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RESEARCH ARTICLE

DAIMS: Data Acquisition via Intelligent Mobile Sink in Wireless Sensor Networks Utilizing Termite Queen and Artificial Fish Swarm Optimization Techniques

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Abstract – Wireless Sensor Network (WSN) is a heterogeneous, distributed network with resource-constrained tiny devices in the Internet of Things (IoT) ecosystem, finding extensive deployment across critical areas like medical systems, infrastructure surveillance, battlefield surveillance, and numerous other domains. Mobile Sink (MS)-based approaches are useful in addressing issues like unequal clustering and routing challenges, which are traditionally adopted for enhancing energy efficiency and longevity of wireless sensor networks (WSNs) operations over a monitoring area. This research paper establishes the Termite Queen and Artificial Fish Swarm Optimization Algorithm (TQAFSOA)-based energy-efficient clustering and routing with mobile sink (MS) for reducing challenges of unequal clustering, use of gateways, and multi-hop communication and to improve the network's lifespan. In order to address traditional clustering challenges and operational issues, Termite Queen Optimization (TQO) is adopted. And scheduling and routing for the objective of an energy-efficient route between the CHs and MS and to improve the network's lifespan. Artificial Fish Swarm Optimization Algorithm (AFSOA) addresses the major issues in traditional clustering and routing algorithms by limiting the unequal clustering, hotspot, and multi-hop communication from CHs to sink node. The algorithm of DAIMS is implemented using MATLAB, and functions are simulated based on simulator NS-2. Simulation results highlighted that the TQAFSOA model is superior to parallel research using clustering and routing with mobile sink such as an energy-efficient mobile sink-based intelligent data routing (EEMSR) algorithm, an energy-aware path construction (EAPC) algorithm, an optimal clustering and network topology for mobile sink (OCNTMS), an ant colony optimization-based mobile sink path determination (ACO-MSPD) scheme, and a weighted rendezvous planning (WRP) algorithm, in terms of battery power utilization, throughput, number of alive nodes, and packet delivery ratio. This proposed research approach is able to uphold wireless sensor network-based IoT operations.

Index Terms – Wireless Sensor Networks, Optimization Algorithms, Clustering, Routing, Data Acquisition, Mobile Sink.

1. INTRODUCTION

Wireless Sensor Networks (WSN) consist of a large number of resource-constrained tiny devices deployed over a monitoring area; they are important in several applications such as environmental monitoring, healthcare, border surveillance, forecasting, wildlife and traffic management systems, and disaster management systems [1-2]. Design and development of an energy-efficient WSN is complex due to limited node resources and the need to operate independently for longer periods, and substitution of new nodes, battery substitution, and rechargeable nodes are costly and impractical in warlike and unfriendly locations [3]. Therefore, maximizing the energy-efficiency of deployed nodes in such environments is a critical issue for long-term monitoring of network activity.

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Clustering is a traditional and trusted approach in WSNs for long-term node activity by minimizing node battery power utilization, decreasing transmission collisions, and enhancing throughput [4][5][6][7]. In WSNs, the selection of a cluster head (CH) and clustering area are important issues in clustering to achieve greater energy efficiency, and importantly, CHs near the base station have faster energy loss, which creates the energy hole and sinkhole issues and leads to partition or unavailability of the deployed sensors. [8][9][10]. A mobile-sink-based approach is used to overcome the hotspot problem in WSNs [11], and it can periodically traverse over the specific area to collect aggregated data from CHs. However, improper configuration of clusters and selection of CHs can lead to a difficult trajectory to collect data from the monitoring area and cause unavoidable delays. The major accomplishments of this paper are as follows.

- To construct a DAIMS strategy, this paper includes two models: one for forming energy-aware-based clusters and identifying collection points using termite queen optimization and another for constructing trajectory paths of mobile sink to gather aggregated data from the WSN in the monitoring area.
- The common intersection points (CMP) approach is applied in DAIMS; it iteratively optimizes the energy consumption function to limit the travel distance and its residual energy.
- The DAIMS uses the termite queen optimization clustering method to identify the effective number of clusters by balancing node distances to cluster heads. In DIAMS, the energy consumption function-driven method of optimizing artificial fish swarms improves a mobile sink traversal duration and energy consumption.
- Simulation analysis of the comparative results is further conducted utilizing TQAFSOA.

The subsequent sections of this paper are represented as follows: Section 2, related work, provides a brief of parallel research on WSNs and IoTs utilizing mobile sinks. Section 3 introduces the problem statement and proposed model (DAIMS) in detail about termite queen optimization and artificial fish swarm optimization strategies. Section 4 demonstrates the proposed model evaluation and simulation results in detail. Finally, the conclusion of this paper is included in Section 5.

2. RELATED WORK

Different configurations are used for collecting data from internet of things (IoT)-based wireless sensor networks (WSNs) monitoring areas. One of the promising approaches in this is mobile sink-based data collection. Many of these approaches were intended to address issues like battery power utilization, delivery ratio and delay, and lifespan [11][12]. Tree structure clustering, ring routing, dynamic route adjustment, dynamic energy-efficient cluster adjustment, centroid routing, and multiple mobile sink-based algorithms are some important approaches in WSNs with mobile sink (MS). During this process, other notable schemes were developed for energy-efficient data collection, such as the grid and chain combined model, the starfish model, delay-aware efficient green clustering, event-driven data dissemination by obtaining the location of resource points (RP), and dynamic route adjustment in heterogeneous sensor nodes [11]. Mobile sink-based IoT has been an evolving research area in wireless sensor networks with nature-inspired or metaheuristic optimization techniques and has witnessed gradual improvement in protocols and strategies in the last decade. Mobile sinks, one of the most exciting and anticipated approaches in wireless sensor networks with optimizations, are evolving in protocols and applications.

In recent years, the parallel approaches have mostly been on using nature-inspired or metaheuristic models for mobile sink-based clustering and routing in WSNs. Some notable developments were the implementation of energy-efficient WSNs using grey wolf optimization, which improves resource point selection; the use of dragonfly optimization to maximize network lifespan; the application of bat algorithm according to the position of resource points; enhanced African buffalo optimization; and various hybrid metaheuristic algorithms [13][14][15]. Many strategies are employed on energy-aware clustering and routing in WSNs using MS, but many of those models are not widely accepted due to limitations in enhancing the performance of WSNs. This section provides a short literature assessment of energy-efficient clustering and MS-based data collection models.

H. Huang et al. [16] proposed an algorithm that uses mobile sink (MS) in WSNs to collect data from targeted areas with traveling vehicles that follow fixed trajectory paths. Simulation results of the algorithm limit hotspot and unequal clustering problems, but scalability and efficient routing and clustering remain unspecified. Rajarajeswari P et al. [17] proposed a hybrid model to address clustering and hotspot problems in WSNs and to improve the network's lifespan; they adopted termite queen optimization to create clusters in targeted areas and choose the optimal cluster heads. Walrus optimization is used to create the optimal trajectory path for MS to collect data from the specific area of WSNs. The proposed hybrid model enhances the lifespan of the network but does not incorporate the fitness measures for clustering, leading to high computational complexity. In 2024, Hanifa Zafor et al. [18] suggested a system for collecting packets from deployed nodes and recharging nodes with mobile sinks. Additionally, the authors presented major advantages and limitations of using mobile sinks for collecting data and recharging devices. The models provided were reasonably effective and adaptable, which makes them acceptable in IoT-

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based WSN for enhancing the lifetime of sensor nodes. In 2024, H. M. Lateef et al. [19] studied and created a system for a mobile sink-based wireless sensor network that uses NP-hard problems to group together for the collection of data from individual deployed nodes. Additionally, the authors presented major advantages and limitations of using mobile sinks for collecting data. They studied and implemented NP-hard problem-based visiting route optimization techniques utilizing an MS in WSNs. The model implemented more precise scores than earlier MS-based WSN studies.

