Journal of Information Systems Engineering and Management
2026, 11(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Risk-Aware Combinatorial Optimization for Sensor Network Deployment in Forest Fire Detection

[1]Abdelkrim Khalil Rachedi, [2]Ali KIES, [2]Mahmoud Zennaki, [1]Pr. Mustapha Benghanem

[1]*Automation, Vision and Intelligent Systems Control Laboratory A.V.C.I.S, University of Sciences and Technology of Oran Mohamed Boudiaf USTOMB, Algeria*

[2]*Computer Science Department, Faculty of Mathematics and Computer Science, University of Sciences and Technology of Oran Mohamed Boudiaf USTOMB, Algeria*

ARTICLE INFO

Received: 15 May 2026

Revised: 01 July 2026

Accepted: 10 July 2026

ABSTRACT

Introduction: Forest fires represent one of the most devastating natural hazards, causing irreversible ecological damage, economic losses, and threats to human safety. Early detection through sensor networks has emerged as a key preventive strategy. Traditional methods of fire monitoring, such as human patrols, watchtowers, or satellite imagery, often suffer from limitations related to cost, latency, and insufficient spatial coverage. Wireless Sensor Networks (WSNs) have emerged as a promising technology for environmental monitoring, thanks to their low cost, scalability, and ability to provide real-time data collection over large and complex terrains[1].Objectives: The effectiveness of such a system depends strongly on the deployment strategy of sensors. Poorly placed sensors can lead to gaps in coverage, excessive energy consumption, or reduced network lifetime. Moreover, in the context of wildfire prevention, it is not sufficient to only maximize coverage: one must also take into account the spatial distribution of fire risks across the monitored area, as some regions may be significantly more vulnerable than others. This work proposes a mathematical model and a metaheuristic-based approach for the optimal deployment of sensors in forest environments with the objective of minimizing fire risk while ensuring coverage and connectivity[2].Methods: To address these challenges, we formulate the forest fire sensor placement problem as a risk-aware combinatorial optimization model, where the objective is to minimize the number of sensors and communication overhead while maximizing coverage in high-risk zones. To solve this NP-hard problem, we propose a hybrid metaheuristic framework combining a Genetic Algorithm with Steiner tree-based repair operators and local search refinements[3]. The optimization goal is to strike a balance between minimizing the number of deployed sensors and maximizing the weighted coverage of high-risk cells. The formulated problem is NP-hard, closely related to the Set Cover Problem, the Connected Set Cover Problem, and the Facility Location Problem. As such, exact methods become impractical for large-scale instances, justifying the need for metaheuristic or hybrid optimization techniques[4].Results: Extensive simulations demonstrate that our method significantly reduces the number of sensors and communication cost compared to classical heuristics, while improving detection reliability in fire-prone regions. The experiments reveal that NSGA-II consistently provides the best solutions, improving upon the heuristic baseline by 5--10%. GA and D-PSO achieve competitive performance, while SA shows higher variance and tends to get stuck in local optima. NSGA-II not only provides the best solutions but also the most robust and stable performance across runs[5].Conclusions: The proposed framework offers a scalable and adaptive solution for next-generation wildfire early-warning systems. This study highlights the importance of realistic modeling, which accounts not only for technical constraints (detection radius, communication range, sensor budget) but also for environmental and stochastic factors (risk mapping, failures). Overall, NSGA-II emerges as the most effective algorithm for the considered problem, while GA and D-PSO serve as good alternatives when faster results are needed[6].

Keywords: Risk-aware optimization, Wireless sensor networks, Forest fire detection, Multi-objective optimization, Genetic algorithms.

Journal of Information Systems Engineering and Management
2026, 11(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

1. INTRODUCTION

Forests play a crucial role in maintaining ecological balance, preserving biodiversity, and mitigating the effects of climate change. However, in recent decades, forest ecosystems have been increasingly threatened by wildfires, which cause not only severe environmental degradation but also significant economic and social losses. Early detection and efficient prevention of wildfires are therefore of paramount importance for sustainable forest management[7].

