. To save electricity, the ant-colony-optimization (ACO) approach finds routes for data-packets channels from CHNs towards the sink. The findings from the experiment indicate that the effectiveness of EEGT surpasses that of the previously established approaches, namely power-efficiency grid-chain routing-protocol (PEGCP), power-efficient-gathering in sensor-information-systems (PEGASIS) and low-energy-adaptive clustering-hierarchical-cluster routing-protocol (LEACH-C), PEGASIS because of enhanced savings in energy and prolonged longevity of the network. Using sensor-data forecasting, introduced an energy-efficient industrial-iot (IIoT) framework which reduces the transfer of data [18]. They suggested a base-station (BS) data forecasting method for maximizing sensor-node energy consumption. A rapid deep-learning (DL) system enabled low-latency network connections was also utilized. Data forecasting efficiency and quick processing were achieved using a DL-based multi-layer-perceptron (MLP) incorporating DC-MLP depth combination. The DC-MLP approach was tested utilizing 6 performance parameters and K-fold-cross-validation (KCV) to prove its reliability. The findings from the study showed that suggested framework lowered energy use by 33 percent relative to standard data transfer, maintained information from sensors, and predicted 81 percent better than current DL approaches.

Vinothkumar *et al.* [19] developed a novel approach using particle-swarm-optimization (PSO) for achieving energy efficiency in the incorporation of smart-grids (SG) systems, called PSO-SG, which leveraged the IoT technology to enhance the overall performance of the SG infrastructure. The present study involved the examination, handling, and storage of a substantial volume of information generated by the electrical system. The linkage and management of numerous device endpoints were facilitated for the establishment of IoT-based electrical networks. These networks allowed real-time assessment and management of extensive information, thereby contributing towards the advancement of SGs. Gupta *et al.* [20] introduced a novel approach called energy-efficient data-communication (EEDC) that leveraged region-based hierarchical-clustering for effective-routing (RHCER). This approach was designed to make energy-aware choices about routing within a multi-tier clustering structure. The primary objective of the suggested routing-protocol was to optimize network efficiency by achieving balanced load and facilitating effective interactions over extended distances through the utilization of multi-hop routing. The performance evaluation of EEDC approach was conducted by comparing it to several present energy-effective approaches across different metrics. The findings of the simulations indicate EEDC yields a significant reduction in energy-consumption, with a nearly 31 percent decrease observed in sensor-nodes. Additionally, EEDC demonstrates a notable enhancement in packet-drop-ratio, exhibiting an improvement of approximately 38 percent. An upgraded-LEACH (U-LEACH) approach for reliable and energy-effective selection of cluster-head (CH) was provided by Sureshand and Prasad [21]. The research aimed to enhance the stability of generating random numbers through the incorporation of rank-based CH decision-making. This selection process takes into account various factors, including energy-consumption level, BS distance characteristic and coverage of node in the network. By consideration this results in a reduction of the energy-consumption for participant nodes when they need to communicate with the CH. Based on the results obtained from the experiments, the U-LEACH yielded a substantial enhancement within the energy effectiveness capability of WSNs, system life expectancy, and communication reliability.

