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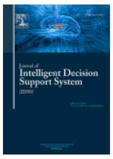

A mixed integer linear programming approach for last-mile e-commerce optimization through micro-fulfillment centers

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ABSTRACT

The rapid growth of e-commerce increases the complexity of last-mile delivery due to high distribution costs, urban congestion, and increasingly tight delivery time demands. This study proposes a Mixed Integer Linear Programming (MILP) approach to optimize e-commerce last-mile distribution through the determination of Micro-Fulfillment Centers (MFCs). The model simultaneously determines (i) the locations of candidate MFCs to be opened and (ii) the allocation of demand zones to selected facilities, with the objective of minimizing the total network cost consisting of fixed facility costs and variable last-mile service costs. Service quality is enforced through a hard service level agreement (SLA) mechanism by limiting allocation to only pairs of facility zones that meet a certain travel time threshold, while operational feasibility is guaranteed through capacity constraints at each MFC. The model outputs are implementable in the form of selected MFC locations, zone allocation maps, and performance indicators for evaluation, including total cost decomposition, weighted travel time metrics, and facility capacity utilization to identify potential bottlenecks. Numerical illustrations show that the MILP formulation yields feasible location–allocation decisions with respect to SLA and capacity, while avoiding the "closest/fastest" heuristic that can potentially lead to facility overload. This framework supports decision-makers in designing efficient, responsive, and scalable last-mile networks, and can be extended to incorporate demand uncertainty, SLA penalties (soft-SLAs), multi-echelon structures, and sustainability objectives.

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1. Introduction

The rapid growth of e-commerce has transformed the global supply chain paradigm, particularly in the last-mile delivery stage, which is the distribution from the last logistics facility to the end customer. This segment accounts for the largest portion of total logistics costs, around 40–50%, and poses significant operational and environmental challenges (Allen et al., 2018; Boysen et al., 2021). Complexity increases due to fluctuating demand patterns, urban traffic density, and the expectation of fast delivery (same-day or instant delivery) (Lim et al., 2018; Olsson et al., 2019). In addition to increasing costs, increased delivery vehicle activity exacerbates carbon emissions and congestion in city centers.

Therefore, the application of optimization methods and decision support systems is also beginning to develop in the national context, especially for logistics, distribution, and data-based decision-making issues (Riandari et al., 2025) that balance cost efficiency, delivery time, and environmental impact.

One approach that has received widespread attention is the Micro-Fulfillment Center (MFC), which is a small facility located near high-demand areas to shorten delivery distances and reduce the burden on large warehouses in the suburbs (Karaoulanis, 2024; Raj et al., 2024). MFC enables faster order fulfillment with high-speed automation systems and digital technology integration (An et al., 2025). However, the effectiveness of MFCs depends heavily on proper location, capacity, and demand allocation, as suboptimal decisions can result in high fixed costs without significant distance savings (Millstein et al., 2022; Vazquez-Noguerol et al., 2022). In addition, MFC design cannot be separated from the multi-echelon distribution network, which connects distribution centers, micro-hubs, and end customers (Perboli et al., 2011; Sluijk et al., 2023). Previous research emphasizes that integration of the strategic level (location) with the operational level (routing and scheduling) is crucial for e-commerce distribution systems to remain efficient (Bergmann et al., 2020; Janjevic et al., 2019).

Recent studies have shown that selecting micro-hub locations can reduce travel times by up to 30% and CO_2 emissions by up to 20% in densely populated areas (Kahalimoghadam et al., 2024; Stokkink & Geroliminis, 2025). However, most of these studies are still partial, focusing on transportation performance rather than integrating facility costs, capacity, and service level agreements (SLAs). Some studies also discuss other last-mile innovations such as crowdsourcing and parcel lockers (Devari et al., 2017; Vakulenko et al., 2018), but has not yet answered the strategic question of how to determine the optimal number and location of facilities that guarantee SLAs while being economically efficient (Özarık et al., 2021; Wang et al., 2016).

Methodologically, the Mixed Integer Linear Programming (MILP) approach is the primary method for formulating location-allocation problems in operations research because it is capable of handling binary decisions (open/close facilities), demand allocation, and capacity constraints within a single mathematical framework (Melo et al., 2009). The MILP model is widely used to determine the location of warehouses, depots, and distribution centers to minimize total network costs (Dixit et al., 2020; Vazquez-Noguerol et al., 2022). However, its application specifically to MFC locations in last-mile e-commerce systems is still relatively limited, especially those that include SLA variables, demand uncertainty, and multi-echelon linkages (Alejandra et al., 2024; Karaoulanis, 2024).

