Energy-Efficient Data Collection Using Mobile Sinks To Minimize Wsn Latency

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ABSTRACT
Reliable data collection is a crucial concern in Wireless Sensor Networks (WSNs), as it guarantees prompt transmission of data to the sink node while reducing network delay. The use of mobile sinks for data gathering has been recognized as a successful approach to improving the efficiency and dependability of wireless sensor networks (WSNs). This study examines two novel algorithms for enhancing data collection efficiency via the use of mobile sinks: the Opportunistic Data Collection Algorithm (ODCA) and the QoS-aware Mobile Sink Selection Algorithm (QMSSA). The ODCA utilizes the mobility of sink nodes by using a heuristic approach. It opportunistically collects data from sensor nodes when they are in close vicinity and dynamically adjusts the direction of the sink depending on real-time chances for data collection. ODCA's capacity to adapt enables it to remain efficient even when there are changes in network topology or failures in nodes. The QMSSA prioritizes the preservation of Quality of Service (QoS) by carefully choosing the most suitable mobile sink, taking into account factors such as network load, sink mobility, and energy use. QMSSA improves the overall performance and reliability of the WSN by selecting the best suitable sink. This research showcases notable improvements in data collecting efficiency and network latency via the use of ODCA and QMSSA, hence contributing to the progress of WSN technology.

Keywords: Network Latency, Opportunistic Data Collection Algorithm, QoS, WSN

1. INTRODUCTION

The environmental monitoring, healthcare, smart city, and industrial automation sectors are just a few that have benefited greatly from the advent of wireless sensor networks (WSNs) [1-2]. There are a lot of sensor nodes in these networks, and they can all sense, analyze, and wirelessly communicate data. In order to make decisions, monitor, and operate various applications in real time, the data acquired by WSNs is essential [3-4]. Optimizing resource consumption, extending network lifespan, and improving data accuracy are three primary goals of efficient data collecting, which is a vital component of WSNs. Common problems with conventional data-gathering methods include high power requirements, slow processing speeds, and inability to scale [5-6]. Harnessing the full potential of WSNs and enabling seamless integration into current systems requires the development of effective data-collecting mechanisms [7-8]. Within this framework, this article delves into a range of approaches, protocols, and algorithms aimed at enhancing the effectiveness of data gathering in Wireless Sensor Networks. It explores current methods and their effects on WSN performance by looking at things like energy efficiency, data aggregation, routing protocols, and quality of service (QoS) issues [9–10].
Several sensor nodes (SNs) with limited resources form WSNs. Sensor nodes (SNs) collect data about their immediate physical surroundings and relay that information to a central base station (BS). The BS has a lot of resources, unlike SNs [11, 12]. Because of this, it collects data, processes it, and then transmits the results to the end-user or cloud server across the internet. The technology behind WSNs has advanced to the point where it can be used for a variety of tasks, including communication, decision-making, military surveillance, monitoring vital signs like humidity, pressure, and temperature, and tracking the movements and speeds of objects [13–14]. They go over the difficulties of sink mobility and how application-specific routing protocols are necessary. Protecting SNs against potential breaches by cybercriminals is a top priority in the design of WSNs [15–16]. Various forms of attacks, including eavesdropping, node capture, and spoofing, allow attackers to alter the typical behavior pattern of SNs [17–18]. One of the most critical concerns, therefore, is ensuring the security of the routed aggregated

data from SNs to the sink. Typically, wireless network sensors can be compromised by an attacker who illegally captures data transfers by sensing the wireless channel [19–21].
The main contribution of the paper is:

- Opportunistic Data Collection Algorithm
- QoS-aware Mobile Sink Selection Algorithm

This section serves as the article's framework. Section 2 contains several authors' discussions on efficient data collection techniques. The proposed model is shown in Section 3. Chapter 4 discusses the study's results. The concluding portion of portion 5 discusses the results and ideas for future study.

