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A Binary Marine Predators Algorithm for Maximum Disjoint Connected K-Cover Scheduling in Heterogeneous Wireless Sensor Networks

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ABSTRACT

Wireless Sensor Networks (WSNs) have gained increasing attention as a low-cost and flexible solution for collecting real-time information in large-scale monitoring systems. They are commonly deployed in critical domains such as border protection, intelligent transportation, structural health monitoring, and industrial safety management. Despite their advantages, the limited energy resources of sensor nodes remain a major limitation, since battery replacement is often impractical after deployment. This constraint significantly impacts network lifetime, communication reliability, and overall Quality of Service (QoS). In heterogeneous wireless sensor networks (HWSNs), the coverage and connectivity problem becomes more complicated due to the unequal sensing ranges, communication radii, and energy levels of sensor nodes. This heterogeneity leads to unbalanced energy consumption and may cause premature failure of critical nodes. Moreover, satisfying k-coverage constraints, where each target must be monitored by at least k sensors, while maintaining network connectivity to the sink node is a challenging optimization problem. Reducing packet loss and minimizing redundant sensing further increase the complexity of achieving an optimal scheduling strategy.To address these challenges, this paper proposes a novel Marine Predators Algorithm based Maximum Disjoint Connected Covers and K-Coverage approach, called MPA–MDCCKC, aimed at maximizing network lifetime and improving energy efficiency in HWSNs. The proposed method constructs a graph-based model that represents target coverage and connectivity relationships, and performs sensor scheduling by selecting optimal disjoint connected cover subsets. To handle the discrete nature of sensor selection, a Binary Marine Predators Algorithm (BMPA) is introduced. In addition, a repair mechanism is incorporated to ensure that each selected subset satisfies k-coverage requirements and preserves connectivity under energy constraints. Simulation experiments are conducted using OMNeT++ under different network sizes and deployment scenarios. The results demonstrate that the proposed MPA–MDCCKC approach significantly extends network lifetime, reduces packet loss ratio, and lowers energy consumption compared to existing methods such as EDTC, ACO-MNCC, BFO-MDCCKC, and MBAT-MDCCKC. Overall, the proposed approach provides an effective metaheuristic-based solution for energy-aware scheduling and reliable target monitoring in heterogeneous wireless sensor networks.

Keywords:— HWSN, Marine Predators Algorithm, MDCCKC, Target Coverage, Disjoint Connected Covers, K-Coverage, Energy Efficiency, Network Lifetime.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are widely used in applications such as environmental monitoring, industrial automation, healthcare, and military surveillance. A WSN consists of a large number of sensor nodes deployed over a region of interest to sense physical parameters and transmit the collected data to a sink node. However, sensor nodes operate with limited battery energy, processing capability, and communication bandwidth. Since battery replacement is often impractical after deployment, improving energy efficiency and maximizing network lifetime are major research challenges.

Coverage is one of the most important performance requirements in WSNs. Coverage scheduling aims to monitor a region or a set of targets while minimizing redundant sensing and reducing energy consumption. Target coverage problems are generally NP-hard, and several studies have proposed subset-based scheduling to extend lifetime. Cardei and Wu introduced an energy-efficient target coverage approach using sensor subset selection [1], and later Cardei et al. improved it by considering adjustable sensing ranges [2]. Wang and Cao provided a detailed survey of coverage optimization techniques and emphasized their impact on lifetime improvement [3].

In real deployments, sensor nodes are often distributed randomly, resulting in overlapping sensing regions and unnecessary activation of redundant sensors. Tian and Georganas proposed a coverage-preserving scheduling scheme that turns off redundant nodes while maintaining coverage [5]. Slijepcevic and Potkonjak proposed cover set scheduling to extend network operation [6], and Huang and Tseng discussed efficient scheduling strategies for coverage maintenance [7].

