Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

GKMSLO-MDC: A Grid K-Means and Sea Lion Optimization Framework for Energy-Efficient and QoS-Aware Cluster Head Localization in Large Scale Wireless Sensor Networks

Laith Talib Rasheed
University of Diyala
Bechir Ben Gouissem
Bechir.gouissem@enit.rnu.tn
National Engineering School of Tunis
Azza Ouled Zaid
National Engineering School of Tunis

Research Article

Keywords: Wireless Sensor Networks, Cluster Head Localization, Sea Lion Optimization, Mobile Data Collector, Energy Efficiency, QoS

Posted Date: November 12th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10502672/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

GKMSLO-MDC: A Grid K-Means and Sea Lion Optimization Framework for Energy-Efficient and QoS-Aware Cluster Head Localization in Large Scale Wireless Sensor Networks

Laith Talib Rasheed[1], Bechir Ben Gouissem[2], Azza Ouled Zaid[2]

laith88@uodiyala.edu.iq *Bechir.gouissem@enit.rnu.tn* *azza.ouledzaid@isi.utm.tn*

[1]College of Engineering, University of Diyala, Ba'qubah, Diyala, Iraq.
[2] Communication System Laboratory Sys'Com (ENIT), University of Tunis El Manar (UTM), Tunis, Tunisia

Bechir Ben Gouissem *ORCID: 0000-0002-4748-4001*

Abstract

Energy-efficient clustering remains one of the most critical challenges in Wireless Sensor Networks (WSNs) due to the limited energy resources of sensor nodes and the increasing Quality of Service (QoS) requirements. While plentiful clustering protocols and metaheuristic optimization techniques have been proposed in literature, prevailing existing solutions suffer from high computational complexity, premature convergence, unbalanced energy consumption, and inadequate consideration of QoS metrics such as packet delivery reliability and communication delay. To address these limitations, this paper introduces a novel clustering and cluster-head (CH) localization framework, termed GKMSLO-MDC (Grid K-Means Sea Lion Optimization with Mobile Data Collector). The proposed approach combines Grid-based K-Means clustering for network partitioning scalability with intelligent CH localization based on a Mobile Data Collector (MDC)-assisted Sea Lion Optimization (SLnO) algorithm. Significant reduce of the clustering search space and computational burden are achieved by the grid decomposition strategy, while the MDC ensures global network awareness by collecting energy and QoS metrics. Moreover, a novel multi-objective fitness function was designed to jointly optimize residual energy, coverage preservation, packet delivery ratio, communication latency, cluster load balancing, and transmission cost.

Extensive simulations involving 100 to 500 sensor nodes aiming to demonstrate the effectiveness of the proposed GKMSLO-MDC framework in large-scale WSN environments. A sub-meter localization accuracy, a Packet Delivery Ratio above 99%, and significant enhances network lifetime while reducing overall energy consumption was achieved by our proposed scheme. Comparative evaluations against concurrent approaches confirm superior performance in terms of energy efficiency, throughput, latency, localization accuracy, and network longevity.

Keywords: Wireless Sensor Networks, Cluster Head Localization, Sea Lion Optimization, Mobile Data Collector, Energy Efficiency, QoS.

I. Introduction

Large-scale Wireless Sensor Networks (LSWSNs) have emerged as a cornerstone technology for modern Internet of Things (IoT) infrastructures, enabling continuous monitoring and data acquisition in diverse domains such as environmental sensing, smart agriculture, healthcare systems, industrial automation, and smart city applications. These networks consist of a large number of low-power sensor nodes deployed over wide and often inaccessible regions to cooperatively sense and transmit data toward a centralized Base Station (BS). However, the inherent constraints of sensor nodes such as limited battery capacity, restricted computational resources, and short communication ranges pose significant challenges to achieving long-term network operation while satisfying Quality of Service (QoS) requirements.

As communication-related energy consumption dominates overall node energy usage energy efficiency remains the primary design objective in WSNs. Clustering-based routing protocols have been broadly investigated to reduce redundant transmissions and balance energy dissipation in order to address this challenge. Although the classical LEACH protocol improves energy efficiency, by introducing distributed clustering, over flat routing schemes. LEACH and its variants suffer from random CH selection and lack of global optimization [1] that frequently leads to an uneven energy depletion, suboptimal cluster formation, and constrained scalability in dense and large-scale networks.

To address these issues, several clustering approaches based on metaheuristic algorithms have been proposed, including Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and the Whale Optimization Algorithm (WOA) [2–5] by formulating the CH selection problem as an optimization task. However, critical performance limitations remain an inherent constraint of these clustering schemas; premature convergence, loss of population diversity, and elevated computational overhead in the case of LSWSN. Conventional swarm intelligence algorithms are very sensitive to the network scale expand, preventing them from consistently achieving globally optimal clustering configurations.

Alongside clustering optimization, node localization is crucial for improving routing efficiency, energy balancing, and QoS metrics. Range based localization techniques such as Received Signal Strength (RSS), Time of Arrival (TOA), and Time Difference of Arrival (TDOA) are extensively adopted for WSN localization owing to their low hardware cost and suitability for distributed architectures. RSS-based schemes estimate distance through signal attenuation models, While TOA and TDOA leverage propagation time measurements for superior accuracy [36]. Nevertheless, all these methods have their own unique shortcomings; RSS is prone to environmental noise and multipath fading, TOA demands stringent time synchronization, and TDOA relies heavily on dense

reference node deployment. Hybrid localization approaches integrating RSS, TOA, and TDOA have emerged to mitigate these constraints, thus delivering superior accuracy in harsh deployment environments [6–8].

This paper introduces a novel hybrid optimization framework, designated as GKMSLO-MDC (Grid K-Means Sea Lion Optimization with Mobile Data Collector). Our approach leverages a Grid-based K-Means clustering strategy to segment the sensing area into subarea. By performing clustering locally, this solution mitigates computational complexity and enhances spatial compactness.

The initial clustering stage is performed by the grid-based K-Means algorithm to identify preliminary CHs. In the second stage, the proposed algorithm focuses on refining CH positioning rather than reconstructing clusters. To this end, an MDC gathers global network information, including residual energy, node density, connectivity status, and localization estimates. By jointly considering network parameters and localization uncertainty, this holistic network view leads to more accurate assessment of CH candidates. Subsequently, the Sea Lion Optimization (SLnO) algorithm is employed to refine the spatial positions of the preselected CHs. The leveraging of the adaptive exploration–exploitation mechanism permits to SLnO algorithm to effectively minimizes communication costs, reduces localization errors, improves QoS performance, and mitigate premature convergence in LSWSN environments [9].

In contrast to traditional clustering schemes, limited by local or static parameters, our MDC-assisted SLnO framework embeds global network intelligence alongside hybrid localization information directly into the optimization process. Therefore, it achieves robust CH refinement by dynamically balancing residual energy, transmission distances, and QoS constraints.

The main contributions of this paper are summarized as follows:

- Propose a scalable, Grid-based K-Means clustering mechanism designed to maximize clustering efficiency and minimize computational complexity in LSWSNs.
- Integrate hybrid localization techniques (RSSI, TOA, and TDOA) to significantly enhance node positioning accuracy.
- Introduce a novel MDC-assisted Sea Lion Optimization (SLnO) framework that leverages global network intelligence for energy-aware and QoS-driven CH localization refinement.
- Formulate a multi-objective optimization model that jointly optimizes energy consumption, communication latency, packet delivery reliability, and network load balancing.
- Conduct extensive simulation-based performance evaluations to make a proof of the effectiveness of the proposed GKMSLO-MDC framework**.**

The remainder of this paper is structured as follows:

Section II provide some necessary background related to WSN clustering, localization and metaheuristics. Section III introduces our system model with problem formulation. Section IV details the proposed GKMSLO-MDC framework. Section V is dedicated to presents simulation results and comparative performance evaluations. Section VI concludes the paper and pinpoint future research directions.

II. Related Work

WSNs have attracted significant research attention due to their essential role in enabling large-scale sensing and IoT applications. A major challenge in these networks lies in optimizing energy consumption while simultaneously maintaining QoS requirements such as latency, reliability, and coverage. Early studies, demonstrated that organizing nodes into clusters with dedicated CHs can significantly reduce communication overhead and extend network lifetime in hierarchical clustering protocols [10]. However, classical hierarchical clustering approaches such as LEACH and its variants suffer from random CH selection and poor adaptability leading to uneven energy depletion and limited scalability in dense and large-scale deployments [1]. A wide range of metaheuristic optimization algorithms have been introduced for CH selection and routing optimization aiming to overcome these limitations. PSO algorithm has been extensively used due to its simplicity and fast convergence, but it is well known to suffer from premature convergence and loss of population diversity, particularly in high-dimensional WSN environments [11]. whereas GWO improves exploration–exploitation balance through a leadership hierarchy mechanism, however its performance degrades in large-scale scenarios due to reduced diversity during later iterations [12]. The WOA algorithm enhances global search capability using spiral and shrinking encircling behaviours, but it often exhibits slow convergence and increased computational overhead when applied to dense sensor networks [13]. Although these algorithms have been shown to improve clustering performance compared to traditional methods, recent comparative studies have demonstrated that none of them consistently achieves optimal results across all QoS metrics in LSWSN deployments, particularly when energy efficiency, delay, and reliability must be jointly optimized [14–15].

