



Research article

Robust resilient-responsive approach for multi-objective healthcare supply chain network design problem

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Abstract: Healthcare supply chains face significant challenges during epidemic outbreaks due to rapidly changing demand, supply disruptions, and limited healthcare resources. These challenges are particularly pronounced for vector-borne diseases, where healthcare resource allocation must be coordinated with vector control operations. This study develops a tri-objective mixed-integer linear programming (MILP) model for healthcare supply chain network design that jointly considers material distribution, patient transportation, resilience, and responsiveness. The proposed network consists of primary suppliers, backup suppliers, distribution centers, VCUs, communities, and hospitals. To address uncertainty in the demand, facility capacity, and transportation costs, the established robust possibilistic programming (RPP) framework with trapezoidal fuzzy numbers is incorporated into the proposed optimization model. The resulting formulation simultaneously minimizes total system cost, critical-node penalties, and response deviations while accounting for both optimality robustness and feasibility robustness through heterogeneous penalty coefficients. The augmented ε -constraint (AEC) method is used to generate the Pareto-optimal frontier and analyze the trade-offs among the robust total objective, resilience, and responsiveness. The proposed model is validated using a real-world case based on the 2025 Chikungunya fever outbreak in Shunde District, Foshan, Guangdong Province, China. The results show that the proposed framework effectively supports healthcare resource allocation under uncertainty, while the RPP model with confidence levels of $\alpha = \beta = 0.5$ exhibits the lowest cross-scenario variability among the tested configurations. The Pareto analysis further provides quantitative guidance for balancing operational cost, resilience, and responsiveness under different epidemic response scenarios. The proposed framework offers a practical decision support tool for healthcare administrators and emergency planners facing uncertain public health emergencies.

Keywords: healthcare supply chain; pandemic; resilience; responsiveness; RPP

1. Introduction

Healthcare supply chains play a critical role in the emergency response by ensuring the timely distribution of medical resources and the efficient transportation of patients during epidemic outbreaks. Recent outbreaks of emerging infectious diseases have repeatedly exposed the vulnerability of healthcare supply chains to rapidly changing demand, facility disruptions, and severe resource shortages [1]. Unlike conventional commercial supply chains, healthcare supply chains must simultaneously maintain service continuity, allocate scarce medical resources efficiently, and respond rapidly to highly uncertain emergency conditions [2]. Consequently, developing healthcare supply chain network design models that support effective resource allocation under uncertainty has become an important research topic in operations research and healthcare management.

Among the emerging infectious diseases that continue to challenge healthcare systems, Chikungunya fever has recently become an important public health concern in subtropical and tropical regions [3–5]. Unlike respiratory infectious diseases, Chikungunya fever is transmitted by mosquitoes and therefore requires not only treatment of the patients but also continuous vector control operations to interrupt disease transmission. Consequently, the epidemic response involves the coordinated allocation of medical resources and vector control resources. These intertwined operational processes create a more complex healthcare supply chain than those typically considered in conventional epidemic response models. As a result, healthcare administrators must simultaneously determine where to allocate limited medical resources, how to coordinate vector control operations, and how to maintain an efficient patient transportation network under rapidly evolving epidemic conditions.

Despite substantial progress in healthcare supply chain optimization, several important challenges remain. Existing studies have investigated healthcare supply chain optimization from different perspectives, including material distribution and patient transportation [6, 7], resilience and responsiveness [8–10], and uncertainty modeling [11]. Although these issues have all received considerable attention, their integration within a unified optimization framework remains limited. In particular, the integration of material distribution, patient transportation, resilience, and responsiveness within a unified optimization framework remains limited. Furthermore, most existing healthcare supply chain models have been developed for disaster relief operations or respiratory infectious diseases, whereas the operational characteristics associated with vector-borne disease responses have received much less attention. These limitations highlight the need for an integrated healthcare supply chain optimization framework capable of coordinating multiple operational decisions under uncertain epidemic conditions.

To address these limitations, this study develops an integrated multiobjective healthcare supply chain network design model for a vector-borne disease response. The proposed model jointly optimizes material distribution and patient transportation while simultaneously incorporating resilience and responsiveness within a unified decision-making framework. To better capture the operational characteristics of vector-borne disease control, the healthcare supply chain network is extended by introducing VCUs, enabling the coordinated allocation of medical resources and vector control resources during epidemic outbreaks. Uncertainty in the epidemic's demand, facilities' capacity, and transportation costs is represented using trapezoidal fuzzy numbers, while the established robust possibilistic programming (RPP) approach [12] is incorporated into the proposed optimization model. The resulting multiobjective optimization model is solved using the augmented ε -constraint (AEC)

method to obtain Pareto-optimal solutions for decision analysis.

The main contributions of this study are summarized as follows.

- (1) An integrated multiobjective healthcare supply chain network design model is developed that unifies material distribution, patient transportation, resilience, and responsiveness within a single optimization framework, enabling coordinated decision-making across multiple operational components of the epidemic response under uncertainty.
- (2) The proposed healthcare supply chain network is designed specifically for a vector-borne disease response by explicitly incorporating VCUs into the optimization framework. This enables the coordinated planning of medical resource allocation and vector control operations, extending existing healthcare supply chain models to a more complex epidemic response scenario.
- (3) The proposed optimization model explicitly captures uncertainty in epidemic-related demand, facilities' capacity, and transportation costs, enabling robust healthcare resource allocation while maintaining operational feasibility under uncertain epidemic conditions.
- (4) The proposed framework is validated using a real-world case based on the 2025 Chikungunya fever outbreak in Shunde District, Foshan, Guangdong Province, China, demonstrating its applicability to healthcare resource allocation under uncertain epidemic conditions.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and identifies the research gaps. Section 3 presents the proposed healthcare supply chain network design model, including the mathematical formulation, uncertainty modeling, and solution methodology. Section 4 introduces the real-world case study and discusses the computational results. Finally, Section 5 concludes the paper with the main findings, practical implications, study limitations, and directions for future research.

2. Literature review

To position the proposed study within the existing body of research, this section reviews the literature related to healthcare supply chain network design, uncertainty modeling, resilience, and responsiveness. Relevant studies were identified primarily through the Web of Science, Scopus, and Google Scholar databases using keywords such as “healthcare supply chain”, “supply chain network design”, “resilience”, “responsiveness”, and “robust possibilistic programming”. Rather than providing a chronological summary of previous studies, the literature is organized according to four research themes that are most closely related to the proposed modeling framework: (1) Healthcare supply chain network design, (2) uncertainty modeling in healthcare supply chains, (3) the supply chain's resilience, and (4) the supply chain's responsiveness. This organization facilitates the identification of current research trends, methodological limitations, and the research gaps addressed in this study.

2.1. Healthcare supply chain network design

Healthcare supply chain network design has long been regarded as a core component of emergency logistics, with the primary objective of ensuring the timely and efficient allocation of medical resources during disasters and public health emergencies. Early studies mainly focused on humanitarian logistics coordination, emphasizing emergency preparedness, facility coordination, and resource distribution across healthcare networks [13]. These studies established the foundation for healthcare supply chain

network design by demonstrating the importance of coordinated logistics in improving the emergency response's efficiency.

As public health emergencies have become increasingly complex, research has gradually evolved from traditional logistics planning toward integrated healthcare supply chain optimization. Recent studies have investigated a broader range of operational problems, including blood supply chain management under disaster-associated uncertainty [6]; the integration of lean, agile, resilient, and green paradigms [14]; digital transformation in healthcare supply chains [15]; and home healthcare logistics incorporating outsourcing decisions and sustainable logistics planning [16, 17]. These studies demonstrate that healthcare supply chain research has gradually expanded from individual logistics activities toward more comprehensive healthcare service planning.

More recently, healthcare supply chain optimization has been increasingly applied to epidemic responses. Mondal and Roy [11] investigated sustainable forward and closed-loop healthcare supply chains under uncertain demand, while Nagurney [7] incorporated labor availability into healthcare supply chain network design during pandemic-related disruptions. Taghvaei et al. [18] integrated pre-disaster and post-disaster operational decisions under demand, donation, and disruption uncertainties. These studies have considerably advanced healthcare supply chain optimization under epidemic conditions.

Despite these advances, existing studies have primarily focused on specific operational problems or individual application scenarios. Comparatively less attention has been paid to simultaneously coordinating multiple operational decisions required for vector-borne disease responses.

2.2. *Uncertainty in the supply chain*

Uncertainty is an inherent characteristic of healthcare supply chains because epidemic-related demand, resource availability, transportation conditions, and facility capacities are often difficult to predict accurately [19, 20]. Consequently, uncertainty modeling has become an important research direction in healthcare supply chain network design.

Existing studies have adopted a variety of approaches to represent and manage uncertainty. Early research mainly used fuzzy optimization and robust optimization techniques to describe uncertain demand, supply, and processing conditions. For example, Peidro et al. [21] proposed a fuzzy optimization framework for supply chain planning under uncertain supply, demand, and production processes, while Pishvae et al. [22] developed a robust optimization model for closed-loop supply chain network design. Azarkish and Hajiali [23] further used multiobjective horse herd optimization, the Pareto Archive, and Non-dominated Sorting Genetic Algorithm II (NSGA-II) based approaches, to address demand uncertainty in healthcare supply chains.

As uncertainty modeling has continued to develop, more sophisticated approaches have been introduced for specific emergency logistics scenarios. Zhong et al. [24] used scenario-based optimization to address uncertainty in disaster relief facility location and vehicle routing. Shahparvari et al. [25] proposed a robust stochastic optimization model for reverse supply chain network redesign, while Yilmaz et al. [26] combined two-stage stochastic programming with machine learning to improve the survivability of humanitarian supply chains under uncertain demand and capacity conditions. These studies indicate a clear evolution from deterministic optimization toward more flexible uncertainty-handling strategies for healthcare and humanitarian supply chain planning.

Among these approaches, RPP has attracted increasing attention because it simultaneously

considers the expected performance, solutions' robustness, and feasibility robustness under fuzzy uncertainty. Pishvae et al. [12] first introduced the RPP framework for socially responsible supply chain network design by representing uncertain parameters with trapezoidal fuzzy numbers. More recently, Ala et al. [27] applied this approach to blood supply chain network design and demonstrated its effectiveness in modeling uncertain supply and demand. Overall, these studies demonstrate that RPP provides an effective framework for representing fuzzy uncertainty in healthcare supply chain optimization.

2.3. Resilience

Resilience has become one of the central objectives in healthcare supply chain network design because it determines the ability of supply chains to withstand disruptions, maintain essential operations, and recover rapidly from unexpected events [28, 29]. Consequently, improving supply chains' resilience has attracted increasing attention in healthcare logistics and humanitarian operations.

Early studies mainly focused on incorporating resilience strategies into healthcare supply chain design through mathematical optimization. Kaur and Singh [30] integrated resilience strategies and environmental considerations into a nonlinear optimization model for humanitarian supply chains, while Mamashli et al. [8] proposed a fuzzy robust stochastic optimization model for sustainable and resilient relief logistics. In parallel, considerable effort has also been devoted to disruption mitigation strategies and resilience-building mechanisms for supply chain systems [31].

Recent research has extended resilience modeling by considering more realistic operational settings and disruption scenarios. Fazel et al. [9] incorporated lateral trans-shipment into pharmaceutical healthcare supply chain design to improve resilience under disruption. Khalili-Fard et al. [32] jointly optimized pre-disaster and post-disaster decisions by integrating pre-positioning strategies, alternative suppliers, quantity flexibility contracts, and multisourcing policies. Taghvaei et al. [18] combined pre-crisis and post-crisis decisions within a two-stage stochastic optimization framework to improve the resilience of humanitarian healthcare supply chains under demand, donation, and disruption uncertainties.

Collectively, these studies demonstrate that resilience has evolved from isolated disruption mitigation strategies toward integrated supply chain planning under uncertainty. Nevertheless, resilience is still commonly investigated as an individual optimization objective, whereas its coordinated integration with responsiveness and other operational decisions remains relatively limited.

2.4. Responsiveness

Responsiveness is another essential objective in healthcare supply chain management because it reflects the ability of the supply chain to respond rapidly to changing demand and emergency conditions. The concept of supply chain responsiveness was first established by Gunasekaran et al. [33], who regarded responsiveness as a key competitive capability in networked supply chains. Subsequent studies further explored the relationship between supply chains' agility and responsiveness, identifying the main operational factors that influence responsive supply chains' performance [34].

Building upon these theoretical foundations, responsiveness has been increasingly incorporated into healthcare supply chain optimization. Cheraghi and Hosseini-Motlagh [35] developed a robust optimization model for responsive blood supply chain network design under disaster conditions.

Yilmaz et al. [36] proposed an optimization-based framework that combines lean management tools with healthcare supply chain planning to improve both resilience and responsiveness during pandemic-related disruptions. More recently, Shekarabi and Mozdgir [10] investigated the joint effects of pandemic-related disruptions, stochastic uncertainty, and deep uncertainty, highlighting the importance of simultaneously incorporating resilience and responsiveness into supply chain network design.

Overall, responsiveness has evolved from a logistics performance measure to an important optimization objective in healthcare supply chain planning. Nevertheless, the existing studies mainly investigate responsiveness together with specific operational decisions or disruption scenarios. Its integration with multiple operational components, particularly material distribution and patient transportation within a unified healthcare supply chain optimization framework, remains relatively limited.

2.5. Comparative analysis and research gap

Representative studies on healthcare supply chain network design are summarized in Table 1, where they are compared from the perspectives of objective functions, uncertainty modeling approaches, solution methods, and application domains.

