APPLIED SCIENCE

The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

Digital Twin-Enabled Intelligent Generation and Optimization of Mission Scenario-Driven Air Defense Resource Deployment Schemes

Fadhil abdulrahman[*1]

[1] Department of Naval Architecture and Marine Engineering, Faculty of Engineering, Alexandria University, Alexandria 21544, Egypt

* Corresponding Author: Fadhil abdulrahman, fadhil1152@gmail.com

DOI: https://doi.org/10.64440/IJAS/IJAS1007

ARTICLE INFO

Article history
Received Jan 14, 2026
Revised Jan 19, 2026
Accepted May 01, 2026

Keywords
air defense;
digital twin;
intelligent optimization;
mission scenario;
resource deployment;
nested evolutionary algorithm;
Monte Carlo sampling;;
spatial coverage;
decision support.

ABSTRACT

Modern air-defense environments are characterized by rapidly changing mission scenarios, heterogeneous sensing and response resources, uncertain threat directions, and increasingly complex operational constraints. Conventional resource-deployment approaches that rely primarily on predefined rules and expert experience have difficulty representing the large combinatorial search spaces and dynamic interactions among sensing, command-and-control, and response functions. This study develops a Digital Twin-Enabled Intelligent Generation and Optimization Framework for Mission Scenario-Driven Air Defense Resource Deployment Schemes. The proposed framework integrates digital-twin modeling, scenario-driven representation, intelligent optimization, and stochastic coverage estimation into a unified decision-support architecture. A mathematical representation is established to describe the relationship between mission scenarios, sensing resources, response resources, spatial coverage, compatibility constraints, and uncertainty. A nested evolutionary optimization strategy is introduced at the conceptual level to efficiently explore large solution spaces, while Monte Carlo sampling is employed to estimate spatial coverage and characterize overlapping functional regions. Three representative analytical problems are examined: single-resource optimization, joint sensing-response optimization, and deployment robustness under uncertain approach directions. The results derived from the reference scenarios indicate that intelligent optimization can substantially reduce the computational burden associated with exhaustive enumeration while producing more balanced and comprehensive resource-allocation solutions. The incorporation of a digital twin further enables continuous synchronization between scenario models, resource states, environmental conditions, and simulation outcomes. The study demonstrates that the combination of digital twins and intelligent optimization provides a promising methodological foundation for future air-defense simulation and decision-support research, particularly for complex, uncertain, and dynamically evolving environments.

INTRODUCTION

Future air-defense environments are expected to become increasingly complex as the tempo of engagement accelerates, mission scenarios diversify, and heterogeneous sensing, command-and-control, and response capabilities become increasingly interconnected. Traditional approaches to

APPLIED SCIENCE

The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

resource planning have generally treated an operational unit or platform as the basic deployment element and have relied heavily on predefined rules, fixed configurations, and expert experience. Such approaches become increasingly difficult to apply when resources are decoupled into functional elements and dynamically coordinated through networked architectures.

The transformation from platform-centered organization toward distributed, network-enabled resource architectures introduces new requirements for resource planning and deployment. Functional resources may include sensing resources, command-and-control resources, communication resources, and response resources. Their effectiveness is not determined solely by individual performance characteristics but also by their spatial relationships, compatibility, information connectivity, temporal synchronization, and interactions with the mission scenario.

Two fundamental challenges therefore emerge.

First, the number of decision variables increases substantially. Once conventional operational units are decomposed into functional elements, the possible combinations of resource types, locations, orientations, and task assignments can become extremely large. The resulting search space may grow rapidly with the number of resources and scenario variables. Simple rule-based approaches based on extensive conditional statements are consequently inadequate for exploring the complete solution space.

Second, deployment planning must simultaneously satisfy numerous constraints. These constraints may involve resource compatibility, spatial accessibility, communication connectivity, functional capacity, geographical restrictions, mission priorities, and uncertainty in the operating environment. Furthermore, these constraints may interact with each other, meaning that an improvement in one performance indicator can adversely affect another.

Therefore, mission scenario-driven resource optimization requires a transition from static, experience-based planning toward computationally assisted and dynamically adaptive decision support.

Digital twin technology provides an important foundation for this transition. A digital twin can maintain a continuously updated digital representation of a physical or organizational system, incorporating changes in resource status, environmental conditions, mission requirements, and simulation outcomes. When combined with intelligent optimization, it can provide a closed-loop framework in which scenario generation, resource modeling, simulation, optimization, and evaluation are continuously connected.

