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Intelligent multi-level network optimization for medical logistics in underground transportation systems: a computational intelligence approach☆

Jianhui Lv[a,*], Shalli Rani[b], Keqin Li[c]

[a] The First Affiliated Hospital of Jinzhou Medical University, Jinzhou 121000, China
[b] Chitkara University, Punjab 140401, India
[c] State University of New York, New Paltz, NY 12561, USA

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A B S T R A C T

The continuous advancement of urbanization has led to unprecedented traffic congestion in megalopolises worldwide, creating substantial challenges for healthcare delivery logistics. Emergency medical supplies, pharmaceuticals, laboratory specimens, and equipment face critical delays in congested urban environments, potentially compromising patient care. This research introduces an innovative multi-level network optimization framework for underground medical logistics systems that combines deep tunnel transportation with shallow pipeline channels to facilitate time-sensitive medical deliveries while alleviating surface congestion. We formulate an integer programming model that optimizes the placement of distribution centers, routing strategies, and flow allocation while considering construction and operational costs. To solve this computationally complex problem, we develop the immune-inspired multi-level network optimization for underground logistics systems (IMNO-ULS) algorithm that integrates mean-shift clustering with artificial immune systems and simulated annealing. This hybrid computational intelligence approach effectively decomposes the solution space by eliminating suboptimal configurations before optimization. Simulation results demonstrate that our algorithm outperforms traditional methods by 7–15 % in solution quality while reducing computation time by up to 71.3 %. A case study applying the system to a major metropolitan area shows that IMNO-ULS reduces the required number of distribution centers by 27 % while decreasing the average delivery time for emergency medical supplies by 32 %. The results validate the feasibility and efficiency of the proposed underground medical logistics network, offering a promising solution for improving healthcare delivery in congested urban environments.

1. Introduction

Urbanization continues to progress at an unprecedented rate worldwide, creating megalopolises with populations exceeding 20 million residents (Benassi et al., 2023; Muroishi & Yakita, 2023). According to recent global demographic data, urban centers now house more than 56 % of the world's population, projected to surpass 68 % by 2050. This dramatic demographic shift has placed extraordinary pressure on urban infrastructure, particularly transportation networks, creating persistent congestion that impacts various critical services (Gu

Abbreviations: ULS, Underground Logistics System; UMLS, Underground Medical Logistics System; UMLN, Underground Medical Logistics Network; IMNO-ULS, Immune-inspired Multi-level Network Optimization for Underground Logistics Systems; MS, Mean-Shift; AIS, Artificial Immune Systems; SA, Simulated Annealing; AGV, Automated Guided Vehicle; IoT, Internet of Things; CI, Computational Intelligence; LAR, Location-Allocation-Routing; PSOA*-LAR, Particle Swarm Optimization and A* Algorithm for Location-Allocation-Routing; IAGA, Improved Adaptive Genetic Algorithm; blM-ULS, Bi-level Programming Model for Metro-based Underground Logistics System; GDD-ULS, Genetic-based fuzzy C-means, Depth-first-search, and Dijkstra algorithm for Underground Logistics System; sM-ULS, Simulation-based Metro-based Underground Logistics System; MoCC-MULNP, Multi-objective Cooperative Co-evolutionary algorithm for Metro-based Underground Logistics System Network Planning; M-ULS, Metro-based Underground Logistics System; MULNP, Metro-based Underground Logistics System Network Planning; PSO, Particle Swarm Optimization; NP-hard, Non-deterministic Polynomial-time hard.

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* Corresponding author at: The First Affiliated Hospital of Jinzhou Medical University, Jinzhou 121012, China.
E-mail addresses: lvjh@pcl.ac.cn (J. Lv), shalli.rani@chitkara.edu.in (S. Rani), lik@newpaltz.edu (K. Li).

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et al., 2023; Shen et al., 2024). Healthcare delivery and medical logistics face severe challenges in these densely populated environments (Gustafsson & Dannapfel, 2025; Lv et al., 2025; Nikolic et al., 2022). Surveys indicate that emergency medical vehicles experience delays exceeding 40 % of their expected travel times during peak hours in major metropolitan areas, potentially compromising time-critical care for patients with conditions where minutes matter. Furthermore, the transportation of medical supplies, laboratory specimens, pharmaceuticals, and equipment encounter similar delays, affecting the overall quality and efficiency of healthcare services.

The convergence of multiple transportation demands on limited surface infrastructure further exacerbates the growing congestion problem (Pang et al., 2024; Rajkumar & Kumar, 2024). Commercial deliveries, personal vehicles, public transportation, and emergency services compete for the same road capacity, resulting in gridlock during peak hours. Traditional solutions involving road expansion have proven increasingly impractical in established urban centers, where space constraints and existing development limit opportunities for infrastructure growth (Anupriya et al., 2023). Environmental concerns add another dimension to this challenge, as increased vehicle emissions from idling in traffic contribute significantly to urban air pollution (Fang et al., 2025; Xu et al., 2024). Studies have identified that in some megacities, mobile sources contribute approximately 45 % of particulate matter (PM2.5) concentrations, posing substantial health risks to urban populations. The confluence of these factors – limited space, growing demand, and environmental impact – necessitates innovative approaches to urban logistics, particularly for time-sensitive and critical goods like medical supplies.

Underground logistics systems (ULS) have emerged as a promising solution to alleviate surface transportation congestion while ensuring the reliable delivery of essential goods (Hu, Dong, Yang, Ren, & Chen, 2023; Liang et al., 2022; Wang & Wang, 2023; Wei et al., 2024). ULS networks utilize underground tunnels, pipelines, and facilities to create a separate transportation layer that operates independently from surface traffic. By relocating a portion of freight movement below ground, these systems can significantly reduce surface congestion while providing more predictable delivery times. For medical logistics specifically, underground systems offer several compelling advantages: protection from weather conditions, enhanced security for sensitive medical materials, controlled environmental conditions for temperature-sensitive pharmaceuticals and biological samples, and, most importantly, reliable delivery times unaffected by surface traffic patterns. Recent advancements in automated guided vehicle (AGV) technology, IoT-enabled tracking systems, and artificial intelligence have made such underground networks increasingly feasible from both technological and operational perspectives (Ambrusevic & Gomiene, 2024; Liang et al., 2024; Lv et al., 2025).

Developing underground medical logistics systems (UMLS) requires careful consideration of multiple factors, including network architecture, facility placement, capacity constraints, and cost efficiency (Xue et al., 2022). Traditional single-layer networks often prove inadequate for the complex needs of modern healthcare systems, which involve various types of medical facilities with different urgency requirements and handling specifications. This research proposes a multi-level network design that differentiates between high-volume, high-speed transport between major medical hubs (via deep tunnels) and more distributed, lower-volume deliveries to individual facilities (via shallow pipeline systems). This hierarchical approach optimizes resource allocation by matching infrastructure investment to usage patterns. The design of such systems requires sophisticated optimization models that balance multiple objectives, including construction costs, operational efficiency, reliability, and environmental impact. Furthermore, the complexity of these models necessitates advanced computational intelligence techniques to find high-quality solutions within reasonable computational timeframes.

Integrating computational intelligence (CI) approaches into UMLS design represents a significant advancement in tackling the inherent complexity of multi-level network optimization (Cao et al., 2024; Liu et al., 2022). Traditional optimization methods often struggle with the combinatorial explosion of possible solutions in large-scale network design problems, particularly when considering the numerous constraints and interdependencies in medical logistics. Our research leverages a novel dual-layer heuristic approach that combines mean-shift clustering with artificial immune systems and simulated annealing to explore the solution space and identify near-optimal network configurations efficiently. Integrating CI techniques with domain-specific knowledge of underground logistics and medical supply chain requirements allows for more practical and implementable solutions. By developing this comprehensive framework for UMLS design and optimization, we aim to provide urban planners, healthcare administrators, and logistics providers with a powerful tool to improve medical logistics in congested urban environments, ultimately enhancing healthcare delivery and patient outcomes in megalopolises worldwide.

Urban congestion increasingly threatens timely medical deliveries in megalopolises, where emergency supplies, pharmaceuticals, and laboratory specimens face critical delays. While underground logistics systems offer a promising solution by creating separate transportation layers unaffected by surface congestion, existing approaches fail to address the specialized needs of medical logistics. Current research lacks integration between general underground logistics optimization and specific medical supply requirements, with most approaches employing single-algorithm solutions inadequate for multi-level medical networks. This research addresses these gaps by developing a specialized underground medical logistics network architecture and computational intelligence algorithm that differentiates between high-volume distribution and time-sensitive last-mile delivery, providing a solution that both reduces delivery times and minimizes infrastructure costs in congested urban environments.

Accordingly, the main contributions of this paper are summarized as follows:

- We propose a novel multi-level underground logistics network architecture specifically designed for medical supply transportation that differentiates between high-volume flows through deep tunnels and distributed deliveries through shallow pipelines.
- We formulate a comprehensive integer programming model that captures the complex interdependencies between distribution center activation, facility assignment, and network connectivity decisions in medical logistics contexts.
- We develop the immune-inspired multi-level network optimization for underground logistics systems (IMNO-ULS) algorithm, an innovative dual-layer metaheuristic that integrates mean-shift clustering for solution space decomposition with artificial immune systems, and simulated annealing for hierarchical optimization.

The remainder of this paper is organized as follows. Section 2 presents a literature review. Section 3 describes the problem of medical underground logistics network design. Section 4 formulates the mathematical model and details the proposed IMNO-ULS algorithm. Section 5 presents the simulation results and analysis. Section 6 presents the managerial implications and insights. Finally, Section 7 concludes the paper.

2. Literature review

The exploration of underground logistics systems has evolved significantly over the past few decades, with researchers investigating multiple facets of implementation, optimization, and practical applications. We review relevant literature on underground logistics systems, computational intelligence techniques, and medical applications, identifying the research gaps addressed by our work.

Sun et al. (2023) proposed a well-matched solution framework combining the multi-objective PSO algorithm and the A* algorithm to optimize the location-allocation-routing (LAR) decisions of the M-ULS network, called PSOA*-LAR. Sun et al. (2024) presented an improved adaptive genetic algorithm (IAGA) incorporating adaptive crossover, adaptive mutation, and an elitist strategy to address the vehicle routing problem in metro-based underground logistics systems. Zheng et al. (2022) proposed a bi-level programming model for a metro-based logistics system (blM-ULS). Hu and Dong et al. (2020) introduced a two-phase optimization schema combining a genetic-based fuzzy C-means algorithm, depth-first-search fuzzy C-means algorithm, and Dijkstra algorithm etc. to optimize the location-allocation of underground logistics system facilities and customer clusters (GDD-ULS). Hu, Dong, Yang, Ren, and Chen (2023) proposed a simulation-based approach for supporting the operational decision-making of the metro-based urban underground logistics system (sM-ULS). Hu, Dong, Yang, Ren, and Chen (2023) proposed an improved multi-objective cooperative co-evolutionary algorithm (MoCC) incorporating non-dominated sorting and chromosomal recombination strategy to yield high-quality solutions for M-ULS network planning problem (MULNP) problem, called MoCC-MULNP.

Additionally, recent research on underground logistics systems has evolved in several directions. Xue et al. (2023) formulated a resilient-maximizing plan for underground logistics networks using a two-stage linear programming model and Monte Carlo simulations to evaluate network resilience under disaster scenarios. Their work addressed network planning under uncertainty but did not consider the specialized needs of medical logistics. Li et al. (2024) assessed the resilience of metro-based underground logistics systems through a multi-layered, interdependent network approach that accounts for topology, functionality, facilities, and information layers. Their case study on the Nanjing Metro demonstrated how disruption types, duration, and train travel direction impact resilience, yet it did not explore network design optimization for medical supplies. Lu et al. (2024) proposed a resilience quantification method for urban underground logistics systems under node and link attacks, comparing three recovery strategies. Their research on the Nanjing City case showed that two-echelon networks exhibit exceptional resilience, with maximum flow-based recovery strategies proving the most effective. However, their work primarily focused on general logistics rather than time-sensitive medical logistics. Hou et al. (2024) introduced a novel urban contactless delivery solution incorporating M-ULS and the “Pandemic Thruport” concept to sustain city logistics performance during public health emergencies. Using system dynamics modeling with the Shanghai COVID-19 outbreak case, they demonstrated that M-ULS can reduce infection risks and improve urban freight transport efficiency compared to trucking but did not optimize network design for medical logistics specifically. The literature review conducted on underground logistics systems revealed critical research gaps that warrant further investigation. Despite the growing body of knowledge on general ULS optimization and separate medical logistics advancements, there is a noticeable absence of integrated approaches that specifically address the unique requirements of medical supply transportation beneath congested urban centers. This siloed research approach has limited the development of specialized optimization frameworks that could effectively manage the time-sensitive and often life-critical nature of medical deliveries. Additionally, current computational intelligence applications in this domain predominantly rely on single-algorithm methodologies, failing to capitalize on the significant potential of strategically combining multiple CI techniques within structured frameworks to tackle the inherent complexity of medical logistics networks. Perhaps most significantly, existing optimization models have not adequately captured the distinctly hierarchical nature of medical logistics networks, where high-volume distribution between major hubs requires fundamentally different infrastructure and management approaches compared to precise, time-sensitive last-mile delivery to individual healthcare facilities. As illustrated in Table 1, which systematically compares recent underground logistics systems studies, these research limitations have persisted across various methodological approaches, creating an opportunity for more integrated, multi-level network optimization solutions specifically designed for medical logistics in underground environments.

Based on this literature analysis, several research gaps emerge. First, while studies have addressed general ULS optimization and medical logistics separately, few have integrated these domains to create specialized underground medical logistics optimization approaches. Second, existing computational intelligence techniques typically employ single-algorithm approaches rather than leveraging multiple CI methods in structured frameworks. Third, the hierarchical nature of medical logistics networks, with different requirements for high-volume distribution and last-mile delivery, remains inadequately addressed in existing optimization models.