Most importantly, Ravindranath and Maheswari [1] proposed a Trapezoidal Fuzzy Membership Genetic Algorithm (TFMGA) for energy and network lifetime maximization under coverage constraints in heterogeneous WSNs. Their work is significant because it demonstrated that combining fuzzy logic with evolutionary optimization can effectively handle uncertainty in heterogeneous network parameters and improve lifetime performance. However, the TFMGA approach mainly focuses on coverage-based lifetime maximization and does not explicitly address the construction of maximum disjoint connected k-cover sets under strict connectivity constraints.

Heterogeneous WSNs (HWSNs) consist of nodes with different sensing ranges, communication radii, and energy capacities. Although heterogeneity improves robustness, it also causes unbalanced energy usage and premature node failures. Therefore, energy-aware scheduling is necessary to satisfy coverage and connectivity constraints for longer durations.

Since the lifetime maximization problem is NP-hard, metaheuristic optimization techniques such as GA, PSO, ACO, and BA have been widely applied. Recently, the Marine Predators Algorithm (MPA) has shown strong performance due to its balanced exploration and exploitation capability [24]. Motivated by this, this paper proposes an MPA-based Maximum Disjoint Connected Covers with k-Coverage approach (MPA–MDCCKC) for network lifetime enhancement in heterogeneous WSNs. The key contributions of this work include an MPA-based optimization framework, binary encoding for sensor selection, a constraint-aware fitness function, and OMNeT++ simulation-based performance evaluation against existing methods.

II. RELATED WORK

Among recent works in heterogeneous WSN optimization, Ravindranath and Maheswari [1] presented a Trapezoidal Fuzzy Membership Genetic Algorithm (TFMGA) for energy and lifetime maximization under coverage constraints. This work is highly important because it effectively integrates fuzzy membership modeling with genetic optimization, enabling better handling of uncertainty in heterogeneous node parameters. The results showed significant improvement in lifetime maximization and energy efficiency. However, the TFMGA method does not explicitly focus on constructing maximum disjoint connected cover sets under k-coverage constraints, and connectivity preservation is not deeply integrated into the optimization framework.

In addition to coverage, connectivity is required to deliver sensed data to the sink. Zhang and Hou analyzed the relationship between sensing coverage and network connectivity and proved connectivity conditions under sufficient communication range [9]. Zhang et al. proposed disjoint cover set scheduling and showed that sequential activation of disjoint sets can significantly extend network lifetime [10]. However, many existing studies do not effectively address heterogeneous sensor capabilities and strict k-coverage requirements.

Energy-efficient routing and clustering protocols have also been used to enhance lifetime. HEED proposed by Younis and Fahmy selects cluster heads based on residual energy and communication cost [11]. Heinzelman et al. introduced clustering-based communication to reduce energy consumption [12], and Abbasi and Younis reviewed clustering methods for scalability and energy balancing [13]. Yu et al. proposed energy-aware routing based on TORA to reduce routing overhead [14], PEGASIS was proposed to improve lifetime using chain-based communication [17].

Since coverage optimization is NP-hard, metaheuristic algorithms such as PSO [18], ACO [19], GA [20], and BA [21] have been applied to obtain near-optimal solutions. However, these algorithms may suffer from premature convergence in large-scale deployments [22], [23]. Recently, Marine Predators Algorithm (MPA) has been introduced as an efficient metaheuristic using Brownian and Lévy movements for balanced exploration and exploitation [24]. Modern algorithms such as SMA [25], AOA [26], HGS [27], and RSA [28] further demonstrate the effectiveness of advanced optimization techniques.

From the literature, it is observed that only limited works address the combined maximum disjoint connected cover set problem under heterogeneous and k-coverage constraints. Therefore, this work proposes an MPA-based framework, called **MPA–MDCCKC**, to maximize disjoint connected covers while ensuring k-coverage and connectivity for network lifetime improvement in heterogeneous wireless sensor networks.

III. SYSTEM MODEL AND PROBLEM DEFINITION

A heterogeneous wireless sensor network (HWSN) with $n$sensor nodes is randomly deployed in a square region of interest (ROI) of size $L \times L$. A sink node $BS$is positioned at the center of the ROI for collecting sensed information. The network continuously monitors a set of $m$stationary targets. Due to heterogeneity, sensor nodes may have different sensing, communication, and energy capacities. Each sensor node is characterized by sensing radius $R_s$and communication radius R_c. A sensor node monitors a target if the Euclidean distance between the sensor and the target is within the sensing range. To ensure reliable monitoring, the network must satisfy the k-coverage condition, where each target is covered by at least $k$active sensor nodes. In addition, the selected active nodes must preserve connectivity with the sink through direct or multi-hop communication, ensuring successful data delivery.