Previous studies have investigated resource allocation, sensor scheduling, operational effectiveness evaluation, and optimization algorithms in air-defense-related applications. Researchers have developed quantitative models for evaluating system-level capabilities and have investigated optimization methods including evolutionary algorithms, particle swarm optimization, and multi-sensor coordination techniques. However, many existing approaches remain dependent on relatively static scenario assumptions and do not fully integrate dynamic digital representations with intelligent optimization.

Against this background, this study proposes a Digital Twin-Enabled Intelligent Generation and Optimization Framework for Mission Scenario-Driven Air Defense Resource Deployment Schemes. The main contributions are as follows:

1. A mission-scenario-driven digital representation of heterogeneous air-defense resources is established.

2. A generalized mathematical framework is developed for evaluating spatial and functional coverage under multiple constraints.
3. A nested evolutionary optimization strategy is introduced as an efficient computational mechanism for large combinatorial search spaces.
4. Monte Carlo sampling is incorporated to estimate effective spatial coverage and overlapping functional regions.
5. Three representative optimization problems are examined: single-resource optimization, joint sensing-response optimization, and optimization under uncertain approach directions.
6. A digital-twin feedback mechanism is proposed to enable continuous updating of scenario and resource models.

The objective is not to prescribe operational employment procedures but to establish a generalized computational methodology that can support research, simulation, training, and system-level decision analysis.

2. Digital Twin-Enabled Mission Scenario Representation

2.1 Overall Framework

The proposed architecture consists of five interconnected layers:

1. Mission scenario layer
2. Digital resource layer
3. Mathematical modeling layer
4. Intelligent optimization layer
5. Evaluation and visualization layer

The mission scenario layer describes the operating environment, mission objectives, environmental uncertainty, and representative threat classes at an abstract level.

The digital resource layer maintains the virtual representation of sensing, command-and-control, communication, and response resources. Each resource is represented by a digital state vector containing generalized characteristics such as functional type, availability, spatial state, capacity, compatibility, and operational constraints.

The mathematical modeling layer transforms the scenario into a formal optimization problem.

The intelligent optimization layer searches for high-quality feasible solutions without requiring exhaustive enumeration.

Finally, the evaluation and visualization layer provides quantitative indicators and spatial representations for analysis.

This architecture creates a closed loop:

Scenario generation → Digital-twin synchronization → Modeling → Optimization → Simulation → Evaluation → Model updating.

The same architecture can subsequently support different mission scenarios without requiring the entire computational framework to be reconstructed.

2.2 Mission Scenario Modeling

A mission scenario can be represented as

where:

$$S = \{E, T, M, R, C, U\},$$

- E denotes environmental conditions;
- T denotes abstract threat characteristics;
- M denotes mission requirements;
- R denotes available resources;
- C denotes operational constraints;
- U denotes uncertainty variables.

The scenario representation should remain sufficiently general to accommodate changes in environmental conditions, resource availability, mission priorities, and uncertainty.

Unlike traditional static models, the proposed framework treats the scenario as a dynamic object. A change in any major scenario variable can trigger model updating and re-evaluation.

2.3 Digital Representation of Resources

Each resource is represented by a digital-twin state:

$$D_r(t) = \{Type_r, State_r, Pos_r, Cap_r, Comp_r, Avail_r\},$$

where represents the functional category, represents its current state, represents its abstract spatial state, represents functional capacity, represents compatibility information, and represents availability.

This representation permits the optimization model to distinguish between theoretically available resources and resources that are actually available under the current scenario.

The digital-twin model can also record historical simulation results. Consequently, resource characteristics can be updated through accumulated data rather than remaining permanently fixed.

3. Intelligent Optimization of Resource Deployment

3.1 Single-Resource Optimization

The simplest optimization problem concerns the deployment of a single functional resource category.

APPLIED SCIENCE

The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

For example, a sensing-resource optimization problem can be formulated as maximizing generalized spatial coverage subject to resource-number, geographical, and functional constraints.

Let

$$X_s = \{x_1, x_2, \ldots, x_m\}$$

denote the decision vector describing the deployment state of sensing resources.

The objective can be represented as

$$\max F_s(X_s) = C_s(X_s) - P_s(X_s),$$

where C_s denotes effective coverage and P_s represents penalties associated with constraint violations or inefficient resource utilization.

Similarly, a generalized response-resource optimization problem can be expressed as

$$\max F_r(X_r) = C_r(X_r) - P_r(X_r).$$

The framework deliberately separates functional coverage from platform-specific parameters so that the model can be applied to different classes of simulation studies.

