Scalable Multi-Objective Optimization for Facility Location Using a Metaheuristic Technique

THANATHORN KAROT, CHOOSAK PORNSING*

Department of Industrial Engineering and Management, Faculty of Engineering and Industrial Technology, Silpakorn University, Nakhon Pathom 73000, Thailand

**Corresponding author: pornsing_c@su.ac.th*

(Received: 30 November 2025; Accepted: 21 February 2026; Published online: 10 May 2026)

ABSTRACT: Rapid growth in e-commerce and service expectations forces large-scale logistics networks to balance facility operating cost, service coverage, and delivery equity simultaneously. This study aims to develop a scalable discrete multi-objective particle swarm optimization (MOPSO-FLP) framework for constraint-rich facility location problems, where traditional exact approaches become impractical. The proposed method integrates discrete encoding, feasibility repair, adaptive parameter control, and an archive-based leader selection strategy, and it is evaluated using benchmark instances and a national postal logistics network case. Across 30 independent runs, MOPSO-FLP achieves superior convergence and diversity compared with representative multi-objective metaheuristics (e.g., NSGA-II and related baselines), and the deployment validation yields a Pareto set of 47 non-dominated solutions that clearly exposes cost–coverage–equity trade-offs. Overall, the results demonstrate that the proposed framework provides decision makers with interpreted alternatives and actionable policies for large-scale logistics planning.

ABSTRAK: Pertumbuhan pesat dalam e-dagang serta peningkatan jangkaan perkhidmatan memaksa rangkaian logistik berskala besar untuk mengimbangi kos operasi fasiliti, liputan perkhidmatan, dan keadilan penghantaran secara serentak. Kajian ini bertujuan membangunkan satu kerangka pengoptimuman zarah berbilang objektif diskret yang berskala, iaitu Multi-Objective Particle Swarm Optimization bagi masalah penentuan lokasi fasiliti (MOPSO-FLP), khusus untuk persekitaran berkekangan tinggi di mana pendekatan tepat tradisional menjadi tidak praktikal. Kaedah yang dicadangkan mengintegrasikan pengekodan diskret, mekanisme pembaikan kebolehlaksanaan, kawalan parameter adaptif, serta strategi pemilihan pemimpin berasaskan arkib, dan dinilai menggunakan set data penanda aras serta kajian kes rangkaian logistik pos kebangsaan. Merentasi 30 ulangan bebas, MOPSO-FLP menunjukkan penumpuan dan kepelbagaian penyelesaian yang lebih baik berbanding metaheuristik berbilang objektif sedia ada seperti NSGA-II dan kaedah asas berkaitan. Pengesahan pelaksanaan menghasilkan satu set Pareto yang mengandungi 47 penyelesaian tidak didominasi, yang secara jelas menggambarkan kompromi antara kos, liputan, dan keadilan. Secara keseluruhan, dapatan kajian ini menunjukkan bahawa kerangka yang dicadangkan mampu menyediakan alternatif yang boleh ditafsir serta dasar yang boleh dilaksanakan oleh pembuat keputusan dalam perancangan logistik berskala besar.

KEYWORDS: *Facility location, Logistics systems, Multi-objective Optimization, Particle swarm optimization, Metaheuristics*

1. INTRODUCTION

Rapid changes in demand patterns, e-commerce growth, and service expectations have complicated the design and management of logistics networks. A central strategic question in such systems is where to locate facilities, such as warehouses, sorting centers, or service hubs, to consistently balance cost, service accessibility, and responsiveness. Facility location problems (FLPs) provide a mathematical framework for this decision, but real applications are rarely driven by a single objective. Instead, planners typically face several criteria that pull in different directions, for example, low cost versus high coverage or short travel times.

Traditional FLP models and solution methods have often been built around a single objective, most commonly cost minimization. While these formulations have contributed to theory and practice, they can mask important trade-offs and fail to account for issues such as service equity, environmental concerns, or robustness to disruptions [1, 2]. In many current applications, decision makers need to see not one “optimal” configuration but a spectrum of alternatives that trade cost for performance in different ways.

To support this need, multi-objective optimization (MOO) approaches that approximate the Pareto front have attracted increasing attention [3, 4]. In a Pareto-based view, a solution is considered efficient if no objective can be improved without worsening at least one other objective. Approximating such a front is particularly demanding when the underlying decision space is discrete and highly constrained, which is typical in realistic FLPs with capacity limits, service radius requirements, and policy rules.

Exact methods can, in principle, handle multi-objective models, but their computational effort tends to grow rapidly with problem size and constraint complexity. For national-scale or highly detailed regional systems, purely exact algorithms become difficult to use as routine planning tools. In contrast, metaheuristic algorithms seek high-quality solutions with more modest computational requirements, trading mathematical guarantees for scalability and flexibility.

Particle Swarm Optimization (PSO) is one such metaheuristic that has seen widespread use in engineering optimization because of its simple structure and few parameters [5, 6]. Its multi-objective variants (MOPSO) extend the original idea by maintaining an archive of non-dominated solutions and using leaders drawn from this archive to guide the swarm. Although a number of MOPSO approaches have been proposed, their direct application to discrete, constraint-rich FLPs remains limited, especially when several real-world considerations, such as coverage, equity, and maximum travel time, must be accounted for simultaneously [7].

