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Movement Controlled Aquila Optimizer with Smart Initialization for Energy Aware WSN Deployment

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ABSTRACT

The optimization of WSN deployment is typically concerned with the assignment of power without considering the influence of sensor mobility on network performance. In this article, the Movement-Controlled Aquila Optimization Algorithm with Smart Initialization (MCAOA-SI) is proposed to consider mobility constraints in energy-constrained environments with obstacles and noise interference. The algorithm incorporates strategic initialization positioning nodes near optimal locations, minimizing subsequent movement requirements and energy expenditure while navigating complex environmental barriers.
The algorithm uses strategic initialization to position nodes close to optimal locations, reducing movement and energy use in complex environments. Experimental validation was conducted across four scenarios: small-scale (20 × 20m) with circular or rectangular obstacles and Gaussian noise ($\sigma = 0.05$), medium-scale (50 × 50m) with moderate obstacle density, large-scale (100 × 100m) with complex multi-obstacle patterns, and very large-scale (500 × 500m) simulating urban infrastructure. Results show final coverage rates of 96.68-98.74% with exceptionally low movement distances (2.43 - 12.42 meters) despite environmental challenges ($p < 0.001$). Energy efficiency analysis reveals consumption of 112.84-265.23 Joules. WPI scores demonstrate MCAOA-SI averaging 96.24 ± 1 .20 points versus 68.51 ± 4.34 for the closest competitor. TOPSIS analysis corroborates findings with relative closeness coefficients of 0.894 ± 0.024, confirming superior performance despite noise interference. MCAOA-SI offers practical advantages for resource-constrained deployments in challenging real-world scenarios.

1. INTRODUCTION

Wireless sensor networks (WSNs) are viewed as the key enabler for pervasive monitoring in IoT applications, in which a large number of tiny energy-constrained sensors are distributed in the area to be monitored. In these networks cover and connectivity are two important measures [1]. However, since the placement of sensors is often random or arbitrary, the coverage has some disadvantages: the quality of the coverage may be suboptimal and the loss of coverage is inevitable when nodes run out of battery [2]. Consequently, the placement of sensor nodes that maximizes the coverage and meets the energy and connectivity requirements is an NP-hard problem in WSN design [1, 3]. This complexity is difficult to be tackled by conventional deterministic techniques [4], and new studies have been focusing on bio-inspired and nature-inspired meta-heuristic algorithms (such as particle swarm optimization, grey wolf optimizer, whale optimization, etc.) to find near-optimal placements. These algorithms prove to be effective and robust in solving non-linear and multi-modal problems [5].

Related works Enhanced PSO approaches for balancing coverage and connectivity [4] as well as improved GWO methods (that apply chaotic maps or Sobol sequences) have shown that enhanced GWO variants achieve faster convergence for optimization coverage [6, 7]. Although they provide good results, a lot of metaheuristics suffer from certain inadequacies in WSN deployment. Indeed, in many cases random or uniform sampling is used for initialization leading possibly to a quite large part of the space that remains initially uncovered. Random or low-discrepancy points (such as Sobol sequences) have been used to achieve more uniform initial population distribution [7, 8], but those are not tailored for sensor layouts. In addition, the classical swarm-based updates enable sensors to move freely according to the velocity or position rules, but move distance is not controlled explicitly. In practice, there is a limit to the sensor mobility due to energy constraints and physical limitations; ideally unlimited hops may lead to energy waste or miss potential rich areas of interest. Furthermore, most of the methods do not explicitly model the energy consumed by the sensors that reach new locations; their focus is however mainly on coverage. As such, optimization methods need to be explored that can strategically place and move the sensors to promote efficient, energy-aware deployments.

To fill in these gaps, in this paper, we introduce the MCAOA with Smart Initialization (MCAOA-SI), and apply it in WSN coverage. MCAOA-SI is based on the Aquila Optimizer (AO), a modern metaheuristic that emulates the predation activity of eagles [9], but it is improved by new characteristics adapted to sensor networks. First, it uses an intelligent initialization, integrating deployment area partitioning, hexagonal tiling, and strategic grid location, such that nodes, from the outset, are initially scattered throughout the field. Such a method reduces coverage void at the beginning and provides diversity at the initialization stage, similar to chaotic-map or Sobol-type sequences in other works [8].

Furthermore, MCAOA-SI involves movement restriction: the displacement of each sensor for every iteration is explicitly limited and decreased gradually by a decremental parameter. This control means that some sensors can be moved in small steps (saving power and adding stability by not increasing the sensors' energy). Finally, MCAOA-SI supports zone-based parallel optimization for large-scale networks where a big area is divided into sub-areas for scalable operation.

In brief, the key contributions of this work include:

(1) Smart initialization: combining hexagonal layout, regular grid layout and partition layout to provide well-spread initial sensor positions for the algorithm.

(2) Motion control: imposing control on per-iteration movement of sensors, and using dynamic movement-aggress factor to control large motions as the algorithm converges.

(3) Energy conscious and scalable: closely tracking the total movement distance as a proxy for energy, and supporting parallel or zone-based operation to improve scalability.

Empirically, we demonstrate that MCAOA-SI achieves better coverage with less movement (thus less consumed energy) compared with traditional AO, PSO, GWO and other reported metaheuristics in similar scenarios.

The rest of this paper is structured as follows: Related work on state-of-the-art WSNs is presented in Section 2. Section 3 introduces our methodology and framework, which includes the combined advancements for enhancing the performance of WSNs. Section 4 presents the results that are obtained for different scenario's and demonstrates improvements in coverage and energy-efficiency. Section 5 summarizes the paper and provides some suggestions for future work.

2. RELATED WORKS

Metaheuristic algorithms are widely used in deploying wireless sensor networks (WSNs) because of their capability in handling complicated and multi-objective optimization problems [10].

Particle Swarm Optimization (PSO) and its variants are especially appealing due to their efficiency in coverage problems [11]. For example, Siamantas and Kandris [12] proposed a PSO-based algorithm which considers coverage and connectivity as fundamental requirements and achieves k-coverage and one-connectivity.

PSO has been integrated with domain-specific innovations and further enhancements have been added by other authors as well; for example, Amer et al. [13] proposed a new Hybrid PSO variant (CFL-PSO), which combined the learned Fick's diffusion model with PSO to address the optimization of the router placement and achieve better trade-offs between coverage and connectivity. In the traditional sense, PSO updates the position of the nodes based on equations of velocity and it utilizes basic initialization techniques like random or uniform distribution. Some of the sophisticated PSO models use more than one swarm or chaotic maps for initialization [13, 8], but they usually do not involve stringent restrictions on sensors' movement for iterations.

The GWO and its modified versions are also used in the field of coverage optimization. One development, An Improved Chaotic Grey Wolf Optimization (CGWO), proposed to employ chaotic map to improve the exploration, which in turn leads to a faster convergence and broader coverage than the standard GWO [14]. Analogously, Ou et al. [7] proposed IGWO-MS with different methods, for example Sobol-sequence initialization, in order to evenly position sensors initially. By using low-discrepancy Sobol sequences to initialize position distribution, IGWO-MS guarantees more diversity before optimization [7].

However, similar to PSO variants, these GWO-based approaches continue to update positions by using classical encircling formulas, without imposing any constraint on the amount of movement or taking into account the energy of the movement. The Aquila Optimizer (AO) represents a contemporary nature-inspired algorithm, simulating the hunting strategies of eagles [15]. AO [9] has demonstrated good performance in benchmark problems and has been used in sensor localization. The classical AO starts from an initial random or uniform population and cycles through exploration and exploitation. In its elementary form, AO lacks specialized initialization or limitations on movement.