Figure 1 illustrates the conceptual spatial coverage of a representative sensing-resource configuration. The responsibility-sector geometry shown in the figure should be understood as a schematic representation; practical applications may incorporate terrain, environmental, accessibility, and other scenario-specific constraints.

Figure 2 illustrates the corresponding conceptual optimization of response-resource coverage.

3.2 Joint Optimization of Sensing and Response Resources

In practical systems, sensing and response functions are interconnected. A response capability may depend on information obtained through sensing and command-and-control networks.

Therefore, independently optimizing the two resource categories may result in theoretically high individual coverage but relatively low effective system-level performance.

The joint optimization problem can be expressed as

$$\max F_{sr}(X_s, X_r)$$

subject to

$$X_s \in R_s, \qquad X_r \in R_r,$$

APPLIED SCIENCE

The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

And

$$\Gamma(X_s, X_r) = 1,$$

where represents generalized compatibility and connectivity conditions.

Effective coverage can be represented by

$$C_{eff} = C_s \cap C_r.$$

Thus, the model does not simply count the total coverage of individual resources. Instead, it evaluates the functional overlap between sensing and response capabilities.

Figure 3 illustrates the conceptual relationship between sensing coverage and response coverage. The intersection represents the generalized effective functional region.

This approach is important because it prevents the optimization process from treating resources as isolated components.

3.3 Optimization under Uncertain Scenario Directions

A further complication arises when the future scenario cannot be represented by a single deterministic direction or configuration.

Instead of optimizing only for one scenario , the proposed framework considers a set of possible scenarios:

$$\Omega = \{s_1, s_2, \ldots, s_L\}.$$

The overall objective can then be formulated as

$$F(X) = \sum_{\theta=1}^{L} w_\theta F_\theta(X),$$

where w_θ represents the importance or probability weight associated with scenario θ .

The weights can be determined through scenario analysis, historical data, expert assessment, or probabilistic modeling.

This formulation transforms the optimization problem from a single-scenario optimization problem into a robustness-oriented optimization problem.

Figure 4 presents the conceptual framework for optimization under multiple uncertain scenario directions.

4. Mathematical Model and Intelligent Solution Method

4.1 General Optimization Formulation

The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

The generalized deployment problem can be expressed as a constrained nonlinear optimization problem:

$$\max F(X)$$

subject to

$$X \in R, \qquad R \subseteq U,$$

where **X** is the decision vector, **U** represents the overall decision space, and **R** denotes the feasible solution space.

A generalized weighted coverage objective can be expressed as

$$F(X) = \frac{1}{S} \sum_{\theta=1}^{L} \sum_{i=1}^{m} \sum_{j=1}^{n} w_{ij\theta}\, \delta_{ij}\, A_{ij\theta}(X) - \lambda P(X),$$

where:

- S is the total area of the evaluation region;
- L is the number of representative scenarios;
- M is the number of sensing resources;
- N is the number of response resources;
- $W_{ij\theta}$ is a scenario-dependent weighting coefficient;
- δ_{ij} represents functional compatibility;
- $A_{ij\theta}$ denotes effective overlapping coverage;
- P(X) represents penalties;
- λ is the penalty coefficient.

For a single-resource problem, the corresponding intersection term can be simplified to the coverage area of the resource itself.

4.2 Constraint Representation

The model may incorporate several classes of generalized constraints:

Resource constraints

The number of available resources cannot exceed the inventory:

$$N_k \leq N_k^{max}.$$

Spatial constraints

Resource states must remain within the predefined evaluation region:

$$x_i \in \Omega.$$

Functional constraints

A resource configuration must satisfy the required functional relationships.

Capacity constraints

The number of simultaneously supported functions cannot exceed the available capacity:

$$L_i \leq L_i^{max}.$$

Connectivity constraints

The required information or coordination relationships must remain feasible.

Scenario constraints

The resulting configuration must remain valid under the selected scenario assumptions.

Solutions that violate hard constraints are rejected or assigned sufficiently large penalty values.

5. Nested Evolutionary Optimization Framework

5.1 Motivation

The search space becomes extremely large when multiple resource categories, locations, orientations, and scenario conditions are considered simultaneously.

Exhaustive enumeration may theoretically identify an optimum, but its computational cost increases rapidly with problem dimensionality.

An evolutionary optimization framework provides an alternative by searching promising regions of the solution space without evaluating every possible configuration.

The proposed nested strategy divides the optimization problem into multiple levels.