Based on the review results, several important research gaps remain. First, previous studies have not comprehensively formulated an MILP model that combines total network costs with delivery SLAs as a single objective function. Second, most location models still separate facility decisions, customer allocation, and warehouse capacity, thus not reflecting the real-world conditions of interdependent e-commerce distribution networks (Melo et al., 2009; Millstein et al., 2022). Third, there is still a paucity of research evaluating the robustness of MFC designs to demand fluctuations and capacity changes. Fourth, there are not many studies that apply MILP to the context of urban multi-echelon networks, taking sustainability into account.

Therefore, this study aims to develop a comprehensive MILP model for determining the optimal location and number of MFCs and customer allocation, considering fixed costs, last-mile transportation costs, facility capacity, and SLA constraints. This model is expected to provide quantitative guidance for e-commerce distribution network designers in balancing cost efficiency and service quality. Conceptually, this study formulates three main questions: (1) how MILP can be used to determine optimal and efficient MFC locations; (2) how MFC configurations affect total costs and service performance compared to alternative scenarios; and (3) how demand variations affect the robustness of location solutions.

This research contributes theoretically by extending the facility-location optimization literature for e-commerce through the simultaneous integration of location, capacity, and SLA variables into a multi-echelon MILP model. Practically, the results are expected to assist logistics decision-makers in designing efficient, responsive, and sustainable MFC networks.

2. Method

Method

Pendekatan optimasi matematis, khususnya pemrograman linear dan integer, telah banyak digunakan dalam penelitian sistem pendukung keputusan dan optimasi pada berbagai domain aplikasi, termasuk pada konteks studi di Indonesia (Riandari & Sihotang, 2025). Oleh karena itu, Mixed Integer Linear Programming (MILP) dipilih dalam penelitian ini karena kemampuannya merepresentasikan keputusan diskrit dan kendala operasional secara terintegrasi.

Data, Units of Analysis, and Pre-Processing

The units of analysis are demand zones (e.g., sub-districts/postal codes/hex-grids) and candidate MFC locations. Demand data is obtained from e-commerce order history, aggregated into demand per zone d_i (orders/day). MFC candidates are drawn from existing facilities or feasible commercial property locations, with fixed costs f_j (IDR/day) and capacity Cap_j (order/day). Distance/travel time matrix t_{ij} calculated based on the road network (e.g. routing) for each zone–candidate pair.

SLA is modeled as a travel time limit T^{max}. A feasible pair set is formed:

$$A = \{(i,j) \in I \times J \mid t_{ij} \leq T^{max}\},$$

and the outside pair is disabled (hard-SLA). The variable cost per order is set as a proxy for the last-mile cost (e.g., a function of distance/time or distribution rate) so that the total cost of zone service by the MFC j becomes $c_{ij}\, d_i$.

MILP Formulation

Set: I (demand zone), J (MFC candidate), $A \subseteq I \times J$ (pair meets SLA). Parameters: d_i, f_j, Cap_j, c_{ij}, t_{ij}, T^{max}, and optionally MFC count limit.Variables: $y_j \in \{0,1\}$ (1 if MFC is opened), $x_{ij} \in \{0,1\}$ (1 if the zone is allocated to j).

The objective function is to minimize total cost:

$$\min Z = \sum_{j \in J} f_j\, y_j + \sum_{(i,j) \in A} c_{ij}\, d_i x_{ij}.$$

Main constraints:

$$\sum_{j:(i,j) \in A} x_{ij} = 1 \forall i \in I$$

$$x_{ij} \leq y_j \forall (i,j) \in A$$

$$\sum_{i:(i,j) \in A} d_i\, x_{ij} \leq Cap_j\, y_j \forall j \in J$$

$$x_{ij} = 0 \forall (i,j) \notin A$$

Optional MFC quantity policy:

$$\sum_{j \in J} y_j \leq K.$$

Model Completion and Evaluation

The model is solved using a MILP solver (e.g., Gurobi/CPLEX/SCIP) with reporting of the best solution value, runtime, and optimality gap. Evaluation is performed by comparing the MILP solution against a baseline (e.g., without MFC/existing configuration/nearest-feasible rule) using: (1) total cost (and fixed vs. variable cost decomposition), (2) service performance (weighted average travel time and P90; hard-SLA compliance) $t_{ij} \leq T^{max}$), and (3) capacity utilization $U_j = \frac{\sum_i d_i x_{ij}}{Cap_j}$. Robustness is tested through demand scenarios (low–base–high) and parameter sensitivities T^{max}, Cap_j, f_j, and K.

