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Multi-Objective Optimization for Electric Vehicle Charging Station Placement: A Hybrid NSGA-II Approach with Locational Fairness Consideration

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Abstract

Electric vehicle (EV) adoption critically depends on equitable charging infrastructure deployment, requiring balance between economic efficiency and equitable service delivery across communities, yet traditional optimization prioritizes efficiency over spatial equity. This study presents a novel hybrid NSGA-II (Non-dominated Sorting Genetic Algorithm II) approach for charging station placement integrating Traveling Salesperson Problem (TSP) station prioritization with Multiple-Choice Multi-Dimensional Knapsack Problem (MMKP) configuration selection to simultaneously maximize demand coverage and locational fairness measured by Jain's Fairness Index. Leveraging high-granularity GPS-based GEOTRA Activity Data from Sapporo, Japan, our approach captures realistic charging demand patterns across origin communities traveling to Chuo ward, enabling accurate representation of actual charging opportunities. We employ a two-phase computational architecture: Phase 1 pre-calculates value-cost-fairness metrics for all candidate station-configuration pairs through comprehensive time-slotted demand simulation; Phase 2 optimizes via custom genetic operators preserving chromosome integrity while exploring the complete solution space. Applied across three budget scenarios (JPY 10, 50, and 100 billion), results reveal systematic coverage-fairness trade-offs along Pareto-optimal frontiers. Knee point analysis identifies balanced solutions that sacrifice less than 1% of potential coverage to secure 8-10% fairness improvements, demonstrating that equitable infrastructure deployment requires explicit multi-objective optimization from initial planning stages, providing actionable decision-support tools for municipal planners.

Keywords
Electric vehicle charging infrastructure, multi-objective optimization, hybrid NSGA-II, locational fairness, high-granularity human flow data.

1. Introduction
The global transition to electric vehicles (EV) represents a critical pathway toward sustainable transportation and carbon emission reduction. However, the success of this transition fundamentally depends on the establishment of robust and strategically deployed public charging infrastructure. Poor infrastructure planning not only undermines public confidence in the entire electric mobility vision but also creates significant barriers to EV adoption, particularly in dense urban environments where space and resources are limited (Deb et al. 2018; LaMonaca and Ryan 2022). Traditional optimization approaches prioritize financial performance, such as maximizing user satisfaction or minimizing installation costs (Zu and Sun 2022), naturally leading to infrastructure concentration in high-demand, affluent urban centers. While economically rational, this strategy risks creating significant locational unfairness where underserved or lower-income communities are systematically excluded from adequate charging access. Recent empirical evidence demonstrates the severity of this spatial inequity. Areas with higher proportions of racial minorities or lower-income populations are significantly less likely to receive public EV charging infrastructure (Ermagun and

Tian 2024; Hsu and Fingerman 2021), with U.S. disadvantaged communities having 64% fewer charging stations per capita (Yu et al. 2025) and Chinese metropolitan study revealing systematic concentration in core business districts that creates accessibility gaps in suburban areas (Li et al. 2022). These patterns confirm that market-driven deployment produces systematically unequal access regardless of geographic or cultural context. The complexity of optimal charging station placement is further compounded by several interdependent factors including realistic temporal demand patterns, various charger configuration options, physical site constraints, budget limitations, and the need to serve geographically dispersed communities fairly, creating a high-dimensional, multi-objective optimization problem that existing single-objective or simplified heuristic approaches struggle to address comprehensively (Haghani et al. 2023; Huang et al. 2019).

Existing placement optimization models exhibit critical limitations that hinder their practical applicability to real-world EV charging infrastructure planning. First, many frameworks oversimplify the problem by adopting static demand assumptions that fail to capture dynamic, time-varying nature of actual charging behavior across different periods of the day and week by ignoring temporal diversity such as hourly demand variation, peak hour usage patterns, and queueing behavior at stations (Franke and Krems 2013; Liu et al. 2026). Second, computational tractability concerns often force researchers to adopt homogeneous facility assumptions and simplified nearest-station choice behaviors, ignoring real-world complexities such as users' dynamic decision-making based on real-time information, varying charger power levels, and heterogeneous user preferences (Meng et al. 2025). Third, few frameworks successfully address the integrated decision-making challenge that requires simultaneous optimization across multiple hierarchical levels including strategic station placement, tactical capacity sizing, and operational charger configuration under strict budget constraints (Haghani et al. 2023; Meng et al. 2025). Finally, the multi-stakeholder nature of the problem demands balancing conflicting objectives where infrastructure operators prioritize cost minimization, grid operators focus on network security, and EV users seek service accessibility, yet most existing models focus narrowly on single-objective cost reduction without providing transparent trade-off analysis among these competing goals (Hopkins et al. 2023). Recent frameworks have begun incorporating equity objectives in EV charging infrastructure planning. Loni and Asadi (2023) demonstrated that pure cost-minimization systematically disadvantages lower-income neighborhoods through multi-objective optimization balancing costs, demand, and social equity in San Francisco. Liu et al. (2026) integrated improved NSGA-II with TOPSIS decision support and nonlinear user satisfaction models, while Pourvaziri et al. (2025) combined machine learning clustering with NSGA-II to ensure similar travel and waiting times for all drivers in Halifax. Li et al. (2025) incorporated grid-side security objectives with adaptive penalty functions. These advances demonstrate NSGA-II's effectiveness for complex, multi-stakeholder EV infrastructure optimization.