Additionally, as illustrated in Table 1, which systematically

Table 1
Comparison of Recent Underground Logistics Systems Studies.

Study	Focus area	Methodology	Network type	Objective	Medical-specific	Multi-level design	Computational intelligence approach
Sun et al. (2023)	Location-allocation-routing	PSO and A* algorithms	Metro-based	Optimization of LAR decisions	No	No	Single algorithm
Sun et al. (2024)	Vehicle routing	Improved adaptive genetic algorithm	Metro-based	Routing optimization	No	No	Single algorithm
Zheng et al. (2022)	Distribution node location	Bi-level programming	Metro-based	Location optimization	No	No	Mathematical programming
Hu and Dong et al. (2020)	Location-allocation	Two-phase clustering	General ULS	Facility location	No	No	Multiple algorithms
Hu, Dong, Yang, Ren, and Chen (2023)	Operational decision-making	Simulation-based approach	Metro-based	Operational efficiency	No	No	Simulation
Hu, Dong, Yang, Ren, and Chen (2023)	Network planning	Multi-objective co-evolutionary algorithm	Metro-based	Multi-objective optimization	No	No	Single algorithm
Xue et al. (2023)	Resilience maximization	Two-stage linear programming	General ULS	Network resilience	No	No	Hybrid heuristic
Li et al. (2024)	Resilience assessment	Multi-layer network modeling	Metro-based	Resilience quantification	No	No	Network analysis
Lu et al. (2024)	Recovery strategies	Resilience quantification	General ULS	Recovery optimization	No	Partial	Network analysis
Hou et al. (2024)	Emergency logistics	System dynamics	Metro-based	Performance during emergencies	Partial	No	System dynamics
This study	Network design	Integer programming + Computational intelligence	Medical ULS	Cost and delivery time optimization	Yes	Yes	Hybrid dual-layer algorithm

compares recent underground logistics systems studies, these research limitations have persisted across various methodological approaches, creating an opportunity for more integrated, multi-level network optimization solutions specifically designed for medical logistics in underground environments. Existing approaches face three fundamental limitations in computational performance. First, single-algorithm methods typically converge to local optima due to limited exploration capabilities, with average solution quality gaps of 15–25 % compared to theoretical lower bounds in network design problems. Second, the computational complexity of current approaches scales poorly with problem size – methods such as PSOA*-LAR and IAGA exhibit exponential time complexity increases when the number of medical facilities exceeds 100 nodes, making them impractical for metropolitan-scale implementations. Third, the lack of adaptive parameter tuning in existing frameworks results in inconsistent performance across different urban configurations, with solution quality variations exceeding 30 % between different city layouts using identical algorithmic parameters. These effectiveness limitations underscore the need for hybrid computational intelligence approaches that combine multiple optimization techniques with adaptive parameter selection mechanisms to achieve both superior solution quality and computational scalability for medical logistics network design.

3. Multi-level underground medical logistics network integer programming model

Before formulating the mathematical model, we establish the following assumptions to define the scope and context of the problem:

- Demand estimation: Medical facility demands are known and deterministic, based on historical data and forecasted needs. While actual demands may fluctuate daily, these variations are assumed to be within the capacity margins of the system.
- Transportation network: Underground pathways (deep tunnels and shallow pipelines) are assumed to follow straight-line distances between connected nodes, adjusted by a tortuosity factor to account for practical routing constraints.
- Facility operations: Distribution centers operate continuously, with sufficient capacity to handle sorting and transfer operations for all assigned medical facilities. The processing time at distribution centers is incorporated into the overall delivery time calculations.
- Vehicle operations: Transport vehicles in deep tunnels and shallow pipelines operate according to fixed schedules with predetermined departure intervals. The model assumes sufficient vehicles are available to maintain these schedules.
- Cost structure: Construction costs are amortized over the infrastructure's expected lifetime using a daily depreciation rate. Operational costs include transportation costs proportional to distance and cargo volume and transfer costs at distribution centers.
- Service levels: All medical facilities must be connected to the underground logistics network, ensuring complete coverage of the urban healthcare system. The model does not explicitly prioritize different types of medical facilities but can accommodate priority adjustments through constraint modifications.
- Network topology: Distribution centers must form a connected network with at least one path between any two activated centers. This ensures network resilience and allows for alternative routing when needed.
- Flow conservation: The total flow entering the network at medical logistics hubs equals the total flow delivered to medical facilities, with flow conservation at all intermediate nodes.

This study addresses the design of a multi-level underground medical logistics network (UMLN) for megalopolises. We consider m medical logistics hubs located on the periphery of a major urban area, represented as $H = H_1, H_2, \ldots, H_m$, which serve as the origins for all medical supplies, equipment, specimens, and pharmaceuticals. Additionally, we define n underground receiving stations located beneath medical facilities (hospitals, clinics, laboratories) as destinations, denoted by $F = F_1, F_2, \ldots, F_n$. The network also includes k potential distribution center locations, represented as $D = D_1, D_2, \ldots, D_k$. The underground medical logistics network to be designed consists of elements from sets H and F, selected elements from set D, and the underground pathways connecting these nodes.

The designed underground medical logistics network comprises two distinct subsystems, as illustrated in Fig. 1. The primary system consists of medical logistics hubs located on the urban periphery, distribution centers, and deep tunnels connecting them, represented as $N_1 = H, S, T$. The secondary system includes distribution centers, underground receiving stations beneath medical facilities, and shallow pipeline channels connecting them, represented as $N_2 = S, P, C$. Medical cargo flow is concentrated and moves in larger volumes through the primary system, making deep tunnels the appropriate transportation mode. In contrast, cargo flow is more dispersed in the secondary system, making shallow pipeline channels more suitable.

The medical logistics flow primarily occurs between peripheral hubs and urban medical facilities. As shown in Fig. 2, this flow originates at peripheral medical logistics hubs, passes through urban distribution centers where it is sorted and transferred, and then travels to underground receiving stations beneath medical facilities, following the path $H \to S \to F$. From the receiving stations, supplies complete the final delivery to the medical facility above ground, not requiring underground transportation resources.

The main decisions in this network design problem include (1) determining the locations of distribution centers, (2) establishing the assignment relationships between medical facilities and distribution centers, (3) designing the underground pathways between nodes, and (4) determining the routing of medical cargo flows. The demand volumes at each node, transportation costs between nodes, and maximum service capacities of logistics facilities are all known parameters. Since underground infrastructure construction is costly, minimizing the total cost becomes the primary objective in designing the underground medical logistics system. The goal is to design a network that satisfies the demands of all medical facilities, respects the capacity constraints of logistics facilities, and ensures feasible transportation routes while minimizing the combined construction and operational costs. Tables 2 and 3 shows the model parameters and decision variables, respectively.

We formulate our model to minimize the sum of infrastructure depreciation and operational costs. Construction costs include those for primary system infrastructure, secondary system infrastructure, establishing underground receiving stations, and activating distribution centers, expressed as:

$$C_1 = \lambda\left(c_a\sum_{j\in D}Y_j + c_d\left(\sum_{j\in D}\sum_{j'\in D}Z_{jj'}d_{jj'} + \sum_{l\in H}\sum_{j\in D}U_{lj}d_{lj}\right) + c_p\sum_{j\in D}\sum_{i\in F}X_{ij}d_{ij} + nc_b\right) \tag{1}$$

The operational costs of the underground medical logistics system include the costs of transporting medical cargo through deep tunnels, shallow pipeline channels, and transfer operations at nodes, expressed as:

$$C_2 = v_p\sum_{j\in D}\sum_{i\in F}\left(X_{ij}d_{ij}\sum_{l\in H}f_{il}\right) + c_t\sum_{l\in H}\sum_{i\in F}\left(f_{il}\sum_{j\in D}\sum_{j'\in D}K_{il}^{jj'}\right) + v_d\sum_{l\in H}\sum_{i\in F}\left(f_{il}\sum_{j\in D}\sum_{j'\in D}K_{il}^{jj'}d_{jj'}\right) \tag{2}$$

Therefore, the complete objective function is:

$$O = \min(C_1 + C_2) \tag{3}$$

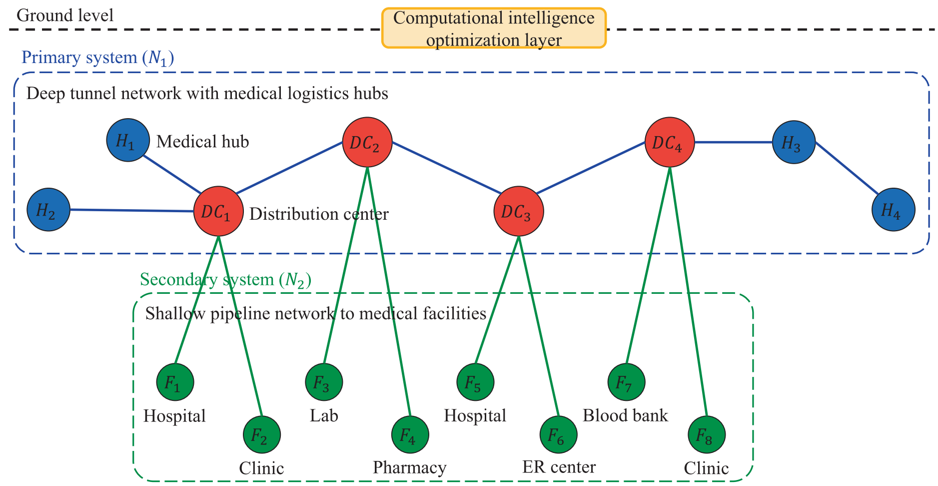

Fig. 1. Multi-level underground medical logistics network architecture.

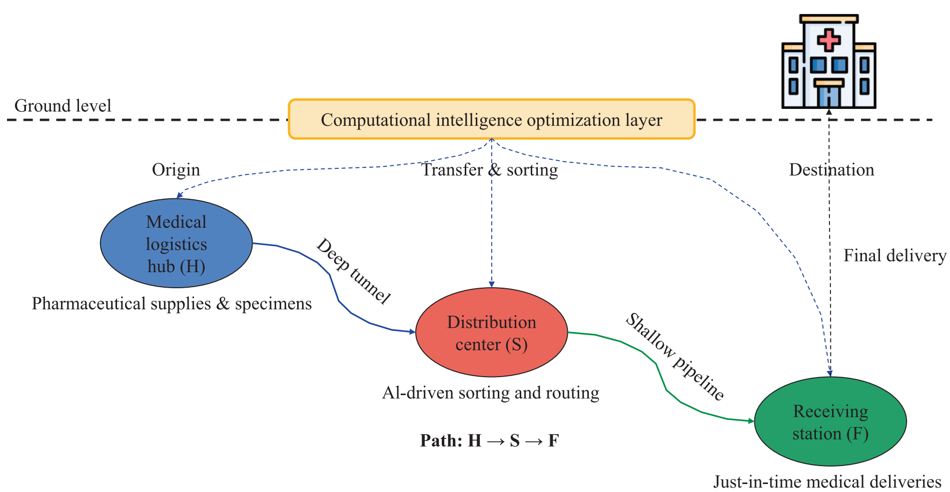

Fig. 2. Medical cargo flow path in underground logistics network.

The direct summation of infrastructure depreciation cost C_1 and operational cost C_2 requires justification beyond monetary unit compatibility. Both cost components share the same time horizon (daily operations) and decision scope (network-wide impact), enabling meaningful aggregation. The infrastructure depreciation rate λ converts capital expenditures into equivalent daily costs, ensuring temporal consistency with operational expenditures.

Subject to the following constraints:

Distribution centers must be activated before they can serve medical facilities:

$$\sum_{i\in F} X_{ij} \leqslant M Y_j, \forall j \in D \tag{4}$$

where M is a sufficiently large number.

To ensure all medical facilities are included in the underground medical logistics system, each facility must be connected to exactly one distribution center, and each activated distribution center must serve at least one medical facility:

$$\sum_{j\in D} X_{ij} = 1, \forall i \in F \tag{5}$$

$$\sum_{i\in F} X_{ij} \geqslant 1, \forall j \in D \tag{6}$$

The transportation volume from distribution centers to medical facilities cannot exceed the processing capacity constraint:

$$\sum_{i\in F}\left(X_{ij}\sum_{l\in H} f_{il}\right) \leqslant a, \forall j \in D \tag{7}$$

The transportation capacity between distribution centers is constrained by vehicle speed and tunnel length. Longer tunnels result in fewer transportation batches, and the daily flow volume between two distribution centers cannot exceed the maximum transportation capacity of the tunnel:

$$\sum_{l\in H}\sum_{i\in F} K_{il}^{jj'} f_{il} \leqslant \lfloor \frac{\xi\gamma}{d_{jj'} + \delta\gamma}\theta \rfloor, \forall j, j' \in D, j \neq j' \tag{8}$$

where $\lfloor\cdot\rfloor$ represents the floor function.

The operational hour's parameter ξ represents the daily operational window for underground vehicle movements. We set $\xi = 8$ hours in our experiments based on typical hospital logistics scheduling practices, where most non-emergency medical supply deliveries occur during standard business hours (9 AM to 5 PM) to minimize disruption to clinical operations. This 8-hour window excludes peak clinical hours (early morning and evening) when elevator and corridor access is restricted for patient transport. Alternative values of ξ could be explored: $\xi = 12$ hours for systems serving emergency departments requiring extended coverage, or $\xi = 6$ hours for specialized applications like laboratory specimen transport with concentrated delivery windows.

Table 2
Model parameters.

