Extreme-Scale EV Charging Infrastructure Planning for Last-Mile Delivery Using High-Performance Parallel Computing

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Motivation

Increasing Freight EV Adoption: Truck sales jumped 35% in 2023 to ~54k units overtaking electric buses for the first time.

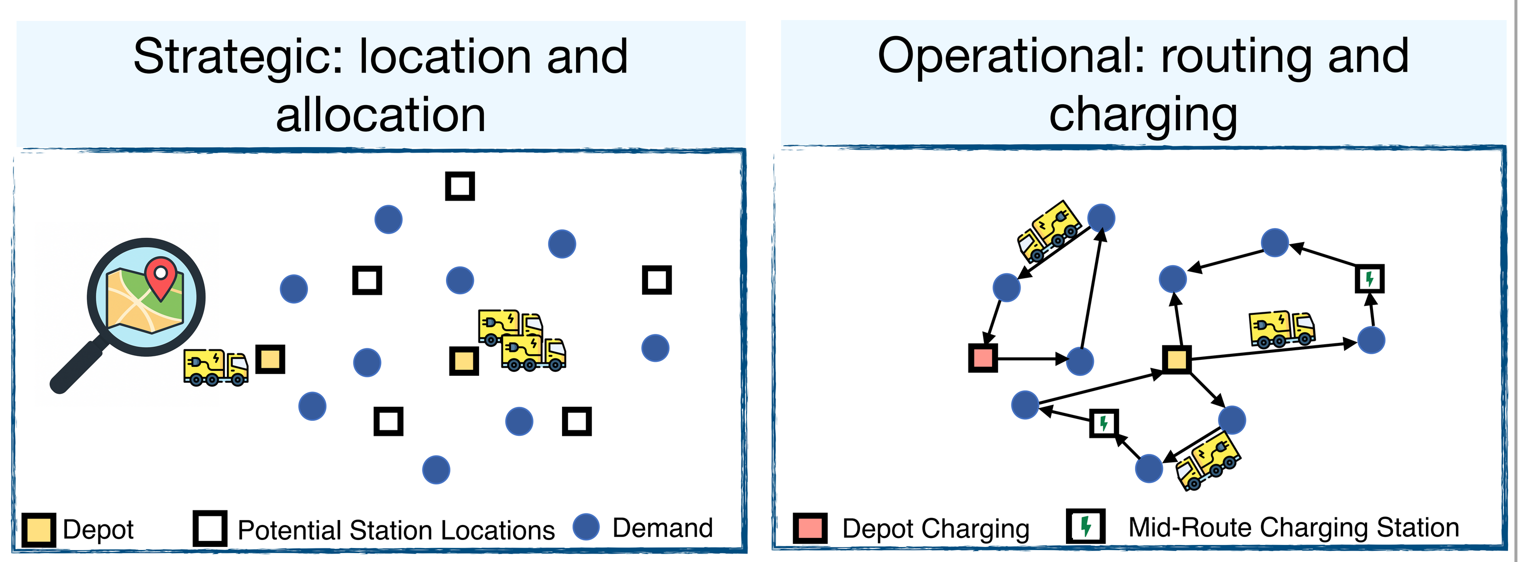
Infrastructure Bottleneck: Charging capacity needs to increase 20x by 2035

Limitations of Prior Methods: Often deterministic, small-scale, ignoring queue congestion.

Stochastic Queue Approach: Congestion + random arrivals = more realistic planning.

Scalability: Exact methods become intractable at large scale → decomposition + High-Performance Computing needed.

Modeling and Formulation



Stochastic Charger Location Allocation (SCLA)

Decision variables: $x_{ijk} \in \{0,1\}$: Assign household i to charger type k at station j, $y_j \in \{0,1\}$: Open station j

$W_{jk} \in \mathbb{R}_{\geq 0}$: Expected waiting + service time for station charger pair (j,k), $s_{jk} \in \mathbb{Z}_{\geq 0}$: Number of chargers of type k at station j

Objective:

$$\mathbb{G}: \min_{x,y,s,w} \quad f_\phi(y) + f_\xi(s) + f_\delta(x) + f_\tau(x,w)$$

(Station opening cost: $f_\phi(y)$; Charger installation cost: $f_\xi(s)$; Travel (detour) cost: $f_\delta(x)$; Congestion (waiting) cost: $f_\tau(x,w)$)

Parameters: γ_i delivery rate to household i (Poisson processes)

λ_i EV charging demand rate (arrival rate) for the of vehicles delivering to household i, μ_k exponential service rate of charger type k