This study formulates charging station placement as a multi-objective optimization problem. The objective is to balance two competing goals: maximizing economic values representing the total charging demand coverage and maximizing locational fairness ensuring equitable service distribution across communities where demand originates. This study addresses the gaps by introducing a multi-objective optimization framework specifically designed for equitable urban planning, offering four primary contributions: (1) integration of high-granularity GPS-based human flow data providing realistic time-slotted demand patterns, (2) specialized hybrid NSGA-II formulation combining TSP station prioritization with MMKP configuration selection while optimizing both economic values and locational fairness via Jain's index, (3) systematic knee point identification using perpendicular distance metrics providing balanced compromise solutions, and (4) two-phase computational architecture where Phase 1 pre-calculates metrics for all station-configuration pairs enabling Phase 2 NSGA-II to explore solutions without repeated simulations. This study substantially advances beyond our prior GA-TSPMMKP framework (Prommakhot et al. 2025) which optimized single-objective demand coverage using TSP-MMKP hybrid approach. While the prior work maximized economic efficiency alone, the present study transforms optimization paradigm by: (1) introducing locational fairness as a co-equal objective alongside coverage, creating a multi-objective framework, (2) implementing NSGA-II to generate comprehensive Pareto frontier providing coverage-fairness trade-offs analysis, (3) incorporating Jain's Fairness Index to quantify spatial equity across all origin communities rather than purely treating all demand points equally, and (4) providing knee point analysis for principled compromise selection. This multi-objective approach addresses critical equity concerns raised by recent policy research (Hsu and Fingerman 2021; Yu et al. 2025) that single-objective efficiency maximization systematically disadvantages underserved communities.

This paper is organized as follows. Section 2 provides the mathematical formulation of the multi-objective problem and defines our key objectives. Section 3 describes the two-phase architecture in detail, including data processing, MMKP item matrix generation, NSGA-II implementation, and experimental design. Section 4 presents results including Pareto frontiers, knee point solutions across budget scenarios, and infrastructure deployment characteristics. Section 5 concludes with key findings and future research directions.

2. Multi-Objective Station Placement Problem Formulation

2.1 Mathematical Formulation

The optimization of EV charging infrastructure involves three hierarchical decision-making components, consisting of identifying which candidate locations should be selected for installation (strategic siting), determining the specific configuration of charger types and quantities for each site (tactical sizing), and establishing the priority order for station deployment (installation sequencing). These decisions collectively define the macro-level strategic placement and micro-level operational characteristics of the charging network (Meng et al. 2025; Liu et al. 2026) and are subject to several physical and financial limitations including total budget caps, spatial constraints at individual sites, maximum allowable travel distances for service, and temporal requirements of time-slotted charger capacity to accommodate demand duration. Building upon our previous GA-TSPMMKP approach (Prommakhot et al. 2025) which optimized single-objective demand coverage using hybrid TSP-MMKP logic for station prioritization and configuration selection, this study fundamentally transforms the framework into a multi-objective optimization problem by integrating locational fairness as a co-equal objective with economic value. While the prior work maximized total demand served without equity considerations, the present study employs Jain's fairness index to quantify spatial equity across all origin meshes, enabling explicit trade-off analysis between efficiency and fairness through NSGA-II-generated Pareto frontiers. Jain's index provides a scalar measure of distribution equality ranging from 0 (perfect inequality) to 1 (perfect equality), with values below 0.4 typically indicating significant inequity requiring policy intervention (Peng et al. 2024). Unlike simple variance or range metrics, this index is population-size-independent and sensitive to transfers between different communities, making it particularly suitable for measuring how fairly charging infrastructure serves spatially distributed demand sources.

To formulate the multi-objective problem, we define the decision variables, parameters, and constraints as follows. Binary decision variable $x_{ik} \in \{0,1\}$ indicates whether configuration k is installed at station i, where $x_{ik} = 1$ if installed and $x_{ik} = 0$ otherwise, for each candidate station $i \in I$ ($|I| = 2{,}827$) and configuration $k \in K$ ($|K| = 121$, where $k = 0$ represents no installation). The permutation vector $\pi = (i_1, i_2, \ldots, i_{|i|})$ represents installation priority order, determining the sequence in which stations are evaluated during the greedy budget decoding process. Parameters include installation cost C_{ik} for configuration k at station i, total budget B, scalar value v_{ik} representing demand points served by station i with configuration k (pre-calculated in Phase 1), and vector component $\vec{v}_{ik,m}$ representing demand from origin mesh $m \in M$ ($|M| = 4{,}589$) served by station i with configuration k. The framework seeks to maximize the objective set $\{V, F\}$ subject to budget constraint $\sum_{(i,k)\in\text{Installed}} C_{ik} \cdot x_{ik} \le B$ and configuration exclusivity constraint $\sum_{k\in K} x_{ik} \le 1$ (at most one configuration per station). Economic values objective (V) is calculated as:

$$V = \sum_{(i,k)\in\text{Installed}} v_{ik} \cdot x_{ik}$$

To quantify locational fairness across M unique origin meshes, we utilize Jain's fairness index to calculate the fairness objective (F), formulated as:

$$F = \frac{\left(\sum_{m=1}^{M} v_m\right)^2}{M \cdot \sum_{m=1}^{M} v_m^2}$$

where $v_m = \sum_{(i,k)\in\text{Installed}} \vec{v}_{ik,m} \cdot x_{ik}$ represents total demand served from origin mesh m and $F \in [0,1]$ where $F = 1$ indicates perfect equality across all origin meshes, $F = 0$ otherwise. The vector $\vec{v}_{ik,m}$ represents demand from each origin mesh m served by a specific (i,k) pair, enabling the fairness calculation to capture how equitably infrastructure serves diverse source communities. Solutions are decoded sequentially following permutation π, where stations $i_{\pi(1)}, i_{\pi(2)}, \ldots, i_{\pi(|I|)}$ are prioritized in order and configurations installed until cumulative cost exceeds budget B. This formulation represents an NP-hard multi-objective combinatorial optimization problem combining TSP (permutation π) and MMKP (configuration selection under budget and exclusivity constraints), with solution space size $O(|I|! \times |K|\hat{}|I|) \approx 10\hat{}7{,}000$, making exhaustive enumeration computationally intractable and necessitating the NSGA-II metaheuristic approach.