Recent research has increasingly focused on multi-objective optimization frameworks that integrate energy efficiency with QoS constraints such as packet delivery ratio, end-to-end delay, load balancing, and coverage preservation. While these approaches provide a more realistic representation of WSN requirements, they significantly increase the complexity of the optimization problem and often lead to unstable convergence behaviour when using conventional swarm intelligence techniques [16–18]. Besides, most existing QoS-aware

clustering methods often rely on locally available or partially updated network information which limits their ability to adapt to dynamic energy variations and large-scale network conditions [19].

CH localization has also been recognized as a critical factor influencing overall network performance. Inaccurate CH positioning can significantly increase transmission distance and energy consumption. Recent studies have shown that optimization-based CH localization methods outperform deterministic and random selection strategies by reducing communication cost and improving load distribution [20–22]. However, most existing works do not explicitly integrate accurate localization models into the clustering optimization process. RSSI-based localization is widely used due to its low complexity. But it is hampered by its high sensitive to environmental noise and multipath effects. TOA and TDOA methods provide higher accuracy but require synchronization and infrastructure support, making them less practical in some scenarios [23–25]. Hybrid localization techniques combining RSSI, TOA, and TDOA have been shown to significantly improve localization accuracy and robustness, particularly in complex and large-scale deployments. However, their integration into cluster optimization remains limited in recent literature.

The use of MDCs or mobile sinks has gained attention as a means to improve data gathering efficiency and reduce energy holes near the BS [37]. WSN architectures based on MDC provide a global view of the network, enabling more informed routing and clustering decisions [38]. However, many existing approaches rely on heuristic or static decision rules rather than intelligent optimization frameworks capable of adapting to the dynamic conditions of the network [26–28]. Recent trends in hybrid metaheuristic design attempt to combine multiple optimization strategies to improve convergence stability and solution quality, but these methods often introduce additional computational complexity without guaranteeing consistent QoS improvements in LSWSN environments [14],[29–31].

From this analysis, it is evident that existing approaches still exhibit critical vulnerabilities, notably premature convergence of swarm-based algorithms, insufficient integration of localization information into clustering decisions, limited exploitation of global network knowledge, and lack of scalable frameworks suitable for large-scale deployments.

To overcome these shortcomings, this paper proposes a novel GKMSLO-MDC framework that integrates Grid-based K-Means clustering for scalable network partitioning with MDC-assisted SLnO for intelligent CH localization. The proposed approach further incorporates hybrid localization techniques based on RSSI, TOA, and TDOA to enhance positioning accuracy and robustness, ultimately improving energy efficiency, QoS performance, and network lifetime in LSWSN environments.

III. System Model and Mathematical Formulation

This section presents the system architecture, network assumptions, hybrid localization framework, and mathematical optimization model of the proposed GKMSLO-MDC system.

3.1. GKMSLO-MDC System Model Definition:

The proposed system architecture is depicted in Figure 1. The model integrates Grid-based K-Means clustering, hybrid RSSI–TOA–TDOA localization, MDC-assisted network monitoring, and SLnO-based CH localization. Initially, hybrid localization information is exploited to improve node position accuracy, followed by grid-based clustering to generate compact and balanced clusters. Subsequently, the MDC collects global network information and employs the SLnO algorithm to optimize the localization of the elected CHs through a multi-objective optimization process.

The proposed flow diagram, illustrated in Figure 1, describes the complete operational process of the GKMSLO-MDC framework for energy-efficient optimization and QoS of LSWSN. This process begins with system initialization: deployment of sensor nodes in the sensing area, definition of network parameters, generation of grids for spatial partitioning, and configuration of clustering and SLnO algorithm parameters. This initialization step ensures a structured foundation for scalable processing in dense network environments. Once the network is established, the system performs sensors hybrid localization estimation for each node by fusing distance measurements based on RSSI, TOA, and TDOA. These heterogeneous estimations are fused into a unified localization model to improve positioning accuracy and robustness against noise, synchronization errors, and environmental uncertainties. The resulting hybrid location information is then used as a key input for clustering and optimization stages.

In the next phase, the sensing field is partitioned using a Grid-based K-Means clustering mechanism, where nodes are grouped within each grid to form compact clusters. Thus, reducing computational complexity and ensures spatially balanced cluster formation. The output of this stage is an initial set of CHs derived from structured clustering rather than random selection.

After the clustering phase, an MDC gathers global network state information, including residual energy, node density, connectivity status, and localization error metrics to centralize knowledge, thereby achieving global network optimization. The MDC then initializes the SLnO process, where each candidate solution represents a possible CH configuration derived from the initially elected CH set during the previous phase.

The SLnO algorithm proceeds through exploration-exploitation iterative optimization phases guided by MDC correction. During exploration, candidate solutions are diversified to enhance global search capability.

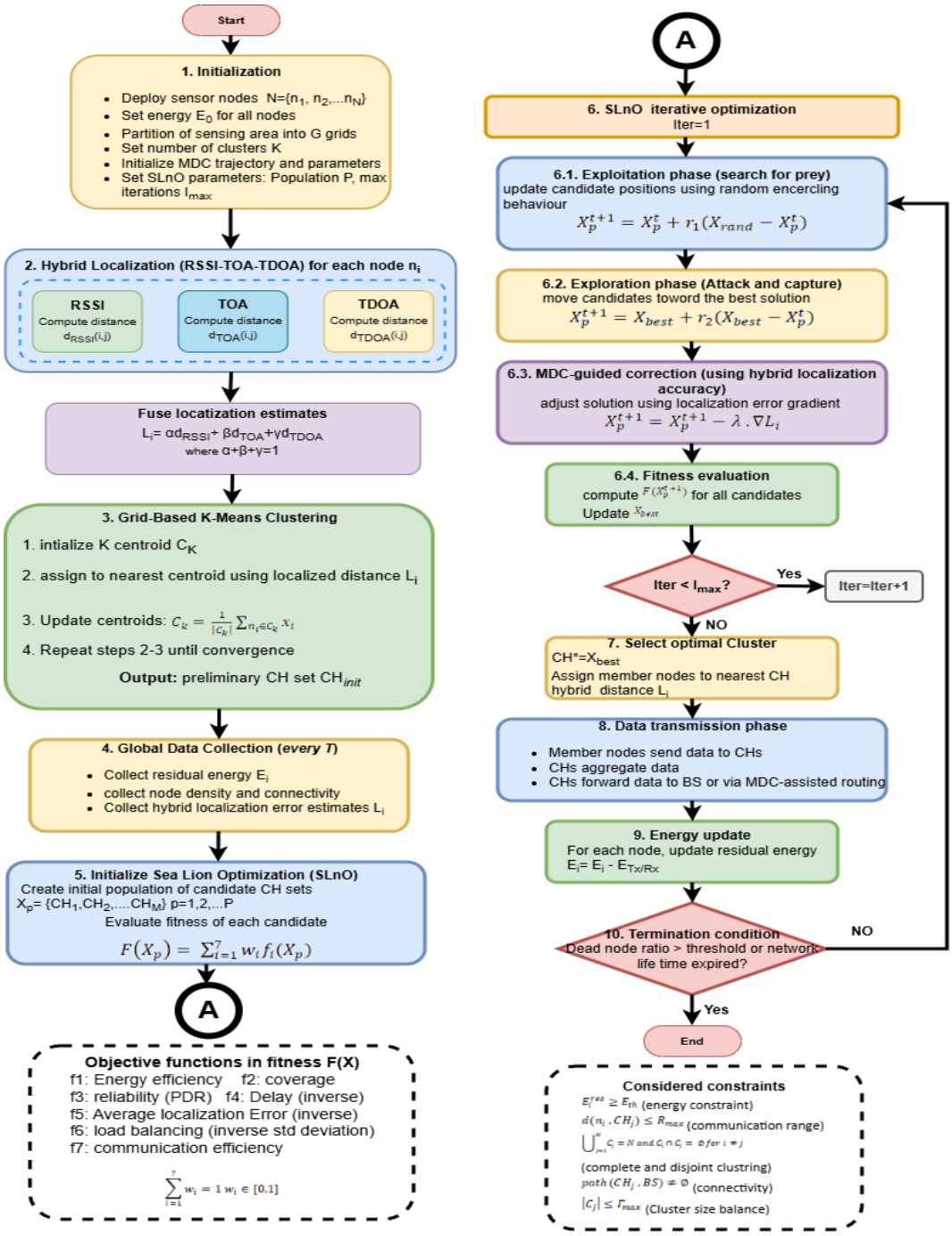


Figure 1. GKMSLO-MDC flowchart for hybrid localization-assisted CH optimization in LSWSNs

While, exploitation phase drives convergence toward the best-performing solution. The MDC-guided correction mechanism further refines candidate solutions using localization error feedback derived from the hybrid RSSI–TOA–TDOA model thus ensuring improved positional accuracy and reduced communication cost.

At each iteration, a multi-objective fitness function evolving energy efficiency, coverage, packet delivery ratio, latency, MDC communication cost, and load balancing, is employed to evaluate candidate solutions. The algorithm updates the best solution until achieving convergence criteria. Upon completion of the optimization

process, the final optimal CHs are selected, and member nodes are assigned based on minimum hybrid distance criteria.

Finally, sensor nodes perform data transmission to their respective CHs, followed by CHs data aggregation and forwarding to the BS. After each communication round, node energy levels are updated and the termination conditions such as node mortality or maximum iteration limits are checked by the system. Overall, the flowchart captures a complete end-to-end adaptive optimization process that integrates clustering, hybrid localization, and metaheuristic optimization to significantly enhance energy efficiency and QoS performance in LSWSN deployments.