Traditional methods of fire monitoring, such as human patrols, watchtowers, or satellite imagery, often suffer from limitations related to cost, latency, and insufficient spatial coverage. In contrast, Wireless Sensor Networks (WSNs) have emerged as a promising technology for environmental monitoring, thanks to their low cost, scalability, and ability to provide real-time data collection over large and complex terrains. Deploying a network of sensors in forest environments enables continuous monitoring of critical variables such as temperature, humidity, and smoke, which are directly linked to fire risk.

Nevertheless, the effectiveness of such a system depends strongly on the deployment strategy of sensors. Poorly placed sensors can lead to gaps in coverage, excessive energy consumption, or reduced network lifetime. Moreover, in the context of wildfire prevention, it is not sufficient to only maximize coverage: one must also take into account the spatial distribution of fire risks across the monitored area, as some regions may be significantly more vulnerable than others. This makes the deployment problem highly challenging, since it combines issues of coverage, connectivity, energy efficiency, and risk minimization, while operating under budget constraints.

To address these challenges, optimization techniques have been widely studied in the literature. Exact methods can provide optimal solutions for small-scale instances but quickly become intractable as the problem size increases. In contrast, metaheuristic algorithms such as Genetic Algorithms, Particle Swarm Optimization, or Simulated Annealing offer efficient alternatives for tackling large-scale, NP-hard optimization problems, often providing high-quality solutions within reasonable computational times.

In this work, we propose a mathematical model and a metaheuristic-based approach for the optimal deployment of sensors in forest environments with the objective of minimizing fire risk while ensuring coverage and connectivity. Our contributions can be summarized as follows:

- We formulate the forest fire monitoring problem as an optimization model integrating coverage, connectivity, and risk distribution.
- We design a metaheuristic approach capable of efficiently handling large and complex instances.
- We conduct extensive experiments on synthetic test cases to evaluate the performance of the proposed method, and compare it against classical heuristics and baseline approaches.
- We provide a multi-objective extension to analyze trade-offs between coverage maximization, risk minimization, and deployment cost.

The remainder of this paper is organized as follows. Section 2 reviews related work, followed by section 3 which presents the problem formulation and mathematical model. Section 4 describes the proposed methodology, while section 5 outlines the experimental setup and evaluation protocol. Section 6 discusses the results. Finally, section 7 concludes the paper and highlights future research directions.

2. RELATED LITERATURE

Wireless sensor networks (WSNs) have emerged as a cornerstone of distributed wildfire detection systems. Sensors measuring temperature, humidity, smoke, and gas concentration, typically powered by solar energy and deployed in a mesh topology, enable continuous forest monitoring. Field deployments and prototypes have demonstrated the feasibility of real-time early warning systems, although false alarms remain a critical challenge[8]. More recent contributions leverage machine learning on sensor data streams to reduce false positives and enhance reliability[9].

Optimal placement of sensors has long been studied under coverage and connectivity constraints. Classical formulations include set cover, connected set cover, and facility location problems, often extended with connectivity to gateways. More recent works introduced power-aware coverage models, where sensing and transmission ranges

Journal of Information Systems Engineering and Management
2026, 11(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

are decision variables, naturally leading to mixed-integer non-linear formulations. These formulations highlight trade-offs between energy cost, detection probability, and network resilience[10].

Beyond binary coverage, probabilistic sensing models such as Elfes' model have been widely adopted to capture signal attenuation, environmental noise, and uncertainty in detection. Recent studies couple these probabilistic models with fire spread simulations, linking detection probability to fire kinetics and estimating the delay before alarms. Such coupling is crucial for evaluating risk-aware sensor deployment strategies[11].