2.2 NSGA-II Evolutionary Process

Because this problem is NP-hard, we utilize the NSGA-II framework (Deb et al. 2002) to manage the multi-objective search. NSGA-II generates diverse Pareto-optimal solutions without predetermined weights through fast non-dominated sorting, crowding-distance calculation, and elitist preservation strategies. Initially, a population of candidate solutions is evaluated based on both V and F objectives and ranked through non-dominated sorting, which organizes them into frontiers based on Pareto dominance where one solution dominates another if it performs no worse in all objectives and strictly better in at least one objective. A crowding distance metric maintains solution diversity within each frontier by measuring the distribution density of solutions and preferring less crowded regions to maintain a well-spread Pareto frontier. The next generation is formed through tournament selection where parent solutions are chosen based on their Pareto rank and diversity, then undergo order crossover (OX) to preserve station-configuration pairs during recombination. The dual-strategy mutation that either swaps station positions or changes a station's configuration is performed with the population filtered by survival selection to retain the most effective solutions until reaching maximum generations. Recent improvements to NSGA-II for EV charging station applications have demonstrated performance enhancement through adaptive constraint handling mechanisms, with Li et al. (2025) introducing adaptive exterior penalty functions and feasibility-first elitism strategies to handle strict electrical constraints, and Liu et al. (2026) employing variable-wise random chaotic initialization and opposition-based learning to improve convergence and solution diversity, addressing limitations of standard NSGA-II when applied to high-dimensional, mixed-variable problems with stringent physical constraints.

2.3 Knee Point Identification

The NSGA-II optimization produces Pareto frontiers containing multiple non-dominated solutions, each offering a different trade-off between coverage (V) and fairness (F). For practical infrastructure planning, we identify the knee point, the location on the Pareto frontier where the curvature is at its maximum and the frontier bends most sharply, representing the best return on compromise, where increasing one objective further would require a disproportionately sacrifice in the other (Branke et al. 2004). To identify this point objectively, we normalize the objective values to [0,1] using formula:

$$V_{\text{normalized}} = \frac{(V - V_{min})}{V_{max} - V_{min}}$$

$$F_{\text{normalized}} = \frac{F - F_{min}}{F_{max} - F_{min}}$$

where V_{max}, V_{min}, F_{max}, F_{min} are the maximum and minimum values observed on the Pareto frontier for each objective, then construct a diagonal reference line connecting the extreme points ($V_{max,\text{ normalized}}, F_{min,\text{ normalized}}$) and ($V_{min,\text{ normalized}}, F_{max,\text{ normalized}}$) representing a theoretically balanced trade-off. We calculate the perpendicular distance from each solution p on the Pareto frontier to the reference line using $d_p = \left|V_{\text{normalized},p} + F_{\text{normalized},p} - 1\right|/\sqrt{2}$, and the solution that yields maximum distance is selected as the knee point, providing the final infrastructure recommendation validated across multiple EV charging optimization studies (Liu et al. 2026).

3. Methodology

A two-phase computational architecture is employed where Phase 1 focuses on data pre-processing and generation of the MMKP item matrix through comprehensive simulations, and Phase 2 utilizes NSGA-II to explore the vast combinatorial space of station and configurations selections, leveraging pre-calculated metrics from Phase 1 for instantaneous fitness evaluation. This separation ensures that resource-intensive demand simulations are performed only once, while the genetic algorithm can rapidly evaluate thousands of candidate solutions without redundant calculations.

3.1 Study Area and Data Synthesis

The study focuses on Chuo ward, Sapporo's primary destination hub. We utilize high-granularity GPS-based GEOTRA Activity Data (GAD) providing time-series trip information including origin-destination coordinates, activity durations, and transportation modes. GAD for demand data is filtered for private car trips destined for Chuo ward with activity duration exceeding 30 minutes, selecting only the longest activity trip per agent to isolate the most likely charging opportunities, yielding 12,985 demand points aggregated 88,806 demand values from 4,589 unique origin 100-meter meshes across Sapporo's major wards (Chuo, Kita, Higashi, Kiyota). Candidate station locations from the Zenrin geospatial database include 2,827 potential sites within business and commercial facilities, intentionally excluding residential buildings to focus on public infrastructure.

3.2 Charger Configuration Options

Each candidate station can accommodate one of 121 pre-defined configurations combining fast chargers and normal chargers, constrained by site-specific spatial availability. Installation costs are approximate from industry reports and official sources, with unit costs set at JPY 10 million for fast chargers and JPY 2 million for normal chargers. Industry sources report that fast charging station installation in Japan can reach JPY 10 million due to strict safety regulations for high-voltage currents (Kantharaj 2025), while the Next Generation Vehicle Promotion Center reports normal 6 kW charger costs averaging JPY 2 million including equipment and construction, with quick charger costs ranging from JPY 1.83 million to JPY 12 million depending on specifications (NeV 2025). Table 1 presents representative configurations including charger quantities, installation costs, parking capacity, and spatial requirements. Configuration index 0 represents the no-install option. The matrix spans from minimal single-charger installations (Config 1: JPY 2 million, 1,516 square feet) to maximum-capacity setups (Config 120: JPY 120 million, 8,396 square feet). Requirement area for charging infrastructure is calculated follows U.S. Access Board EV charging guidelines (Shoultz 2023). Each charging space is allocated 18.3 feet in length and 16 feet in width, totaling 292.8 square feet per space, with the 16-foot width accommodating both vehicle parking area and one charging stand housing two charger units. When additional charger units are needed beyond the initial parking-integrated stand, additional stands are added at 8 feet width each with the same 18.3-foot length, occupying more 146.4 square feet. Baseline site area is 1,076 square feet (100 square meters), representing minimum fixed structure footprint such as retail space or building envelope, besides the charging infrastructure.

Table 1. Representative charger configurations from the 121-configuration matrix

Config ID	Fast Chargers	Normal Chargers	Installation Cost (JPY Million)	Configuration Type	Required Area (square feet)
0	0	0	0	0 Stand, 0 Parking	1,076
1	0	1	2	1 Stand, 1 Parking	1,516
5	0	5	10	3 Stands, 5 Parking	2,980
10	0	10	20	5 Stands, 10 Parking	4,736
11	1	0	10	1 Stand, 1 Parking	1,516
12	1	1	12	1 Stand, 2 Parking	1,808
16	1	5	20	3 Stands, 6 Parking	3,272
21	1	10	30	6 Stands, 11 Parking	5,176
50	5	0	50	3 Stands, 5 Parking	2,980
56	5	1	52	3 Stands, 6 Parking	3,272
60	5	5	60	5 Stands, 10 Parking	4,736
65	5	10	70	8 Stands, 15 Parking	6,640
110	10	0	100	5 Stands, 10 Parking	4,736
111	10	1	102	6 Stands, 11 Parking	5,176
115	10	5	110	8 Stands, 15 Parking	6,640
120	10	10	120	10 Stands, 20 Parking	8,396

Note: Representative sample of 16 from full 121-configuration matrix. Fast charger: JPY 10M/unit. Normal charger: JPY 2M/unit. Required area includes parking space and charging stands (292.8 sq. ft.), plus more 146.4 sq. ft. for an additional stand. Baseline site: 1,076 sq. ft. (100 sq. m).