The objective of this work is to maximize network lifetime by constructing the maximum number of disjoint connected cover sets. Each cover set must satisfy both k-coverage and sink connectivity constraints. These cover sets are activated sequentially to reduce energy consumption and extend overall network operation.

IV. PROPOSED METHODOLOGY

This section presents the proposed Marine Predators Algorithm based Maximum Disjoint Connected Covers with K-Coverage (MPA–MDCCKC) approach for maximizing network lifetime in heterogeneous wireless sensor networks. The proposed method selects optimal sensor subsets that satisfy coverage and connectivity constraints while reducing energy consumption. Since the MDCCKC problem is NP-hard, a metaheuristic optimization technique is adopted to obtain near-optimal solutions efficiently. Marine Predators Algorithm (MPA) is employed due to its balanced exploration and exploitation capability.

A. Network Model

Consider a heterogeneous wireless sensor network consisting of Nsensor nodes deployed randomly in a two-dimensional region of interest (ROI). The sensor set is:

$$S = \{s_1, s_2, \ldots, s_N\}$$

A set of Mtargets must be monitored:

$$T = \{t_1, t_2, \ldots, t_M\}$$

A sink node $BS$is assumed to be located inside or outside the ROI. Due to heterogeneity, sensor nodes have different initial energy, sensing radius $R_s(i)$, and communication radius $R_c(i)$. A sensor node $s_i$covers target $t_j$if:

$$d(s_i, t_j) \leq R_s(i)$$

Two nodes $s_i$and $s_k$can communicate if:

$$d(s_i, s_k) \leq R_c(i)$$

The communication network is modeled as an undirected graph:

$$G = (V, E)$$

where $V = S$and Erepresents communication links.

B. MDCCKC Problem Formulation

A cover set $C_k$is defined as a subset of active sensor nodes:

$$C_k \subseteq S$$

The objective is to generate a set of disjoint connected cover subsets:

$$C = \{C_1, C_2, \ldots, C_L\}$$

subject to the following constraints:

(a) Disjointness Constraint

$$C_a \cap C_b = \emptyset \forall a \neq b$$

(b) K-Coverage Constraint

$$\sum_{s_i \in C_k} \delta_{ij} \geq K \forall t_j \in T$$

where:

$$\delta_{ij} = \begin{cases} 1, & d(s_i, t_j) \le R_s(i) \\ 0, & \text{otherwise} \end{cases}$$

(c) Connectivity Constraint

All nodes in C_k must have a multi-hop path to the sink node BS.

The objective is to maximize L, the number of feasible disjoint connected cover sets, which directly increases network lifetime.

C. Energy Consumption Model

The radio energy model is used to compute energy consumption. The energy required to transmit a b-bit packet over distance d is:

$$E_{tx}(b, d) = bE_{elec} + b\epsilon d^2$$

The energy required for reception is:

$$E_{rx}(b) = bE_{elec}$$

Thus, the total energy consumed by a cover set is:

$$E_{total} = \sum_{s_i \in C_k} (E_{tx}(i) + E_{rx}(i))$$

D. Solution Encoding

Sensor selection is represented using a binary vector:

$$X = [x_1, x_2, \ldots, x_N]$$

where:

$$x_i = \begin{cases} 1, & \text{if } s_i \text{ is active} \\ 0, & \text{otherwise} \end{cases}$$

Each binary solution represents one candidate connected cover set.

