

GAPSO : A Hybrid Metaheuristic Approach for the Optimized Deployment of Buried Nodes within a Wireless Underground Sensor Network

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Abstract—Wireless Underground Sensor Networks (WUSNs) are increasingly used in applications such as precision agriculture, environmental monitoring, and smart infrastructure. However, reliable communication among underground sensors is strongly affected by soil characteristics, particularly soil moisture and burial depth, making sensor deployment a challenging optimization problem. This paper proposes a soil-aware optimization framework for three-dimensional WUSN deployment using six metaheuristic algorithms: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), Artificial Bee Colony (ABC), Grey Wolf Optimizer (GWO), and a hybrid Genetic Algorithm–Particle Swarm Optimization (Hybrid-GAPSO) approach. Using a soil-dependent path loss model, the deployment problem is formulated to maximize network coverage and connectivity while minimizing energy consumption. Experimental results show that the proposed Hybrid-GAPSO algorithm achieves the highest overall fitness value of 0.833 and the highest connectivity of 38.5%, while GA achieves the highest sensing coverage. The results further demonstrate the effectiveness of Hybrid-GAPSO in producing robust deployment solutions under varying underground environmental conditions.

Index Terms—Wireless Underground Sensor Networks (WUSN), Sensor deployment, Metaheuristic optimization, Energy efficiency.

I. INTRODUCTION

Wireless Underground Sensor Networks (WUSNs) are used in applications such as precision agriculture, underground infrastructure management, and environmental monitoring. However, signal attenuation and communication unreliability are heavily influenced by the properties of the soil, especially moisture content and burial depth, which are major communication challenges in WUSNs [1].

Reliable coverage, network sensing connectivity, and low energy consumption are therefore key criteria of sensor deployment in WUSNs [2]. These objectives can conflict, since improving coverage and connectivity most likely increase communication energy. In addition, the three-dimensional deployment area and soil-dependent propagation characteristics make deployment a difficult computational problem.

This study formulates WUSN deployment as a nonlinear multi-objective optimization problem with continuous three-dimensional sensor positions, soil dependent propagation characteristics, and three objectives: coverage, connectivity, and energy. Metaheuristic optimization is used due to its ability to explore difficult search spaces and obtain high-quality solutions in a reasonable computational time. The following six representative algorithms are considered: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), Artificial Bee Colony (ABC), Grey Wolf Optimizer (GWO), and Hybrid Genetic Algorithm-Particle Swarm Optimization (Hybrid GAPSO). These algorithms provide complementary search behaviors, while Hybrid GAPSO is considered to investigate whether combining GA exploration with PSO exploitation improves deployment performance.

The proposed framework includes a soil-aware underground path-loss model, three-dimensional sensor deployment, burial-depth constraints, and a multi-objective fitness function that maximizes both coverage and network connectivity while minimizes energy consumption. Experiments are conducted under different soil moisture conditions, network configurations, and maximum burial depth. It is found that Hybrid GAPSO achieves the highest overall fitness and connectivity, while GA achieves the highest sensing coverage.

The main contributions of this paper are:

- Development of a soil-aware three-dimensional WUSN deployment framework incorporating underground path-loss and burial-depth effects.
- Formulation of a multi-objective fitness function for coverage, connectivity, and energy optimization.
- A comparative evaluation of six representative metaheuristic algorithms for soil-aware WUSN deployment optimization under a common simulation framework.
- Performance evaluation under different soil moisture and deployment conditions.

