A Demand-Driven Multi-Model Framework for Optimal Facilities Siting

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***Abstract*—This paper studies the optimal placement of demand-driven facilities when a finite number of sites must be selected from a set of candidates. Rather than committing to a single formulation, a comparative framework is developed that (i) learns site-level demand signals via ML regression, (ii) searches combinatorial site subsets using a GA guided by learned scores, and (iii) guarantees minimum service through a classical MCLP. The pipeline reflects the core families of location science: covering-type models for guaranteed access, distance-minimizing models used as complementary baselines, and scalable metaheuristics for large candidate sets. Empirical evaluation on real spatial data selects a model-of-record by directly comparing outcomes under identical inputs and constraints—reporting covered population within a service radius, demand-weighted coverage, and RMSE for learned signals. Results indicate that ensemble ML predictors (for demand scoring) combined with GA search produce competitive site sets, while MCLP yields strong guaranteed coverage under budget limits; the integrated, multi-model selection process therefore supports robust siting decisions across policy priorities.**

***Index Terms*—Amplitude alignment, federated learning over-the-air, magnitude-scaled one-bit quantization, truncated channel inversion power control**

I. Introduction

Facility location models formalize the siting of a limited number of facilities to serve spatially distributed demand [1], [2]. Covering-type formulations such as the set covering and maximal covering location problems provide transparent access guarantees, while median- and center-type models minimize average and worst-case access distances [3], [4]. This paper focuses on model selection for demand-driven siting using a multi-method framework that keeps the deterministic guarantees of covering models, scales via evolutionary search, and adapts to local signals through learned demand. The contribution is a reproducible blueprint that evaluates methods under identical inputs and constraints and reports policy-facing metrics to support defensible siting decisions.

II. Related Work

Classical covering models encode minimum-service standards and budget-limited access. Their interpretability is strong, but binary coverage is sensitive to the service radius and ignores diminishing returns with distance. Median and center families complement coverage by controlling access burden, yet they do not enforce explicit coverage counts. Scalability concerns have motivated metaheuristics, with genetic algorithms showing strong performance on large instances. Decision-aware learning emphasizes alignment between prediction targets and downstream combinatorial objectives. Accordingly, this paper integrates learned-demand scoring with evolutionary search and benchmarks against a deterministic coverage model under the same data and constraints, enabling objective selection consistent with policy priorities [5]–[8].

III. Methods

This section first consolidates common mathematical definitions and metrics used throughout the paper, then explains each method conceptually with explicit references to those definitions, and finally specifies a unified protocol for fair and reproducible comparison. Additions extend modeling fidelity (capacity, k-coverage, variable radii), search robustness (penalty and repair), and evaluation breadth (coverage rate, access burden, percentiles, equity surrogates) while preserving the single source of truth for formulas.

A. Common Definitions and Metrics

The great-circle distance between demand node i at (φ_i, λ_i) and candidate site j at (φ_j, λ_j) on a sphere of radius r is given by

$$d_{ij} = 2r\,\arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\varphi_{ij}}{2}\right) + \cos\varphi_i\,\cos\varphi_j\,\sin^2\left(\frac{\Delta\lambda_{ij}}{2}\right)}\right), \tag{1}$$

where φ and λ are latitude and longitude in radians, $\Delta\varphi_{ij} = \varphi_j - \varphi_i$, and $\Delta\lambda_{ij} = \lambda_j - \lambda_i$.

A smooth distance-decay weight used to construct distance-aware features from a base quantity P is

$$W(d) = P\,e^{-\alpha d^2}, \tag{2}$$

where $\alpha > 0$ controls how fast influence diminishes with distance d.

The learned site score that combines predicted demand and accessibility is

$$\text{Score}_{\text{ML}}(j) = \beta_1\,\hat{y}_j + \beta_2\,A_j, \tag{3}$$

where $\hat{y}_j$ is the ML prediction at site j, A_j is an accessibility summary, and $\beta_1, \beta_2 \geq 0$ are fixed on validation to set the demand–access trade-off.

The genetic algorithm evaluates any subset $S \subseteq J$ of selected sites using

$$\mathrm{Fitness}(S) = \sum_{j \in S} \mathrm{Score}_{\mathrm{ML}}(j), \tag{4}$$

which aligns the evolutionary search with the learned site score in Eq. (3). When using an unconstrained encoding, an oversize subset can be discouraged by

$$\mathrm{Fitness}_{\lambda}(S) = \sum_{j \in S} \mathrm{Score}_{\mathrm{ML}}(j) \; - \; \lambda \, \max\{0, \; |S| - p\}, \tag{5}$$

where $\lambda > 0$ is a penalty weight and p is the facility budget.