3.2. GKMSLO-MDC Network Model Formulation:

This subsection presents the mathematical foundations of the proposed GKMSLO-MDC framework. The following mathematical formulation describes the network model, hybrid localization process, optimization constraints, and multi-objective fitness function used by the MDC-assisted SLnO algorithm to determine the optimal CH localization configuration in LSWSN environments.

Consider a LSWSN composed of N homogeneous sensor nodes randomly deployed over a two-dimensional sensing field, $A = L \times W$, where A the total sensing area, L *is* the length of the sensing field, and W represents its corresponding width. The set of sensor nodes is represented as $N = \{n_1, n_2, \dots, n_N\}$ where each node $n_i = (x_i, y_i, E_i, R_i, L_i)$ is characterized by its geographical coordinates, (x_i, y_i), residual energy, E_i, communication range, R_i, and the estimated position L_i, obtained through the proposed hybrid localization mechanism. We assume that the BS possess unlimited energy and computational resources and are located at a fixed position: $BS = (x_{BS}, y_{BS})$. An MDC periodically navigates in the area to collect global network information regarding node energy, connectivity status, cluster structure, and localization measurements. Thus, the MDC provides a global network view, enabling more accurate optimization decisions and reducing suboptimal CH placements probability. The sensing area is partitioned into multiple non-overlapping grids to improve scalability and reduce computational overhead in large-scale deployments. Let $G = \{G_1, G_2, \dots, G_g\}$ denote the set of grid regions such that $A = \bigcup_{i=1}^{g} G_i$ and $G_i \cap G_j = \emptyset$ for $i \neq j$ Within each grid. The K-Means clustering algorithm is employed to organize sensor nodes into compact and balanced clusters. In this stage an initial cluster structure that reduces the search space of the subsequent optimization process is generated. The clustering objective consists in minimizing the total intra-cluster variance, as expressed in Equation (1):

$$J_{KM} = \sum_{k=1}^{K} \sum_{n_i \in C_k} \|x_i - c_k\|^2 \tag{1}$$

where C_k denotes the k-th cluster and c_k represents its centroid. The Grid-based K-Means generates spatially compact clusters that reduce communication overhead and facilitate balanced energy consumption by minimizing the distance between cluster members and their corresponding centroid.

High-precision coordinate data, accurate node localization are a cornerstone of the proposed framework since communication overhead and CH placement directly rely on. To mitigate localization uncertainty, a hybrid scheme leveraging RSSI, TOA, and TDOA measurements is deployed. Considering that each localization technique exhibits different strengths and weaknesses, a hybrid localization estimator is constructed through weighted fusion according to Equation (2):

$$L_i = \alpha L_{RSSI} + \beta L_{TOA} + \gamma L_{TDOA} \text{ subject to } \alpha + \beta + \gamma = 1, \quad (2)$$

where α, β, and γ symbolise weighting coefficients associated with RSSI, TOA, and TDOA, respectively. This hybrid formulation improves localization robustness by mitigating RSSI noise sensitivity while benefiting from the higher accuracy provided by TOA and TDOA measurements.

Following the Grid K-Means clustering phase, where a set of preliminary CHs is identified. Let $CH = \{CH_1, CH_2, \dots, CH_M\}$ represents the set of elected CHs, where $M \ll N$. In our proposal, the SLnO algorithm is exclusively used to optimize the localization of the already selected CHs, unlike most metaheuristic-based clustering approaches, that employ optimization algorithms for cluster formation or CH election. This design leads to significantly reduced optimization search space, and consequently mitigates computational complexity. Each candidate solution handled by the SLnO is represented as a position vector, $X = \{(x_{CH_1}, y_{CH_1}), \dots, (x_{CH_M}, y_{CH_M})\}$. The decision variables correspond to the optimized CH positions derived from hybrid localization information. Notably, the CH localization is formulated as a constrained multi-objective optimization problem in order to jointly balance energy efficiency, communication reliability, network coverage, localization accuracy, and load balancing against communication distance and latency:

$$X^* = \arg\max_X F(X) \quad (3)$$

where $F(X)$ denotes the global fitness function. The energy efficiency objective is defined as $f_E = \frac{1}{M}\sum_{j=1}^{M}\frac{E_{CH_j}^{res}}{E_{max}}$ which promotes the selection of energetically sustainable CHs. Network coverage is represented by $f_C = \frac{N_{covered}}{N}$, ensuring that sensing performance is preserved throughout the optimization process. Communication reliability is quantified using the Packet Delivery Ratio (PDR) as $f_R = \frac{P_{received}}{P_{sent}}$ while latency performance is represented as $f_D = \frac{1}{Delay}$ to favour lower end-to-end transmission delays. Because CH localization is directly influenced by localization accuracy, a dedicated localization objective is introduced. The average localization error is calculated

as $LE = \frac{1}{M}\sum_{j=1}^{M}\sqrt{\left(x_i - \hat{x_j}\right)^2 + \left(y_i - \hat{y_j}\right)^2}$ and the corresponding fitness component becomes $f_L = \frac{1}{1+LE}$ which encourages solutions with highly accurate CH positioning. Load balancing is modelled through cluster size variance as $f_B = \frac{1}{1+\sigma_C}$ where σ_C denotes the standard deviation of cluster cardinalities. Finally, communication efficiency is represented through the average communication cost as $Cost_{comm} = \frac{1}{N}\sum_{i=1}^{N} d\left(n_i, CH_j\right) + \frac{1}{M}\sum_{j=1}^{M} d(CH_j, BS)$ and the corresponding objective function becomes $f_{Comm} = \frac{1}{1+Cost_{Comm}}$.

The overall multi-objective fitness function is therefore formulated as:

$$F(X) = w_1 f_E + w_2 f_C + w_3 f_R + w_4 f_D + w_5 f_L + w_6 f_B + w_7 f_{Comm} \qquad \text{subject to} \sum_{i=1}^{7} w_i = 1 \tag{4}$$

where w_i are weighting coefficients reflecting the relative importance of each optimization criterion.

The optimization process is further constrained by residual energy requirements, communication range limitations, connectivity preservation, and complete cluster coverage. Consequently, the proposed mathematical formulation enables the MDC-assisted Sea Lion Optimization algorithm to identify optimal CHs locations based on hybrid RSSI–TOA–TDOA localization information while simultaneously improving network lifetime, energy efficiency, packet delivery ratio, latency performance, and overall QoS in LSWSN.

IV. Complexity Analysis: Computation, Time, and Communication

The performance and scalability of any clustering and CH optimization framework depend directly on its computational complexity, execution time, and communication overhead. This dependency is especially critical in LSWSN case, where sensor nodes operate under stringent energy and processing constraints. The proposed GKMSLO-MDC framework has been specifically designed to address these scalability challenges. The proposed framework restricts the optimization process to a significantly smaller set of preliminary CHs, contrary to conventional metaheuristic approaches that perform optimization directly over the entire sensor population. This design choice substantially reduces the search space while maintaining optimization effectiveness. Therefore, this design led to a lower computational complexity, a shorter execution time, and reduced communication costs.

4.1. Computational Complexity Analysis:

The computational complexity of the GKMSLO-MDC framework can be analysed by examining the contribution of each processing stage. Initially, the hybrid localization phase computes RSSI, TOA, and TDOA measurements for each sensor node and combines them through a weighted fusion mechanism. The computational cost of this stage grows linearly with the number of deployed nodes since every node independently performs a constant number of localization operations, yielding to a complexity of $O(N)$.

Subsequently, the sensing field is partitioned into G grid regions. A single traversal of the node population is needed for the sensor nodes assignment to their corresponding grids, therefore exhibits a complexity of $O(N)$. Following grid formation stage, where K-Means clustering is independently executed within each grid. Each region contains approximately $\frac{N}{G}$ nodes by assuming a relatively balanced node distribution among grids. Consequently, the clustering complexity becomes $O(\frac{NKI_{KM}}{G})$ where K denotes the number of clusters and I_{KM} represents the number of required K-Mean iterations for convergence per cluster. This grid-based decomposition significantly reduces the computational burden compared to conventional K-Means applied to the entire network, which would otherwise incur a complexity of $O(NKI_{KM})$.

The MDC data collection phase gathers residual energy information, node density metrics, connectivity status, and localization estimate from all sensor nodes. Given that each sensor node transmits a deterministic data payload, the resulting communication overhead remains strictly linear with respect to the network size, i.e., $O(N)$. The primary computational bottleneck of the proposed framework lies within the SLnO optimization process. However, the proposed system does not execute SLnO over the entire sensor node population. Instead, by restricting the search space, optimization is restricted to the preliminary CHs generated during the Grid K-Means phase. Letting M represent the number of elected CHs (where $M \ll N$), the optimization complexity is bounded by $O(PI_{max}M)$ operations for a population size P and maximum iteration count I_{max}. Because M constitutes a minor fraction of the total network size, the computational overhead scales gracefully with increasing network density. By combining all stages, the overall computational complexity of the GKMSLO-MDC framework can be expressed as:

$$O\left(\frac{NKI_{KM}}{G} + PI_{max}M\right) \tag{5}$$

This result demonstrates that the proposed framework benefits simultaneously from spatial decomposition through grid partitioning and search-space reduction through CH-only optimization. Crucially, the resulting complexity is considerably lower than the $O(PI_{max}N)$ complexity typical of conventional PSO, GWO, and WOA optimization schemes. As a result, the computational growth rate scales gracefully, even within highly dense LSWSN deployments.