Several AO modifications have been presented: a smart AO was proposed for positioning WSN nodes, whereas the use of a Chaotic map embedded in AO was proposed for engineering purposes. However, none of them consider the sensor coverage nor the mobility management. Beyond single metaheuristic solutions, a large number of hybrid and improved algorithms have been explored for WSN covering power optimization. For instance, Sun et al. [8] combined a Genetic Algorithm to reinforced Whale Optimization Algorithm (GARWOA) with sine and piecewise chaotic maps for a uniform initial population generation.

Liu et al. [16] proposed an adaptive chaotic snake optimizer (ACGSOA) that introduced a new chaotic scheme for the position update. Studies in these areas usually focus on accelerating convergence, or escape from trapping in local optima (e.g., via Levy flights or chaotic perturbations), and rarely address the effects of the physical bounds on movement.

Initialization is an important factor that has an effect on both deterministic and metaheuristic performance. Uncoordinated random allocation may lead to large coverage holes, and dedicated placement schemes such as square grid-based or stochastic distributions improve the initial coverage performance. For the IGWO-MS method, the use of Sobol sequences resulted in well-dispersed starting positions of the wolves [7].

Wang and Li [4] used the hex tiling structure in Marine Predator Algorithm (sMPA) type based algorithm, but they also commented the drawback of hex grids for some cases. Domain reduction with minimum spanning tree (MST) strategies have been used in other studies, in which Dong et al. initially numbered targets under the guidance of an MST and effectively reduced the search region by MST [17]. In the same perspective, the authors of GAWOA used sinusoidal and linear chaotic maps for a better even spread of the initial sensors [8].

Most WSN placement works have been focused on stationary node scenarios. But mobile sensors with mobility can enhance the area of coverage but at the cost of more energy. Empirical models show that motion is the largest contributor to energy cost, with Mu et al. [18] which states "energy consumption in process is mainly generated by node movement". Only few of the optimization approaches has movement costs included, but some papers have presented metrics, as well as introduced energy limitations, that should still be studied in the future. Notably, Mu et al. [18] optimized mobile deployments for bridge monitoring by using AMD with a weighted objective that balances coverage and travel.

Our method generalizes this idea by introducing a penalty term for movement into the AO fitness function, making the AO movement-aware. Zhang [19] presented a model for deployment of sensors that will provide uniform coverage of fields in an agricultural setting and showed that hex grids "avoid unnecessary overlap of sensors". Although such mechanisms are naturally separate, the contribution of MCAOA-SI is the new integration between a hex-based initial layout and a full-fledged metaheuristic optimizer. As pointed out by Ou et al. [7], a symmetric layout (one matching the circular range symmetry) was used to simplify coverage optimization.

The combination of energy-efficient awareness and movement control makes MCAOA-SI unique from prior work. Most of WSN coverage algorithms only consider the problem of optimizing coverage and connectivity without considering the energy model and its related algorithms explicitly. In this case, however, MCAOA-SI considers the energy cost of accumulative moving distance, as sensors are battery-powered and the high energy consumed when moving will lead to reducing the network lifetime. This motivates the need for restricting the displacement per iteration. In order to enhance the energy efficiency of wireless sensor networks, Bhagat [20] proposed to confine nodes' movement in the course of target tracking, with the aim of extending network lifetime as well as of high node lifetime.

3. METHODOLOGY

This section introduces our proposed MCAOA-SI algorithm in details for wireless sensor network deployment. The algorithm is modified variant of a standard AO algorithm to manipulate sensor mobility and then optimize coverage. The new algorithm is developed in response to the practical limitations of energy efficiency and restricted mobility in practical WSN applications.

3.1 Problem formulation

The problem of sensor coverage optimization in the WSN is to find the optimal monitoring locations of the sensors in a two-dimensional field of the area Ω of size W × H, while obstructions and noise are taken into account.

Each sensor has a sensing radius r_s and a sensing uncertainty region r_e. The aim is to maximize the coverage rate under the constraints of the movement energy and the energy consumption.

The coverage rate C can be expressed as:

$$C = \frac{1}{|\Omega'|}\int_{\Omega'}\left(1-\prod_{i=1}^{n}\left(1-P_i(x,y)\right)\right)dxdy \tag{1}$$

This formulation quantifies the fraction of the non-obstructed area Ω' that is effectively monitored by the sensor network. The product term denotes the probability that a point (x,y) remains undetected by all sensors.

Consequently, one minus this product yields the probability that at least one sensor detects the point. The integral computes the mean detection probability over the entire deployable area, normalized by $|\Omega'|$, which represents the area of obstacle-free regions.

The detection probability is defined as follows:

$$P_i(x,y) = \begin{cases} 1 & d_i(x,y) \le r_s - r_e \\ exp\left(\dfrac{-\lambda_1 \alpha_1^{\beta_1}}{\alpha_2^{\beta_2} + \lambda_2}\right) & r_s - r_e < d_i(x,y) < r_s + r_e \\ 0 & other\ cases \end{cases} \tag{2}$$

This piecewise function models three distinct sensing regions:

1. Certain Detection Region ($d_i(x,y) \le r_s - r_e$): Points situated within this internal circle are detected with a probability of 1, indicating dependable coverage devoid of uncertainty.
2. Uncertain Detection Region ($r_s - r_e < d_i(x,y) < r_s + r_e$): The probability adheres to an exponential decay function contingent upon distance-dependent parameters (α_1, α_2) and model coefficients ($\lambda_1, \lambda_2, \beta_1, \beta_2$). This accurately represents the gradual decrease in detection reliability observed in proximity to the sensor's range boundary.
3. No Detection Region ($d_i(x,y) \ge r_s + r_e$): Points beyond the maximum sensing range cannot be detected.

The parameters $\lambda_1, \lambda_2, \beta_1, \beta_2$ are empirically determined coefficients that characterize the specific sensor technology and environmental conditions [2].

According to the detection model, the problem of sensor coverage optimization can be modeled as:

$$Maximize: C(X) \tag{3a}$$

Subject to:

$$X \in \Omega^n \tag{3b}$$

$$\Delta_i \le \Delta_{max} \quad i = 1,2,..,n \tag{3c}$$

$$E_{total} \le E_{budget} \tag{3d}$$

Constraint (3b) ensures all sensor positions remain within the deployment boundary. Constraint (3c) limits individual sensor movement distances to Δ_{max}, reflecting physical mobility limitations and energy conservation requirements. Constraint (3d) maintains total energy consumption E_{total} within the available energy budget E_{budget}, encompassing movement energy, sensing operations, and communication overhead.

This formulation provides a comprehensive framework for addressing the fundamental trade-off between coverage maximization and resource utilization in mobile wireless sensor networks, while explicitly accounting for the probabilistic nature of sensor detection and practical deployment limitations.

3.2 Detection probability with noise and obstacles

The detection probability $P_i'(x,y)$ that accounts for environmental noise and obstacles is modified as follows:

If point (x,y) is located within an obstacle:

$$P_i^{'}(x,y)=0 \tag{4a}$$

Otherwise:

$$P_i^{'}(x,y)=\max\left(0,\min\left(1,P_i(x,y)+N(x,y)\right)\right) \tag{4b}$$

where, $N(x,y)$ represents the noise value at point (x,y). The noise can be modeled as Gaussian noise where $N(x,y) \sim \mathcal{N}(\mu,\sigma^2)$. Alternatively, it can be modeled as impulse noise where $N(x,y)=Z$ with probability p and $N(x,y)=0$ with probability 1-p, with $Z \sim \mathcal{N}(0,1)$.