Queue $M/M/s_{jk}$ constraints:

Utilization: $\mu_k s_{jk}(1-\epsilon) \geq \sum_{i \in \mathcal{I}_j} \lambda_i x_{ijk}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K} \implies \rho_{jk} < 1$, where $\rho_{jk} = \frac{\sum_i \lambda_i x_{ijk}}{\mu_k s_{jk}}$

Probability Chargers Busy $(\mathbb{P})$: $\mathbb{P}\left(\sum_{i \in \mathcal{I}_j} \lambda_i x_{ijk}, \mu_k, s_{jk}\right) = \frac{(\rho_{jk} s_{jk})^{s_{jk}}}{(1-\rho_{jk})\, s_{jk}!} \Big/ \left[\frac{(\rho_{jk} s_{jk})^{s_{jk}}}{(1-\rho_{jk})\, s_{jk}!} + \sum_{r=0}^{s_{jk}-1} \frac{(\rho_{jk} s_{jk})^r}{r!}\right]$

Expected Waiting Time $(\mathbb{W})$: $\mathbb{W}(.) = \frac{\mathbb{P}(.)}{\mu_k s_{jk}(1-\rho_{jk})} + \frac{1}{\mu_k}, \quad W_{jk} \geq \mathbb{W}$

Budget & capacity constraints:

Budget: $f_\phi(y) \leq B^\phi$, $f_\xi(s) \leq B^\xi$, and $f_\phi(y) + f_\xi(s) \leq B^\phi + B^\xi$

Station/Charger: $\sum_j y_j \leq \bar{Y}$ (max open stations) and $s_{jk} \leq \bar{S}_{jk}$ (max chargers per j)

Challenges with the Formulation

Bilinear Term: Congestion cost $f_\tau(x, W)$ includes products like $W_{jk} \cdot x_{ijk}$

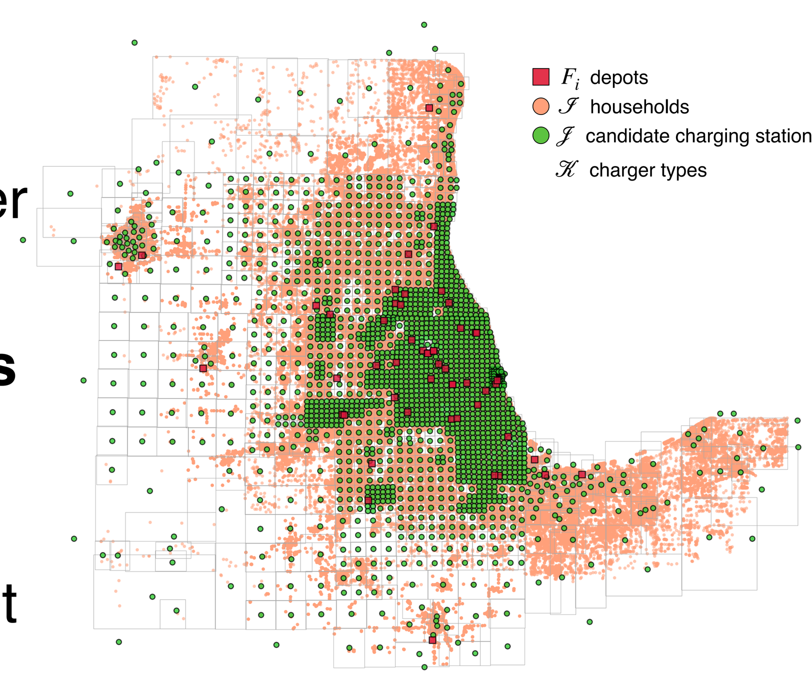
Nonlinearity from Waiting-Time W_{jk} constraints

Problem Scale:

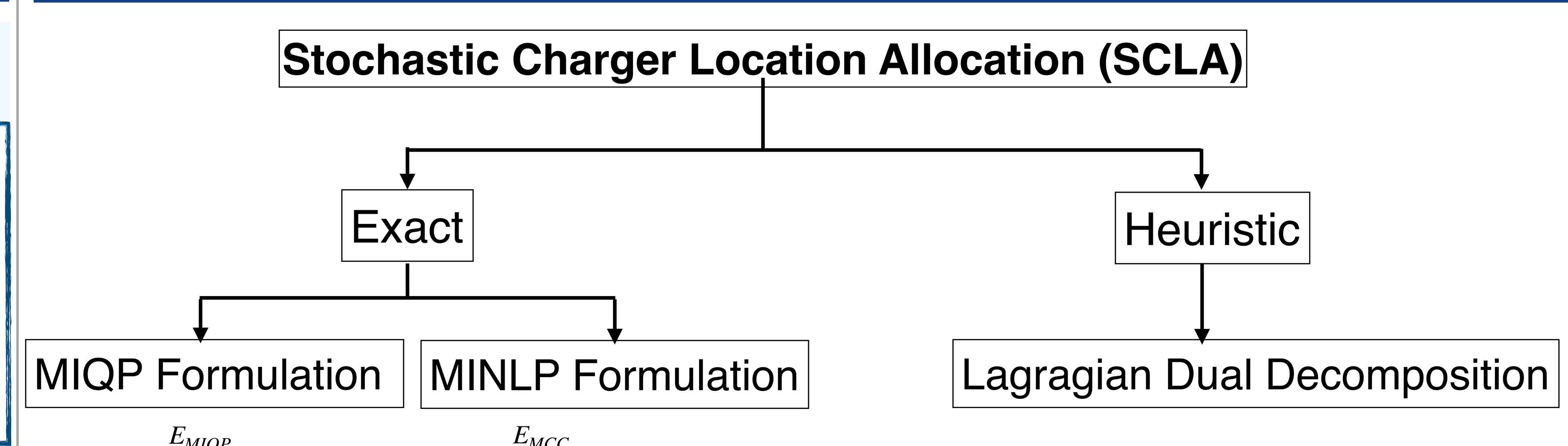
Up to half million households ($\mathcal{I}$), ~ 2000 stations ($\mathcal{J}$), and multiple charger types ($\mathcal{K}$)

The indexing set (i,j,k) can yield **millions** of binary variables x_{ijk}

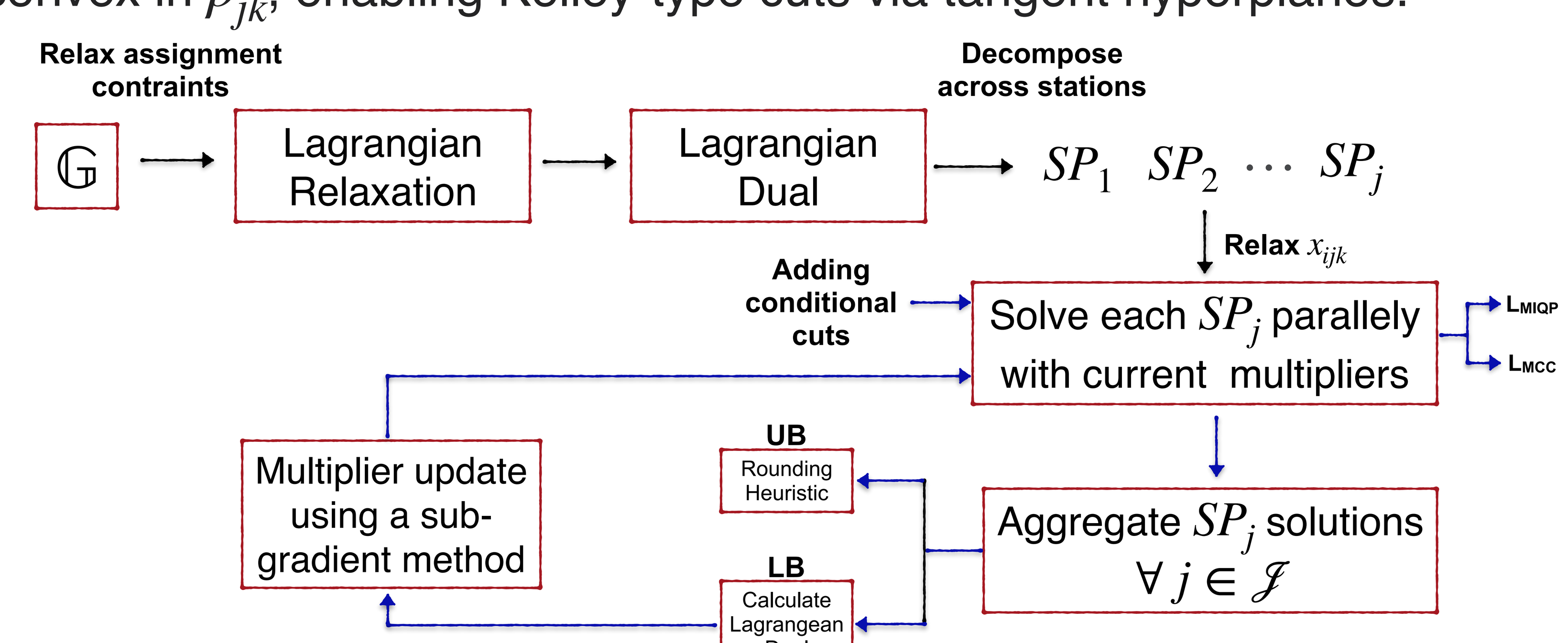
Largest problem instance to date. Constructing the model alone is difficult, let alone solving it.