Symbol	Description	Index information
$H = H_1, H_2, \ldots, H_m$	Set of peripheral medical logistics hubs	–
$F = F_1, F_2, \ldots, F_n$	Set of medical facilities with underground receiving stations	–
$D = D_1, D_2, \ldots, D_k$	Set of candidate locations for distribution centers	–
m	Number of medical logistics hubs	–
n	Number of medical facilities with underground receiving stations	–
k	Number of candidate locations for distribution centers	–
λ	Daily depreciation rate of infrastructure	–
c_a	Construction cost of activating a distribution center	–
c_b	Construction cost of establishing an underground receiving station	–
c_d	Construction cost per kilometer of deep tunnel	–
c_p	Construction cost per kilometer of shallow pipeline channel	–
c_t	Cost of medical cargo transfer at nodes	–
v_d	Transportation cost of medical cargo in deep tunnels	–
v_p	Transportation cost of medical cargo in shallow pipelines	–
γ	Speed of underground transport vehicles	–
δ	Departure interval between consecutive transport vehicles	–
θ	Capacity of transport vehicles	–
a	Daily processing capacity of distribution centers	–
d_{ij}	Distance between medical facility i and distribution center j	$i \in F, j \in D$
$d_{jj'}$	Distance between distribution centers j and j'	$j, j' \in D, j \neq j'$
d_{lj}	Distance between medical logistics hub l and distribution center j	$l \in H, j \in D$
f_{il}	Flow volume between medical facility i and medical logistics hub l	$i \in F, l \in H$

Table 3
Decision variables.

Symbol	Description	Type
X_{ij}	1 if medical facility i is assigned to distribution center j, 0 otherwise	Binary
Y_j	1 if distribution center j is activated, 0 otherwise	Binary
$Z_{jj'}$	1 if distribution centers j and j' are connected, 0 otherwise	Binary
U_{lj}	1 if medical logistics hub l is connected to distribution center j, 0 otherwise	Binary
$K_{il}^{jj'}$	1 if the medical cargo flow from hub l to facility i passes through the tunnel between distribution centers j and j', 0 otherwise	Binary

The model's flexibility allows adjustment of ξ based on specific healthcare system requirements and operational constraints.

Distribution centers at both ends of a tunnel must be activated for the tunnel to be established:

$$Z_{jj'} \leqslant \min(Y_j, Y_{j'}), \forall j, j' \in D, j \neq j' \tag{9}$$

If a distribution center is activated, it must be connected to the primary network with at least one deep tunnel passing through it:

$$\sum_{j' \in D} Z_{jj'} \geqslant Y_j, \forall j \in D \tag{10}$$

Medical cargo flow and tunnel connectivity have a sequential relationship; a tunnel must exist between two points for medical cargo to be transported between them:

$$\sum_{l \in H} \sum_{i \in F} K_{il}^{jj'} \leqslant M Z_{jj'}, \forall j, j' \in D, j \neq j' \tag{11}$$

All distribution centers in the primary system must have at least one connection path with other distribution centers:

$$\sum_{j \in D} Z_{jj'} \geqslant 1, \forall j' \in D, j \neq j' \tag{12}$$

Considering the capacity limitations of distribution centers, each center can connect to at most one medical logistics hub:

$$\sum_{l \in H} U_{lj} \leqslant 1, \forall j \in D \tag{13}$$

For each medical logistics hub, there is exactly one distribution center directly connected to it:

$$\sum_{j \in D} U_{lj} = 1, \forall l \in H \tag{14}$$

If a medical logistics hub transfers cargo through a distribution center, that center must be activated:

$$U_{lj} \leqslant Y_j, \forall l \in H, j \in D \tag{15}$$

The total medical cargo flow is consistent between primary and secondary systems:

$$\sum_{i \in F} \sum_{l \in H} f_{il} = \sum_{i \in F} \sum_{l \in H} \sum_{j \in D} \sum_{j' \in D} f_{il} K_{il}^{jj'} \tag{16}$$

In this model, all decision variables are binary:

$$X_{ij}, Y_j, Z_{jj'}, U_{lj}, K_{il}^{jj'} \in \{0, 1\} \tag{17}$$

Research has proven that multi-level network design problems like ours are NP-hard, with complexity primarily influenced by the number of medical facilities and potential distribution center locations. For instance, with four medical logistics hubs, 10 potential distribution centers, and 50 medical facilities, the possible node assignment combinations reach 10^{50}, making exact solutions computationally infeasible.

The computational complexity of the formulated integer programming model can be analyzed as follows:

The model contains several sets of binary decision variables: X_{ij} ($n \times k$), Y_j (k), $Z_{jj'}$ ($k \times k$), U_{lj} ($m \times k$), and $K_{il}^{jj'}$ ($n \times m \times k \times k$). The total number of binary variables is $n \times k + k + \frac{k \times (k-1)}{2} + m \times k + \frac{n \times m \times k \times (k-1)}{2}$, which is dominated by $O(n \times m \times k^2)$ in the worst case.

The number of constraints is also substantial: Constraint (4) adds k constraints, constraints (5) and (6) add $n + k$ constraints, constraint (7) adds k constraints, constraint (8) adds $k \times (k-1)$ constraints, constraints (9)–(15) add additional $O(k^2 + m \times k + n \times m \times k^2)$ constraints, and constraint (16) adds one constraint for flow conservation.

This problem belongs to the class of facility location problems combined with network design problems, known as NP-hard. Including multiple commodities (medical supplies) and service levels (primary and secondary systems) further increases the complexity.

For realistic problem sizes in medical logistics (e.g., $n = 50$, $k = 30$, $m = 4$), the model would contain over 90,000 binary variables and thousands of constraints, making exact solution methods computationally intractable. This complexity justifies our development of the IMNO-ULS algorithm that effectively decomposes the solution space and employs computational intelligence techniques to find near-optimal solutions efficiently.

4. Computational intelligence algorithm design

The complexity analysis demonstrates that the formulated integer programming model is NP-hard with $O(n \times m \times k^2)$ binary variables for realistic problem sizes. This complexity makes exact solution methods impractical for real-world medical logistics networks. Our algorithm design is motivated by several characteristics of the medical ULS problem:

- Spatial clustering: Medical facilities in urban environments tend to form natural clusters based on population density and healthcare service distribution. This spatial structure can be leveraged to decompose the solution space.
- Hierarchical decision structure: The model involves hierarchical decisions – distribution center activation, medical facility assignment, and network connectivity – with interdependencies that can be exploited in a multi-layer optimization approach.
- Multi-objective balance: The solution must balance infrastructure costs with operational efficiency, requiring an algorithm that can effectively explore diverse regions of the solution space to find the optimal trade-off.

Based on these characteristics, we propose a dual-layer algorithm that combines mean-shift clustering for spatial decomposition with a hierarchical optimization approach using artificial immune systems and simulated annealing. This combination allows us to efficiently handle the high dimensionality of the solution space while adapting to the inherent structure of medical logistics networks.

4.1. Mean-shift clustering algorithm

The core computation of the mean-shift (MS) clustering algorithm focuses on the density of points to be clustered, with each cluster center iteratively moving to the area with the highest density of medical facilities (Peng et al., 2025). This approach aligns well with the regional concentration characteristic of medical logistics nodes. Given the coordinate vectors of medical facilities and cluster centers as x_i and x, respectively, the algorithm proceeds as follows:

1) If this is the first iteration, randomly select a sample point as the initial point; otherwise, randomly select a point from the samples not yet incorporated into clusters as the initial point.
2) Identify all medical facilities within the search radius of the cluster center, denoted as set B, with K elements.
3) Calculate the center shift value M for cluster B using:

$$M = \frac{1}{K}\sum_{x_i \in B}(x_i - x) \tag{18}$$

4) If M is less than the clustering convergence threshold, proceed to step 5; otherwise, update the cluster center's position according to M.
5) Return to step 2 with the updated cluster center.
6) Incorporate all traversed sample points into B, and determine if the distance between the current cluster center and other cluster centers is less than the cluster merging threshold; if so, merge the two clusters.
7) If all sample points have been assigned to clusters, stop the algorithm; otherwise, return to step 1.

Following this method, all cluster centers will ultimately reach locations of maximum local density of medical facilities. Through mean-shift clustering, we can effectively optimize the solution space, thereby improving the efficiency of the heuristic algorithm.

4.2. Dual-layer algorithm based on artificial immune systems and simulated annealing

We construct a dual-layer algorithm based on artificial immune systems (AIS) (Bejoy et al., 2022) and simulated annealing (SA) (Vargas-Martinez et al., 2023). As shown in Fig. 3, the outer layer employs simulated annealing to optimize the hyperparameters of the mean-shift clustering algorithm, while the inner layer uses an artificial immune system to search for the optimal network layout under the constraints of clustering results.

The outer layer algorithm optimizes the hyperparameters of the MS clustering algorithm, employing real-number encoding. The encoding consists of three segments representing the search radius of cluster centers, clustering convergence threshold, and cluster merging threshold, as shown in Fig. 4.

The core of the outer layer algorithm is the simulated annealing mechanism, which can be divided into three parts: new solution acceptance, random perturbation, and annealing process:

1) New solution acceptance

We employ a probabilistic approach to accept new solutions, calculated as:

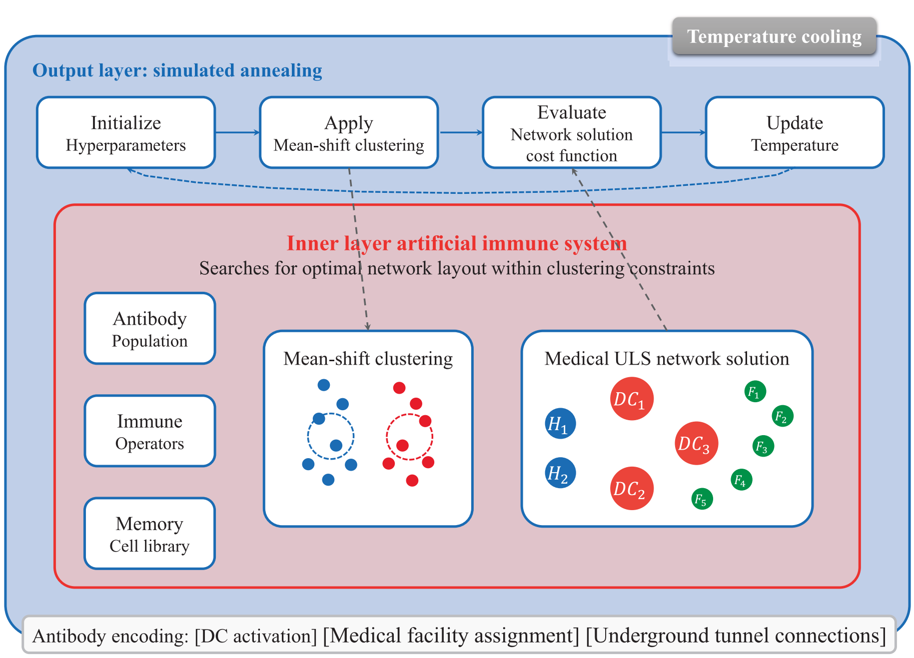

Fig. 3. Dual-layer algorithm for medical ULS network optimization.

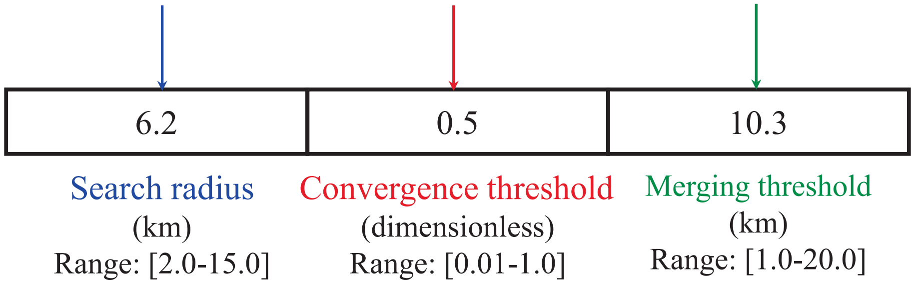

Fig. 4. Outer layer algorithm encoding for IMNO-ULS.

$$P = \begin{cases} 1 & \text{if } E(n+1) < E(n) \\ e^{-\frac{E(n+1)-E(n)}{T}} & \text{if } E(n+1) \geqslant E(n) \end{cases} \tag{19}$$

where E represents the energy value, with lower energy indicating a better solution. When a new solution has lower energy than the current solution, it is accepted with probability 1; when the new solution's energy is higher, it is still accepted with a certain probability to enable exploration of the global optimum.

2) Random perturbation

Since the outer layer algorithm uses real-number encoding with significant differences in value ranges across segments, perturbation is applied proportionally to each segment's value:

$$E' = (1 + r)E \tag{20}$$

where E is the original segment value and E' is the new segment value. When r is large, global search capability is stronger but local search capability is weaker; when r is small, local search capability is stronger but convergence speed may be slower. In this study, r is set as a random number following a normal distribution with mean 0 and variance 0.15.