Pedditi and Debasis [22] suggested an IoT-based WSN approach called energy-efficient routing-protocol (EERP) for finding forest fires. The model lowered the amount of energy used by sensing nodes by making CHs selection. EERP's efficiency was contrasted with current medium-access-control (MAC) methods in a number of different situations. The findings of the experiment show EERP makes sensing nodes use less energy. Saba *et al*. [23] presented a novel approach for secure handling information in cloud environments. Their protocol leveraged distributed load distribution and utilized PSO technique. The primary objective of this method was to reduce the delay in responding experienced by cloud consumers while ensuring that the reliability of network connections is efficiently maintained. The suggested approach exhibited a reduction in energy usage by approximately 20 percent, an increase rate of success by approximately 17 percent, a decrease in end-to-end latency by approximately 14 percent and a decrease in networking cost by approximately 19 percent. Ahmmad and Alabady [24] introduced an innovative approach called improved-energy-efficient PEGASIS-based (IEEPB) routing, which aims to reduce energy usage. In this study, an alternative approach is employed wherein data transmission occurs through multiple smaller parallel pathways, as opposed to a singular elongated pathway. The analysis from the simulation outcomes revealed the findings that the IEEPB routing exhibited superior performance compared to the LEACH and modified IEEPB (M-IEEPB) routing approaches. Ekler *et al.* [25] proposed novel routing methods that aimed to enhance the longevity of WSNs. These methods focused on attaining the best possible energy balancing while ensuring that each of the packets are transmitted towards the BS having a predetermined likelihood. The comparative analysis of developed methods was conducted in relation to the existing LEACH. Based on the results of comprehensive simulations, it has been demonstrated that the newly implemented routing methods exhibit a high degree of energy efficiency. Moreover, these methods have been shown to successfully fulfill the predetermined reliability standards. Zeb *et al*. [26] introduced a novel routing approach that aimed to optimize energy efficiency by minimizing energy use. The protocol has been designed to include a highly effective link selection mechanism that relies on determining the nearest position relative to the location nodes. The approach endeavors to enhance network lifespan by integrating energy-harvesting approaches. The experimental findings provide compelling evidence of the effective routing strategies employed, resulting in highly beneficial results when it comes to of energy efficiency and usage of resources approaches.

3. ENERGY EFFICIENT RELIABLE DATA TRANSMISSION (EERDT) MODEL

In Figure 1, the framework for smart city enhanced by IoT-Cloud integration for EERDT is presented. The proposed framework for a smart city, enhanced by IoT-Cloud integration, employs an innovative approach with unequal clusters categorized as large size cluster (Far from BS), medium size cluster (intermediaries), and smaller size cluster (Near to BS). Each cluster consists of distinct IoT sensor nodes strategically positioned for optimal coverage. The CHs efficiently collect information from the IoT sensor nodes within their cluster. This aggregated data is then transmitted to the BS, subsequently relayed to the edge server, and ultimately forwarded to the cloud for comprehensive analysis. This hierarchical structure ensures an organized and efficient flow of information, facilitating seamless data collection and analysis for enhanced smart city functionalities.

The EERDT model has considered the cross-layer architecture which helps in enhancing the overall connectivity of the IoT node within the network along with increasing the total lifetime of the IoT node. According to the existing work [21], LEACH which considers a set of IoT nodes to select the CH in a random manner. The process of selecting a CH in the LEACH protocol operates in the following manner. In each iteration, an IoT node denoted as d acquires a randomized consistent value ranging from 0 to 1. This randomized value is subsequently evaluated with the corresponding IoT node threshold, denoted as $H(d)$. When the measured value is found to be below the value of the threshold $H(d)$, the IoT nodes autonomously designate themselves as CHs for that specific phase. Additionally, the threshold value is modified for each subsequent phase. The given operation explained above is represented using (1).

$$H(d) = \begin{cases} \frac{r}{1-r\times[\varphi mod(1/r)]}, & if\ d\epsilon S; \\ 0, Otherwise \end{cases} \quad (1)$$

The variable "r" denotes the average percentage of CH in each phase to the overall number of IoT nodes. The variable "φ" represents the present stage value, wherein φ is a non-negative value less than infinity, i.e., $\varphi, 0 \leq \varphi < \infty$. The set "$S$" consists of IoT nodes which have not been selected as CH during an interval of $\frac{1}{r}$ phases. This period includes phases $0\ to \frac{1}{r-1}$, phases $\frac{1}{r}\ to \frac{2}{r-1}$, and so forth. According to (1), it can be observed that each IoT node exhibits the characteristics of a CH during a specific time interval within a given phase. In the subsequent iteration, the IoT nodes are excluded from consideration as potential candidates for CH selection.