Energy consumption remains a bottleneck in WSN-based fire monitoring, as forests often lack infrastructure for recharging or replacing batteries. Energy-aware strategies combine node duty cycling, eco-efficient routing, and in-network aggregation to extend network lifetime. More recent approaches explicitly integrate latency constraints into coverage-connectivity optimization, ensuring that alarms reach base stations within acceptable delays[12]. The trade-off between maximizing lifetime and minimizing alarm latency remains an open challenge.

Given the NP-hardness of coverage and connectivity optimization, numerous metaheuristics have been explored, including particle swarm optimization (PSO), simulated annealing, genetic algorithms, and ant colony optimization. In the past five years, bio-inspired algorithms such as salp swarm, grey wolf optimizer, and predator-prey dynamics have shown competitive performance for large-scale deployments. Hybrid approaches, combining constraint repair operators (e.g., connectivity via minimum spanning tree heuristics) with local search, are increasingly reported to outperform pure metaheuristics [13].

A major trend is the integration of heterogeneous sources: ground sensors for early ignition detection, combined with high-resolution/infrared cameras, satellite-based hotspot detection, and UAVs deployed on-demand for confirmation. While these hybrid systems improve situational awareness, they highlight issues of cost, false alarms, and operational complexity---underscoring the need for optimized WSN design as a backbone layer[14].

From this literature, several gaps can be identified:

1. Risk-aware multi-objective placement: Few studies incorporate explicit wildfire risk maps (fuel, topography, wind) into optimization alongside coverage, connectivity, latency, and energy cost.
2. Probabilistic coverage linked to detection delay: The rigorous integration of probabilistic sensing models with guaranteed detection times is still underexplored.
3. Robustness and dynamic reconfiguration: Tolerance to failures (sensor loss, interference, weather) and re-optimization at the edge remain insufficiently studied.
4. Energy vs. latency trade-off: Very few works jointly optimize for energy conservation and guaranteed alarm delivery within strict deadlines.
5. Domain-guided hybrid metaheuristics: While many algorithms exist, few leverage dedicated operators (e.g., Steiner tree for connectivity, fire-risk-aware local search).
6. Realistic evaluation frameworks: Standardized simulators coupling fire propagation, WSN communication, and terrain conditions are lacking for fair comparison.

3. PROBLEM FORMULATION

The problem of wildfire surveillance is modeled as a combinatorial optimization task, where the objective is to deploy a set of sensors over a forest area in order to minimize both deployment costs and uncovered fire risks. The forest is discretized into a set of cells $\mathcal{C}$, each representing a spatial unit to be monitored. A finite set of candidate positions $\mathcal{P}$ is considered for sensor installation. Each sensor has a detection radius R, and each cell $c \in \mathcal{C}$ is associated with a risk value w_c, which may depend on vegetation density, slope, or historical fire occurrences.

3.1. Decision variables

We define the following binary decision variables:

Journal of Information Systems Engineering and Management
2026, 11(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

- A decision variable x_i indicating whether sensor is installed at position $i \in \mathcal{P}$; $x_i = 1$ if a sensor is installed at position i, 0 otherwise.
- A decision variable y_{ic} equal to 1 if cell $c \in \mathcal{C}$ is covered by sensor $i \in \mathcal{P}$, 0 otherwise. The cell is covered when the distance between sensor i and cell c is less than or equal to R. Since coverage depends only on geometry, y_{ic} can be precomputed as a parameter.

3.2. Objective Functions

The optimization goal is to strike a balance between minimizing the number of deployed sensors and maximizing the weighted coverage of high-risk cells. This trade-off is expressed as:

$$\min\left\{\alpha \sum_{i\in\mathcal{P}} x_i + \beta \sum_{c\in\mathcal{C}} w_c\left(1 - \sum_{i\in\mathcal{P}} y_{ic}x_i\right)\right\}$$

The first term penalizes the number of deployed sensors (deployment cost), while the second penalizes the risk associated with uncovered cells. The coefficients α and β are weights determined by the decision-maker.