In 2024, Al Aghbari et al. [20] created a novel intelligent mobile sink-based enhanced Capuchin Search Algorithm (iCapSA) to obtain a better collection of data collection points and improved Ant Colony Optimization (ACO) trajectory design. The model employed residual energy and distance to sort DPCs and to collect data from sensors. The framework was separated into two sections: selection of the best DCPs and selection of the best trajectory for MS. The model was evaluated for lifespan, power utilization, and packet delivery ratio. The evaluated results of that iCapS-ACO with the MS model outperform existing methods based on several performance metrics. In 2023, Boyineni S et al. [21] assessed and diagnosed the energy hole and sinkhole problems of wireless sensor networks using mobile sinks. Additionally, the authors focused on obstacles contained in wireless sensor networks. Authors developed the RRTMT model, which performs efficient resource point (RP) identification and obstacle-aware visiting routes for an MS in the monitoring area with hurdles. A unique technique called the spectral clustering algorithm was employed, which combined remaining battery power and the gap among nodes method for selecting the efficient RPs.

The findings have demonstrated the exciting prospects of mobile sink in WSNs for detection and tracking, allowing for the collection of data and improved results for IoT-based WSNs. V. Agarwal et al. [22] suggested an intelligent routing algorithm used to determine the data collection points called rendezvous points and construct a path for MS to travel over the targeted area. The analysis of the proposed model indicates that while it improves energy efficiency and extends the network's lifespan, it does not take into account the location and position of CHs in the targeted area when creating rendezvous points, which results in inaccurate aggregated data. Utilizing MS in WSNs for collecting data from a monitoring area, W. Wen et al. [23] proposed a minimum cost spanning tree-based model. The proposed model creates an energy-efficient route for the MS that reduces the computing effort needed to build the path based on the energy of CHs, but it overlooks how to choose the best CHs for the shortest route to collect data, which can cause delays. P. K. Donta et al. [24] presented an extended ant colony optimization–mobile sink path determinization based on event-driven WSNs. The mechanism is adopted for reselection of collecting points and optimization of the MS route to get data from CHs in the monitoring area. The EACO approach uses stable energy utilization and collection point optimization to reduce data transmission. The proposed system can determine an efficient MS route and therefore improve the network's lifespan but fails in computational complexity for reselection of collection points. The MS attached to public transport vehicles studied in [25][26] is able to get information from CHs in an unequal clustering when it is traveling in a static route. This mechanism reduces the computational complexity of cluster formation and cluster head selection in the monitoring area. The simulation analysis of this model outperforms other models at the cost of invited delay. The summary of parallel research contributions and key approaches, along with their limitations, is presented in Table 1.

There are also contradictory interpretations of the important techniques for mobile sink-based clustering and routing. While some authors uphold the use of mobile sink-based optimization models because of enhanced packet delivery ratio (PDR) and average case energy consumption, other authors recommend the ultimatum related to deployment, routing intricacy, and the necessity for many hostile applications. This discussion highlights the existence of mobile sinks to extend research and innovation to implement battery-efficient and scalable mobile sink-based clustering and routing in WSNs using metaheuristic optimization.

Table 1 Summary of Previous Research on Mobile Sink-Based Wireless Sensor Networks

Author(s) and Year	Research Contribution	Key Approach/Algorithm	Pros	Cons
H. Huang et al. [16] and 2017	Mobile sink-based data collection with fixed trajectory.	MS with traveling vehicles following fixed routes.	Limits hotspot problem. And addresses unequal clustering issues.	Scalability remains unattended. Efficient routing and clustering not clearly defined
Rajarajeswari P et al. [17]	Hybrid clustering and hotspot mitigation.	Termite Queen Optimization for clustering and Walrus	Enhances network lifespan and addresses	No fitness measures for clustering and high

and 2025		Optimization for MS trajectory.	clustering and hotspot problems.	computational complexity.
Hanifa Zafar et al. [18] and 2024	Data collection and node recharging	Mobile sink-based technique for data collection from the monitoring area and recharging nodes.	Reasonably effective and adaptable. Enhances sensor node lifetime. Suitable for IoT-based WSN	Cluster head (CH) selection and reselection of CHs are not clearly defined.
H. M. Lateef et al. [19] and 2024	NP-hard problem-based clustering.	NP-hard optimization for traversing trajectory.	More efficient than earlier research studies. Systematic approach to route optimization.	Computational complexity of NP-hard problems and trajectory route creation, and limited scalability potential.
Al Aghbari et al. [20] and 2024	Intelligent mobile sink optimization.	Enhanced Capuchin Search Algorithm (iCanSA). Improved Ant Colony Optimization (ACO).	Outperforms existing methods on multiple metrics. The model considers residual energy and distance. Significant performance in lifespan, power utilization, and PDR.	Cluster head and routing computational overhead.
Bayineni S et al. [21] and 2023	Energy hole and sinkhole problems.	RRTMT Model, Spectral Clustering Algorithm, and Obstacle-Aware Routing.	Efficient resource point identification handles obstacles in the monitoring area, and the model reduces remaining battery power.	Models have scalability issues with obstacles.
V. Agarwal et al. [22] and 2022	Intelligent routing with rendezvous points	Rendezvous point-based data collection.	Improves energy efficiency. Extends network lifespan.	Algorithms fail to consider CH location. Results in inaccurate aggregate data.
W. Wen et al. [23] and 2018	Minimum cost spanning tree-based system.	Energy-efficient route based on CH energy.	Reduces computing effort for route building and energy-efficient path creation.	Complex optimal CH selection process. Can cause delays in data collection.
P. K. Donta et al. [24] and 2021	Event-driven WSN optimization	Extended Ant Colony Optimization (EACO).	Efficient MS-based route determination. Improves network lifespan. Stable energy utilization.	High computational complexity and complex reselection of collection points.
S. Najjar-Ghabel, L. Farzinvash,	With a static trajectory, mobile sink-based data	Hierarchical Agglomerative Clustering (HAC), Ant Colony Optimization, and Genetic	Improvement in energy consumption over existing	High computational complexity and implementation

S.N. Razavi. [25] and 2020	gathering is being performed.	Algorithms discover efficient clustering solutions and refine existing cluster configurations. Multi-Agent Reinforcement Learning for Sink Trajectory Construction.	algorithm. Intelligent clustering minimizes intra-cluster communication complexity. Improves network lifespan. The HAC and ACO combination effectively navigates physical obstacles.	complexity. High coverage issues. Mobile sink movement consumes additional energy.
H. Huang and A. V. Savkin [26] and 2017	Creates unequal clusters based on energy levels and node density in the deployed area. Selects cluster heads based on residual energy levels and considers energy consumption for both data transmission and network overhead.	Energy-Aware Unequal Clustering Algorithm for cluster formation based on remaining energy and density. And it uses a load-balancing mechanism to distribute network overhead across all nodes.	Unequal clustering prevents energy hotspot problems. Mobile sink minimizes long-distance communications. Energy-aware mechanisms can enhance network lifetime. Less computational complexity.	Data collection from deployed areas depends on public transportation schedules and leads to coordination complexity. Network coverage issues. Intermittent connectivity, unequal energy depletion, and timing synchronization.