3.3 Simulation and MMKP Item Matrix Generation (Phase 1)

Phase 1 performs detailed time-slotted demand assignment simulation for every feasible station-configuration pair, initializing 48 half-hour time slots to track charger and parking capacity over 24-hour period. Demand points processed chronologically based on their arrival times and marked as served if within 1.0 km radius of a station, matches required charger type (fast or normal), with sufficient temporal capacity. The simulation decreases available charger capacity for the occupied time slots when a demand is served and updates the mesh demand vector based on their origin mesh. The final output is a comprehensive MMKP item matrix containing pre-calculated installation costs, served demand values, and the corresponding mesh-specific demand vectors for all candidate station-configuration pairs, enabling rapid fairness computation during evolutionary optimization in Phase 2.

3.4 Multi-Objective Optimization using NSGA-II (Phase 2)

Phase 2 implements a hybrid NSGA-II framework to solve the combined challenges of station priority ordering and configuration selection. Each solution is encoded as a chromosome consisting of an ordered list of (station_index, config_id) tuples. To explore the solution space effectively, we utilize custom genetic operators integrating the configuration-aware sampling for population initialization ensuring diverse starting points across the feasible region, the order crossover (OX) to preserve station-configuration associations during recombination, and the dual-strategy mutation that either swaps station positions (exploring different priority orderings) or changes a station's configuration (exploring different charger type combinations). The decoder evaluates each chromosome using a greedy budget enforcement strategy, iterating through the prioritized list of (station, configuration) pairs and installing each configuration sequentially until the cumulative cost exceeds the available budget, at which point no further stations and charger configurations are added. The fitness values are then determined by total economic values (V) and the fairness index (F) using the formulas in Section 2. This greedy decoding strategy efficiently enforces budget constraints while enabling rapid fitness evaluation since all station-configuration metrics were pre-computed in Phase 1. Upon completion of the evolutionary process, we identify the knee point representing the most balanced compromise on the Pareto frontier by calculating the maximum perpendicular distance from a diagonal reference line connecting the front's extreme points as described in Section 2, providing decision-makers with a single actionable recommendation that balances optimal return on compromise between demand coverage efficiency and locational fairness.

3.5 Experimental Design and Scenarios

The framework is tested across distinct budget scenarios to examine infrastructure network evolution. Three budget scenarios (JPY 10 billion, 50 billion, and 100 billion) represent realistic early-to-intermediate municipal deployment phases based on typical infrastructure investment timelines. These budgets constitute approximately 1%, 5%, and 10% of theoretical maximum installation capacity, calculated as equipping all 2,827 candidate stations with the highest-cost configuration (approximately JPY 1,000 billion total). This focus on practical deployment scales enables investigation of coverage-fairness trade-offs during initial network expansion phases when municipal planners face critical resource allocation decisions. However, this scope limits conclusions about system behavior at near-saturation conditions. Investigation of higher budget scenarios to distinguish between fairness limitations imposed by resource scarcity versus fundamental spatial constraints remains important future work. The NSGA-II is configured with a population size of 500 individuals evolving across a maximum of 500 generations. To ensure robustness and identify optimal parameter configurations for different budget scales, a systematic grid search is performed over various crossover rates CR = [0.5, 0.6, 0.7, 0.8, 0.9] and mutation rates MR = [0.01, 0.1, 0.5]. Performance is measured through primary objectives (V and F) and knee point characteristics, enabling identification of budget-specific optimal operator parameters that balance exploitation and exploration consistent with evolutionary algorithm theory.

4. Computational Results

The NSGA-II algorithm demonstrated stable convergence across all budget scenarios, with Pareto frontiers reaching consistent quality within 500-generation limit. The population size of 500 individuals maintained adequate diversity throughout the evolutionary process, generating 471 to 2,043 non-dominated solutions depending on budget scale. Solutions from different generations confirmed consistent frontier quality, with final populations maintaining diversity across the coverage-fairness trade-off space.

4.1 Pareto Frontier Analysis

Pareto frontiers across budget scenarios in Figure 1 reveal distinct evolutionary characteristics in how the infrastructure network balances efficiency and equity. At JPY 10 billion budget level shown in Figure 1a, the tight, convex frontier with 2,043 non-dominated points shows well-defined coverage-fairness trade-offs (V = 7,251-8,031, F = 0.083-0.134), with particularly steep trade-off regions forcing explicit priority decisions. At JPY 50 billion budget shown in Figure 1b, the more scattered frontier with 1,391 points shows increased solution flexibility, yet the narrow fairness range of 0.025 (0.092 and 0.117) relative to fivefold coverage expansion reveals diminishing equity returns. At JPY 100 billion budget shown in Figure 1c, the fragmented frontier with 471 distinct clusters, with the trade-off region visible between demand coverage of 70,601 to 73,370 and fairness index ranging from 0.122 to 0.130, suggests multiple viable strategies exist with greater configuration complexity as the network approaches 78% site saturation.