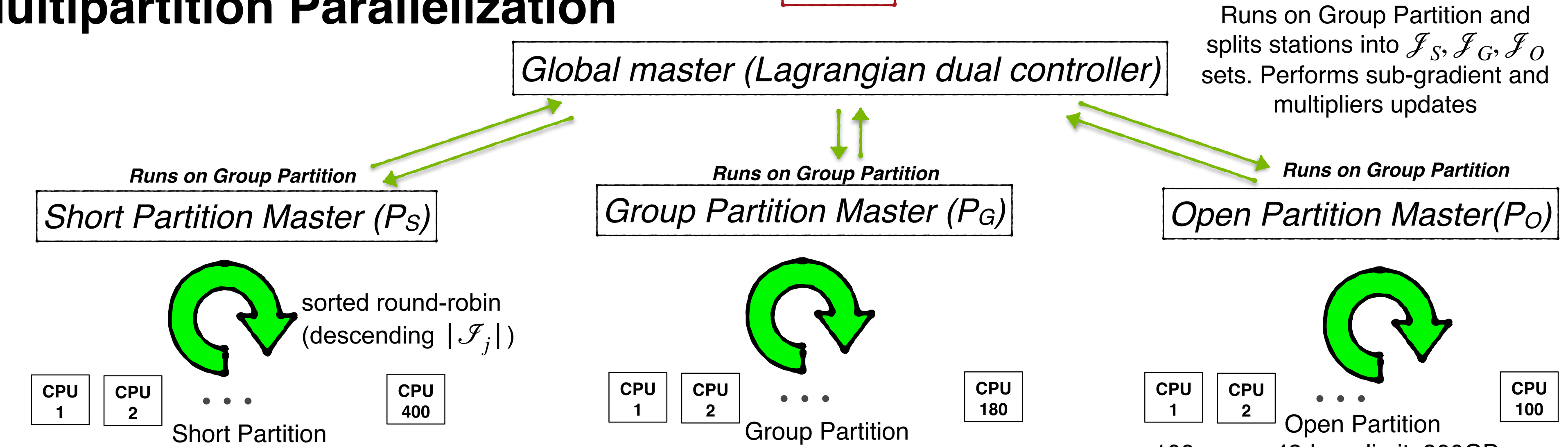
Solution Approaches



Convexity leverage: For all $s_{jk} \in \mathbb{Z}_{>0}$, the expected waiting time $\mathbb{W}(\rho_{jk}, s_{jk})$ is strictly convex in ρ_{jk}, enabling Kelley-type cuts via tangent hyperplanes.