Several observations can be drawn from the comparison. First, material logistics has been extensively investigated in existing healthcare supply chain research, whereas patient transportation has received comparatively less attention. Similarly, resilience has become an increasingly important optimization objective, while responsiveness is incorporated in only a limited number of studies, and patient responsiveness is considered even less frequently. Although several recent studies jointly consider resilience and responsiveness, these objectives are generally investigated together with only part of the healthcare supply chain decision process rather than within an integrated optimization framework.

Second, uncertainty has been addressed using a wide range of modeling approaches, including deterministic optimization, robust optimization, stochastic programming, data-driven optimization, and RPP. These studies have provided valuable methodologies for modeling uncertainty in healthcare supply chains. However, most existing applications focus on specific operational settings, such as blood supply chains, pharmaceutical logistics, home healthcare, humanitarian relief, or pandemic-related response, with comparatively limited attention paid to vector-borne disease scenarios.

The observations above indicate that healthcare supply chain research has gradually evolved from isolated logistics planning toward more comprehensive optimization frameworks. Nevertheless, opportunities remain to further integrate material distribution, patient transportation, resilience, and responsiveness within a unified healthcare supply chain optimization model, particularly for a vector-borne disease response where medical treatment and vector control operations must be coordinated simultaneously. Motivated by these observations, the present study develops an integrated multiobjective healthcare supply chain network design model that addresses these aspects within a unified optimization framework while incorporating an established uncertainty handling approach to represent the epidemic's uncertainty.

Table 1. Comparison of literature on healthcare supply chain network design.

Study	Objective function						Capacity constraint	Uncertainty modeling	Solution method	Application domain
	Material logistics	Patient transportation	Material resilience	Healthcare Service resilience	Material responsiveness	Patient responsiveness				
Nagurney (2021) [7]	✓	–	–	–	✓	–	✓	Deterministic	Exact	Labor-inclusive SC (pandemic)
Mamashli et al. (2021) [8]	✓	–	✓	–	–	–	✓	Fuzzy robust stochastic	Heuristic (MCGP)	Relief routing allocation
Fathollahi-Fard et al. (2022) [16]	✓	–	–	–	–	–	✓	Deterministic (bi-level)	Heuristic	Home health-care SC
Fathollahi-Fard et al. (2022) [17]	✓	–	✓	–	–	–	✓	Robust optimization	Heuristic	Home healthcare logistics (pandemic)
Lotfi et al. (2022) [37]	✓	–	✓	–	–	–	✓	Robust optimization	Exact	Medical waste SC (viable)
Fazel et al. (2023) [9]	✓	–	✓	–	✓	–	✓	Robust optimization	Exact	Pharmaceutical relief SC
Yilmaz et al. (2023) [36]	✓	–	✓	–	✓	–	✓	dynamic uncertainty	Review of OR methods	Healthcare service-pandemic
Yilmaz and Haghani (2023) [38]	✓	✓	–	✓	–	–	✓	Deterministic (lean-based)	Exact	Medical SC (pandemic)
Chowdhury et al. (2024) [39]	✓	–	–	✓	–	✓	✓	fsQCA	Exact	Healthcare service(pandemic)
Lotfi et al. (2024) [40]	✓	–	✓	–	–	–	✓	Data-driven robust	Exact	Viable SC (blockchain)
Ala et al. (2024) [27]	✓	–	✓	–	✓	–	✓	RPP (trapezoidal fuzzy)	Exact	Blood SC (lateral resupply)
Entezari et al. (2024) [6]	✓	–	✓	–	–	–	✓	Two-stage stochastic	Exact	Blood SC (disaster)
Khalili-Fard et al. (2024) [32]	✓	–	✓	–	✓	–	✓	Scenario-based	Exact	Humanitarian relief (pre-post-crisis)
Nazari-Shirkouhi and Samadi (2025) [14]	✓	–	✓	–	✓	–	–	Fuzzy DEMATEL + BN	Exact	Healthcare SC (LARG paradigms)
Taghvaei et al. (2025) [18]	✓	–	✓	–	✓	–	✓	Two-stage stochastic	Exact	Humanitarian relief
Yilmaz et al. (2025) [26]	✓	–	✓	–	–	–	✓	Two-stage stochastic + ML	Exact	Resilient humanitarian SC
Shekarabi and Mozdgir (2025) [10]	✓	–	✓	–	✓	–	✓	Robust + deep uncertainty	Exact	Food SC (pandemic)
DiStefano et al. (2026) [41]	✓	✓	–	✓	–	✓	–	–	Qualitative	Healthcare SC
Chai and Sun (2026) [42]	–	✓	–	✓	–	✓	✓	Monte Carlo with fragility curves	Exact	Healthcare SC
This study (2026)	✓	✓	✓	✓	✓	✓	✓	RPP (trapezoidal fuzzy)	Exact (CPLEX + ε -constraint)	Healthcare SC, vector-borne pandemic (Chikungunya)

*Notes: ✓ = feature present; – = not considered; SC = supply chain; ML = machine learning; BN = bayesian network; MCGP = multichoice goal programming; RPP = robust possibilistic programming; LARG = lean, agile, resilient, green. fsQCA = fuzzy set qualitative comparative Analysis; DEMATEL = decision making trial and evaluation laboratory; CPLEX = IBM ILOG CPLEX Optimizer, a commercial MILP solver.

3. Healthcare supply chain network design model under uncertainty

Section 3 presents the proposed healthcare supply chain network design model. Section 3.1 introduces the healthcare supply chain network and the problem setting. Section 3.2 describes the modeling assumptions. Section 3.3 defines the notation used throughout the paper. Section 3.4 formulates the multiobjective mixed-integer linear programming model, including the cost, resilience, and responsiveness objectives. Section 3.5 presents the corresponding model constraints. Section 3.6 introduces the uncertainty modeling framework by representing uncertain parameters with trapezoidal fuzzy numbers and incorporating the established RPP approach. Finally, Section 3.7 presents the AEC method used to generate the Pareto-optimal solutions of the proposed optimization model.

3.1. Problem description

This subsection introduces the healthcare supply chain network considered in this study. The proposed model is designed for a vector-borne disease response, where effective epidemic control requires the coordinated planning of medical treatment and vector control operations. Accordingly, the healthcare supply chain network simultaneously considers medical resource allocation, vector control resource allocation, and patient transportation within a unified optimization framework.

The proposed network consists of six types of facilities: Primary suppliers (P), backup suppliers (B), distribution centers (D), vector control units (VCUs) (V), communities (M), and hospitals (L), as illustrated in Figure 1. Primary suppliers and backup suppliers provide epidemic prevention materials and vector control materials. Distribution centers receive these materials and distribute them to hospitals, communities, and VCUs according to operational requirements. VCUs are responsible for mosquito surveillance, environmental disinfection, insecticide deployment, and other vector control activities, and subsequently allocate vector control materials to the communities they serve. Communities represent the locations where the epidemic prevention materials are consumed and vector control operations are implemented, while hospitals provide treatment for hospitalized patients transferred from the affected communities.

The proposed network explicitly models the interactions among material distribution, vector control operations, and patient transportation. Compared with conventional healthcare supply chain networks, the inclusion of VCUs enables the coordinated allocation of medical resources and vector control resources, thereby better capturing the operational characteristics of vector-borne disease responses under uncertain epidemic conditions.

3.2. Assumptions

To formulate the proposed healthcare supply chain network design model, the following assumptions are adopted.

- A1. Primary suppliers and backup suppliers are assumed to possess flexible production capacity that can be adjusted within a limited time horizon in response to emergency-related demand fluctuations [43].
- A2. The assignment of communities to VCUs and the transportation of hospitalized patients to hospitals are determined endogenously by the optimization model rather than being predefined [44].

- A3. Community-level epidemic response activities, including the distribution of epidemic prevention materials and vector control operations, are assumed to be coordinated through local emergency organizations, allowing the optimization model to focus on strategic resource allocation rather than operational personnel scheduling [7].
- A4. The hospitals included in the proposed network are existing designated treatment facilities and are assumed to remain available throughout the planning horizon. Therefore, hospital activation is not treated as an endogenous location decision, which is consistent with previous patient allocation models that optimize patient distribution among a predefined set of available hospitals subject to treatment capacity constraints [45].

These assumptions are commonly adopted in healthcare supply chain optimization and provide the basis for developing a tractable multiobjective network design model under epidemic-related uncertainty.

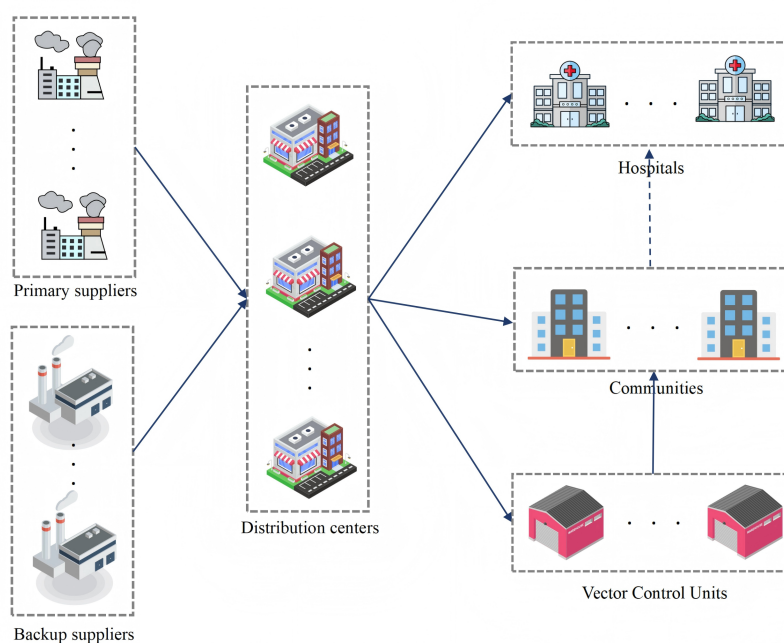


Figure 1. Healthcare supply chain network structure during a pandemic.

3.3. Notations

The notation follows that of Fathollahi-Fard and Li [46].

Indices and sets

- $\bar{P}$ Set of primary suppliers, $p = 1, \dots, P$
- $\bar{I}$ Set of backup suppliers, $i = 1, \dots, I$
- $\bar{V}$ Set of VCUs, $v = 1, \dots, V$
- $\bar{K}$ Set of distribution centers (DC), $k = 1, \dots, K$
- $\bar{L}$ Set of hospitals, $l = 1, \dots, L$

$\bar{M}$	Set of communities, $m = 1, \dots, M$
$\bar{Q}$	Set of epidemic prevention materials (including both general medical supplies and vector control materials), $q = 1, \dots, Q$
$\bar{Q}^M$	Set of general medical materials, $q=1,2$
$\bar{Q}^V$	Set of vector control materials, $q=3,4$
$\bar{S}$	Set of patients, $s = 1, \dots, S$

Parameters

$\tilde{D}_{ql}$	Demand for epidemic prevention materials q at hospital l
$\tilde{D}_{qm}$	Demand for epidemic prevention materials q at community m
$\tilde{D}_{sm}$	Demand for patients s at community m
$\tilde{D}_{qv}$	Demand for epidemic prevention materials q at VCU v , $q \in \bar{Q}^V$
$\tilde{D}_{qm}^{VC}$	Demand for vector control material q at community m
$\tilde{T}_{pk}$	Transportation cost of epidemic prevention materials from primary supplier p to DC k
$\tilde{T}_{ik}$	Transportation cost of epidemic prevention materials from backup supplier i to DC k
$\tilde{T}_{km}$	Transportation cost of epidemic prevention materials from DC k to community m
$\tilde{T}_{kl}$	Transportation cost of epidemic prevention materials from DC k to hospital l
$\tilde{T}_{kv}$	Transportation cost of epidemic prevention materials from DC k to VCU v
$\tilde{T}_{vm}$	Transportation cost of epidemic prevention materials from VCU v to community m
$\tilde{T}_{ml}$	Transportation cost of patients s from community m to hospital l
$\tilde{F}_k$	Fixed cost of opening DC k
$\tilde{F}_v$	Fixed cost of opening VCU v
$\tilde{\sigma}_k$	Operating cost at DC k
$\tilde{\sigma}_p$	Operating cost at primary supplier p
$\tilde{\sigma}_i$	Operating cost at backup supplier i
d_{pk}	Distance between primary supplier p and DC k
d_{ik}	Distance between backup supplier i and DC k
d_{kl}	Distance between DC k and hospital l
d_{kv}	Distance between DC k and VCU v
d_{km}	Distance between DC k and vector community m
d_{vm}	Distance between VCU v and community m
d_{ml}	Distance between community m and hospital l
$\tilde{\gamma}_1$	Penalty cost for the criticality of DC k
$\tilde{\gamma}_2$	Penalty cost for the criticality of primary supplier p and backup supplier i
W_{ql}	Weight of epidemic prevention materials at hospital l
W_{qv}	Weight of epidemic prevention materials at VCU v
W_{qm}	Weight of epidemic prevention materials at community m
W_s	Importance weight of patient s
$\tilde{S}P_p$	Supply capacity of primary supplier p for all materials
$\tilde{S}B_i$	Supply capacity of backup supplier i for all materials
$\tilde{S}D_k$	Distribution capacity of DC k for all materials
$\tilde{M}_{sl}$	Maximum capacity of hospital l for patients

$\widetilde{S}_v$	Maximum processing capacity of VCU v (e.g., for disinfection and insecticide deployment)
R_0	Target service level for materials in the healthcare supply chain
R_1	Target service level for patients in the healthcare supply chain
L_q	Importance coefficient of material q responsiveness
L_s	Importance coefficient of patient s responsiveness
$U1_p$	Predefined threshold for the criticality of primary supplier p
$U2_i$	Predefined threshold for the criticality of backup supplier i
$U3_k$	Predefined threshold for the criticality of DC k

Decision variables

P_p	1 if primary supplier p is selected; 0 otherwise
B_i	1 if backup supplier i is selected; 0 otherwise
V_v	1 if VCU v is established; 0 otherwise
D_k	1 if DC k is established; 0 otherwise
ND_k	1 if DC k is a critical node; 0 otherwise
NP_p	1 if primary supplier p is a critical node; 0 otherwise
NB_i	1 if backup supplier i is a critical node; 0 otherwise
Y_{vm}	1 if VCU v serves community m ; 0 otherwise
Q_{qpk}	Quantity of material q transported from primary supplier p to DC k
Q_{qik}	Quantity of material q transported from backup supplier i to DC k
Q_{qkl}	Quantity of material q transported from DC k to hospital l
Q_{qkv}	Quantity of vector control material q transported from DC k to VCU v
Q_{qkm}	Quantity of material q transported from DC k to community m
Q_{qvm}	Quantity of vector control material q transported from VCU v to community m
Q_{sml}	Quantity of patients s transported from community m to hospital l
η_q^0	Response deviation of the material satisfaction level for material q
η_s^1	Response deviation of the patient satisfaction level for patient s
α_q	Responsiveness level of materials
α_s	Responsiveness level of patients

3.4. Objectives

The proposed healthcare supply chain network design problem is formulated as a multiobjective mixed-integer linear programming (MILP) model with three objectives representing economic efficiency, supply chain resilience, and supply chain responsiveness, respectively.