4.2. Convergence Analysis and Optimization

The convergence behaviour of the GKMSLO-MDC framework, along with PSO, GWO, and WOA, was simulated across network scales ranging from 100 to 1000 nodes to evaluate optimization performance. Figure 2 illustrate the convergence plots of the evolution of the normalized multi-objective fitness function during the

optimization process for a 1000 node network. Corresponding numerical values at various iterations for 100, 200, 500 and 1000 nodes are reported in Table 1, providing a comprehensive quantitative analysis.

The fitness function simultaneously considers energy efficiency, network coverage, packet delivery ratio, communication latency, localization accuracy, load balancing, and communication cost, thereby providing a comprehensive evaluation of CH localization quality (refer to equation (4)). All algorithms initially exhibit a rapid increase in fitness values during the early optimization iterations, owing to the intensive exploration of the search space as reported in Table 1 and the curves in Figure 2. However, significant performance gaps emerge as the optimization progresses. The proposed GKMSLO-MDC framework consistently achieves the fastest convergence rate and the highest final fitness value across all evaluated network sizes.

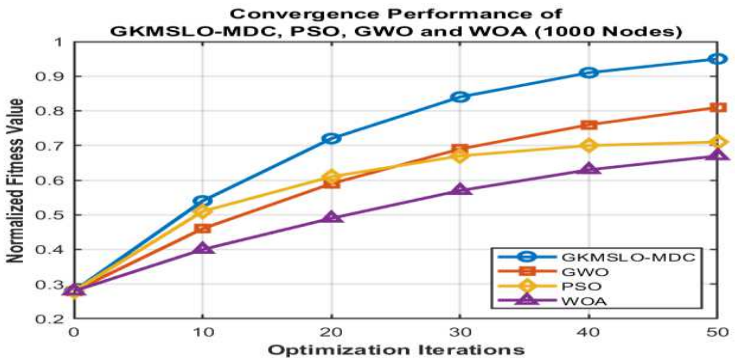


Figure 2. Convergence performance of GKMSLO-MDC, PSO, GWO, and WOA for a 1000-node wireless sensor network size.

For the 100-node scenario, GKMSLO-MDC reaches a fitness value of 0.99, whereas GWO, PSO, and WOA converge to 0.92, 0.88, and 0.84, respectively. The proposed approach maintains superior performance despite the increasing optimization complexity for larger network sizes.

The convergence superiority of GKMSLO-MDC becomes more evident in dense deployments. For a network consisting of 1000 sensor nodes, the proposed framework achieves a final fitness value of 0.95, compared with 0.81 for GWO, 0.71 for PSO, and 0.67 for WOA. This corresponds to fitness improvements of approximately 17.3% over GWO, 33.8% over PSO, and 41.8% over WOA. Moreover, GKMSLO-MDC reaches more than 90% of its final fitness value before the 40^{th} iteration, demonstrating significantly faster convergence than competing methods. The superior convergence characteristics of GKMSLO-MDC can be explained firstly by the combined effect of its architectural components by reducing the dimensionality of the optimization problem. Second, the global knowledge gathered by MDC allows the optimization process to evaluate candidate solutions using more accurate and comprehensive fitness information. Third, the SLnO algorithm provides an effective balance between exploration and exploitation through its adaptive hunting-inspired search strategy. Unlike PSO, which often suffers

from premature convergence due to the loss of particle diversity, or WOA, which exhibits slower exploitation dynamics, SLnO maintains solution diversity while progressively intensifying the search around promising regions.

Table 1. Comparative convergence performance of GKMSLO-MDC, PSO, GWO, and WOA under different network sizes (100–1000 Nodes)

Number of nodes	100						200					
iterations	0	10	20	30	40	50	0	10	20	30	40	50
GKMSLO-MDC	0.38	0.67	0.84	0.92	0.97	0.99	0.35	0.61	0.79	0.89	0.94	0.97
GWO	0.38	0.61	0.76	0.84	0.89	0.92	0.35	0.55	0.69	0.78	0.84	0.88
PSO	0.38	0.64	0.78	0.83	0.86	0.88	0.35	0.59	0.71	0.77	0.79	0.80
WOA	0.38	0.54	0.65	0.73	0.80	0.84	0.35	0.48	0.58	0.66	0.72	0.76
Number of nodes	500						1000					
iterations	0	10	20	30	40	50	0	10	20	30	40	50
GKMSLO-MDC	0.31	0.57	0.75	0.87	0.93	0.96	0.28	0.54	0.72	0.84	0.91	0.95
GWO	0.31	0.50	0.63	0.74	0.81	0.85	0.28	0.46	0.59	0.69	0.76	0.81
PSO	0.31	0.55	0.66	0.72	0.75	0.76	0.28	0.51	0.61	0.67	0.70	0.71
WOA	0.31	0.43	0.53	0.61	0.68	0.72	0.28	0.40	0.49	0.57	0.63	0.67

Another key finding from the results reported in Table 1 is the remarkable scalability of the proposed framework. As network size increases from 100 to 1000 nodes, the final fitness value of GKMSLO-MDC decreases only slightly and the reduction is of approximately 4%. In contrast, for PSO, GWO, and WOA the degradation observed is significantly more pronounced. This stability validates that the proposed framework is capable of preserving optimization effectiveness even in LSWSN environments. The reduced sensitivity to network growth is mainly attributed to the fact that SLnO operates only on the set of CHs generated by Grid K-Means rather than on the entire sensor population. This reduced sensitivity resulting in a substantially smaller search space and lower optimization complexity.

Overall, the convergence results presented in Figure 2 and Table 1 confirm that GKMSLO-MDC achieves faster convergence, higher fitness values, and better scalability than PSO, GWO, and WOA based approaches. These results validate the effectiveness of combining grid-based K-Means clustering, hybrid localization (RSSI, TOA, TDOA), MDC-assisted global optimization, and Sea Lion optimization for CH localization in LSWSN with limited energy resources. The improved convergence behaviour directly contributes to enhanced energy efficiency, longer network lifetime, lower communication cost, and better Quality of Service, thereby demonstrating the suitability of the proposed framework for next-generation LSWSN deployments.

4.3. Time Complexity Analysis

Although computational complexity provides a theoretical estimate of algorithmic cost, execution time offers a more practical measure of scalability. Processing time is significantly reduced in the proposed framework

by distributing clustering operations across multiple grid regions and by limiting metaheuristic optimization to the already elected CHs.

The localization and grid assignment stages exhibit linear execution time as it requires only a single pass through the sensor population. Similarly, MDC information gathering contributes only marginally to the total runtime as it involves one communication cycle per node. The dominant factor affecting execution time is the iterative optimization process. However, in GKMSLO-MDC the runtime per iteration is proportional to M rather than N, because SLnO manipulates candidate CH configurations rather than all network nodes and each iteration processes a significantly smaller solution vector rather than PSO, GWO, and WOA, where each optimization iteration evaluates the entire sensor set. Furthermore, our proposal improves solution quality during each iteration by the integration of MDC-guided localization correction and reducing the number of iterations required to reach convergence. As network size increases, the execution-time advantage becomes increasingly pronounced because the optimization dimension remains bounded by the number of CHs rather than by the total number of sensor nodes. Therefore, GKMSLO-MDC framework exhibits superior scalability and faster convergence characteristics, from a temporal perspective, than most existing metaheuristic-based clustering approaches, making it particularly suitable for real-time or near-real-time WSN management applications.

4.4. Communication Complexity Analysis

It is well known that the most critical factors affecting network lifetime in WSNs is communication overhead as radio transmissions consume significantly more energy than local computations. Consequently, minimizing communication complexity directly contributes to extending network longevity and improving overall QoS performance. In the proposed system, communication overhead arises primarily from three stages: localization information exchange, MDC data collection, and data transmission. Each sensor node exchanges a limited number of messages with anchor nodes to obtain RSSI, TOA, and TDOA measurements in the localization phase. Furthermore, the communication complexity of this stage is $O(N)$ since the number of localization exchanges per node remains constant.

During clustering and MDC-assisted monitoring phase, each node periodically reports residual energy, connectivity information, and localization metrics. The communication cost of this stage also scales linearly with network size, yielding $O(N)$, because each sensor communicates only once per collection cycle. Member nodes transmit sensed information to their associated CHs, resulting in an intra-cluster communication complexity of $O(N)$. Subsequently, CHs aggregate received data and forward summarized information toward the BS, either directly or through MDC-assisted routing. The corresponding communication complexity is $O(M)$ during normal

network operation since only M CHs participate in inter-cluster forwarding. The total communication complexity of the proposed framework can therefore be expressed as $O(N + M)$. Given that $M \ll N$, the communication complexity can be simplified to $O(N)$.

This result is particularly significant because the proposed framework achieves improved localization accuracy and optimization performance without introducing additional communication overhead. From a network-wide perspective, the integration of Grid K-Means clustering reduces average transmission distances, while MDC-assisted optimization improves CH placement and balances traffic loads among clusters. Consequently, the asymptotic communication complexity remains linear and the communication distance, and energy expenditure per transmission are significantly reduced. This leads to lower packet loss rates, decreased end-to-end latency, enhanced packet delivery ratios, and prolonged network lifetime.