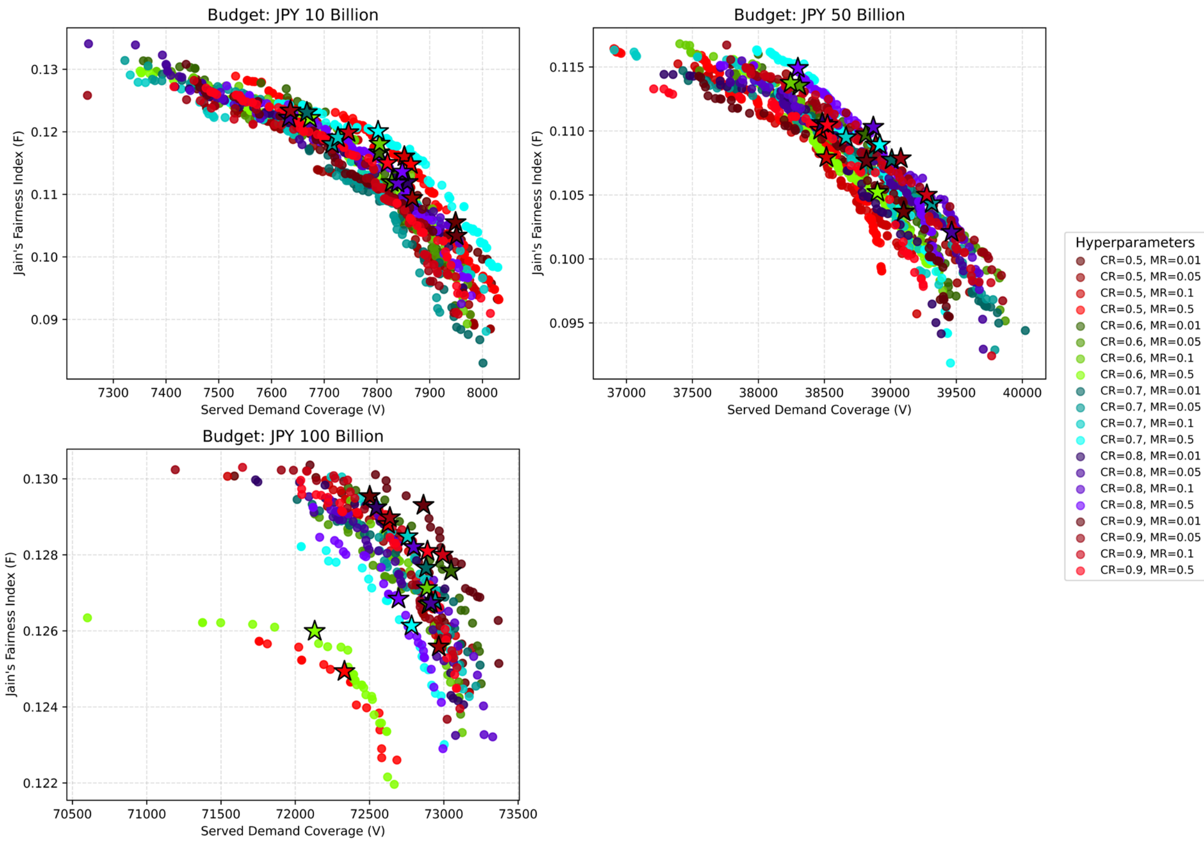


Figure 1. Pareto frontier comparisons across budget scenarios: (a) JPY 10 billion budget, (b) JPY 50 billion budget, (c) JPY 100 billion budget

4.2 Knee Point Analysis and Trade-off Quantification

Table 2 presents knee point solutions alongside Pareto frontier extremes across budget scenarios, revealing systematic patterns in coverage-fairness trade-offs and optimal operator parameters. Through systemic grid search over sets of operator parameter combinations, these settings were identified as producing the highest-quality frontiers with well-defined coverage-fairness trade-off regions. All three solution points (maximum coverage, knee point, and maximum fairness) are extracted from the same Pareto-optimal operator parameters, enabling direct comparison of trade-offs along a single frontier.

The maximum coverage solutions represent the frontier extreme prioritizing pure economic value, achieving 7,964 demands (F = 0.095) at JPY 10 billion, 39,704 demands (F = 0.093) at JPY 50 billion, and 73,251 demands (F = 0.124) at JPY 100 billion, all utilizing the same operator combinations as their corresponding knee points. The maximum fairness solutions represent the opposite extreme, achieving F = 0.131 (7,438 demands) at JPY 10 billion, F = 0.115 (37,714 demands) at JPY 50 billion, and F = 0.130 (72,357 demands) at JPY 100 billion. Knee points occupy the frontier region where curvature maximizes, achieving 7,951 demands with F = 0.103 at JPY 10 billion using CR = 0.9 and MR = 0.01, 39,464 demands with F = 0.102 at JPY 50 billion using CR = 0.8 and MR = 0.05, and 73,049 demands with F = 0.128 at JPY 100 billion using CR = 0.6 and MR = 0.01.

The trade-off ratios quantify the efficiency cost of moving from maximum coverage to knee point solutions. At JPY 10 billion, the knee point sacrifices 13 demands (0.2% reduction) to achieve 8.4% fairness improvement relative to maximum coverage solutions. At JPY 50 billion, the knee point sacrifices 240 demands (0.6% reduction) for 9.7% fairness improvement. At JPY 100 billion, the knee point sacrifices 202 demands (0.3% reduction) for 3.2% fairness improvement. Comparing knee points to maximum fairness solutions reveals complementary patterns. At JPY 10 billion, maximum fairness costs an additional 513 demands (6.5% further reduction) for 27.2% additional fairness gain beyond knee point. At JPY 50 billion, it costs an additional 1,750 demands (4.4% further reduction) for 12.7% additional fairness. At JPY 100 billion, it costs an additional 692 demands (0.9% further reduction) for 1.6% additional fairness. These ratios demonstrate that marginal fairness costs increase substantially beyond knee points, with particularly steep diminishing returns evident at the highest budget level where the Pareto frontier becomes notably flatter.

Table 2. Knee point solutions and coverage-fairness trade-offs across budget scenarios

Budget (JPY Billion)	**Solutions Point**	***V* (Demands)**	***F* (Index)**	**Trade-off Ratio***	**Operator Parameters**
10	Max Coverage	7,964	0.095	Baseline	CR=0.9, MR=0.01
	Knee Point	**7,951**	**0.103**	**-13 / +8.4%**	
	Max Fairness	7,438	0.131	-526 / +37.9%	
50	Max Coverage	39,704	0.093	Baseline	CR=0.8, MR=0.05
	Knee Point	**39,464**	**0.102**	**-240 / +9.7%**	
	Max Fairness	37,714	0.115	-1,990 / +23.7%	
100	Max Coverage	73,251	0.124	Baseline	CR=0.6, MR=0.01
	Knee Point	**73,049**	**0.128**	**-202 / +3.2%**	
	Max Fairness	72,357	0.130	-894 / +4.8%	

Note: Trade-off Ratio: ΔV demands from baseline / ΔF% improvement from baseline.