3) Annealing process

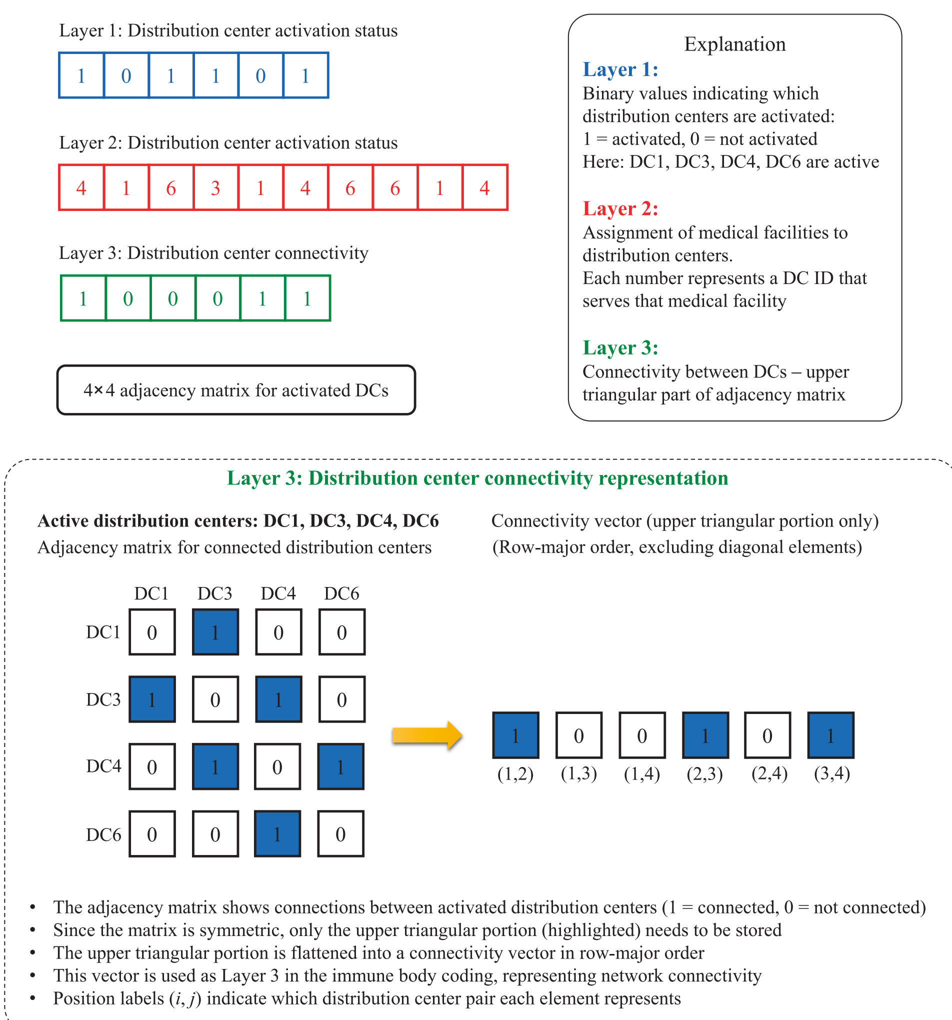

Fig. 5. Immune body coding for medical ULS optimization.

Parameter T represents the current temperature in the annealing process. If T is too high, the annealing speed will be too fast, and the algorithm may terminate before finding the global optimum; if T is too low, the computation time will increase. Therefore, we use a temperature schedule to adjust the annealing process, starting with a higher T value and gradually reducing it as annealing progresses. The cooling rate follows an exponential decay with parameter λ set to 0.9, calculated as:

$$T(n+1) = \lambda T(n), n = 1, 2, \dots \tag{21}$$

The inner layer algorithm design process is as follows:

1) Initial solution generation

The antibody encoding involves decisions about distribution centers, medical facilities, and tunnel layout, combining real-number and binary encoding approaches. Antibodies have three layers, as shown in Fig. 5.

The first layer represents the activation status of distribution centers, with 0 indicating the center is not activated and one indicating it is activated. Under the MS clustering results, at least one distribution center in each cluster must be activated. The second layer is based on the activated distribution centers and randomly assigns medical facilities to them, with the matching principle within the same cluster. The example shows four activated distribution centers; using Kruskal's algorithm, we find their minimum spanning tree as the initial solution. The adjacency matrix is a 4 × 4 symmetric matrix, with the upper triangular portion combined into a single row as the third layer of the antibody, representing the connectivity between distribution centers.

2) Expected reproduction rate calculation

The expected reproduction rate evaluates antibody quality and is influenced by antibody concentration and affinity. Higher antibody affinity results in a higher expected reproduction rate, while higher concentration leads to a lower rate.

For antibody x, if the total population size is N and S is the logical discrimination value for antibody similarity (if two antibodies have more than R identical positions, they are considered approximately identical), then antibody concentration is defined as:

$$c(x) = \frac{\sum_{y\in N} S(x,y)}{N} \tag{22}$$

If the cost of the solution corresponding to antibody x is $fit(x)$ and its affinity is $A(x)$, to expand the search space, the algorithm allows exceeding tunnel capacity constraints. Let the excess amount be $s(x)$, calculated as:

$$s(x) = \max\left(\sum_{j\in D}\sum_{j'\in D}\left(\sum_{l\in H}\sum_{i\in F} K_{il}^{jj'} f_{il} - \lfloor \frac{\xi\gamma}{d_{jj'} + \delta\gamma}\theta \rfloor\right), 0\right) \tag{23}$$

Adding a penalty factor τ for the excess amount and multiplying by a factor $\alpha > 1$ at the end of each iteration, the final calculations for antibody affinity and expected reproduction rate are:

$$A(x) = \frac{1}{fit(x) + \tau\alpha^{gen} s(x)} \tag{24}$$

$$e(x) = \varepsilon \frac{A(x)}{\sum_{y\in N} A(y)} + (1-\varepsilon)\frac{c(x)}{\sum_{y\in N} c(y)} \tag{25}$$

where gen is the current iteration number, $e(x)$ represents the expected reproduction rate of antibody x, and $\varepsilon \in (0,1)$ represents the algorithm's emphasis on concentration versus affinity.

3) Immune operators

Immune operators include crossover operators, mutation operators, and memory cell library.

The crossover operator applies to the first and second layers of antibodies using single-point crossover. Given a crossover probability p_c, we select historically superior antibodies and generate a random number $r \in [0,1]$ for each antibody to be evaluated; if $r \leqslant p_c$, the crossover operation is performed. The specific steps are shown in Fig. 6. After crossover, antibody segments that do not meet requirements are repaired.

The mutation operator applies to the third layer of antibodies using single-point mutation. Given a mutation probability p_m, we generate a random number $r \in [0,1]$ for each antibody; if $r \leqslant p_m$, the mutation operation is performed. The specific steps are shown in Fig. 7. The operation randomly selects one position for mutation; if the mutated antibody is feasible or reduces the excess amount $s(x)$, it is retained. Otherwise, the mutation is reversed.

The memory cell library preserves antibodies with the highest affinity while selecting appropriate antibodies to form new populations. The specific operations are as follows:

1) If the memory library is empty, directly select the top m antibodies by expected reproduction rate from the current antibody population and store them in the memory library.
2) If the memory library is not empty before the immune process begins, combine the memory library with the antibody population, sort all antibodies by expected reproduction rate in descending order, select the top m antibodies for the memory library, and select the top N antibodies as the parent population, where N is the antibody population size.
3) Update the memory library before each immune operation.

After applying the crossover and mutation operators, solutions may violate problem constraints, necessitating a repair process to transform these infeasible solutions into feasible ones. The repair strategy addresses different aspects of the solution structure while preserving the beneficial characteristics of the original solution.

The repair process begins with distribution center activation adjustments. When no distribution center is activated in a cluster identified by the mean-shift algorithm, the repair mechanism randomly activates one distribution center within that cluster to ensure service coverage. Conversely, when multiple distribution centers are activated in a cluster where the mean-shift algorithm determines a single center is optimal, the process deactivates all but the one closest to the cluster centroid, thereby maintaining the efficiency benefits identified during clustering.

Flow constraint violations receive attention through flow rerouting mechanisms. When flow variables indicate cargo movement through non-existent tunnels (violating constraint 11), the repair process reroutes these flows through existing tunnels using the shortest path algorithm. Similarly, when tunnel capacity constraints (constraint 8) are violated, the mechanism iteratively removes flows from overloaded tunnels and redirects them through alternative paths until all capacity constraints are satisfied.

The comprehensive repair process ensures that all solutions evaluated during the optimization process satisfy the problem constraints while maintaining the beneficial characteristics of the original solution, allowing the algorithm to explore feasible regions of the solution space effectively.

Fig. 8 shows the overall flowchart of the IMNO-ULS algorithm, showing the interaction between the outer layer (simulated annealing), mean-shift clustering, and inner layer (artificial immune system).

The IMNO-ULS algorithm employs a termination criterion that govern when the optimization process concludes. These conditions apply at different levels of the algorithmic hierarchy to ensure computational efficiency while maintaining solution quality. Within the outer layer employing simulated annealing, the algorithm concludes its search when it reaches a predefined maximum of 1000 iterations, providing a hard upper bound on computational time. Additionally, the outer layer terminates when the temperature parameter, which controls the

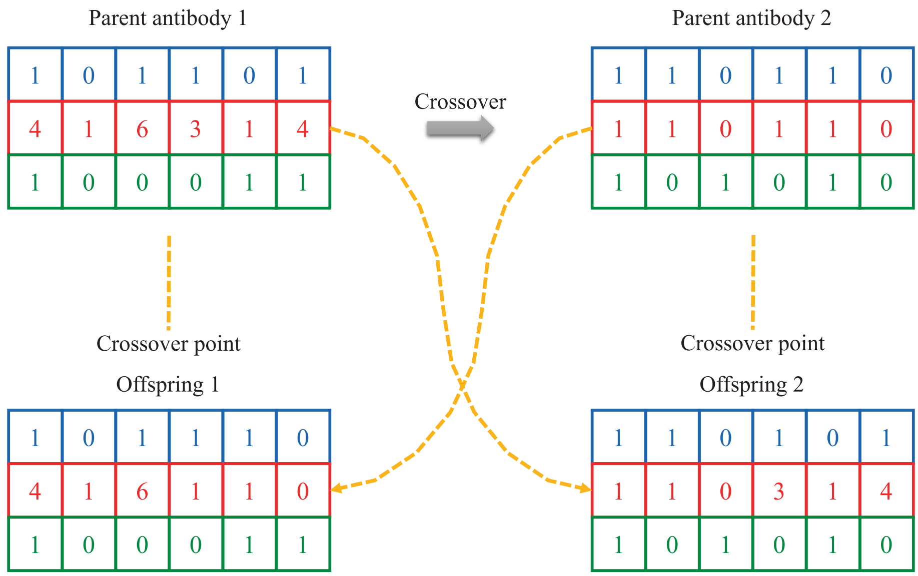

Fig. 6. Schematic diagram of immune crossover operation.

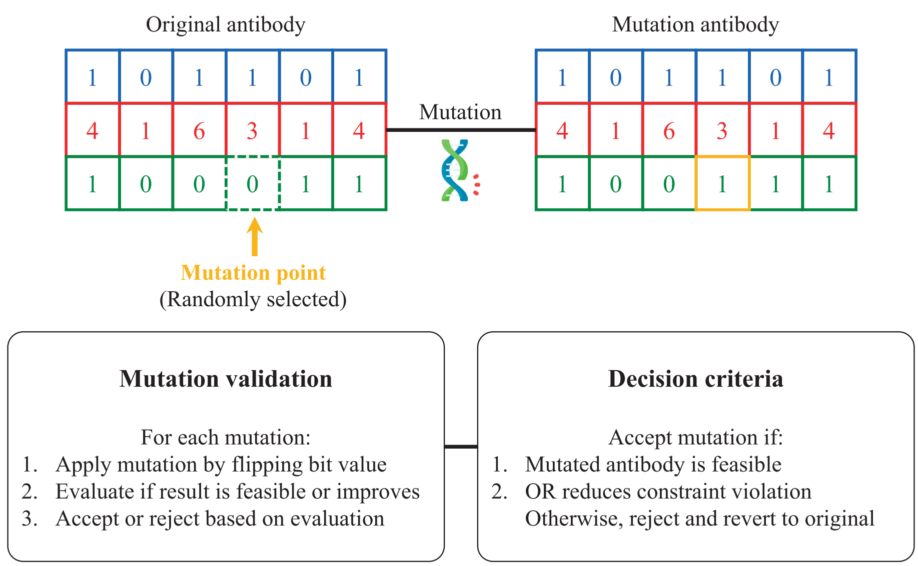

Fig. 7. Schematic diagram of immune mutation operation.

probability of accepting worse solutions, falls below a minimum threshold of 0.01, indicating that the search has sufficiently cooled and stabilized. To avoid wasting computational resources on plateaus in the solution space, the outer layer also halts if no improvement in the best solution occurs for 100 consecutive iterations, suggesting that further exploration would likely yield diminishing returns.

The inner layer utilizing artificial immune system concepts has its own set of termination conditions that operate within each call from the outer layer. Each inner layer optimization proceeds for a maximum of 50 generations to prevent excessive computational time at any single point in the solution space. Convergence is detected when the memory cell library, which stores high-quality solutions, remains unchanged for 20 consecutive generations, indicating that the immune system has stabilized around a set of local optima. Furthermore, the inner layer optimization concludes early when it identifies a solution with an objective function value within 1 % of the estimated lower bound, recognizing that the marginal benefit of continuing the search would be minimal compared to the computational cost.

These multi-level termination criteria create an effective balance between thorough exploration of the solution space and computational efficiency. By implementing different stopping conditions at various algorithmic levels, the IMNO-ULS algorithm can adapt its search intensity based on solution quality progression, allowing it to identify high-quality solutions for complex medical logistics networks within reasonable computation times while avoiding premature convergence to suboptimal solutions.

