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A Multi-Objective Particle Swarm Optimization Framework for Defense Logistics Decision-Making under Dynamic and Crisis Conditions

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ABSTRACT

The complexity of decision-making in defense logistics systems has increased significantly due to demands for cost efficiency, distribution speed, and operational resilience in dynamic and crisis conditions. Conventional optimization approaches generally fail to capture these conflicting objectives simultaneously. This study aims to develop and evaluate a multi-objective optimization framework based on Multi-Objective Particle Swarm Optimization (MO-PSO) to support adaptive and performance-based defense logistics decision-making. The proposed method optimizes three main objective functions, namely minimizing operational costs, minimizing distribution time, and maximizing logistics readiness levels, with numerical parameter adjustments designed for the defense environment. Simulation results show that MO-PSO is capable of producing a more convergent and evenly distributed Pareto Front compared to comparison methods such as NSGA-II and standard MOPSO, with a 12.4–18.7% increase in hypervolume and a 21.3% decrease in solution dominance error. These findings indicate that the proposed approach is more effective in simultaneously balancing multi-objective trade-offs. Practically, the research results provide policy implications for defense planners in designing logistics strategies that are more efficient, responsive, and resilient to operational uncertainty.

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1. INTRODUCTION

In the context of increasingly complex, uncertain, and rapidly changing global security dynamics, defense logistics plays a strategic role as the backbone of a country's military and non-military operations . The success of modern defense systems is determined not only by superior weaponry or combat technology, but also by the effective management of logistical resources, including the procurement, distribution, storage, and allocation of equipment and other operational requirements. Various strategic reports indicate that logistical failures are often a major factor in weakening defense readiness, even when combat capabilities are technically adequate. Therefore, optimizing defense logistics decision-making has become a crucial issue at both the global and national levels, especially in an environment characterized by high uncertainty, limited resources, and demands for rapid and adaptive responses.

In Indonesia, defense logistics challenges are increasingly complex due to the vast geographical area, diverse infrastructure conditions, and potential multidimensional threats, including conventional conflicts, natural disasters, and other non-traditional threats. Defense logistics management is faced with the need to balance various conflicting objectives, such as minimizing operational costs, accelerating distribution times, reducing the risk of delivery failures, and maintaining the readiness level of defense units. However, logistics decision-making practices in many defense organizations are still dominated by conventional rule-based approaches or single optimization that are less capable of capturing the complexity and dynamics of today's strategic environment. Despite increasing data volumes and advances in computing technology, the use of intelligent computational methods to support defense logistics decisions is still relatively limited and not yet optimally integrated.

The main problem in defense logistics decision-making lies in its intrinsically multi-objective and large-scale nature. Every logistics decision simultaneously affects various performance indicators that are often in conflict with each other. For example, efforts to minimize distribution costs can have an impact on increased delivery times or the risk of failure, while increasing readiness often requires greater resource allocation. Moreover, defense operational conditions are dynamic, where parameters such as logistics demand, distribution route conditions, and threat levels can change significantly in a short period of time. Therefore, static and deterministic decision-making approaches are inadequate to address these strategic needs. This condition necessitates the development of intelligent optimization models that are capable of handling multiple conflicting objectives while remaining adaptive to environmental changes.

In line with these issues, various studies in the field of logistics and supply chain management have adopted artificial intelligence-based optimization approaches, particularly metaheuristic algorithms, to address complex and nonlinear problems. Research by Deb et al. (2002) introduced the concept of Pareto-based multi-objective optimization, which became the foundation for the development of various modern evolutionary algorithms. In the context of logistics, metaheuristics such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have been used to solve scheduling, distribution route, and resource allocation problems (Gen & Cheng, 2015; Zhang et al., 2019). However, most of these studies focus on the commercial or civil industrial sectors, assuming a relatively stable environment and limited optimization objectives.

In the field of defense, several studies have begun to examine the application of optimization to support military logistics decisions. Parnell et al. (2013) emphasize the importance of a multi-objective approach in defense decision analysis, particularly to balance the trade-off between operational effectiveness and cost efficiency. Another study by Kress and Snyder (2014) examines a military logistics model based on mathematical optimization for distribution planning, but still uses a deterministic approach with one or two main objectives. Meanwhile, a study by Li et al. (2020) applied heuristic algorithms to military supply chain optimization, but focused on static scenarios and did not explicitly consider risk dynamics and preparedness. Despite these contributions, the application of artificial intelligence-based multi-objective optimization algorithms specifically designed for defense logistics characteristics is still very limited.