This work aims to narrow that gap by developing a discrete MOPSO framework tailored specifically to multi-objective FLPs. The algorithm uses a binary encoding for facility opening decisions, while assignments and coverage are determined deterministically from those decisions. In addition to the basic swarm update rules, the algorithm uses adaptive parameter settings, an archive from which leaders are selected, and simple repair and local-search moves to satisfy constraints while preserving sufficient diversity in the swarm. The main contributions of the study are: 1) A discrete multi-objective facility location formulation is proposed that integrates elements of the p-median, maximal covering, and p-center models into a unified framework capturing cost, service coverage, and spatial equity, 2) A MOPSO-based solution procedure is developed, featuring problem-oriented encoding, feasibility-repair mechanisms, and adaptive parameter control to address large-scale and highly constrained search spaces, 3) The algorithm is examined through an extensive set of experiments on benchmark and synthetically generated instances of various sizes, with performance evaluated by several quality indicators and supported by statistical analyses of robustness and scalability, and 4) The framework is further demonstrated in the context of redesigning a national postal logistics network, where the obtained Pareto solutions are used to illustrate how alternative network configurations can inform managerial decision-making.

Novelty and contributions: This work advances the multi-objective facility location literature in three ways. (i) It proposes a discrete MOPSO formulation tailored to facility location decisions with practical constraints, including discrete site selection and operational feasibility handling. (ii) It integrates adaptive parameter control, feasibility repair, and archive-based leader selection to improve scalability and maintain diversity in high-dimensional, discrete search spaces. (iii) It establishes a consistent evaluation protocol with benchmark comparisons and statistical validation and demonstrates managerial interpretability through a national postal logistics network redesign case.

The paper is divided into five main sections. Section 2 presents a focused review of facility location and multi-objective metaheuristics. Section 3 describes the mathematical formulation and the proposed MOPSO-FLP algorithmic design. Section 4 reports computational experiments, sensitivity analyses, and validation of the national postal network deployment. Section 5 concludes the paper and outlines directions for future research.

2. PREVIOUS WORKS

2.1. Facility Location Problems

Facility location problems have been a core topic in location science and logistics for many decades. The earliest formulations were typically deterministic and relied on a single performance measure. Classic examples include the p-median model, which seeks to minimize the total demand-weighted distance or transportation cost, and the p-center model, which focuses on reducing the worst (maximum) distance between demand points and open facilities. A third foundational model is maximal covering, where the aim is to maximize the amount of demand served within a given service distance or time limit. These three formulations have shaped much of the subsequent work in the area and still serve as reference points for more elaborate models.

Over time, researchers have moved from these basic formulations to more elaborate FLPs that more closely mirror real planning contexts. Contemporary models often combine several objectives, introduce capacity constraints at facilities, and incorporate uncertainty in demand levels or travel times. Issues of fairness and equity in access to services have also become more visible, especially in public-sector and humanitarian applications. Fugaro and Sgalambro [8] review this evolution and note a growing interest in multi-criteria formulations that reflect social and environmental concerns alongside traditional economic objectives.

2.1. Metaheuristics in FLPs

As FLP formulations become more complex, metaheuristics have emerged as practical tools to search large solution spaces. Genetic Algorithms (GAs), Ant Colony Optimization (ACO), PSO, and other nature-inspired techniques have been successfully employed in various location and layout settings.

Koosha et al. [10], for instance, applied a GA to an unequal-area facility layout problem, balancing safety and cost under geometric constraints. ACO-based methods have been effective in routing and distribution problems on realistic road networks [11]. PSO, with its swarm-based search, has been adapted for tasks such as selecting locations for logistics centers or emergency facilities, particularly when decisions must be updated in response to changing conditions [12].

Within multi-objective optimization, MOPSO extends PSO by maintaining a collection of non-dominated solutions and using archive-based leaders to guide particles toward different regions of the Pareto front. Work by Makhadmeh et al. [13] and Kaveh et al. [14] demonstrates that carefully designed MOPSO variants can deliver competitive hypervolume and diversity metrics in industrial and construction applications, highlighting the potential of PSO-based methods for problems with conflicting criteria.

2.3. Multi-Objective Particle Swarm Optimization (MOPSO)

MOPSO variants differ mainly in how they manage the external archive, how leaders are selected, and how diversity is preserved along the Pareto front. Common strategies include grid-based mechanisms, crowding distance measures, and restricted tournament selection. These design choices influence both convergence speed and the spread of solutions across the objective space.

In most studies, the quality of a multi-objective algorithm is judged using the hypervolume indicator, which quantifies the region of the objective space dominated by the obtained solutions, together with measures such as inverted generational distance and spacing. Empirical comparisons indicate that carefully tuned MOPSO variants can achieve high hypervolume values and compete on a wide range of engineering benchmarks [13].

MOPSO has also been applied to problems well beyond traditional logistics and scheduling. Recent examples include renewable energy planning and microgrid design, where economic, technical, and, sometimes, environmental objectives must be considered simultaneously. These applications illustrate that MOPSO can handle heterogeneous objectives and large, complex search spaces, though problem-specific modifications are often needed to achieve good performance in each new domain.