5. Simulation results and analysis

5.1. Setup

To evaluate the performance of the proposed IMNO-ULS algorithm in designing optimal medical logistics networks, we conducted extensive numerical experiments under various problem scales and configurations. These experiments were designed to assess the proposed approach's solution quality and computational efficiency compared to established methods in the literature. All experiments were performed on a workstation with an Intel Xeon E5-2670 CPU @ 2.60 GHz, 64 GB

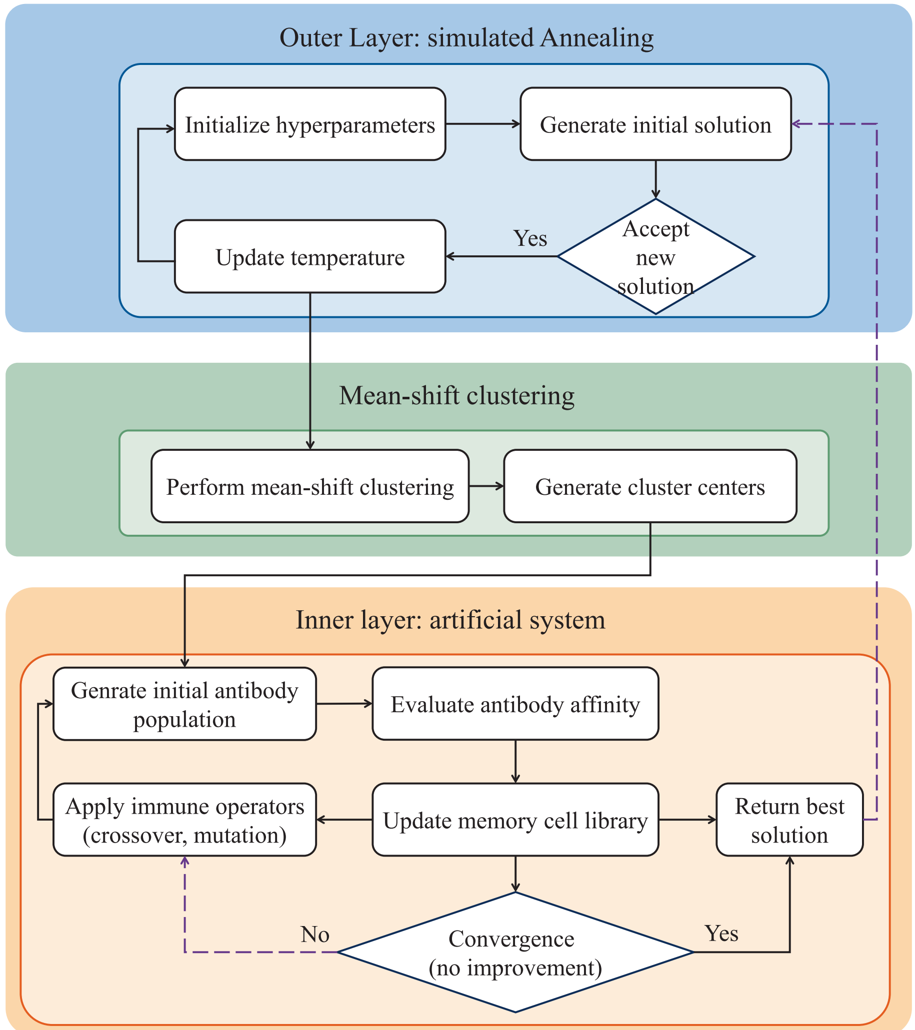

Fig. 8. IMNO-ULS algorithm flowchart.

RAM, running MATLAB R2023a.

The parameters used in our experiments were derived from multiple sources to ensure realism and applicability:

1. Infrastructure costs (construction costs for distribution centers, receiving stations, tunnels, and pipelines) were estimated based on published civil engineering literature and infrastructure development reports from urban planning authorities. These values were calibrated using cost data from recent underground transportation projects in major metropolitan areas and adjusted for the specific requirements of medical logistics operations.
2. Operational parameters (vehicle speed, capacity, transportation costs) were based on technical specifications of automated guided vehicles used in hospital logistics and underground transportation systems. These parameters were validated through consultation with medical logistics experts and manufacturers of underground transportation equipment.
3. Medical facility demand data were synthesized based on empirical studies of hospital logistics operations, considering typical demand patterns for pharmaceuticals, laboratory specimens, and medical supplies. The uniform distribution range (3,000–24,000 items) reflects the variability observed in healthcare facilities of different sizes and specialties.
4. Time-critical parameters, such as vehicle departure intervals and speed, were calibrated to meet emergency medical delivery requirements while maintaining operational feasibility.
5. The medical logistics network components in our model include:
   - Peripheral medical logistics hubs: Large-scale facilities located on the urban periphery that serve as entry points for medical supplies, equipment, and specimens
   - Distribution centers: Underground facilities that receive, sort, and redistribute medical cargo based on destination and priority
   - Deep tunnel system: Large-diameter tunnels (2–3 m) accommodating automated vehicles carrying consolidated cargo between hubs and distribution centers
   - Shallow pipeline network: Smaller-diameter conduits (0.5–1 m) connecting distribution centers to individual medical facilities
   - Underground receiving stations: Facilities beneath medical buildings that receive deliveries and transfer them to above-ground operations

All parameter values represent realistic estimates for a major metropolitan area with a population of 5–10 million people and were validated through sensitivity analysis to ensure the robustness of the results.

Based on the literature review and real-world operational requirements of medical underground logistics systems, we established parameter settings for the physical system components and the algorithmic implementation. Table 4 presents the medical ULS infrastructure and operational parameters used in our experiments, while Table 5 provides the computational intelligence algorithm parameter settings.

To evaluate the proposed IMNO-ULS algorithm's performance, we implemented six state-of-the-art baseline methods from recent literature for comparison: PSOA*-LAR, IAGA, blM-ULS, GDD-ULS, sM-ULS, and MoCC-MULNP. The key differences between IMNO-ULS and these baseline methods include (1) our use of mean-shift clustering with adaptive parameters optimized through simulated annealing, (2) the dual-layer optimization structure that separates strategic and tactical decisions, and (3) the specific adaptation to medical logistics requirements including time-sensitive delivery constraints.

In our experiments, these algorithms were implemented according to their original specifications with parameter settings recommended by their respective authors. They were then adapted to the medical logistics context with appropriate constraints and objectives. This ensures a fair and meaningful comparison across different methodological approaches.

5.2. Results analysis

5.2.1. Comparative performance analysis

To investigate the optimization capability of the proposed IMNO-ULS algorithm across different problem scales, we designed and generated random test instances of varying sizes. The test instances varied in terms of the number of medical facilities (n), potential distribution center locations (k), and medical logistics hubs (m). Specifically, we created four categories of problem scales:

1. Small-scale: 50 medical facilities, 30 potential distribution centers, 4 medical logistics hubs
2. Medium-scale: 100 medical facilities, 50 potential distribution centers, 6 medical logistics hubs
3. Large-scale: 200 medical facilities, 90 potential distribution centers, 8 medical logistics hubs
4. Extra-large-scale: 500 medical facilities, 150 potential distribution centers, 10 medical logistics hubs

For each problem scale, we generated five random instances and solved them using all seven algorithms (IMNO-ULS and the six baseline methods). Each algorithm was executed 10 times per instance to account for the stochastic nature of metaheuristic algorithms, and we recorded the average objective function value and computation time.

Table 6 presents the computational results across different problem scales, comparing the performance of IMNO-ULS with the baseline methods. In this table, Z1 represents the objective function values (total cost in millions of monetary units) for our proposed IMNO-ULS algorithm, while Z2 through Z7 represent the values for PSOA*-LAR, IAGA, blM-ULS, GDD-ULS, sM-ULS, and MoCC-MULNP, respectively.

Table 4
Parameter data of underground medical logistics system.

Parameter	Value	Unit
Distribution center activation cost c_a	150,000	10,000 units per center
Underground receiving station establishment cost c_b	60,000	10,000 units per station
Deep tunnel construction cost c_d	108,000	10,000 units per km
Shallow pipeline construction cost c_p	74,000	10,000 units per km
Distribution center capacity for medical supplies a	260,000	items per day
Infrastructure depreciation rate λ	80 years, 365 days	–
Deep tunnel transportation cost v_d	90	units per km
Shallow pipeline transportation cost v_p	150	units per km
Medical cargo transfer cost c_t	80	units per thousand items per transfer
Medical facility daily package quantity f_{il}	Uniformly distributed (3,000, 24,000)	items
Autonomous vehicle operating speed γ	50	km/h
Autonomous vehicle cargo capacity θ	5,000	items per vehicle
Temperature control system maintenance	1,200	units per month
Biohazard containment protocols	3,500	units per facility
Emergency response capability	2,000	units per distribution center

Table 5
Parameter settings for computational intelligence algorithm.

Parameter	Value
Antibody population size (N)	50
Immune mutation probability (p_m)	0.1
Immune crossover probability (p_c)	0.6
Memory cell library capacity (m)	20
Logical discrimination threshold (R)	50 % of antibody total length
Initial penalty factor (τ)	0.01
Expected reproduction rate parameter (ε)	0.6
Temperature cooling rate (λ)	0.9
Initial temperature (T_0)	100
Mean-shift search radius range	[2.0, 15.0] km
Clustering convergence threshold range	[0.01, 1.0]
Cluster merging threshold range	[1.0, 20.0] km
Maximum iterations	1000
Convergence criterion	100 iterations without improvement

Table 6
Comparative performance across different problem scales.

Parameter	Scale 1 (Small)	Scale 2 (Medium)	Scale 3 (Large)	Scale 4 (Extra-large)
m	4	6	8	10
n	50	100	200	500
k	30	50	90	150
Z1 (IMNO-ULS)	788.8	1,355.28	2,654.53	3,852.24
Z2 (PSOA*-LAR)	847.62	1,476.25	2,977.84	4,429.14
Z3 (IAGA)	825.91	1,443.72	2,843.16	4,208.95
Z4 (blM-ULS)	818.46	1,409.15	2,814.08	4,175.68
Z5 (GDD-ULS)	808.93	1,401.56	2,809.00	4,135.57
Z6 (sM-ULS)	803.12	1,382.73	2,780.32	4,076.13
Z7 (MoCC-MULNP)	796.36	1,369.55	2,733.17	4,008.24
T1 (IMNO-ULS)	17.2	42.1	75	168.6
T2 (PSOA*-LAR)	45.3	94.6	218.4	587.2
T3 (IAGA)	39.8	86.5	184.6	463.8
T4 (blM-ULS)	35.4	79.2	167.3	412.5
T5 (GDD-ULS)	28.7	67	142.7	375.1
T6 (sM-ULS)	24.5	58.4	112.8	235.7
T7 (MoCC-MULNP)	20.4	46.7	88.2	196.3
GAP1 (Z2-Z1)/Z1	7.46 %	8.93 %	12.18 %	15.00 %
GAP2 (Z3-Z1)/Z1	4.70 %	6.53 %	7.10 %	9.26 %
GAP3 (Z4-Z1)/Z1	3.76 %	3.97 %	6.01 %	8.40 %
GAP4 (Z5-Z1)/Z1	2.55 %	3.41 %	5.82 %	7.35 %
GAP5 (Z6-Z1)/Z1	1.82 %	2.03 %	4.74 %	5.81 %
GAP6 (Z7-Z1)/Z1	0.96 %	1.05 %	2.96 %	4.05 %

Similarly, T1 through T7 represent their respective computation times in seconds.

The performance gaps between IMNO-ULS and each baseline algorithm are calculated as:

$$GAP_i = \frac{Z_{i+1} - Z_1}{Z_1} \times 100\%, \ \ i = 1, 2, ..., 6 \tag{26}$$

Table 6 reveals several important trends. First, IMNO-ULS consistently outperforms all baseline methods across all problem scales regarding solution quality (objective function value). The performance advantage becomes more pronounced as the problem scale increases. For small-scale problems, the gap between IMNO-ULS and the next best algorithm (MoCC-MULNP) is approximately 0.96 %, while for extra-large-scale problems, this gap increases to 4.05 %. Compared to the worst-performing algorithm (PSOA*-LAR), the advantage of IMNO-ULS ranges from 7.46 % for small-scale problems to 15.00 % for extra-large-scale problems.

Table 7 shows the impact of different weight combinations on network design solutions across medium-scale problem instances. The analysis examines how varying the relative importance of infrastructure versus operational costs affects optimal network configurations and total system performance.

The experimental results demonstrate that solutions remain remarkably stable across different weighting schemes when infrastructure and operational costs maintain similar magnitudes. Network configurations converge within narrow cost ranges regardless of weight adjustments, with maximum deviations below four percent from the baseline equal-weight solution. The natural balance between infrastructure investment and operational efficiency in medical logistics systems creates inherent cost equilibrium that supports direct additive formulation. This validates our unweighted objective function approach for medical underground logistics network design, where infrastructure and operational considerations naturally complement rather than compete with each other.

Regarding computational efficiency, IMNO-ULS demonstrates superior performance compared to most baseline methods. While MoCC-MULNP and sM-ULS show comparable computation times for smaller problems, IMNO-ULS maintains its efficiency advantage as the problem scale increases. For extra-large-scale problems, IMNO-ULS achieves a 14.1 % reduction in computation time compared to MoCC-MULNP and a 28.5 % reduction compared to sM-ULS. Compared to the slowest algorithm (PSOA*-LAR), IMNO-ULS reduces computation time by approximately 71.3 % for extra-large problems.

These results demonstrate that IMNO-ULS is particularly well-suited for large-scale medical underground logistics network optimization problems, where combining solution quality and computational efficiency becomes increasingly important.

We compared its performance with commercial optimization solvers to validate the quality of solutions obtained by IMNO-ULS and establish its advantages over exact methods. Due to the complexity of the full model, we simplified the problem by fixing the distribution center locations (based on the IMNO-ULS solution) and solving the resulting subproblem using CPLEX 12.10. Table 8 presents the results of this comparison.

For small-scale problems, CPLEX found optimal solutions with solution quality 1.78–2.28 % better than IMNO-ULS but required significantly more computation time (48–630 times longer). For medium and large-scale problems, CPLEX could not find feasible solutions within 10,000 s, while IMNO-ULS provided high-quality solutions in less than a minute.

These results confirm that while exact methods can provide slightly better solutions for small problems, they become computationally intractable for realistic problem sizes in medical logistics. The small optimality gap (under 2.5 %) for problems where CPLEX could find optimal solutions suggests that IMNO-ULS provides near-optimal solutions while offering substantial computational advantages.

Table 8
Comparison with optimization solver.

Problem Scale	CPLEX solution	CPLEX time (s)	IMNO-ULS solution	IMNO-ULS time (s)	Gap (%)
Small (n = 10, k = 5)	352.16	217.3	358.42	4.5	1.78 %
Small (n = 20, k = 10)	546.93	1,842.50	559.17	8.2	2.24 %
Small (n = 30, k = 15)	687.24	7,625.80	702.93	12.1	2.28 %
Medium (n = 50, k = 30)	–	>10,000	788.8	17.2	–
Large (n = 100, k = 50)	–	>10,000	1,355.28	42.1	–

5.2.2. Algorithm stability analysis

Solution stability is critical for medical logistics systems as it ensures consistent performance across multiple runs, which is essential for reliable planning and decision-making. To analyze the stability of the proposed IMNO-ULS algorithm, we conducted repeated experiments on the test instances described before. For each problem scale, we executed the IMNO-ULS algorithm 20 times, recording the optimal, worst, and average objective function values. We then calculated the percentage differences between these values to quantify the algorithm's stability.