Particle Swarm Optimization (PSO), introduced by Kennedy and Eberhart (1995), is known as an efficient and simple metaheuristic algorithm for solving continuous optimization problems. Further development in the form of Multi-Objective Particle Swarm Optimization (MO-PSO) allows this algorithm to handle more than one objective function simultaneously through the Pareto dominance mechanism and non-dominated solution archives. Several studies show that MO-PSO has advantages in terms of convergence and solution diversity compared to other multi-objective algorithms (Coello Coello et al., 2004; Reyes-Sierra & Coello Coello, 2006). In the context of logistics, MO-PSO has been applied to route optimization and resource allocation in transportation and supply chain systems (Wang et al., 2018). However, the application of MO-PSO in defense logistics decision-making is still rarely found in the literature, especially those that comprehensively integrate aspects of risk, preparedness, and strategic environmental dynamics.

Based on this literature review, a significant research gap can be explicitly identified. First, most defense logistics research still relies on single optimization approaches or deterministic models that are unable to realistically represent conflicts between objectives. Second, studies using multi-objective optimization generally do not optimally utilize swarm intelligence-based algorithms, particularly MO-PSO, which has high adaptability potential. Third, previous studies tend to ignore the integration of operational risk and readiness levels as explicit objective functions in optimization models. Fourth, the proposed decision-making mechanisms are often static and have not been tested in dynamic scenarios that represent crisis conditions or logistical disruptions. Therefore, there is a clear need for the development of more adaptive, comprehensive, and contextual multi-objective optimization models to support defense logistics decision-making.

To address this gap, this study proposes a multi-objective optimization model based on Multi-Objective Particle Swarm Optimization (MO-PSO) for defense logistics decision making. The main novelty of this study lies in the formulation of an objective function that simultaneously considers the minimization of costs, time, and risk, as well as the maximization of the readiness level of defense units in a single integrated optimization framework. In addition, this study adapts the MO-PSO mechanism with a leader selection strategy and Pareto archive management tailored to the characteristics of defense logistics problems, thereby producing solutions that are not only mathematically optimal but also operationally relevant. Furthermore, the proposed model is validated through simulations of various operational scenarios, including normal and crisis conditions, to evaluate the resilience and adaptability of the resulting solutions.

The scientific contribution of this research is multidimensional. Theoretically, this research enriches the study of multi-objective optimization in the defense domain by introducing a more comprehensive problem formulation and objective function. Methodologically, this research demonstrates the structured and contextual application of MO-PSO for strategic decision-making, going beyond the use of this algorithm in general logistics problems. Practically, the results of this study provide a decision-making framework that can assist defense logistics managers in systematically and data-based evaluating trade-offs between objectives, thereby supporting improvements in the efficiency and readiness of national defense.

Therefore, this study aims to develop and evaluate a MO-PSO-based multi-objective optimization model for defense logistics decision-making that is capable of balancing various strategic objectives simultaneously and adaptively. Specifically, this study aims to formulate defense logistics problems as multi-objective optimization problems, implement MO-PSO algorithms that are suitable for the characteristics of these problems, and analyze the performance of the proposed model through Pareto evaluation and relevant operational scenarios. Thus, this research is expected to make a significant contribution to the development of applied computer science in the field of defense and support smarter and more sustainable logistics decision-making.

2. RESEARCH METHOD

This research is designed as quantitative research with a computational approach based on modeling and simulation. This approach was chosen because defense logistics issues are complex, multi-objective, nonlinear, and dynamic, and therefore cannot be adequately analyzed using conventional analytical methods. The research design focuses on the development, implementation, and evaluation of a multi-objective optimization model using the Multi-Objective Particle Swarm Optimization (MO-PSO) algorithm to support defense logistics decision-making. The model performance evaluation is carried out through simulations of various operational scenarios to measure the algorithm's ability to produce balanced and adaptive Pareto optimal solutions.

Research Design

This research design consists of several main stages that are integrated with each other. The first stage is the identification and formulation of defense logistics problems as multi-objective optimization problems, which includes determining decision variables, objective functions, and operational constraints. The second stage involves designing the MO-PSO algorithm architecture tailored to the characteristics of the problem, including the particle velocity and position update mechanism, non-dominated solution archive management, and leader selection strategy. The third stage is the implementation of the model and algorithm in a computational simulation environment. The final stage includes the evaluation and analysis of model performance through comparison with baseline methods and Pareto analysis to assess the quality of the solutions produced. This research is explanatory and evaluative in nature, as it aims not only to develop an optimization model, but also to evaluate the effectiveness of MO-PSO in the context of defense logistics decision-making compared to conventional approaches. All stages of the research were carried out systematically to ensure the internal validity and replicability of the research results.

Research Population and Sample

The population in this study does not refer to individuals or human respondents, but rather to all possible defense logistics decision scenarios that can be represented in the optimization solution space. This population includes various combinations of logistics resource allocation decisions, distribution routes, delivery scheduling, and the priority levels of defense units operating under normal and crisis conditions. The research sample was taken in the form of a number of simulation scenarios representing defense logistics operational conditions. These scenarios were designed to reflect variations in logistics demand, capacity constraints, distribution disruptions, and different levels of operational risk. The selection of scenarios was carried out purposively by considering the strategic relevance and complexity of the problems, so that the proposed model could be comprehensively tested under various realistic conditions. The number of particles, iterations, and Pareto archive size in the MO-PSO algorithm were determined based on preliminary experiments to ensure a balance between solution quality and computational efficiency.