1.1 Motivation of the paper

This paper is motivated by the pressing need to address data collection challenges in WSNs to ensure timely and efficient delivery of data while minimizing network latency. By exploring innovative algorithms like the Opportunistic Data Collection Algorithm (ODCA) and the QoS-aware Mobile Sink Selection Algorithm (QMSSA), this study aims to optimize data collection using mobile sinks, thus enhancing the overall efficiency, reliability, and QoS of WSNs. Through these advancements, the paper seeks to contribute significantly to the advancement of WSN technology by improving data collection efficiency and reducing network latency.

2. BACKGROUND STUDY

Ahmed, N. et al. [1] In order to make WSNs more effective and efficient, this study suggests a complete structure. Within a hexagonal network architecture with 100 sensor nodes and a mobile sink, it offers novel approaches to energy-efficient clustering, balanced cluster formation, optimal routing with Hop-to-Hop Directed Acyclic Graph (DAG) and Tri-state Markov Chain Model (Tri-MCM), and intelligent node placement using Intelligent Triangulation Method (ITM) and Multi-Objective Spider Monkey Optimization (MOsMO) algorithms.
Farzinvash, L. et al. [6] The suggested technique, Energy-efficient Emergency Data collection in WSNs with Mobile Sinks (EEDMS), uses two distinct approaches to collect normal and emergency data. Using the spanning tree, we are able to gather data for emergencies. As it travels the network, the MS collects sensed data from each cluster head (CH). Not only that but the grid is regularly adjusted so that energy depletion occurs uniformly across the WSN.
Gowthami, D. et al. [8] In contrast to the current method, this one finds the best VPs and the best route, which is neither too long nor too short, extremely efficiently. The computational overhead of this strategy is lower than that of these alternatives as well. In addition, the writers need to specify the positions of the barriers, which this method is unable to do. Additionally, the task can be expanded to take into account various circumstances and expedite the identification of impediments.
Idan, Z. S., & Al-Fatlawi, A. [10], the proposed method efficiently selects CH from among typical sensor nodes. Our first proposal for solving the CH selection issue was based on Linear Programming (LP). Our next topic of discussion was the Improved Particle Swarm Optimization (IPSO)-based approach to fixing this problem. Additionally, the authors covered the step of creating clusters. Fitness performance is also achieved by considering diverse distance and residual energy characteristics in order to build the IPSO approach based on energy efficiency. The particle velocity formula is where the PSO algorithm excels in comparison to its forerunners. This enhancement updates the particle's status by a comparison that considers individual experiences, societal experiences, or a mix of the two.
Karegar, P. et al. [12] Three distinct stages comprised the Software-defined wireless sensor network (SDWSN)-enabled ground network communication: pre-orchestration scanning topology, orchestration notification, and post-orchestration sensing data gathering.
Pravin Renold, A., & Balaji Ganesh, A. [17] The design and implementation aspects of secure MRL were considered in this article, with an eye on ensuring that authentic messages were sent to the mobile sink via convex nodes. The energy-aware convex hull method is used to produce convex nodes. Gathering information at convex nodes eliminates the requirement for the mobile sink to traverse the network.

2.1 Problem definition

The existing methods of Improved Particle Swarm Optimization (IPSO) and Energy Efficient Data Gathering in Mobile Sink (EEDMS) for WSNs face drawbacks. IPSO can struggle with convergence speed and scalability in large networks, while EEDMS can lead to increased energy consumption due to frequent sink movement, impacting network longevity. These limitations underscore the necessity for more efficient and scalable data collection approaches in WSNs.

3. MATERIALS AND METHODS

In this section, we detail the proposed methods for addressing the drawbacks of existing techniques in Wireless Sensor Networks (WSNs). Our approach focuses on enhancing data collection efficiency and network reliability through novel algorithms and protocols.