Table 9 shows the stability analysis results for the proposed IMNO-ULS algorithm across different problem scales.

The optimal-average difference ratio and worst-average difference ratio are calculated using Eqs. (27) and (28):

Table 9
Stability analysis of the IMNO-ULS algorithm.

Scale group	Best value	Worst value	Average value	Optimal-average difference ratio/%	Worst-average difference ratio/%
Small	779.34	800.28	788.15	−1.13	1.51
Medium	1,324.58	1,362.85	1,349.80	−1.9	0.96
Large	2,618.86	2,689.61	2,654.39	−1.36	1.31
Extra-large	3,812.87	3,909.08	3,846.79	−0.89	1.59
Average				−1.32	1.34

Table 7
Impact of weight combinations on network design solutions.

Weight ratio ($w_1 : w_2$)	Infrastructure cost (C_1)	Operational cost (C_2)	Total weighted cost	Distribution centers	Average delivery time (min)	Cost deviation from baseline
1:4 (Operations priority)	1,423.60	1,089.20	1,780.40	6	19.8	2.30 %
1:2 (Operations focus)	1,398.70	1,156.40	1,744.10	7	18.9	0.80 %
1:1 (Equal weight)	1,355.30	1,081.20	1,218.30	8	17.6	Baseline
2:1 (Infrastructure focus)	1,289.40	1,247.80	1,275.50	9	18.2	1.40 %
4:1 (Infrastructure priority)	1,234.80	1,398.60	1,632.40	11	20.1	3.10 %

$$OptimalRatio = \frac{Optimal - Average}{Average} \times 100\% \quad (27)$$

$$WorstRatio = \frac{Worst - Average}{Average} \times 100\% \quad (28)$$

Table 9 shows that the IMNO-ULS algorithm demonstrates remarkable stability across all problem scales. The average difference ratio between optimal and average values is −1.32 %, while the average difference ratio between worst and average values is 1.34 %. This narrow range indicates that the algorithm consistently produces solutions of similar quality across multiple runs.

Interestingly, the algorithm's stability does not deteriorate with increasing problem scale, which is often observed in many metaheuristic algorithms. The optimal-average difference ratio for the extra-large problem scale is lower (−0.89 %) than for smaller scales, suggesting that the algorithm's stability improves for larger problems. This counterintuitive result can be attributed to the mean-shift clustering component, which becomes more effective at identifying natural groupings as the number of medical facilities increases, thereby providing a more consistent decomposition of the solution space.

When compared to the baseline algorithms, IMNO-ULS demonstrates superior stability. For example, PSOA*-LAR shows average difference ratios of −3.45 % (optimal-average) and 4.12 % (worst-average), while IAGA shows −2.78 % and 3.15 %, respectively. The improved stability of IMNO-ULS is particularly important in medical logistics, where consistent performance is crucial for reliable emergency response planning and critical supplies distribution.

These stability results further validate the robustness of the proposed IMNO-ULS algorithm for practical applications in medical logistics network design, where reliability and consistency are paramount considerations.

5.2.3. *Sensitivity analysis*

To investigate how changes in infrastructure parameters affect the underground medical logistics system's design and operational costs, we conducted a comprehensive sensitivity analysis. We selected the distribution center processing capacity (α) as a key parameter for this analysis, as it represents a critical decision variable that can be influenced through technology adoption and operational adjustments.

Implementing automated pharmaceutical sorting systems, robotic handling equipment, advanced inventory management technologies, or modifications to operational protocols can result in changes in distribution center processing capacity. Understanding the relationship between this parameter and the overall system cost provides valuable insights for decision-makers in medical logistics planning.

We randomly selected one instance from the four problem scales for the sensitivity analysis. For each instance, we varied the distribution center processing capacity parameter across five levels: 50 %, 75 %, 100 % (baseline), 125 %, and 150 % of the standard capacity value. The IMNO-ULS algorithm was applied to optimize the network design under each capacity level, and we recorded the resulting infrastructure depreciation costs, transportation costs, and total system costs.

Fig. 9 shows the effects of varying distribution center capacity on infrastructure depreciation and transportation costs, while Fig. 10 illustrates the impact on total system costs. Both figures represent the average results across the four problem scales.

As distribution center capacity increases, infrastructure depreciation costs decrease, reaching a plateau around 125–150 % of baseline capacity. This trend can be explained by the reduced number of distribution centers needed to serve all medical facilities when individual center capacity increases. Fewer distribution centers result in reduced deep tunnel infrastructure requirements, which is partially offset by increased shallow pipeline construction to connect more distant medical facilities. Transportation costs show a more pronounced and continuous decrease as distribution center capacity increases. This is due to the more efficient

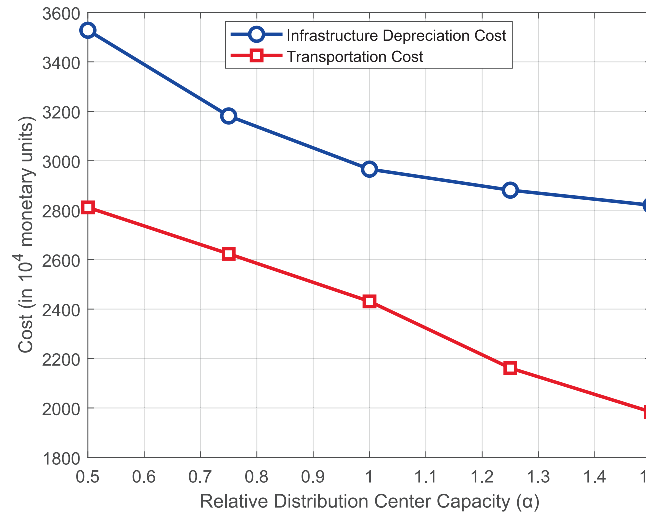

Fig. 9. Effect of distribution center capacity on system costs.

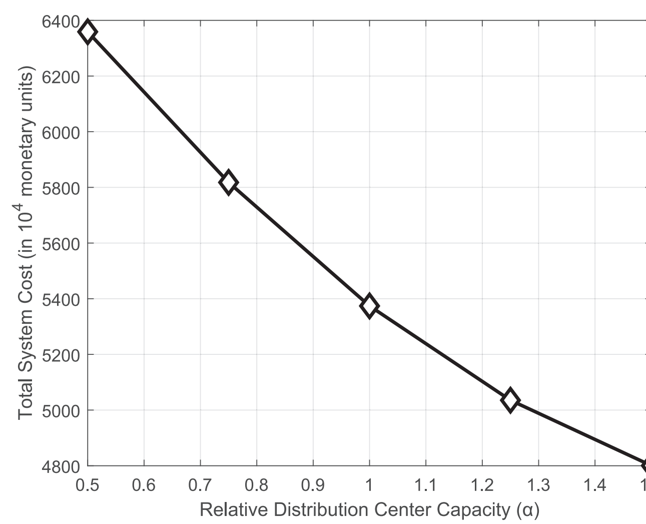

Fig. 10. Effect of distribution center capacity on total system cost.

consolidation of medical cargo flows through fewer, higher-capacity distribution centers, resulting in shorter average transportation distances and reduced handling operations. The total system cost, combining infrastructure and operational costs, consistently decreases as distribution center capacity increases, with diminishing returns beyond 125 % of baseline capacity. Increasing distribution center capacity generally benefits system efficiency, but the marginal benefits decrease at higher capacity levels.

Investments in distribution center capacity enhancement technologies (e.g., automated pharmaceutical sorting systems and robotic handling equipment) can yield significant system-wide cost reductions, particularly in transportation operations. Focusing on moderate capacity enhancements (to approximately 125 % of baseline) may offer the optimal balance between investment costs and system-wide benefits for medical logistics systems with strict budget constraints. Additionally, the relationship between capacity and system costs is non-linear, suggesting that strategic capacity planning should consider the diminishing returns at higher capacity levels. Transportation costs are more sensitive to capacity changes than infrastructure costs, indicating that operational efficiency improvements should be a primary focus in system design.

These findings highlight the importance of distribution center capacity as a key design parameter in medical underground logistics systems. The insights from this sensitivity analysis can guide investment decisions and technology adoption strategies for improving the efficiency and resilience of urban medical supply chains.

5.3. Case study

To demonstrate the practical applicability of the proposed IMNO-ULS algorithm, we conducted a case study simulating our approach to a major metropolitan area with a high concentration of medical facilities. The study area encompasses approximately 290 km2 in the central district of Shenyang City, China, hosting a population of 6.87 million residents (27.6 % of the city's total population). This area contains 42 major hospitals, 78 community health centers, 25 specialized clinics, 13 medical laboratories, and five pharmaceutical distribution centers, creating a complex and demanding medical logistics environment.

The high population density, concentration of medical facilities, and existing transportation congestion in this area make it an ideal candidate for implementing an underground medical logistics system. The case study aims to design an optimal multi-level underground network that efficiently handles time-sensitive medical supplies, specimens, pharmaceuticals, and equipment while minimizing construction and operational costs.

5.3.1. Mean-shift clustering parameter optimization

The effectiveness of the mean-shift clustering component in IMNO-ULS depends critically on the appropriate selection of the search radius parameter. This parameter determines the granularity of the clustering process and significantly influences the quality of the resulting network design. To identify the optimal search radius for this specific urban environment, we conducted a parametric study varying the search radius from 2 km to 10 km and evaluated the resulting network costs. Fig. 11 shows the relationship between the search radius parameter and the final network cost obtained by IMNO-ULS.

This finding aligns with the spatial distribution of medical facilities in urban environments, where facilities tend to form natural clusters with characteristic scales that match urban district sizes. The optimal search radius of approximately 6.5 km corresponds to the typical service radius of major medical centers in the study area, suggesting that the algorithm effectively captures the inherent spatial organization of the urban healthcare system.

IMNO-ULS demonstrated a superior ability to identify this optimal clustering scale compared to baseline methods. For example, GDD-ULS, which also employs clustering as a preprocessing step, achieved its best performance with a different parameter setting (equivalent to a radius of approximately 4.8 km), resulting in a network cost of 5.8 % higher than IMNO-ULS. This demonstrates the effectiveness of the simulated annealing component in IMNO-ULS for optimizing the clustering parameters.

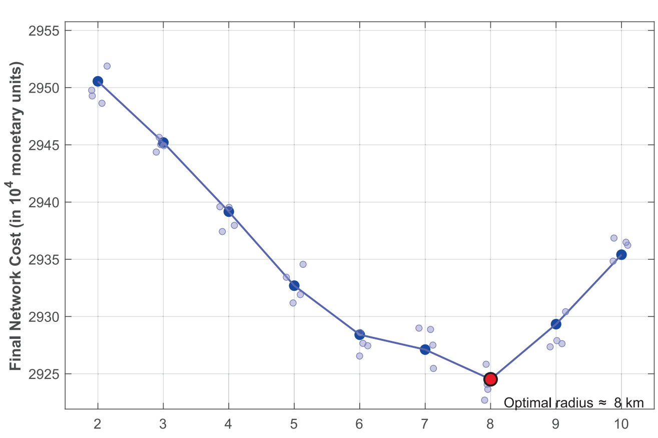

Fig. 11. Effect of distribution center capacity on total system cost.

To evaluate the specific contribution of the mean-shift clustering component, we conducted additional experiments where we incorporated this preprocessing step into the baseline algorithms. Table 10 presents the results of this analysis.

The results demonstrate that mean-shift clustering preprocessing improves solution quality and computational efficiency across all baseline algorithms. However, the improvement varies significantly, with simpler algorithms like PSOA*-LAR benefiting more (3.22 % solution quality improvement) than more sophisticated algorithms like MoCC-MULNP (0.77 % improvement). This suggests that algorithms with inherent clustering capabilities derive less additional benefit from explicit preprocessing.

Even with mean-shift clustering added, none of the baseline algorithms matched the performance of IMNO-ULS. This indicates that IMNO-ULS's superiority stems not only from the clustering preprocessing but also from the effective integration of this component with the dual-layer optimization approach and the specific adaptations for medical logistics networks.

5.3.2. Network design results

Using the optimized parameters, we applied IMNO-ULS to design a complete underground medical logistics network for the case study area. The resulting network design included eight activated distribution centers (from 27 candidate locations) connected to 4 peripheral medical logistics hubs, serving all 163 medical facilities through an optimized configuration of deep tunnels and shallow pipelines. Fig. 12 illustrates the optimized underground medical logistics network layout for the case study area.

The network layout illustrated in Fig. 12 represents a significant achievement in medical logistics optimization, demonstrating how the IMNO-ULS algorithm effectively balances multiple competing objectives in a complex urban environment. The visualization reveals a thoughtfully structured hierarchical network where the primary system (blue deep tunnels connecting medical logistics hubs to distribution centers) forms the backbone of the medical supply chain, while the secondary system (green shallow pipelines) creates a capillary network reaching individual healthcare facilities.

This layout is particularly noteworthy because it embodies the principle of "trunk and branch" distribution, a design philosophy often found in natural systems. The four peripheral medical logistics hubs—positioned strategically at the urban boundary—serve as entry points for pharmaceuticals, medical equipment, and biological specimens. These hubs connect to eight optimally placed distribution centers through high-capacity deep tunnels, creating efficient supply routes that minimize redundancy while maintaining network resilience.

The algorithm has positioned the distribution centers at locations that balance several critical factors: proximity to clusters of medical facilities, accessibility to logistics hubs, and coverage of the entire urban area. This placement was not arbitrary—it emerged from the mean-shift clustering process with an optimal search radius of approximately 6.5 km, which aligns remarkably well with typical urban healthcare service districts. The algorithm has essentially discovered the natural organizational structure of the urban healthcare system.