2.4. Thematic Synthesis: Methodological Gaps and Future Directions

Although considerable progress has been made in MOPSO and related approaches, several open issues remain in the literature. A large share of existing MOPSO variants has been developed with continuous decision spaces in mind, using real-valued positions and velocities. When these schemes are transferred to discrete facility location settings without further adaptation, they often generate infeasible solutions or converge to configurations that are clearly suboptimal [15].

Another concern relates to how algorithms are benchmarked. Different authors rely on different instance sets, performance indicators, and stopping rules, making it difficult to compare results across studies or to reproduce reported findings consistently [16]. Hybrid strategies that combine metaheuristics with decomposition, column generation, or other exact techniques have been proposed as a possible remedy, but their role in multi-objective FLPs remains only partially explored [17].

In terms of application domains, most published work focuses on logistics, emergency response, or healthcare. Areas such as climate-resilient infrastructure, autonomous or intelligent transportation systems, and equity-oriented urban planning have received much less attention so far. Uncertainty is frequently addressed through a small set of static scenarios, rather than through richer stochastic or dynamic models, and ethical dimensions, such as equitable access to services or the explicit involvement of stakeholders in defining objectives, are only starting to appear systematically [8].

The present study is motivated by these observations and proposes a discrete MOPSO framework tailored to the combinatorial nature of FLPs, uses standardized benchmarks and common performance indicators, and incorporates equity-related objectives directly into the formulation, allowing issues of fairness to be examined alongside cost and efficiency.

2.5. Positioning the Current Study

In light of the above discussion, the proposed MOPSO-FLP framework is a discrete, multi-objective metaheuristic specifically tailored to facility location problems under realistic constraints and explicit equity considerations. Facilities are encoded as a binary vector indicating which sites are open, while assignments and coverage levels are determined by simple deterministic rules. This separation keeps feasibility checks relatively straightforward and allows us to design repair moves and local search operators that act directly on the location decisions.

A second feature of the study is the emphasis on a consistent evaluation protocol. We test the algorithm on both benchmark and synthetically generated instances of varying sizes, use commonly used performance indicators, and perform statistical analyses to compare results across algorithms. The intention is to make the assessment as transparent and reproducible as possible. Finally, the framework is exercised on the redesign of a national postal logistics network, which serves as a concrete illustration of how the method can be used in practice and how the resulting trade-off solutions may be relevant not only to postal services but also to related areas such as disaster logistics, environmentally oriented infrastructure planning, and equitable provision of public services.

3. METHOD

This section presents the methodological framework adopted for modeling and solving the multi-objective facility location problem. The approach combines a multi-objective facility location formulation with a discrete MOPSO algorithm and a systematic experimental design.

3.1. Problem Formulation

3.1.1. Multi-objective Facility Location Model

The considered FLP is defined on a bipartite graph $G = (I \cup J, E)$, where $I = \{1,2,\ldots,n\}$ denotes demand nodes and $J = \{1,2,\ldots,m\}$ denotes candidate facility sites. Each demand node $i \in I$ has demand w_i, and opening a facility at the site $j \in J$ incurs a fixed cost f_j. The distance between the demand point i and the site j is d_{ij}, which may represent Euclidean or network distance. Two global parameters are specified: the maximum number of facilities p and a service radius r.

The decision variables are:

- $y_j \in \{0,1\}$: 1 if a facility is opened at the site j, 0 otherwise;
- $x_{ij} \in \{0,1\}$: 1 if the demand node i is assigned to the facility j;
- $c_i \in \{0,1\}$: 1 if demand node i is considered covered within the radius r.

Three conflicting objectives are modeled:

1. Total cost (fixed plus transportation):

$$F_1 = \sum_{j\in J} f_j y_j + \sum_{i\in I} \sum_{j\in J} w_i d_{ij} x_{ij} \tag{1}$$

2. Weighted service coverage (to be maximized):

$$F_2 = \sum_{i\in I} w_i c_i \tag{2}$$

3. Maximum allocation distance (to be minimized):

$$F_3 = \max_{i \in I, j \in J} \{d_{ij} x_{ij}\} \tag{3}$$

The model is subject to the following constraints:

$$\sum_{j \in J} x_{ij} = 1, \quad \forall i \in I \tag{4}$$

$$x_{ij} \leq y_j, \quad \forall i \in I, \forall j \in J \tag{5}$$

$$\sum_{j \in J} y_j \leq P \tag{6}$$

$$\sum_{j \in N} y_j \geq c_i, \quad \forall i \in I, where\ N_i = \{j \in J: d_{ij} \leq r\} \tag{7}$$

Equation (4) ensures that each demand node is assigned to exactly one facility, while Eq. (5) enforces that assignments can only be made to open facilities. The cardinality constraint in Eq. (6) limits the total number of facilities that may be opened, and Eq. (7) defines the coverage variable c_i in terms of the service radius r. Taken together, these equations capture the trade-offs between investment and operating cost, service coverage, and spatial equity

3.1.2. Problem Characteristics

The resulting optimization problem is combinatorial and NP-hard. The binary facility decisions induce a vast number of possible network configurations, and assignment and coverage variables are tightly linked to those decisions. The objectives are structurally conflicting: reducing the number of facilities typically lowers fixed costs but may deteriorate coverage and increase the maximum distance; expanding the network has the opposite effect. Because of these features, exact methods scale poorly to large instances, which motivates the use of an efficient multi-objective metaheuristic.