V. Performance evaluation and analysis:

In order to demonstrate the effectiveness of the proposed GKMSLO-MDC system, a comprehensive performance evaluation was conducted. The proposed system was implemented and evaluated using MATLAB under various network configurations and operating conditions. Multiple performance metrics, including energy consumption, network lifetime, packet delivery ratio, end-to-end delay and localization accuracy were assessed. The obtained results were further compared with those of state-of-the-art clustering and metaheuristic-based approaches to validate the superiority and scalability of the proposed framework.

In our simulation scenarios, the adopted configuration, encompasses network topology, communication characteristics, energy consumption parameters, localization settings, and MDC operation. Sensor nodes are deployed using a Poisson Disk Sampling strategy to achieve a spatially balanced distribution and to avoid deployment-induced clustering effects that could influence performance evaluation. Furthermore, the simulation environment integrates hybrid RSSI–TOA–TDOA localization and Grid-Based K-Means clustering to accurately reflect the operational conditions targeted by the proposed framework. The complete set of network and simulation parameters, employed throughout the experimental study, is summarized in Table 2.

Table 2. Simulation parameters and network configuration.

Parameter	**Symbol**	**Value**
Simulation Area	A	100 *100, 200*200, 300*300 400*400 and 500*500 m²
Number of Sensor Nodes	N	100, 200, 300, 400 and 500
Node Deployment Model	–	Poisson Disk Sampling (PDS)
Minimum Inter-Node Distance	d_{min}	15 m
Initial Energy per Node	E_0	2 J
Communication Range	R_{max}	80 m
Sensing Range	R_s	30 m
Grid Structure	G	(5 * 5)

Localization Techniques	–	RSSI, TOA, TDOA, Hybrid RSSI–TOA–TDOA
MDC Speed	V_{MDC}	5 m/s to 20m/s
Packet Size	(L)	4000 bits
Radio Energy Model	–	First-Order Radio Model
E_{elec}	–	50 nJ/bit
ε_{fs}	–	10 pJ/bit/m²
ε_{mp}	–	0.0013 pJ/bit/m⁴
E_{DA}	–	5 nJ/bit/signal

The simulation parameters were selected to ensure performance evaluation of the proposed GKMSLO-MDC framework under different network scales and operating conditions. in order to assess the scalability of the proposed framework under increasing network density we vary the sensing area from 100×100m² to 500×500m² and the number of sensor nodes ranges from 100 to 500. Sensor deployment is generated using Poisson Disk Sampling (PDS). In order to ensure a spatially balanced topology and prevent excessive node concentration, the PDS is configured with a minimum inter-node distance of 15 m. Each sensor node is initialized with 2 J of energy, which is a commonly adopted value in WSN studies and allows meaningful observation of energy consumption and network lifetime. To provide adequate network connectivity and preserve the multi-hop

Table 3. MDC-assisted Sea Lion Optimization algorithm parameters.

Category	Parameter	Value
Population Initialization	Search Agents	30
Optimization Control	Maximum Iterations	50
Optimization Control	Search Space Dimension	(2M)
Exploration Mechanism	Adaptive Exploration Parameter	Dynamic
Exploitation Mechanism	Adaptive Exploitation Parameter	Dynamic
MDC Integration	MDC Correction Factor λ	0.3
Localization Module	Localization Fusion Weights (α, β, γ)	(0.3, 0.35, 0.35)
Stopping Condition	Maximum Iterations	50

communication characteristics of large-scale deployments, communication and sensing ranges are set to 80 m and 30 m, respectively. Furthermore, a 5×5 grid structure is employed to reduce clustering complexity and improve scalability.

Note that the performance of the proposed optimization framework is strongly influenced by the configuration of the SLnO algorithm. The parameter values selected in this study were chosen to ensure stable convergence behaviour and computational efficiency across different network scales. The complete SLnO configuration used in all simulation scenarios is presented in Table 3.

For the hybrid localization module, the fusion weights $(\alpha, \beta, \gamma) = (0.30, 0.35, 0.35)$ assign slightly greater importance to TOA and TDOA measurements due to their generally higher positioning accuracy compared with RSSI. Finally, the optimization process terminates after reaching the maximum number of iterations or satisfying the convergence criterion.

5.1. Localization Accuracy Analysis

Figure 3 illustrates the localization performance of the proposed GKMSLO-MDC framework under different network scales. The average localization error achieved by the hybrid (RSSI, TOA, TDOA) localization mechanism is 0.24 m for the 100 x 100 m^2 network with 100 nodes, 0.20 m for the 200 x 200 m^2 network with 200 nodes, 0.17 m for the 300 x 300 m^2 network with 300 nodes, and approximately 0.18 m for both 400 x 400 m^2 and 500 x 500 m^2 deployment scenarios. These results demonstrate that the proposed system consistently maintains a localization error below 0.25 m regardless of network size. This localization performance indicates a high level of positioning precision suitable for energy-aware data collection and CH localization in LSWSNs.

From Figure 3, one may observe the consistently low localization error across all network sizes, which demonstrates the scalability and robustness of the proposed system. The slight improvement observed in larger deployments is attributed to enhanced anchor-node geometry and improved spatial diversity. This performance is achieved through the hybrid integration of RSSI, TOA, and TDOA measurements. Notably, localization updates are performed periodically, limiting synchronization overhead and reducing energy consumption. The resulting high-accuracy position estimates improve CH placement, shorten communication distances, optimize MDC trajectories, and ultimately enhance overall network efficiency and QoS performance.

From an application perspective, the achieved sub-meter localization accuracy is particularly valuable for mission-critical WSN deployments. As in the case of this application type, positioning errors can significantly affect network performance and decision-making processes. It is worth noting that infrastructure monitoring, industrial automation, environmental surveillance, military sensing, and healthcare monitoring systems often require highly reliable location information to ensure operational effectiveness.

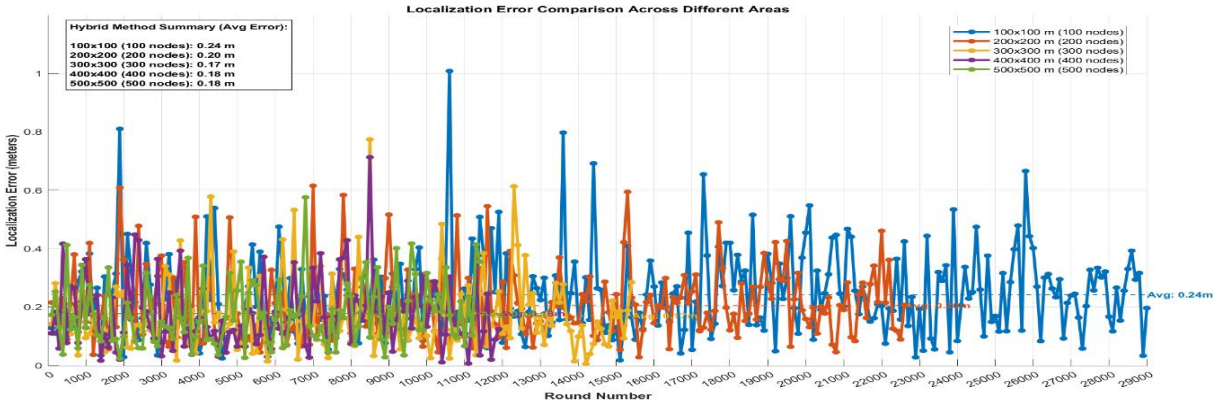


Figure 3. Localization accuracy evaluation of GKMSLO-MDC.

5.2. Network lifetime and survivability analysis

Figure 4 shows the network survivability performance of the proposed GKMSLO-MDC framework under different deployment scales, evaluated using three widely adopted metrics: First Node Death (FND), Half

Node Death (HND), and overall Network Lifetime. The obtained results demonstrate the ability of the proposed framework to maintain long-term network operation and preserve a high percentage of active sensor nodes. Results presented in figure 4, demonstrate that these performances are achieved even under increasingly challenging large-scale deployment conditions.

From Figure 4, we can notice that network survivability decreases gradually as the deployment area expands. This can largely be attributed to the increased of communication distances leading to higher transmission energy requirements associated with larger sensing fields. Consequently, the FND, HND, and overall network lifetime metrics exhibit a moderate decline with network scale. Despite this expected behaviour, the proposed GKMSLO-MDC framework maintains a high proportion of active nodes over a prolonged operational period due to the effective energy balancing and the strong robustness. GKMSLO-MDC efficiently distributes the communication load and mitigates hotspot formation, thereby preventing premature energy depletion owing to the MDC-assisted data collection strategy, combined with optimized CH localization. Furthermore, scalable energy management across different deployment scenarios was enabled by the integration of Grid-Based K-Means clustering, hybrid RSSI–TOA–TDOA localization, and SLnO-based optimization. These results confirm the ability of GKMSLO-MDC to sustain long-term network operation and reliable monitoring performance in LSWSN.