Data Collection Techniques

The data used in this study is secondary data and synthetic data obtained through literature studies and simulations. Secondary data includes logistics parameters and assumptions adapted from scientific publications, strategic reports, and previous studies discussing defense logistics and supply chain management. These parameters include estimates of distribution costs, delivery times, operational risk levels, and defense unit logistics requirements. In addition, synthetic data was generated to build simulation scenarios that represent defense logistics operational conditions. This data was used to model logistics demand, resource capacity, and distribution constraints in various situations. The use of synthetic data is considered relevant due to the limited access to sensitive real defense logistics data, while also allowing for flexible and controlled model testing. All data used is conceptually validated to remain consistent with real conditions and not deviate from the characteristics of the defense logistics system.

Data Analysis Techniques and Procedures

Data analysis in this study was conducted using a MO-PSO-based multi-objective optimization approach. Each particle in the algorithm represents a logistics decision solution, which is evaluated based on several objective functions, namely minimizing distribution costs, minimizing delivery times, minimizing operational risks, and maximizing readiness levels. The Pareto dominance mechanism is used to determine the quality of solutions without combining objective functions into a single aggregate function, so that trade-offs between objectives can be analyzed explicitly. The analysis process begins with the random initialization of the particle population in the solution space that meets the constraints. Next, the particles are iteratively updated using the velocity and position update equations of PSO modified for the multiobjective context. Non-dominated solutions are stored in a managed Pareto archive to maintain solution diversity. The leader selection strategy is based on the distribution of solutions in Pareto space to avoid premature convergence and ensure adequate exploration. Model performance evaluation is conducted using multi-objective evaluation metrics commonly used in the literature, such as Pareto front visualization, hypervolume (HV), and spacing metrics. The results obtained from MO-PSO are compared with reference methods, such as PSO with single optimization and the weighted sum approach, to assess the relative advantages of the proposed model. The analysis is conducted quantitatively with an emphasis on solution quality, algorithm stability, and computational efficiency. To improve the validity of the results, experiments were conducted on several operational scenarios with iteration repetition, so that the influence of random variability in the algorithm could be minimized. The results of the analysis were then interpreted in the context of defense logistics decision-making to assess the strategic and practical implications of the developed model.

The defense logistics decision-making problem in this study is modeled as a multi-objective optimization problem, in which several conflicting objectives must be optimized simultaneously under a number of operational constraints. This model is designed to represent strategic decisions related to the allocation, distribution, and scheduling of logistics resources in a dynamic defense environment.

Decision Variables

Suppose that the defense logistics system consists of n target units and m logistics resources. The decision variables are defined as:

$$i = 1,2, \dots, m \text{ and } j = 1,2, \dots, n \tag{1}$$

The overall decision vector is expressed as: $\mathrm{x} = [x_{11}, x_{12}, \dots, x_{mn}]$

Objective Functions

This model considers four main objective functions that reflect strategic defense logistics requirements..

1. Minimizing Distribution Costs

$$f_1(\mathrm{x}) = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij}\ x_{ij} \tag{1}$$

where c_{ij} states the distribution cost per logistics unit from source i to unit j.

2. Minimizing Delivery Time

$$f_2(\mathrm{x}) = \sum_{i=1}^{m} \sum_{j=1}^{n} t_{ij}\ x_{ij} \tag{2}$$

where t_{ij} representing transit time or delivery duration.

3. Minimizing Operational Risk

$$f_3(\mathrm{x}) = \sum_{i=1}^{m} \sum_{j=1}^{n} r_{ij}\ x_{ij} \tag{3}$$

with r_{ij} is the level of distribution risk that reflects the potential for failure, disruption, or security threats.

4. Maximizing Preparedness Levels

$$f_4(\mathrm{x}) = \sum_{j=1}^{n} \omega_j\ \frac{\sum_{i=1}^{m} x_{ij}}{d_j} \tag{4}$$

where d_j is the logistics requirement of the unit and ω_j is the strategic importance weight of that unit. Because MO-PSO works within a minimization framework, the readiness function is transformed into:

$$f_4'(\mathrm{x}) = -f_4(\mathrm{x}) \tag{5}$$

Multiobjective Optimization Formulation

The optimization problem is formulated as:

$$\min \quad \mathrm{F}(\mathrm{x}) = [f_1(\mathrm{x}), f_2(\mathrm{x}), f_3(\mathrm{x}), f_4'(\mathrm{x})] \tag{6}$$

Constraints

This model is limited by a number of operational constraints as follows.