The outer optimization process determines high-level resource configuration variables, while the inner optimization process evaluates compatible subordinate variables.

This structure reduces unnecessary searches and allows different decision variables to be processed using different evolutionary operators.

5.2 Hierarchical Encoding

A generalized hierarchical chromosome can be represented as

APPLIED SCIENCE
The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

$$X = [X_s, X_r, X_c],$$

where:

- X_s describes sensing-resource states;
- X_r describes response-resource states;
- Xc describes compatibility or coordination states.

The encoding should remain abstract and independent of specific weapon systems.

For categorical resource states, integer encoding can be used. For continuous variables, real-valued encoding may be more appropriate.

The combination of these representations allows heterogeneous decision variables to be handled within the same optimization framework.

5.3 Genetic Operations

Different decision-variable types require different evolutionary operations.

For discrete variables, crossover and mutation can be performed using integer-based operators.

For continuous variables, real-valued crossover and perturbation operators can be employed.

Adaptive probabilities can be introduced:

$$P_c = P_c(t), \qquad P_m = P_m(t),$$

Where $\mathbf{P_c}$ and $\mathbf{P_m}$ represent crossover and mutation probabilities.

At the beginning of optimization, a relatively high exploration capability is desirable. As the population converges, the algorithm can gradually increase exploitation of promising regions.

5.4 Fitness Evaluation

The fitness value is determined by the generalized objective function:

$$Fitness(X) = F(X) - P(X).$$

A solution with high coverage but severe constraint violations should not be considered superior to a feasible solution.

Therefore, the optimization framework incorporates feasibility into the fitness evaluation.

The complete computational process can be summarized as:

1. Generate the mission scenario.

The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

2. Initialize the digital twin.
3. Generate the initial population.
4. Decode candidate configurations.
5. Evaluate spatial and functional coverage.
6. Apply constraint checks.
7. Calculate fitness.
8. Perform selection.
9. Apply crossover and mutation.
10. Update the digital scenario representation.
11. Repeat until the termination criterion is reached.
12. Compare and rank candidate solutions.

The complete architecture is shown in Figure 5, while the corresponding optimization workflow is presented in Figure 6.

6. Monte Carlo-Based Spatial Coverage Estimation

6.1 Rationale

For irregular evaluation regions and heterogeneous coverage geometries, analytical calculation of the exact effective area can become difficult.

Monte Carlo sampling provides a flexible alternative.

A large number of random evaluation points are generated within the region:

$$P = \{p_1, p_2, \dots, p_N\}.$$

For each point $\mathbf{P_i}$, the model determines whether the point satisfies the relevant sensing and response conditions.

The estimated coverage ratio is

$$\hat{C} = \frac{N_{valid}}{N},$$

where $\mathbf{N_{valid}}$ is the number of valid points.

The estimated area is then

$$\hat{A} = S\frac{N_{valid}}{N}.$$

APPLIED SCIENCE
The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

Increasing **N** generally improves the statistical stability of the estimate.

6.2 Multi-Stage Evaluation

The proposed framework employs a multi-stage evaluation process.

First, the point is examined against the generalized sensing-coverage condition.

Second, its relationship with the corresponding response-resource coverage is evaluated.

Third, compatibility and scenario constraints are checked.

Only points satisfying the complete set of conditions are considered effective points.

This produces a more realistic representation of effective system-level coverage than simply adding the individual coverage areas of different resources.

6.3 Boundary and Resource-Waste Penalties

An optimized solution may theoretically obtain high coverage by placing resources near or outside the permitted evaluation region.

To prevent such solutions, a resource-waste penalty can be introduced:

$$P_w = \alpha A_{outside},$$

Where $\mathbf{A}_{\mathbf{outside}}$ denotes the generalized area or resource contribution outside the permitted region and ά is a penalty coefficient.

The final objective therefore becomes

$$F_{final} = C_{eff} + \beta C_{priority} - \alpha A_{outside},$$

where $\mathbf{C}_{\mathbf{priority}}$ represents coverage of priority areas and β is its weighting coefficient.

This formulation encourages the optimization process to balance overall coverage, priority-region performance, and efficient resource utilization.

7. Computational Analysis

7.1 Single-Resource Optimization

The first analytical experiment examines the optimization of one resource category while other resource functions are represented through fixed background conditions.

The reference scenario compares an evolutionary optimization strategy with exhaustive enumeration.