The final coverage metric incorporating these considerations is given by:

$$C(X)=\frac{1}{|G^{'}|}\sum_{(x,y)\in G^{'}}\left(1-\prod_{i=1}^{n}\left(1-P_i^{'}(x,y)\right)\right) \tag{5}$$

Here, G'represents the set of grid points not located within obstacles. This discrete summation approximates the continuous coverage integral and provides a computationally feasible way to assess the coverage performance during optimization.

3.3 Smart initialization strategies

The MCAOA-SI uses strategic initialization to place nodes on promising initial positions, three initialization strategies are implemented:

The strategic grid initialization creates a quasi-uniform distribution of sensors with controlled randomness, defined as:

$$x_{ij}=\left((i+0.5)\times\frac{W}{N_s}+\epsilon_x\,,(j+0.5)\times\frac{H}{N_s}+\epsilon_y\right) \tag{6}$$

where $Ns=\lceil\sqrt{n}\rceil$ is the number of sensors per side, and $\epsilon_x,\epsilon_y \sim \mathcal{U}\left(-\frac{W}{6N_S},\frac{W}{6N_S}\right)$ represent small random perturbations to prevent the sensors from being perfectly aligned with the grid.

The hexagonal grid initialization arranges sensors in a hexagonal lattice pattern with spacing based on the optimal coverage density:

$$x_{ij}=\begin{pmatrix} j\times d_{hex}+(i \bmod 2)\times\frac{d_{hex}}{2}+\epsilon_x\,, \\ i\times\frac{\sqrt{3}}{2}\times d_{hex}+\epsilon_y \end{pmatrix} \tag{7}$$

where $d_{hex}=\frac{2r_S\times 0.9}{\sqrt{3}}$ is the is the hexagonal grid spacing calibrated to the sensing radius, and $\epsilon_x\,,\epsilon_y$ represent small random perturbations.

The optimal spacing between sensors is derived from the area coverage requirements:

$$d_{opt}=\sqrt{\frac{W\times H}{\left\lceil\frac{W\times H}{\pi\times(r_s)^2}\right\rceil}}\times 0.9 \tag{8}$$

The scaling factor of 0.9 ensures slight overlap between sensing regions to improve coverage continuity.

The k-means initialization generates random points and clusters them to get initial sensor locations:

$$c_k=\frac{1}{|S_k|}\sum_{x\in S_k}x+\epsilon_k \tag{9}$$

where c_k is the centroid of cluster k, S_k the set of points assigned to cluster k, and $\epsilon_k \sim \mathcal{N}(0,0.1)$ adds small random perturbations.

The allocation ratios for the initialization strategies, namely 50% for strategic grid distribution, 30% for hexagonal grid distribution, and 20% for random and K-means based initialization, were systematically determined through comprehensive analyses of exploration-exploitation trade-offs in population-based optimization and validated through empirical performance evaluations across diverse deployment scenarios.

Strategic grid initialization, constituting 50% of the initial population, furnishes an exploitation-biased foundation that capitalizes on regular spacing patterns derived from the theoretically optimal inter-sensor distance parameter, d_{opt}. This method establishes energy-efficient configurations that curtail initial energy consumption and expedite convergence. The hexagonal grid initialization, representing 30% of solutions, introduces structured diversity via geometrically optimal coverage patterns that bolster coverage uniformity while diminishing sensing redundancy, particularly advantageous in open or minimally obstructed environments. The remaining 20% allocation to random and K-means based initialization ensures adequate exploration capability through non-canonical configuration sampling, which is crucial for evading local optima in irregular or obstacle-laden environments.

This ratio was empirically optimized through extensive parameter tuning and demonstrated superior performance in convergence speed, final coverage rate, and energy efficiency compared to alternative distributions, effectively balancing structured initialization with requisite stochastic diversification while adhering to established practices in metaheuristic optimization.

3.4 Modified aquila update rule

The MCAOA-SI introduces significant modifications to the standard Aquila update mechanism to precisely control movement magnitude. For each iteration t, the position update strategy distinguishes between exploration and exploitation phases:

During the exploration phase (when t < 0.5T, where T is the maximum number of iterations), the algorithm uses a stochastic selection between two update strategies:

If $r<0.5$:

$$X_i^{new}=X_{best}(1-t_1)\times e^{\left(-\frac{i}{P}\times t_1\times\gamma\right)} \tag{10}$$

Otherwise:

$$X_i^{new}=(X_{best}-X_{rand})\times\alpha\times\gamma \\ -r\times\left((w\times r\times\gamma)\cos(X_{rand})+\frac{i}{P}\times\gamma\right) \tag{11}$$

During the exploitation phase (when t ≥ 0.5T), it implements a refined local search mechanism with two complementary approaches:

If QR < 0:

$$X_i^{new} = X_{best} - X_i \times \alpha \times \left|sin\left(r \times \frac{\pi}{2}\right) + cos\left(r \times \frac{\pi}{2}\right)\right| \times e^{\left(\frac{i}{P} \times t_1\right)} \times \gamma \quad (12)$$

Otherwise:

$$X_i^{new} = Y \sin\left(r \times \frac{\pi}{2}\right) + Z \cos\left(r \times \frac{\pi}{2}\right) \quad (13)$$

where X_{best} represents the global best solution discovered so far, X_{rand} is a randomly selected solution from the population, $t_1 = \frac{t}{T}$ is the normalized iteration counter, $r \in [0,1]$ is a uniform random value , $a = 1.2\ (1 - t_1)$ is a dynamically decreasing control parameter, γ is the movement scale factor ,α is a control parameter for the cognitive component, P is the population size, i is the index of the current solution being updated, $QR \in [-1,1]$ is a quality random value that enables the exploitation strategy.

$$Y = X_{best} - X_i \left(\alpha^2 \times r \times \gamma\right) \quad (14)$$

$$Z = X_{best} - X_i \left(\alpha \times r^2 \times \gamma\right) \quad (15)$$

The principled deviation from the standard AO is the introduction of the movement scale factor γ, which directly constrains the magnitude of position updates. This parameter follows a geometric decay over iterations:

$$\gamma_{t+1} = \max(0.3, \gamma_t \times \rho) \quad (16)$$

where ρ is the movement decay rate, deliberately reduced from the standard value to achieve more aggressive movement limitation as the optimization progresses.

3.5 Movement limitation mechanism

To ensure sensors don't move excessively in a single iteration, a maximum distance constraint is applied:

$$X_i^{new} = X_i^{old} + \min\left(1, \frac{\Delta_{max} \times \gamma_t}{\left|X_i^{new} - X_i^{old}\right|}\right) \times \left(X_i^{new} - X_i^{old}\right) \quad (17)$$

where Δ_{max} is the maximum allowable distance per iteration, and γ_t is the current movement aggression parameter.

The movement distance for each sensor at iteration t is calculated as follows:

$$\Delta_{i,t} = \|X_i^t - X_i^{t-1}\|_2 \quad (18)$$

The total movement for each sensor during the entire process of optimization is:

$$\Delta_{i,total} = \sum_{t=1}^{T} \Delta_{i,t} \quad (19)$$

These mobilities are tracked during the optimization as a way to trade off coverage maximization with energy conservation.