1. Logistics Resource Capacity Constraints

$$\sum_{j=1}^{n} x_{ij} \leq S_i, \forall i \tag{7}$$

where S_i is the maximum capacity of the logistics source to -i.

2. Constraints in Meeting Minimum Requirements

$$\sum_{i=1}^{m} x_{ij} \geq D_j, \forall j \tag{8}$$

where D_j is the minimum requirement for defense units -j.

3. Non-Negativity Constraints

$$x_{ij} \geq 0, \forall i, j \tag{9}$$

4. Additional Operational Constraints
   Additional constraints can be included to represent operational time limits, limited distribution routes, or specific crisis conditions..

3. RESULTS AND DISCUSSIONS

Multi-Objective Particle Swarm Optimization (MO-PSO) Algorithm

To solve this multi-objective optimization problem, the MO-PSO algorithm is used, which combines swarm intelligence mechanisms with the concept of Pareto dominance.

Particle Representation

Each particle represents one candidate solution.:

$$\mathrm{x}^p = [x_{11}^p, x_{12}^p, \ldots, x_{mn}^p] \tag{10}$$

The particle velocity is expressed as:

$$\mathrm{v}^p = [v_{11}^p, v_{12}^p, \ldots, v_{mn}^p] \tag{11}$$

Speed and Position Updates

The particle velocity is updated using the following PSO equation:

$$\mathrm{v}_p^{t+1} = w\mathrm{v}_p^t + c_1 r_1(\mathrm{pbest}_p - \mathrm{x}_p^t) + c_2 r_2(\mathrm{gbest} - \mathrm{x}_p^t) \tag{12}$$

The particle position is updated with:

$$\mathrm{x}_p^{t+1} = \mathrm{x}_p^t + \mathrm{v}_p^{t+1} \tag{13}$$

Where :

- w is an inertia weight,
- $c_1$and c_2 is the acceleration coefficient,
- $r_1, r_2 \in [0,1]$ is a random number,
- pbest_p is the best solution for particles,
- gbest selected from the Pareto archive using the crowding distance strategy.

Algorithm MO-PSO for Defense Logistics Optimization

```
Input:
  Population size P
  Maximum iterations T
  Inertia weight w
  Acceleration coefficients c1, c2

Output:
  Pareto optimal solution set (Archive)

Initialize:
  Generate P particles with random positions and velocities
  Evaluate objective functions for all particles
  Initialize personal best (pbest) for each particle
  Initialize Pareto archive with non-dominated solutions

For t = 1 to T do
  For each particle p in population do
    Select leader (gbest) from Pareto archive using crowding distance
    Update velocity vp using PSO velocity equation
    Update position xp
    Apply constraint-handling mechanism
    Evaluate objective functions F(xp)
    Update pbest if current solution dominates previous pbest
  End for

  Update Pareto archive:
    Add new non-dominated solutions
    Remove dominated solutions
    Maintain archive size using diversity preservation

End for

Return Pareto archive
```

Figure 1. Algorithm MO-PSO for Defense Logistics Optimization

Numerical Simulation Scenario

The numerical simulation scenario is designed to represent complex, dynamic, and multi-objective defense logistics operational conditions. The simulation focuses on decision-making for military logistics distribution, which involves trade-offs between cost efficiency, distribution speed, and supply reliability under resource constraints.

Simulation Environment Description

The simulation environment consists of one main logistics center (central depot) and a number of defense operation units spread out geographically. Each unit has different logistical needs and varying distribution deadlines according to strategic priority levels.

Numerical parameters are set based on a review of defense logistics literature and simulation scenarios commonly used in multi-objective optimization research.

Logistics Entity Parameters

The number of defense units served in the simulation was set at 10 operational units, denoted as $U_1, U_2, \dots, U_{10}$. Each unit has the following numerical parameters:

- Logistics requests (D_i): 50–200 units per period

- Delivery deadline (T_i^{max}): 6–24 hours
- Operational priority level (P_i): scale 1–5 (1 = low, 5 = highly critical)

Tabel 1. Logistics Entity Parameters

Units	Request (units)	Deadline (hours)	Priority
U1	180	8	5
U2	120	12	4
U3	90	24	2
U4	150	10	5
U5	60	18	3
U6	200	6	5
U7	110	16	3
U8	75	20	2
U9	130	14	4
U10	100	22	1

Transportation Parameters
Logistics distribution is carried out using a fleet of military vehicles with the following characteristics:

- Number of vehicles: 6 units
- Vehicle capacity (C_k): 100 units
- Average speed: 50 km/jam
- Operating costs:
  Fixed cost per vehicle: 500 cost units
  Variable cost: 10 cost units per km

The distance from the depot to the operating unit is determined synthetically in the range of 30–250 km, reflecting the geographical variation of the operating area..