The results reveal several observable patterns. First, knee point solutions achieve nearly maximum coverage while substantially improving fairness. At JPY 10 billion, the knee point serves 7,951 demands compared to 7,964 at maximum coverage (99.8% achievement), while fairness improving 8.4% from their respective baseline. Similar patterns appear at JPY 50 billion (99.4% of maximum coverage, 9.7% fairness improvement) and at JPY 100 billion (99.7% of maximum coverage, 3.2% fairness improvement). Second, demand coverage at knee points scales sub-linearly with budget. When budget increases 5 times (from JPY 10 to 50 billion), demand coverage grows by 4.97 times (from 7,951 to 39,464), representing 99% proportional growth. However, when budget doubles (from JPY 50 to 100 billion), demand coverage increases by 1.85 times (from 39,464 to 73,049), representing 93% of proportional growth. Third, fairness at knee points follows a U-shaped trajectory. The fairness index starts at $F = 0.103$ at JPY 10 billion, dips slightly to $F = 0.102$ at JPY 50 billion, then rises to $F = 0.128$ at JPY 100 billion. Fourth, maximum fairness solutions reach F values around 0.13 (0.131, 0.115, 0.130) across the tested budget range, indicating below theoretical value ($F = 0.4$). The Pareto frontier spans 37.9% fairness range at the lowest budget level, compressing to 23.7% at intermediate budget, and further narrowing to 4.8% at the highest tested budget. This progressive compression from 526 demands (at JPY 10 billion) through 1,990 demands (at JPY 50 billion) to 894 demands (at JPY 100 billion) at maximum fairness indicates diminishing spatial optimization opportunities within early deployment phases. Fifth, genetic algorithm operator configurations shift systematically across budgets, with crossover rates declining from CR = 0.9 to CR = 0.6 and mutation rates fluctuating between 0.01 and 0.05. These absolute fairness values remain well below unity due to structural measurement design, as the index quantifies equity across 4,589 origin meshes contributing demand to a single destination district where geographic concentration of charging stations at destination points inherently constrains equitable service distribution.

4.3 Infrastructure Composition and Spatial Distribution

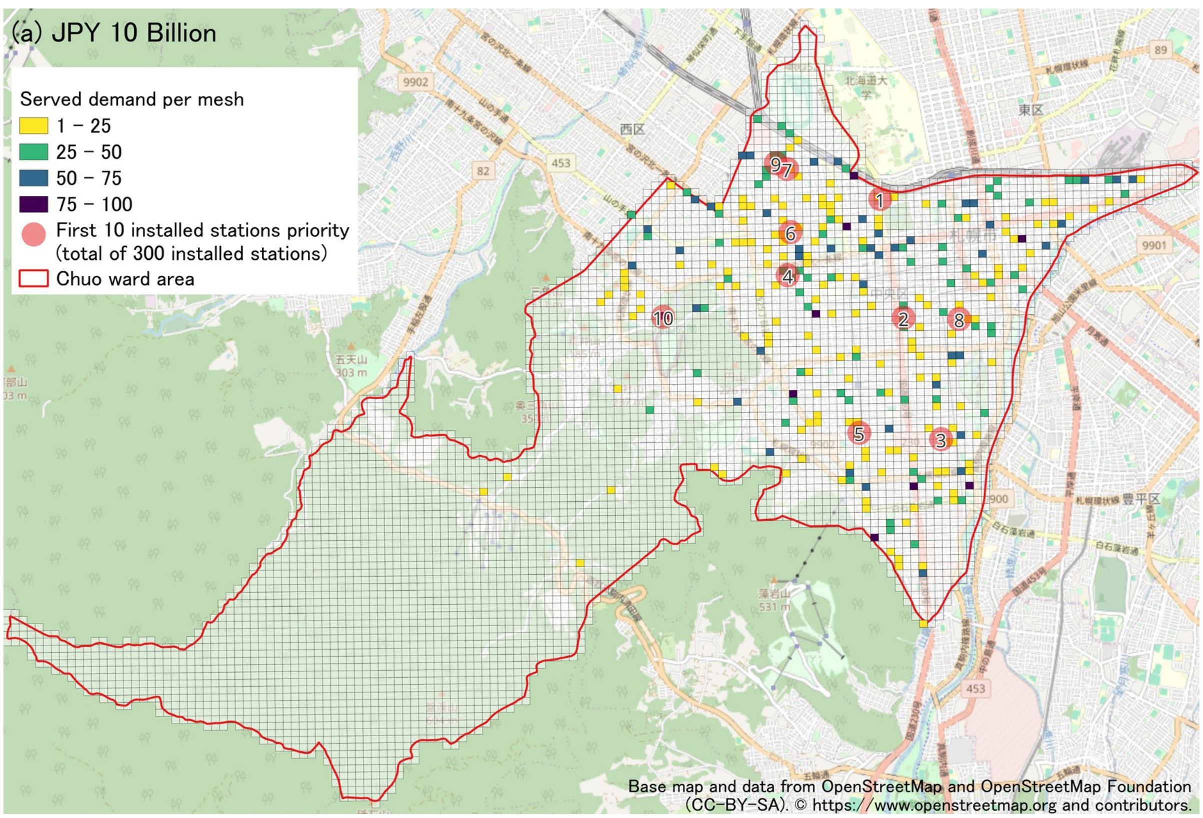
The physical composition of charging network at each knee point is summarized in Table 3. At JPY 10 billion scenario, 300 stations utilize 99.9% of budget with balanced charger deployment (fast-to-normal ratio 0.68) achieving JPY 1.26 million cost per demand. As the budget scales to JPY 50 billion, 1,606 stations maintain similar efficiency (ratio of 0.70, cost at JPY 1.27 million per demand). At JPY 100 billion scenario, 2,204 stations (78% of available sites, 99.98% budget utilization) shift toward capacity enhancement with fast chargers more than doubling (ratio rises to 1.19) and cost increasing 8.7% to JPY 1.37 million per demand, reflecting diminishing returns as the algorithm serves harder-to-reach peripheral population.