E. Fitness Function

The fitness function integrates coverage, connectivity, energy usage, and routing distance. The coverage count of target t_j is computed as:

$$cov(t_j) = \sum_{i=1}^{N} x_i \, \delta_{ij}$$

The overall k-coverage satisfaction is:

$$KC = \sum_{j=1}^{M} \min(K, cov(t_j))$$

Connectivity violation is penalized using:

$$P_{conn} = \text{number of disconnected components}$$

The routing distance cost is:

$$D = \sum_{s_i \in active} d(s_i, BS)$$

The final fitness function is defined as:

$$F = w_1 \left(\frac{1}{1 + KC} \right) + w_2 \left(\frac{E_{total}}{E_{max}} \right) + w_3 \left(\frac{D}{D_{max}} \right) + w_4 (P_{conn})$$

where w_1, w_2, w_3, w_4 are weighting coefficients. The objective is to minimize F.

F. Binary Marine Predators Algorithm (BMPA)

Marine Predators Algorithm (MPA) is an optimization method that is inspired by predator and prey interact. It uses Brownian motion and Lévy flight to balance searching in the whole area and close areas. Since the MDCCKC problem is discrete, MPA is changed to Binary MPA (BMPA). The population is written as:

$$X = \{X_1, X_2, \dots, X_P\}$$

where $P$is the number of solutions, and the best solution is called Elite.

MPA performs three phases based on iteration number $Iter$and maximum iterations $MaxIter$:

Phase 1: Exploration

$$X_i^{Iter+1} = X_i^{Iter} + B \cdot (Elite - B \cdot X_i^{Iter})$$

Phase 2: Transition

$$X_i^{Iter+1} = Elite + L \cdot (Elite - X_i^{Iter})$$

Phase 3: Exploitation

$$X_i^{Iter+1} = Elite + 0.1L \cdot (Elite - X_i^{Iter})$$

where $B$and $L$are Brownian and Lévy random vectors.

G. Binary Conversion and Repair Mechanism

After position updating, continuous values are mapped into binary form using a sigmoid transfer function:

$$S(x) = \frac{1}{1 + e^{-x}}$$

$$x_i = \begin{cases} 1, & rand < S(x_i) \\ 0, & \text{otherwise} \end{cases}$$

To ensure feasibility, a repair mechanism is applied. If a target does not satisfy k-coverage, additional sensors covering that target are activated based on residual energy. If connectivity is violated, relay nodes are added until all active sensors are connected to the sink. Nodes with energy below $E_{min}$are replaced by higher-energy alternatives.

H. BMPA–MDCCKC Algorithm

The overall procedure is summarized as follows:

1. Deploy sensors, targets, and sink node.
2. Construct communication graph $G(V, E)$.
3. Initialize BMPA population randomly.
4. Evaluate fitness and select Elite solution.
5. Update solutions using MPA phases and binary conversion.
6. Apply repair mechanism for k-coverage and connectivity.
7. Update Elite until maximum iterations are reached.
8. Output best cover set, remove selected sensors, and repeat to generate disjoint cover sets.
9. Activate cover sets sequentially to maximize network lifetime.

I. Complexity Analysis

Coverage verification requires $O(NM)$operations and connectivity checking requires $O(N + E)$. Hence, the total complexity for population size $P$and $MaxIter$iterations is:

$$O(MaxIter \times P \times (NM + N + E))$$

Although computationally expensive, the proposed approach is suitable for offline scheduling and provides effective solutions for the NP-hard MDCCKC problem.

V. SIMULATION SETUP

The proposed MPA–MDCCKC approach is implemented using the OMNeT++ simulator. Sensor nodes and targets are deployed randomly in a 100 × 100 m² region of interest. The number of sensor nodes is varied from 10 to 100 to analyze performance under different node densities. The sink node is fixed at the center of the sensing field. Network lifetime is measured based on the coverage failure condition, i.e., when the network fails to satisfy the required k-coverage and connectivity constraints. The proposed method is evaluated using performance metrics such as network lifetime, energy consumption, packet delivery ratio (PDR), packet loss ratio (PLR), and success ratio. The simulation is repeated for different node densities, and all results are averaged to minimize randomness and ensure fair comparison. Data transmission is assumed to occur through multi-hop routing from selected active nodes toward the sink node.