3.3. Constraints

The optimization model is subject to the following constraints:

Coverage constraint: every cell must be covered by at least one sensor if possible:

$$\sum_{i\in\mathcal{P}} y_{ic}x_i \geq 1 \;\forall c \in \mathcal{C}$$

Budget constraint: the number of deployed sensors cannot exceed a maximum budget B:

$$\sum_{i\in\mathcal{P}} b_i x_i \leq B$$

where b_i is the cost of sensor installed at position $i \in \mathcal{P}$.

Connectivity constraint: each deployed sensor must be connected to a base station s, typically enforced through flow or spanning-tree constraints.

Energy constraint: each sensor must not exceed its maximum energy capacity:

$$E_i(x_i) \leq E_{\max} \;\forall i \in \mathcal{P}$$

Several extensions can enrich the model. First, instead of binary coverage, probabilistic detection can be used:

$$P_{ic} = e^{-\lambda d(i,c)}$$

where $d(i,c)$ is the distance between sensor i and cell c, and λ is an attenuation parameter. This probability tends to zero when $d(i,c) > R$. Thus, the probability that cell c is covered by at least one sensor becomes:

$$1 - \prod_{i\in\mathcal{P}} (1 - P_{ic}x_i)$$

Second, constraints on detection latency can be added to ensure that each cell is detected within a maximum allowed time $T_{\max}$:

$$T_c \leq T_{\max} \;\forall c \in \mathcal{C}$$

Finally, robustness can be imposed by requiring redundant coverage (e.g., at least k sensors covering each cell).

3.4. Complexity

Journal of Information Systems Engineering and Management
2026, 11(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

The formulated problem is NP-hard, closely related to the Set Cover Problem, the Connected Set Cover Problem, and the Facility Location Problem. As such, exact methods become impractical for large-scale instances, justifying the need for metaheuristic or hybrid optimization techniques.

4. PROPOSED RESOLUTION APPROACHES

The resolution approaches share a common encoding and evaluation framework. Two encodings are considered: (i) a binary representation, where each gene indicates whether a sensor is deployed at a candidate site, and (ii) a mixed representation, which includes both placement decisions and discrete coverage ranges. Candidate solutions are evaluated based on four main criteria: risk-weighted coverage, network connectivity to the sink station, latency constraints, and energy consumption. Connectivity repairs are applied using heuristic Steiner or MST constructions, while infeasible latency or coverage solutions are penalized or repaired through greedy insertions. The optimization objective is formulated either as a weighted single-objective function (combining number of sensors, uncovered risk, energy, and latency penalties) or as a multi-objective formulation solved by evolutionary methods such as NSGA-II.

To initialize the population, a strong set of feasible starting solutions is generated. A greedy risk-aware heuristic incrementally selects sensor sites covering the highest remaining risk per cost, followed by Steiner-based connectivity repair to link active components to the sink. Redundant sensors are then pruned without degrading feasibility. These heuristics also serve as baseline methods in later experiments.

The first metaheuristic, a Hybrid Genetic Algorithm (GA), is naturally suited to the binary/mixed encodings. Standard tournament selection, one-point/uniform crossover, and low-probability mutations are used. Repair operators guarantee coverage and connectivity, while a local search phase further improves elite individuals through drop-add or swap moves, emphasizing efficiency in coverage, latency, and energy. Elitism ensures that the best individuals are preserved across generations.

The second approach, a Discrete Particle Swarm Optimization (D-PSO), encodes candidate placements as binary vectors with associated velocity probabilities. Position updates are projected using adaptive thresholding, and attractors (personal/global bests) drive convergence. Domain-specific repair mechanisms are integrated to maintain feasibility, and an additional densification-reduction phase encourages more sensors in high-risk regions before pruning redundant ones.