3.2. MOPSO-FLP Algorithm Design

The proposed MOPSO-FLP algorithm adapts PSO to the multi-objective and binary setting of FLPs. Each particle encodes a candidate set of open facilities through a binary vector $y \in \{0,1\}^m$. Given a facility vector, assignments x_{ij} and coverage variables c_i are derived by deterministic rules, for example, by assigning each demand node to its nearest open facility, which simplifies evaluation and ensures feasibility once y satisfies the facility limit.

Particle velocities are interpreted as probabilities of switching bits in y. A standard binary PSO update is used: for each component, the velocity combines inertia, cognitive, and social terms; a sigmoid function maps the velocity to a probability; and the bit is flipped with that probability. An external archive of non-dominated solutions is maintained, and leaders are drawn from this archive using a roulette mechanism weighted by a diversity indicator (e.g., crowding distance) to encourage exploration of different regions of the Pareto front.

Adaptive parameter control is employed: the inertia weight ω decreases from a high initial value to a lower final value over the iterations, gradually shifting the search from exploration to exploitation. The acceleration coefficients c_1 and c_2 can also be adjusted over time to balance individual learning and social influence. The main steps of the proposed MOPSO-FLP procedure are summarized in the flowchart shown in Fig. 1, which highlights the initialization phase, archive update, leader selection, velocity and position updates, repair and local search operators, and the stopping condition.

```
Input:
    - Set of demand points $I$, candidate facilities $J$
    - Distance matrix $D = [d_{ij}]$, fixed costs $c_j$, demand weights $w_i$
    - Parameters: $P$ (max facilities), $r$ (service radius), $T$ (max iterations)
    - $M$ (population size), $A$ (archive size), $w_{init}$, $w_{final}$, $c_1$, $c_2$
Output:
    - External archive $A^*$ containing non-dominated solutions
Begin
    1. Initialize the population of $M$ particles:
        For each particle:
            - Randomly initialize binary position vector $y \in \{0,1\}^{|J|} s.t. \sum y_j \leq P$
            - Set velocity vector $v \leftarrow 0$
            - Derive $x_{ij}$ and $z_i$ deterministically from $y$
            - Evaluate objectives $F_1, F_2, F_3$
            - Set personal best $p_j \leftarrow y$
    2. Initialize external archive $A^*$ with non-dominated solutions from the population
    3. For iteration $t = 1$ to $T$ do:
        3.1 Update inertia weight:
            $w_t \leftarrow w_{init} - (w_{init} - w_{final}) \times (t / T)$
        3.2 For each particle, do:
            a. Select leader $g_j$ from $A^*$ using crowding-distance roulette
            b. Update velocity for each dimension $j$:
                $v_j \leftarrow w_t \times v_j + c_1 \times rand1 \times (p_j - y_j) + c_2 \times rand2 \times (g_j - y_j)$
            c. Apply sigmoid transformation:
         $s_j \leftarrow 1 / (1 + exp(-v_j))$
            d. Update position $y_j$:
                $y_j \leftarrow 1$ if $rand() < s_j$ else 0
            e. Apply feasibility repair:
                - If $\sum y_j > P$, remove facilities based on the utility ratio
                - Ensure every demand point is assigned, and the coverage constraint holds
            f. Derive $x_{ij}$ and $z_i$ from $y$
            g. Evaluate objectives $F_1, F_2, F_3$
            h. Update personal best if current solution dominates $p_j$
        3.3 Update archive $A^*$:
            - Insert non-dominated solutions from the population
            - Remove dominated solutions
            - If $|A^*| > A$, prune using the crowding distance
        3.4 Apply local search to a subset of $A^*$:
            - Use swap, add/drop, or reassignment moves to refine selected solutions
    End For
Return archive $A^*$ containing an approximated Pareto front
End
```

Figure 1. MOPSO-FLP pseudo code.

3.3. Specialized Operators

To maintain feasibility with respect to the facility limit and coverage constraints, MOPSO-FLP uses a repair operator whenever a particle violates the upper bound on the number of facilities. Facilities are ranked according to a utility measure that combines their contribution to coverage and their fixed costs, and the least useful facilities are closed until the limit is met.

Local search procedures are applied to selected non-dominated solutions in the archive. Typical moves include swapping facilities (open one, close another), reassigning demand nodes between facilities, and add-drop operations. These moves refine solutions without losing the archive's overall diversity. Diversity is explicitly monitored using crowding distance and related measures, and the archive is pruned when it becomes too large by removing overly similar solutions in objective space.

3.4. Experimental Design

To evaluate the proposed algorithm, both benchmark and synthetically generated instances are used. Standard instances from the OR-Library provide comparability with prior studies and allow indirect comparison with existing results. Synthetic FLP instances are constructed to vary systematically in size and key characteristics, including the number of demand points and candidate sites, their spatial distribution, demand heterogeneity, and cost structures. The main characteristics of the synthetic instances are summarized in Table 1, which groups them into small, medium, and large categories.