TABLE I
COMPARISON OF RELATED WORKS IN SENSOR DEPLOYMENT OPTIMIZATION

Author	Year	Method	Contribution	Metrics	Limitations
Kim & Jo	2024	Simulation	Virtual deployment optimization	Efficiency	No soil modeling
Liu et al.	2020	LSDNet (ML)	Learning-based deployment	Coverage	Needs training data
Nagendrappa et al.	2025	FFNN	Predictive maintenance	QoS	High complexity
Balivada et al.	2022	Field WUSN	Real-world validation	Soil moisture	No optimization
Sambo et al.	2017	Path loss model	Soil-aware modeling	Accuracy	No deployment
Civera et al.	2021	GA (NSGA-II)	Multi-objective optimization	Coverage	No WUSN focus
Njoya et al.	2020	GA + Greedy	Coverage + connectivity	Connectivity	No soil factors
Kennedy & Eberhart	1995	PSO	Swarm optimization	Convergence	Local optima
Yan et al.	2019	WOA	Strong exploration	Coverage	2D only
Karaboga	2007	ABC	Exploration ability	Coverage	Slow convergence
Miao et al.	2020	GWO (Enhanced)	Coverage optimization	Accuracy	No WUSN
Fauzan et al.	2025	EGWO	Power optimization	Energy	No soil modeling

II. BACKGROUND AND RELATED WORKS

WUSN performance significantly depends on underground soil conditions, such as moisture level, soil density, and burial depth, which affect signal attenuation and communication reliability. Early deployment approaches commonly used random or grid-based placement because of their simplicity, but such approaches may lead to poor network coverage and connectivity. Kim and Jo [3] conducted simulation-based deployment optimization, while learning-based approaches such as LSDNet [4] and predictive maintenance based on Feedforward Neural Network (FFNN) have also been explored. However, none of these methods directly addresses soil-aware three-dimensional deployment optimization.

Modeling of underground communication is one of the important aspects of WUSN design. Balivada et al. [5] showed the effect of soil moisture on signal loss in agricultural WUSNs, while Sambo et al. [2] developed a soil-aware path-loss under different underground conditions. Despite valuable contributions related to communication modeling, none of these studies directly optimize sensor deployment. Table I summarizes some representative studies related to WUSN communication and deployment optimization.

Metaheuristic algorithms have been widely used for complex wireless sensor deployment problems. In particular, GA provides reliable global search capabilities [6], [7], PSO offers fast convergence [8], WOA provides a complementary exploration-exploitation strategy, ABC performs adaptive neighborhood search [9], and GWO provides robust search behavior [10], [11]. These algorithms were selected because they represent different optimization strategies and allow a meaningful comparison under the same WUSN formulation. In addition, hybrid approach is developed for testing the effectiveness of combining GA's exploration and PSO's exploitation (Hybrid GAPSO). Despite the fact that all these algorithms have already been used for wireless sensor optimization, comprehensive comparisons under soil-aware three-dimensional WUSN deployment conditions remain limited.

III. PROPOSED APPROACH

The suggested framework for Wireless Underground Sensor Networks (WUSNs) is presented in this section. The objective is to investigate and compare the effectiveness of different metaheuristic algorithms to optimize underground sensor deployment while balancing sensing coverage, network connectivity, and energy consumption.

Figure 1 illustrates the entire process involved in the proposed framework. Underground environment modeling, path loss estimation, mathematical problem formulation optimization, and performance evaluation are all part of the process.

A. Problem Statement and Assumptions

This study considers the deployment optimization problem of Wireless Underground Sensor Networks (WUSNs) for precision agriculture applications. The underground environment is modeled as a three-dimensional area where sensor nodes are deployed within a maximum burial depth of 0.4 m to monitor underground targets. The position of each sensor node s_i is defined by (x_i, y_i, z_i) where x_i and y_i denote the horizontal coordinates, while z_i represents the burial depth. Similarly, each target t_j is represented by coordinates (x_j, y_j, z_j) .

The deployment objective is to determine the optimal sensor positions that maximize sensing coverage and network connectivity while minimizing energy consumption under underground channel conditions.

A candidate deployment solution is represented as:

$$X = \{(x_1, y_1, z_1), (x_2, y_2, z_2), \dots, (x_K, y_K, z_K)\} \quad (1)$$

where K denotes the total number of deployed sensors.