The first objective minimizes the total operational cost of the healthcare supply chain, including transportation costs, operating costs, and facility establishment costs across all network echelons.

$$\begin{aligned}
\min F1 = & \sum_{p=1}^P \sum_{k=1}^K \sum_{q=1}^Q Q_{qpk} \cdot (\tilde{T}_{pk} \cdot d_{pk} + \tilde{\sigma}_p) + \sum_{i=1}^I \sum_{k=1}^K \sum_{q=1}^Q Q_{qik} \cdot (\tilde{T}_{ik} \cdot d_{ik} + \tilde{\sigma}_i) \\
& + \sum_{k=1}^K \sum_{m=1}^M \sum_{q=1}^Q Q_{qkm} \cdot (\tilde{T}_{km} \cdot d_{km} + \tilde{\sigma}_k) + \sum_{k=1}^K \sum_{v=1}^V \sum_{q=1}^Q Q_{qkv} \cdot (\tilde{T}_{kv} \cdot d_{kv} + \tilde{\sigma}_k) \\
& + \sum_{k=1}^K \sum_{l=1}^L \sum_{q=1}^Q Q_{qkl} \cdot (\tilde{T}_{kl} \cdot d_{kl} + \tilde{\sigma}_k) + \sum_{v=1}^V \sum_{m=1}^M \sum_{q=1}^Q \tilde{T}_{vm} \cdot d_{vm} \cdot Q_{qvm} \\
& + \sum_{m=1}^M \sum_{l=1}^L \sum_{s=1}^S \tilde{T}_{ml} \cdot d_{ml} \cdot Q_{sml} + \sum_{k=1}^K \tilde{F}_k \cdot D_k + \sum_{v=1}^V \tilde{F}_v \cdot V_v
\end{aligned} \tag{3.1}$$

Specifically, the terms in F1 account for (i) transportation and operating costs from primary suppliers p and backup suppliers i to distribution centers k ; (ii) transportation and operating costs from distribution centers k to communities m , VCUs v , and hospitals l ; (iii) vector control material transfer costs from VCUs v to communities m and patient transfer costs from communities m to hospitals l ; and (iv) fixed costs for opening distribution centers and VCUs.

The second objective minimizes the penalty associated with critical facilities in the healthcare supply chain network.

$$\min F2 = \sum_{k=1}^K \tilde{\gamma}_1 \cdot ND_k + \sum_{p=1}^P \tilde{\gamma}_2 \cdot NP_p + \sum_{i=1}^I \tilde{\gamma}_2 \cdot NB_i \tag{3.2}$$

where $\tilde{\gamma}_1$ and $\tilde{\gamma}_2$ are fuzzy penalty costs associated with critical distribution centers and critical suppliers, respectively. A node is classified as critical when its total throughput exceeds a predefined threshold, indicating that the network is heavily reliant on that facility. By minimizing this objective, the model discourages over concentration of material flows through any single node, thereby reducing the vulnerability of the supply chain to localized disruptions and strengthening overall resilience.

The third objective minimizes the weighted response deviation associated with both epidemic prevention materials and patient transportation.

$$\min F3 = \sum_{q=1}^Q \left(\sum_{l=1}^L W_{ql} + \sum_{v=1}^V W_{qv} + \sum_{m=1}^M W_{qm} \right) \cdot \eta_q^0 + \sum_{s=1}^S (W_s \cdot \eta_s^1) \tag{3.3}$$

A larger weight assigned to a material or patient type amplifies the penalty associated with its response deviation, ensuring that high-priority demands receive greater attention during resource allocation. By minimizing F3, the model drives the supply chain to respond rapidly and accurately to fluctuating demand, thereby enhancing overall responsiveness.

3.5. Constraints

For clarity, the constraints of the proposed model are classified into five groups: (i) Activation, capacity, and flow-balance constraints; (ii) critical-node identification constraints; (iii) material-responsiveness and service-level constraints; (iv) patient-flow and patient-responsiveness constraints; and (v) variable-domain constraints.

Activation, capacity, and flow-balance constraints. Constraints (3.4) and (3.5) state that for each primary and backup supplier, the total quantity of material shipped to all distribution centers must not exceed the available supply capacity of that supplier.

$$\sum_{q=1}^Q \sum_{k=1}^K Q_{qpk} \leq \widetilde{S}P_p \cdot P_p, \quad \forall p \in \bar{P} \quad (3.4)$$

$$\sum_{q=1}^Q \sum_{k=1}^K Q_{qik} \leq \widetilde{S}B_i \cdot B_i, \quad \forall i \in \bar{I} \quad (3.5)$$

Constraint (3.6) ensures that the total quantity of materials shipped by each distribution center to hospitals, VCUs, and communities does not exceed its throughput capacity.

$$\sum_{q=1}^Q \left(\sum_{l=1}^L Q_{qkl} + \sum_{v=1}^V Q_{qkv} + \sum_{m=1}^M Q_{qkm} \right) \leq \widetilde{S}D_k \cdot D_k, \quad \forall k \in \bar{K} \quad (3.6)$$

Constraint (3.7) ensures material flow balance at each distribution center k for each material type q . The total inflow from primary and backup suppliers must equal the total outflow to VCUs, hospitals, and communities.

$$\sum_{p=1}^P Q_{qpk} + \sum_{i=1}^I Q_{qik} = \sum_{m=1}^M Q_{qkm} + \sum_{l=1}^L Q_{qkl} + \sum_{v=1}^V Q_{qkv}, \quad \forall q \in \bar{Q}, \forall k \in \bar{K} \quad (3.7)$$

Constraint (3.8) ensures that each community is covered by at least one VCU. Constraint (3.9) restricts the number of VCUs serving a given community to not exceed the total number of established units. Constraint (3.10) limits the total material inflow of each VCU by its processing capacity. Constraint (3.11) links community assignment decisions with vector control material flows, ensuring that vector control materials can be transported from VCU v to community m only when community m is assigned to that unit. This big- $\mathcal{M}$ constraint prevents material flows between unassigned VCU–community pairs. Constraint (3.12) enforces flow balance at each VCU, where the inflow from distribution centers equals the outflow to communities.

$$\sum_{v=1}^V Y_{vm} \geq 1, \quad \forall m \in \bar{M} \quad (3.8)$$

$$Y_{vm} \leq V_v, \quad \forall v \in \bar{V}, \forall m \in \bar{M} \quad (3.9)$$

$$\sum_{q=1}^Q \sum_{k=1}^K Q_{qkv} \leq \widetilde{S}_v \cdot V_v, \quad \forall v \in \bar{V} \quad (3.10)$$

$$Q_{qvm} \leq MY_{vm}, \quad \forall q \in \bar{Q}, \forall v \in \bar{V}, \forall m \in \bar{M} \quad (3.11)$$

$$\sum_{k=1}^K Q_{qkv} = \sum_{m=1}^M Q_{qvm}, \quad \forall v \in \bar{V}, \forall q \in \bar{Q} \quad (3.12)$$

Critical-node identification constraints. Constraints (3.13) and (3.14) determine whether primary supplier p is a critical node. Similarly, Constraints (3.15)–(3.18) determine whether backup suppliers and distribution centers are critical nodes. For distribution centers, a node's workload is defined as the total handled material volume, including both inbound and outbound flows. Therefore, both inflows and outflows are included when evaluating node criticality. The big- $\mathcal{M}$ value in constraints (3.13), (3.15), and (3.17) is set to be equal to the total system supply capacity, i.e., $\mathcal{M} = \sum_p S P_p^4 + \sum_i S B_i^4$, evaluated at the upper bound of each trapezoidal distribution. This choice ensures that the logical forcing constraints remain valid for all feasible flow values while avoiding artificially loose linear relaxation bounds.

$$\sum_{q=1}^Q \sum_{k=1}^K Q_{qpk} \leq \mathcal{M} \cdot NP_p + U1_p, \quad \forall p \in \bar{P} \quad (3.13)$$

$$\sum_{q=1}^Q \sum_{k=1}^K Q_{qpk} \geq U1_p \cdot NP_p, \quad \forall p \in \bar{P} \quad (3.14)$$

$$\sum_{q=1}^Q \sum_{k=1}^K Q_{qik} \leq \mathcal{M} \cdot NB_i + U2_i, \quad \forall i \in \bar{I} \quad (3.15)$$

$$\sum_{q=1}^Q \sum_{k=1}^K Q_{qik} \geq U2_i \cdot NB_i, \quad \forall i \in \bar{I} \quad (3.16)$$

$$\sum_{q=1}^Q \left(\sum_{i=1}^I Q_{qik} + \sum_{p=1}^P Q_{qpk} + \sum_{l=1}^L Q_{qkl} + \sum_{v=1}^V Q_{qkv} + \sum_{m=1}^M Q_{qkm} \right) \leq \mathcal{M} \cdot ND_k + U3_k, \quad \forall k \in \bar{K} \quad (3.17)$$

$$\sum_{q=1}^Q \left(\sum_{i=1}^I Q_{qik} + \sum_{p=1}^P Q_{qpk} + \sum_{l=1}^L Q_{qkl} + \sum_{v=1}^V Q_{qkv} + \sum_{m=1}^M Q_{qkm} \right) \geq U3_k \cdot ND_k, \quad \forall k \in \bar{K} \quad (3.18)$$

Material-responsiveness and service-level constraints. Constraints (3.19)–(3.22) define the proportional material responsiveness indices across all key demand nodes in the network. Specifically, (3.19) and (3.20) require that the ratio of allocated material volumes to the corresponding fuzzy demands must be at least α_q for hospitals and VCUs, while (3.21) and (3.22) impose analogous fulfillment rate requirements for communities and the final vector control deployment stage. These constraints ensure that the model prioritizes an efficient matching between supply and demand under scarcity. Constraint (3.23), on the other hand, establishes the quality of service guarantee. It links the achieved responsiveness level α_q , the importance coefficient L_q , and the response deviation η_q^0 to ensure that their aggregated performance strictly complies with the target service level R_0 . This coupling mechanism effectively balances the system's ability to meet demand with the reliability of its operations under uncertainty.

$$\alpha_q \leq \frac{\sum_{k=1}^K Q_{qkl}}{\bar{D}_{ql}}, \quad \forall q \in \bar{Q}^M, \forall l \in \bar{L} \quad (3.19)$$

$$\alpha_q \leq \frac{\sum_{k=1}^K Q_{qkv}}{\bar{D}_{qv}}, \quad \forall q \in \bar{Q}^V, \forall v \in \bar{V} \quad (3.20)$$

$$\alpha_q \leq \frac{\sum_{k=1}^K Q_{qkm}}{\bar{D}_{qm}}, \quad \forall q \in \bar{Q}^M, \forall m \in \bar{M} \quad (3.21)$$

$$\alpha_q \leq \frac{\sum_{v=1}^V Q_{qvm}}{\bar{D}_{qm}^{VC}}, \quad \forall q \in \bar{Q}^V, \forall m \in \bar{M} \quad (3.22)$$

$$L_q \cdot \alpha_q + \eta_q^0 \geq R_0, \quad \forall q \in \bar{Q} \quad (3.23)$$

Patient-flow and patient-responsiveness constraints. Constraint (3.24) ensures that the total number of patients transported from each community does not exceed the corresponding patient demand, thereby preventing unnecessary patient transfers. Constraint (3.25) limits the total number of patients assigned to each hospital by its treatment capacity, preventing hospital overloading during the epidemic response. Constraint (3.26) defines the patient responsiveness level as the ratio between transported patients and community-level patient demand. Constraint (3.27) ensures that the overall patient service level, together with the response deviation variable η_1 , satisfies the prescribed service target. The deviation variable η_1 provides flexibility in evaluating the overall patient responsiveness by measuring the deviation from the target service level. Together, these constraints regulate patient allocation, hospital capacity utilization, and patient responsiveness within the proposed healthcare supply chain network. If $\sum_l Q_{sml} = 0$, Constraint (3.26) implies $\alpha_s = 0$, and Constraint (3.27) therefore requires $\eta_s^1 \geq R_1$. Since η_s^1 is positively weighted in OF_3 , zero patient flow necessarily incurs a positive responsiveness penalty.