Table 1. Characteristics of generated facility location problem instances

Instance Type	Demand Points (*I*)	Candidate Locations (*J*)	Spatial Distribution	Demand Distribution	Cost Structure
Small	50-100	10-20	Uniform	Uniform	Low/High fixed cost
Medium	200-300	30-50	Clustered	Normal	Mixed ratios
Large	400-500	80-100	Random	Exponential	Variable ratios

For each instance, MOPSO-FLP and the comparator algorithms are run multiple times using different random seeds. Performance is summarized using three common multi-objective indicators: hypervolume, inverted generational distance, and spacing. Wall-clock time is also recorded to gauge computational effort.

Comparisons are made against Non-dominated Sorting Genetic Algorithm II (NSGA-II), a multi-objective simulated annealing variant (MO-SA), a greedy multi-objective heuristic (GMOH), and a variable neighborhood search for multi-objective optimization (VNS-MO). All algorithms share similar stopping rules, such as a maximum number of iterations and a limit on consecutive iterations without improvement, to provide a fair basis for comparison.

3.5. Implementation Details

The algorithm is implemented in C++ using a modular architecture that separates problem representation, objective evaluation, and search operators. Objective evaluations are parallelized using multi-threading to speed up runs on multi-core hardware. Experiments are conducted on a workstation with an Intel Core i7-8700K processor, 32 GB of RAM, and Windows 10 Professional, with compiler optimization flags enabled.

Table 2. Experimental parameter settings for MOPSO-FLP

Parameter	Value / Range	Justification
Population size	100 particles	Balances exploration and computational efficiency
Maximum iterations	1000	Provides sufficient convergence for large instances
Archive size	100 solutions	Prevents archive overflow while maintaining diversity
Inertia weight	0.9 → 0.1	Decreases nonlinearly to promote exploration, then exploitation
Acceleration coefficients	$c_1 = c_2 = 2.0$	Standard PSO setting with adaptive adjustment
Mutation rate	0.01	Introduces diversity and prevents stagnation

Parameter values such as population size, number of iterations, archive size, initial and final inertia weights, acceleration coefficients, and mutation rate are selected based on preliminary experiments and insights from the literature. The chosen settings aim to balance solution quality and runtime (see Table 2).

3.6. Statistical Analysis Framework

To assess the robustness and statistical significance of the results, each algorithm–instance combination is run 30 times. For each performance indicator, sample means and standard deviations are reported. Non-parametric tests such as the Mann–Whitney U test and Kruskal–Wallis test are used to compare algorithms, and corrections for multiple comparisons are applied when necessary. Effect sizes (e.g., Cohen's d or Cliff's delta) are also calculated to judge the practical relevance of observed differences.

3.7. Validation

Algorithmic correctness is checked through unit tests for core components such as the velocity update, repair operations, and archive management, and through integration tests on small instances where high-quality or optimal solutions are known. Pareto fronts obtained in these tests are inspected for consistency with the model's trade-off structure before running large-scale experiments.

4. RESULTS AND ANALYSIS

4.1. Benchmark Performance

MOPSO-FLP was tested on small (50×10), medium (150×30), and large (500×100) instances. Results confirmed consistent performance across scales. The summary statistics for hypervolume, inverted generational distance, spacing, and runtime across the three instance groups are reported in Table 3.

- Small problems: HV = 0.847 (±0.023), IGD = 0.011 (±0.004), SP = 0.042 (±0.010). Pareto fronts were nearly optimal in 87% of runs.
- Medium problems: HV = 0.792 (±0.031), IGD = 0.034 (±0.008), SP = 0.058 (±0.011). Runtimes scaled to ~392s.
- Large problems: HV = 0.718 (±0.042), IGD = 0.067 (±0.015), SP = 0.071 (±0.014). Runtimes ~847s, feasible for planning tasks.

Table 3. Benchmark performance of MOPSO-FLP

Scale	HV (±SD)	IGD (±SD)	SP (±SD)	Time (s)
Small	0.847±0.023	0.011±0.004	0.042±0.010	134±29
Medium	0.792±0.031	0.034±0.008	0.058±0.011	392±71
Large	0.718±0.042	0.067±0.015	0.071±0.014	847±127

To ensure the reliability and statistical significance of the results, each algorithm is executed 30 times per instance.

4.2. Convergence and Trade-offs

Convergence followed a three-phase trajectory: rapid early improvements, steady mid-phase gains, and late-stage stabilization. Final Pareto sets averaged 70–75 solutions, including extreme and knee points.

Trade-off slopes indicated that each 1% service improvement required ~1.34% higher cost, while each 1% equity gain required ~2.17% additional cost. Service and equity were positively correlated ($\rho \approx 0.62$), meaning higher service generally enhanced equity, though with diminishing returns.

4.3. Comparative Evaluation

MOPSO-FLP was benchmarked against NSGA-II, MOSA, VNS-MO, and GMOH (30 runs each).

- Small problems: MOPSO-FLP (HV = 0.847) outperformed NSGA-II (0.821) and GMOH (0.692).
- Medium problems: MOPSO-FLP (0.792) exceeded NSGA-II (0.751) and VNS-MO (0.718).
- Large problems: MOPSO-FLP (0.718) surpassed VNS-MO (0.673) and NSGA-II (0.651).

Diversity was best preserved (SP = 0.067 vs. 0.089 for NSGA-II), and runtime scaled better than NSGA-II due to reduced dominance-sorting overhead.