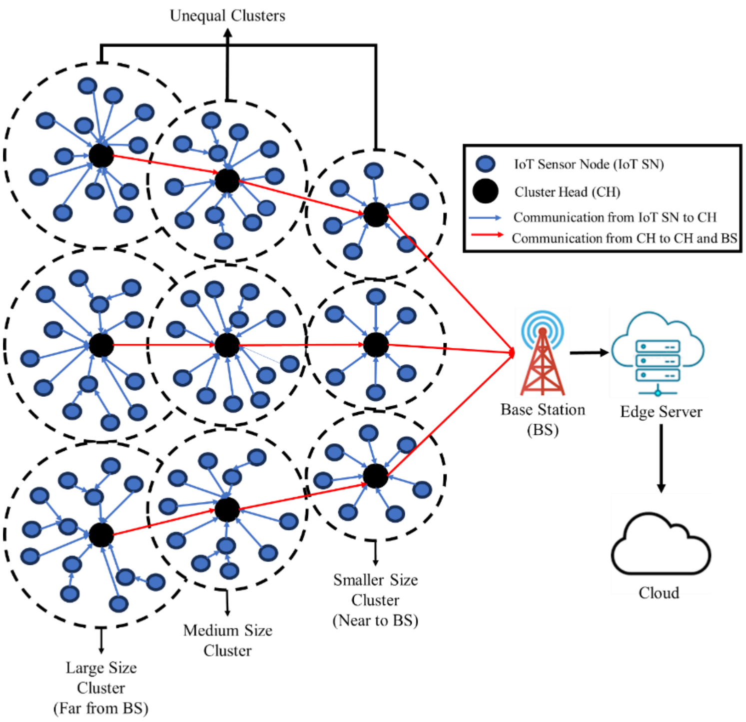

Figure 1. Framework for smart city enhanced by IoT-Cloud integration for EERDT

3.1. Modeling of system channels based on cross layers

The loss of energy during the radio transmission within the IoT nodes is directly correlated with the specific transmission method being considered. The propagation method under consideration can be expressed using (1). The loss during the radio propagation, denoted as $M(l)$, represents an indication of the attenuation of radio signals in $Decibel - Watt$ (dB) units at a given distance l between the receiver and the transmitter. The value α represents the route loss variable, that characterizes the rate of signal attenuation with distance l. Additionally, $M(l_0)$ represents the loss during the radio propagation for a given reference distance l_0.

$$M(l) = M(l_0) + 10\alpha\log_{10}(l/l_0,) \qquad (2)$$

In this study, we examine the scenario where a sensing area of activity F is equipped with K IoT nodes. This study examines the consequences of a stochastic distribution of IoT nodes inside the designated coverage area. The IoT nodes utilize a routing protocol to transmit the collected information to a central BS located beyond the sensing area of activity F. The IoT nodes exhibit a homogeneous nature, characterized by uniform energy levels and sensing ranges denoted as P. Consequently, the collective sensing region of such nodes is calculated as πP^2. In this analysis, this work examines an approach for energy consumption that is based upon first-order principles. The D_{amp} parameter quantifies the amount of energy needed for the enhancement of transmitters energy in order to successfully send a single bit towards the recipient, considering a fixed distance of $l = 1$. However, the D_{elec} parameter symbolizes the energy consumption associated with the operation of the transceiver circuitry, and is usually expressed in nanojoules (nj). Hence, the determination of the energy needed for the transmission of a given number of message bits, denoted as j, to a remote receiving IoT node, denoted as l, can be accurately assessed by taking into account (2) as evaluated using (3). Further, (4) is used to calculate the amount of energy that the recipient needs in order to retrieve a j bit of information.