$$\sum_{l=1}^L Q_{sml} \leq \bar{D}_{sm}, \quad \forall s \in \bar{S}, \forall m \in \bar{M} \quad (3.24)$$

$$\sum_{m=1}^M Q_{sml} \leq \bar{M}_{sl}, \quad \forall s \in \bar{S}, \forall l \in \bar{L} \quad (3.25)$$

$$\alpha_s \leq \frac{\sum_{l=1}^L Q_{sml}}{\bar{D}_{sm}}, \quad \forall s \in \bar{S}, \forall m \in \bar{M} \quad (3.26)$$

$$L_s \alpha_s + \eta_s^1 \geq R_1, \quad \forall s \in \bar{S} \quad (3.27)$$

Variable domain constraints. Constraints (3.28)–(3.30) specify the domains of the continuous and binary decision variables. All material flow variables, patient flow variables, and responsiveness variables are non-negative. The facility selection, facility activation, critical node, and community–VCU assignment variables are binary.

$$Q_{qpk}, Q_{qik}, Q_{qkl}, Q_{qkv}, Q_{qkm}, Q_{qvm}, Q_{sml}, \eta_q^0, \eta_s^1 \geq 0 \quad (3.28)$$

$$\alpha_q, \alpha_s \in [0, 1] \quad (3.29)$$

$$P_p, B_i, V_v, D_k, ND_k, NP_p, NB_i, Y_{vm} \in \{0, 1\} \quad (3.30)$$

3.6. Robust possibilistic programming transformation

The proposed healthcare supply chain optimization model is subject to considerable uncertainty arising from epidemic-related demand, transportation costs, operating costs, and facility capacities. In healthcare supply chain optimization, uncertainty has traditionally been addressed using stochastic programming, robust optimization, and possibilistic programming. Stochastic programming [47] generally relies on reliable probability distributions or representative scenario sets, which are difficult to obtain during emerging infectious disease outbreaks. Classical robust optimization [48] provides protection against worst-case realizations but may result in overly conservative decisions. Consequently, this study adopts the established RPP approach proposed by Pishvae et al. [12], which simultaneously considers the expected system performance, the solution's robustness, and feasibility robustness under fuzzy uncertainty.

It should be emphasized that the contribution of this study lies in the development of the integrated healthcare supply chain network design model rather than in the RPP methodology itself. In the proposed framework, RPP serves as the uncertainty-handling technique that transforms the uncertain optimization model into an equivalent deterministic formulation while preserving robustness under epidemic-related uncertainty.

To represent uncertain parameters, trapezoidal fuzzy numbers are adopted throughout the model. Specifically, transportation costs ($\tilde{T}$), operating costs ($\tilde{\sigma}$), facility establishment costs ($\tilde{F}$), material demand ($\tilde{D}$), facility capacities ($\tilde{SP}$, $\tilde{SB}$, $\tilde{SD}$, $\tilde{SV}$, $\tilde{M}$), and resilience penalty coefficients ($\tilde{\gamma}$) are represented by trapezoidal fuzzy numbers of the form

$$\tilde{\xi} = (\xi_{(1)}, \xi_{(2)}, \xi_{(3)}, \xi_{(4)})$$

as illustrated in Figure 2. Following Heilpern [49], the expected value of a trapezoidal fuzzy number is calculated as

$$E[\tilde{\xi}] = \frac{\xi_{(1)} + \xi_{(2)} + \xi_{(3)} + \xi_{(4)}}{4} \quad (3.31)$$

Applying the RPP transformation to the proposed multiobjective healthcare supply chain optimization model yields the following deterministic formulation (Model 1).

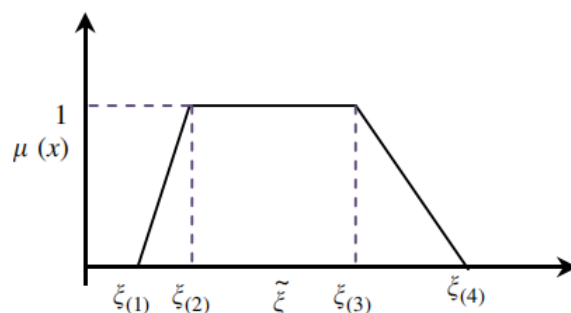


Figure 2. Trapezoidal fuzzy number.

Model 1

$$\min \text{OF}_1 = \text{OF}_{11} + \text{OF}_{12} \quad (3.32)$$

where

$$\begin{aligned} \text{OF}_{11} = & \sum_{p=1}^P \sum_{k=1}^K \sum_{q=1}^Q Q_{qpk} \times (E[T_{pk}] \cdot d_{pk} + E[\sigma_p]) + \sum_{i=1}^I \sum_{k=1}^K \sum_{q=1}^Q Q_{qik} \times (E[T_{ik}] \cdot d_{ik} + E[\sigma_i]) \\ & + \sum_{k=1}^K \sum_{m=1}^M \sum_{q=1}^Q Q_{qkm} \times (E[T_{km}] \cdot d_{km} + E[\sigma_k]) + \sum_{k=1}^K \sum_{v=1}^V \sum_{q=1}^Q Q_{qkv} \times (E[T_{kv}] \cdot d_{kv} + E[\sigma_k]) \\ & + \sum_{k=1}^K \sum_{l=1}^L \sum_{q=1}^Q Q_{qkl} \times (E[T_{kl}] \cdot d_{kl} + E[\sigma_k]) + \sum_{v=1}^V \sum_{m=1}^M \sum_{q=1}^Q (E[T_{vm}] \cdot d_{vm} \cdot Q_{qvm}) \\ & + \sum_{m=1}^M \sum_{l=1}^L \sum_{s=1}^S (E[T_{ml}] \cdot d_{ml} \cdot Q_{sml}) + \sum_{k=1}^K (E[F_k] \cdot D_k) + \sum_{v=1}^V (E[F_v] \cdot V_v) \end{aligned} \quad (3.33)$$

and

$$\begin{aligned} \text{OF}_{12} = & \Theta \left[\left(\sum_{p=1}^P \sum_{k=1}^K \sum_{q=1}^Q Q_{qpk} (T_{pk}^4 d_{pk} + \sigma_p^4) + \sum_{i=1}^I \sum_{k=1}^K \sum_{q=1}^Q Q_{qik} (T_{ik}^4 d_{ik} + \sigma_i^4) + \sum_{k=1}^K \sum_{m=1}^M \sum_{q=1}^Q Q_{qkm} (T_{km}^4 d_{km} + \sigma_k^4) \right. \right. \\ & + \sum_{k=1}^K \sum_{v=1}^V \sum_{q=1}^Q Q_{qkv} (T_{kv}^4 d_{kv} + \sigma_k^4) + \sum_{k=1}^K \sum_{l=1}^L \sum_{q=1}^Q Q_{qkl} (T_{kl}^4 d_{kl} + \sigma_k^4) + \sum_{v=1}^V \sum_{m=1}^M \sum_{q=1}^Q T_{vm}^4 d_{vm} Q_{qvm} \\ & + \sum_{m=1}^M \sum_{l=1}^L \sum_{s=1}^S T_{ml}^4 d_{ml} Q_{sml} + \sum_{k=1}^K F_k^4 D_k + \sum_{v=1}^V F_v^4 V_v \Big) \\ & - \left(\sum_{p=1}^P \sum_{k=1}^K \sum_{q=1}^Q Q_{qpk} (T_{pk}^1 d_{pk} + \sigma_p^1) + \sum_{i=1}^I \sum_{k=1}^K \sum_{q=1}^Q Q_{qik} (T_{ik}^1 d_{ik} + \sigma_i^1) + \sum_{k=1}^K \sum_{m=1}^M \sum_{q=1}^Q Q_{qkm} (T_{km}^1 d_{km} + \sigma_k^1) \right. \\ & + \sum_{k=1}^K \sum_{v=1}^V \sum_{q=1}^Q Q_{qkv} (T_{kv}^1 d_{kv} + \sigma_k^1) + \sum_{k=1}^K \sum_{l=1}^L \sum_{q=1}^Q Q_{qkl} (T_{kl}^1 d_{kl} + \sigma_k^1) + \sum_{v=1}^V \sum_{m=1}^M \sum_{q=1}^Q T_{vm}^1 d_{vm} Q_{qvm} \Big) \end{aligned}$$

$$\begin{aligned}
& + \sum_{m=1}^M \sum_{l=1}^L \sum_{s=1}^S T_{ml}^1 d_{ml} Q_{sml} + \sum_{k=1}^K F_k^1 D_k + \sum_{v=1}^V F_v^1 V_v \Bigg] \\
& + \delta_1 \sum_{q \in \bar{Q}^M} \sum_{l=1}^L \left[D_{ql}^4 - (1 - \beta) D_{ql}^3 - \beta D_{ql}^4 \right] + \delta_2 \sum_{q \in \bar{Q}^V} \sum_{v=1}^V \left[D_{qv}^4 - (1 - \beta) D_{qv}^3 - \beta D_{qv}^4 \right] \\
& + \delta_3 \sum_{q \in \bar{Q}^M} \sum_{m=1}^M \left[D_{qm}^4 - (1 - \beta) D_{qm}^3 - \beta D_{qm}^4 \right] + \delta_4 \sum_{q \in \bar{Q}^V} \sum_{m=1}^M \left[(D_{qm}^{VC})^4 - (1 - \beta) (D_{qm}^{VC})^3 - \beta (D_{qm}^{VC})^4 \right] \\
& + \delta_5 \sum_{s=1}^S \sum_{m=1}^M \left[D_{sm}^4 - (1 - \beta) D_{sm}^3 - \beta D_{sm}^4 \right] + \pi_1 \sum_{p=1}^P \left[\alpha S P_p^1 + (1 - \alpha) S P_p^2 - S P_p^1 \right] P_p \\
& + \pi_2 \sum_{i=1}^I \left[\alpha S B_i^1 + (1 - \alpha) S B_i^2 - S B_i^1 \right] B_i + \pi_3 \sum_{v=1}^V \left[\alpha S V_v^1 + (1 - \alpha) S V_v^2 - S V_v^1 \right] V_v \\
& + \pi_4 \sum_{k=1}^K \left[\alpha S D_k^1 + (1 - \alpha) S D_k^2 - S D_k^1 \right] D_k + \pi_5 \sum_{m=1}^M \sum_{s=1}^S \left[\alpha D_{sm}^1 + (1 - \alpha) D_{sm}^2 - D_{sm}^1 \right] \\
& + \pi_6 \sum_{s=1}^S \sum_{l=1}^L \left[\alpha M_{sl}^1 + (1 - \alpha) M_{sl}^2 - M_{sl}^1 \right] \tag{3.34}
\end{aligned}$$

$$\min \text{OF}_2 = \left(\frac{\gamma_1^1 + \gamma_1^2 + \gamma_1^3 + \gamma_1^4}{4} \right) \sum_{k=1}^K N D_k + \left(\frac{\gamma_2^1 + \gamma_2^2 + \gamma_2^3 + \gamma_2^4}{4} \right) \left(\sum_{p=1}^P N P_p + \sum_{i=1}^I N B_i \right) \tag{3.35}$$

$$\min \text{OF}_3 = \sum_{q=1}^Q \left(\sum_{l=1}^L W_{ql} + \sum_{v=1}^V W_{qv} + \sum_{m=1}^M W_{qm} \right) \cdot \eta_q^0 + \sum_{s=1}^S (W_s \cdot \eta_s^1) \tag{3.36}$$

subject to (3.7)–(3.9), (3.11)–(3.18), (3.23), (3.27)

$$\sum_{q=1}^Q \sum_{k=1}^K Q_{qpk} \leq \left[(1 - \alpha) \cdot \text{SP}_p^2 + \alpha \cdot \text{SP}_p^1 \right] \cdot P_p, \quad \forall p \in \bar{P} \tag{3.37}$$

$$\sum_{q=1}^Q \sum_{k=1}^K Q_{qik} \leq \left[(1 - \alpha) \cdot \text{SB}_i^2 + \alpha \cdot \text{SB}_i^1 \right] \cdot B_i, \quad \forall i \in \bar{I} \tag{3.38}$$

$$\sum_{q=1}^Q \sum_{k=1}^K Q_{qkv} \leq \left[(1 - \alpha) \cdot \text{S}_v^2 + \alpha \cdot \text{S}_v^1 \right] \cdot V_v, \quad \forall v \in \bar{V} \tag{3.39}$$

$$\sum_{q=1}^Q \left(\sum_{l=1}^L Q_{qkl} + \sum_{v=1}^V Q_{qkv} + \sum_{m=1}^M Q_{qkm} \right) \leq \left[(1 - \alpha) \cdot \text{SD}_k^2 + \alpha \cdot \text{SD}_k^1 \right] \cdot D_k, \quad \forall k \in \bar{K} \tag{3.40}$$

$$\sum_{l=1}^L Q_{sml} \leq \left[(1 - \alpha) \cdot \text{D}_{sm}^2 + \alpha \cdot \text{D}_{sm}^1 \right], \quad \forall s \in \bar{S}, \forall m \in \bar{M} \tag{3.41}$$

$$\sum_{m=1}^M Q_{sml} \leq \left[(1 - \alpha) \cdot M_{sl}^2 + \alpha \cdot M_{sl}^1 \right], \quad \forall s \in \bar{S}, \forall l \in \bar{L} \quad (3.42)$$