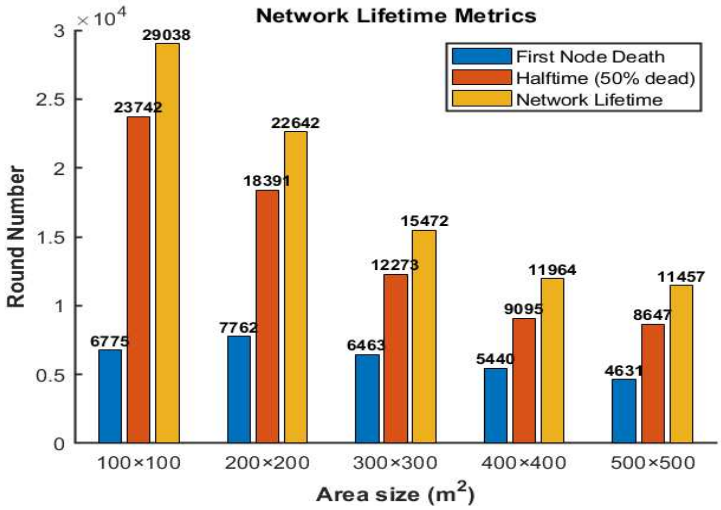


Figure 4. Network Stability, half Life time and Life time metrics for different network sizes.

5.3. QoS performance analysis: Packet Delivery Ratio, Throughput, and End-to-End Delay

Figure 5 evaluates the QoS performance of the proposed GKMSLO-MDC framework in terms of PDR, throughput, and end-to-end delay across different network scales. As shown in Figure 5(a), the proposed GKMSLO-MDC consistently maintains a high PDR, exceeding 90% in all deployment scenarios. The PDR results, despite increasing network size and communication complexity, demonstrates that GKMSLO-MDC permit reliable data delivery. The slight reduction of PDR observed in larger networks is primarily associated with longer

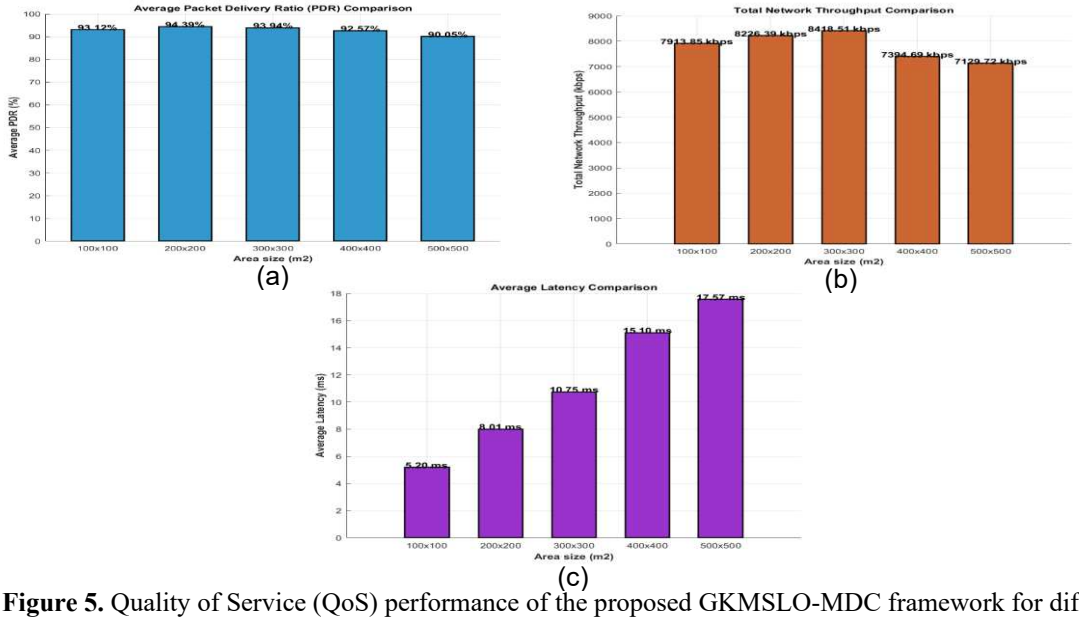


Figure 5. Quality of Service (QoS) performance of the proposed GKMSLO-MDC framework for different network scales: (a) Packet Delivery Ratio (PDR), (b) Average Throughput, and (c) End-to-End Delay.

transmission distances and higher multi-hop communication requirements. Figure 5(b) further shows that GKMSLO-MDC sustains a high throughput level across different area sizes that indicate the efficient data collection and forwarding capabilities of our proposed framework. Although due to the balanced clustering structure and MDC-assisted communication strategy the throughput moderately decreases in larger deployments but this reduction remains limited. Moreover, Figure 5(c) reveals that the proposed GKMSLO-MDC achieves low end-to-end latency, making it suitable for delay-sensitive applications. The end-to-end values remain within acceptable operational limits while latency gradually increases with network scale. Notably, GKMSLO-MDC enables reliable, efficient, and scalable QoS performance in LSWSN environments. These obtained performances are by dint of the combination of Grid-Based K-Means clustering, hybrid RSSI–TOA–TDOA localization, MDC-assisted optimization, and SLnO-based CH refinement. Substantially, the results presented in Figure 5 demonstrate that the proposed GKMSLO-MDC framework successfully achieves a favourable balance between reliability, transmission efficiency, and communication responsiveness. The consistently high PDR, sustained throughput performance, and low end-to-end delay collectively confirm the effectiveness of our proposal. These findings validate the capability of GKMSLO-MDC to provide robust QoS support while preserving scalability in LSWSN.

5.4. Comparative Analysis with Existing Clustering and MDC-Based Protocols

5.4.1 Localization Accuracy Comparison

Figure 6 demonstrates that the proposed GKMSLO-MDC framework, utilizing a hybrid RSSI–TOA–TDOA mechanism, achieves a high-precision average localization error of 0.20 m, outperforming state-of-the-art

approaches for CH localization and MDC-assisted data collection. The results highlight the method's capacity to deliver superior, precise position estimates for efficient mobile data collection.

Localization results demonstrate that GKMSLO-MDC improves localization accuracy by 22.5% over the MDC-IR-DV-Hop-K scheme [32], and reduces error by 50% relative to the HCEDV-Hop approach [33]. Such significant improvements are attributed to the synergistic integration of multiple localization techniques by effectively compensates for the individual limitations of RSSI-, TOA-, and TDOA-based measurements. The proposed hybrid localization model exploits both signal strength and temporal measurements to generate more reliable position estimates, whereas traditional DV-Hop-based methods are highly dependent on hop-count estimation and are therefore susceptible to cumulative distance estimation errors.

Moreover, GKMSLO-MDC continuously refine the spatial positioning of communication nodes and contribute to minimizing localization uncertainty by the MDC-assisted optimization process and the SLnO-based CH localization strategy. This enhanced positioning accuracy directly led to improved cluster organization, a reduce of communication distances, and strengthen the overall network connectivity. Consequently, this localization improvements achieved by GKMSLO-MDC not only enhance node positioning precision but also positively impact energy efficiency and QoS metrics throughout the network.

Overall, the results confirm that the proposed framework provides a highly accurate and scalable localization solution for LSWSN. The achieved sub-meter localization error significantly outperforms existing approaches and demonstrates the effectiveness of combining hybrid localization with intelligent MDC-assisted optimization for next-generation energy-efficient and QoS-aware WSN deployments.

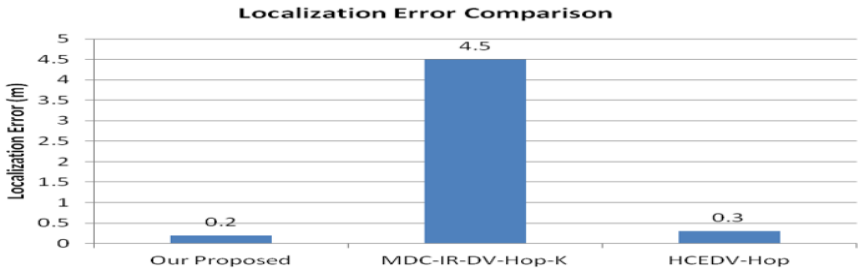


Figure 6. Localization Error Comparison.

5.4.2. Energy consumption analysis

Figure 7 illustrates the comparative energy consumption performance of the proposed GKMSLO-MDC framework against representative state-of-the-art approaches. The results clearly demonstrate the effectiveness of the proposed optimization strategy in minimizing energy expenditure and extending network sustainability. Obtained results also indicate a highly efficient utilization of sensor resources and a balanced energy dissipation process across the network. Specifically, the energy

consumption after 10,000 communication rounds, GKMSLO-MDC consumes only 41.43% of the total available network energy.

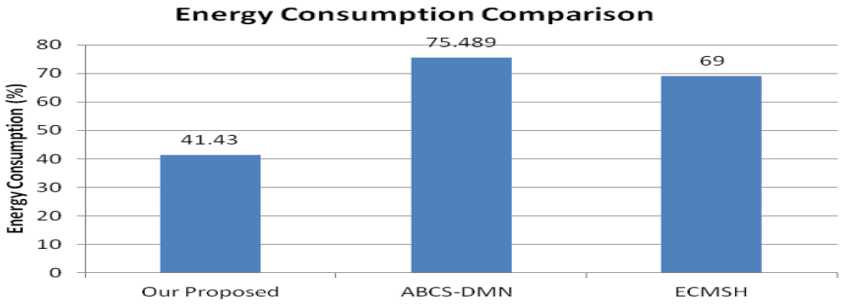


Figure 7. Energy consumption comparison.