Table 3. Knee point charging infrastructure composition across budget scenarios

Budget (JPY Billion)	Stations Installed	Fast Chargers	Normal Chargers	Total Cost (JPY Billion)	Demands Served	Cost per Demand* (JPY Million)
10	300	773	1,129	9.988	7,951	1.26
50	1,606	3,886	5,570	50.000	39,464	1.27
100	2,204	8,563	7,173	99.976	73,049	1.37

Note: Cost per Demand = Total Cost ÷ Demands Served (expressed in JPY million per demand). This metric quantifies deployment efficiency, with increasing values indicating declining marginal returns as networks expand.

Figure 2 visualizes the spatial distribution of selected charging stations at knee point solution across the three budget scenarios. Each 100-meter mesh grid is colored to represent served demand intensity: yellow (1-25 demands per mesh), green (25-50), blue (50-75), and dark purple (75-100). Red-circled markers indicate selected station locations, with numbered labels showing the installation priority sequence for the first 10 stations. At the JPY 10 billion budget level shown in Figure 2a, the 300 installed stations are concentrated primarily in the central and northern portions of Chuo ward. The served demand distribution shows mostly yellow meshes distributed with isolated green and blue clusters. The priority sequence shows the first installations targeting locations in dense commercial zones before expanding outward. At the JPY 50 billion budget in Figure 2b, the network expands to 1,606 stations, with the served demand pattern shows increased presence of green and blue meshes throughout the ward and darker colors appearing in northern and eastern sections. At the JPY 100 billion budget shown in Figure 2c, the network reaches 2,204 stations occupying 78% of available candidate locations. The served demand map displays extensive coverage with dense concentrations of blue and dark purple meshes across the ward, particularly in the northern, central, and eastern areas, though some peripheral and edge areas maintain lower served demand levels.



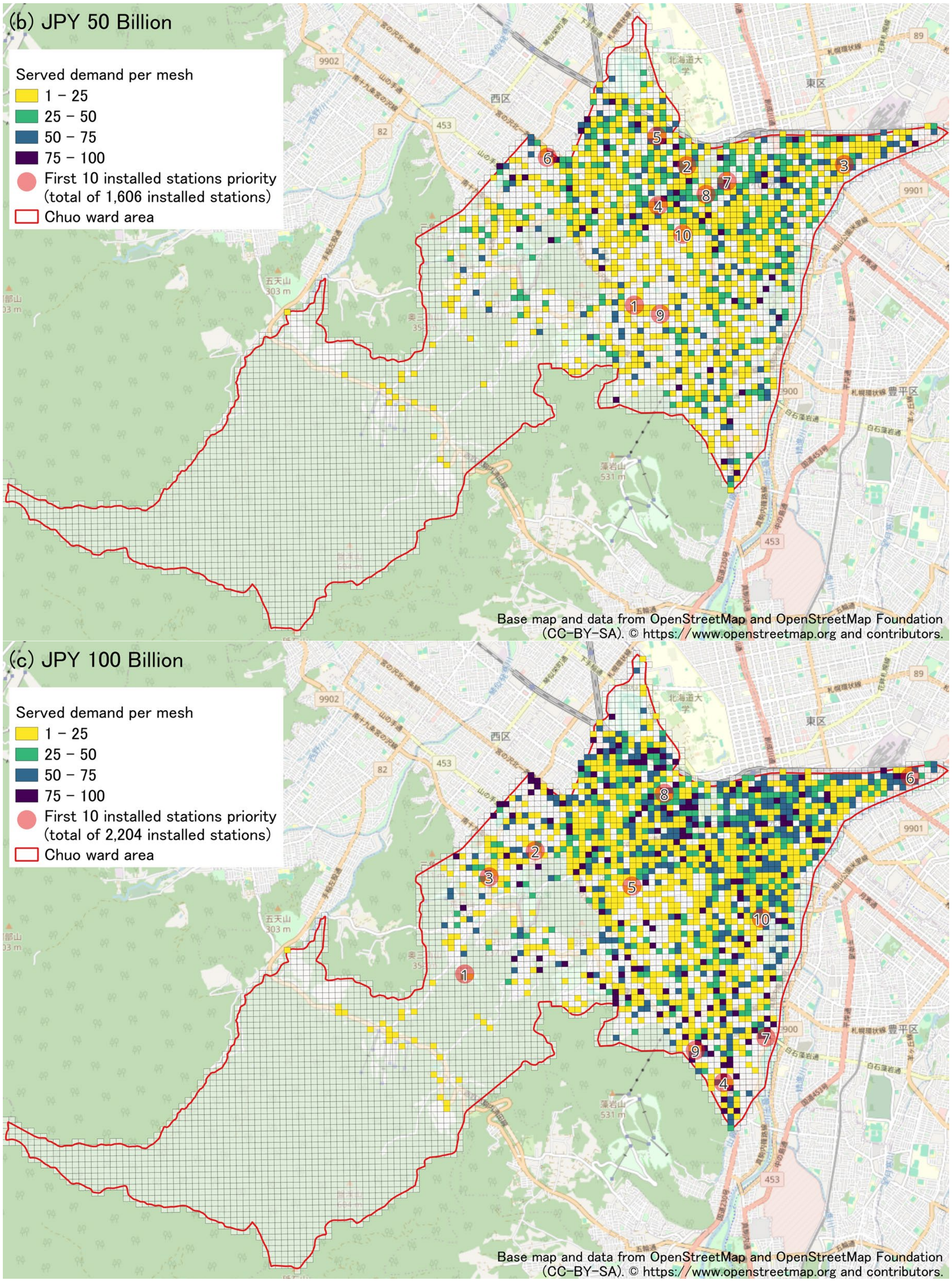


Figure 2. Spatial deployment patterns demonstrating coverage-fairness trade-offs at knee point solutions: (a) JPY 10 billion budget (300 stations, F = 0.103), (b) JPY 50 billion budget (1,606 stations, F = 0.102), (c) JPY 100 billion budget (2,204 stations, F = 0.127). *Note: Mesh color intensity represents served demand concentration (yellow: 1-*

25 demands, green: 25-50, blue: 50-75, dark purple: 75-100), visualizing how infrastructure deployment affects locational fairness across 4,589 origin meshes. Red circles indicate selected station locations, with numbered labels showing installation priority sequence for the first 10 stations. Base map from OpenStreetMap.