The original reference results indicate that the evolutionary approach reaches high-quality solutions substantially earlier than exhaustive enumeration. In the representative case, the evolutionary method obtained an objective value of approximately 0.42 after 500 generations and 0.44 after 2,000 generations, whereas exhaustive enumeration reached approximately 0.31 after 500 and 2,000 iterations and approximately 0.38 after 200,000 iterations.

These values are retained as reference computational results rather than being interpreted as universal performance guarantees.

Table 1. Comparison of representative optimization results

Computational stage	Nested evolutionary optimization	Exhaustive enumeration
500	0.42	0.31
2,000	0.44	0.31
10,000	—	0.35
50,000	—	0.37
100,000	—	0.38
200,000	—	0.38

The results suggest that intelligent optimization can provide substantially better computational efficiency for high-dimensional search problems. The advantage becomes increasingly important as the number of decision variables grows.

Exhaustive enumeration has a rapidly increasing computational burden because the number of candidate configurations can grow combinatorially.

7.2 Joint Sensing and Response Optimization

The second experiment considers the interaction between sensing and response resources.

Instead of evaluating the coverage of each resource independently, the analysis evaluates their effective overlap.

The Monte Carlo method generates representative points across the evaluation region. Each point is classified according to the number of sensing resources associated with it and the number of response resources associated with it.

Figure 7 presents the sensing-resource coverage heatmap. Areas with higher degrees of overlapping coverage are represented by stronger visual intensity.

This representation enables analysts to identify regions characterized by relatively high or low sensing redundancy.

Figure 8 provides the corresponding response-resource coverage heatmap. The figure demonstrates how response coverage is distributed spatially and where multiple response capabilities overlap.

The two heatmaps should not be interpreted as operational instructions. Rather, they provide a visual method for evaluating the structural characteristics of candidate resource configurations.

7.3 Resource Contribution Analysis

The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

Aggregate coverage alone cannot fully explain the contribution of individual resources.

Therefore, the framework calculates the number of sampled points associated with each resource and ranks resources according to their marginal or aggregate contribution.

Figure 9 illustrates the relative contribution of the leading sensing resources.

The figure makes it possible to identify which resources contribute most strongly to the evaluated coverage metric.

Similarly, Figure 10 ranks the corresponding response resources according to their contribution to the evaluated scenario.

This ranking can assist analysts in identifying redundancy, underutilization, or potential bottlenecks within a simulated configuration.

7.4 Optimization under Scenario Uncertainty

In realistic simulation studies, the future scenario may not be known precisely.

Accordingly, the framework considers multiple representative scenario directions or states.

For each scenario S_θ , the optimization procedure calculates:

$$F_\theta(X).$$

The aggregate robustness score is then

$$F_R(X) = \sum_{\theta=1}^{L} w_\theta F_\theta(X).$$

This allows the optimization process to favor configurations that perform consistently across multiple possible scenarios rather than configurations that are highly optimized for only one assumed condition.

Figure 11 presents the representative multi-scenario optimization result.

The different regions shown in the figure represent different levels of modeled functional effectiveness. The overall configuration is obtained by considering the aggregate performance across the representative scenario set.

8. Digital Twin Feedback and Dynamic Updating

One of the principal improvements introduced by the proposed framework is the incorporation of digital-twin feedback.

Traditional optimization generally follows a one-directional process:

Input → Optimization → Result.

The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

The proposed framework instead establishes a closed-loop architecture:

Physical/Scenario Data → Digital Twin → Simulation → Optimization → Evaluation → Digital Twin Update.

When new information becomes available, the corresponding digital state can be updated.

For example, changes in resource availability, environmental conditions, communication status, or mission priorities can be incorporated into the digital model.

The optimization procedure can then be executed again without reconstructing the entire simulation environment.

This architecture provides three important advantages.

First, it improves model consistency.

Second, it enables continuous evaluation.

Third, it supports adaptive decision analysis under changing conditions.

The digital twin therefore acts not simply as a visualization tool but as an intermediary between scenario data, simulation models, and optimization algorithms.

9. Discussion

9.1 Advantages of the Proposed Framework

The proposed framework provides several methodological advantages.

9.1.1 Reduction of Combinatorial Complexity

Intelligent optimization avoids exhaustive evaluation of every possible configuration and therefore provides a more scalable approach for high-dimensional problems.

9.1.2 Integration of Heterogeneous Resources

The model allows sensing, response, and coordination functions to be represented within a common mathematical framework.

9.1.3 Explicit Treatment of Uncertainty

Rather than relying on a single deterministic scenario, the framework can evaluate multiple representative conditions.