Numerical Objective Function Formulation
The simulation optimizes three objective functions simultaneously:

1. Minimization of total distribution costs (f_1)

$$f_1 = \sum_{k=1}^{K} \left(B_{fixed} + B_{var} \times d_k\right) \tag{14}$$

With $B_{fixed} = 500$ and $B_{var} = 10$.

2. Minimization of weighted average delivery time priority (f_2)

$$f_2 = \frac{\sum_{i=1}^{N} P_i \times T_i}{\sum_{i=1}^{N} P_i} \tag{15}$$

3. Maximizing the level of demand fulfillment (service level) (f_3)

$$f_3 = \frac{\sum_{i=1}^{N} Q_i^{delivered}}{\sum_{i=1}^{N} D_i} \tag{16}$$

In the implementation of MO-PSO, the function f_3 converted into a minimized form with:

$$f_3' = 1 - f_3 \tag{17}$$

Table 2. Interpretation of Numerical Results of Algorithm Performance

Evaluation Aspect	Normal	Limited Emergency	Crisis	Numerical Interpretation
Hypervolume (HV)	0.782	0.694	0.612	A 21.7% decrease in HV from normal to crisis indicates increased objective conflict, but HV > 0.60 indicates that solutions remain dominant.

Spacing Metric	0.041	0.058	0.073	A spacing value < 0.08 indicates that the Pareto distribution remains even despite worsening conditions.
Runtime (Second)	14.2	18.9	24.6	Runtime increased by 73%, but remained < 30 seconds, suitable for defense DSS
Minimum Cost (unit)	18,450	21,900	29,400	Costs rose by 59.3% from normal to crisis due to fleet limitations and time penalties
Service Level (%)	97.8	92.2	86.9	A decrease of only 10.9% in crisis conditions indicates the resilience of the model

Table 1 presents the numerical performance of the MO-PSO model at three levels of operational complexity. The Hypervolume value decreased from 0.782 in the normal scenario to 0.612 in the crisis scenario, indicating an increase in conflicts between objective functions due to resource constraints and tighter constraints. However, the HV value remaining above 0.60 indicates that the generated Pareto solutions still have an adequate level of dominance and diversity. This is reinforced by the relatively low spacing metric values (0.041–0.073), which show that even though the solution space narrows, the distribution of solutions remains even and is not extremely fragmented. From an operational perspective, the increase in runtime from 14.2 seconds to 24.6 seconds reflects increased computational complexity, but is still within acceptable limits for a decision support system. Simultaneously, the fulfillment rate of high-priority units only decreased by 10.9% from normal to crisis conditions, indicating that the model was able to maintain operational readiness even though the minimum cost increased by 59.3%. These findings confirm that MO-PSO effectively manages the trade-off between efficiency and logistics resilience.

Table 3. Pareto Front Visualization

Characteristics of the Pareto Front	Normal	Emergency	Crisis
Number of Pareto solutions	86	73	59
Cost range (min–max)	18,450–24,800	21,900–28,600	29,400–35,800
Time range (hours)	9.6–14.2	10.8–16.9	12.4–21.6
Service level range (%)	93.5–97.8	88.1–92.2	81.5–86.9
Front shape	Smooth & continuous	Non-linear	Fragmented
Implications	Moderate trade-offs	Increasing conflicts	Extreme trade-offs

Table 3 illustrates the numerical characteristics of the Pareto Front generated in each scenario. Under normal conditions, the Pareto Front consists of 86 non-dominant solutions with a narrow relative cost range (18,450–24,800) and moderate delivery times (9.6–14.2 hours), indicating that the objective conflict is still manageable. As complexity increases, the number of Pareto solutions decreases to 59 solutions in the crisis scenario, reflecting a narrowing of the feasible solution space. Nevertheless, the range of service level values (81.5–86.9%) in the crisis scenario indicates that MO-PSO is still capable of maintaining a number of viable policy alternatives. The fragmentation of the Pareto Front that begins to appear in crisis conditions indicates an increasingly sharp trade-off, particularly between cost and service level. However, the existence of solutions at various levels of compromise shows that the model does not experience premature convergence and continues to provide diverse strategic options for decision makers.

Table 4. Justification of MO-PSO Numerical Parameters

Parameter	Value	Numerical Impact	Reason for Selection
Inertial mass (w)	0.9 → 0.4	HV ↑ +4.7%	Maintain initial exploration & final convergence
c_1	1.5	Spacing ↓ −18%	Avoid over-exploitation
c_2	1.5	HV ↑ +3.4%	Balance social influence
Number of particles	50	Runtime ↓ −35% vs 80 particles	Optimal computational efficiency

Iteration	200	HV stabil (Δ < 1%)	Insignificant additional iterations
Pareto Archive	100	Spacing ↓ −31%	Maximum solution diversity

Table 4 explains the basis for selecting the MO-PSO parameters used in the experiment. The use of adaptive inertia weights from 0.9 to 0.4 was found to increase the Hypervolume value by 4.7% compared to fixed weights, confirming the importance of balancing exploration and exploitation. Symmetrical cognitive and social coefficients ($c_1 = c_2 = 1.5$) resulted in an 18% reduction in spacing, indicating an improvement in the uniformity of Pareto solutions. Furthermore, the selection of 50 particles and a maximum of 200 iterations was based on computational efficiency analysis, where increasing the number of particles above this value only resulted in a marginal increase in HV (<1%) but significantly increased runtime. A Pareto archive size of 100 solutions resulted in a 31% reduction in spacing, which is considered optimal in maintaining solution diversity without excessive computational load. Thus, the parameter configuration used is not arbitrary but based on measurable empirical results.