3. PROPOSED METHODOLOGY

3.1. Network Model Definition

In this paper, the traditional wireless sensor networks (WSNs) architecture as "$G = (V, E)$" where 'V' represents the number of limited resource homogenous nodes, and 'E' represents the communication paths between nodes in monitoring areas. These devices are carefully deployed over the monitoring area; its dimensions are $a * b$. Deployed limited resource devices can monitor events in their region and gather data of events at different rates and forward collected data to the cluster head in a multi-hop communication. One mobile sink (MS) is used for data collection from cluster heads in the environments. And MS is equipped with unlimited energy sources and can travel effortlessly over the monitoring area. Tiny nodes usually don't have a lot of battery power. Some important measurements of node energy are initial energy (S_{in}), energy used to send data to CH (S_{dc}) or neighbor node (S_{ds}), remaining energy (S_r), and energy threshold (S_{th}), which can be obtained by using equations. In many WSNs, the remaining energy of the deployed nodes had been contemplated while selecting the CHs. But in this research establishment, remaining energy, active and sleep schedule of CHs, visiting path, distance from CHs to MS, and link quality are used for collecting data from monitoring areas in WSNs. One of the issues in clustering is the formation of clusters and selecting the optimal cluster head (CH).

In WSNs, energy-efficiency is a significant factor depending on the number of deployed devices and the mobile sink (MS). Dynamic random unequal clusters and cluster heads are constructed in a network; within it, each node can communicate monitored data to CH, and then CHs are responsible for forwarding data to the mobile sink whenever MS is near to CH. Because of this, the route between the CHs and MS must be efficient in terms of latency, power, and traffic. The necessity of obtaining the shortest route to cover all possible CHs in the monitoring area cannot be neglected, and the routing schedule insists on adopting the optimal route. Some key responsibilities in routing technique are distance from CH to location of MS, link quality, and optimal path. An energy-efficient termite queen optimization algorithm for clustering and data collection is proposed to overcome these network issues. Evolutionary is adopted to address the link quality, network traffic, distance, and time complexity will be extremely minimized.

3.2. Multi-Objective Optimization Problem

The clustering and routing problem is formulated as a multi-objective optimization framework. The problem formulation encompasses four mathematical components: equation (1) for the overall multi-objective optimization function, energy consumption modeling for sensor nodes in equation (2), distance computation between nodes and their cluster heads in equation (3), link quality metrics for sink-cluster head communication evaluated with equation (4), and additionally equation (5) for assessing the load balance between nodes and cluster heads.

$$F = \theta_1 f_1(\mathrm{energy}) + \theta_2 f_2(\mathrm{distance}) + \theta_3 f_3(\mathrm{linkQality}) + \theta_4 f_4(\mathrm{loadBalance}) \quad (1)$$

Where

$$f_1(\mathrm{energy}) = \sum_{i=1}^{n} \left(E_o^{ch^i} - E_t^{ch^i} \Big/ E_o^{ch^i} \right) (\text{energy depletion ratio});\ \forall E_t^{ch^i} \geq E_{th}(\text{energy threshold}) \quad (2)$$

$$f_2(\mathrm{distance}) = \sum_{i=1}^{n} \sum_{j} \in C_i\, d(S_i, CH_i)(\text{Clustercommunication});\ \forall S_j \in C_i, d(S_i, CH_i) \geq R_{tj} \quad (3)$$

$$f_3(\mathrm{linkQuality}) = \sum_{i=1}^{n} (1 - LQ_i)\ (\text{link quality degradation}) \quad (4)$$

$$f_4(\mathrm{loadBalance}) = \sigma^2(|C_1||C_2||C_3|, \dots, |C_n|)(\text{cluster size variance});\ \bigcup_{k=1}^{n} C_k = V\ (\text{all nodes must be clustered}) \quad (5)$$

3.3. Termite Queen Optimization Approach

Traditional ant colony optimization (ACO) approaches suffer from premature convergence and limited exploration in WSN clustering schemes. The proposed Termite Queen Optimization Algorithm (TQOA) introduces several key aspects like hierarchical structure, dynamic parameter adaptation, and multi-criteria decisions. The proposed methodology, a Termite Queen Optimization approach, and an energy-efficient evolutionary optimization routing system that minimizes the node battery utilization and balances energy usage between CHs and MS in a WSN are proposed. A novel metric to select the CHs is considered in the Termite Queen Optimization Algorithm (TQOA), and these CHs are responsible for collecting data from all deployed non-cluster heads and communicating data to the mobile sink. Four parameters were carefully adopted when TQOA was considered to elect CHs and merge the remaining energy, distance, link quality, and schedule of the CHs in the sensor network to minimize battery power utilization and enhance the lifespan of sensor networks.

In the proposed model, the tiny devices are constructed into ‘m’ clusters and an optimal number of CHs by using TQOA. The proposed model introduced these CHs as collection points within the monitoring area. The model also uses the TQOA to reconfigure clusters and CHs based on the leftover battery power and energy threshold. The collection points are CHs, which receive data from other tiny devices in a cluster that the MS can traverse on its trajectory to get aggregated packets from CHs.

After cluster formation and optimal cluster head selection, an optimal trajectory for mobile sink (MS) is constructed by using the Artificial Fish Swarm Optimization Algorithm that covers all collection points. The only MS build with GPS obtains exact collection point locations and travels over trajectory by covering all collection points and gathering aggregated data.

The MS can determine trajectory time by considering the time spent at each collection point to receive the data and also maintain the active and sleep schedule of CHs. The proposed model network assumption is shown in the stepwise representation (Figure 1).

Step 1: The deployment and initialization of devices and MS in the monitoring area $a * b$ is a pivotal aspect of the construction of this model, where most of the energy consumption obstruction is appended to the MS that is enabled with sufficient energy resources. This model ensures that CMs and CHs are not overwhelmed with major communication operations, thereby reducing the effect on

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their resources, like battery power utilization, by limiting the gap between collection points and CHs.

Step 2: The cluster creation, CH selection, and collection point identification specify a novel scheme of partitioning the entire area into a number of unequal-sized clusters (a_i, b_i), where 'a_i' and 'b_i' represent the width and height of any constructed cluster. The mobile sink organizes the constructed clusters in an unequal-size grid structure. Initially, the MS assumes that the basic cluster is based on the transmission range and node energy, as well as the distance to the initial collection points. The formation of cluster heads and collection points are discussed in algorithm 1. After the construction of clusters, a crucial process is to nominate and fix the optimal CH in each cluster. The CH is more performant among the CMs; therefore, CMs are expected to drain node battery power due to the heavy communication overhead among them. This process breaks down into two promising approaches and mathematical formulations for pheromone concentration of TQOA given in equation (6) and equation (7) for probability selection functions discussed as follows:

$$T_{mn}(t+1) = (1-p)T_{mn}(t) + \sum_{i=1}^{j} \Delta T_{mn}^{i} \quad (6)$$

Where

$T_{mn}(t)$ is pheromone concentration

between sensors m and n at time t

p is evaporation rate ($0 < p < 1$)