The optimization problem is subject to the following constraints:

- Sensor positions must remain within the deployment boundaries:

$$0 \leq x_i \leq L_w, \quad 0 \leq y_i \leq L_l, \quad 0 \leq z_i \leq Z_{max}$$

The framework assumes static targets, homogeneous sensor nodes, identical target distributions across algorithms, and a fixed soil-aware communication model throughout the simulations.

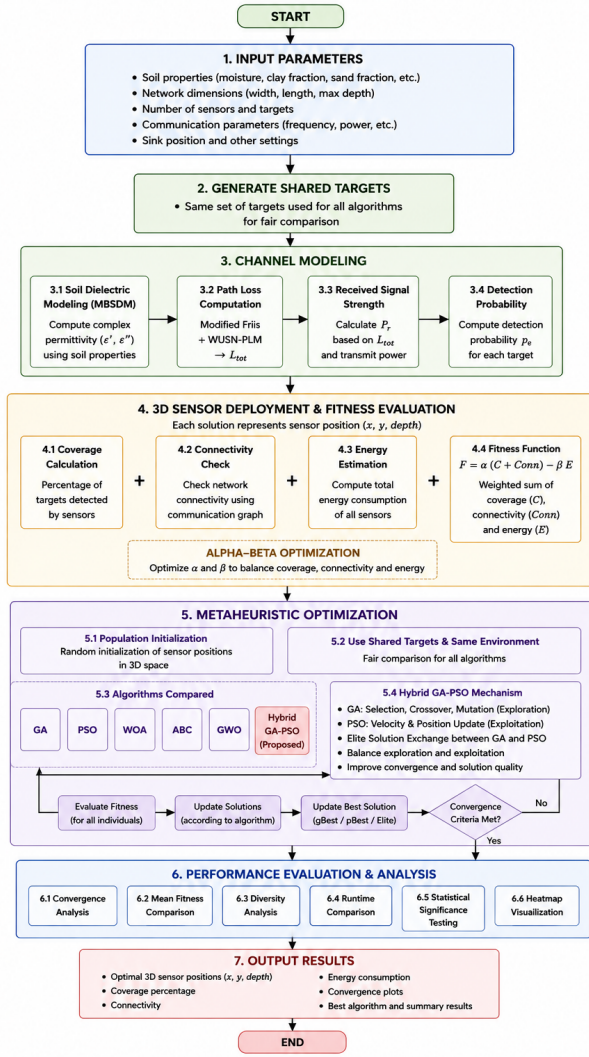


Fig. 1. Framework of the proposed WUSN deployment optimization approach

B. WUSN communication background

Underground wireless communication is strongly affected by soil characteristics, especially soil moisture, which increases signal attenuation and reduces communication reliability. In this work, the underground path loss model proposed by Sambo *et al.* [2] is adopted to model realistic underground propagation conditions. The total underground path loss (L_{tot}) is expressed as follows:

$$L_{tot} = 6.4 + 20 \log_{10}(d) + 20 \log_{10}(\beta) + 8.69\alpha d \quad (2)$$

where d represents the distance between communicating nodes, while α and β denote the attenuation and phase constants of the underground channel.

$$P_r(d) = P_t + G_t + G_r - L_{tot} \quad (3)$$

Where $P_r(d)$ denotes the received power in dBm at distance d , P_t is transmitter power, and G_t and G_r are the transmitter and receiver antenna gain, respectively.

Link Probability Function

The probability of successful signal reception between two communicating nodes is modeled using the logistic function:

$$P_{\text{success}}(d) = \frac{1}{1 + \exp(-0.5 \cdot (P_r(d) - P_{\text{sens}}))} \quad (4)$$

where:

- $P_r(d)$ is the received power at distance d (3) ;
- P_{sens} is the receiver sensitivity ($P_{\text{sens}} = -100\text{dBm}$ [2]);

This function provides a smooth transition from reliable to unreliable communication, with $P_{\text{success}} \approx 1$ when $P_r \gg P_{\text{sens}}$, and $P_{\text{success}} \approx 0$ when $P_r \ll P_{\text{sens}}$.