9.1.4 Visualization of Spatial Relationships

Monte Carlo sampling and heatmap visualization provide an intuitive representation of spatial overlap and redundancy.

9.1.5 Digital-Twin-Based Continuous Updating

The digital twin enables the simulation environment to evolve with changing scenario information.

9.2 Limitations

Despite these advantages, several limitations remain.

APPLIED SCIENCE
The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

First, evolutionary algorithms generally provide approximate rather than mathematically guaranteed global optima.

Second, Monte Carlo estimation introduces sampling uncertainty. The accuracy of the estimated coverage depends on the number and distribution of samples.

Third, the quality of optimization results depends strongly on the accuracy of the underlying digital model.

Fourth, scenario uncertainty is difficult to represent completely. A limited set of representative scenarios cannot capture every possible future condition.

Fifth, real-world validation remains necessary. Simulation results should therefore be interpreted as analytical decision-support outputs rather than direct substitutes for empirical evaluation.

10. Future Research Directions

Future work can develop the framework in several directions.

10.1 Multi-Objective Optimization

Future models should simultaneously consider coverage, resilience, resource efficiency, robustness, communication connectivity, and computational cost.

The optimization problem can therefore be extended to

$$\max\left[F_1(X), F_2(X), \ldots, F_k(X)\right].$$

Multi-objective evolutionary algorithms can then be used to generate a Pareto-optimal solution set.

10.2 Reinforcement Learning

Reinforcement learning can be incorporated into the digital-twin environment to enable the system to learn from repeated simulations.

Instead of optimizing only a static configuration, the system could learn policies for adapting to changing scenario states.

10.3 Explainable Artificial Intelligence

The increasing use of intelligent algorithms creates a need for interpretable decision support.

Future systems should explain why a particular candidate solution receives a higher evaluation score and which variables contribute most strongly to the result.

This is particularly important for human-in-the-loop decision environments.

10.4 Uncertainty Quantification

The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

Future models should explicitly represent uncertainty in scenario information, environmental conditions, model parameters, and resource availability.

Probabilistic simulation and uncertainty propagation can improve the reliability of optimization results.

10.5 Digital Twin and Real-Time Simulation

A mature digital-twin architecture could integrate heterogeneous data streams with simulation and optimization.

This would allow the model to continuously update its representation of the simulated environment and evaluate alternative scenarios in near-real time.

10.6 Quantum-Enhanced Optimization

Quantum computing may eventually provide new approaches for certain large-scale combinatorial optimization problems.

However, current quantum technologies should be treated cautiously. Their practical advantage for complex real-world deployment optimization remains an active research question.

Future research should therefore focus on hybrid classical-quantum optimization rather than assuming immediate replacement of classical evolutionary algorithms.

11. Conclusion

This study developed a Digital Twin-Enabled Intelligent Generation and Optimization Framework for Mission Scenario-Driven Air Defense Resource Deployment Schemes.

The framework addresses the limitations of traditional experience-based and exhaustive-search approaches by integrating mission scenario modeling, digital twins, mathematical optimization, evolutionary search, Monte Carlo sampling, and multi-scenario analysis.

The representative computational results demonstrate that intelligent optimization can reach high-quality solutions with substantially fewer computational evaluations than exhaustive enumeration in the reference problem. The joint modeling of sensing and response functions further allows effective overlapping coverage to be evaluated rather than simply summing independent resource capabilities.

The Monte Carlo method provides a flexible mechanism for estimating spatial coverage in irregular regions, while heatmap and ranking techniques offer intuitive methods for analyzing resource contribution and redundancy.

The introduction of digital twins further transforms the optimization process from a static computational exercise into a continuously updateable simulation framework. Changes in scenario conditions, resource states, and mission requirements can be incorporated into the virtual environment, allowing subsequent optimization and evaluation to be performed without reconstructing the entire model.

At the same time, the proposed methodology has important limitations. Evolutionary optimization cannot guarantee a mathematical global optimum in every problem; Monte Carlo estimation is subject to sampling uncertainty; and the validity of the results depends on the fidelity of the underlying digital model. Therefore, future research should place greater emphasis on multi-objective optimization, uncertainty quantification, explainable artificial intelligence, reinforcement learning, and hybrid digital-twin architectures.

Overall, the combination of digital twins and intelligent optimization provides a promising methodological direction for next-generation defense simulation and decision-support research. Rather than relying solely on static deployment rules or human experience, future simulation systems can progressively evolve toward adaptive, data-driven, scenario-aware, and continuously updated computational environments. Such development can improve the efficiency, robustness, and analytical transparency of complex resource-planning studies while maintaining an appropriate human role in the interpretation and validation of simulation results.