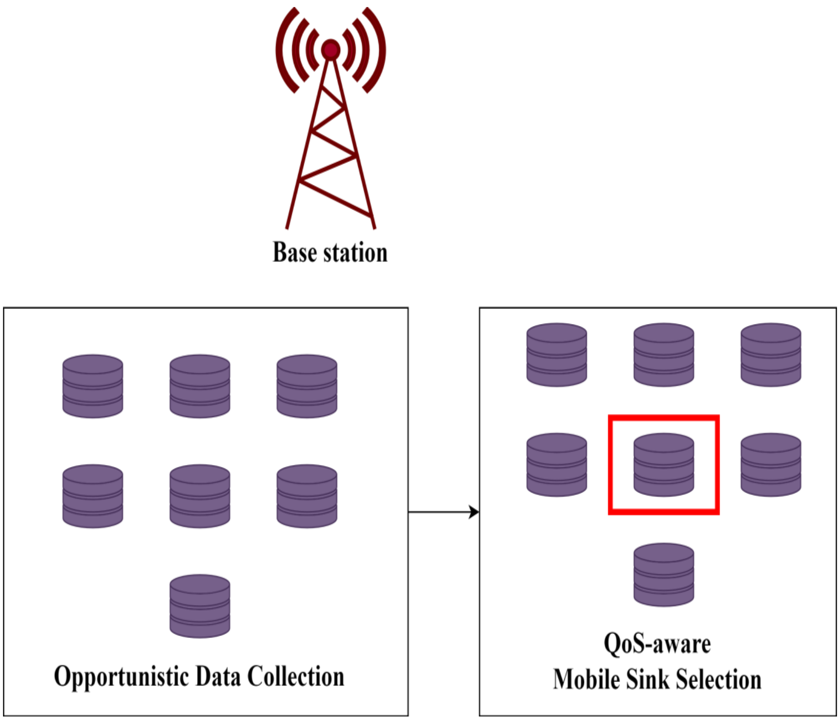

Figure 1. Proposed workflow architecture

3.1 Network model

In this section, we describe the network model used to evaluate the performance of the Opportunistic Data Collection Algorithm (ODCA) and the QoS-aware Mobile Sink Selection Algorithm (QMSSA).

Assumptions and Network Setup

1. **WSN Structure**: The WSN consists of NN stationary sensor nodes uniformly distributed over a two-dimensional area. These nodes are responsible for sensing and transmitting data.
2. **Mobile Sinks**: MM mobile sinks traverse the network area to collect data from the sensor nodes.
3. **Communication Model**: Sensor nodes communicate with mobile sinks using single-hop communication. Each sensor node has a transmission range RR.

Objective Function

The primary objectives are to minimize network latency LL and to maximize energy efficiency EE. The network latency is defined as the time taken for a data packet to be delivered from a sensor node to the sink node. The energy efficiency is defined as the total energy consumed by the network for data collection.

Latency Calculation

The latency LL for a data packet from node ii to reach the sink j is given by:

$L_{ij} = T_{ij} + W_{ij}$ ------------ (1)

where T_{ij} is the travel time of the mobile sink from its current position to the node i, and W_{ij} is the waiting time for the mobile sink at node i.

Energy Consumption Model

The energy consumption E is modeled based on the transmission and reception energy. The energy E_{tx} consumed by a node to transmit a packet over distance d is:

$E_{tx} = E_{elec} . k + E_{amp} . k . d^2$ ---------- (2)

Where E_{elec} the energy is dissipated per bit to run the transmitter or receiver circuitry, E_{amp} is the energy dissipated by the transmitter amplifier, and k is the number of bits in the packet.

The energy E_{tx} consumed to receive a packet is:
$E_{tx} = E_{elec}.k$ ------------- (3)