$\Delta^{i}_{mn} = Q/L_i$ for i − th termite contribution

$$P_{ij}{}^{k}(t) = [T_{ij}(t)]^\alpha \times [\eta_{ij}(t)]^\beta \times [\varphi_{ij}(t)]^\gamma / \Sigma_{l \in N_i{}^k} [T_{il}(t)]^\alpha \times [\eta_{il}(t)]^\beta \times [\varphi_{il}(t)]^{\gamma} \quad (7)$$

$\eta_{ij}(t) = 1/d(i,j)$ (heuristic information − inverse distance)

$\varphi_{ij}(t) = E_{rj}(t)/E_{0j} \times LQ_{ij}$ (energy − link quality factor)

α, β, γ are influence parameters for pheromone,

Distance, and composite factor

Step 3: This is a process implemented in subsequent rounds $R = 0, 1, 2, 3, \ldots.$, the CMs in the monitoring area operated in a scheduled manner to gather information about events and forward it to CHs. Initially, each CH sends a one-time message about active and sleep schedules, as well as collection point data, to the MS. The MS uses that data to determine the trajectory path to get information from the CHs. If the leftover battery power of the cluster head is less than the energy limit, then the monitoring system will choose the best cluster head and path to collect data without any communication between the cluster members or between the members and their cluster head, but they will update their energy levels, locations, distances to the cluster heads, and distances to the collection points in the vector. Once MS constructs the optimal trajectory, then MS will reset the round value of all CHs to 0. In case only CHs are elected and configured, MS will reset that CH round count to '0'; the remaining CHs round count will be incremented usually. Round values are useful to determine the complexity of the process.

Step 4: Reconfiguration of clusters and cluster heads (CHs) by using step 2.

Input: Number of limited resource sensor nodes randomly deployed in the monitoring area $N \rightarrow \{S_1, S_2, \ldots, S_i\}$, and k – number of clusters.

Output: Clusters $(ai * bi) \in (a * b)$, k – Cluster Heads (CHs), and Collection Points (CPs).

for each node Si in $(a * b)$ do

broadcast hello-message to neighbor nodes

for each node Sj in $(a * b)$ do

if Si and Sj node within transmission range (S_{ij}^{tr})

obtain distance (d_{ij}) using elucidation equation

for each node Sk in $(a * b)$ and $k \neq j$ do

sum = $sum + d_{ij}^{T} + d_{jk}^{T}$

if S_i, S_j, S_k $not\ in\ C_i and\ i \leq k$

append S_i, S_j, S_k $into\ C_i$

end for

arrange the nodes in descending order based on node energy (S_i^e) and distance (d^T).

end for

end for

for each node Si in cluster C_i

if $i \leq k$ then

obtain avg distance (d^T) of vector select node

determine remaining energy of node (S_i^{re})

append node to Cluster Head (CHi) list.

end for

for each CHi in cluster C_i

broadcast hello-msg to CHn, where $n = 1, 2, 3, \ldots.$

obtain distance (Cd_{ij}) using elucidation equation select collection points (CPs)

end for

return {Clusters C_i, Cluster Heads (CHi), and Collection Points (CPs), where $1 \leq i \leq k$}

Algorithm 1 Process to Construct Clusters, Cluster Heads (CHs), and Collection Points (CPs) in the Monitoring Area of $(a * b)$

3.4. Artificial Fish Swarm Optimization Model for Mobile Sink Trajectory

The mobile sink trajectory optimization is transformed into a Traveling Salesman Problem (TSP) system with additional functionalities. The objective function to obtain optimal trajectory is represented in an equation (8), and constraints are defined as follows:

$$t_{total} = \Sigma_{i=1}^{k} t_{travel(CP_i, CP_i+1)} + \Sigma_{i=1}^{k} t_{data_{collection(CP_i)}} \quad (8)$$

Energy consumed by CH_i during waiting $\leq$ E_threshold

MS must visit active CHs within their wake − up windows

Total trajectory length $\leq d_{max}$.

The trajectory construction process for MS, in the constructed clusters of area, the common intersecting point of two or more clusters is defined as a collection point (CP). The entire process to represent a path based on CPs implemented in algorithm 2. The intersecting points are implemented to accomplish important purposes like avoiding the transmission range of any CMs from IP, establishing the trajectory path of MS, and obtaining the primary position of the collection points. An optimal energy-aware strategy for the MS trajectory shall reduce the overall energy consumption of CMs and CHs by minimizing the distance between the CHs and Ms. Occasionally, the identification of intersecting points as collection points may not be accurate for all subsequent rounds because of changes in the CHs. Hence, some new intersecting points are added as CPs to reduce delay in data collection from CHs.

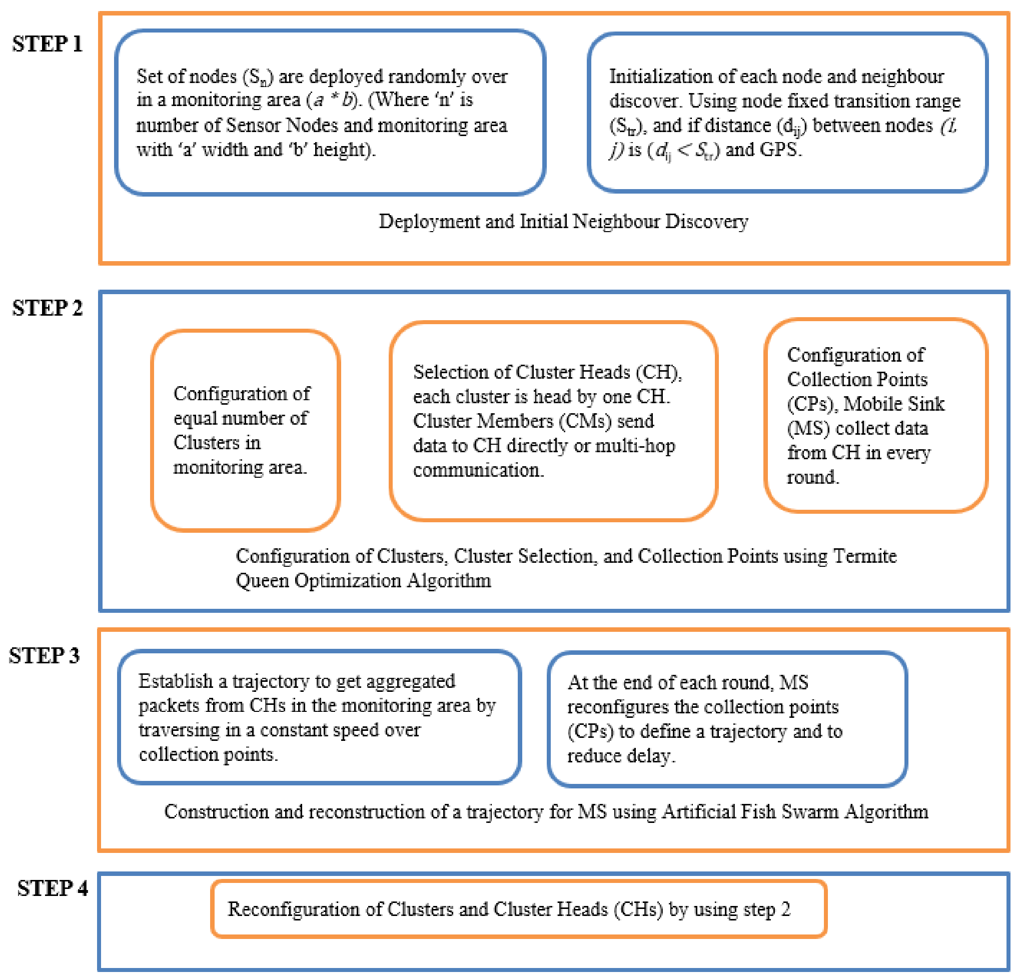

Figure 1 Stepwise Implementation of the Proposed Model

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Input: Cluster (Ci), Cluster Heads (CHi), and Intersecting Points in the monitoring area ($a * b$).