$$D_{H_x}(j, l) = j\left(D_{elec} + \varepsilon_{amp} l^{\alpha}\right) \qquad (3)$$

$$D_{P_x}(j) = jD_{elec} \qquad (4)$$

3.2. Unequal clustering and CH selection by modelling overlap of IoT nodes

In addressing the hotspot problem, the work uses unequal clustering as shown in Figure 1. Thus, the cluster size closer to BS has smaller radius and the radius size increases as it goes away from the BS. In typical deployment scenarios, IoT sensor nodes are often positioned in a non-deterministic manner across a given area to respond to a range of applications. Consequently, it is common to be some overlap between the sensing regions of various IoT sensor nodes within the deployment region. The observed phenomenon indicates that in instances where the IoT sensor node's density in a given region deviates substantially from the average, there is a notable difference in the number of IoT sensor nodes covering an objective location. Specifically, whenever the IoT sensor node density within the local region is smaller compared to the mean, it is observed that a single IoT sensor node covers the desired location. Conversely, whenever the IoT sensor node density in a local region exceeds compared to the mean, it is observed that multiple IoT sensor nodes cover the concentrated region. When trying to achieve the objective of obtaining two interconnecting O_F IoT sensor nodes alongside a distance, p, between them, where p ranges from 0 to $2P$, it is necessary to follow a particular method. The estimation process involves the utilization of a mathematical framework that focuses on the meeting point of two circles. This theory is outlined as (5).

$$O_F = 2P^2\left[\theta - \frac{p}{2P}\sqrt{1 - \left(\frac{p}{2P}\right)^2}\right] \qquad (5)$$

The value of θ can be determined by taking the inverse cosine of the ratio p divided by $2P$, i.e., $\theta = \cos^{-1}(p/2P)$. The technique for acquiring a standardized overlapping coefficient, denoted as ω, for an IoT sensor node within a network is outlined using (6). The variable r is constrained to an extent of 0 to 1, i.e., $0 \leq r \leq 1$, inclusive, where r is defined as the ratio of p divided by $2p$, i.e., $r = p/2p$. Additionally, the variable ω is also bounded between 0 and 1, inclusive.

$$\omega = O_F/\pi P^2 = 2\left[\cos^{-1}(r) - r\sqrt{1 - r^2}\right]/\pi \qquad (6)$$

Various IoT sensor nodes are given varying probabilities of becoming the CH in order to increase network efficiency through improved accessibility to networks. These probabilities are calculated based upon the standardized active sensing region of each IoT sensor node. Active sensing area is a graphical representation of the greatest sensor zone which is divided by the active sensing coverage area. Let's take into account an IoT sensor node where μ_0% of its sensing region is surrounded alone by itself and μ_n% of its sensing region is surrounded by itself and its nearest n neighbors. Now imagine that this IoT sensor node, along with the three IoT nodes immediately to its left and right, forms a square with a perimeter of μ_3% (i.e., 4 IoT sensor nodes which includes the considered IoT sensor node where the 3 other IoT sensor nodes are considered to be adjacent of the considered IoT sensor node). Thus, the subsequent equation describes the active sensing area of the aforementioned IoT sensor node after normalization.

$$\mu = \mu_0 + \sum_{n=1}^{\infty} \frac{\mu_n}{n+1} \tag{7}$$

The evaluation of the parameter μ falls within the interval $(0,1)$. When multiple IoT sensor nodes intersect in their sensing areas, the resulting evaluation of μ is found to be below one. Conversely, when a IoT sensor node does not intersect alongside any IoT sensor node, the evaluation of μ is determined to be equivalent to one. However, the practicality of determining a certain amount of adjacent IoT sensor nodes through the considered IoT sensor node is limited through the constraints on resources imposed by its battery. In order to tackle this issue, this work utilizes the level of signal emitted through the neighboring IoT sensor nodes. Consequently, the average signal energy obtained through these neighboring IoT sensor nodes is employed to calculate the established active sensing region for a given IoT sensor node. The following is achieved by determining their equivalent distance between the IoT sensor nodes and considered IoT sensor node. Upon the completion, i.e., the execution of IoT sensor nodes, each individual IoT sensor node initiates the transmission of a hello message to its neighboring IoT sensor node, thereby facilitating the detection and identification of neighboring IoT sensor nodes. The computation of the amount of energy needed for transmitting the hello message is performed according (8).