$$\alpha_q \leq \frac{\sum_{k=1}^K Q_{qkl}}{(1 - \beta) \cdot D_{ql}^3 + \beta \cdot D_{ql}^4} \quad \forall q \in \bar{Q}^M, \forall l \in \bar{L} \quad (3.43)$$

$$\alpha_q \leq \frac{\sum_{k=1}^K Q_{qkv}}{(1 - \beta) \cdot D_{qv}^3 + \beta \cdot D_{qv}^4} \quad \forall q \in \bar{Q}^V, \forall v \in \bar{V} \quad (3.44)$$

$$\alpha_q \leq \frac{\sum_{k=1}^K Q_{qkm}}{(1 - \beta) \cdot D_{qm}^3 + \beta \cdot D_{qm}^4} \quad \forall q \in \bar{Q}^M, \forall m \in \bar{M} \quad (3.45)$$

$$\alpha_q \leq \frac{\sum_{v=1}^V Q_{qvm}}{(1 - \beta) \cdot (D_{qm}^{VC})^3 + \beta \cdot (D_{qm}^{VC})^4} \quad \forall q \in \bar{Q}^V, \forall m \in \bar{M} \quad (3.46)$$

$$\alpha_s \leq \frac{\sum_{l=1}^L Q_{sml}}{(1 - \beta) \cdot D_{sm}^3 + \beta \cdot D_{sm}^4} \quad \forall s \in \bar{S}, \forall m \in \bar{M} \quad (3.47)$$

$$Q_{qpk}, Q_{qik}, Q_{qkl}, Q_{qkv}, Q_{qkm}, Q_{qvm}, Q_{sml}, \eta_q^0, \eta_s^1 \geq 0 \quad (3.48)$$

$$P_p, B_i, V_v, D_k, ND_k, NP_p, NB_i, Y_{vm} \in \{0, 1\} \quad (3.49)$$

$$\alpha, \beta \in (0, 1] \quad (3.50)$$

$$\alpha_q, \alpha_s \in [0, 1] \quad (3.51)$$

In Model 1, only the first objective contains both optimality and feasibility robustness terms because the uncertainty directly affects the cost coefficients and fuzzy constraints, whereas the other two objectives are transformed using their expected values. Therefore, the deterministic optimization problem remains tri-objective. OF_{12} is an additive robustness term that combines the optimality robustness deviation with the feasibility robustness penalties and is incorporated into the first objective function. The coefficients δ_1 , δ_2 , δ_3 , and δ_4 weight the feasibility robustness penalties for the fuzzy material demand constraints at hospitals, VCUs, communities, and community vector control operations, respectively, while δ_5 weights the penalty for the fuzzy patient demand denominator in the patient responsiveness constraint. Similarly, the coefficients π_1 , π_2 , π_3 , and π_4 weight the feasibility robustness penalties associated with the capacity constraints of primary suppliers, backup suppliers, VCUs, and distribution centers, respectively, while π_5 and π_6 correspond to the feasibility robustness penalties associated with communities' patient demand and hospital treatment capacity. These coefficients scale the contribution of different sources of feasibility uncertainty to OF_{12} . The terms associated with facility activation variables may affect the selected network configuration, whereas the demand and treatment-capacity related terms primarily quantify the robustness cost at fixed confidence levels.

3.7. Augmented ε -constraint method for Pareto frontier generation

To solve the tri-objective deterministic model obtained after the RPP transformation, the AEC method is used [50, 51]. Unlike the conventional ε -constraint method, the AEC method introduces normalized slack variables into the constrained objectives, thereby eliminating weakly Pareto-optimal solutions while preserving the original Pareto structure.

The objective functions OF_1 , OF_2 , and OF_3 considered in this section denote the deterministic

objectives obtained after the RPP transformation presented in Section 3.6. Accordingly, the proposed healthcare supply chain optimization remains a tri-objective problem throughout the solution procedure.

Let $\mathcal{X}$ denote the feasible region of Model 1. The AEC procedure consists of four stages.

3.7.1. Construction of the lexicographic payoff table

For each objective OF_j , a lexicographic optimization problem is solved by assigning OF_j the highest priority and using the remaining objectives as successive tie-breakers. The corresponding representative solution is obtained as follows:

$$x^{j,*} = \operatorname{lexmin}_{x \in \mathcal{X}} (OF_{\pi_{j,1}}(x), OF_{\pi_{j,2}}(x), OF_{\pi_{j,3}}(x)) \quad (3.52)$$

where the priority orders are $\pi_1 = (1, 2, 3)$, $\pi_2 = (2, 3, 1)$, $\pi_3 = (3, 1, 2)$.

The optimization is implemented sequentially using a lexicographic objective-fixing tolerance τ_{lex} . In this study, $\tau_{\text{lex}} = 10^{-6}$. Specifically, if the optimal value of a previously optimized higher-priority objective OF_h is z_h^* , then the subsequent lexicographic optimization stage imposes

$$OF_h(x) \leq z_h^* + \tau_{\text{lex}} \max \{1, |z_h^*|\} \quad (3.53)$$

This relative tolerance prevents numerical inaccuracies from making the subsequent lexicographic stage infeasible while ensuring that the previously optimized objective remains fixed at its optimal value up to the prescribed numerical tolerance.

The i -th objective evaluated at the lexicographic solution associated with the j -th primary objective is recorded as

$$\text{PayOff}_{ij} = OF_i(x^{j,*}), \quad i, j = 1, 2, 3 \quad (3.54)$$

Therefore, the complete payoff matrix is written as

$$\mathbf{P} = \begin{pmatrix} \text{PayOff}_{11} & \text{PayOff}_{12} & \text{PayOff}_{13} \\ \text{PayOff}_{21} & \text{PayOff}_{22} & \text{PayOff}_{23} \\ \text{PayOff}_{31} & \text{PayOff}_{32} & \text{PayOff}_{33} \end{pmatrix} \quad (3.55)$$

The diagonal elements correspond to the ideal values, whereas the off-diagonal elements quantify the trade-offs among objectives.

For each objective OF_i , the ideal value, payoff-based nadir estimate, and objective range are calculated as follows:

$$OF_i^I = \min_{j=1,2,3} \{\text{PayOff}_{ij}\} = \text{PayOff}_{ii} \quad (3.56)$$

$$OF_i^N = \max_{j=1,2,3} \{\text{PayOff}_{ij}\} \quad (3.57)$$

$$R(OF_i) = OF_i^N - OF_i^I \quad (3.58)$$

for $i = 1, 2, 3$. The payoff matrix is subsequently used to estimate the ideal and payoff-based nadir values of each objective. Their ranges are used to generate the ε grids and normalize objectives with different numerical scales.

3.7.2. Generation of the ε grids

In the proposed model, OF_1 is retained as the robust primary objective, whereas OF_2 and OF_3 are transformed into ε -bounded constraints. Their admissible intervals are

$$\varepsilon_i \in [OF_i^I, OF_i^N], \quad i = 2, 3 \quad (3.59)$$

Let N_i denote the number of grid points specified for the objective OF_i . For each constrained objective participating in the ε -grid generation, at least two grid points are required, i.e.

$$N_2 \geq 2, \quad N_3 \geq 2$$

For the nondegenerate case considered in the AEC formulation, the constrained objective ranges satisfy

$$R(OF_2) > 0, \quad R(OF_3) > 0$$

The corresponding grid values are generated by

$$\varepsilon_i^{(k)} = OF_i^N - \frac{k-1}{N_i-1} R(OF_i), \quad k = 1, \dots, N_i, \quad i = 2, 3 \quad (3.60)$$

If $R(OF_i) = 0$ for any $i \in \{2, 3\}$, then $OF_i^I = OF_i^N$ and that objective is excluded from the ε -grid generation and slack normalization. Its ε value is fixed at $\varepsilon_i = OF_i^I$, and no normalization coefficient φ_i is calculated for that objective.

Equation (3.60) generates the grid from the payoff-based nadir value to the ideal value. Larger values of N_i provide a denser approximation of the Pareto frontier at the expense of additional computational effort. For the two constrained objectives considered in this study, at most $N_2 N_3$ AEC subproblems must be examined.

3.7.3. Formulation of the AEC subproblem

For every grid pair $(\varepsilon_2^{(k)}, \varepsilon_3^{(\ell)})$, where $k = 1, \dots, N_2$ and $\ell = 1, \dots, N_3$, the following single-objective MILP is solved:

$$\min_{x, s_2, s_3} \quad OF_1(x) - \rho_{AEC} (\varphi_2 s_2 + \varphi_3 s_3) \quad (3.61)$$

$$\text{subject to} \quad OF_2(x) + s_2 = \varepsilon_2^{(k)} \quad (3.62)$$

$$OF_3(x) + s_3 = \varepsilon_3^{(\ell)} \quad (3.63)$$

$$x \in \mathcal{X} \quad (3.64)$$

$$s_2, s_3 \geq 0 \quad (3.65)$$

The normalization coefficients φ_i defined in Eq (3.66) scale the normalized slack variables according to the numerical range of each constrained objective. The parameter ρ_{AEC} is a sufficiently small positive augmentation coefficient and is set to 10^{-6} in the computational experiments. Since $0 \leq s_i \leq R(OF_i)$ for $i = 2, 3$, the absolute value of the augmented term is bounded above by $2\rho_{AEC} R(OF_1)$, which is negligible compared with the primary objective scale $R(OF_1)$. Consequently, OF_1 retains the

highest optimization priority, while the augmented term becomes active only when several feasible solutions achieve the same or nearly identical primary objective value. In such cases, the augmented term favors larger slack values, which correspond to lower values of the constrained objectives, thereby eliminating weakly Pareto-optimal solutions. The selected value of ρ_{AEC} lies within the range commonly recommended for the augmented epsilon constraint (AUGMECON) method [51], and was retained throughout all Pareto frontier calculations.

$$\varphi_i = \frac{R(\text{OF}_1)}{R(\text{OF}_i)}, \quad i \in I^+, \quad I^+ = \{i \in \{2, 3\} : R(\text{OF}_i) > 0\} \quad (3.66)$$

$$\rho_{\text{AEC}} = 10^{-6} \quad (3.67)$$

3.7.4. Pareto solution generation and filtering

For each grid pair $(\varepsilon_2^{(k)}, \varepsilon_3^{(\ell)})$, the corresponding AEC subproblem is solved. If the subproblem is feasible, the associated decision vector together with its objective vector

$$(\text{OF}_1(x^{k\ell}), \text{OF}_2(x^{k\ell}), \text{OF}_3(x^{k\ell})) \quad (3.68)$$

is added to the candidate solution set $\mathcal{S}$.

Different ε combinations may converge to identical objective vectors because multiple grid pairs can lead to the same efficient solution. To ensure reproducible duplicate removal, a relative numerical tolerance $\tau_{\text{dup}} = 10^{-6}$ is used. Two objective vectors associated with the solutions x^a and x^b are regarded as duplicates if

$$\frac{|\text{OF}_i(x^a) - \text{OF}_i(x^b)|}{\max\{1, |\text{OF}_i(x^a)|, |\text{OF}_i(x^b)|\}} \leq \tau_{\text{dup}}, \quad \forall i \in \{1, 2, 3\} \quad (3.69)$$

Only one representative objective vector is retained from each group of duplicates before applying the Pareto dominance test.

For two feasible solutions x^a and x^b , solution x^a dominates solution x^b if

$$\text{OF}_i(x^a) \leq \text{OF}_i(x^b), \forall i \in \{1, 2, 3\}, \text{ and } \text{OF}_r(x^a) < \text{OF}_r(x^b) \text{ for at least one } r \quad (3.70)$$

All dominated solutions are discarded, and the remaining nondominated solutions constitute the final Pareto-optimal frontier. The complete computational procedure is summarized in Algorithm 1.

Algorithm 1 AEC algorithm for generating the Pareto-optimal frontier

Require: Feasible region $\mathcal{X}$; objective functions OF_1, OF_2, OF_3 ; grid sizes $N_2, N_3 \geq 2$; augmentation coefficient ρ_{AEC} ; lexicographic objective-fixing tolerance $\tau_{lex} = 10^{-6}$; duplicate removal tolerance $\tau_{dup} = 10^{-6}$.

Ensure: Pareto-optimal solution set $\mathcal{P}$.

```

1: Define the lexicographic priority orders  $\pi_1 = (1, 2, 3)$ ,  $\pi_2 = (2, 3, 1)$ ,  $\pi_3 = (3, 1, 2)$ .
2: for  $j = 1, 2, 3$  do
3:   Solve the corresponding lexicographic optimization problem according to priority order  $\pi_j$ .
4:   Sequentially optimize the objectives by fixing each previously optimized objective value
   according to Equation (3.53) with  $\tau_{lex} = 10^{-6}$ .
5:   Obtain the representative solution  $x^{j*}$ .
6:   for  $i = 1, 2, 3$  do
7:     Compute  $\text{PayOff}_{ij} \leftarrow OF_i(x^{j*})$ .
8:   end for
9: end for
10: for  $i = 1, 2, 3$  do
11:   Compute the ideal value  $OF_i^I$ , payoff-based nadir value  $OF_i^N$ , and objective range  $R(OF_i)$ .
12: end for
13: Generate the  $\varepsilon$ -grids  $\{\varepsilon_2^{(k)}\}_{k=1}^{N_2}$  and  $\{\varepsilon_3^{(\ell)}\}_{\ell=1}^{N_3}$  using Equation (3.60).
14: Compute the normalization coefficients  $\varphi_2$  and  $\varphi_3$  using Equation (3.66).
15: Set the augmentation coefficient  $\rho_{AEC} \leftarrow 10^{-6}$ .
16: Initialize the candidate solution set  $\mathcal{S} \leftarrow \emptyset$ .
17: for  $k = 1, \dots, N_2$  do
18:   for  $\ell = 1, \dots, N_3$  do
19:     Solve the augmented subproblem (3.61)–(3.65) using  $\varepsilon_2^{(k)}$ ,  $\varepsilon_3^{(\ell)}$ ,  $\varphi_2$ ,  $\varphi_3$ , and  $\rho_{AEC} = 10^{-6}$ .
20:     if a feasible solution is obtained then
21:       Store the objective vector together with the corresponding solution.
22:     end if
23:   end for
24: end for
25: Remove duplicate objective vectors from  $\mathcal{S}$  using the duplicate removal tolerance  $\tau_{dup} = 10^{-6}$ 
   according to Equation (3.69).
26: Remove dominated solutions using the Pareto dominance criterion defined in Equation (3.70).
27: Set the remaining nondominated solutions as  $\mathcal{P}$ .
28: Sort  $\mathcal{P}$  in ascending order of  $OF_1$  for Pareto-frontier presentation.
29: return  $\mathcal{P}$ .