Output: Trajectory path for collecting data from CHs.

Initially cluster (Ci), cluster heads (CHi), and IPs. Where $i = 1, 2, 3, 4, ...$ and $1 \leq i \leq k$ 'k' is the number of clusters.

Formation of clusters and CHs using Termite Queen optimization defined in Algorithm 1

Assume $T \rightarrow \{\}$ and d_j^T overall distance travelled by MS and j indicates round

for i to k do

use artificial fish swarm optimization to determine sub path T_i of clusters

if T_i not in T then

add T_i to T

update d_j^T

end for

for i to k-1 do

establish link to the last CP of the T_i to the start CP of the T

update d_j^T

end for

return T

Algorithm 2 Process to Construct an Initial Trajectory Path of MS and an Optimal Trajectory Path of MS

In the WSN monitoring area, there are 'n' sensor nodes, clusters (Ci), for each cluster exactly only one CH, and common intersecting points to define as collection points. The time complexity of algorithm 1 for the initial configuration of clusters, cluster head selection, and obtaining a collection points list is $\emptyset(N * K * M)$. The time complexity of MS to determine the trajectory path to collect data from CH is $\emptyset(k)$.

In this implemented model, the essence of the construction mode is a special aspect that leads to a key role in the entire model. The configuration model is significantly implemented to decentralize the computational process at MS and reduce the hotspot problem in traditional WSNs. By acquiring these optimization techniques, ensured that sequential and repeated computational operations do not overwhelm the sensors and the MS. This deliberate decentralization of computational operation load reduces the resource and power utilization of sensors and MS.

This comprehensive methodology addresses the identified weaknesses by providing detailed mathematical formulations and algorithmic specifics. Therefore, the proposed model improves the overall effectiveness of the system with respect to the battery power utilization, throughput, packet delivery ratio, and delay.

4. RESULTS AND DISCUSSION

Termite Queen Artificial Fish Swarm Optimization Algorithm (TQAFSOA) model based on the MATLAB 2023a tool. Initially deployed the tiny resource-constrained devices randomly over a predetermined monitoring area. And partition the deployed devices into unequal-size clusters using Termite Queen Optimization; deployed devices were portioned. Initially, each node in the cluster selects the remaining energy and distance among nodes and cluster heads. The mobile sink (MS) initiates to get information from the monitoring area; the CH gathers all data from non-cluster heads and forwards it directly to the mobile sinks whenever MS is near to CH using the evolutionary optimization algorithm based on the optimal routing scheme.

In this paper, each simulation setup randomly ran 50 samples to show the unpredictable identity of the metaheuristic techniques and the random packet creation system. The sample outcomes and deviation changes were determined to show differences. The evaluations were carried out in the monitoring area, studying 500 m by 500 m, with 50 to 250 devices randomly deployed. Each device had a communication range of 50 m and a primary battery power of 2 joules and is represented in figure 2. The MS was equipped with built-in mobility to gather data from CHs and had unlimited battery resources. The packet creation interval (I) was 20 min, and the data packet size (B) was 1024 bits. For overall evaluation parameter settings and associated values of the proposed energy model and algorithms, refer to Table 2.

A lot of work has already been done on clustering and routing algorithms with mobile sinks, such as EEMSR [12], EAPC [13], OCNTMS [5], ACO-MSPD [14], and WRP. The proposed TQAFSOA evaluation setup has been compared with the aforementioned approaches. The model is judged on its throughput, packet delivery rate (PDR), battery power utilization (EC), end-to-end delay (E2ED), and lifespan. These are studied by increasing the number of deployed devices from 50 to 250 in a fixed-size monitoring area and comparing them to results from previous research.

Table 2 Proposed Model Simulation Parameters and their Values

Simulation Parameters	Values
Network Monitoring Area Size (a ∗ b)	$500 * 500$
Number of nodes	$50 - 250$
Mobile Sink	1

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Mobile Sink Speed	2 m/s
Transmission range	50m
Primary Energy of Sensor (Si)	2J
Energy Utilization for Transmission of bits (Set)	30nJ/b
Energy Utilization to receive bits (Ser)	20nJ/b
Data Packet Size	1024bits

Control Packet Size	80bits
Physical medium wireless and Network Type	IEEE802.11 and WSN
Energy Utilization of data aggregation at CH	10nJ/b
Number of cluster heads	10 – 20%
Number of CPs	≤ 75 of CHs
Data generation interval (I)	20min