Multipartition Parallelization

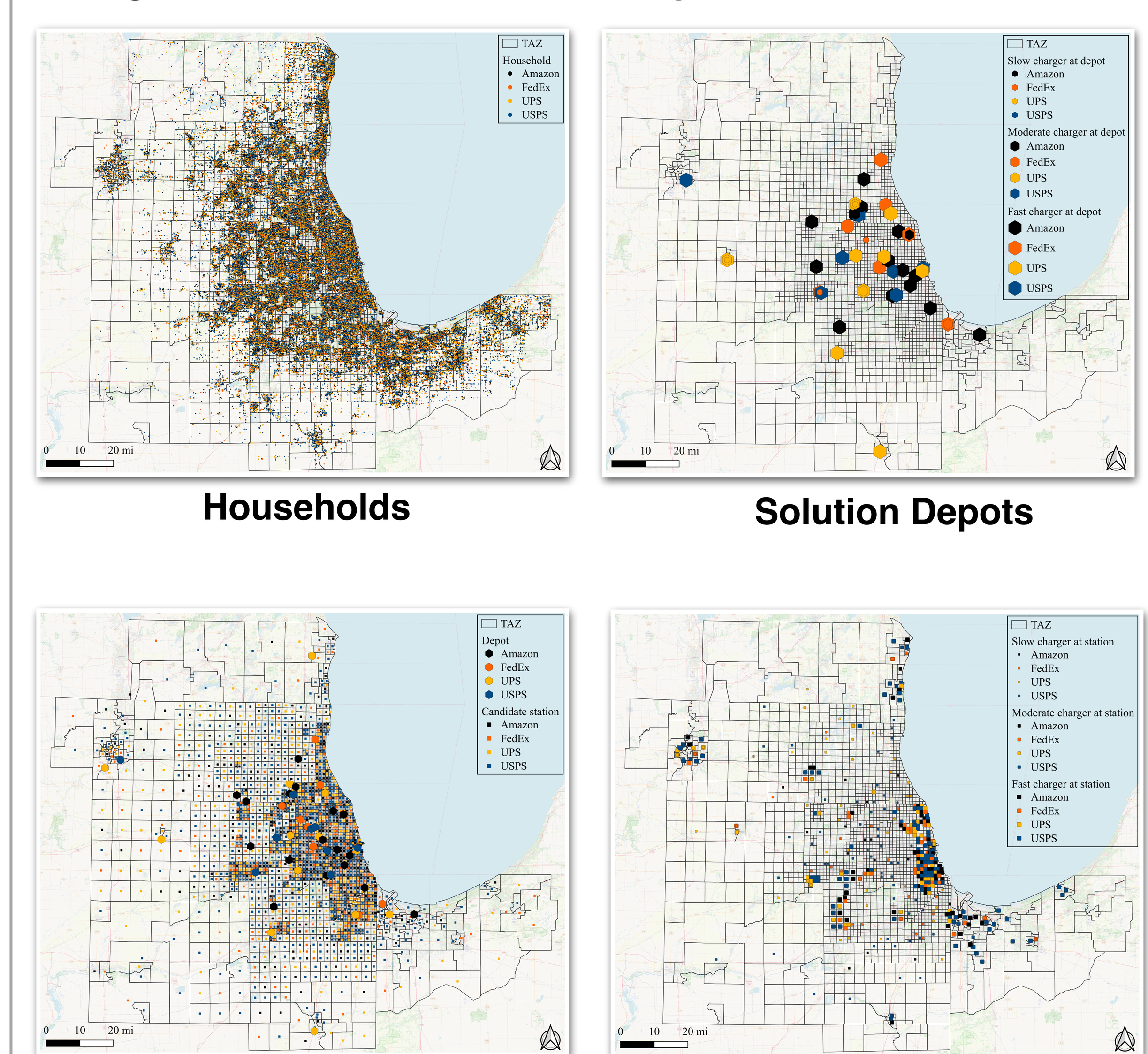


Computational Experiments

Data & Scale: e-commerce demand and road network data from **POLARIS** (*Auld, Joshua et al, 2016*)

449K+ households, 1,958 potential station sites, 53 existing depots, 3 charger types

Large - Scale Case Study:



Households | Solution Depots | Potential Station Locations | Solution TAZs

Faster Chargers: Deployed near high-demand corridors; lower queue/wait times, albeit at a higher cost.

Scalability: Decomposition + HPC is critical for real-world, large-scale EV planning; standard exact solvers fail to build/solve models of this magnitude.

Case Study Results using the L_{MCC} with a 6-hour time limit

Charging Location		Policy		$\lvert\mathcal{J}\rvert$	J^{open}	Total Chargers $\left(\sum_{j \in \mathcal{J}} S_{jk}\right)$			$\overline{W}_{jk}$ (min)			Gap^m (%)
TAZs	Depots	Single	Multi			k_1	k_2	k_3	k_1	k_2	k_3	
✓	✓	×	✓	2014	436	218	109	302	123.57	31.53	16.59	78.5

Charging Location Strategies and Policy Frameworks:

Multi-Agency Collaboration: Allows every household access to any open station, reducing overall infrastructure costs.

% Change in the Objective for Various Scenarios using L_{MCC}

Scenario	Charging Location		Policy		% ↑ in $\mathbb{C}$			
	TAZs	Depots	Single	Multi	Mean	Std Dev	Min	Max
1	✓	×	✓	×	91.24	7.82	82.79	100.74
2	✓	×	×	✓	44.82	10.08	32.61	62.46
3	×	✓	✓	×	42.33	11.14	27.39	60.93
4	×	✓	×	✓	32.23	3.95	25.34	35.93
5	✓	✓	✓	×	14.51	3.97	8.07	19.18
6	✓	✓	×	✓	-	-	-	-

Depot + TAZ Combination: Integrating existing depots and new TAZ sites balances coverage, reduces queue times, and avoids overconcentration.