3.2 Opportunistic Data Collection

Optimizing data collection efficiency in WSNs via the use of sink nodes' mobility is the goal of the Opportunistic Data Collection Algorithm (ODCA). It uses a heuristic-based strategy in which mobile sinks adapt their routes on the fly in response to chances for collecting data in real time. Opportunistic data collection by mobile sinks, as they approach sensor nodes, reduces latency and energy waste caused by short-range transmission. By keeping an eye on things like network topology, node availability, and data traffic, ODCA lets sinks adjust their routes to prioritize regions with more data density or urgent demands. Improving overall network performance and energy efficiency, this flexibility reduces long-range communication needs and dynamically balances the network load, making it resilient to node failures and shifting traffic patterns.
The ODCA problem is intractable because it is NP-hard. It is not feasible to do an extensive search due to the complexity of the processing and the absence of accessible contextual information. Topics covered include node power consumption, as well as the instant benefits or value of detected data.
Gathering massive amounts of real-time sensory data from devices in various RoIs is the biggest obstacle to solving the ODCA issue efficiently. High latency and increased backhaul traffic might result from the cloud directly controlling all interactions. Alternatively, UO-DCA takes advantage of the MEC paradigm by offloading processing and communication to mobile users located at the network's periphery.
Every Region of Interest (RoI) has a local coordinator who reports device energy utilization and the average usefulness of sensory data to the edge servers. At the beginning of its journey, every MU gets in touch with the closest edge server to get the RoIs' background data, including their actual distances. One approach is to use GPS to locate them. The MU compiles all of this historical information in order to choose the optimal RoI to visit. Traveling to the RoI, gathering data from sensors there, and sending it to an edge server close by all take time. Reaching the deadline associated with the whole data-collecting period, however, yields the locally maximum weighted social welfare. With no way for MUs to know how long it will take for sensors in each unexplored RoI to transmit data, we provide an online heuristic to determine the locally feasible weighted social welfare roughly.

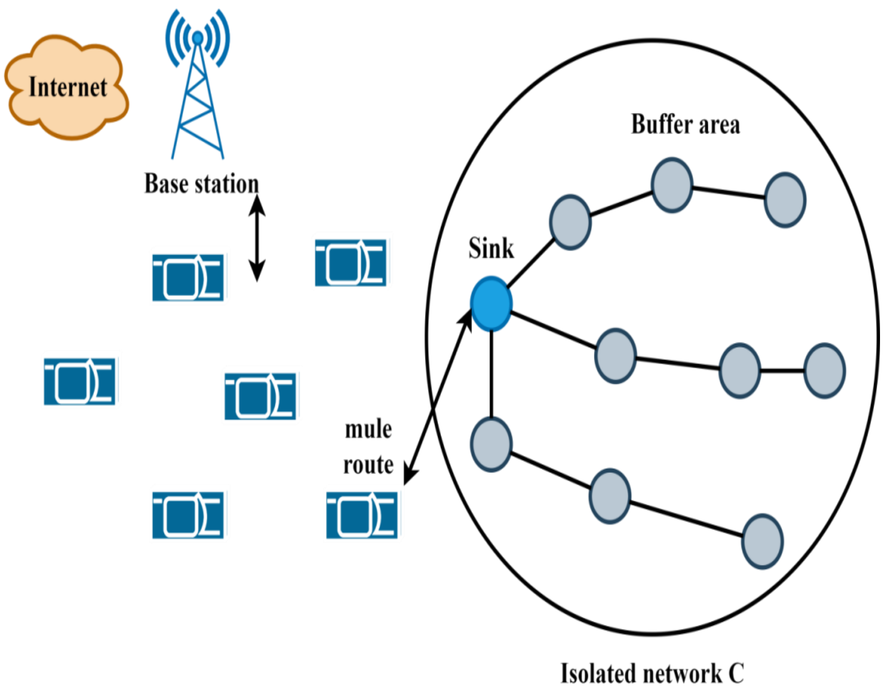

Figure 2. Opportunistic Data Collection

If the user is tasked with selecting the next nearby unexplored RoI to visit. Following the acquisition of necessary data from the edge server e ∈ E, the MU determines the possible gain for the sensors using the following method.
$e = argmin\left\{d_{ne'}^{(t)} \forall e' \in E\right\}$ ----------- (4)

The physical distance d (t) ne0 in time slot t is the measurement of the distance between the mobile user un and the edge server e 0 ∈ E. The data shown here comes from a nearby edge server and comprises the following: average utility $\phi\bar{i}$, power consumption $P^{-}i$, and the physical distance di to every unexplored area ri $d_{ne'}^{(t)} \forall e' \in E$. Re is a representation of the collection of RoIs that edge server e is capable of handling.