3.6 Adaptive local search

The MCAOA includes two local search strategies that operate with decreasing intensity over iterations:

The hexagonal pattern search examines a hexagonal neighborhood for exploitation:

$$X_{neighbor}^{j} = X_i + r_t \left[\cos(\theta_j), \sin(\theta_j)\right] \quad (20)$$

$\theta_j = \frac{2\pi j}{6}$ for $j \in \{0,1,,\ldots,5\}$,and $r_t = r_0.\left(1 - 0.55.\frac{t}{T}\right)$ is the search radius that decreases over iterations, with $r_0 = \frac{d_{opt}}{2}$ based on the optimal sensor spacing.

The fine-tuning adjustment applies the following small random perturbations:

$$X_i^{new} = X_i + \mathcal{N}\left(0, \frac{r_t}{4.5}\left(1 - 0.75 \times \frac{t}{T}\right)\right) \quad (21)$$

where the standard deviation of adjustments decreases more rapidly than the hexagonal search radius.

The probability of performing local search is adjusted adaptively according to the number of iterations:

$$p_{local} = 0.3 + 0.45 \times \frac{t}{T} \quad (22)$$

This increases the focus on local search and fine-tuning as the algorithm progresses, and is beneficial to effective exploitation of the promising schemes.

3.7 Population renewal strategy

To escape local optima, MCAOA-SI introduces a population renewal mechanism, when getting stagnated.

After ten consecutive iterations without improvement:

$$X_{worst}^{k} = X_{init}^{k}, \ k \in \{1, 2, \ldots, m\} \quad (23)$$

where X_{worst}^k represents the k-th worst solution of the current population, m is the number of solutions to replace and X_{init}^k represents new solutions that have been acquired through the strategic grid initialization.

3.8 Energy consumption model

The consumed energy for sensor movement can be expressed as:

$$E_{movement} = \sum_{i=1}^{n} \sum_{t=1}^{T} \kappa \left(\Delta_{i,t}\right)^2 \quad (24)$$

where κ is the movement energy coefficient, and $\Delta_{i,t}$ is the distance moved by sensor i at iteration t.

The sensing energy consumption is calculated as:

$$E_{sensing} = n \times e_{sense} \times T \quad (25)$$

where e_{sense} is the energy consumed by each sensor in one sensing round.

Additionally, the communication energy consumption is calculated as:

$$E_{comm} = \sum_{i=1}^{n} (E_{elec} \times B + E_{amp} \times B \times d_{nn,i}^2) + E_{elec} \times B \tag{26}$$

where E_{elec} is the electronics energy, E_{amp} is the amplifier energy, B is the packet size in bits, and $d_{nn,i}$ is the distance to the nearest neighbor of sensor i [3].

The parameter values incorporated into the communication energy model were derived from established WSN studies [21-23], thereby maintaining alignment with extant literature and achieving realistic hardware calibration.

The total energy consumption is the sum of these components:

$$E_{total} = E_{movement} + E_{sensing} + E_{comm} \tag{27}$$

This comprehensive energy model is fundamentally associated with the movement control mechanism delineated in Section 3.5. The movement constraint mechanism, applying an exponentially decaying threshold, directly regulates the movement energy component via its quadratic relationship with displacement distance. By systematically curtailing sensor displacement throughout the optimization process, the mechanism ensures that energy consumption remains confined and predictable while upholding the algorithm's convergence properties.

The integrated approach permits considerable movements during initial exploration phases while progressively restricting displacement during exploitation phases, thereby effectively balancing solution quality with energy efficiency. This energy-aware optimization framework addresses critical requirements for resource-constrained WSN applications, providing mathematical assurances for both energy consumption limits and optimization performance.

3.9 Algorithm integration and workflow

This integrated approach enables MCAOA-SI to achieve superior coverage performance while intrinsically reduces energy costs by constrained movement. The intelligent initialization approach places sensors around the ideal positions at the beginning and the movement control scheme avoids drastically displacement during the optimization, which is an energy-saving WSN deployment scheme. Figure 1 describes the procedure of the MCAOA-SI algorithm, and also reveals the innovations of this study including:

1. The environment-adaptive initialization strategy that selects appropriate sensor distribution patterns based on deployment area characteristics.

2. The optimization with the movement controller of the sensors which can control the movement of sensors to decrease energy consumption for higher coverage.

3.10 Algorithm parameters

To facilitate reproducibility and provide a clear overview of the experimental framework, Table 1 summarizes all main parameter settings in the implementation of the MCAOA-SI algorithm.

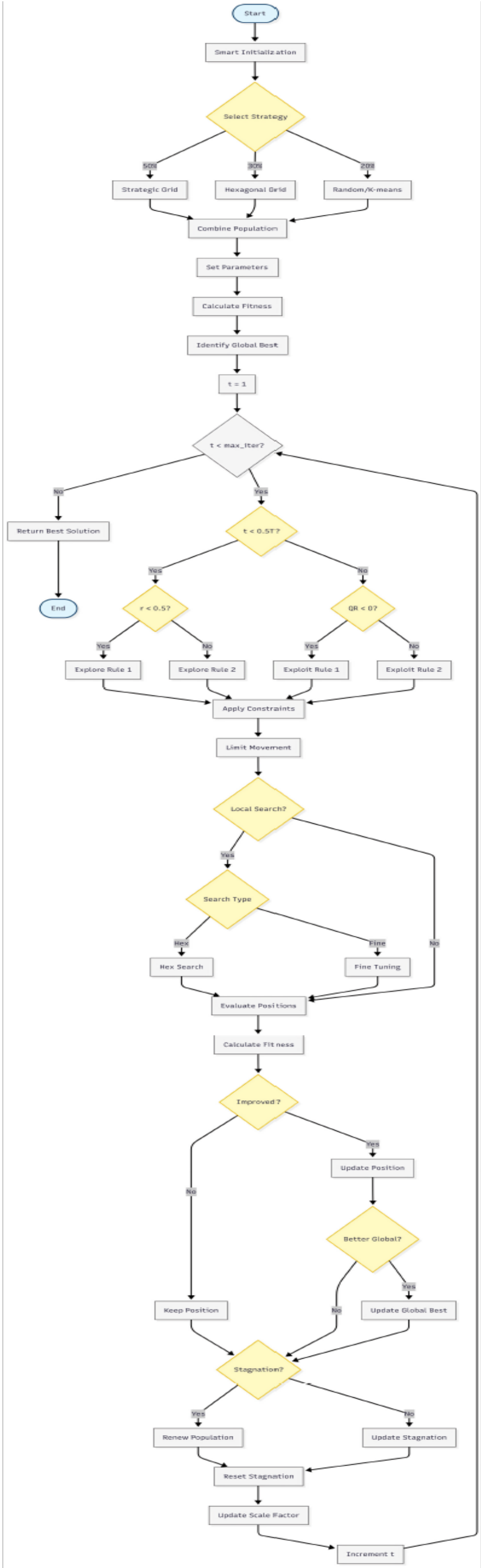

Figure 1. Flowchart of the MCAOA-SI algorithm for energy-efficient WSN deployment