The maximal covering location problem chooses up to p sites to maximize covered demand. A centered-and-aligned statement is

$$\begin{aligned} \max \quad & \sum_{i \in I} w_i \, z_i \\ \text{s.t.} \quad & z_i \leq \sum_{j \in J} a_{ij} \, x_j, \quad \forall i \in I, \\ & \sum_{j \in J} x_j \leq p, \\ & x_j, \, z_i \in \{0, 1\}. \end{aligned} \tag{6}$$

Here I indexes demand nodes with weights $w_i \geq 0$, J indexes candidate sites, x_j indicates selection of site j, z_i indicates whether demand i is covered, p is the facility budget, and $a_{ij} = \mathbb{I}\big(d_{ij} \leq r_{\mathrm{cov}}\big)$ is the coverage indicator computed from Eq. (1) with service radius r_{cov}.

Normalized coverage and its complement are

$$\begin{aligned} \mathrm{CovRate}(S) &= \frac{\sum_{i \in I} w_i \, z_i}{\sum_{i \in I} w_i}, \\ \mathrm{Uncovered}(S) &= \sum_{i \in I} w_i \, (1 - z_i), \end{aligned} \tag{7}$$

where z_i is the coverage decision from Eq. (6).

The demand-weighted mean access distance and an access quantile are

$$\begin{aligned} \bar{d}(S) &= \frac{\sum_{i \in I} w_i \, \min_{j \in S} d_{ij}}{\sum_{i \in I} w_i}, \\ d_q(S) &= \inf\Big\{ t : \; \frac{\sum_{i \in I} w_i \, \mathbb{I}(\min_{j \in S} d_{ij} \leq t)}{\sum_{i \in I} w_i} \geq q \Big\}, \end{aligned} \tag{8}$$

where d_{ij} is the geodesic distance in Eq. (1) and $q \in (0, 1)$.

Optional capacity and multi-coverage extensions are

$$\begin{aligned} & \sum_{i \in I} u_i \, a_{ij} \, y_{ij} \; \leq \; \mathrm{cap}_j \, x_j \quad \text{for all } j \in J, \\ & \sum_{j \in J} y_{ij} = 1, \quad y_{ij} \leq a_{ij} \, x_j, \end{aligned} \tag{9}$$

$$\sum_{j \in J} a_{ij} \, x_j \; \geq \; k \, z_i \quad \text{for all } i \in I, \tag{10}$$

where u_i is per-node demand, $y_{ij} \in \{0, 1\}$ assigns node i to site j, cap_j is site capacity, and $k \geq 1$ is the required redundancy level.

The accuracy metric used for ML model selection is

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{j=1}^{N} \big(y_j - \hat{y}_j\big)^2}, \tag{11}$$

where y_j is the observed target, $\hat{y}_j$ is the prediction, and N is the number of observations.

B. Machine Learning Regression

This method learns a continuous site-level demand proxy from spatial and contextual features [9], [10]. Proximity is computed using Eq. (1) and can be transformed by Eq. (2) to encode diminishing influence. Candidate regressors include ensemble trees and linear baselines. The predictor of record is chosen by minimizing held-out error in Eq. (11). Predictions are converted to siting utility via the site score in Eq. (3). This paper follows predict-then-optimize principles to align learning with prescriptive objectives [11], [12].

C. Genetic Algorithm

This method [13] performs evolutionary subset selection under a facility budget p. A solution is a subset $S \subseteq J$ with $|S| \leq p$. The population is initialized by a mix of random draws and heuristic seeds. Selection, crossover, mutation, and elitism are configured so that the best-so-far objective in Eq. (4) (or the penalized form in Eq. (5)) improves across generations. Feasibility is enforced by repair (drop lowest-score sites when $|S| > p$) or by the penalty weight λ. Stopping criteria include a generation cap and stagnation tolerance. Complexity per generation is $O(P \, |J|)$ for population size P under precomputed scores. GA is a standard scalable approach for large location instances where exact search is costly [14].

D. Maximal Covering Location Problem

This method provides a deterministic coverage baseline. It selects up to p sites to maximize covered demand as defined by Eq. (6). Coverage indicators a_{ij} are derived from geodesic proximity using Eq. (1). The key policy levers are the budget p and service radius r_{cov}. Extensions in Eqs. (9)–(10) admit capacity limits and k-coverage when reliability or redundancy are required. The formulation is widely used due to transparency and interpretability.

E. Unified Training and Selection Protocol

All spatial layers share a common CRS; distances use Eq. (1). Feature construction, including Eq. (2), fits strictly within training folds to avoid leakage. Data is split once into train and held-out test sets with spatial stratification where appropriate. Within training, K-fold cross-validation selects the ML predictor by Eq. (11) and fixes β_1, β_2 in Eq. (3). MCLP receives the same candidate set, budget p, and service radius r_{cov}; when testing extensions, the same k and capacities are used across methods. MCLP uses the same solver and optimality gap or time limit across runs. Reported metrics include coverage rate, uncovered demand, mean access distance, and RMSE in Eq. (11) as shown in Fig. 1.