The proposed framework achieves an energy consumption reduction of approximately 27.57% compared to ECMSH [35], while outperforming ABCS-DMN [34] by nearly 34%. These improvements are particularly significant considering that the competing approaches were evaluated over shorter operational periods, whereas GKMSLO-MDC maintains lower energy consumption while sustaining network activity for a substantially longer duration. This behaviour highlights the ability of the proposed framework to preserve energy resources without compromising communication performance or network coverage. These superior energy efficiency of GKMSLO-MDC stems from the synergistic integration of several optimization mechanisms leading to compact and balanced clusters Grid-based K-Means clustering and improves CH positioning accuracy and communication efficiency. In addition, the MDC-assisted architecture mitigates hotspot formation and long-range transmission overhead. Whereas the SLnO algorithm dynamically refines CH positions to achieve balanced energy consumption and prolong network lifetime.

5.4.3. QoS comparison analysis: Packet Delivery Ratio and End-to-End Delay

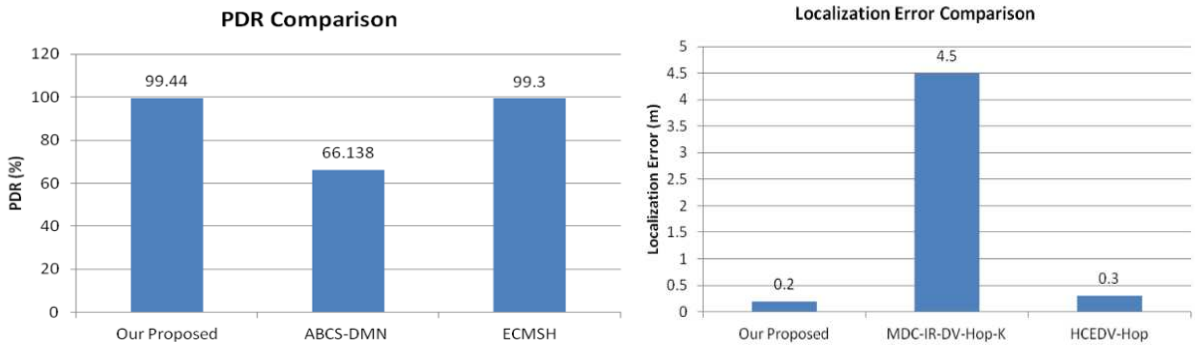
Figure 8 shows a comparative evaluation of the Quality of Service (QoS) performance achieved by the proposed GKMSLO-MDC framework in terms of Packet Delivery Ratio (PDR) and End-to-End Delay. These metrics are fundamental indicators of communication reliability and responsiveness in WSNs, particularly in large-scale and mission-critical deployment scenarios.

As depicted in Figure 8(a), the proposed GKMSLO-MDC system achieves an average PDR of 99.44% after 10,000 communication rounds. This result indicates an exceptionally reliable data delivery process with a tiny packet loss rate. This performance provides an improvement of approximately 33.3% against ABCS-DMN [34], while also slightly outperforming ECMSH [35]. Such a high PDR demonstrates the effectiveness of the proposed clustering and localization mechanisms in maintaining stable communication links during the network lifetime. The superior PDR performance can be attributed to several key design features of GKMSLO-MDC. The

adopted hybrid localization model enhances the accuracy of CH positioning thus reducing communication errors caused by inaccurate node localization. In addition, compact and well-structured clusters that minimize transmission distances and reduce packet collisions due to Grid-Based K-Means clustering. Furthermore, MDC-assisted data collection improves link reliability and increases successful packet reception rates by alleviating traffic congestion and mitigating bottleneck formation near the BS. Consequently, it can be claimed that the proposed system maintains highly reliable communications even under large-scale deployment conditions, making it particularly suitable for applications requiring dependable data delivery.

Figure 8(b) demonstrates that GKMSLO-MDC achieves an average end-to-end delay of 5.2 ms, substantially outperforming MDC-IR-DV-Hop-K [33] with an approximately 80% latency reduction. This improvement is primarily attributed to the accurate localization and optimization of the CH positions. Accurate localization permits to shorten communication paths and reduce transmission overhead. Moreover, MDC-assisted data collection and balanced Grid-Based K-Means clustering minimize routing congestion and queuing delays, thereby enabling faster and more reliable packet delivery across the network.

Overall, the results presented in Figure 8 confirm that GKMSLO-MDC delivers outstanding QoS performance by



(a) (b)

Figure 8. QoS comparison of the proposed GKMSLO-MDC framework: (a) Average Packet Delivery Ratio (PDR) and (b) End-to-End Delay.

simultaneously achieving near-perfect PDR and extremely low communication latency that demonstrate the effectiveness of combining hybrid localization, MDC-assisted optimization, and Sea Lion-based CH localization even in LSWSN case.

VI. Conclusion

This paper presented GKMSLO-MDC, a novel method for LSWSN, that integrates Grid-Based K-Means clustering, hybrid RSSI–TOA–TDOA localization, MDC-assisted optimization, and Sea Lion Optimization (SLnO)-based CH localization. Contrary to conventional metaheuristic approaches, that simultaneously optimize cluster formation and CH selection, our proposal adopts a hierarchical optimization strategy in which Grid-Based

K-Means establishes balanced cluster structures. Furthermore, SLnO is exclusively employed to optimize the localization of the already elected CHs by Grid-Based K-Means leading to a significant reduction in the optimization search space and computational complexity while preserving high solution quality.

A comprehensive mathematical formulation was developed to model the CH localization problem as a constrained multi-objective optimization task where the proposed fitness function jointly considers energy efficiency, network coverage, packet delivery ratio, communication latency, localization accuracy, load balancing, and communication cost.

The effectiveness of the proposed framework was demonstrated by an extensive simulation experiments conducted under various network scales. The obtained results revealed excellent localization performance with sub-meter positioning accuracy and exhibited a superior energy efficiency, prolonged network lifetime, and high survivability across all deployment scenarios. In terms of communication performance, GKMSLO-MDC consistently maintained a PDR, sustained high throughput, and achieved very low end-to-end latency, confirming its ability to satisfy stringent QoS requirements even in LSWSN case. Comparative evaluations against recent state-of-the-art localization, clustering, and MDC-assisted optimization techniques was conducted. The comparison results demonstrated that our proposal overwhelms in terms of localization accuracy, energy consumption, reliability, and communication responsiveness.

Future research directions will focus on extending the designed system to heterogeneous and mobile sensor networks. Furthermore, we plan to integrate deep reinforcement learning and federated learning mechanisms for adaptive decision-making and network security. Additionally, the extended system will be validated in real-world testbeds and large-scale Internet of Things environments. Ultimately, these advancements are expected to further enhance the adaptability, intelligence, security, and scalability of the proposed framework for next-generation autonomous sensing systems.

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript; no fund received for the research, authorship, and/or publication of this article.

References

[1] BEN GOUISSEM, Bechir, GANTASSI, Rahma, et HASNAOUI, Salem. Energy efficient grid based k-means clustering algorithm for large scale wireless sensor networks. *International Journal of Communication Systems*, 2022, vol. 35, no 14, p. e5255. https://doi.org/10.1002/dac.5255

[2] IDAN, Zainab S. et AL-FATLAWI, Ahmed. Energy efficient clustering using improved particle swarm optimization in wireless sensor networks. In : *BIO Web of Conferences*. EDP Sciences, 2024. p. 00106. https://doi.org/10.1051/bioconf/20249700106

[3] DHAKA, Raghuveer Singh, KHURANA, Manju, et LAMBA, Sonu. Energy-Efficient Cluster-Based Routing in WSNs Using a Hybrid GWO-PSO Optimization Technique. *IEEE Access*, 2026. 10.1109/ACCESS.2025.3650158

[4] KADDI, Mohammed, OMARI, Mohammed, SALAMEH, Khouloud, *et al.* Energy-efficient clustering in wireless sensor networks using Grey Wolf Optimization and enhanced CSMA/CA. *Sensors*, 2024, vol. 24, no 16, p. 5234. https://doi.org/10.3390/s24165234

[5] BALI, Himani, GILL, Amandeep, CHOUDHARY, Abhilasha, *et al.* Multi-objective energy efficient adaptive whale optimization based routing for wireless sensor network. *Energies*, 2022, vol. 15, no 14, p. 5237. https://doi.org/10.3390/en15145237

[6] MAO, Guoqiang, FIDAN, Barış, et ANDERSON, Brian DO. Wireless sensor network localization techniques. *Computer networks*, 2007, vol. 51, no 10, p. 2529-2553. https://doi.org/10.1016/j.comnet.2006.11.018

[7] GEZICI, Sinan, TIAN, Zhi, GIANNAKIS, Georgios B., *et al.* Localization via ultra-wideband radios: a look at positioning aspects for future sensor networks. *IEEE signal processing magazine*, 2005, vol. 22, no 4, p. 70-84. https://doi.org/10.1109/MSP.2005.1458289

[8] MESMOUDI, Asma, FEHAM, Mohammed, et LABRAOUI, Nabila. Wireless sensor networks localization algorithms: a comprehensive survey. *arXiv preprint arXiv:1312.4082*, 2013. https://doi.org/10.5121/ijcnc.2013.5603

[9] MASADEH, Raja, MAHAFZAH, Basel A., et SHARIEH, Ahmad. Sea lion optimization algorithm. *International Journal of Advanced Computer Science and Applications*, 2019, vol. 10, no 5. https://doi.org/10.14569/IJACSA.2019.0100548

[10] BOYINBODE, Olutayo, LE, Hanh, et TAKIZAWA, Makoto. A survey on clustering algorithms for wireless sensor networks. *International Journal of Space-Based and Situated Computing*, 2011, vol. 1, no 2-3, p. 130-136. https://doi.org/10.1109/NBiS.2010.59