4.4. Sensitivity Analysis

Parameter sensitivity indicated that the best performance was achieved with 100 particles, an archive size of 100, and a linearly decreasing inertia weight. Larger populations gave a slight hypervolume (HV) gains but nearly doubled runtime, reflecting diminishing returns and confirming earlier insights on swarm optimization efficiency.

Problem sensitivity indicated that clustered demand improved HV (0.834) compared with uniform (0.792) and random (0.751) distributions. Greater demand heterogeneity also reduced solution quality, with HV dropping from 0.823 to 0.756 as the coefficient of variation rose from 0.2 to 0.8.

4.5. Deployment Validation in a National Postal Logistics Network

The National Post, a state-owned logistics provider, faces rising e-commerce volumes and the challenge of serving both dense urban centers and remote rural areas. To evaluate MOPSO-FLP in a real-world setting, 89 existing post offices were modeled as candidate facilities (m = 89) and 247 districts as demand nodes (n = 247), see Fig. 2. The objectives mirrored strategic priorities: minimize operational costs, maximize service coverage, and reduce maximum delivery times.

4.5.1. Data Preparation

Data transparency and confidentiality: Deployment validation relies on operational planning data from the national postal logistics context. To protect confidentiality, identifiers and sensitive operational attributes were anonymized and, where necessary, aggregated to planning zones; the analysis uses derived distance/time matrices and normalized cost parameters consistent with the operator's planning practice. While the raw dataset cannot be publicly released due to organizational restrictions, all algorithm parameters, evaluation settings, and the facility-location instance structure are fully reported to support replication using comparable datasets or synthetic instances.

Deployment validation was based on an integrated dataset that combined geographic attributes, demand patterns, cost information, and operational constraints. Geographic data were drawn from the National Post's internal GIS and provided GPS coordinates for candidate facility sites and district centers. A road-distance matrix was constructed using the Google Maps API to reflect actual routes and physical barriers, including rivers and mountainous terrain. Demand records for 2022–2023 reported annual parcel volumes at the district level and indicated pronounced heterogeneity, with a coefficient of variation of 0.67, highlighting the contrast between dense urban areas and sparsely populated rural districts. Cost information covered both fixed operating expenditures at facilities and variable transportation costs; all values were converted to an annual basis to allow consistent comparison across network configurations. In addition, a maximum delivery time of 5 hours was adopted as a soft service-level constraint, aligned with the National Post's operational guidelines, to explicitly embed realistic delivery speed expectations into the optimization model.

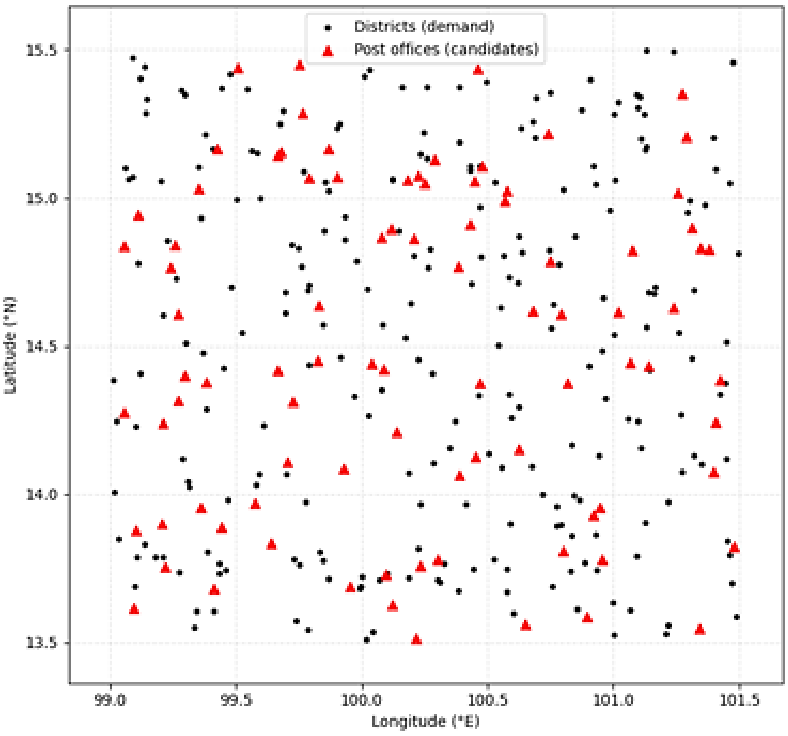

Figure 2. A National Post central region schematic diagram.

4.5.2. *Optimal Results*

The MOPSO-FLP search produced a Pareto front comprising 47 non-dominated network designs, providing the National Post with a broad portfolio of candidate configurations. Within this set, three representative solutions were identified as particularly illustrative of the key trade-offs between cost, service coverage, and delivery equity.

One extreme of the frontier corresponds to a cost-focused configuration with 23 open facilities and an annual operating cost of US$ 3.54 million. This design achieves 89% service coverage and a maximum delivery time of 4.7 hours. Although financially attractive, it leaves several remote districts relatively weakly served and therefore does not align well with equity-oriented objectives.