C. Optimization Formulation

Hybrid GAPSO combines GA exploration with PSO exploitation and is evaluated alongside the individual algorithms under identical conditions.

The same fitness function is used for all algorithms to ensure a fair comparison of their search capabilities under identical optimization objectives:

$$F(X) = \alpha \times (f_1(X) + f_2(X)) - \beta \times f_3(X) \quad (5)$$

where $f_1(x)$, $f_2(x)$, and $f_3(x)$ represent the coverage, connectivity, and normalized energy consumption objectives, respectively, while α and β control their relative weighting within the fitness function.

Coverage Maximization: Using the link probability function $P_{\text{success}}(d)$ defined in Equation (4). Let $d(s_i, t_j)$ denote the Euclidean distance between sensor s_i and target t_j . The probability that target t_j is detected by sensor s_i is:

$$p_e(s_i, t_j) = P_{\text{success}}(d(s_i, t_j)) \quad (6)$$

The overall network coverage is then:

$$\text{Coverage} = \frac{1}{N_t} \sum_{j=1}^{N_t} \max_i p_e(s_i, t_j) \quad (7)$$

where N_t denotes the total number of underground targets and $p_e(s_i, t_j)$ represents the probability that target t_j is detected by sensor s_i .

Connectivity Rate: evaluates the network's ability to transmit data from each sensor to the sink. The packet reception probability between two communicating nodes u and v is defined as:

$$\text{PRR}(u, v) = P_{\text{success}}(d(u, v)) \quad (8)$$

Where $d(u, v)$ denotes the Euclidean distance between two communicating nodes u and v .

Let P_i denote the set of all feasible communication paths connecting sensor i and the sink.

The end-to-end reliability from sensor i to the sink is:

$$R_i = \max_{\text{path} \in \mathcal{P}_i} \prod_{(u,v) \in \text{path}} \text{PRR}(u,v) \quad (9)$$

The overall network connectivity is:

$$\text{Connectivity} = \frac{1}{K} \sum_{i=1}^K R_i \times 100\% \quad (10)$$

Energy Model: Underground signals weaken significantly in wet or dense soil. Energy consumption is included as one component of the multi-objective fitness function to evaluate the trade-off between communication performance and power efficiency.

The average normalized transmission energy is computed as:

$$E_{\text{norm}} = \frac{1}{N_s} \sum_{i=1}^{N_s} \frac{bE_{\text{elec}}(1 + L_i/100)}{E_{\text{max}}} \quad (11)$$

where $b = 4000$ bits, $E_{\text{elec}} = 50$ nJ/bit, and E_{max} is the worst-case energy for normalization. This ensures $E_{\text{norm}} \in [0, 1]$.

D. Main approach

The proposed Hybrid GAPSO combines the exploration capability of GA with the fast convergence behavior of PSO to investigate whether the complementary characteristics of the two algorithms can produce deployment solutions with improved overall performance compared with the individual optimization methods. This design allows broad exploration during the early search stage and intensive refinement during the later stage.

The optimization process starts by initializing a population of candidate sensor deployments inside the three-dimensional underground area. Each candidate solution is evaluated using the fitness function based on coverage, connectivity, and energy efficiency. The hybrid algorithm operates in two sequential phases: (i) Phase 1 (60% of iterations) uses Genetic Algorithm for global exploration, (ii) Phase 2 (40% of iterations) uses Particle Swarm Optimization for local refinement.

GA applies crossover and mutation operations to generate diverse candidate solutions, while PSO updates particle velocities and positions to accelerate convergence toward promising regions of the search space. Elite solutions discovered by GA are transferred to PSO to guide swarm convergence and improve quality of the solution. Figure 2 illustrates the proposed Hybrid GAPSO optimization framework.