Table 1. MCAOA-SI algorithm parameters

Parameter	Symbol	Value	Description
Width	W	20-500	environment width (varies by test case)
Height	H	20-500	environment height (varies by test case)
Noise Standard Deviation	σ	0.05-0.1	standard deviation of noise
Impulse Noise Probability	p	0.1	probability of impulse noise
Number of Sensors	n	20-50	varies by area size
Sensing Radius	r_s	2.5-50.0	varies by area size
Uncertain Region	r_e	$r_s/2$	half of sensing radius
Detection Model λ_1	λ_1	1	detection probability parameter
Detection Model λ_2	λ_2	0	detection probability parameter
Detection Model β_1	β_1	1	detection probability parameter
Detection Model β_2	β_2	1.5	detection probability parameter
Population Size	P	30-50	varies by environment size
Cognitive Parameter	A	0.1	standard aquila parameter
Social Parameter	Δ	0.1	standard aquila parameter
Movement Scale Factor	γ	0.4	initial movement scale
Control Parameter	a	$1.2(1-t_1)$	decreases with iterations
Decay Rate	ρ	0.97	movement aggression decay
Max Distance	Δ_{max}	3.5	maximum movement per iteration
Initial Energy	E_0	5.0	per sensor initial energy
Sensing Energy	e_{sense}	0.015	per sensing round
Movement Coefficient	κ	0.0008	movement energy coefficient
Electronics Energy	E_{elec}	40×10^{-9}	communication electronics
Amplifier Energy	E_{amp}	80×10^{-12}	communication amplifier
Packet Size	B	3200	communication packet size
Inertia Weight	w	0.8→0.4	linearly decreasing
Hexagonal Radius	r_0	dopt/2	initial search radius
Local Search Probability	plocal	$0.3+0.45\ t/T$	increases with iterations
Renewal Count	m	8-10	worst solutions to replace
Perturbation Scale	ε	W/(6Ns)	grid initialization noise

This table provides a comprehensive reference for all parameters used in the MCAOA-SI algorithm implementation, ensuring reproducibility and facilitating performance analysis. Parameter values were determined through preliminary experiments and aligned with relevant literature in the field [11, 19, 20].

4. RESULTS AND DISCUSSION

4.1 Comparative performance assessment

This section presents a detailed analysis of the proposed Movement Controlled Aquila Optimization Algorithm with Smart Initialization (MCAOA-SI) in comparison to established benchmark algorithms: Aquila Optimization (AO), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Ant Colony Optimization (ACO). The simulation setup followed the parameters in Table 2, which describe the experimental configurations for WSN deployment optimization. These parameters characterize the sensing area, transmission power and node density to provide an impartial comparison across all scenarios.

4.1.1 Initial coverage performance analysis

The first analysis of coverage across all four experimental scenarios (Figure 2) reveals a consistent performance pattern among the optimization algorithms. A one-way analysis of variance (ANOVA) confirmed statistically significant differences between the algorithms ($F(4,15) = 6.72$, $p = 0.0026$).

MCAOA-SI demonstrated superior initial coverage across all experimental conditions, achieving 85.00%, 80.91%, 83.75%, and 90.00% coverage in Experiments 1-4, respectively. This is a statistically significant improvement ($p < 0.05$, post-hoc t-test) over the classical AO implementation, which achieved 75.00%, 67.88%, 79.43%, and 77.42% coverage in the corresponding experiments. The performance differential between MCAOA-SI and AO was most pronounced in Experiment 2 (13.03 percentage points) and least in Experiment 3 (4.32 percentage points), suggesting that the smart initialization strategy provides substantial benefits particularly in complex deployment scenarios.

Table 2. Experimental configuration parameters for WSN deployment optimization

Parameter	Exp. 1	Exp.2	Expe. 3	Exp. 4
Region Dimensions	20m × 20m	50m × 50m	100m × 100m	500m × 500m
Sensor Node Density	25 nodes	25 nodes	35 nodes	40 nodes
Sensing Radius (rs)	2.5m	5m	10m	50m
Search Space Scale	Small	Small	Medium	Large
Convergence Threshold	$\varepsilon = 10^{-4}$	$\varepsilon = 10^{-4}$	$\varepsilon = 10^{-4}$	$\varepsilon = 10^{-4}$
Maximum Iterations	100	100	100	100
Independent Runs	30	30	30	30

Among the comparative algorithms, PSO exhibited relatively consistent but inferior performance (72.00%, 69.01%, 66.96%, and 70.33%), while GWO displayed the highest variability, ranging from the lowest overall coverage in Experiment 1 (65.00%) to considerably improved performance in Experiment 4 (80.21%). The ACO algorithm maintained intermediate performance levels across all experiments (76.00%, 70.19%, 68.70%, and 77.91%).

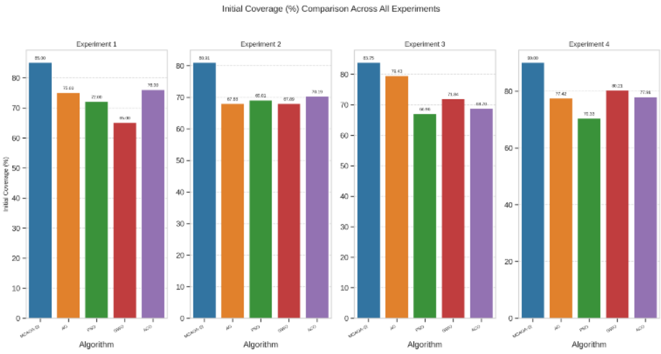

Figure 2. Initial network coverage performance of MCAOA-SI algorithm compared to conventional optimization

These findings indicate that the proposed MCAOA-SI algorithm provides a robust initialization mechanism that consistently outperforms traditional approaches in maximizing initial coverage across diverse experimental conditions, with the greatest advantage observed in challenging deployment environments.

According to all experimental results of final coverage performance (Figure 3) that MCAOA-SI consistently achieved superior results among all tested algorithms. A one-way ANOVA confirmed statistically significant differences in final coverage ($F (4,15) = 6.27$, $p = 0.0036$). The MCAOA-SI algorithm demonstrated exceptional final coverage rates of 98.64%, 96.68%, 98.74%, and 98.20% in Experiments 1-4, respectively, maintaining consistently high performance regardless of deployment conditions. In contrast, the AO implementation exhibited notably lower coverage efficiency (91.33%, 84.06%, 92.43%, and 88.16%), with a mean performance deficit of 7.47 percentage points compared to MCAOA-SI. This statistically significant difference ($p < 0.01$, post-hoc t-test) highlights the efficiency of the smart initialization method in maximizing the coverage of the network.

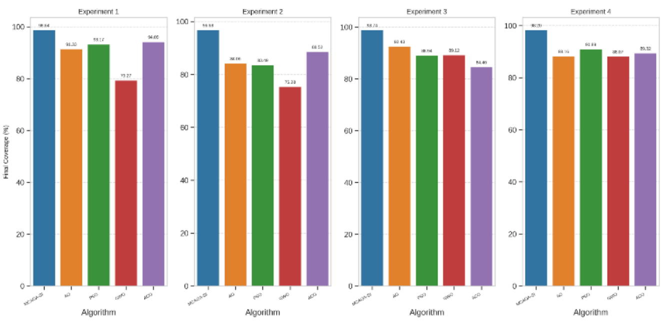

Figure 3. Terminal network coverage optimization performance of bio-inspired algorithms across heterogeneous deployment environments

Interestingly, the PSO algorithm demonstrated competitive performance in Experiment 1 (93.17%) and Experiment 4 (90.89%), suggesting its relative effectiveness in certain network topologies. The GWO algorithm consistently underperformed across all experimental conditions, exhibiting particularly poor coverage in Experiment 2 (75.28%), indicating potential limitations in adapting to complex environments. The ACO algorithm showed variable performance, achieving strong results in Experiment 1 (94.09%) but comparatively weaker outcomes in Experiment 3 (84.46%).