```

4. Case study

Section 4 presents a real-world case study based on the 2025 Chikungunya fever outbreak in Shunde District, Foshan, China. Section 4.1 introduces the outbreak's background and explains the selection of the study area. Section 4.2 describes the data sources and parameter assignment. Section 4.3 reports the optimal facility location, material allocation, and patient transportation strategies. Section 4.4

analyzes the Pareto-optimal frontier generated by the AEC method. Sections 4.5 and 4.6 investigate the uncertainty sensitivity and elasticity sensitivity of the proposed model, respectively.

All computations were implemented in MATLAB R2022a using the CPLEX 12.10 interface on a computer equipped with an Intel(R) Core(TM) i5-1155G7 processor(2.50 GHz), 32 GB RAM, and Windows 11. To ensure that the augmentation term ρ_{AEC} was numerically resolvable by the solver, the relative MIP gap tolerance was set to 10^{-6} and the absolute mixed integer programming (MIP) gap tolerance was set to 10^{-4} . All other CPLEX parameters were left at their default values. The average computational time over the 10 scenarios was approximately 847 seconds (about 14 minutes per scenario) for the main optimization runs, while the AEC procedure required approximately 4 hours to generate the resulting approximation of the Pareto frontier over the specified ε -grid.

4.1. Description of the case study

To demonstrate the practical applicability of the proposed healthcare supply chain network design model, a real-world case study is conducted based on the 2025 Chikungunya fever outbreak in Shunde District, Foshan City, Guangdong Province, China. Shunde was selected because it represents the most severely affected region during the outbreak, accounting for more than 95% of all confirmed cases reported in Foshan. Moreover, the district contains densely populated communities, multiple levels of healthcare facilities, and geographically dispersed outbreak locations, making it a representative case for evaluating integrated healthcare resource allocation and vector control planning under epidemic conditions.

Unlike respiratory infectious diseases, Chikungunya fever requires not only medical treatment for infected patients but also continuous vector control operations to suppress mosquito-facilitated transmission. Consequently, the epidemic response relies on the coordinated distribution of medical supplies, vector control materials, and patient transportation resources. These operational characteristics are consistent with the structure of the proposed healthcare supply chain network and therefore provide a suitable validation scenario for the proposed optimization framework.

According to reports from the Foshan Health Commission and the Shunde District Health Bureau, the most critical materials required during the outbreak included personal protective equipment (PPE), diagnostic reagents, antipyretic and analgesic drugs, insecticides, disinfectants, mosquito nets, and mosquito surveillance equipment. To match the structure of the proposed optimization model, these materials are classified into four categories:

- q_1 : Personal protective equipment (masks, gloves, and protective clothing);
- q_2 : Clinical medical supplies (diagnostic reagents and antipyretic/analgesic drugs);
- q_3 : Vector control materials (insecticides and disinfectants);
- q_4 : Mosquito surveillance materials (mosquito traps, monitoring equipment, and mosquito nets).

This classification reflects the dual objectives of Chikungunya fever control: Providing timely medical treatment for infected patients while simultaneously reducing mosquito-based transmission through coordinated vector control operations.

4.2. Parameter value assignment

The parameter values used in this case study were obtained from multiple sources, including official statistical reports, healthcare administrative records, geographic information systems (GIS),

and expert consultation. To improve the reliability of the case study, demographic information, healthcare facilities' characteristics, and transportation distances were collected from publicly available government sources, while the fuzzy cost and capacity parameters were calibrated using historical epidemic response records together with expert judgement. Table 2 summarizes the 10 community demand nodes corresponding to the four subdistricts and six towns of Shunde District. Population statistics were obtained from the 2025 *Foshan Statistical Yearbook* and cross-validated using reports released by the Shunde District Health Bureau. These communities constitute the primary demand nodes of the healthcare supply chain network.

Table 2. Location and demographics of community demand points.

ID	Demand point (town/subdistrict)	Population
m1	Lecong Town	359,187
m2	Beijiao Town	377,357
m3	Chencun Town	205,411
m4	Daliang Subdistrict	517,957
m5	Ronggui Subdistrict	573,587
m6	Lunjiao Subdistrict	233,187
m7	Leiliu Subdistrict	294,187
m8	Longjiang Town	309,997
m9	Jun'an Town	163,367
m10	Xingtang Town	194,876

Among the 16 officially designated Chikungunya treatment hospitals in Shunde District, 6 representative hospitals were selected according to their administrative level, service capacity, and geographic coverage. The selected hospitals include provincial referral hospitals, district general hospitals, and town-level hospitals, allowing the proposed model to capture the hierarchical structure of the regional healthcare system while maintaining computational tractability. Their hospitalized patient capacities are represented by trapezoidal fuzzy numbers, as summarized in Table 3.

Table 3. Selected hospitals in Shunde district and hospitalized patient capacity.

ID	Hospital name	Hospitalized patient capacity
11	Southern Medical University Shunde Hospital	(800, 1000, 1200, 1400)
12	Guangzhou University of Chinese Medicine Shunde Hospital	(600, 800, 1000, 1200)
13	Guangdong Medical University Shunde Women & Children's Hospital	(400, 500, 600, 700)
14	Shunde District Third People's Hospital (Beijiao)	(380, 400, 420, 440)
15	Lecong Hospital of Shunde District	(300, 350, 400, 450)
16	Ronggui Hospital (Affiliated Shunde Hospital of Jinan University)	(520, 540, 560, 580)

To support mosquito surveillance and vector control operations, five VCUs were established according to the spatial distribution of confirmed cases. Three VCUs were located in the high-incidence towns of Lecong, Beijiao, and Chencun, while the remaining two VCUs were positioned to cover the southern and western areas of Shunde District. Each VCU performs mosquito surveillance, environmental disinfection, insecticide deployment, and outbreak containment. Their maximum

handling capacities are listed in Table 4.

Table 4. VCUs and material handling capacity.

ID	Location service area	Capacity range
v1	Lecong Town (high-incidence zone)	(2000, 2200, 2400, 2600)
v2	Beijiao Town (high-incidence zone)	(1800, 2000, 2200, 2400)
v3	Chencun Town (high-incidence zone)	(1500, 1700, 1900, 2100)
v4	Daliang–Ronggui area (southern cluster)	(1200, 1400, 1600, 1800)
v5	Lunjiao–Leiliu–Longjiang–Jun’an–Xingtang area	(1000, 1200, 1400, 1600)

The trapezoidal fuzzy cost parameters used in the proposed model include transportation costs, operating costs, facility establishment costs, and critical-node penalty costs. These parameters were estimated from historical emergency material dispatch records provided by the Shunde District Health Bureau and refined through consultation with local public health and healthcare logistics experts. Transportation costs are expressed in RMB per unit per km, while all transportation distances were calculated using the GIS of Shunde District. The resulting fuzzy cost parameters are summarized in Table 5.

Table 5. Trapezoidal fuzzy cost parameters.

Cost category	Parameter	Trapezoidal range	Cost category	Parameter	Trapezoidal range
Fixed cost	$\widetilde{F}_k$	(40 50 60 70)	Operating cost	$\widetilde{\sigma}_p$	(3 5 7 9)
	$\widetilde{F}_v$	(150 200 250 300)		$\widetilde{\sigma}_i$	(0.7 0.8 0.9 1.0)
	$\widetilde{T}_{pk}$	(1.5 2.0 2.5 3.0)		$\widetilde{\sigma}_k$	(0.3 0.4 0.5 0.6)
	$\widetilde{T}_{ik}$	(2.0 2.5 3.0 3.5)	Penalty cost	$\widetilde{\gamma}_1$	(10 15 20 25)
Transportation cost	$\widetilde{T}_{km}$	(1.0 1.2 1.5 2.0)		$\widetilde{\gamma}_2$	(5 8 10 12)
	$\widetilde{T}_{kv}$	(1.5 2.0 2.5 3.0)			
	$\widetilde{T}_{kl}$	(1.5 2.0 2.5 3.0)			
	$\widetilde{T}_{vm}$	(2.0 2.5 3.0 3.5)			
	$\widetilde{T}_{ml}$	(2.0 2.5 3.0 3.5)			

Table 6. Maximum material capacity constraints (trapezoidal fuzzy numbers).

Facility	Capacity range	Facility	Capacity range
p1	(1300 1500 1600 1700)	i3	(400 600 800 1000)
p2	(1900 2200 2300 2400)	k1	(1500 2000 2500 3000)
p3	(1700 1800 1900 2000)	k2	(2500 3000 3500 4000)
p4	(8000 10000 11000 12000)	k3	(4500 5000 5500 6000)
p5	(1800 2000 2100 2200)	k4	(3500 4000 4500 5000)
i1	(800 1000 1200 1400)	k5	(5500 6000 6500 7000)
i2	(500 700 900 1100)		

The production capacities of the suppliers, processing capacities of the distribution centers and VCUs, and treatment capacities of the hospitals were represented by trapezoidal fuzzy numbers. For

each parameter, the second and third values correspond to the most likely operating range observed during the outbreak, while the first and fourth values represent conservative lower and upper bounds determined from historical operational records and expert consultation. The capacity parameters adopted in this study are summarized in Table 6.

Distance matrices were computed using the GIS data of Shunde District. Tables 7–13 report the Euclidean distances (in km) between facility pairs. These values are used in Constraints (3.1) and (3.7)–(3.11) of the main model.

Table 7. Distance matrix d_{km} (km) from DC k to community m .

DC	m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}
k_1	12.3	14.7	10.5	18.2	21.6	13.8	17.4	19.1	22.5	24.8
k_2	16.9	19.4	15.3	23.7	25.1	18.0	21.2	22.6	26.3	28.7
k_3	8.5	10.1	6.8	14.6	17.3	9.2	13.5	15.0	18.8	20.4
k_4	20.1	22.3	18.7	7.2	9.6	15.9	12.4	14.0	16.5	19.2
k_5	24.6	26.8	22.9	12.5	15.0	20.3	17.1	8.9	11.3	14.7

Table 8. Distance matrix d_{vm} (km) from VCU v to community m .

VCU	m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}
v_1	7.2	9.5	5.3	13.8	16.4	8.7	12.1	14.3	17.9	19.6
v_2	10.8	12.3	8.9	17.5	19.8	11.6	15.2	16.7	20.3	22.1
v_3	14.6	16.0	12.4	9.8	11.2	15.9	13.7	10.4	13.2	15.8
v_4	19.3	21.0	17.5	6.5	8.4	16.4	11.9	13.6	9.7	12.5
v_5	23.1	25.2	21.8	11.7	14.2	20.6	17.8	15.1	12.9	8.4

Table 9. Distance matrix d_{ml} (km) from community m to hospital l .

Community	l_1	l_2	l_3	l_4	l_5	l_6
m_1	16.2	19.4	22.7	25.3	27.8	20.1
m_2	18.5	21.0	24.2	26.9	29.4	22.6
m_3	14.8	17.5	20.3	23.0	25.6	18.9
m_4	8.7	11.3	14.2	17.1	19.8	13.5
m_5	10.2	12.8	15.9	18.6	21.2	15.4
m_6	13.9	16.6	19.5	22.4	24.9	18.2
m_7	11.5	14.2	17.0	19.9	22.5	16.1
m_8	9.8	12.1	15.0	17.9	20.6	14.3
m_9	12.7	15.3	18.2	21.1	23.7	17.0
m_{10}	14.2	16.8	19.6	22.5	25.1	18.4

Table 10. Distance matrix d_{pk} (km) from primary supplier p to DC k .

Primary supplier	k_1	k_2	k_3	k_4	k_5
p_1	30.0	30.6	29.5	13.6	18.0
p_2	38.8	42.6	35.0	23.7	13.8
p_3	25.8	30.0	22.2	32.1	33.0
p_4	28.2	26.7	30.8	48.4	56.8
p_5	31.3	27.3	35.0	37.1	47.4

Table 11. Distance matrix d_{ik} (km) from backup supplier i to DC k .

Backup supplier	k_1	k_2	k_3	k_4	k_5
i_1	54.5	56.1	52.7	34.5	28.8
i_2	50.5	54.2	47.5	57.8	56.9
i_3	51.4	46.9	55.7	64.1	74.6

Table 12. Distance matrix d_{kl} (km) from DC k to hospital l .