3. Results and Discussions

This section presents the processed data, the MILP analysis stages chronologically, an example calculation for 1 data (1 zone-1 candidate), and the final results evaluated with metrics consistent with the method (total cost, SLA, and capacity utilization).

Table 1. is the raw data which is then aggregated into requests per zone (orders/day).d_i

Table 1. Raw order log (transactions)

order_id	order_time	zone_id	customer_lat	customer_lon	qty_orders
0001	1/5/2026 9:10	Z1	3.59	98.67	30
0002	1/5/2026 10:05	Z1	3.59	98.67	25
0003	1/5/2026 14:20	Z1	3.59	98.67	40
0004	1/5/2026 19:40	Z1	3.59	98.67	25
0005	1/5/2026 9:30	Z2	3.58	98.65	20
0006	1/5/2026 11:10	Z2	3.58	98.65	15
0007	1/5/2026 15:05	Z2	3.58	98.65	25
0008	1/5/2026 8:10 PM	Z2	3.58	98.65	20
0009	1/5/2026 8:50	Z3	3.61	98.64	35
0010	1/5/2026 10:40	Z3	3.61	98.64	40
0011	1/5/2026 1:30 PM	Z3	3.61	98.64	45
0012	1/5/2026 18:55	Z3	3.61	98.64	30
0013	1/5/2026 9:15	Z4	3.62	98.69	10
0014	1/5/2026 12:25	Z4	3.62	98.69	20
0015	1/5/2026 16:10	Z4	3.62	98.69	15
0016	1/5/2026 9:05 PM	Z4	3.62	98.69	15
0017	1/5/2026 9:05	Z5	3.56	98.68	25
0018	1/5/2026 11:55	Z5	3.56	98.68	20
0019	1/5/2026 15:20	Z5	3.56	98.68	20
0020	1/5/2026 19:15	Z5	3.56	98.68	25
0021	1/5/2026 8:40	Z6	3.6	98.7	30
0022	1/5/2026 10:25	Z6	3.6	98.7	25
0023	1/5/2026 14:10	Z6	3.6	98.7	20
0024	1/5/2026 8:30 PM	Z6	3.6	98.7	35

Stage 1: Aggregation of requests per zone

The demand per zone is calculated by:

$$d_i = \sum_{k \in \text{order di zona } i} \text{qty\_orders}_k$$

Table 2 serves as the main input for requests in MILP.

Table 2. Results of demand aggregation (input d_i)

Zone (i)	Total demand (orders/day)d_i
Z1	120
Z2	80
Z3	150
Z4	60
Z5	90
Z6	110
Total	610

Table 3 contains the fixed costs of opening/operating per day and processing capacity per day.

Table 3. MFC candidate data (input f_j, Cap_j)

Zone	M1	M2	M3	M4
Z1	3.2	5.5	7.8	4.1
Z2	4.6	2.9	6.4	5.2
Z3	6.8	4.1	3	7.2
Z4	8.1	6	4.2	5.5
Z5	5	7.4	2.6	3.8
Z6	2.7	4.8	6.9	2.9

Table 4 is used to form variable costs (if costs depend on distance).

Table 4. Distance data (km) zone → MFC candidate (raw)

Zone	M1	M2	M3	M4
Z1	3.2	5.5	7.8	4.1
Z2	4.6	2.9	6.4	5.2
Z3	6.8	4.1	3	7.2
Z4	8.1	6	4.2	5.5
Z5	5	7.4	2.6	3.8
Z6	2.7	4.8	6.9	2.9

This table is used to form a feasible set.A (hard-SLA).