Table 1: Simulation Parameters

Parameter	Value
Area size	100 m × 100 m
Nodes	10 to 100
Targets	25
Sink position	(50, 50)
Sensing range	25 m
Communication range	40 m
Initial energy	0.5 J
Packet size	4000 bits
Population size	30
Iterations	50
Coverage requirement	$k = 2$

VI. RESULTS AND PERFORMANCE ANALYSIS

The proposed MPA–MDCCKC method is compared with EDTC, ACO-MNCC, BFO-MDCCKC, and MBAT-MDCCKC. Simulation results demonstrate that the proposed method improves network lifetime due to effective formation of disjoint connected cover sets and balanced energy-aware scheduling. The repair mechanism ensures stable connectivity, thereby reducing packet loss and improving successful data delivery.

6.1 Network Lifetime

Table 2 shows the network lifetime comparison. The proposed method achieves the highest lifetime for all node densities due to optimal subset scheduling and reduced redundant activation.

Table 2: Network Lifetime vs Number of Nodes

Nodes	EDTC	ACO-MNCC	BFO-MDCCKC	MBAT-MDCCKC	Proposed MPA–MDCCKC
10	45	52	61	68	82
20	68	75	88	96	118
30	90	104	118	130	155
40	115	128	143	157	185
50	138	150	168	184	218
60	160	176	195	210	250
70	182	198	218	236	278
80	205	224	245	265	312
90	230	250	272	292	345
100	252	275	298	320	382

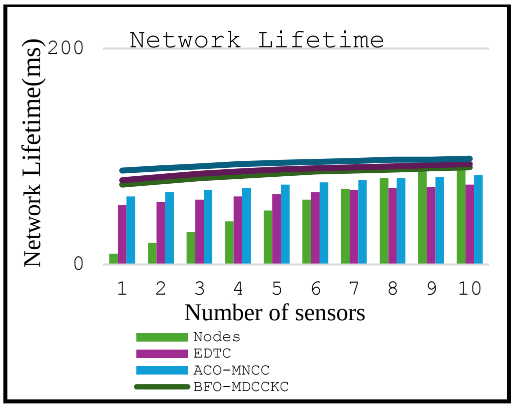

Fig. 1 shows network lifetime versus number of nodes.

6.2 Success Ratio

Table 3 presents success ratio comparison. The proposed method achieves higher success ratio due to better connectivity maintenance and efficient scheduling.

Table 3: Success Ratio vs Number of Nodes

Nodes	EDTC	ACO-MNCC	BFO-MDCCKC	MBAT-MDCCKC	Proposed MPA–MDCCKC
10	55	63	74	78	87
20	58	67	77	81	89
30	60	69	80	84	91
40	63	71	82	86	93
50	65	74	84	88	94
60	67	76	86	89	95
70	69	78	87	90	96
80	71	80	88	91	97
90	72	81	89	92	97
100	74	83	90	93	98

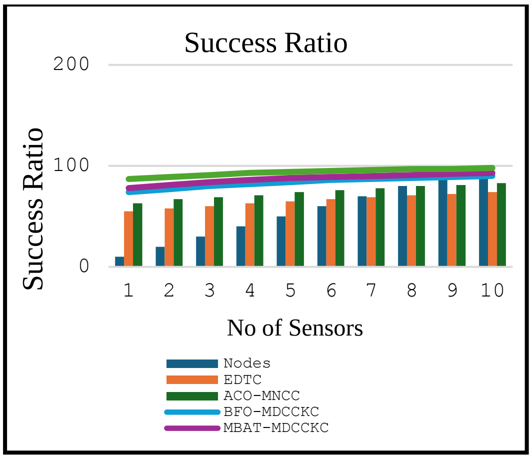

Fig. 2 illustrates success ratio comparison

6.3 Packet Loss Ratio (PLR)

Table 4 shows packet loss ratio results. The proposed method achieves lower PLR due to reliable routing and improved sink connectivity.