DC	l_1	l_2	l_3	l_4	l_5	l_6
k_1	17.7	19.3	21.2	23.0	24.7	19.3
k_2	20.3	21.4	22.9	24.1	25.5	21.0
k_3	15.5	17.5	19.9	22.0	24.2	18.0
k_4	3.0	1.1	3.4	6.2	8.9	2.9
k_5	11.7	11.7	12.4	14.1	16.0	13.2

Table 13. Distance matrix d_{kv} (km) from DC k to VCU v .

DC	v_1	v_2	v_3	v_4	v_5
k_1	5.3	2.1	15.0	23.4	33.2
k_2	9.8	6.6	17.4	26.4	37.1
k_3	1.0	2.2	13.1	20.6	29.3
k_4	17.9	19.2	5.2	5.8	20.0
k_5	25.4	27.6	14.7	5.6	11.8

The following Tables 14 and 15 give the trapezoidal fuzzy demand (d_1, d_2, d_3, d_4) for each material type at each community. These values are used as $\tilde{D}_{qm}$ and $\tilde{D}_{qm}^{VC}$ in the model.

Table 14. Fuzzy demand $\tilde{D}_{qm}$ for materials $q = 1, 2$ (PPE and clinical supplies).

Community	$q = 1$ (PPE)				$q = 2$ (clinical)			
	d_1	d_2	d_3	d_4	d_1	d_2	d_3	d_4
m_1	214	239	264	289	171	191	211	231
m_2	224	251	277	303	179	200	221	242
m_3	122	137	151	165	98	109	121	132
m_4	308	345	381	417	247	276	305	334
m_5	341	382	422	462	273	305	337	369
m_6	139	155	171	187	111	124	137	150
m_7	175	196	216	237	140	157	173	189
m_8	184	206	228	249	147	165	182	199
m_9	97	109	120	132	78	87	96	105
m_{10}	116	130	143	157	93	104	115	126

Table 15. Fuzzy demand $\tilde{D}_{qm}^{VC}$ for materials $q = 3, 4$ (insecticides and surveillance).

Community	$q = 3$ (insecticides)				$q = 4$ (surveillance)			
	d_1	d_2	d_3	d_4	d_1	d_2	d_3	d_4
m_1	193	215	238	260	118	131	145	159
m_2	202	226	249	273	123	138	152	167
m_3	110	123	136	149	67	75	83	91
m_4	278	310	343	375	170	189	209	229
m_5	307	343	379	415	188	210	232	254
m_6	125	140	154	169	76	85	94	103
m_7	157	176	194	213	96	107	118	130
m_8	166	185	205	224	102	113	125	137
m_9	88	98	108	118	54	60	66	72
m_{10}	104	117	129	141	64	71	79	86

Hospital material demand is defined as $\tilde{D}_{q1l} = 0.15\tilde{M}_{sl}$ and $\tilde{D}_{q2l} = 0.12\tilde{M}_{sl}$. VCU-level demand is allocated according to the relative handling capacity of each VCU, while community patient demand is estimated from the population using a baseline rate of 7.0×10^{-4} . The coefficients 0.15 and 0.12 were calibrated according to historical emergency response records and expert consultation, representing the relative material requirements associated with hospital treatment capacity. The resulting values are reported in Tables 16–18.

Table 16. Calibrated fuzzy hospital material demand $\tilde{D}_{ql}$.

Hospital	$q = 1$ (PPE)				$q = 2$ (clinical)			
	d_1	d_2	d_3	d_4	d_1	d_2	d_3	d_4
l_1	120.0	150.0	180.0	210.0	96.0	120.0	144.0	168.0
l_2	90.0	120.0	150.0	180.0	72.0	96.0	120.0	144.0
l_3	60.0	75.0	90.0	105.0	48.0	60.0	72.0	84.0
l_4	57.0	60.0	63.0	66.0	45.6	48.0	50.4	52.8
l_5	45.0	52.5	60.0	67.5	36.0	42.0	48.0	54.0
l_6	78.0	81.0	84.0	87.0	62.4	64.8	67.2	69.6

Table 17. Calibrated fuzzy VCU material demand $\tilde{D}_{qv}$.

VCU	$q = 3$ (insecticides)				$q = 4$ (surveillance)			
	d_1	d_2	d_3	d_4	d_1	d_2	d_3	d_4
v_1	442.1	494.0	545.6	597.2	270.4	301.3	333.0	364.9
v_2	403.7	451.0	498.2	545.3	246.9	275.1	304.0	333.2
v_3	346.0	386.6	427.0	467.4	211.6	235.8	260.6	285.6
v_4	288.3	322.2	355.8	389.5	176.3	196.5	217.2	238.0
v_5	249.9	279.2	308.4	337.6	152.8	170.3	188.2	206.3

Table 18. Calibrated fuzzy community patient demand $\tilde{D}_{sm}$ for $s = 1$.

Community	d_1	d_2	d_3	d_4
m_1	225	251	278	304
m_2	236	264	292	319
m_3	129	144	159	174
m_4	325	363	401	438
m_5	359	402	444	485
m_6	146	163	180	197
m_7	184	206	228	249
m_8	194	217	240	262
m_9	102	114	126	138
m_{10}	122	136	151	165

The remaining scalar parameters used in the computational experiments are summarized in Table 19.

The robustness penalty coefficients were selected according to the relative criticality of the corresponding constraints in the healthcare supply chain. Specifically, larger weights were assigned to hospitals' material demand, primary suppliers' capacity, community patient demand, and hospital treatment capacity ($\delta_1 = \delta_5 = \pi_1 = \pi_5 = \pi_6 = 10$), because violations of these constraints directly affect patients' treatment and the emergency response. Moderate weights were assigned to VCUs' material demand, community material demand, vector control material demand, backup suppliers' capacity, VCUs' capacity, and distribution centers' capacity ($\delta_2 = \delta_3 = \delta_4 = \pi_2 = \pi_3 = \pi_4 = 5$),

whose deviations primarily influence operational efficiency rather than life-critical healthcare services. These settings reflect the relative operational importance of different constraints and are consistent with the objective of prioritizing life-critical healthcare services while maintaining overall supply chain robustness.

Table 19. Baseline scalar parameter values used in the computational case study.

Parameter	Baseline value	Interpretation
R_0	1.0	Target service level for materials
R_1	1.0	Target service level for patients
L_q	1.0, $\forall q$	Material responsiveness importance coefficient
L_s	1.0, $\forall s$	Patient responsiveness importance coefficient
W_{ql}	1.0 for $q \in \bar{Q}^M$; 0 otherwise	Hospital material response weight
W_{qv}	1.0 for $q \in \bar{Q}^V$; 0 otherwise	VCU material response weight
W_{qm}	1.0, $\forall q$	Community material response weight
W_s	21.0, $\forall s$	Patient response weight
α	0.5	Possibility confidence level for fuzzy capacities
β	0.5	Possibility confidence level for fuzzy demands
Θ	0.5	Optimality robustness weight in OF_{12}
λ_t	1.0	Baseline criticality-threshold scale factor
$U1_p$	1392.41, $\forall p$	Primary supplier criticality threshold
$U2_i$	1392.41, $\forall i$	Backup supplier criticality threshold
$U3_k$	4641.38, $\forall k$	DC criticality threshold
$\mathcal{M}$	23800	Big- $\mathcal{M}$ upper bound

4.3. Optimal facility location, allocation, and patient transportation strategies

The proposed optimization model simultaneously determines the facility activation, material allocation, vector control assignment, and patient transportation decisions. The resulting network configuration reflects a balance among demand coverage, transportation efficiency, facility capacity, and operating cost. Among the five candidate distribution centers, k_3 , k_4 , and k_5 are activated, whereas k_1 and k_2 remain inactive because their additional contribution to transportation efficiency does not justify the associated establishment and operating costs. Four primary suppliers (p_1 , p_2 , p_3 , and p_5) and two backup suppliers (i_1 and i_2) are also selected to support material supply across the network.

Table 20 presents the material allocation strategy of the activated distribution centers. The assignments show a clear spatial and operational structure. Distribution center k_3 mainly serves the northern outbreak cluster comprising $\{m_1, m_2, m_3\}$ and also supports VCU v_1 and hospital l_4 . Distribution center k_4 serves the relatively high-demand communities $\{m_4, m_5, m_6, m_7\}$ while supplying VCUs v_3 and v_4 and several hospitals. Distribution center k_5 extends coverage to the southern and western communities and partially overlaps with k_4 at m_4 , m_6 , and m_7 . This partial overlap allows material flows to be shared between facilities when necessary, reducing excessive dependence on a single distribution center and improving the flexibility of the overall network.

Table 20. Optimal distribution centers' material allocation strategy.

DC	Communities served	VCUs served	Hospitals served
k3	{m1, m2, m3}	{v1}	{l4}
k4	{m4,m5,m6,m7}	{v3,v4}	{l1, l2,l3, l6}
k5	{m4, m6, m7, m8, m9, m10}	{v4,v5}	{l5}

The assignment of VCUs further indicates that vector control resources are allocated according to both the epidemic's severity and spatial accessibility rather than geographic distance alone. Communities m_1 , m_2 , and m_3 , corresponding to the high-incidence towns of Lecong, Beijiao, and Chencun, are assigned to v_1 , thereby concentrating vector control resources in areas with a relatively high transmission risk. Other communities share available vector control resources according to their service range and processing capacity. Table 21 summarizes the corresponding VCU and hospital assignments for each community.

Table 21. Transport strategy: VCU and hospital assignment per community.

Community	Assigned VCU(s)	Assigned hospital
m1	v1	l6
m2	v1	l2,l6
m3	v1	l4,l6
m4	v4	l2,l4
m5	v4	l1
m6	v1	l1
m7	v3	l1,l3
m8	v3	l3
m9	v3	l1,l2
m10	v5	l3

Patient allocation is primarily driven by capacity constraints and system-wide load balancing, while transportation distance acts as a secondary cost factor. Communities m_2 , m_3 , m_4 , m_7 , and m_9 transfer patients to more than one hospital, indicating that patient flows are distributed across the available treatment facilities when assignment to a single hospital is insufficient. Hospital l_1 receives patients from several communities, consistent with its relatively large treatment capacity, whereas other hospitals primarily serve geographically closer demand nodes. Overall, the resulting configuration coordinates material distribution, vector control operations, and patient transportation while avoiding unnecessary facility deployment. The average computational time is approximately 847 seconds per scenario, indicating that the proposed model remains computationally tractable for district-scale healthcare supply chain planning.

4.4. Pareto frontier analysis

The proposed tri-objective optimization model was solved using the AEC method with $N_2 = N_3 = 4$. After duplicate elimination and Pareto dominance filtering, 13 nondominated solutions were retained from the examined ε -grid combinations. Figure 3 presents these solutions in the three-dimensional

objective space (OF_1, OF_2, OF_3), where $OF_1 = OF_{11} + OF_{12}$ denotes the robust total objective, OF_2 represents the critical node resilience penalty, and OF_3 represents the weighted response deviation. The color scale indicates the robustness-related component OF_{12} . Therefore, OF_{12} should be interpreted as a component of the first objective rather than as an independent fourth optimization objective.

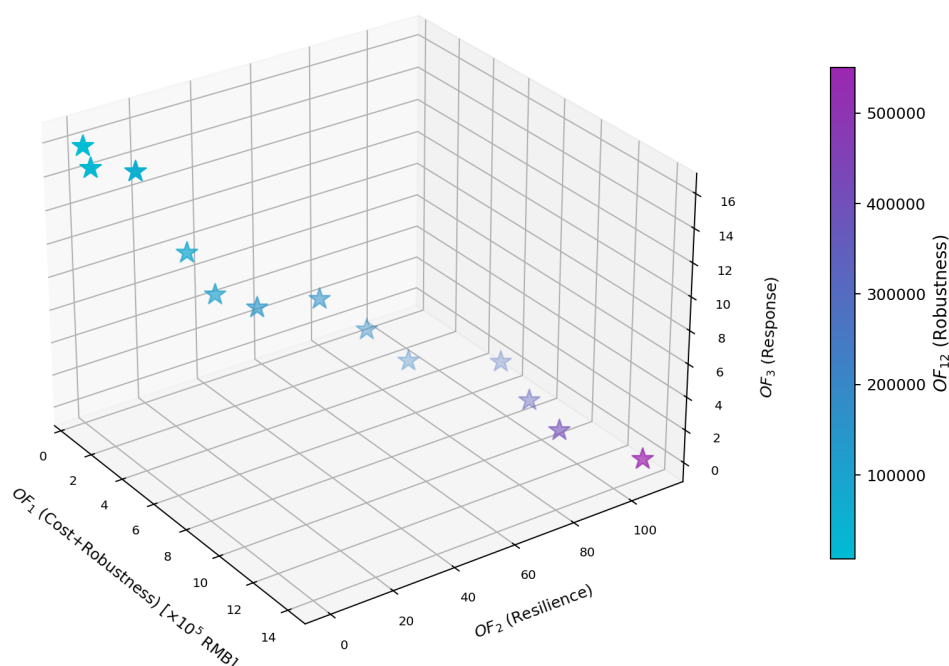


Figure 3. The Pareto frontier obtained using the AEC method.

The Pareto solutions reveal a clear progression from low- OF_1 configurations with relatively large response deviations to high- OF_1 configurations with substantially improved responsiveness. At the lower end of the frontier, the network operates with limited resource deployment and relatively small critical-node penalties, but the corresponding response deviations remain high. In the intermediate region, moderate increases in the robust total objective lead to substantial reductions in the response deviation, providing comparatively balanced solutions among the three objectives. At the higher end of the frontier, the response deviation approaches zero, but further improvements require increasingly large increases in OF_1 . This pattern indicates that the marginal benefit of additional robust expenditure gradually decreases as the system approaches very high service levels.