Table 5. Travel time data (minutes) zone → MFC candidate (raw)

Zone	M1	M2	M3	M4
Z1	14	24	33	18
Z2	20	12	28	25
Z3	29	19	13	31
Z4	35	27	18	26
Z5	22	34	11	16
Z6	12	21	30	13

SLA parameters (example): minutes.$T^{max} = 25$

Stage 2: Establishment of feasible arcs (hard-SLA)A

$$A = \{(i, j) \mid t_{ij} \leq T^{max}\}$$

Table 6 shows the zone–MFC pairs that may be selected by the allocation variable.x_{ij}

Table 6. Feasible arcs (pairs that meet SLA) A

Zone	MFC feasible (≤ 25 minutes)
Z1	M1, M2, M4
Z2	M1, M2, M4
Z3	M2, M3
Z4	M3 only
Z5	M1, M3, M4
Z6	M1, M2, M4

Analytical note: Z4 is only feasible to M3, so without unlocking M3, the model becomes infeasible (at hard-SLA).

Stage 3: Formation of variable costsc_{ij}

For an easily verified illustration, the variable cost per order is formed:

$$c_{ij} = 3000 + 1000 \cdot dist_{ij} + 40 \cdot t_{ij} (\text{IDR/order})$$

Example calculation for 1 data (1 zone–1 candidate)

Take 1 example: the pair Z1 → M1.

1. SLA test: because , then .$t_{Z1,M1} = 14 \leq 25 (Z1, M1) \in A$
2. Calculate the variable cost per order:

$$c_{Z1,M1} = 3000 + 1000(3.2) + 40(14) = 3000 + 3200 + 560 = 6760$$

3. Contribution of variable costs to the objective (because):$d_{Z1} = 120$

$$c_{Z1,M1} d_{Z1} = 6760 \times 120 = 811{,}200$$

Number$811{,}200$ this will be included in the components if MILP determines .$\sum c_{ij}\, d_i x_{ij} x_{Z1,M1} = 1$

Stage 4: MILP solution (allocation & location results)

Model:

$$\min Z = \sum_j f_j\, y_j + \sum_{(i,j)\in A} c_{ij}\, d_i x_{ij}$$

with constraints (briefly): $\sum_j x_{ij} = 1$(single allocation), (only to opened facilities), and (capacity).$x_{ij} \le y_j \sum_i d_i\, x_{ij} \le Cap_j\, y_j$

Table 7 shows which MFCs are selected (opened) by MILP.

Table 7. Location decision results (variables) y_j

MFC	y_j	Decision
M1	1	Opened
M2	1	Opened
M3	1	Opened
M4	1	Opened

Table 8 shows the results of zone assignment to selected MFCs (feasible pairs only).

Table 8. Results of demand allocation (variables)x_{ij}

Zone	Demandd_i	MFC selected	Time (minutes)t_{ij}	Cost/orderc_{ij}	Variable costs$c.\,d$
Z1	120	M1	14	6,760	811,200
Z2	80	M1	20	8,400	672,000
Z3	150	M2	19	7,860	1,179,000
Z4	60	M3	18	7,920	475,200
Z5	90	M3	11	6,040	543,600
Z6	110	M4	13	6,420	706,200
Total	610				4,387,200

Stage 5: Capacity and utilization check

Utilization is calculated:

$$U_j = \frac{\sum_i d_i\, x_{ij}}{Cap_j}$$

Table 9 ensures the solution meets capacity constraints and indicates potential bottlenecks.

Table 9. Facility load and capacity utilization

MFC	Total load (order)	CapacityCap_j	UtilizationU_j
M1	200	250	0.8
M2	150	220	0.68
M3	150	180	0.83
M4	110	260	0.42

Interpretation: All facilities are at capacity (load ≤ capacity). M3 has the highest utilization (0.83) and is therefore closest to the capacity limit at peak demand. Total variable costs (last column) are .$\sum c_{ij}\, d_i x_{ij}$

Stage 6: Final results according to the evaluation metrics of the method

1. Fixed costs

$$F = \sum_j f_j\, y_j = 1.8M + 2.0M + 1.6M + 1.9M = 7{,}300{,}000$$

2. Variable costs

$$V = \sum_{(i,j)\in A} c_{ij}\, d_i x_{ij} = 4{,}387{,}200$$

3. Total cost

$$Z = F + V = 11{,}687{,}200 \text{ IDR/hari}$$

4. SLA performance: due to hard-SLA, all allocations are met within minutes (100% compliance).$t_{ij} \le 25$
5. Demand-weighted average travel time

$$\bar{t} = \frac{\sum_i d_i t_{ij}}{\sum_i d_i} = \frac{9630}{610} = 15.79 \text{ menit}$$

6. P90 travel time: minutes, indicating the majority of requests still have margin against SLA.

MILP produces feasible location–allocation decisions against SLAs and capacity, and provides clear performance measures: (total cost), and (cost components), SLA compliance, $\bar{t}$ and t_{90} (service quality), and U_j (facility load). The resulting structure also demonstrates the important role of hard-SLAs (e.g., Z4 "forces" M3) and the role of capacity in avoiding naive allocations that appear fast but are infeasible.