For each unvisited RoI i, the MU must determine the potential weighted social welfare in real-time if it wishes to go to the next ideal RoI. Prior prediction of the number of time slots used by sensors in each RoI to send data to the MU (ds−as) is not possible. This necessitates the MU's prior estimation of this data. A MU in UO-DCA can use the following approximation to roughly predict how long it will take to gather data from the chosen sensors in that area (t (i) s) and send it to a nearby edge server (t (i) e):

Algorithm 1: Opportunistic Data Collection
Input: **RoIs Information:** Average utility ($\phi\bar{i}$), power consumption (P_i), and physical distance (d_i) of devices in each Region of Interest (RoI). **Contextual Information:** Physical distances between mobile users (MUs) and edge servers (e). **Steps:** 1. **Initialization:** o Each local coordinator in an RoI informs nearby edge servers about utility, power consumption, and distances. o MUs receive contextual information about RoIs and their physical distances from the nearest edge server. 2. **Decision Making:** o MUs aggregate received information to select the most suitable RoI based on locally-maximum weighted social welfare and deadline constraints. o The MU computes achievable profit for sensors in RoIs based on contextual information and physical distances. 3. **Estimation and Approximation:** o MUs estimate the time required for data collection and transmission using approximations based on physical distances and data from sensors. o To choose the next RoI to visit, the online heuristic uses the weighted social welfare that is locally reachable from the unvisited RoIs. **Output:** **Optimal RoI Selection:** UO-DCA outputs the RoI that maximizes the weighted social welfare while meeting data collection time constraints.

3.3 QoS-aware Mobile Sink Selection Algorithm

In WSNs, the Quality of Service (QoS)--aware Mobile Sink Selection Algorithm (QMSSA) maximizes data collection efficiency without sacrificing QoS. It analyzes sink mobility patterns to make sure data is collected quickly and keeps an eye on network load to prioritize regions with heavy data traffic. With energy consumption in mind, QMSSA chooses mobile sinks with low power consumption, allowing the network to run for longer. Data priority levels and data delivery deadlines are some of the quality of service (QoS) characteristics that the algorithm takes into account to guarantee accurate and timely data collecting. The total performance and dependability of WSNs are improved by this all-encompassing method.

As an objective function, the probability (P_{ijd}) seeks to find the path from node i to node j's neighbor d as efficiently as possible. The likelihood can be calculated using the following formula:

$$P_{ijd} = \frac{[t_{ij}]^{\alpha}[n_{ijd}]^{\beta}}{\sum_{l \epsilon N_i}[t_{il}]^{\alpha}[n_{ild}]^{\beta}} \text{------------- (5)}$$

Among all neighbor nodes of i, which is denoted as N_i, is every neighbor node l that can be reached from destination d. To ensure that the two criteria are given equal weight, these values are originally set to 0.5. The following equation is used to calculate the heuristic factor, which represents the route quality:

$$n_{ijd} = \frac{[B_{ijd}]^{\beta_B}}{[D_{ijd}]^{\beta_D} \times [L_{ijd}]^{\beta_L}} \text{----------- (6)}$$

The influence of each quality of service characteristic (bandwidth, latency, and packet loss) on the route p(i, j, d) is shown by the adjustment factors β_B, β_D, and β_L. In order to accomplish the first study's goal, we set the QoS parameters to 0.1, assuming they are equally important.

Negative feedback in the form of a pheromone evaporation rate ρ keeps the routing database free of out-of-date solutions and stops the connection from going through an infinite pheromone surge.

$T_{ij} = (1-p)t_{ij} + \Delta t_{ij}$ ------------ (7)

The probability (1) and pheromone (3) calculation formulae are based on versions provided in.