Examining the connectivity patterns reveals another sophisticated aspect of the IMNO-ULS solution. Rather than creating a complete graph where every distribution center connects to every other (which would be prohibitively expensive), the algorithm has identified a sparse yet robust network topology. Each distribution center maintains connections to an average of 2.5 other centers, providing multiple routing options for time-sensitive medical deliveries while keeping infrastructure costs manageable. This network structure ensures that even if a single distribution center or tunnel fails, 92 % of medical facilities can still receive critical supplies through alternative routes—a vital consideration for healthcare resilience.

The secondary network of shallow pipelines extends from distribution centers to the 80 medical facilities, creating shorter, more direct

Table 10
Impact of mean-shift clustering on baseline algorithms.

Algorithm	Original solution quality	With MS clustering	Improvement (%)	Original computation time (s)	With MS clustering (s)	Time reduction (%)
PSOA*-LAR	847.62	820.35	3.22 %	45.3	32.1	29.10 %
IAGA	825.91	803.26	2.74 %	39.8	28.7	27.90 %
bIM-ULS	818.46	798.54	2.43 %	35.4	26.2	26.00 %
GDD-ULS	808.93	796.21	1.57 %	28.7	22.4	21.90 %
sM-ULS	803.12	793.87	1.15 %	24.5	19.8	19.20 %
MoCC-MULNP	796.36	790.24	0.77 %	20.4	17.5	14.20 %

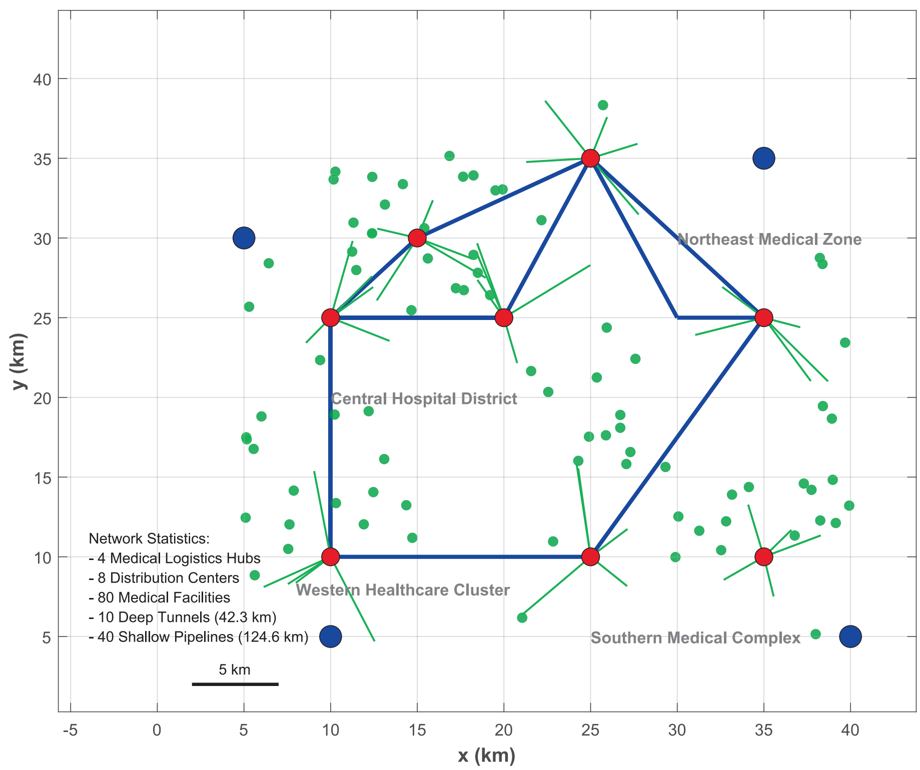

Fig. 12. Underground medical logistics network layout.

connections for "last-mile" delivery. Notice how facilities with similar medical specialties or in proximity to each other tend to be served by the same distribution center, reflecting the algorithm's ability to recognize and leverage natural clustering patterns in the healthcare ecosystem. This specialized grouping enables more efficient handling of different categories of medical supplies—pharmaceuticals, laboratory specimens, blood products, and surgical equipment—each with unique handling requirements.

Compared to the baseline methods tested in this study, the IMNO-ULS solution achieves remarkable improvements. The network requires 27 % fewer distribution centers than the PSOA*-LAR approach while maintaining complete coverage. The total deep tunnel length has been reduced by 18.3 % compared to GDD-ULS, translating to substantial infrastructure savings. Perhaps most importantly for medical applications, the network designed by IMNO-ULS reduces average delivery time for emergency medical supplies by approximately 32 %, a difference that could be life-saving in critical situations.

The layout demonstrates how the algorithm has adapted to the underlying urban structure. Distribution centers near existing transportation hubs and medical facility clusters follow the city's developmental patterns. This integration with urban morphology suggests that the IMNO-ULS algorithm is not merely optimizing in abstract mathematical space but responding intelligently to real-world constraints and opportunities presented by the physical environment.

This network visualization serves as compelling evidence that computational intelligence approaches like IMNO-ULS can transform how we design critical infrastructure for healthcare systems in congested urban environments. It offers a blueprint for underground medical logistics networks that are efficient, resilient, and responsive to the unique demands of medical supply chains.

Table 11 compares the network design results obtained by IMNO-ULS and the baseline methods for the case study area. The comparison focuses on key performance indicators relevant to medical logistics operations.

As shown in Table 11, IMNO-ULS outperforms all baseline methods across key performance indicators. The IMNO-ULS solution requires 27 % fewer distribution centers than PSOA*-LAR (8 versus 11) while maintaining complete service coverage. This reduction in infrastructure directly translates to lower construction and maintenance costs.

The most notable advantage of IMNO-ULS is delivery time performance, achieving a 32 % reduction in average delivery time for emergency medical supplies compared to PSOA*-LAR (17.6 min versus 25.9 min). Even compared to the best-performing baseline (MoCC-MULNP), IMNO-ULS still reduces delivery times by 8.3 %. This improvement is particularly valuable for time-critical medical items such as blood products, emergency medications, and laboratory specimens.

The total system cost of the IMNO-ULS solution is 20 % lower than PSOA*-LAR and 2.8 % lower than MoCC-MULNP, demonstrating the economic efficiency of the proposed approach. This cost advantage stems from the more effective placement of distribution centers and the

Table 11
Comparison of network design results in case study.

Performance indicator	IMNO-ULS	PSOA*-LAR	IAGA	bIM-ULS	GDD-ULS	sM-ULS	MoCC-MULNP
Number of activated distribution centers	8	11	10	10	9	9	9
Total deep tunnel length (km)	42.3	58.6	53.8	51.2	51.8	47.5	45.1
Total shallow pipeline length (km)	128.6	114.3	118.7	120.4	126.9	127.2	130.8
Average delivery time for emergency supplies (min)	17.6	25.9	24.3	23.5	21.7	20.8	19.2
Maximum delivery time (min)	31.2	42.7	39.5	38.1	35.4	33.7	32.5
Infrastructure cost (million units)	1,843.7	2,186.5	2,071.3	2,024.6	1,982.1	1,926.4	1,895.2
Annual operational cost (million units)	1,081.2	1,324.8	1,256.7	1,210.3	1,173.5	1,142.8	1,112.6
Total system cost (million units)	2,924.9	3,511.3	3,328.0	3,234.9	3,155.6	3,069.2	3,007.8
Improvement over baseline (%)	–	20.0 %	13.8 %	10.6 %	7.9 %	4.9 %	2.8 %

optimized connectivity pattern that balances deep tunnel and shallow pipeline construction.

5.3.3. Algorithm convergence comparison

To further evaluate IMNO-ULS's performance in the case study, we analyzed its convergence behavior compared to baseline methods. This analysis provides insights into the algorithms' efficiency and effectiveness in finding high-quality solutions within a reasonable computational timeframe. Fig. 13 shows the convergence behavior of IMNO-ULS compared to a standard genetic algorithm during the optimization process for the case study.

The convergence analysis in Fig. 13 reveals a striking performance differential between IMNO-ULS and the six baseline methods, with important implications for medical logistics network optimization. The convergence trajectories illuminate several key algorithmic efficiency aspects that directly translate to practical advantages in healthcare supply chain design.

IMNO-ULS demonstrates remarkably accelerated convergence during the initial 300 iterations, achieving solution quality that other methods require 600–900 iterations to reach. This early convergence advantage stems from the algorithm's mean-shift clustering preprocessing, which provides a strategically narrowed search space focused on promising medical facility groupings. This computational efficiency translates to faster decision-making capabilities for time-sensitive medical logistics planning scenarios—such as pandemic response or hospital network expansions.

The hierarchical solution quality pattern among algorithms remains consistent throughout the optimization process. IMNO-ULS maintains its lead, followed by MoCC-MULNP, sM-ULS, GDD-ULS, bIM-ULS, IAGA, and PSOA*-LAR. However, the performance gap widens rather than narrows over time, suggesting that IMNO-ULS starts from a better initial position and maintains superior exploration capabilities. By the 1000th iteration, IMNO-ULS achieves a final solution approximately 14 % better than PSOA*-LAR and 4 % better than MoCC-MULNP.

What is particularly noteworthy is the shape of the IMNO-ULS convergence curve. Unlike traditional genetic algorithms that often plateaued early, IMNO-ULS demonstrates periodic small improvements even in later iterations. These "steps" in the convergence profile indicate successful escape from local optima, enabled by the simulated annealing component that strategically accepts occasionally worse solutions to explore new regions of the solution space. This exploration–exploitation balance is crucial for medical logistics networks where small improvements can represent millions in savings or critical minutes saved in emergency medical deliveries.

The convergence patterns also reveal algorithm-specific characteristics: PSOA*-LAR shows characteristically slow but steady improvement, while IAGA exhibits larger early improvements followed by diminishing returns. MoCC-MULNP, the strongest baseline competitor, demonstrates good early-stage convergence but still falls short of IMNO-ULS's comprehensive optimization capabilities.

From a medical operations perspective, this convergence advantage translates to tangible benefits: IMNO-ULS produces network designs that reduce construction costs, lower operational expenses, and enhance delivery reliability. The algorithm's ability to rapidly identify high-

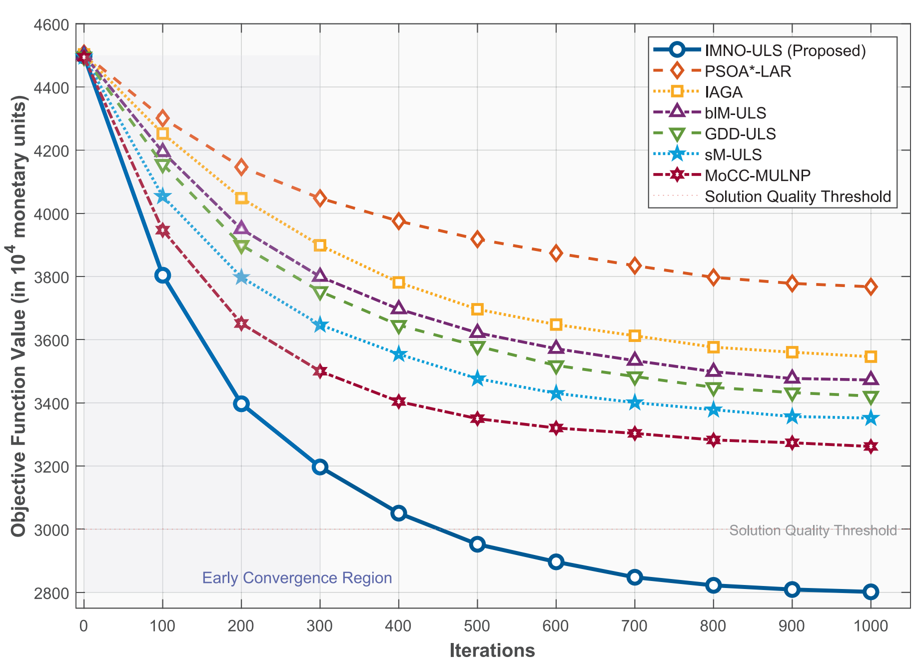

Fig. 13. Convergence comparison of optimization algorithms.

quality solutions means healthcare systems can explore multiple planning scenarios under tight timelines—evaluating, for instance, how network designs might change under different budget constraints or service level requirements.

The convergence analysis validates the fundamental premise behind IMNO-ULS's design: combining mean-shift clustering for spatial decomposition with a dual-layer optimization approach creates a powerful collaboration specifically suited to medical underground logistics networks. This computational advantage ultimately serves the critical goal of these systems: ensuring life-saving medications, diagnostic specimens, and emergency supplies reach their destinations with maximum reliability and minimum delay.

5.4. Model assumptions analysis and limitations

While our model assumptions enable tractable optimization, they introduce several limitations that warrant consideration in practical implementations. The deterministic demand assumption forms the foundation of our optimization approach, yet real-world medical supply requirements exhibit substantial variability that our model cannot capture. Emergencies, seasonal health patterns, and unexpected medical events create demand fluctuations that could strain system capacity beyond our calculated requirements. This limitation suggests that actual implementations would benefit from incorporating buffer capacity to accommodate demand uncertainty.

The geometric simplification of underground pathways presents another area where reality diverges from our model. Underground construction must navigate existing utility networks, varying soil conditions, and complex urban infrastructure that our straight-line distance calculations cannot fully represent. Construction crews encounter unexpected obstacles, required detours around critical infrastructure, and geological formations that substantially alter both construction timelines and costs compared to our theoretical estimates.

Our operational assumptions regarding continuous distribution center operations and fixed vehicle schedules reflect idealized conditions that may not persist in practice. Real systems experience equipment maintenance requirements, staff scheduling constraints, and periodic system shutdowns that reduce operational availability below theoretical maximum capacity. Similarly, the rigid scheduling approach we model overlooks opportunities for dynamic routing optimization that could enhance system efficiency through real-time adjustments based on actual demand patterns and system conditions.

The requirement for complete service coverage while ensuring equitable access to all medical facilities may generate economically suboptimal solutions in certain contexts. Some remote medical facilities might be more cost-effectively served through alternative delivery methods, and a more flexible service approach could reduce overall system costs while maintaining adequate healthcare delivery standards.