$$R_h = R_{sen} + M(2P) \tag{8}$$

The variable $M(2P)$ is used to represent the radio's transmission loss through a radius of $2P$, while R_{sen} represents the receiver's radio sensitiveness. The outcome concerning this process means that exclusively the IoT sensor nodes situated inside a $2P$ range are going to be the recipients with the hello message, while the non-overlapping IoT sensor nodes are not going to receive said message. It is important to note that this method is executed solely a single time, with the goal of forecasting the established active sensing region. In the context of this study, we examine an IoT sensor node denoted as d which is receiving a series of D hello messages. Each hello message is associated within a specific acquired radio signal's power, denoted as R_n, where n represents the index of the hello message in the sequence $(1, 2, 3, \ldots, D)$. The computation of the average level of signal acquired by IoT sensor node d, denoted as R_p, is performed according (9).

$$R_p = 10\log_{10}\left[\sum_{n=1}^{D} 10^{R_n/10}/D\right] \tag{9}$$

The computation of neighboring IoT sensor nodes for a considered IoT sensor node, denoted as node d, involves identifying other IoT sensor nodes that are located at a radius $\bar{P}$ from IoT sensor node d. The (8) can be expressed using (10). Upon evaluating the mechanism of propagation outlined in (2), it is observed that the equivalent average distance $\bar{P}$ can be determined using (11).

$$R_h = R_p + M(\bar{P}) = R_{sen} + M(2P) \tag{10}$$

$$\bar{P} = 2P \times 10^{[R_{sen} - R_p]/10\alpha} \tag{11}$$

The adjusted interconnecting area $\omega(d)$ for IoT sensor node d can be obtained by utilizing (6) with the condition $r = \bar{P}/2P$. According to the mathematical expression denoted in (7), the standardized active region of sensing can be determined using (12).

$$\mu(d) = \mu_0 + \frac{\mu_1}{2} = [1 - \omega(d)] + \frac{\omega(d)}{2} = 1 - \frac{\omega(d)}{2} \tag{12}$$

From the preceding equation, the probability that an IoT sensor node will serve as CH increases for the lower values of $\mu(d)$, and decreases for greater values of $\mu(d)$. Consequently, by adjusting the variable r in (1) so that it is equal towards the standardized overlapping area of a given IoT sensor node d, we acquire the result using (13). The symbol $\propto$ is used to represent the proportionality between variables, specifically in this case, the average number of CH. The suggested threshold $H(d)$ for IoT sensor node d can be reformulated using (14).

$$r(d) = \propto \times\ \omega(d) \tag{13}$$

$$H(d) = \begin{cases} \frac{r(d)}{1-r(d)\times[\varphi mod(1/r(d))]},\ if\ d \in \bar{S}; \\ 0,\ Otherwise \end{cases} \tag{14}$$

The collection of IoT sensor nodes denoted as $\bar{S}$, which had not been assigned to be a CH in the current session, is considered. The IoT sensor node denoted as d is designated as the CH in session $1/r(d)$. In accordance with this research, it has been determined that the selection of CHs among IoT sensor nodes is carried out with varying probabilities. The probability of an IoT sensor node getting designated as a CH is inversely proportional to the measurement of $\mu(d)$ it possesses. Conversely, an IoT sensor node having a lower $\mu(d)$ value is assigned a higher $r(d)$ value, which is subsequently used as an input parameter in (14). As a result, the IoT sensor node will assume the role of CH, although for a limited duration. The following utilization of IoT sensor nodes with higher $\mu(d)$ values is expected to contribute to enhanced energy utilization, primarily owing to their role as CHs. Conversely, IoT sensor nodes with less $\mu(d)$ values are anticipated to bear the responsibility of serving as CHs, potentially resulting in increased workload for these devices. The findings indicate the use of the cluster choosing approach, which relies upon the normalization of the active sensing selection, has resulted in notable enhancements in both network lifespan and coverage. This is primarily due to the fact that IoT sensor nodes using less standardized active sensing ranges tend to exhaust their energy reserves earlier, thereby contributing to an overall improvement in the network's performance. Once we get set of active nodes a path is constructed towards BS using multi-objective function defined in (15) where $\mathcal{E}$ defines residual energy, $\mathcal{H}$ defines hop count, and $\mathcal{F}$ defines failure rate. In finding the best path this work uses Dragonfly Algorithm (DA) [25]. The objective of minimization function to find optimal path is given in (16).