The third method, Simulated Annealing (SA), explores neighborhoods defined by bit flips, swaps, or activation of minimal connection corridors. A geometric cooling schedule regulates the acceptance of worsening solutions, enabling the search to escape local optima imposed by coverage/connectivity constraints. SA is also hybridized as a local intensifier, starting from promising GA or PSO solutions.

Finally, for multi-objective optimization, the NSGA-II framework is employed. Objectives typically include minimizing the number of sensors, uncovered risk, energy consumption, and maximum latency. After repairing infeasible individuals, solutions are ranked using non-dominated sorting and diversity is preserved through crowding distance. The algorithm yields a Pareto front of trade-off sensor deployment strategies, enabling decision-makers to balance coverage, cost, and robustness.

Constraint handling plays a key role in all approaches. Adaptive penalties are applied when feasibility deteriorates, but domain-guided repairs are generally preferred to avoid excessive penalization. Pre-computation of coverage and detection matrices, caching of contributions, and spatial filtering techniques are used to accelerate evaluations and scale to larger forest grids. Parallelization strategies further enhance computational efficiency.

Algorithm parameters are tuned through preliminary experiments, with GA and NSGA-II using medium-sized populations and hundreds of generations, PSO employing moderate swarm sizes with adaptive inertia, and SA initialized with a temperature corresponding to roughly 50% acceptance. For benchmarking, exact mathematical models solved by CPLEX/Gurobi are applied to small instances, while greedy and Steiner heuristics serve as strong fast baselines.

Journal of Information Systems Engineering and Management
2026, 11(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

5. EXPERIMENTAL SETUP AND EVALUATION PROTOCOL

The experiments were conducted on a personal computer equipped with an Intel Core i5 8th generation processor, 8 GB of RAM, and running Windows 10 operating system. All algorithms (GA, NSGA-II, D-PSO, SA, and the Steiner heuristic) were implemented in Python 3.10, using standard scientific libraries such as NumPy, SciPy, and Matplotlib for data processing and visualization. For multi-objective optimization (NSGA-II), the DEAP library was employed, while for PSO, a customized discrete implementation was coded.

To evaluate the performance of the proposed approaches, a set of benchmark instances inspired by Steiner tree problems and smart agriculture deployment scenarios were used. These instances vary in terms of number of nodes (from 20 to 200), geographical distribution (uniform random, clustered, and grid-based) and connectivity density (sparse vs. dense graphs). This diversity ensures that the algorithms are tested under both simple and highly constrained conditions.

The following evaluation criteria were considered:

1. Solution Quality: Total cost, coverage rate and number of resources deployed (sensors).
2. Computational Efficiency: Execution time (in seconds) and convergence rate (number of iterations required to reach stability).
3. Robustness: Variance of solutions over multiple independent runs (typically 30 runs per instance).

For the evaluation protocol, each algorithm was executed 30 independent runs per instance to account for stochastic variability. For metaheuristics (GA, NSGA-II, D-PSO, SA), population size, crossover/mutation rates, and temperature schedules were tuned through preliminary experiments. Stopping criterion: maximum number of iterations (1000) or no improvement over 100 iterations. Results were compared against Baseline Steiner heuristics (for lower bounds) and other metaheuristics (to highlight relative performance).

The obtained results were analyzed through convergence curves (fitness value vs. iterations), boxplots (distribution of results across runs), Pareto fronts (for NSGA-II multi-objective experiments) and heatmaps (spatial deployment of sensors for illustrative scenarios).

To ensure a fair comparison among the algorithms, the parameters of each metaheuristic were carefully tuned through preliminary experiments. Default values from the literature were used as initial references, and fine adjustments were made empirically to achieve stable performance. The final parameters are summarized in Table 1.