Algorithm 2: QoS-aware Mobile Sink Selection Algorithm
Input: **Network Load Information:** Data on network congestion and load distribution. **Sink Mobility Patterns:** Mobility patterns of mobile sinks within the network. **Energy Consumption Data:** Information regarding energy consumption of mobile sinks. **Steps:** • QMSSA monitors network load to identify areas with high data congestion and prioritize them for sink selection. • It evaluates sink mobility patterns to ensure timely data collection. • The algorithm integrates QoS parameters such as data delivery deadlines, data priority levels, bandwidth, delay, and packet loss to ensure reliable and timely data collection. • Adjustment factors (β_B,β_D,β_L) are used to set the importance of QoS parameters. • Calculates the probability (P_{ijd}) of finding an efficient path from node i to destination d through a neighbor node j. • Probability formula: $P_{ijd} = \frac{[t_{ij}]^{\alpha}[n_{ijd}]^{\beta}}{\sum_{l\epsilon N_i}[t_{il}]^{\alpha}[n_{ild}]^{\beta}}$ • τ_{ij} denotes the pheromone trail on link (i,j), n_{ild} is a heuristic factor, and α and β are relative weight factors. • Computes the heuristic factor n_{ijd} representing the quality of the path based on bandwidth, delay, and packet loss. • Heuristic factor formula: $n_{ijd} = \frac{[B_{ijd}]^{\beta B}}{[D_{ijd}]^{\beta D}\times[L_{ijd}]^{\beta L}}$ • Adjustment factors (β_B, β_D, β_L) set the importance of QoS parameters. **Output:** **Optimal Sink Selection:** QMSSA outputs the optimal mobile sink(s) based on probability calculations and heuristic factor evaluation.

4. RESULTS AND DISCUSSION

In this section, we present and analyze the results obtained from the implementation of our proposed methods in WSNs. We discuss the performance metrics, compare against existing approaches, and draw insights into the effectiveness and implications of our methods.

4.1Throughput

Throughput= $\frac{Number\ \ of\ Packet\ \ Size}{Arrival\ \ Time\ \ duration\ *Successful\ \ average\ \ Packet\ \ size}$ ----------- (8)

Table 1. Throughput comparison table

	Throughput levels		
Packet Size	IPSO	EEDMS	QMSSA
50	0.370	0.434	0.588
100	0.740	0.869	1.176
150	1.11	1.304	1.764
200	1.481	1.739	2.352
250	1.851	2.173	2.941

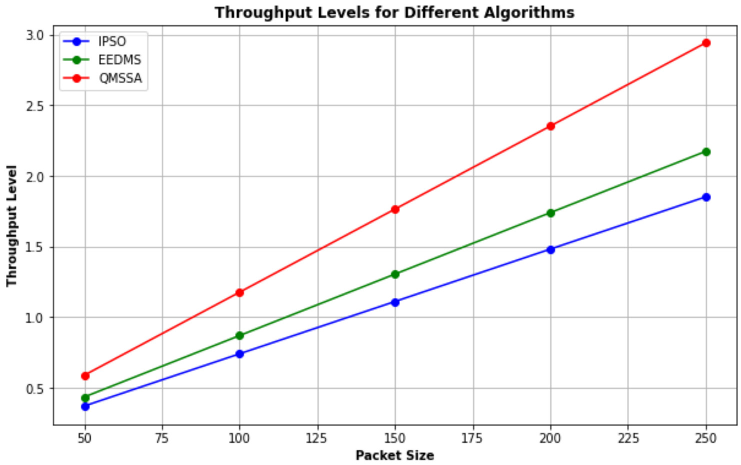

Figure 3. Throughput comparison chart

Table 1 and Figure 3 show that the throughput levels of IPSO, EEDMS, and QMSSA exhibit distinct performance trends across varying packet sizes. IPSO starts with the lowest throughput at 0.370 for a packet size of 50, gradually increasing to 1.851 for a packet size of 250. EEDMS shows slightly higher throughput levels, starting at 0.434 and reaching 2.173 for the same packet sizes. QMSSA consistently outperforms the other algorithms, starting at 0.588 and peaking at 2.941 for packet sizes from 50 to 250. This analysis indicates that QMSSA maintains the highest efficiency in data transfer across all packet sizes, followed by EEDMS. At the same time, IPSO exhibits comparatively lower throughput levels throughout the range of packet sizes.