Algorithm 1 summarizes the proposed hybrid optimization procedure.

where $T = 1000$ is the maximum number of iterations, and the population size is $P = 100$.

The parameters used for all optimization algorithms are summarized in Table II.

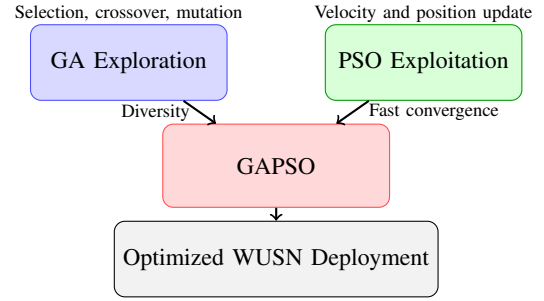


Fig. 2. Proposed GAPSO framework

Algorithm 1 GAPSO Optimization

- 1: Initialize population
- 2: Evaluate fitness
- 3: **Phase 1: GA Exploration (60% of iterations)** gen = 1 to $0.6 \times T$
- 4: Apply tournament selection
- 5: Apply uniform crossover
- 6: Apply adaptive Gaussian mutation
- 7: Evaluate fitness
- 8: Update best solution
- 9: **Transfer population to PSO**
- 10: **Phase 2: PSO Exploitation (40% of iterations)** iter = 1 to $0.4 \times T$
- 11: Update velocities and positions
- 12: Apply inertia weight $w = 0.7$
- 13: Evaluate fitness
- 14: Update personal and global best
- 15: **Return** best deployment solution

IV. EXPERIMENTATIONS AND SIMULATION

This section presents the simulation setup and experimental configuration used to evaluate the proposed framework.

A. Simulation assessment

The performance of the six algorithms was evaluated through simulations. The simulation framework incorporates key characteristics of WUSN, including 3D underground deployment, soil moisture attenuation, underground path loss, connectivity, and energy. All experiments were implemented in python and executed on a computer equipped with an Intel Core processor, 16 GB RAM, and the Ubuntu/Linux operating system. Table III summarizes the simulation parameters used throughout the experiments.

For a fair comparison of the algorithms, an equal number of population sizes and a 1000-iteration search budget were applied. Runtime results are also reported to address differences in per-iteration computational cost.

B. Evaluation metrics

Performance was evaluated using the following metrics:

Coverage: is computed using Equation (7), which calculates the average maximum detection probability of all underground targets.

Connectivity: is computed using Equation (10), which measures the communication reliability between underground sen-

TABLE II
OPTIMIZATION ALGORITHM PARAMETERS

Parameter	GA	PSO	WOA	ABC	GWO	GAPSO
Population size	100	100	100	100	100	100
Iterations	1000	1000	1000	1000	1000	1000
Crossover rate	0.8	—	—	—	—	0.8
Mutation rate	0.05	—	—	—	—	0.05
Inertia weight (w)	—	0.7	—	—	—	0.7
Acceleration coef. (c_1/c_2)	—	1.5	—	—	—	1.5
GA contribution	—	—	—	—	—	60%
PSO contribution	—	—	—	—	—	40%
Elite transfer	—	—	—	—	—	Enabled

TABLE III
SIMULATION PARAMETERS

Parameter	Value
Deployment area	$100 \times 100 \times 0.4$ m
Population size	100
Maximum iterations	1000
Number of sensors	20
Number of targets	30
Maximum burial depth	0.4 m
Soil moisture	20%
Number of runs	10
Fitness parameters	$\alpha = 0.9, \beta = 0.1$

sor nodes and the sink through the probabilistic communication model.

Energy consumption: Normalized transmission energy is calculated using Equation (11). Lower energy values indicate better energy efficiency.