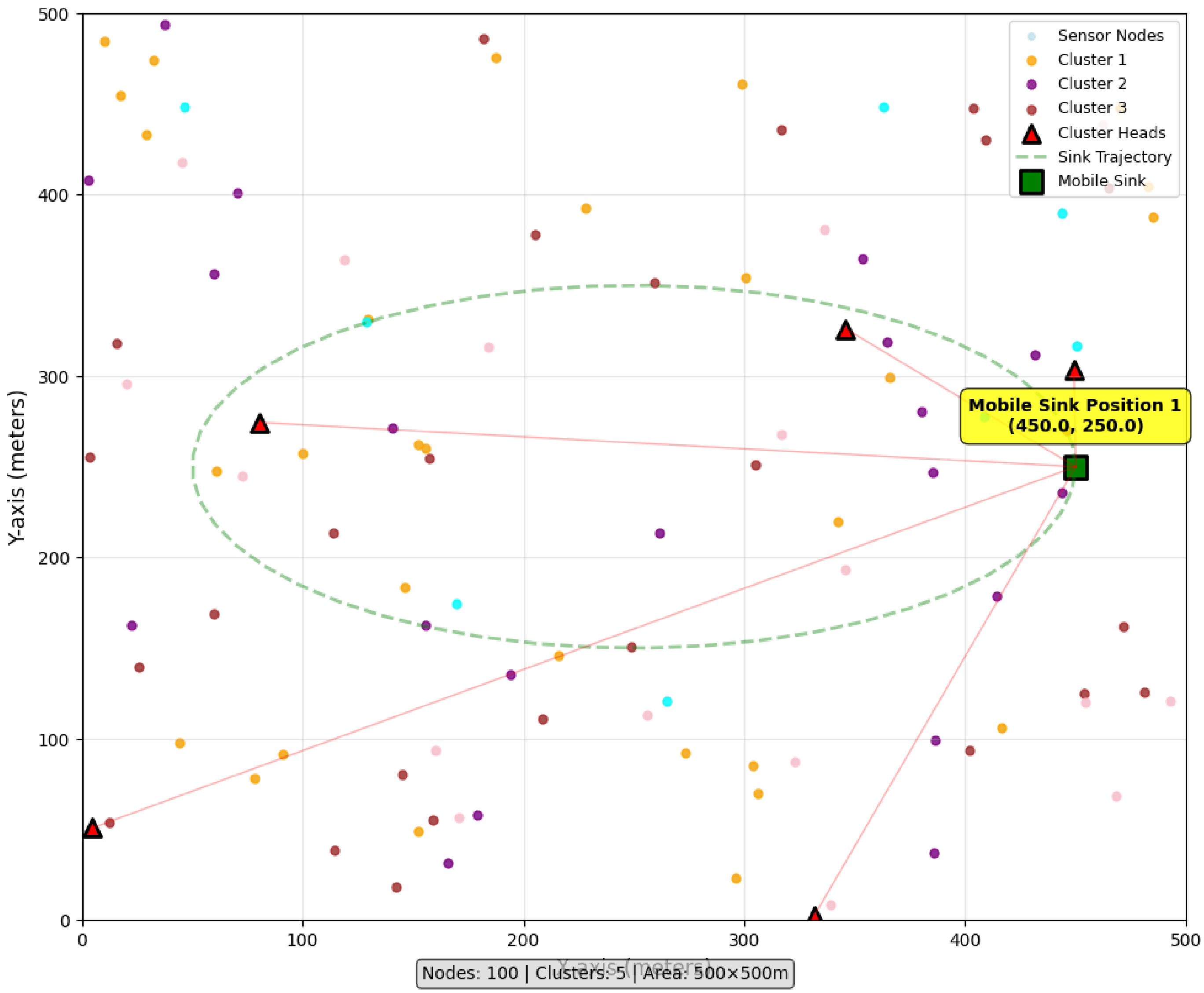

Figure 2 Randomly Deployed Sensor Nodes, Constructed Clusters and Cluster Heads (CHs), and Mobile Sink (MS) in the 500 * 500 Monitoring Area

According to the monitoring scheme, the network efficiency was evaluated in terms of the packet delivery ratio (PDR), EC, throughput, E2ED, and lifetime. There is a relationship between evaluation parameters such as PDR, lifespan, EC, and E2ED and the number of deployed devices in a monitoring area.

4.1. Energy Consumption (EC)

Amount of battery power utilized for transmitting, receiving, and idle listening, as well as deployed node count. Figure 3 shows the best-case power utilization of deployed nodes in a network using the Termite Queen and Artificial Fish Swarm Optimization Algorithm (TQAFSOA) model and compares it with the results of other parallel research outcomes. Based on the analysis, the establishment utilized less battery power for 50-250 deployed nodes in a 500 * 500 m monitoring area. Table 3 shows that the termite queen and artificial fish swarm optimization algorithm have the best average and worst-case energy consumption of nodes in a static field with mean, median, and standard deviation.

Table 3 Network Energy Consumption (J) for Termite Queen and Artificial Fish Swarm Optimization Algorithm

Node Count	Best	Worst	Mean	Median	Std	Var
50	27.418	31.582	28.842	28.912	0.652	0.536
100	31.890	38.501	34.538	36.367	0.982	0.964
150	38.717	44.684	41.026	40.957	0.831	0.691
200	40.782	49.329	45.361	45.279	1.057	1.117
250	43.433	57.217	50.166	54.072	1.095	1.199

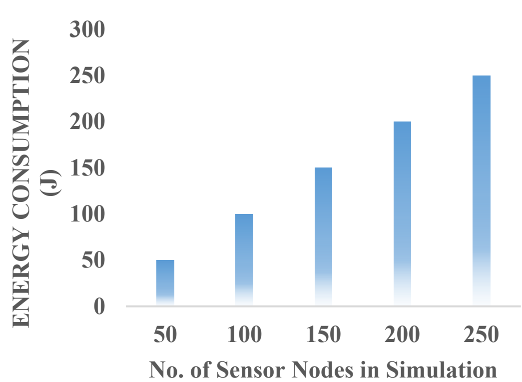

Figure 3 Best-Case Energy Consumption of Nodes in Each Round Using Termite Queen Artificial Fish Swarm Optimization Algorithm (TQAFSOA)

Figure 4 demonstrates that the proposed TQAFSOA model performs significantly better when compared to other models such as EEMSR, EAPC, OCNTMS, ACO-MSPD, and WRP. The x-axis indicates the number of nodes deployed in the monitoring area, evaluated during each test's simulation. The y-axis particularizes the overall network lifespan of various models. For 50 deployed nodes in a 500 ∗ 500 area, the achieved values indicate that the proposed technique minimizes the battery power utilization of devices in each round up to 9.86, 8.27, 6.15, 3.26, and 1.64 percent when compared with parallel research techniques, respectively. As shown in table 4, for 250 nodes, the experimental outputs indicate that battery power utilization of devices reduces up to 16.25, 12.70, 10.30, 7.26, and 3.74 percentage over parallel research results of WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS, respectively.

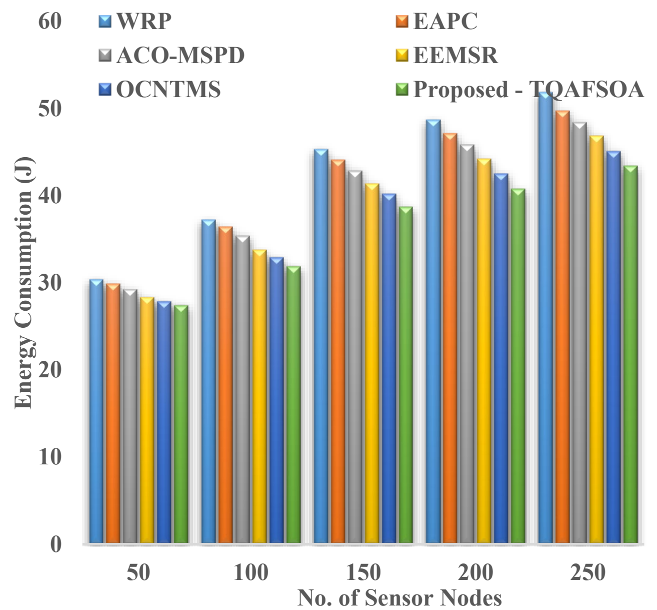

Figure 4 Energy Consumption of Nodes in MS-Based WSNs

4.2. Network Lifetime

The total duration of time deployed nodes operate on the intended task monitoring area or the time taken for the last node to die from the monitoring area. Table 5 demonstrates the simulation results of network lifespan based on best-case energy consumption of sensor devices in the monitoring area. Figure 5 highlights the network lifetime of the proposed TQAFSOA model over parallel research models. If the deployed node count increases, the network's lifespan increases gradually.

Figure 5 demonstrates the accomplished results of network lifespan for the proposed model compared with WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS, respectively. The x-

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axis indicates the number of nodes deployed in the monitoring particularizes the overall network lifespan of various models. For 50 deployed nodes in a 500 ∗ 500 area, the achieved values indicate that the proposed techniques improve the network's lifespan by around 55.42, 52.40, 44.57, 30.12, and 21.68 percent when compared with parallel research techniques, respectively. For 250 nodes, the experimental outputs are 59.11, 57.49, 49.96, 38.45, and 25.31 percent for

area, evaluated during each test's simulation. The y-axis WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS, respectively. The ginormous output variations are accomplished due to an improvement in the total energy added to the additional nodes. The demonstrated simulations for 250 nodes show a significant variation compared to 50 nodes.