Interpretation of spatial patterns and equivalent solutions: For a fixed number of facilities, multiple location configurations may achieve very similar objective values because demand clusters and geographic symmetry can create near-equivalent alternatives. To support implementation, we recommend selecting representative solutions using a transparent tie-break rule, for example: (i) robustness under demand or travel-time perturbations, (ii) reuse of existing sites and ease of staffing, and (iii) regional fairness considerations (e.g., avoiding systematic under-service of remote subregions). In general, cost-focused solutions tend to concentrate facilities near high-demand centers, whereas service-oriented solutions add peripheral sites to reduce maximum travel time and improve coverage; balanced solutions combine a central backbone with a small number of strategically placed edge facilities.

At the opposite end is a service-oriented configuration that expands the network to 34 facilities. In this case, annual operating costs increase to US$4.36 million, but service coverage rises to 98% and the maximum delivery time falls to 2.1 hours. The configuration is clearly superior from a service perspective, yet the additional cost makes it difficult to justify as a long-term baseline.

Table 4. Key deployment validation solutions

Configuration	Facilities	Cost (M US$)	Coverage (%)	Max Delivery (h)
Cost-efficient	23	3.54	89.2	4.7
Service-optimized	34	4.36	97.8	2.1
Balanced	28	3.83	94.3	3.2

Between these two extremes lies a balanced configuration with 28 facilities that offers a more even compromise across the three objectives. It incurs an annual cost of US$ 3.83 million, delivers 94% service coverage, and limits the maximum delivery time to 3.2 hours. This design was selected by the National Post for pilot implementation. Monitoring after deployment indicated a 12.3% reduction in average delivery times and an 8.7% increase in service coverage, achieved with only a 4.2% rise in operating costs. Customer satisfaction also improved, increasing from 7.2 to 8.1 on a 10-point scale (see Table 4).

4.5.3. Managerial Insights

The managerial insights derived from the National Post deployment highlight several important patterns. First, optimized networks achieved facility utilization rates between 70% and 85%, which balanced efficiency with resilience by preventing both underutilization and capacity saturation. Second, the results confirmed a clear pattern of diminishing returns, as extending service coverage beyond 95% required disproportionately higher operational costs. Third, geographic constraints, such as rivers and mountain ranges, strongly shaped the configuration of service clusters, underscoring the value of incorporating geospatial information into facility location models. Finally, the scalability of MOPSO-FLP was confirmed, as the algorithm solved a national-scale problem in less than 30 minutes, demonstrating its feasibility for integration into real operational planning cycles.

4.5.4. Deployment Summary

The National Post deployment validated that MOPSO-FLP not only generates theoretically optimal solutions but also delivers actionable strategies. The improvements in delivery efficiency, service coverage, and customer satisfaction demonstrate its practical value for national-scale logistics.

4.6. Robustness and Component Analysis

The ablation experiments indicate that adaptive parameter control, the local search phase, and the use of a crowding-distance-based archive all play a substantial role in MOPSO-FLP's performance, together yielding an improvement in hypervolume of almost 20%. In terms of robustness, the algorithm continues to perform satisfactorily under 20% perturbations in distances and 30% variability in demand, with hypervolume values remaining above 0.74. Scalability tests further show that the approach can handle instances with up to 1,000 demand points and 200 candidate facilities; although runtimes exceed 2,300 seconds at this upper end, they remain acceptable for networks with 500–1,000 nodes, which is typical of national-scale logistics systems.

4.7. Statistical Validation

Across 30 runs, HV was bounded within [0.771, 0.813], IGD within [0.029, 0.039], and SP within [0.061, 0.073]. ANOVA $(F = 23.7, p < 0.001, \eta^2 = 0.34)$ confirmed significant performance differences. Tukey's HSD identified MOPSO-FLP as superior to all comparators. Non-parametric Kruskal–Wallis and Mann–Whitney U tests supported the same conclusion, with large effect sizes (Cohen's d > 0.8). These results establish that MOPSO-FLP's improvements are statistically significant and practically meaningful.

In summary, MOPSO-FLP demonstrated consistent superiority in benchmark tests, robust trade-off exploration, and statistical reliability. Its resilience to uncertainty and ability to solve national-scale problems, as demonstrated in a postal logistics deployment, confirm its scalability and practical relevance. Future work will explore hybridization with exact methods and dynamic extensions incorporating real-time data to further enhance adaptability for complex logistics and infrastructure systems.

5. CONCLUSION AND FUTURE WORK

This work presented a discrete multi-objective particle swarm optimization framework (MOPSO-FLP) tailored to facility location problems that must balance cost efficiency, service coverage, and spatial equity. The method combines a discrete representation of facility decisions with adaptive parameter control and targeted feasibility-repair operators, enabling an effective search of complex Pareto fronts. In benchmark tests, the proposed algorithm consistently outperformed reference methods, including NSGA-II and VNS-MO. Statistical analysis further indicated that MOPSO-FLP is both robust and scalable, supporting its use in large-scale facility location applications.

The application of the framework to a national postal logistics network confirmed its practical value, revealing a rich set of trade-off solutions and underscoring the advantages of balanced designs that enhance delivery performance and equity while keeping additional costs moderate. The same modeling principles can be transferred to other settings, including healthcare provision, smart-city services, and environmentally oriented infrastructure planning. Promising directions for further work include combining the metaheuristic with exact optimization components, incorporating real-time operational data, and embedding equity considerations within participatory planning processes so that MOPSO-FLP remains a versatile tool for multi-objective infrastructure optimization.