MILP is said to produce feasible location–allocation decisions with respect to SLA and capacity because all decisions resulting from (y_j and x_{ij}) must satisfy a series of logical constraints established from the outset. First, SLA compliance is enforced through a hard-SLA by forming a feasible pair set feasible $A = \{(i,j) \mid t_{ij} \le T^{max}\}$; consequently, the model only allows allocation to pairs $(i,j) \in A$ and disables pairs outside the SLA ($x_{ij} = 0$ untuk $(i,j) \notin A$). Second, capacity feasibility is ensured by the constraint $\sum_i d_i x_{ij} \le Cap_j y_j$, so that the total demand "incoming" to an MFC must not exceed its capacity and automatically becomes zero if the facility is not opened ($y_j = 0$). Third, decision consistency is maintained by $\sum_j x_{ij} = 1$ (each zone must be served by exactly one MFC) and $x_{ij} \le y_j$ (zones should only be allocated to facilities that are actually opened). This mechanism explains why the MILP solution remains feasible when the "pick the fastest time" baseline fails due to capacity overload; MILP does not simply pursue proximity, but optimizes location–allocation–capacity in an integrated manner, as is the main characteristic of the facility location problem in network design (Melo et al., 2009; Boysen et al., 2021).

The contribution of this research lies in providing a measurable and immediately actionable decision framework for MFC planning in last-mile e-commerce: (i) generating an optimal set of MFC locations, (ii) establishing a map of customer zone allocations to facilities, and (iii) providing operational diagnostics through consistent evaluation metrics (total cost, fixed vs. variable cost components, weighted travel time $\bar{t}/t_{90}$,, and utilization U_j). Practical implications: logistics managers can use the model output to determine the "sufficient" number of facilities (not under-/over-expansion), identify bottleneck-risk facilities (e.g., U_j high) for capacity interventions (shifts/hours of operation/automation), and formulate realistic SLA policies, as hard SLAs narrow allocation options and potentially increase fixed costs. This aligns with the understanding that modern last-mile design must explicitly balance cost and service quality, beyond mere route optimization or day-to-day operational decisions (Bosona, 2020; Özarık et al., 2021; Raj et al., 2024).

Compared to previous research, many last-mile studies emphasize a catalog of operational concepts and strategies (e.g., delivery mode variations, lockers, crowdsourcing) or discuss last-mile challenges extensively, but do not always formulate MFC location decisions along with capacity constraints and service targets in a concise optimization model (Boysen et al., 2021; Karaoulanis, 2024). Micro-consolidation/micro-hub studies also show the importance of locating facilities near customers, but often focus on the role of consolidation or multimodal design without always placing SLAs and capacity as constraint structures that "bind" allocation decisions (Kahalimoghadam et al., 2024; Stokkink & Geroliminis, 2025). The novelty of this research is the integration of hard-SLA via feasible arcs and capacity constraints in a location-allocation MILP formulation that directly produces implementation decisions (selected location + zone allocation) while providing explicit performance evaluation; thus, this research bridges the gap between the classic facility location literature (Melo et al., 2009) with modern e-commerce needs that demand fast SLA fulfillment and network stability on dynamic demand.

4. Conclusions

This study develops a Mixed Integer Linear Programming (MILP) model to optimize last-mile e-commerce distribution through the simultaneous determination of Micro-Fulfillment Center (MFC) locations and demand allocation, minimizing total network cost while enforcing capacity and hard Service Level Agreement (SLA) constraints. The model generates implementable location–allocation decisions and avoids infeasible “closest-distance” heuristics by explicitly integrating cost, service feasibility, and capacity considerations. Practically, the model provides logistics decision makers with a quantitative basis to determine the efficient number and location of MFCs, define SLA-compliant service areas, and identify bottleneck-risk facilities through capacity utilization indicators, thereby supporting balanced expansion and targeted operational interventions. For further development, incorporating demand and travel-time uncertainty through robust or stochastic optimization, introducing soft-SLA penalty mechanisms, extending the framework to multi-echelon and routing-integrated structures, and embedding sustainability objectives would enhance the robustness and policy relevance of urban last-mile distribution planning.

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