$$Inter_{Cluster} = \mathcal{E} * \mathcal{H} * \mathcal{F} \tag{15}$$

$$MOF = min[\delta_1(\mathcal{E}) + \delta_2(\mathcal{H}) + \delta_2(\mathcal{F})] \tag{16}$$

The dragonfly algorithm (DFA) [27] is a metaheuristic function for obtaining optimal routing performance. The complete flow of the EDA is presented in [27]. The primary aim of the EERDT is to investigate and analyze the routing objective function which is given in (16). The primary aim of EERDT is to allocate the gathered packets to the CH to go in the direction of the IoT gateway server. This allocation is accomplished through the utilization of the DDA method, which effectively reduces the overall energy usage, reduces the overall number of hops, and mitigates failure rates. Additionally, the suggested technique incorporates the concept of load distribution as a multi-objective parameter, further enhancing its performance as shown in simulation study.

4. RESULTS AND DISCUSSION

In this experimental setup, the operating system utilized was Windows 11, running on a system equipped with a Pentium Intel Core i7 processor and 16 GB of RAM. The simulation environment employed the Sensoria simulator [28] to simulate both existing and proposed methodologies. The energy-aware iot-routing (EAIR) [25] and location-centric energy-harvesting aware-routing (LCEHAR) [26] algorithms, pivotal to the experimental framework, were implemented in the C# programming language. The Visual Studio. NET framework served as the development environment to execute the existing EAIR and LCEHAR methods, as well as the proposed EERDT method. The chosen simulation parameters, detailed in the subsequent section, provided the necessary inputs for evaluating and comparing the performance of the methods within this controlled and well-defined experimental setting.

4.1. Simulation parameters

The simulation parameters for evaluating the presented EERDT and existing EAIR and LCEHAR method. The simulation parameter is given in Table 1. These parameters play a pivotal role in determining the reliability, efficiency, and effectiveness of the proposed EERDT method in comparison to the established EAIR and LCEHAR methods.

Table 1. Simulation parameter

Simulation parameters	Value
Simulation area considered	$50m \times 50m$
Total considered base-station	1
Total IoT sensor nodes considered	500 to 1000
Communication radius of IoT sensor node	$5m$
Sensing radius of IoT sensor node	$3m$
Initial energy of IoT sensor node	$0.05 - 0.2\ Joules\ (j)$
Wireless energy dissipation	$50\ nj/bit$
Length of control packets	$248\ bits$
Length of data packets	$2000\ bits$
Speed of transmission of data	$100\ bit/s$
Bandwidth	$10000\ bit/s$
IoT sensor sensing time	$0.1\ s$
IoT sensor device type	Temperature
Idle energy consumption (E_{elec})	$50\ nj/bit$
Amplification energy (E_{mp})	$100\ pJ/bit/m2$

4.2. Communication overhead

The presented Figure 2 shows the communication overhead values for three distinct method LCEHAR, EAIR and EERDT across varying numbers of nodes in a sensor network, denoted by values ranging from 500 to 1000. Analyzing the results, it is evident that LCEHAR consistently exhibits relatively lower communication overhead across the spectrum of nodes, with values ranging from 0.184 to 0.806. In contrast, EAIR consistently demonstrates higher communication overhead, escalating from 0.105 to 0.264 as the number of nodes increases. Notably, the proposed EERDT method showcases competitive performance, maintaining a comparatively lower and stable communication overhead, ranging from 0.087 to 0.128. This analysis suggests that EERDT exhibits potential efficiency in managing communication overhead, presenting a promising alternative to existing methods such as LCEHAR and EAIR in sensor network applications.