ACKNOWLEDGEMENT

This research project was granted by the Silpakorn University Research, Innovation, and Creative Fund, 2025. We express our gratitude to the anonymous reviewers for their meticulous examination of our work and their numerous astute observations and recommendations.

REFERENCES

[1] Amin-Tahmasbi H, Sadafi S, Ekren BY, Kumar V. (2023) A multi-objective integrated optimisation model for facility location and order allocation problem in a two-level supply chain network. Annals of Operations Research, 324:993–1022. https://doi.org/10.1007/s10479-022-04635-1

[2] Goodarzian F, Hosseini-Nasab H, Fakhrzad MB. (2020) A multi-objective sustainable medicine supply chain network design using a novel hybrid multi-objective metaheuristic algorithm. International Journal of Engineering, 33(10):1986–1995.

[3] Mirghaderi SD, Modiri M. (2021) Application of meta-heuristic algorithm for multi-objective optimization of sustainable supply chain uncertainty. Sādhanā, 46:52. https://doi.org/10.1007/s12046-020-01554-4

[4] Yan T, Lu F, Wang S, Wang L, Bi H. (2023) A hybrid metaheuristic algorithm for the multi-objective location-routing problem in the early post-disaster stage. Journal of Industrial and Management Optimization, 19(6):1. https://www.aimsciences.org/article/doi/10.3934/jimo.2023104

[5] Pourghader CA, Sabk Ara M, Moradi Pirbalouti S, Khadem M, Bahrami S. (2022) A multi-objective location-routing problem model for multi-device relief logistics under uncertainty using meta-heuristic algorithm. Journal of Applied Research on Industrial Engineering, 9(3):354–373. https://doi.org/10.22105/jarie.2021.299798.1365

[6] Hemici M. (2024) Multi-objective optimization for supply chain management. PhD thesis, Université de Bordj Bou Arreridj, Faculty of Mathematics and Computer Science.

[7] Suryawan RF, Fatchoelqorib M, Septiano R, Sari L, Widodo S, Yosepha SY, Devi NK. (2022) Two meta-heuristic algorithms for solving multi-objective model for the service quality and price in the digital supply chain. Industrial Engineering and Management Systems, 21(3):440–448. https://doi.org/10.7232/iems.2022.21.3.440

[8] Fugaro S, Sgalambro A. (2025) Multi-objective facility location problems: Systematic literature review and research agenda. Available: https://doi.org/10.2139/ssrn.5178615 (accessed 3 June 2025). https://ssrn.com/abstract=5178615

[9] Arevalo-Ascanio R, De Meyer A, Gevaers R, Guisson R, Dewulf W. (2024) Location-routing problem for integrated supply chain network design with first and last mile: A critical literature review. Operations and Supply Chain Management: An International Journal, 17(2):206–219. https://doi.org/10.31387/OSCM0570423

[10] Koosha H, Mirsaeedi F, Assadi MT. (2025) A multi-objective genetic algorithm for unequal area facility layout problem considering safety and cost. Soft Computing, 29:3869–3887. https://doi.org/10.1007/s00500-025-10605-z

[11] Liu M, Song Q, Zhao Q, Li L, Yang Z, Zhang Y. (2022) A hybrid BSO–ACO for dynamic vehicle routing problem on real-world road networks. IEEE Access, 10:118302–118312. https://doi.org/10.1109/ACCESS.2022.3221191

[12] Cakmak E, Önden İ, Acar AZ, Eldemir F. (2021) Analyzing the location of city logistics centers in Istanbul by integrating geographic information systems with binary particle swarm optimization algorithm. Case Studies on Transport Policy, 9(1):59–67. https://doi.org/10.1016/j.cstp.2020.07.004

[13] Makhadmeh SN, Kassaymeh S, Rjoub G, Bataineh B, Sanjalawe Y, Al-Betar MA. (2025) Recent advances in multi-objective whale optimization algorithm, its versions and applications. Journal of King Saud University – Computer and Information Sciences, 37(7):1–38. https://doi.org/10.1007/s44443-025-00184-2

[14] Kaveh A, Javid AAS, Vazirinia Y. (2025) Multi-objective variants of water strider algorithm for construction engineering optimization problems. Periodica Polytechnica Civil Engineering, 69(3):925–943. https://doi.org/10.3311/PPci.40442

[15] Zhang W, Xiao G, Gen M, Geng H, Wang X, Deng M, Zhang G. (2024) Enhancing multi-objective evolutionary algorithms with machine learning for scheduling problems: Recent advances and survey. Frontiers in Industrial Engineering, 2:1337174. https://doi.org/10.3389/fieng.2024.1337174

[16] Ezugwu AES. (2023) Metaheuristic optimization for sustainable unrelated parallel machine scheduling: A concise overview with a proof-of-concept study. IEEE Access, 12:3386–3416. https://doi.org/10.1109/ACCESS.2023.3347047

[17] Alqahtani H, Kumar G. (2024) Efficient routing strategies for electric and flying vehicles: A comprehensive hybrid metaheuristic review. IEEE Transactions on Intelligent Vehicles, 9(9):5813–5852. https://doi.org/10.1109/TIV.2024.3358872