Table 4: PLR vs Number of Nodes

Nodes	EDTC	ACO-MNCC	BFO-MDCCKC	MBAT-MDCCKC	Proposed MPA–MDCCKC
10	45	37	26	20	13
20	42	33	23	17	11
30	40	31	20	15	9
40	37	29	18	13	8
50	35	26	16	11	7
60	33	24	14	10	6
70	31	22	13	9	5
80	29	20	12	8	4
90	28	19	11	7	3
100	26	17	10	6	2

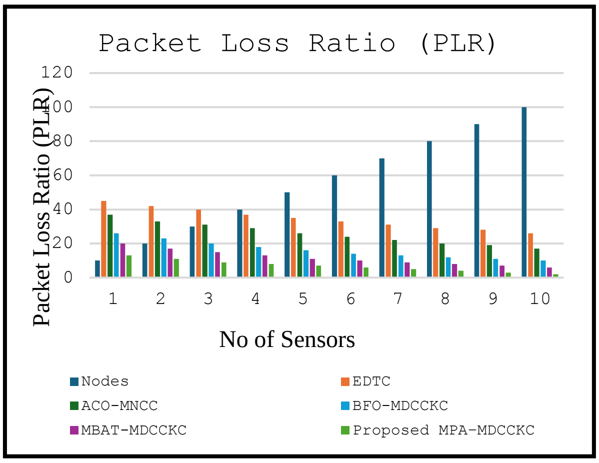

Fig. 3 presents packet loss ratio comparison.

6.4 Energy Consumption

Table 5 shows energy consumption comparison. The proposed approach consumes less energy because it activates only necessary sensors and forms optimal disjoint connected cover sets.

Table 5: Energy Consumption vs Number of Nodes

Nodes	EDTC	ACO-MNCC	BFO-MDCCKC	MBAT-MDCCKC	Proposed MPA–MDCCKC
10	0.410	0.365	0.312	0.285	0.245
20	0.489	0.440	0.390	0.350	0.305
30	0.565	0.510	0.455	0.410	0.355

40	0.640	0.582	0.520	0.470	0.410
50	0.715	0.655	0.595	0.535	0.460
60	0.792	0.728	0.670	0.605	0.520
70	0.870	0.805	0.748	0.680	0.580
80	0.945	0.880	0.825	0.755	0.645
90	1.020	0.960	0.910	0.830	0.715
100	1.105	1.040	0.980	0.900	0.785

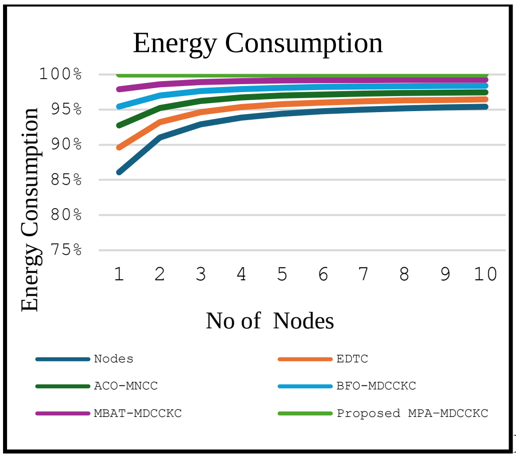

Fig. 4 shows energy consumption results.

VII. CONCLUSION

This paper proposed a Marine Predators Algorithm based Maximum Disjoint Connected Covers with K-Coverage approach (MPA–MDCCKC) for network lifetime maximization in heterogeneous wireless sensor networks. The proposed method effectively forms disjoint connected cover sets while ensuring k-coverage and sink connectivity constraints. A binary version of MPA along with a repair mechanism was applied to handle discrete sensor selection and feasibility constraints. Simulation results show that the proposed MPA–MDCCKC approach achieves higher network lifetime, lower energy consumption, reduced packet loss ratio, and improved success ratio compared to EDTC, ACO-MNCC, BFO-MDCCKC, and MBAT-MDCCKC.

VIII. FUTURE WORK

In future work, the proposed method can be extended by integrating clustering-based routing, mobile sink deployment, and multi-objective optimization to improve QoS metrics such as delay and throughput. Security-aware scheduling strategies and fault-tolerant coverage mechanisms can also be explored for robust deployment in hostile environments.

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