5. Discussion and Conclusion

The multi-objective NSGA-II framework addresses critical limitations in traditional charging infrastructure planning by making coverage-fairness trade-offs transparent and actionable. Pure coverage maximization sacrifices substantial equity to capture marginal efficiency gains, while pursuing maximum fairness alone abandons thousands of demands that balanced solutions successfully serve. Traditional weighted-sum approaches require planners to commit to predetermined objective weights before understanding actual trade-off landscapes (Das and Dennis 1997). Our approach generates hundreds of diverse Pareto-optimal solutions that reveal precisely how coverage-fairness trade-offs evolve across investment scales. Knee point identification provides mathematically principled compromise selection, enabling planners to justify decisions through demonstrable return on compromise rather than arbitrary preference assignments.

These methodological innovations enable four key advances in EV charging infrastructure planning. Methodologically, we demonstrate that hybrid genetic algorithms integrating TSP station prioritization with MMKP configuration selection can navigate complex multi-objective problems through specialized operators that preserve solution integrity. Empirically, we provide quantitative evidence of coverage-fairness trade-offs using high-granularity GPS data capturing 12,985 demand points across 4,589 origin communities, representing observed travel patterns rather than projected estimates. Computationally, our two-phase architecture enables city-scale optimization across 2,827 candidate stations and 121 configurations without computationally prohibitive repeated simulations. Practically, we deliver decision-support tools that convert technical complexity into accessible discourse through Pareto frontiers for transparent stakeholder deliberation and knee point identification for principled compromise selection. Applying this framework to Sapporo's charging infrastructure reveals critical trade-off patterns. The empirical evidence demonstrates that incorporating fairness objectives requires minimal efficiency sacrifice at lower deployment budgets but faces substantial constraints as investment scales increase within early deployment phases. Knee point solutions sacrifice less than 1% of potential coverage to secure substantial fairness improvements. At lower investment levels, coverage reductions of 0.2% to 0.6% yield fairness gains approaching 10%, reflecting abundant spatial optimization opportunities when networks can expand strategically across unconstrained areas. However, at the highest tested investment level, fairness gains decline to 3% despite similar coverage costs, while the Pareto frontier compresses into a 4.8% fairness range spanning 894 demands. This compression reflects both spatial optimization challenges and resource constraints on achievable network density within early deployment scales.

The analysis reveals three critical insights into coverage-fairness dynamics within resource-constrained deployment scenarios. First, trade-off favorability evolves systematically across budget scales. Maximum fairness solutions reach values around 0.13 within the tested budget range. The Pareto frontier compresses from 37.9% fairness range at lowest budgets to 4.8% at highest tested levels, indicating diminishing spatial optimization opportunities as networks expand. This challenge combines budgetary and spatial factors. Concentrating charging stations at a single destination district to serve 4,589 dispersed origin communities creates geometric barriers to equitable service distribution, a pattern observed across metropolitan regions where downtown concentration disadvantages peripheral residents (Li et al. 2022; Peng et al. 2024; Zhang and Fan 2025). Second, deployment strategy evolves from geographic expansion to capacity intensification as budgets increase. Lower investment levels succeed through network expansion, capturing concentrated demand with balanced infrastructure mixes and stable costs. As investment scales increase, the system transitions toward high-power fast chargers serving increasingly dispersed populations. This transition manifests in declining scaling efficiency (from 99% to 93%) and increasing marginal costs per demand served. The genetic algorithm's systematic adaptation from high crossover rates exploiting constrained solution spaces to low rates exploring complex possibility spaces reflects this strategic requirement. Planning that fails to recognize this evolution will either under-deploy during initial stages or over-extend during later stages. Third, algorithmic behavior reveals fundamental principles about problem complexity and resource allocation strategy. Under tight constraints, effective solutions require intensive local exploitation to extract maximum value from limited options. As resource availability expands, maintaining solution quality requires preserving population diversity to prevent premature convergence, enabling exploration across expanding solution spaces (Das and Dennis 1997; Deb et al. 2002; Katoch et al. 2021). Scarce resources demand careful optimization of established approaches, while abundant resources justify exploratory investigation to discover alternative opportunities.

For municipal planners operating within typical budget constraints, the implications are direct. Cities must incorporate explicit fairness objectives during initial planning stages, when equity integration requires negligible efficiency sacrifice, rather than adding it as a constraint after efficiency-optimized networks are deployed. The U-shaped fairness trajectory reveals that intermediate budgets prioritize coverage expansion over equity considerations, while the near-flat Pareto frontier at highest tested levels suggests diminishing returns within early deployment phases. Addressing fairness limitations within resource-constrained scenarios requires either multi-district optimization that distributes infrastructure across multiple destinations, deliberate over-provisioning policies that subsidize peripheral stations as public goods, or substantially higher investment levels to achieve greater network density across metropolitan areas. Equity in public infrastructure determines which communities participate meaningfully in transportation transformation. Market-driven deployment concentrates benefits in affluent areas, systematically excluding communities whose participation is essential for broad adoption. This study demonstrates that multi-objective optimization can build networks serving diverse communities within practical budget constraints. Cities deploying EV infrastructure without explicit equity objectives make a choice to accept systematically unequal access across their communities.

Future work must extend this framework's scope and validation. Comprehensive analysis of higher budget scenarios represents the highest priority to distinguish between fairness limitations imposed by resource scarcity versus fundamental spatial constraints inherent to single-destination network structures. This investigation would clarify whether observed fairness values represent ceilings imposed by geometric distribution challenges or intermediate plateaus that substantially higher investment levels could overcome, informing long-term infrastructure policy regarding the necessity of multi-district optimization strategies versus the sufficiency of extensive over-provisioning at concentrated destinations. Additional priorities include comprehensive sensitivity analysis on key parameters, systematic comparison with alternative baseline approaches, expansion across multiple destination districts throughout the research area, incorporation of induced demand modeling, integration of grid capacity constraints, and development of multi-period investment strategies reflecting gradual adoption curves. These refinements will advance the framework toward comprehensive city-wide planning that achieves both economic viability and social equity under realistic operational and physical constraints.

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