Table 4 Comparison of TQAFSOA Best-Case Energy Consumption of Nodes in Each Round with Other Models

	Deployed Node Count	Models					
		WRP	EAPC	ACO-MSPD	EEMSR	OCNTMS	Proposed - TQAFSOA
Energy Consumption (EC)	50	30.418	29.890	29.217	28.344	27.876	27.418
	100	37.235	36.429	35.387	33.768	32.917	31.890
	150	45.321	44.127	42.874	41.358	40.214	38.717
	200	48.721	47.137	45.826	44.253	42.517	40.782
	250	51.863	49.752	48.421	46.837	45.124	43.433

Table 5 Simulation Results of Network Lifespan Based on Best-Case Energy Consumption

	Deployed Node Count	Models					
		WRP	EAPC	ACO-MSPD	EEMSR	OCNTMS	Proposed - TQAFSOA
Network Lifetime	50	3700	3950	4600	5800	6500	8300
	100	3900	4150	4850	6400	7900	9200
	150	4050	4450	5200	6950	8100	9980
	200	4450	4910	5800	7600	9240	10500
	250	5540	5760	6780	8340	10120	13550

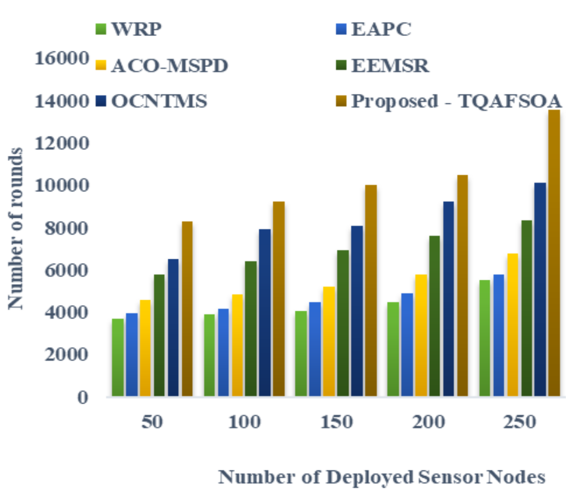

Figure 5Network Lifespan in MS-Based WSNs

4.3. Packet Delivery Ratio (PDR)

Ratio between the amount of data received at MS and sent by the CHs. The evaluation outcomes of the proposed TQAFSOA model are shown in Figure 6 and Table 6, which show that the proposed model performs significantly better than other models, such as WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS. As per the results, by increasing the number of nodes in the monitoring area, PDR is significantly more efficient when compared with parallel research models. Figure 6 demonstrates the accomplished results of the overall network packet delivery ratio for the proposed model compared with WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS, respectively. The x-axis indicates the number of nodes deployed in the monitoring area, evaluated during each test's simulation. The y-axis particularizes the overall network PDR of various models. For 50 deployed nodes in a 500 ∗ 500 area, the achieved values indicate that the proposed techniques enhance the packet delivery ratio by around

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5.73%, 5.05%, 3.82%, 7.12%, and 9.03% when compared with parallel research techniques, respectively. For 250 nodes, the experimental outputs are 8.03%, 6.42%, 4.62%, 9.82%, and 12.76% for WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS, respectively.

Table 6 Simulation Results of Packet Delivery Ratio Based on Best-Case Energy Consumption

	Deployed Node Count	Models					
		WRP	EAPC	ACO-MSPD	EEMSR	OCNTMS	Proposed - TQAFSOA
Packet Delivery Ratio (PDR)	50	92.5	93.1	94.2	91.3	89.7	97.8
	100	90.8	91.6	92.7	89.5	87.2	96.5
	150	89.7	90.1	91.3	87.8	85.1	95.3
	200	87.5	88.6	90.0	86.2	83.8	94.1
	250	85.9	86.2	88.7	84.5	81.8	92.8

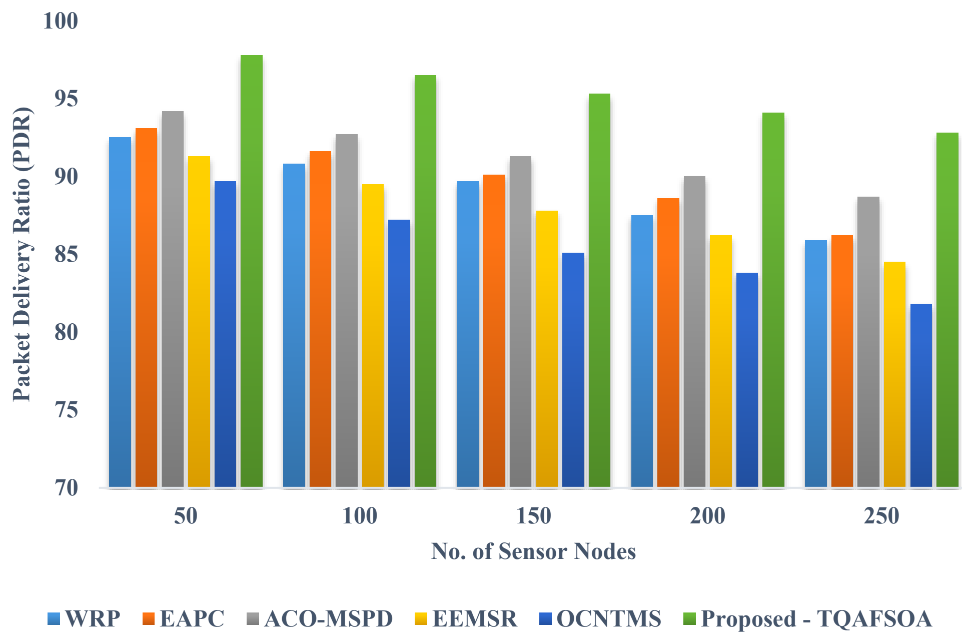

Figure 6 Packet Delivery Ratio of Nodes in MS-Based WSNs

4.4. Throughput

The total amount of data received from the CH with respect to the time it took for data to be sent to the mobile sink. The evaluation outcomes demonstrate that the proposed TQAFSOA model has been enhanced with respect to the throughput. The proposed TQAFSOA model outperformed parallel research establishments with respect to throughput, and results have been specified in Table 7.

Figure 7 demonstrates the accomplished results of overall network throughput of the proposed model compared with WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS, respectively. The x-axis indicates the number of nodes deployed in the monitoring area, evaluated during each test's simulation. The y-axis particularizes the overall network throughput of various models.

For 50 deployed nodes in a 500 $*$ 500 area, the achieved values indicate that the proposed techniques enhance the throughput by around 23.60%, 22.01%, 16.62%, 32.47%, and 42.13% when compared with parallel research techniques, respectively. For 250 nodes, the experimental outputs are 36.11%, 32.04%, 21.51%, 41.64%, and 59.53% for WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS, respectively.