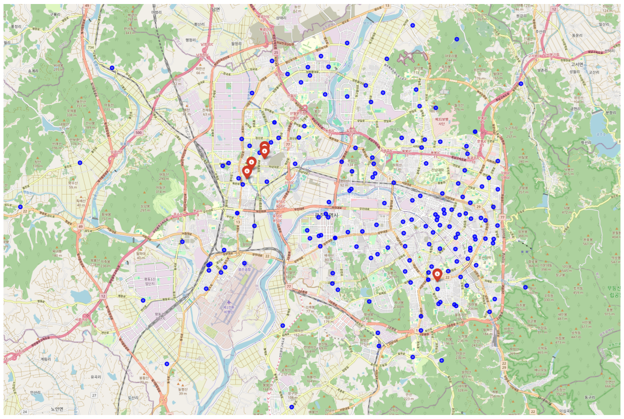

Fig. 1: Integrated optimal facility placement illustration.

IV. Conclusion

This paper presented a unified framework for siting demand-driven facilities that compares learned scoring, evolutionary search, and deterministic covering under identical inputs and constraints. The approach preserves coverage guarantees, scales to large candidate sets, and adapts to local signals via learned demand. Extensions to capacity and k-coverage broaden applicability. Future deployments can incorporate equity-aware objectives, multi-type facilities with capacity, and decision-aware learning losses tailored to coverage and access metrics.

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References

[1] J. Oh, D. Lee, D. S. Lakew, and S. Cho, "DACODE: Distributed adaptive communication framework for energy efficient industrial IoT-based heterogeneous WSN," *ICT Express*, vol. 9, no. 6, pp. 1085–1094, December 2023.

[2] S. Park, H. Baek, and J. Kim, "Spatio-temporal multi-metaverse dynamic streaming for hybrid quantum-classical systems," *IEEE/ACM Transactions on Networking*, vol. 32, no. 6, pp. 5279–5294, 2024.

[3] S. Jung, Y. Yoo, G. Yang, and C. Yoo, "Prediction of permissioned blockchain performance for resource scaling configurations," *ICT Express*, vol. 10, no. 6, pp. 1253–1258, 2024.

[4] J.-T. Oh and S. Kim, "Azimuth estimation based on cnn and lstm for geomagnetic and inertial sensors data," *ICT Express*, vol. 10, no. 3, pp. 626–631, 2024.

[5] R. Church and C. ReVelle, "The maximal covering location problem," *Papers of the Regional Science Association*, vol. 32, pp. 101–118, 1974.

[6] C. S. ReVelle and H. A. Eiselt, "Location analysis: A synthesis and survey," *European Journal of Operational Research*, vol. 165, no. 1, pp. 1–19, 2005.

[7] M. S. Daskin, *Network and Discrete Location: Models, Algorithms, and Applications*, 2nd ed. Hoboken, NJ: Wiley, 2013.

[8] A. T. Murray, "Maximal coverage location problem: Impacts, significance, and evolution," *International Regional Science Review*, vol. 39, no. 1, pp. 5–27, 2016.

[9] M. C. Ho, A.-T. Tran, D. Lee, J. Paek, W. Noh, and S. Cho, "A DDPG-based energy efficient federated learning algorithm with SWIPT and MC-NOMA," *ICT Express*, vol. 10, no. 3, pp. 600–607, June 2024.

[10] J. Oh, Y. Park, H.-J. Kwon, S. Lee, Y. Kim, and S.-Y. Lee, "Azimuth estimation based on cnn and lstm for geomagnetic and inertial sensors," *ICT Express*, vol. 10, no. 3, pp. 626–631, 2024.

[11] D. Bertsimas and N. Kallus, "From predictive to prescriptive analytics," *Management Science*, vol. 66, no. 3, pp. 1025–1044, 2020.

[12] A. N. Elmachtoub and P. Grigas, "Smart "predict, then optimize"," *Management Science*, vol. 68, no. 1, pp. 9–26, 2022.

[13] I. H. Sarker, A. S. M. Kayes, P. Watters, S. Badsha, Z. B. Sikder, H. Alqahtani, R. Islam, A. Khan, S. F. Abedin, and et al., "Explainable ai for cybersecurity automation, intelligence, and defense: A comprehensive survey," *ICT Express*, vol. 10, no. 4, pp. 735–762, 2024.

[14] O. Alp, E. Erkut, and Z. Drezner, "An efficient genetic algorithm for the p-median problem," *Annals of Operations Research*, vol. 122, no. 1, pp. 21–42, 2003.