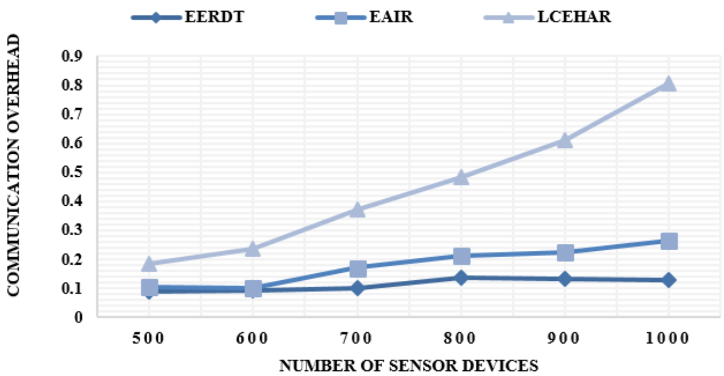

Figure 2. Communication overhead

4.3. Data processing latency

The presented Figure 3 illustrates the data processing latency values for three different methods LCEHAR, EAIR and EERDT across varying numbers of nodes in a sensor network, ranging from 500 to 1000 nodes. Analyzing the results, it is apparent that LCEHAR consistently exhibits higher data processing latency, with values ranging from 181.76 to 189.02. In contrast, EAIR consistently demonstrates lower data processing latency, with values ranging from 288.62 to 301.91. Notably, the proposed EERDT method showcases competitive performance, maintaining intermediate data processing latency values, ranging from 127.512 to 161.412. This analysis suggests that EERDT performs favorably in terms of data processing latency, providing a balance between the relatively higher latency of EAIR and the lower latency of LCEHAR. The efficiency of EERDT in processing data makes it a promising method for scenarios where minimizing latency is crucial for timely decision-making within the sensor network.

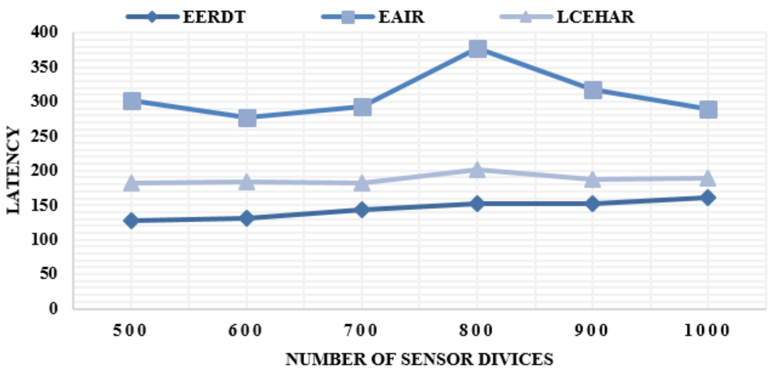

Figure 3. Data processing latency

4.4. Network lifetime performance

In Figure 4, the analysis of network lifetime performance reveals that EERDT consistently achieves a high network lifetime across varying node counts (500 to 1000). This longevity in network lifetime for EERDT implies an efficient utilization of energy resources, allowing a substantial number of devices to remain operational. The resilience of EERDT to changes in the number of nodes is particularly noteworthy, as evidenced by the relatively stable network lifetime, ranging from 1495 at 500 nodes to 1487 at 1000 nodes. This stability suggests that EERDT manages and optimizes energy consumption effectively, contributing to a prolonged operational lifespan for the overall network. Unlike EAIR and LCEHAR, which exhibit a decreasing trend in network lifetime with an increasing number of nodes, EERDT's ability to maintain high performance underscores its energy-efficient characteristics. The fluctuations observed in the network lifetime for EERDT further highlight its adaptability and capability to respond robustly to dynamic scenarios, emphasizing its suitability for energy-conscious applications across diverse node densities. In summary, EAIR experiences a steady decline in network lifetime, LCEHAR shows variability with an initial increase followed by a decrease, and EERDT consistently maintains a high network lifetime.