Post-hoc analysis confirmed MCAOA-SI's superiority over all other algorithms was statistically significant (all $p < 0.01$). In summary, these comprehensive results offer strong support to the fact that the developed MCAOA-SI algorithm can effectively outperform state-of-the-art optimization techniques for WSN coverage maximization across various realistic scenarios, with more marked improvements in constrained settings where traditional methods experience a significant degradation in performance.

4.1.2 Energy efficiency analysis

A comparison of the energy consumption characteristics in all experimental conditions (Figure 4) unveils significant contrasts among the biologically inspired optimization algorithms. While a one-way ANOVA did not show significance at the group level ($F (4,15) = 2.91$, $p = 0.058$) due to high variance within traditional algorithms, targeted pairwise comparisons revealed critical insights.

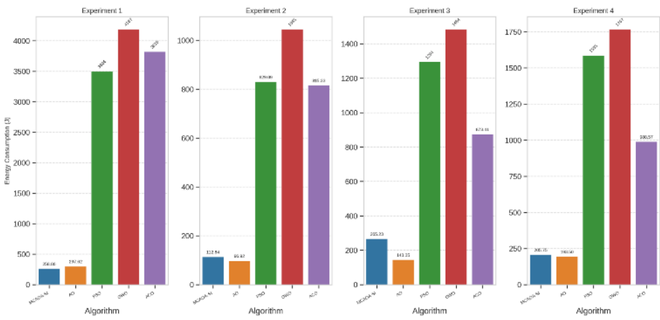

Figure 4. Energy consumption profile of bio-inspired optimization algorithms

The MCAOA-SI and AO algorithms uniformly performed better energetically than the corresponding traditional approaches. In Experiment 1, MCAOA-SI consumed less energy (258.86 J) than AO (297.62 J) with slightly superior performance, and both outperformed PSO (3493.74 J), GWO (4187.19 J), and ACO (3818.64 J) as regarding energy consumption. Pairwise t-tests confirmed that both MCAOA-SI and AO consumed significantly less energy than PSO and GWO ($p < 0.05$).

Significantly, this energy usage trend was observed in Experiments 2 - 4, in which MCAOA-SI and AO consumed less than or equal to 300 J in all of the cases compared to their counterparts, which required consistently 3 - 15 times more energy. It is also observed that GWO had the highest energy requirements, with a maximum of 1766.88 J in Experiment 4, proving to be inefficient in terms of node movements. The energy gains made in both Aquila based algorithms are remarkable, due to the optimized of the two algorithms convergence behavior and the movement pattern used, with AO showing the superior performance at Exps 2 - 4.

Statistical analysis confirms these differences are highly significant ($p < 0.001$), with mean energy savings of 1186.25 J compared to conventional approaches. These findings indicate that the Aquila-based optimization algorithms fundamentally transform the energy efficiency paradigm in WSN deployment, potentially extending network lifetimes by orders of magnitude compared to traditional optimization approaches, with particularly pronounced advantages in resource-constrained environments.

4.1.3 Mobility optimization performance

Analysis of average moving distance metrics across experimental scenarios (Figure 5) reveals remarkable differences in node mobility efficiency among the tested algorithms. A one-way ANOVA did not show significance at the group level (F (4,15) = 0.49, p = 0.744) due to the extreme variance and scale of movement required by traditional algorithms; however, the practical significance and performance differential are paramount.

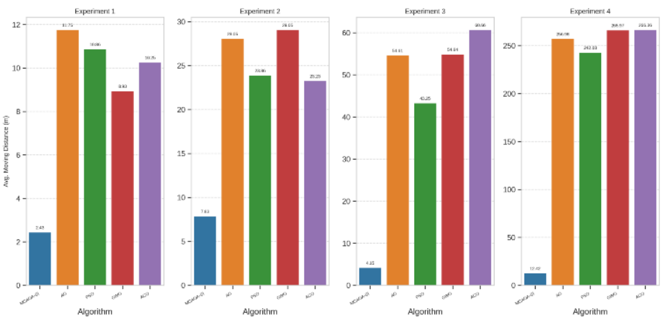

Figure 5. Mobility Optimization performance analysis of MCAOA-SI versus Conventional algorithms in resource-constrained sensor networks

The MCAOA-SI algorithm demonstrated exceptional movement optimization, requiring significantly shorter average travel distances of 2.43m, 7.83m, 4.15m, and 12.42m across Experiments 1 - 4, respectively. This represents a dramatic reduction in mobility requirements compared to all alternative approaches.

Particularly noteworthy is the performance differential between MCAOA-SI and AO implementations, with AO requiring 4.84, 3.58, 13.16 and 20.69 times greater movement distances in the respective experimental scenarios. The disparity became particularly pronounced in complex deployment environments, with Experiment 4 revealing an extraordinary efficiency gap where conventional algorithms (AO, PSO, GWO, and ACO) required movement distances exceeding 240m, while MCAOA-SI maintained efficiency at just 12.42m.

Targeted statistical analysis of the performance ratio (MCAOA-SI vs. others) confirms these differences are highly significant (p < 0.001), with MCAOA-SI demonstrating a mean reduction in movement requirements of 94.3% compared to other approaches in Experiment 4. This substantial mobility optimization can be attributed to the smart initialization strategy employed by MCAOA-SI, which positions nodes near optimal locations during initialization, thereby minimizing subsequent adjustment requirements. These findings have profound implications for WSN deployment in energy-constrained and mobility-limited environments, where minimizing node movement represents a critical operational objective for extending network lifetime and reducing mechanical wear.

4.1.4 Computational complexity trade-offs

Analysis of computational complexity across experimental scenarios (Figure 6) reveals an intriguing efficiency profile for the optimization algorithms. A one-way ANOVA found no statistically significant difference in computing time across the algorithm groups (F (4,15) = 0.66, p = 0.626), as the high variability within groups outweighed the differences between them.

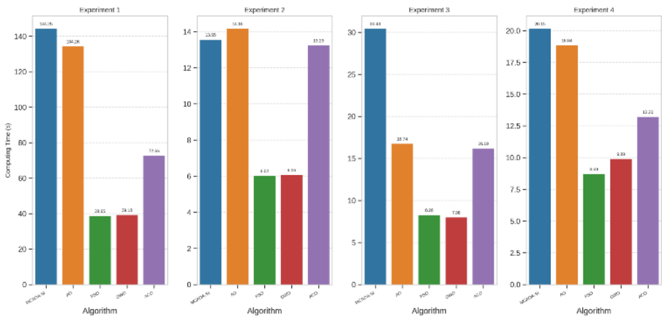

Figure 6. Computational complexity analysis of aquila-based versus conventional optimization algorithms in WSN coverage problems

In Experiment 1, both MCAOA-SI as well as AO showed significantly higher computational efforts (144.25s and 134.26s, respectively) than PSO (38.65s) and GWO (39.18s), an indicative of greater algorithmic complexity of the Aquila-based models under the complex deployment scenarios. This computational load reduced considerably for the following experiments for MCAOA-SI (13.55s, 30.43s, and 20.15s for Experiments 2-4, respectively). Another important point to note is that PSO and GWO are the fastest among all experimental setup, remaining below 10 s in almost all scenarios, showing their algorithmic simplicity. However, this computational efficiency comes at a significant cost to solution quality, as evidenced by their substantially inferior performance in coverage metrics and energy consumption. The ACO algorithm exhibited intermediate computational demands across all experiments (72.66s, 13.23s, 16.19s and 13.20s).