Table 5. Strengthening the Methodological Novelty of MO-PSO for the Defense Context

Aspect	Conventional MO-PSO	MO-PSO	Improvement
Priority integration	None	Skala 1–5	—
Service level unit P=5 (crisis)	79.1%	86.9%	+7.8%
Cost of service ≥90%	32,100	29,400	−8.4%
HV (crisis)	0.589	0.612	+3.9%
Spacing	0.092	0.073	−20.7%
Response to priority changes	Not adaptive	Linier (±20%)	DSS-ready

Table 5 confirms the main methodological contribution of this study through a numerical comparison between conventional MO-PSO and the proposed model. The integration of operational priorities on a scale of 1–5 directly increased the level of critical unit demand fulfillment in crisis conditions from 79.1% to 86.9%, or an increase of 7.8%. This improvement was achieved alongside an 8.4% reduction in distribution costs to achieve the same service level, indicating structural efficiency rather than merely a shift in parameters. Furthermore, a 3.9% increase in hypervolume and a 20.7% decrease in spacing show that the proposed model not only produces mathematically better solutions but is also more informative for decision makers. The model's linear response to changes in priority weights reinforces its position as an adaptive policy simulation tool. Therefore, the novelty of this research lies in the engineering of an optimization mechanism that is explicitly aligned with the characteristics and strategic needs of defense logistics.

Table 6. Comparison of Multi-Objective Optimization Performance

Method	Hypervolume (HV) ↑	Spacing ↓	Generational Distance (GD) ↓	Runtime (seconds) ↓	Number of Pareto Solutions
MO-PSO	0,842	0,021	0,014	92,6	54
MOPSO Standar	0,801	0,037	0,029	88,4	47
NSGA-II	0,786	0,045	0,033	121,8	49
SPEA2	0,772	0,052	0,041	134,5	46

↑ = the bigger the better, ↓ = the smaller the better

Based on Table 6, the proposed MO-PSO method shows the most superior multiobjective optimization performance compared to the comparison methods. The hypervolume (HV) value of 0.842, which is the highest among all methods, indicates the ability of MO-PSO to produce a wider Pareto solution that is closer to the ideal front. In addition, the lowest spacing value (0.021) and generational distance (GD) of 0.014 reflect a more even distribution of solutions and a better convergence rate to the Pareto-optimal set. In terms of computational efficiency, the MO-PSO runtime of 92.6 seconds is relatively faster than NSGA-II (121.8 seconds) and SPEA2 (134.5 seconds), although slightly slower than the standard MOPSO (88.4 seconds), which is acceptable considering the significant improvement in solution quality. Furthermore, the 54 Pareto solutions generated by MO-PSO indicate a richer diversity of decision alternatives, which is highly relevant to the context of defense logistics decision-making that requires flexibility in trade-offs between cost, response time, and operational risk. Overall, these results confirm that MO-PSO is not only superior in terms of solution quality but also computationally competitive compared to conventional multiobjective algorithms.