C. Evaluation of fitness parameters

The first experiment focused on determining the optimal fitness weighting parameters α and β . Five weighting pairs (0.5, 0.5), (0.6, 0.4), (0.7, 0.3), (0.8, 0.2), and (0.9, 0.1) were evaluated. The pair $\alpha = 0.9$ and $\beta = 0.1$ produced the highest average fitness over the 10 independent runs and was used in subsequent experiments.

V. RESULTS AND DISCUSSIONS

The results obtained from the evaluated optimization algorithms under realistic underground communication conditions are presented in this section.

A. Optimal Hybrid Ratio Selection

To determine the optimal balance between GA exploration and PSO exploitation, the proposed Hybrid GAPSO was evaluated using four different GA/PSO iteration ratios: 50/50, 60/40, 70/30, and 80/20. Table IV summarizes the obtained results.

TABLE IV
PERFORMANCE FOR DIFFERENT GA/PSO RATIOS

GA %	PSO %	Fitness	Coverage	Connectivity
50%	50%	0.8076	57.79%	33.00%
60%	40%	0.833	55.13%	38.50%
70%	30%	0.8042	56.89%	33.50%
80%	20%	0.7930	57.14%	32.00%

Among the evaluated configurations, the 60/40 ratio achieved the highest fitness value among the tested hybrid configurations. This balance provides enough GA exploration to maintain diversity and enough PSO exploitation to refine solutions. Therefore, the 60% GA and 40% PSO ratio was selected.

B. Convergence Analysis

Figure 3 illustrates the convergence behavior of the evaluated optimization algorithms. Hybrid GAPSO achieved the highest final fitness value and showed stable convergence. GA obtained the second-highest fitness value while PSO converged rapidly but showed premature stagnation. WOA, GWO, and ABC converged more slowly to lower fitness values.

C. Impact of Soil Moisture

The results confirm that soil moisture is one of the most influential factors affecting underground wireless communication performance. As soil moisture increased, underground path loss increased, resulting in reduced communication reliability, higher energy consumption, and lower deployment fitness. Consequently, all evaluated algorithms experienced performance degradation under wetter soil conditions. These findings highlight the importance of incorporating soil characteristics into WUSN deployment optimization. The soil-moisture sensitivity analysis used a reduced simulation budget to evaluate multiple moisture levels, whereas the main algorithm comparison used 10 independent runs and 1000 iterations. Figure 4 therefore shows the relative effect of soil moisture rather than the main benchmark performance.

D. Algorithm Performance Analysis

Figure 5 compares the performance of the evaluated algorithms. Hybrid GAPSO achieved the highest overall fitness (0.833), connectivity (38.5%), and competitive coverage (55.1%), while maintaining low normalized energy consumption (0.095). GA obtained the highest coverage (55.8%) and the lowest energy consumption (0.088), making it the strongest standalone algorithm. PSO showed moderate connectivity but lower overall fitness because of premature convergence. WOA and GWO achieved intermediate performance, whereas ABC consistently produced the lowest fitness, coverage, and connectivity together with the highest energy consumption.

VI. CONCLUSION AND FUTURE DIRECTIONS

In this paper, we presented a soil-based 3D deployment framework for WUSNs using GA, PSO, WOA, ABC, GWO, and Hybrid GAPSO. The framework incorporates soil moisture, depth of burial, probabilistic connectivity, and energy consumption into a multi-objective deployment formulation. From our experimental results, Hybrid GAPSO achieved the highest overall fitness and connectivity, while GA achieved the highest sensing coverage and lowest normalized energy consumption. These results show that Hybrid GAPSO provides