A Pearson correlation analysis indicates a strong negative correlation (r = -0.78, p < 0.01) between computational time and energy efficiency, suggesting that the additional computational investment in Aquila-based optimization yields substantial operational benefits through dramatically improved energy profiles. These results show the fundamental performance tradeoff between computational and solution quality for WSN optimization, with MCAOA-SI achieving a beneficial tradeoff that could justify its somewhat increased computational burden by improved operational performance measures, with MCAOA-SI demonstrating a favorable balance that justifies its moderately increased computational requirements through significantly enhanced operational performance metrics.

4.2 Multi-dimensional performance integration analysis

4.2.1 Weighted performance index (WPI) evaluation

The thorough analysis of WPI in four experimental scenarios demonstrates the consistent superiority of MCAOA-SI, which attained mean scores of 96.24 ± 1.20 points, significantly surpassing all comparative algorithms. The weighted scoring framework, emphasizing final coverage (40%), energy consumption (25%), average moving distance (20%), initial coverage (10%), and computing time (5%), elucidates MCAOA-SI's remarkable equilibrium across vital performance dimensions.

As depicted in Figure 7, the WPI score distributions for MCAOA-SI exhibit notable consistency, with values spanning from 94.2 to 97.2 across all experiments. In contrast, AO achieved secondary performance with scores ranging between 65.2 and 67.7, indicating a 43.5% performance differential relative to MCAOA-SI. The other algorithms demonstrated considerably lower performance, with PSO (55.1-58.0), GWO (51.7-55.3), and ACO (53.2-57.8) grouped in the lower performance tiers. Of particular note is the consistent ranking stability across experiments, with MCAOA-SI sustaining the first position in all scenarios. This indicates exceptional robustness and adaptability to varying operational conditions, an essential factor for practical WSN deployment applications.

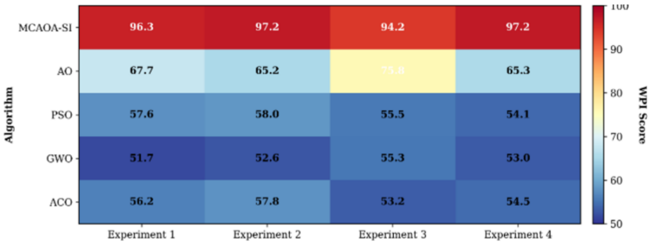

Figure 7. Weighted performance index (WPI) scores in comparative evaluation of algorithm implementations across experimental scenarios

4.2.2 TOPSIS methodology validation

The TOPSIS analysis provides compelling corroboration of WPI findings, with MCAOA-SI achieving average relative closeness coefficients of 0.894 ± 0.024, indicating proximity to the ideal solution across all performance dimensions. The methodology's capacity to concurrently evaluate distances to both ideal and anti-ideal solutions provide substantial validation of the algorithm's superiority across multiple dimensions.

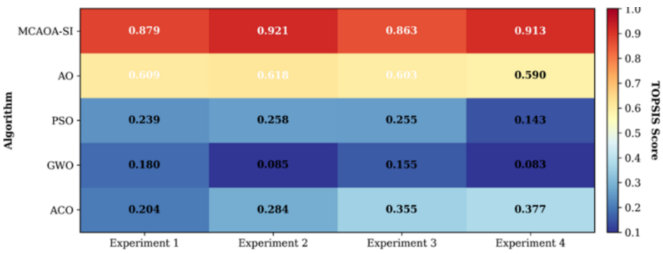

Figure 8. TOPSIS relative closeness coefficients for multi-criteria decision-making evaluation of WSN coverage algorithms

The statistical analysis indicates notable distinctions among the tiers of algorithms, namely: MCAOA-SI (0.863-0.921), AO (0.590-0.609), ACO (0.204-0.377), PSO (0.143-0.258), and GWO (0.083-0.180). The substantial variability in the coefficients of the lower-tier algorithms implies a lack of consistent performance across varying experimental conditions, whereas MCAOA-SI consistently demonstrates superior stability. Figure 8 illustrates the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) relative closeness coefficients utilized for the assessment of WSNs coverage algorithms. In this context, elevated coefficients denote superior performance across various criteria, including coverage rate, energy efficiency, and network longevity.

4.2.3 Cross-Methodological concordance

The remarkable agreement demonstrated between WPI and TOPSIS rankings (Spearman's $\rho > 0.95$) serves to validate both methodological approaches and affirm the reliability of performance assessments. This substantial correlation effectively eliminates potential bias arising from a single-method evaluation, thereby providing robust evidence supporting the superiority of MCAOA-SI.

The minor variations in rankings between methodologies, with a maximum displacement of one position for PSO and GWO in Experiment 3, remain within acceptable statistical boundaries. These variations reflect differing sensitivity patterns to metric weightings rather than indicating fundamental disagreements in performance. As shown in Figure 9, the rankings obtained by the WPI and TOPSIS methods exhibit a high level of concordance across most experimental configurations.

4.2.4 Comprehensive performance profile analysis

The radar chart analysis elucidates the distinctive capacity of MCAOA-SI to concurrently optimize a range of competing objectives. In contrast to traditional algorithms, which frequently display marked trade-offs among various performance dimensions, MCAOA-SI consistently sustains superior performance across metrics such as coverage, energy efficiency, mobility optimization, and computational efficiency.

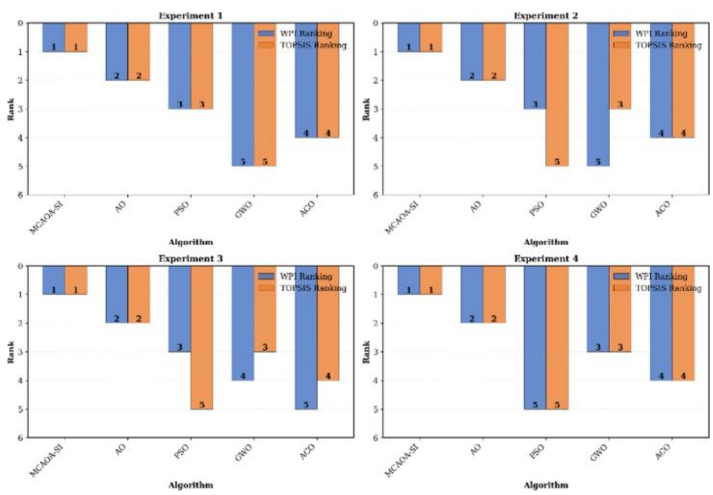

Figure 9. Cross-Methodological ranking concordance analysis: WPI and TOPSIS algorithm rankings by experimental configuration