4.2 Energy

Energy= $\frac{Number\ \ of\ Sensor\ \ nodes}{Energy\ \ consumption\ \ \ for\ sending\ \ packets\ \ at\ a\ times}\ x\ 100$ ----------- (9)

Table 2. Energy comparison table

	Energy level in joules		
Number of Nodes	IPSO	EEDMS	QMSSA
10	90	76	62
20	181	153	125
40	363	307	250
60	545	461	375
80	727	615	500
100	909	769	625

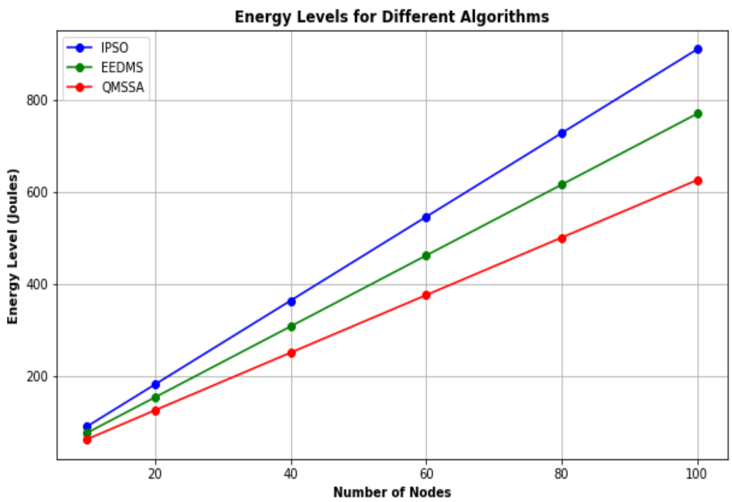

Figure 4. Energy comparison chart

Table 2 and Figure 4 show energy levels in joules for IPSO, EEDMS, and QMSSA across different numbers of nodes that display varying consumption patterns. Starting with 10 nodes, IPSO consumes 90 joules, EEDMS consumes 76 joules, and QMSSA consumes 62 joules. As the number of nodes increases, so does the energy consumption, with IPSO reaching 909 joules at 100 nodes, EEDMS reaching 769 joules, and QMSSA consuming 625 joules. This data illustrates a consistent trend where QMSSA exhibits the lowest energy consumption across all node counts, followed by EEDMS. At the same time, IPSO consistently consumes the most energy throughout the range of node numbers.

4.3 Time Delay

$$\text{Time Delay}=\frac{Number\ \ of\ Sensor\ \ nodes}{energy\ \ consumption\ \ \ for\ sending\ \ packets\ \ at\ a\ times\ \ x\ forwarding\ \ \ time\ \ in\ ms}\ \text{-----------}\ (10)$$

Table 3. End to End delay comparison table

	Time (End to End Delay)		
Number of Nodes	IPSO	EEDMS	QMSSA
10	0.084	0.069	0.063
20	0.169	0.139	0.127
40	0.338	0.279	0.255
60	0.508	0.419	0.382
80	0.677	0.559	0.510
100	0.847	0.699	0.637

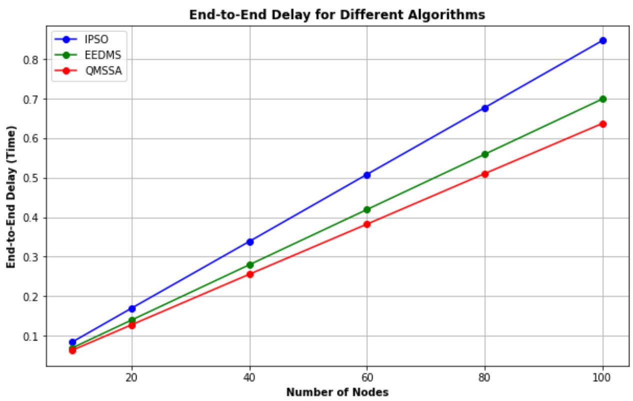

Figure 5. End to End delay comparison chart

Table 3 and Figure 5 show end-to-end delay (in time units) for IPSO, EEDMS, and QMSSA across different numbers of nodes demonstrating varying performance in data transmission. Beginning with 10 nodes, IPSO exhibits an end-to-end delay of 0.084 time units, EEDMS shows 0.069 time units, and QMSSA demonstrates 0.063 time units. As the number of nodes increases, the end-to-end delay also rises, with IPSO reaching 0.847 time units at 100 nodes, EEDMS reaching 0.699 time units, and QMSSA showing 0.637 time units. This data indicates that QMSSA consistently maintains the lowest end-to-end delay across all node counts, followed by EEDMS, while IPSO consistently exhibits the highest delay throughout the range of node numbers.