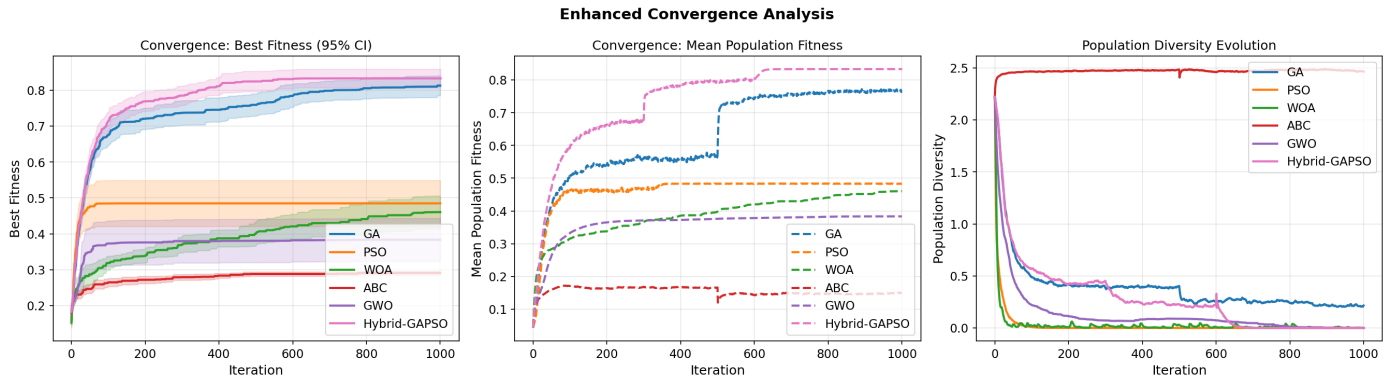


Fig. 3. Enhanced convergence analysis including best fitness evolution, mean population fitness, and population diversity.

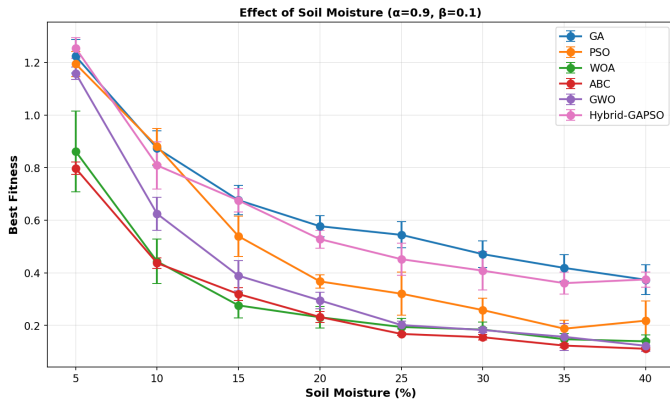


Fig. 4. Effect of soil moisture on optimization fitness performance.

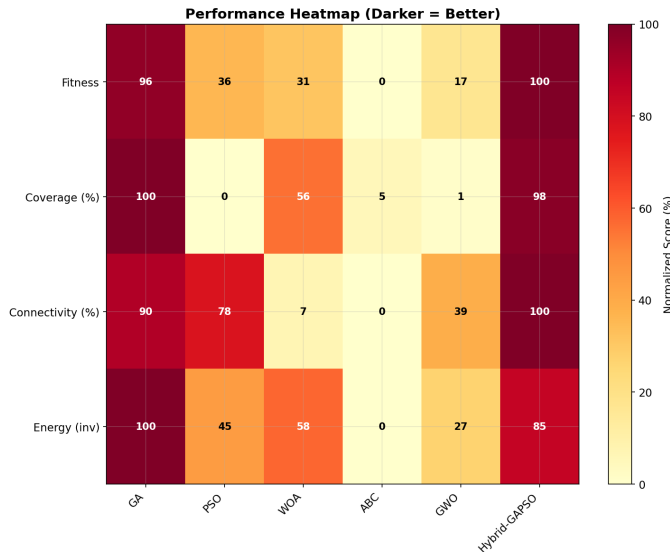


Fig. 5. Performance heatmap comparison of evaluated optimization algorithms.

the best overall compromise among the considered objectives

under the evaluated underground conditions.

Future work will focus on field validation, adaptive fitness weighting using machine learning, heterogeneous sensors, large deployment areas, time-varying soil moisture, and comparisons with exact optimization and baseline deployment strategies.

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