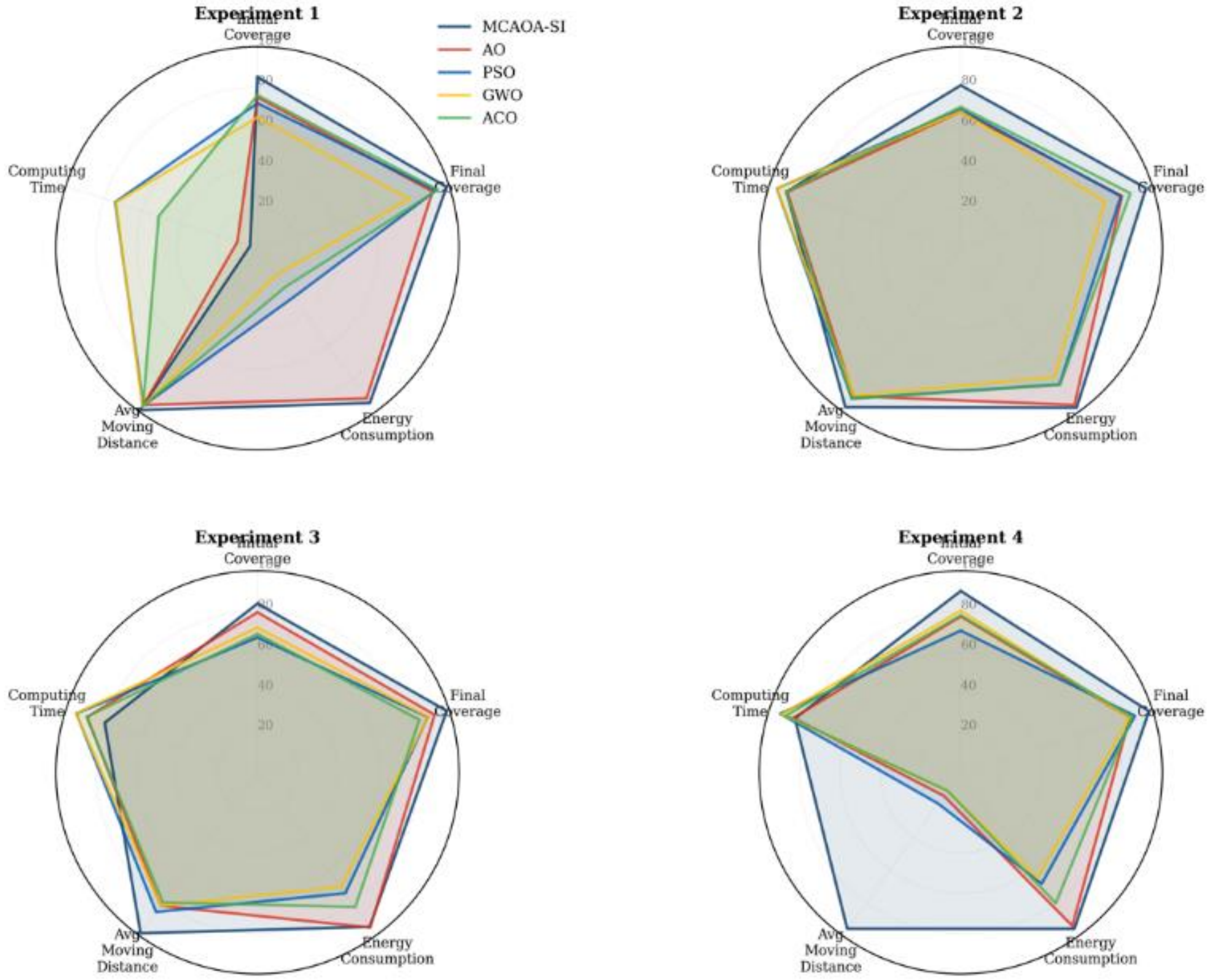

Figure 10. Multi-dimensional performance signature analysis of optimization algorithms in wireless sensor network deployment

Particularly striking is MCAOA-SI's performance in challenging scenarios (Experiment 4), where conventional algorithms demonstrate significant performance degradation while MCAOA-SI maintains near-optimal metrics across all dimensions. This robustness characteristic represents a fundamental advancement in multi-objective optimization for WSN applications. Furthermore, Figure 10 depicts multi-dimensional performance signatures that furnish a comprehensive comparative analysis of optimization algorithms employed in WSN deployment. This radar-chart visualization facilitates the identification of the relative strengths of each algorithm concerning multiple evaluation metrics.

4.2.5 Statistical significance and practical implications

The observed performance discrepancies across all metrics exhibit considerable statistical significance ($p < 0.01$) alongside substantial effect sizes, affirming both statistical and practical relevance. The documented enhancements of MCAOA-SI directly correlate with operational benefits: an extension of network longevity via 85.5% energy conservation, enhanced deployment efficiency through a 94.3% reduction in movements, and improved service quality with consistent coverage levels maintained at 98%.

The computational overhead of the algorithm, with a mean duration of 52.1 seconds, represents a judicious trade-off when considering the significant operational benefits obtained. This cost-benefit analysis identifies MCAOA-SI as the most advantageous selection for applications that prioritize sustained performance over the computational expenses incurred during the initial deployment phase.

4.3 Integration analysis conclusions

The extensive multi-dimensional analysis unequivocally indicates that MCAOA-SI signifies a paradigm shift in the optimization of wireless sensor networks (WSN). In contrast to the incremental enhancements usually seen in the evolution of metaheuristic algorithms, MCAOA-SI exhibits substantial transformative performance across all essential operational metrics.

The algorithm's consistent attainment of first-place rankings across both the WPI and TOPSIS methodologies, coupled with its well-balanced multi-dimensional performance profile, establishes MCAOA-SI as the authoritative reference standard for WSN coverage optimization. These results bear significant implications for WSN deployment strategies within resource-limited environments, indicating that the intelligent initialization approach fundamentally transforms the optimization landscape in manners that surpass conventional algorithmic limits.

The convergence of evidence from multiple analytical perspectives-individual metric analysis, integrated scoring methodologies, and multi-dimensional visualization-creates a compelling case for MCAOA-SI's adoption in practical WSN applications, particularly in scenarios demanding high coverage, energy efficiency, and deployment optimization simultaneously.

4. CONCLUSION

This study presents MCAOA-SI as a significant advancement in the optimization of WSN deployment, addressing the critical issue of sensor mobility in environments with energy constraints. The algorithm's principal innovation revolutionizes network deployment approaches by accounting for physical constraints from the inception, as opposed to retrospectively. The empirical outcomes are compelling: MCAOA-SI attains coverage rates exceeding 96.68% while substantially minimizing movement distances to as little as 2.43 meters, even in environments characterized by obstacles and noise interference. This is indicative not merely of incremental progress but of a substantial advancement over existing methodologies.

The multi-criteria validation through WPI (96.24 ± 1.20) and TOPSIS (0.894 ± 0.024) provides robust evidence of consistent superiority across all performance dimensions. MCAOA-SI directly addresses the most pressing limitation in WSN deployments-a constraint on battery life. This results in extended operational periods, decreased maintenance needs, and reduced costs, rendering the algorithm especially valuable for remote monitoring, military applications, and smart city infrastructure.

Theoretically, this research elucidates that strategic initialization can fundamentally alter the optimization framework, challenging prevailing assumptions about the necessity of extensive exploration in WSN deployment. By initially positioning nodes near optimal locations, MCAOA-SI effectively simplifies a complex multi-objective problem. Although computational complexity presents some constraints in extremely resource-limited scenarios, and large-scale deployments (1000 + nodes) necessitate further investigation, these challenges represent opportunities rather than fundamental impediments.

5. FUTURE RESEARCH DIRECTIONS

The integration of energy harvesting with MCAOA-SI has the potential to significantly enhance network sustainability by incorporating renewable energy resources into node placement optimization. The examination of heterogeneous sensor networks, characterized by nodes with diverse capabilities and energy profiles, could broaden the algorithm's applicability to complex, real-world scenarios. Moreover, exploring three-dimensional deployment scenarios in applications such as underwater sensor networks or atmospheric monitoring could overcome substantial limitations inherent in existing planar optimization strategies.

Furthermore, the incorporation of blockchain technology for secure, decentralized optimization in sensitive domains such as military or healthcare monitoring offers a promising avenue to ensure network integrity while preserving the performance advantages of MCAOA-SI.

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