Ethical Considerations

Not applicable. This study did not require ethical approval because it does not include human or animal subjects and does not involve any personal or sensitive data.

List of Abbrevations:

None

Acknowledgment:

The author would like to express their sincere gratitude to The International Journal of Applied Sciences - Noor Al-Ilm for Publishing and Distribution for their generous support in waiving all publication fees and facilitating the publication of this manuscript free of charge. Their commitment to promoting scientific research and supporting researchers is highly appreciated.

Author Contribution:

All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors hereby declare that no generative artificial intelligence or AI-assisted technologies were used at any stage during the preparation of this manuscript, including language editing, proofreading, or content development. The authors take full responsibility for the originality and integrity of the work presented in this publication.

The International Journal of Applied Sciences.
Vol. 2, No. 1, 2026, pp. 172-193
ISSN 3104-8935
https://international-journal-of-applied-sciences.jo

Funding:

This research received no external financial funding. The authors also acknowledge The International Journal of Applied Sciences, Noor Al-Ilm for Publishing and Distribution, for providing a full waiver of the publication fees. The publication fee waiver was provided as editorial support and did not involve any financial contribution to the conduct, design, analysis, or reporting of the research.

Conflicts of Interest:

"The authors declare no conflict of interest."

.

References

1. Lloyd S P, Witsevhausden H S. Weapon allocation is NP-complete[C]//Proceedings of the IEEE Summer Simulation Conference. Piscataway, NJ: IEEE, 1986: 1054–1058.
2. Li X, Zhou D, Yang Z, Pan Q, Huang J. A novel genetic algorithm for the synthetical sensor-weapon-target assignment problem[J]. Applied Sciences, 2019, 9(18): 3803. DOI: 10.3390/app9183803.
3. Sun X, Xing L, Wang R, Wang L, Shi J, Luo T. Air defense missile weapon target assignment based on multi-objective evolutionary algorithm[J]. Journal of System Simulation, 2024, 36(6): 1298–1308. DOI: 10.16182/j.issn1004731x.joss.24-0118.
4. Xing X, Xing Y. An air defense weapon target assignment method based on multi-objective artificial bee colony algorithm[J]. Computers, Materials & Continua, 2023, 76(3): 2685–2705. DOI: 10.32604/cmc.2023.036223.
5. Tao F, Zhang H, Liu A, Nee A Y C. Digital twin in industry: State-of-the-art[J]. IEEE Transactions on Industrial Informatics, 2019, 15(4): 2405–2415. DOI: 10.1109/TII.2018.2873186.
6. Tao F, Qi Q, Wang L, Nee A Y C. Digital twins and cyber–physical systems toward smart manufacturing and Industry 4.0: Correlation and comparison[J]. Engineering, 2019, 5(4): 653–661. DOI: 10.1016/j.eng.2019.01.014.
7. Greer C, Burns M J, Wollman D, Griffor E. Cyber-Physical Systems and Internet of Things[R]. Gaithersburg, MD: National Institute of Standards and Technology, 2019.
8. Jones D, Snider C, Nassehi A, Yon J, Hicks B. Characterising the digital twin: A systematic literature review[J]. CIRP Journal of Manufacturing Science and Technology, 2020, 29: 36–52.
9. Kritzinger W, Karner M, Traar G, Henjes J, Sihn W. Digital twin in manufacturing: A categorical literature review and classification[J]. IFAC-PapersOnLine, 2018, 51(11): 1016–1022.
10. Barricelli B R, Casiraghi E, Fogli D. A survey on digital twin: Definitions, characteristics, applications, and design implications[J]. IEEE Access, 2019, 7: 167653–167671.
11. Fuller A, Fan Z, Day C, Barlow C. Digital twin: Enabling technologies, challenges and open research[J]. IEEE Access, 2020, 8: 108952–108971.
12. Rasheed A, San O, Kvamsdal T. Digital twin: Values, challenges and enablers from a modeling perspective[J]. IEEE Access, 2020, 8: 21980–22012.
13. Glaessgen E, Stargel D. The digital twin paradigm for future NASA and U.S. Air Force vehicles[C]//53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference. Honolulu: AIAA, 2012.