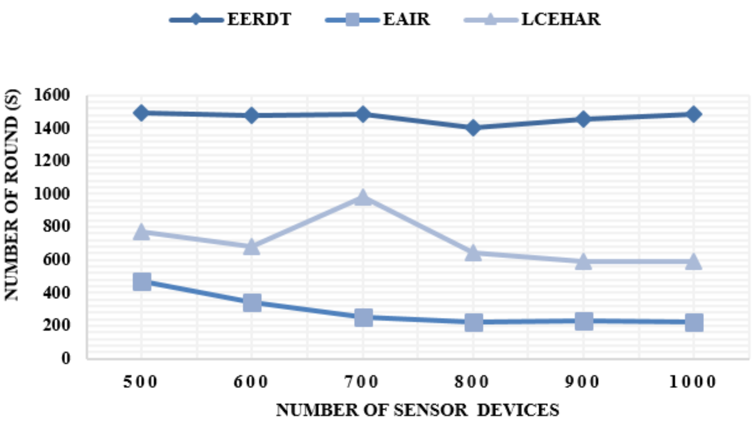

Figure 4. Network lifetime performance considering total node death

5. CONCLUSION

In conclusion, this work has presented a comprehensive and innovative approach to address the challenges associated with data collection and transmission in an IoT-enabled smart city framework. The proposed design incorporates an IoT-Cloud integration for efficient data collection and analysis, coupled with the EERDT model for optimizing data transmission in IoT networks. The enhanced dragonfly routing algorithm, integrating the firefly algorithm for optimization, has been employed to enhance the efficiency of data routing in the proposed framework. The experimental results demonstrate the superiority of the proposed EERDT model over existing methods such as LEACH and PSO. Notably, the results showcase significant improvements in various performance metrics, including communication overhead, routing overhead, data processing latency, average energy consumption, and network lifetime. This indicates the effectiveness of the

Enhanced Dragonfly routing algorithm and the EERDT model in achieving more efficient and reliable data transmission in the IoT network. A specific highlight from the results is the substantial reduction in communication and routing overhead, contributing to improved overall network performance. The EERDT model exhibits lower data processing latency and energy consumption compared to LEACH and PSO, emphasizing its potential for resource-efficient data transmission in IoT applications. As a direction for future work, there is a need to focus on designing an effective Cloud Resource Provisioning Model tailored for analyzing data-intensive application workloads. This would involve exploring optimized cloud resource allocation strategies to handle the increasing demands of data-intensive applications, ensuring scalability, reliability, and cost-effectiveness. This future endeavor would contribute to the holistic enhancement of the proposed smart city framework, aligning with the evolving landscape of cloud computing and data analytics in IoT environments.

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BIOGRAPHIES OF AUTHORS

Ruchita Desai received the B.E. degree in Information Technology from the D. Y. Patil College of Engineering, Shivaji University, the M.E. degree in Computer Science Engineering from Bharati Vidyapeeth college of engineering, Shivaji University of Kolhapur and the Ph.D. degree in Computer Science and Engineering with specialization in Data Analytics from The Shivaji University of Kolhapur, Maharashtra. Her research interests include machine learning, Data analytics, and Cloud Computing. She can be contacted at email: ruchitaadresearch@gmail.com.

Raj Bhimashankar Kulkarni is Head of Department in Department of Information Technology, Government College of Engineering, Karad, Maharashtra. He Holds a PhD degree in Computer Engineering with specialization in Web engineering. His research areas are Web engineering, IOT, Data analytics, Machine learning, Data Science and Cloud computing. He is member of Board of Studies in Information Technology, and in Computer Science and Engineering, Solapur University. Dr R. B. Kulkarni has published a number of Research Papers in International journals on his innovative ideas. His research interests include Web engineering, IOT, Data analytics, Machine learning, Data Science and Cloud computing. He can be contacted at email: raj_joy@yahoo.com.