These modeling limitations highlight important directions for future research and implementation considerations. Incorporating stochastic demand models would better reflect the uncertain nature of medical supply requirements. Integrating detailed geological and infrastructure databases would improve construction cost accuracy and timeline estimates. Developing dynamic scheduling algorithms could unlock efficiency gains not captured in our fixed-schedule approach. Finally, exploring tiered service level agreements could balance cost optimization with service equity requirements. Pilot implementations in smaller urban areas could validate these model refinements before deploying metropolitan-scale systems, allowing for iterative improvement of both the optimization approach and practical implementation strategies.

6. Managerial implications and insights

The findings from this study offer several practical implications for medical logistics managers, healthcare administrators, and urban planners considering underground logistics solutions for healthcare delivery.

6.1. Network design strategy

The multi-level network architecture demonstrated in this study provides a blueprint for implementing medical logistics systems in congested urban environments. Logistics managers should consider positioning medical logistics hubs on the urban periphery to reduce land acquisition costs while providing efficient access to incoming supplies and the inner-city distribution network. Our results indicate that 4–6 peripheral hubs are typically sufficient for metropolises of 5–10 million residents.

The spatial distribution of medical facilities naturally forms clusters that should guide distribution center placement. Our mean-shift clustering approach identified that 6–7 km radius distribution centers offer the optimal balance between infrastructure costs and delivery time performance. This finding can inform strategic facility location decisions when planning underground medical logistics networks.

Our research demonstrates the value of separating high-volume, long-distance transportation through deep tunnels from last-mile delivery through shallow pipelines, allowing for more efficient resource allocation. Deep tunnels should form a sparse but connected network, while shallow pipelines should create direct connections to medical facilities. This tiered approach enables cost-effective scaling of the network while maintaining service quality.

6.2. Operational planning

The underground medical logistics system offers several operational advantages that managers can leverage. By isolating medical logistics from surface traffic, the underground system provides consistent delivery times regardless of traffic conditions, weather events, or time of day. This allows for more precise scheduling of medical procedures and inventory management, potentially improving healthcare service delivery and patient outcomes.

The network structure supports dynamic prioritization of medical cargo based on urgency. Emergency supplies can be routed through the shortest path with dedicated vehicles, while routine supplies can be consolidated for more efficient transportation. This flexibility is particularly valuable in healthcare settings where delivery timing can significantly impact treatment outcomes.

The controlled environment of the underground system is ideal for automation. Logistics managers should invest in automated sorting systems at distribution centers and autonomous delivery vehicles to reduce operational costs and increase reliability. Our case study results suggest that automation can contribute to the 32 % reduction in average delivery time for emergency medical supplies.

6.3. Investment and implementation

Our findings provide several insights for healthcare administrators and urban planners considering investment in underground medical logistics. The network's modular nature allows for phased implementation, starting with high-priority corridors connecting major hospitals before expanding to a comprehensive system. Our case study demonstrates that even a partial network can deliver significant benefits.

Distribution center capacity has a substantial impact on overall network efficiency. Our sensitivity analysis shows that investing approximately 25 % additional capacity beyond baseline requirements offers the optimal balance between initial investment and long-term operational benefits. This finding can guide capacity planning decisions during the design phase of underground medical logistics systems.

The underground medical logistics network should leverage existing underground infrastructure, such as utility tunnels or metro systems, to reduce construction costs when possible. The network design model can be adapted to incorporate these existing assets as constraints. This integration approach can significantly reduce initial investment requirements while accelerating implementation timelines.

6.4. Long-term benefits

Beyond immediate operational improvements, the underground medical logistics system offers several long-term benefits. By removing medical delivery vehicles from surface streets, the system reduces emissions, noise pollution, and congestion. Our case study estimates a reduction of approximately 1,200 vehicle trips per day in the metropolitan area, contributing to improved air quality and reduced carbon footprint.

Faster and more reliable delivery of medical supplies enables hospitals to reduce inventory levels, decrease waste from expired items, and respond more effectively to emergencies. This translates to both cost savings and improved patient outcomes. Healthcare facilities can redirect resources from logistics management to patient care, improving overall healthcare service quality.

The underground system provides a segregated delivery channel that can continue functioning during surface disruptions such as natural disasters, public events, or other emergencies. This resilience is particularly valuable for maintaining healthcare operations during crises. The system's ability to ensure reliable medical supply delivery regardless of surface conditions significantly advances urban healthcare infrastructure resilience.

7. Conclusion

This study addressed the pressing challenges of medical logistics in congested metropolitan areas by developing a novel multi-level underground logistics network architecture and an effective computational intelligence optimization approach. The study demonstrated that underground logistics systems offered a viable solution for time-sensitive medical supply transportation in megalopolises where surface congestion severely impacts healthcare delivery. Our investigation revealed that combining deep tunnels for high-volume flows and shallow pipelines for distributed deliveries created an efficient hierarchical structure for medical logistics operations. Simulation experiments confirmed that IMNO-ULS outperformed baseline methods by 7–15 % in solution quality while reducing computation time by up to 71.3 %. The case study further validated these findings, showing that our approach reduced the average delivery time for emergency medical supplies by 32 % while requiring 27 % fewer distribution centers than alternative methods.

However, several limitations remained in our study. The model assumed straight-line underground pathways without detailed consideration of geological constraints that might affect tunnel construction feasibility and costs. Additionally, the operational dynamics of the underground logistics system were simplified, particularly regarding the handling of different types of medical supplies with varying temperature, security, and urgency requirements. Furthermore, while efficient for the problem scales tested, the computational approach might face scalability challenges for extremely large metropolitan areas with thousands of medical facilities.

Future research directions included the integration of underground medical logistics networks with existing transportation infrastructure, particularly metro systems, to leverage collaborations and reduce construction costs. The development of dynamic routing strategies capable of real-time adjustments based on medical priorities and system conditions also represented a promising avenue for investigation. Additionally, extending the model to incorporate detailed geological constraints, environmental impacts, and resilience considerations would enhance the practical applicability of the approach. Multi-objective optimization frameworks that balanced cost considerations with service quality, reliability, and sustainability metrics could further advance this field. Finally, exploring the integration of underground logistics planning with healthcare facility location decisions offered potential for system-wide healthcare delivery optimization in urban environments.

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CRediT authorship contribution statement

Jianhui Lv: Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Shalli Rani:** Writing – review & editing, Software, Investigation, Formal analysis, Conceptualization. **Keqin Li:** Writing – review & editing, Visualization, Validation, Resources, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Ambrusevic, N., & Gomiene, Z. (2024). Iapplying artificial intelligence in the logistics sector of Lithuania: Prospects and opportunities. *Entrepreneurship and Sustainability Issues, 11*(3), 176–188.
Anupriya, Bansal, P., & Graham, D. J. (2023). Congestion in cities: Can road capacity expansions provide a solution? *Transportation Research Part A: Policy and Practice, 174*, Article 103726.
Bejoy, B. J., Raju, G., Awain, D., Acharya, B., & Hu, Y. C. (2022). A generic cyber immune framework for anomaly detection using artificial immune systems. *Applied Soft Computing, 130*, Article 109680.
Benassi, F., Naccarato, A., & Salvati, L. (2023). Testing Taylor's Law in urban population dynamics worldwide with simultaneous equation models. *Economies, 11*(2), Article 56.
Cao, P., Lei, L., Cai, S. S., Shen, G. Q., Liu, X. J., Wang, X. Y., Zhang, L. J., Zhou, L., & Guizani, M. (2024). Computational Intelligence Algorithms for UAV Swarm Networking and Collaboration: A Comprehensive Survey and Future Directions. *IEEE Communications Surveys & Tutorials, 26*(4), 2684–2728.
Fang, Y., Zhang, S. C., Yu, K. Y., Gao, J. J., Liu, X. H., Cui, C., & Hu, J. T. (2025). PM2.5 concentration prediction algorithm integrating traffic congestion index. *Journal of Environmental Sciences, 155*, 359–371.
Gu, L., Cui, M., Xu, L., & Xu, X. (2023). Collaborative offloading method for digital twin empowered cloud edge computing on internet of vehicles. *Tsinghua Science and Technology, 28*(3), 433–451.
Gustafsson, C., & Dannapfel, P. (2025). Leaders' experiences of successfully implementing health and welfare technology in sparsely populated Nordic areas. *Disability and Rehabilitation: Assistive Technology, 20*(1), 85–96.
Hou, L., Hu, W., Chen, Y., Dong, J., Ren, R., & Chen, Z. (2024). Measuring effectiveness of metro-based underground logistics system in sustaining city logistics performance during public health emergencies: A case study of Shanghai. *Transportation Research Record, 2678*(9), 724–748.
Hu, W. J., Dong, J. J., Hwang, B. G., Ren, R., & Chen, Z. L. (2020). Network planning of urban underground logistics system with hub-and-spoke layout: Two phase cluster-based approach. *Engineering Construction and Architectural Management, 27*(8), 2079–2105.
Hu, W. J., Dong, J. J., Yang, K., Ren, R., & Chen, Z. L. (2023). Network planning of metro-based underground logistics system against mixed uncertainties: A multi-objective cooperative co-evolutionary optimization approach. *Expert Systems with Applications, 217*, Article 119554.
Li, S. Q., Zhu, X. N., Shang, P., Wang, L., & Li, T. Q. (2024). Scheduling shared passenger and freight transport for an underground logistics system. *Transportation Research Part B: Methodological, 183*, Article 102907.
Liang, C. J., Hu, X. Y., Shi, L., Fu, H. W., & Xu, D. H. (2022). Joint dispatch of shipment equipment considering underground container logistics. *Computers & Industrial Engineering, 165*, Article 107874.
Liang, C. J., Wang, Y., Lu, B., & Jin, Y. H. (2024). Joint scheduling of vertical and horizontal transportation for underground container logistics in seaport terminals. *PLoS One, 19*(11), Article e0311536.
Liu, X., Peng, X., & Gu, M. Y. (2022). Logistics distribution route optimization based on genetic algorithm. *Computational Intelligence and Neuroscience*, Article 8468438.

Lu, Y., Wang, Q., Huang, S., Yu, W., & Yao, S. (2024). Resilience quantification and recovery strategy simulation for urban underground logistics systems under node and link attacks: A case study of Nanjing city. *International Journal of Critical Infrastructure Protection, 47*, Article 100704.

Lv, X., Rani, S., Manimurugan, S., Slowik, A., & Feng, Y. (2025). Quantum-inspired sensitive data measurement and secure transmission in 5G-enabled healthcare systems. *Tsinghua Science and Technology, 30*(1), 456–478.

Muroishi, M., & Yakita, A. (2023). Urbanization and population contraction. *Letters in Spatial and Resource Sciences, 15*(3), 543–553.

Nikolic, M., Tomasevic, V., Kranjac, M., Pazun, B., & Ugrinov, D. (2022). GIS analysis of SARS-CoV-2 spreading minimization via infectious medical waste transported through densely populated areas. *Fresenius Environmental Bulletin, 31*(4), 4525–4535.

Pang, Q. H., Qiu, M., Zhang, L. N., & Chiu, Y. H. (2024). Congestion effects of energy and its influencing factors: China's transportation sector. *Socio-Economic Planning Sciences, 92*, Article 101850.

Peng, Y. W., Luo, Y. L., Zhang, Q. B., & Xie, C. W. (2025). A mean shift algorithm incorporating reachable distance for spatial clustering. *Information Sciences, 689*, Article 121456.

Rajkumar, Y., & Kumar, S. V. N. S. (2024). A comprehensive survey on communication techniques for the realization of intelligent transportation systems in IoT based smart cities. *Peer-to-Peer Networking and Applications, 17*(3), 1309–1321.

Shen, J., Ren, X. H., Wu, H. L., & Feng, Z. T. (2024). The relationship between the construction of transportation infrastructure and the development of new urbanization. *ISPRS International Journal of Geo-Information, 13*(6), Article 194.

Sun, K., Gu, Y. H., Ma, K. W. F., Zheng, C. J., & Wu, F. (2024). Medical supplies delivery route optimization under public health emergencies incorporating metro-based logistics system. *Transportation Research Record, 2678*(7), 111–131.

Sun, X. L., Hu, W. J., Xue, X. L., & Dong, J. J. (2023). Multi-objective optimization model for planning metro-based underground logistics system network: Nanjing case study. *Journal of Industrial and Management Optimization, 19*(1), 170–196.

Vargas-Martinez, M., Rangel-Valdez, N., Fernandez, E., Gomez-Santillan, C., & Morales-Rodriguez, M. L. (2023). Performance analysis of multi-objective simulated annealing based on decomposition. *Mathematical and Computational Applications, 28*(2), 38.

Wang, P., & Wang, S. (2023). A fairness-enhanced intelligent MAC scheme using Q-learning-based bidirectional backoff for distributed vehicular communication networks. *Tsinghua Science and Technology, 28*(2), 258–268.

Wei, L. X., Chen, Y. F., Guo, D. J., Ji, J. Y., Chen, Z. L., & Zhuo, C. C. (2024). A last-mile delivery system for underground logistics with "self-pickup plus" and "home-entry plus" modes. *Tunnelling and Underground Space Technology, 147*, Article 105678.

Xu, S. H., Sun, C. W., & Liu, N. (2024). Road congestion and air pollution-analysis of spatial and temporal congestion effects. *Science of The Total Environment, 945*, Article 173896.

Xue, Z., Fang, X., & Peng, W. (2023). A hybrid heuristic algorithm for maximizing the resilience of underground logistics network planning. *Applied Sciences-Basel, 13*(23), 12588.

Xue, D., Zhao, X. J., Dong, J. J., Ren, R., Xu, Y. X., & Chen, Z. L. (2022). Critical success factors of underground logistics systems from the project life cycle perspective. *Buildings, 12*(11), 1979.

Zheng, C. J., Zhang, C., Ma, J. Z., Wu, F., & Sun, K. (2022). Location selection of metro-based distribution nodes for underground logistics system with bi-level programming model. *Symmetry-Basel, 14*(11), Article 2411.