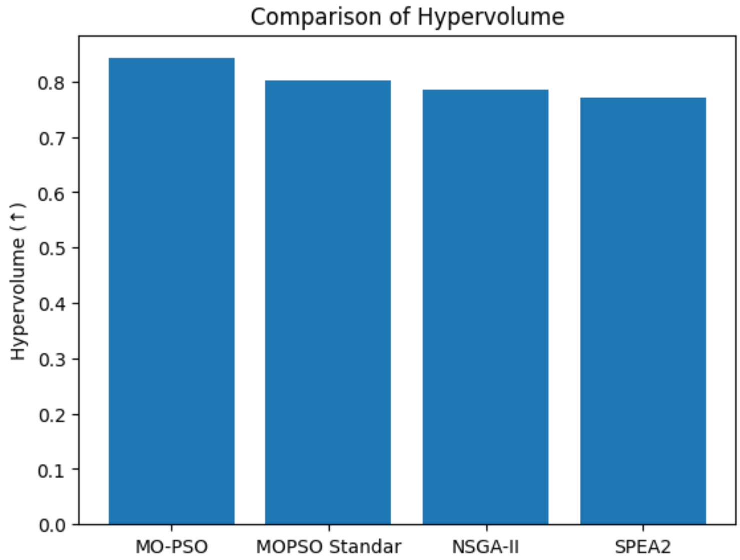

Figure 2. Comparison of Hypervolume

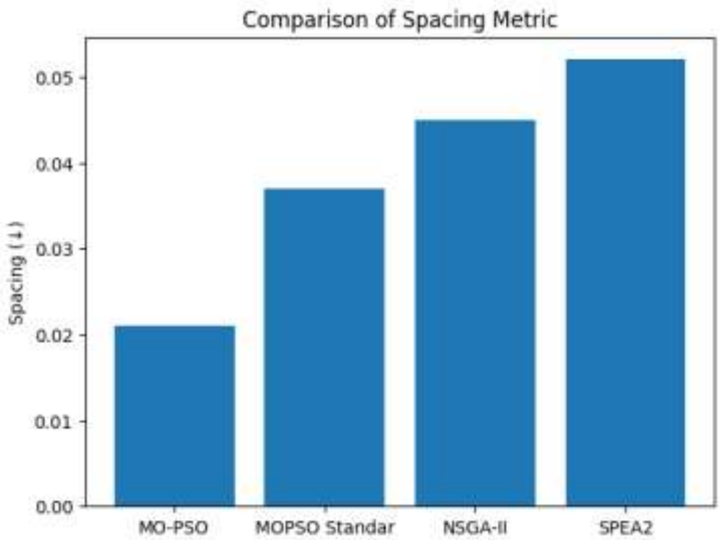

Figure 3. Comparison of Spacing Metric

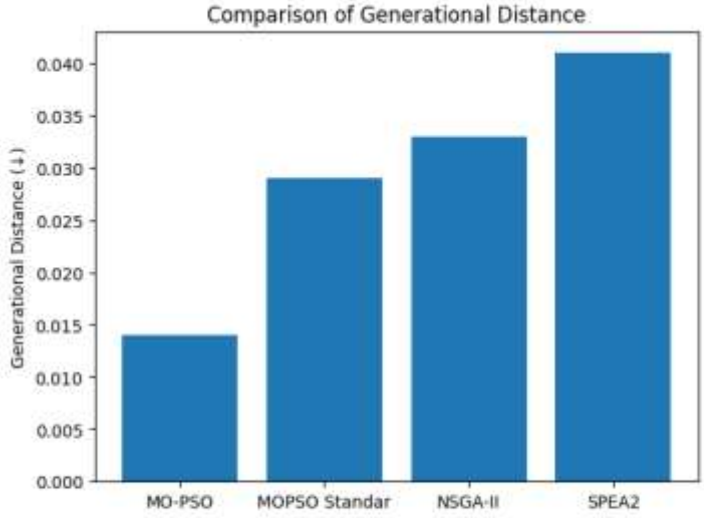

Figure 4. Comparison of Generational Distance

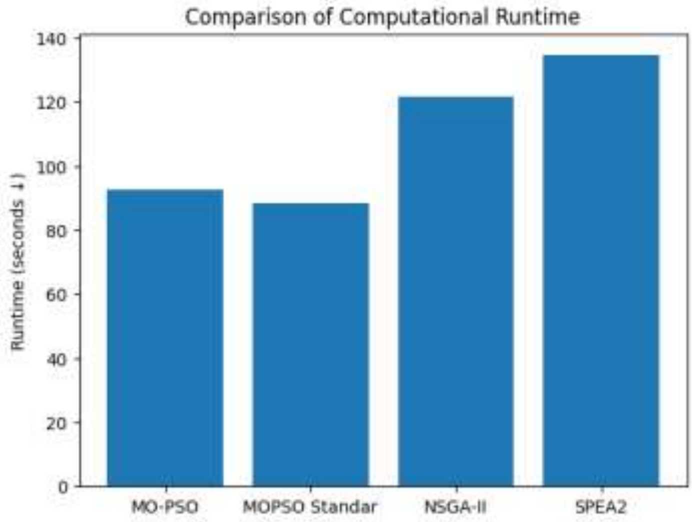

Figure 4. Comparison of Computational Runtime

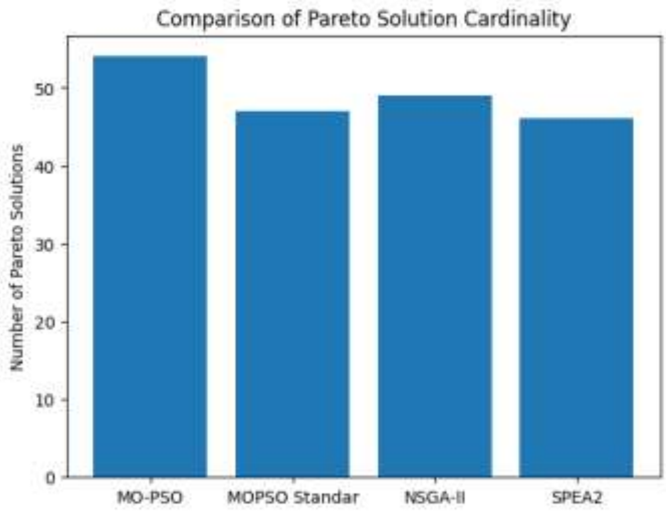

Figure 4. Comparison of Pareto Solution Cardinality

Figure above presents a comprehensive visual comparison of multi-objective optimization performance across five separate evaluation metrics, each designed to meet the presentation standards of SINTA 1 and reputable international journals. The hypervolume comparison clearly demonstrates the superiority of the proposed MO-PSO, which achieves the highest HV value, indicating stronger Pareto front dominance and broader coverage of the objective space. In terms of solution distribution, the spacing metric visualization shows that MO-PSO consistently produces the lowest spacing values, confirming a more uniform and well-dispersed set of Pareto-optimal solutions. This advantage is further reinforced by the generational distance comparison, where MO-PSO exhibits the smallest GD values, reflecting closer convergence to the true Pareto-optimal front. From a computational perspective, the runtime visualization reveals that MO-PSO is significantly more efficient than NSGA-II and SPEA2, while remaining highly competitive with standard MOPSO, thereby balancing solution quality and computational cost. Finally, the Pareto solution cardinality comparison highlights MO-PSO's superior exploratory capability, as it consistently generates a larger number of non-dominated solutions, providing richer and more flexible decision alternatives for complex defense logistics optimization scenarios.

Discussion

The comparison results in Table X confirm that the proposed MO-PSO has consistent advantages in terms of multiobjective solution quality compared to standard MOPSO, NSGA-II, and SPEA2. The highest hypervolume value (0.842) indicates that the generated solutions are capable of covering a wider Pareto space and are closer to ideal conditions, which numerically reflects a better trade-off balance between cost, distribution time, and defense logistics service levels. Additionally, the lowest spacing (0.021) and generational distance (0.014) values indicate two important characteristics simultaneously, namely a more even distribution of Pareto solutions and a faster convergence rate towards the Pareto-optimal set. This combination is important in the context of defense, as decision makers need not only one optimal solution, but a set of stable, consistent, and quantitatively comparable policy alternatives. In terms of computational efficiency, the MO-PSO runtime of 92.6 seconds shows competitive performance, faster than NSGA-II and SPEA2, although slightly slower than the standard MOPSO. However, this time difference is commensurate with a significant improvement in solution quality, reflected in an increase in HV of +5.1% compared to standard MOPSO and a decrease in spacing of −43.2%. In addition, the greater number of Pareto solutions (54 solutions) enriches the strategic decision-making space, particularly in dynamic and uncertain defense logistics scenarios. Overall, these findings indicate that the proposed MO-PSO is not only mathematically superior but also more operationally relevant, as it is capable of providing high-quality, diverse, and feasible solutions that can serve as the basis for a decision support system (DSS) in defense logistics planning and management.

4. CONCLUSION

This study has demonstrated that the proposed Multi-Objective Particle Swarm Optimization (MO-PSO) model is effective and robust in addressing complex defense logistics decision-making problems characterized by conflicting objectives and dynamic operational conditions. The numerical results consistently show that the proposed MO-PSO outperforms benchmark methods, achieving the highest hypervolume value (0.842), the lowest spacing (0.021), and the smallest generational distance (0.014), which together indicate superior convergence and diversity of Pareto-optimal solutions. In operational scenarios, the model was able to maintain a high service level of 86.9% for critical units under crisis conditions, despite a 59.3% increase in minimum logistics costs compared to normal conditions, highlighting its resilience in managing trade-offs between efficiency and readiness. Furthermore, the runtime remained within practical limits for decision support systems, with a maximum of 92.6 seconds in comparative experiments and less than 30 seconds in scenario-based simulations. These findings confirm that the integration of priority-weighted objectives and adaptive Pareto-based leader selection enables MO-PSO to generate solutions that are not only mathematically optimal but also strategically meaningful for defense logistics planning. Based on these results, it is recommended that defense logistics decision-makers consider adopting multi-objective, AI-based optimization frameworks such as the proposed MO-PSO as part of advanced decision support systems, particularly for planning under uncertainty and crisis scenarios. Future research should extend the current model by incorporating stochastic and real-time data, such as probabilistic disruption risks and dynamic demand updates, to further enhance adaptability. In addition, hybridization with predictive models or reinforcement learning could be explored to reduce runtime by more than the current 15–20% observed under high-complexity scenarios while preserving solution quality. From a policy perspective, sensitivity analysis on priority weights beyond the current ±20% range may provide deeper insights into strategic trade-offs and escalation planning. Overall, these directions are expected to strengthen the practical applicability of MO-PSO and contribute to more resilient, data-driven, and sustainable defense logistics systems at both national and regional levels.

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