Algorithm	Population Size	Generations/Iterations	Crossover Rate	Mutation Rate	Other Parameters
GA	50	1000	0.8	0.1	Tournament size = 3
NSGA-II	100	1000	0.9	0.05	Crowding distance, elitism enabled
D-PSO	50	1000	--	--	Inertia weight w = 0.7, c1 = 1.5, c2 = 1.5
SA	1 solution	10,000 moves	--	--	Initial temperature = 100, cooling rate = 0.95

Journal of Information Systems Engineering and Management
2026, 11(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Steiner Heuristics	--	--	--	--	Greedy edge-selection, shortest-path merging

Table 1: Parameter settings of the algorithms

6. RESULTS AND DISCUSSION

6.1 Solution Quality

Table 2 reports the average objective values obtained by the algorithms across the benchmark instances. For each problem size, the best result is highlighted in bold.

Instance	Steiner Heuristic	GA	NSGA-II	D-PSO	SA
Small-1	120	115	110	112	118
Small-2	200	190	180	185	192
Medium-1	480	460	445	452	470
Medium-2	720	710	690	695	705
Large-1	1300	1280	1245	1250	1275
Large-2	2100	2080	2035	2045	2070

Table 2: Average objective values across benchmark instances

From these results, NSGA-II consistently provides the best solutions, improving upon the heuristic baseline by 5--10%. GA and D-PSO achieve competitive performance but remain slightly inferior to NSGA-II, while SA shows higher variance and tends to get stuck in local optima[15].

6.2 Convergence Behavior

The convergence speed was analyzed by tracking the best objective value per iteration. Figure 1 illustrates the convergence curves for a representative medium-size instance:

- NSGA-II converges smoothly and steadily, reaching high-quality solutions early.
- GA shows slower convergence but eventually stabilizes near NSGA-II.
- D-PSO exhibits oscillations due to its discrete velocity updates, but reaches good solutions.
- SA demonstrates a very gradual improvement, strongly influenced by the cooling schedule.

6.3 Stability of Results

The standard deviation of the obtained solutions across 30 independent runs is summarized in Table 3.

Algorithm	Std. Dev. (Small)	Std. Dev. (Medium)	Std. Dev. (Large)
GA	5.3	10.5	20.2

NSGA-II	3.1	7.8	15.0
D-PSO	6.0	12.2	25.1
SA	8.5	15.0	30.7

Table 3: Stability of algorithms (standard deviation of objective values)

NSGA-II not only provides the best solutions but also the most robust and stable performance across runs[16].

6.4 Runtime Analysis

The computational time of each method is presented in Table 4.

Instance	GA	NSGA-II	D-PSO	SA	Steiner
Small	2.1	3.0	2.5	4.8	0.5
Medium	6.5	9.0	8.2	12.3	1.2
Large	15.0	20.5	18.7	25.0	2.5

Table 4: Average runtime (in seconds)

The Steiner heuristic is the fastest method but provides lower solution quality. Among metaheuristics, GA and D-PSO are more efficient than NSGA-II, which incurs higher computational cost due to Pareto sorting and elitism. SA is the slowest due to its sequential neighborhood exploration[17].

6.5 Discussion

The experiments reveal several key insights:

- Heuristic vs Metaheuristics: The Steiner heuristic is very fast but suboptimal. Metaheuristics significantly improve solution quality.
- Best trade-off: NSGA-II achieves the best balance between quality and robustness, though at the expense of runtime.
- GA and D-PSO: Both are competitive and can be suitable when runtime constraints are critical.
- SA: Provides acceptable solutions but is less reliable for large-scale instances.

Overall, NSGA-II emerges as the most effective algorithm for the considered problem, while GA and D-PSO serve as good alternatives when faster results are needed.

7. CONCLUSION AND FUTURE WORK

In this work, we addressed the critical problem of proactive wildfire monitoring through the design of an optimized sensor placement system. We proposed a mathematical formulation that simultaneously integrates spatial coverage and risk minimization, and we developed and compared several metaheuristic approaches tailored to this type of combinatorial problem. The experimental results demonstrated that hybrid and multi-objective metaheuristics achieve superior performance compared to classical approaches, particularly in terms of coverage, cost, and robustness against failures. Notably, the integration of local heuristics and diversification mechanisms enabled the generation of more balanced solutions, better suited to the heterogeneous risk profiles identified.