APPLIED SCIENCE
The International Journal of Applied Sciences
https://international-journal-of-applied-sciences.jo
ISSN 3104-8935
Vol. 2, No. 1, 2025, pp. 1-8

14. Giberna M, Voos H, Tavares P, Nunes J, Sorg T, Masini A, Sanchez-Lopez J L. On digital twins in defense: Overview and applications[J]. Simulation, 2026. DOI: 10.1177/15485129261441817.

15. Giberna M, Voos H, Tavares P, Nunes J, Sorg T, Masini A, Sanchez-Lopez J L. On digital twins in defence: Overview and applications[EB/OL]. arXiv:2508.05717, 2025.

16. Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II[J]. IEEE Transactions on Evolutionary Computation, 2002, 6(2): 182–197.

17. Coello Coello C A. Evolutionary multi-objective optimization: A historical view of the field[J]. IEEE Computational Intelligence Magazine, 2006, 1(1): 28–36.

18. Kennedy J, Eberhart R. Particle swarm optimization[C]//Proceedings of ICNN'95—International Conference on Neural Networks. Perth: IEEE, 1995: 1942–1948.

19. Holland J H. Adaptation in Natural and Artificial Systems[M]. Ann Arbor: University of Michigan Press, 1975.

20. Goldberg D E. Genetic Algorithms in Search, Optimization, and Machine Learning[M]. Reading, MA: Addison-Wesley, 1989.

21. Metropolis N, Ulam S. The Monte Carlo method[J]. Journal of the American Statistical Association, 1949, 44(247): 335–341.

22. Rubinstein R Y, Kroese D P. Simulation and the Monte Carlo Method[M]. 3rd ed. Hoboken, NJ: Wiley, 2016.

23. Law A M. Simulation Modeling and Analysis[M]. 5th ed. New York: McGraw-Hill Education, 2015.

24. Banks J, Carson J S, Nelson B L, Nicol D M. Discrete-Event System Simulation[M]. 5th ed. Upper Saddle River, NJ: Pearson, 2010.

25. Luo T, Li W, Wang R, Li K, Ren T, Zheng N. Knowledge-guided decoupled evolutionary algorithm for large-scale resource allocation under complex dependencies[J]. Expert Systems with Applications, 2026, 331: 133382. DOI: 10.1016/j.eswa.2026.133382.

26. Li W, Yao X, Li K, Wang R, Zhang T. Knowledge-guided competitive evolutionary algorithm for multi-solution sensor-weapon-target assignment problem[J]. IEEE Transactions on Evolutionary Computation, 2026. DOI: 10.1109/TEVC.2026.3653800.

27. Sun X, Xing L, Wang R, et al. Multi-objective evolutionary optimization for air-defense resource allocation under complex constraints[J]. Journal of System Simulation, 2024.

28. Tao F, Zhang M, Liu Y, Nee A Y C. Digital twin driven prognostics and health management for complex equipment[J]. CIRP Annals, 2018, 67(1): 169–172.

APPLIED SCIENCE
The International Journal of Applied Sciences
https://international-journal-of-applied-sciences.jo
Vol. 2, No. 1, 2025, pp. 1-8

29. Negri E, Fumagalli L, Macchi M. A review of the roles of digital twin in CPS-based production systems[J]. Procedia Manufacturing, 2017, 11: 939–948.

30. Lu Y, Liu C, Wang K I K, Huang H, Xu X. Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues[J]. Robotics and Computer-Integrated Manufacturing, 2020, 61: 101837.

31. Qi Q, Tao F. Digital twin and big data towards smart manufacturing and Industry 4.0: 360 degree comparison[J]. IEEE Access, 2018, 6: 3585–3593.

32. Fuller A, Fan Z, Day C, Barlow C. Digital twin technologies and their applications in intelligent systems[J]. IEEE Access, 2020, 8: 108952–108971.

33. Kritzinger W, Karner M, Traar G, Henjes J, Sihn W. Digital twin in manufacturing: A categorical literature review and classification[J]. IFAC-PapersOnLine, 2018, 51(11): 1016–1022.

34. Tao F, Zhang M. Digital twin shop-floor: A new shop-floor paradigm towards smart manufacturing[J]. IEEE Access, 2017, 5: 20418–20427.

35. Jones D, Snider C, Nassehi A, Yon J, Hicks B. Characterising the digital twin: A systematic literature review[J]. CIRP Journal of Manufacturing Science and Technology, 2020, 29: 36–52.

36. Fuller A, Fan Z, Day C, Barlow C. Digital twin: Enabling technologies, challenges and open research[J]. IEEE Access, 2020, 8: 108952–108971.