Table 7 Simulation Results of Throughput Based on Best-Case Energy Consumption

	Deployed Node Count	Models					
		WRP	EAPC	ACO-MSPD	EEMSR	OCNTMS	Proposed - TQAFSOA
Throughput	50	198.7	201.3	210.6	185.4	172.8	245.6
	100	181.2	185.2	196.6	172.6	158.4	232.8
	150	169.7	172.5	180.2	162.6	145.8	221.4
	200	157.3	164.6	167.2	154.7	138.6	214.9
	250	145.5	155.1	154.1	141.4	129.2	207.4

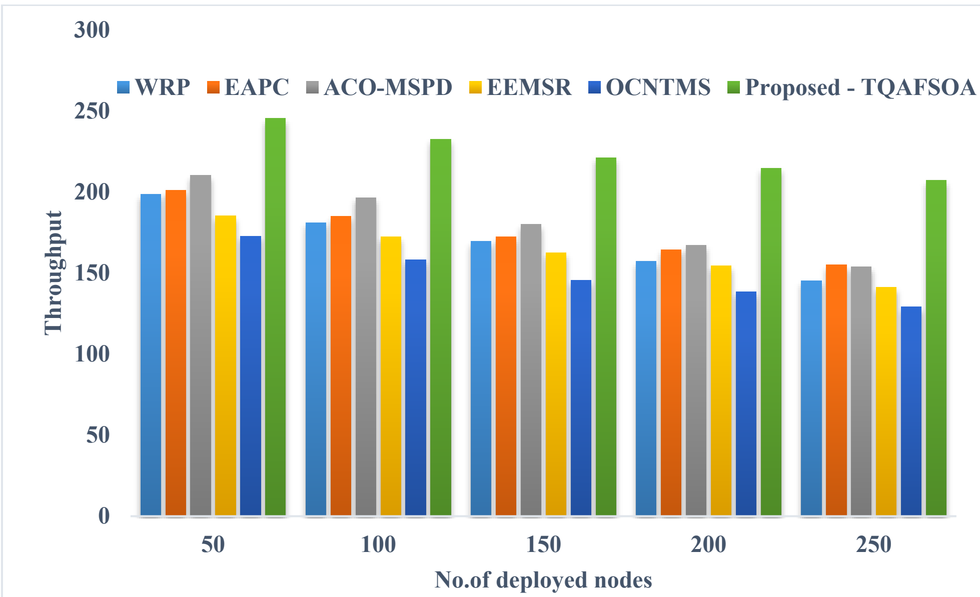

Figure 7 Throughput in MS-Based WSNs

4.5. End-to-End Delay

Ratio between the total amount of time spent to forward packets to the MS and the amount of data received. The figure demonstrates the end-to-end delay (E2ED) comparison with other optimization models. The proposed TQAFSOA model maintained a smaller E2ED than other mobile sink-based research models. The simulation results in table 8 clearly indicate that an increase in deployed node count in the monitoring area leads to a significant reduction in E2ED. Figure 8 demonstrates the accomplished results of overall network E2ED of the proposed model compared with WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS, respectively. The x-axis indicates the number of nodes deployed in the monitoring area, evaluated during each test's simulation. The y-axis particularizes the overall network delay of various models. For 50 deployed nodes in a 500 $*$ 500 area, the achieved values indicate that the proposed techniques reduce the delay by up to 38.25%, 35.62%, 29.26%, 46.59%, and 51.71% when compared with parallel research techniques, respectively. For 250 nodes, the experimental outputs are 40.28%, 37.26%, 31.02%, 48.06%, and 52.13% for WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS, respectively. The critical performance of the proposed TQAFSOA stems from its hybrid optimization technique. The Termite Queen mechanism constructs optimal unequal-sized clusters by simulating the hierarchical organization of termite colonies, ensuring balanced energy distribution among nodes over the network. Meanwhile, the Artificial Fish Swarm component optimizes routing trajectory through collective intelligence, similar to how fish find optimal feeding locations. This hybrid technique addresses the primary limitations of existing systems and results in the observed improvements in energy efficiency, network lifetime, and overall performance.

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Table 8 Simulation Results of End-to-End Delay Based on Best-Case Energy Consumption

	Deployed Node Count	Models					
		WRP	EAPC	ACO-MSPD	EEMSR	OCNTMS	Proposed - TQAFSOA
End-to-end Delay	50	68.5	65.7	59.8	79.2	87.6	42.3
	100	86.2	82.5	75.4	98.7	109.3	53.6
	150	110.4	105.8	96.2	124.6	136.8	67.8
	200	139.7	133.2	121.8	158.3	172.5	84.5
	250	172.8	164.5	149.6	198.7	215.6	103.5

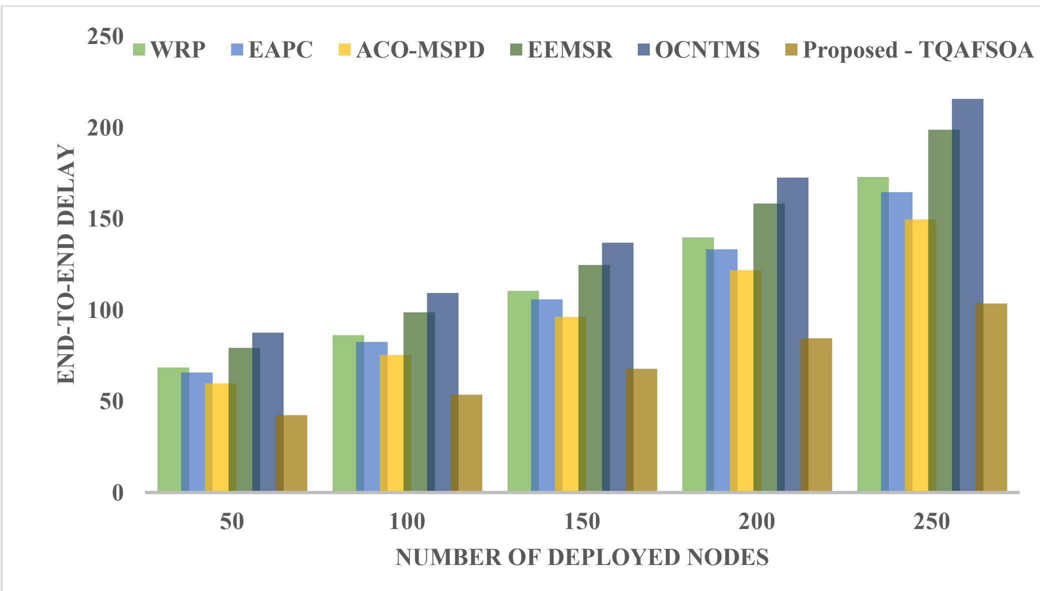

Figure 8 End-to-End Delay in MS-Based WSNs

5. CONCLUSION

This document introduces an enhanced data collection mechanism using a mobile sink (MS) for wireless sensor networks (WSNs). The establishment of the proposed approach is implemented in two sequential phases: configuration of clusters and trajectory path for MS. The configuration phase includes cluster formation, CH selection, and common intersection point selection. The self-configuration ability of nodes in the monitoring area to select the CHs without any communication among the CMs. The common intersection points are configured for the MS-based efficient and energy-aware trajectory path to gather aggregated data from CHs. In the second phase, the CMPs are used to select a trajectory path among the CHs. Evaluations of the proposed TQAFSOA model that have been implemented assert the advantage of the system. The evaluation outcomes assure that the proposed approach is better performing than the parallel research approaches like WRP, EAPC, ACO-MSPD, EEMSR, and OCNTMS in terms of the end-to-end delay, best-case battery power utilization, network lifespan, and throughput. There are several promising directions for future work: dynamic cluster reconfiguration based on real-time network conditions, node failures, and energy depletion patterns; multi-mobile sink for better path coordination and to cover large areas efficiently; efficient energy management that proactively adjusts cluster head selection and mobile sink trajectories before high energy consumption occurs; and advanced path optimization such as deep learning or reinforcement techniques to enhance trajectory route preparation based on historical data collection patterns and network performance metrics.

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