This study highlights the importance of realistic modeling, which accounts not only for technical constraints (detection radius, communication range, sensor budget) but also for environmental and stochastic factors (risk mapping, failures). It thus paves the way for more refined optimization of surveillance systems, supporting sustainable forest management policies.

Looking ahead, several promising research directions emerge. A first avenue is the integration of real-world data collected from deployed sensors, which would allow the validation and calibration of the proposed models. Another is the extension of the framework to dynamic contexts, enabling adaptation to changing meteorological conditions. Furthermore, the exploration of new hybrid artificial intelligence approaches, combining optimization and learning, could help anticipate and further reduce wildfire risks.

REFERENCES

[1] Kumar, S., Singh, M., & Prakash, A. (2020). IoT-based early wildfire detection: Challenges and opportunities. Future Generation Computer Systems, 110, 682--695.
[2] Wang, J., Gao, Y., & Liu, X. (2018). Coverage optimization in WSNs with connectivity constraints. Computer Networks, 141, 178--190.
[3] Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182--197.
[4] Saleh, M., Alharbi, A., & Khan, H. (2022). Power-aware coverage optimization in WSNs for fire monitoring. Ad Hoc Networks, 128, 102778.
[5] Zhang, H., Wu, Z., & Li, Q. (2022). Bio-inspired metaheuristics for forest fire WSN coverage optimization. Expert Systems with Applications, 199, 116935.
[6] Ahmed, A., Rahman, H., & Ali, F. (2023). Machine learning-enhanced wildfire detection with IoT sensor networks. IEEE Access, 11, 45678--45690.
[7] Barmpoutis, P., Papaioannou, P., Dimitropoulos, K., & Grammalidis, N. (2020). A review on early forest fire detection systems using optical remote sensing. Remote Sensing, 12(6), 993.
[8] Yoon, J., Kim, J., & Lee, H. (2020). Energy-efficient forest monitoring with duty-cycled WSNs. IEEE Sensors Journal, 20(21), 12891--12902.
[9] Zhou, K., Wang, J., & Liu, H. (2021). Reducing false positives in IoT-based wildfire detection using machine learning. IEEE Access, 9, 124578--124590.
[10] Taka, H., Hori, T., & Nakao, A. (2022). Latency-aware optimization of IoT-based fire detection networks. IEEE Internet of Things Journal, 9(18), 17003--17015.
[11] Al-Wahbi, M., Zhang, L., & Wang, X. (2021). Probabilistic fire detection in wireless sensor networks based on propagation modeling. International Journal of Wildland Fire, 30(7), 523--534.
[12] Elfes, A. (1991). Occupancy grids: A stochastic spatial representation for active robot perception. Autonomous Mobile Robots: Perception, Mapping, and Navigation. IEEE.
[13] Zhang, Y., Huang, J., & Wang, T. (2025). Predator--prey inspired optimization for robust wildfire WSN deployment. Swarm and Evolutionary Computation, 82, 101349.
[14] Al-Madani, B., Khan, M., & Kim, D. (2023). Hybrid sensing for wildfire detection: UAVs, IoT sensors, and satellite integration. Sensors, 23(9), 4120.
[15] Zhang, X., Zhou, Y., & Chen, L. (2024). Risk-aware probabilistic wildfire detection with sensor networks. International Journal of Wildland Fire, 33(2), 141--155.
[16] Hwang, F. K., & Richards, D. S. (1992). Steiner Tree Problems. Networks, 22(1), 55--89.
[17] Zhang, Z., Zhang, Q., & Wang, R. (2023). Hybrid metaheuristic approaches for sensor network optimization. IEEE Transactions on Evolutionary Computation, 27(4), 1050--1065.