[11] YARAT, Serhat, SENAN, Sibel, et ORMAN, Zeynep. A comparative study on PSO with other metaheuristic methods. *Applying particle swarm optimization: New solutions and cases for optimized portfolios*, 2021, p. 49-72. https://doi.org/10.1007/978-3-030-70281-6_4

[12] AGRAWAL, Deepika, WASIM QURESHI, Muhammad Huzaif, PINCHA, Pooja, *et al.* GWO-C: Grey wolf optimizer-based clustering scheme for WSNs. *International Journal of Communication Systems*, 2020, vol. 33, no 8, p. e4344. 10.1002/dac.4344

[13] JIANG, Zihao, CHEN, Renwen, LIU, Hao, *et al.* A WSN clustering routing method based on an improved WOA-optimized K-means clustering algorithm. In : *Journal of Physics: Conference Series*. IOP Publishing, 2023. p. 012019. 10.1088/1742-6596/2670/1/012019

[14] HOUSSEIN, Essam H., SAAD, Mohammed R., DJENOURI, Youcef, *et al.* Metaheuristic algorithms and their applications in wireless sensor networks: Review, open issues, and challenges. *Cluster Computing*, 2024, vol. 27, no 10, p. 13643-13673. https://doi.org/10.1007/s10586-024-04619-9

[15] DEL-VALLE-SOTO, Carolina, RODRÍGUEZ, Alma, et ASCENCIO-PIÑA, Cesar Rodolfo. A survey of energy-efficient clustering routing protocols for wireless sensor networks based on metaheuristic approaches. *Artificial intelligence review*, 2023, vol. 56, no 9, p. 9699. https://doi.org/10.1007/s10462-023-10402-w

[16] FEI, Zesong, LI, Bin, YANG, Shaoshi, *et al.* A survey of multi-objective optimization in wireless sensor networks: Metrics, algorithms, and open problems. *IEEE communications surveys & tutorials*, 2016, vol. 19, no 1, p. 550-586. https://doi.org/10.1109/COMST.2016.2610578

[17] RAO, Chuchu, KAN, Mingqi, ZHOU, Peng, *et al.* A novel multi objective energy efficient clustering optimization scheme based on heuristic intelligence for wireless sensor networks. *Scientific Reports*, 2025, vol. 15, no 1, p. 36988. https://doi.org/10.1038/s41598-025-21918-2

[18] AMIR, Rida, NAEEM, Haisem, ALI, Arshad, *et al.* MultiObjective Optimization in Wireless Mesh Networks–A Survey. *ACM Computing Surveys*, 2026, vol. 58, no 11, p. 1-36. https://doi.org/10.1145/3800685

[19] HOLLA, B. Ashutosh, RAVI, B., et SHENOY, Udaya Kumar K. Data gathering in Wireless Sensor Network using optimum mobile sink path. In : *2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*. IEEE, 2017. p. 425-429. https://doi.org/10.1109/WiSPNET.2017.8299791

[20] REGILAN, S. et HEMA, L. K. Optimizing energy efficiency and routing in wireless sensor networks through genetic algorithm-based cluster head selection in a grid-based topology. *Journal of High Speed Networks*, 2024, vol. 30, no 4, p. 569-582. https://doi.org/10.3233/JHS-230209
[21] DIVYA, P. et SUDHAKAR, B. Route optimization and optimal cluster head selection for cluster-oriented wireless sensor network utilizing circle-inspired optimization algorithm. *International Journal of Computational Intelligence Systems*, 2024, vol. 17, no 1, p. 302. https://doi.org/10.1007/s44196-024-00708-0
[22] MURALI, J. et SHANKAR, T. A survey on localization and energy efficiency in UWSN: bio-inspired approach. *Discover Applied Sciences*, 2024, vol. 6, no 12, p. 633. https://doi.org/10.1007/s42452-024-06318-x
[23] LAASSIRI, F., BISHI, Hager Hadi, ALTHINI, Amaal O., *et al.* Wireless Sensor Network Localization using RSSI and TOA Techniques. In : *2025 IEEE 22nd International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA)*. IEEE, 2025. p. 752-758. https://doi.org/10.1109/STA66620.2025.11364726
[24] PAUL, Anup Kumar et SATO, Takuro. Localization in wireless sensor networks: A survey on algorithms, measurement techniques, applications and challenges. *Journal of sensor and actuator networks*, 2017, vol. 6, no 4, p. 24. https://doi.org/10.3390/jsan6040024
[25] HADA, Rupendra Pratap Singh, AGGARWAL, Uttkarsh, et SRIVASTAVA, Abhishek. A study and analysis of a new hybrid approach for localization in wireless sensor networks. *Journal of Web Engineering*, 2023, vol. 22, no 2, p. 279-302. https://doi.org/10.13052/jwe1540-9589.2224
[26] MAJID LATEEF, Hadeel, AL-QURABAT, Kadhum M., *et al.* An overview of using mobile sink strategies to provide sustainable energy in wireless sensor networks. *International Journal of Computing and Digital Systems*, 2024, vol. 16, no 1, p. 797-812. http://dx.doi.org/10.12785/ijcds/160158
[27] LI, Hui, DAI, Yuzhou, CHEN, Qian, *et al.* Energy efficient mobile sink driven data collection in wireless sensor network with nonuniform data. *Scientific Reports*, 2024, vol. 14, no 1, p. 28190. https://doi.org/10.1038/s41598-024-79825-x
[28] BOYINENI, Srinivasulu, KAVITHA, K., et SREENIVASULU, Meruva. Mobile sink-based data collection in event-driven wireless sensor networks using a modified ant colony optimization. *Physical Communication*, 2022, vol. 52, p. 101600. https://doi.org/10.1016/j.phycom.2022.101600
[29] SALAMAH, Ketty Siti et GUNAWAN, Dadang. Metaheuristic Optimization Techniques in Wireless Sensor Networks: Current Trends and Future. In : *2025 IEEE 15th Symposium on Computer Applications & Industrial Electronics (ISCAIE)*. IEEE, 2025. p. 331-335. https://doi.org/10.1109/ISCAIE64985.2025.11080987
[30] HARTONO, Rudi, MUSTIKA, I. Wayan, et SULISTYO, Selo. Metaheuristic Approaches for Energy Optimization in Wireless Sensor Networks: A Systematic Review of Trends, Challenges, and Future Directions. *EAI Endorsed Transactions on Internet of Things*, 2024, vol. 11. https://doi.org/10.4108/eetiot.10328
[31] LAKSHMANNA, Kuruva, SUBRAMANI, Neelakandan, ALOTAIBI, Youseef, *et al.* Improved metaheuristic-driven energy-aware cluster-based routing scheme for IoT-assisted wireless sensor networks. *Sustainability*, 2022, vol. 14, no 13, p. 7712. https://doi.org/10.3390/su14137712
[32] R. Gantassi, S. Messous, Z. Masood, Q. A. Sias, and Y. Choi, "Enhanced network QOS in large scale and high sensor node density wireless sensor networks using (IR-DV-HOP) localization algorithm and mobile Data collector (MDC)," IEEE Access, vol. 12, pp. 37957–37973, Jan. 2024, https://doi.org /10.1109/access.2024.3370432
[33] M. Fawad, M. Khan, K. Ullah, H. Alasmary, D. Shehzad, and B. Khan, "Enhancing localization efficiency and accuracy in wireless sensor networks," Sensors, vol. 23, no. 5, p. 2796, Mar. 2023, https://doi.org/10.3390/s23052796
[34] C. Kaur, S. M. Hassen, M. S. A. Boush, and H. Anandaram, "Energy prediction for mobile sink placement by deep maxout network in WSN," Journal of Advances in Information Technology, Jan. 2023, https://doi.org/10.12720/jait.14.1.112-121.
[35] M. Rahnemay, L. Farzinvash, M. Zolfi, and A. Taherkordi, "ECMSH: An Energy-efficient and Cost-effective data harvesting protocol for Mobile Sink-based Heterogeneous WSNs using PSO-TVAC," Ad Hoc Networks, vol. 164, p. 103629, Aug. 2024, https://doi.org/10.1016/j.adhoc.2024.103629.
[36] N. A. Azmi, S. Samsul, Y. Yamada, M. F. Mohd Yakub, M. I. Mohd Ismail, and R. A. Dziyauddin, A Survey of Localization using RSSI and TDoA Techniques in Wireless Sensor Network: System Architecture, 2018 2nd International Conference on Telematics and Future Generation Networks (TAFGEN), (2018) 131-136. https://doi.org/10.1109/TAFGEN.2018.8580464.

[37] MAZUMDAR, Nabajyoti, ROY, Saugata, NAG, Amitava, et al. An adaptive hierarchical data dissemination mechanism for mobile data collector enabled dynamic wireless sensor network. Journal of Network and Computer Applications, 2021, vol. 186, p. 103097. https://doi.org/10.1016/j.jnca.2021.103097.
[38] GANTASSI, Rahma, MASOOD, Zaki, SIAS, Quota Alief, et al. I-QoS-WSN-S-MDC: Improving Quality of Service of Wireless Sensor Networks Using a Smart Mobile Data Collector. IET Wireless Sensor Systems, 2025, vol. 15, no 1, p. e70005. https://doi.org/10.1049/wss2.70005.