4.4 Packet Delivery ratio

$$\text{PDR}=\frac{Number\ \ of\ Packets\ \ Receive}{Total\ \ Packets}*100\ \ \text{-----------}\ (11)$$

Table 4. Packet delivery ratio comparison table

	Packet Delivery ratio		
Number of packets	IPSO	EEDMS	QMSSA
50	97.6	98.4	99.4
100	98.8	99.2	99.7
150	99.2	99.46	99.8

200	99.4	99.6	99.85
250	99.52	99.68	99.88

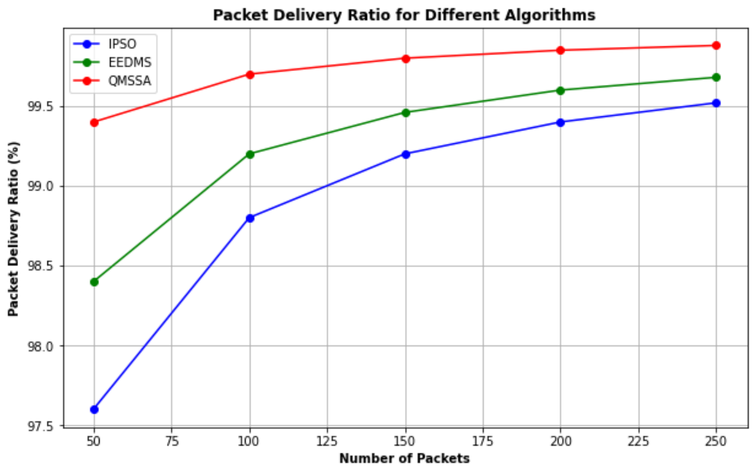

Figure 6. Packet delivery ratio comparison chart

Table 4 and Figure 6 show packet delivery ratios for IPSO, EEDMS, and QMSSA across different numbers of packets, demonstrating their efficiency in successfully delivering packets. Starting with 50 packets, IPSO achieves a delivery ratio of 97.6%, EEDMS shows 98.4%, and QMSSA demonstrates the highest at 99.4%. As the number of packets increases, all algorithms show improved delivery ratios, with QMSSA consistently leading, reaching 99.88% for 250 packets. This data indicates that QMSSA maintains the highest packet delivery ratio across all packet counts, followed by EEDMS, while IPSO consistently exhibits slightly lower delivery ratios throughout the range of packet numbers.

5. CONCLUSION

In conclusion, mobile sinks are a great way to tackle the problem of inefficient data collection in WSNs. This paper introduces two novel approaches to improving network performance and data collection efficiency: the Opportunistic Data Collection Algorithm (ODCA) and the QoS-aware Mobile Sink Selection Algorithm (QMSSA). ODCA is able to adapt to different network circumstances and keep running efficiently despite changes in topology and node failures because it uses a heuristic approach and dynamic route modification. To keep the quality of service in place, QMSSA takes into account important factors, including network load, sink mobility, and energy consumption, to guarantee the best choice of mobile sinks. By significantly improving data-gathering efficiency and reducing network latency, these algorithms demonstrate their potential to advance WSN technology when implemented. Improving the data-collecting process via the integration of ODCA and QMSSA is crucial for WSNs in many different applications, such as industrial automation and environmental monitoring. These results can be expanded upon in future studies by looking at how well the algorithms work in larger-scale and more varied WSN settings or by developing hybrid systems that include the best features of both algorithms. ODCA and QMSSA are huge leaps forward in the race for better and more dependable WSNs.

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