Figure 4(a) presents the pairwise relationship between the robust total objective OF_1 and the resilience penalty OF_2 . Unlike a conventional two-objective trade-off, the two quantities generally increase together along the sampled Pareto solutions. This pattern arises because improvements in responsiveness require larger material flows and greater utilization of the supply network, which increases the likelihood that suppliers and distribution centers exceed their predefined criticality thresholds. The stepwise behavior of OF_2 is also consistent with the binary critical node formulation. Once a facility is classified as critical, additional throughput through the same facility does not further increase its critical node indicator; the penalty changes primarily when additional facilities cross their corresponding thresholds. The observed plateau in OF_2 should therefore be interpreted partly as a

structural consequence of the threshold-based resilience formulation.

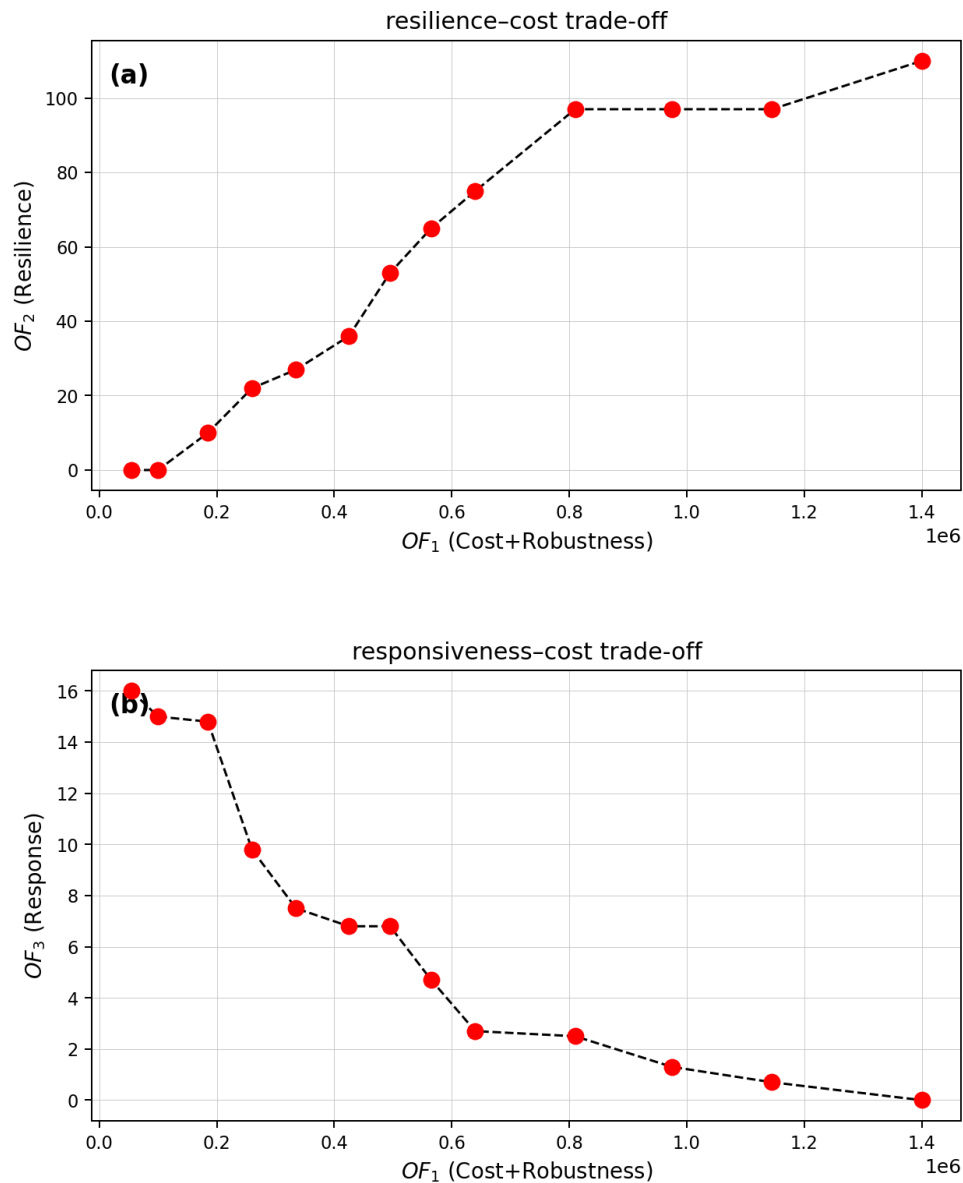


Figure 4. Pairwise relationships among the performance measures.

Figure 4(b) shows a clear relationship between the robust total objective OF_1 and the response deviation objective OF_3 . Response deviation decreases rapidly over the lower to intermediate range of OF_1 , indicating that a substantial improvement in responsiveness can initially be achieved with moderate additional robust expenditure. As OF_1 increases further, however, the reduction in OF_3 becomes progressively smaller. Approaching zero response deviation therefore requires disproportionately larger increases in the robust total objective. The resulting pattern provides evidence of diminishing marginal returns in responsiveness and suggests that intermediate Pareto solutions may provide attractive compromises when both service performance and resource expenditure are considered.

The color variation in Figure 3 provides additional information regarding the robustness-related component OF_{12} . Higher- OF_1 solutions generally exhibit larger values of OF_{12} , reflecting the fact that larger network flows expose a greater volume of operations to uncertain costs, demands, and capacities. Because OF_{12} is included directly in OF_1 , this relationship should not be interpreted as an independent Pareto trade-off between cost and robustness. Instead, it illustrates how the robustness-related component contributes to the growth of the robust total objective as the scale and utilization of the healthcare supply chain increase.

4.5. Uncertainty sensitivity analysis

To examine the effect of the robustness term, the proposed RPP model is compared with a basic possibilistic chance constrained programming (BPCCP) benchmark following Pishvae et al. [12]. For the RPP model, the first deterministic objective is defined as $OF_1 = OF_{11} + OF_{12}$, where OF_{11} is the operating cost component and OF_{12} is the robustness-related component. The BPCCP model excludes OF_{12} but retains the same network structure, fuzzy parameters, deterministic chance constraints, and requirements for resilience and responsiveness.

Model 2: RPP model

$$\min_{\mathbf{x}} \quad Z_{\text{RPP}} = OF_{11}(\mathbf{x}) + OF_{12}(\mathbf{x}) \quad (4.1)$$

$$\text{subject to} \quad OF_2(\mathbf{x}) \leq \bar{\varepsilon}_2 \quad (4.2)$$

$$OF_3(\mathbf{x}) \leq \bar{\varepsilon}_3 \quad (4.3)$$

$$\mathbf{x} \in \mathcal{X}(\alpha, \beta) \quad (4.4)$$

Model 3: BPCCP model

$$\min_{\mathbf{x}} \quad Z_{\text{BPCCP}} = OF_{11}(\mathbf{x}) \quad (4.5)$$

$$\text{subject to} \quad OF_2(\mathbf{x}) \leq \bar{\varepsilon}_2 \quad (4.6)$$

$$OF_3(\mathbf{x}) \leq \bar{\varepsilon}_3 \quad (4.7)$$

$$\mathbf{x} \in \mathcal{X}(\alpha, \beta) \quad (4.8)$$

Here, $\mathcal{X}(\alpha, \beta)$ denotes the deterministic feasible region associated with confidence levels α and β . At a matched confidence level, the main difference between Models 2 and 3 is the inclusion of OF_{12} in the RPP's objective.

The common bounds $\bar{\varepsilon}_2$ and $\bar{\varepsilon}_3$ were determined from the Pareto set obtained at the baseline setting $\alpha = \beta = 0.5$. Following the ideal-point method discussed by Wang and Rangaiah [52], the objective values of each Pareto solution $\mathbf{x}^{(r)}$, $r = 1, \dots, R$, were normalized as

$$z_i^{(r)} = \frac{OF_i(\mathbf{x}^{(r)}) - \min_{h=1, \dots, R} OF_i(\mathbf{x}^{(h)})}{\max_{h=1, \dots, R} OF_i(\mathbf{x}^{(h)}) - \min_{h=1, \dots, R} OF_i(\mathbf{x}^{(h)})}, \quad i = 1, 2, 3 \quad (4.9)$$

Since no prior preference was specified for the three objectives, equal weights were used. The distance from each normalized solution to the ideal point was calculated as

$$d^{(r)} = \sqrt{\frac{1}{3} \sum_{i=1}^3 (z_i^{(r)})^2}, \quad r = 1, \dots, R \quad (4.10)$$

The compromise solution was selected by

$$r^c = \arg \min_{r=1, \dots, R} d^{(r)} \quad (4.11)$$

The selected solution yielded

$$OF_1(x^c) \approx 4.40 \times 10^5 \text{ RMB}, \quad OF_2(x^c) = 35, \quad OF_3(x^c) = 8.5$$

The corresponding values of OF_2 and OF_3 were used as the common bounds in the comparative models

$$\bar{\varepsilon}_2 = 35, \quad \bar{\varepsilon}_3 = 8.5 \quad (4.12)$$

The same bounds were used in all comparative experiments. Feasibility was verified for BPCCP at $\alpha = \beta = 0.5$ and for RPP at $\alpha = \beta = 0.5, 0.7$, and 0.9 .

Ten uncertainty scenarios were generated from the support intervals of the trapezoidal fuzzy parameters. For an uncertain parameter $\tilde{\xi}_j = (\xi_j^{(1)}, \xi_j^{(2)}, \xi_j^{(3)}, \xi_j^{(4)})$, its realized value in scenario ω was generated by

$$\xi_j^{(\omega)} = \xi_j^{(1)} + u_j^{(\omega)} (\xi_j^{(4)} - \xi_j^{(1)}), \quad u_j^{(\omega)} \sim \mathcal{U}(0, 1), \quad \omega = 1, \dots, 10 \quad (4.13)$$

The draws were independent across uncertain parameters and scenarios. A fixed random seed of 42 was used, and the same 10 realized parameter vectors were applied to all model settings. Parameters not included in the scenario generation were kept at their baseline values. Random sampling was used only to construct common stress test scenarios and does not reinterpret the trapezoidal fuzzy parameters as probability distributions.

For each scenario, the RPP and BPCCP models were solved again from scratch. All decision variables, including facility selection variables, material flows, vector control assignments, patient allocation, responsiveness variables, and auxiliary variables, were reoptimized under the realized scenario conditions. The scenario realizations are used for the numerical stress test and are kept separate from the construction of the RPP robustness term. In the RPP model, OF_{12} continues to represent the robustness effect derived from the original trapezoidal fuzzy ranges and the specified confidence levels, while the realized scenario parameters are used to evaluate the operating environment in each run. In each stress-test run, the realized demand and capacity values replace their baseline counterparts in the operational constraints, while the realized transportation cost values are used in the calculation of $OF_{11}^{(\omega)}$. The robustness term OF_{12} itself remains defined from the original trapezoidal fuzzy parameter ranges.

Because RPP and BPCCP have different optimization objectives, their model-specific objective values are not directly comparable. The operating cost component is therefore used as the common evaluation metric. Let $OF_{11}^{(\omega)}$ denote the operating cost evaluated under the realized parameter values in scenario ω . After each model is reoptimized, the corresponding $OF_{11}^{(\omega)}$ value is recorded. The mean,

standard deviation, and coefficient of variation reported below are calculated from these scenario-specific values.

The BPCCP benchmark is evaluated at $\alpha = \beta = 0.5$, matching the baseline RPP setting. The direct comparison between the two models is therefore made at $\alpha = \beta = 0.5$ (as shown in Table 22), so that the effect of adding OF_{12} can be examined under the same confidence level. The RPP results at $\alpha = \beta = 0.7$ and 0.9 are reported separately as a confidence level sensitivity analysis.

Table 22. Comparative performance under uncertainty using the common OF_{11} metric.

Scenario	BPCCP	RPP		
	$\alpha = \beta = 0.5$	$\alpha = \beta = 0.5$	$\alpha = \beta = 0.7$	$\alpha = \beta = 0.9$
1	330350.22	330536.65	344821.11	359361.29
2	331780.43	331973.08	346243.44	360776.59
3	320015.44	321780.01	335259.11	348283.03
4	325967.94	327655.69	340311.34	354720.79
5	321749.44	323413.48	335955.16	350240.77
6	311387.21	312681.11	326218.58	338999.59
7	329308.08	329492.99	343769.23	358299.46
8	321747.56	323097.12	336029.35	350419.09
9	326581.95	326780.63	340818.15	355123.58
10	317072.94	318384.12	331061.25	345117.41
Mean	323596.12	324579.49	338048.67	352134.16
Std. Dev.	6420.68	5962.40	6355.68	6861.09
CV (%)	1.984	1.837	1.880	1.948
Std. Dev. reduction relative to matched BPCCP (%)	—	7.14	N.A.	N.A.

At the matched confidence level $\alpha = \beta = 0.5$, the standard deviation of the common operating cost metric decreases from 6420.68 for BPCCP to 5962.40 for RPP, a reduction of approximately 7.14%. The coefficient of variation also decreases from 1.984% to 1.837%. Thus, under the baseline confidence level, the RPP model produces less variable reoptimized operating cost outcomes across the ten scenarios.

Within the RPP model, increasing the confidence level from 0.5 to 0.7 and 0.9 raises the mean operating-cost component and does not further reduce cross-scenario variability. Among the three RPP settings, $\alpha = \beta = 0.5$ gives the lowest standard deviation and coefficient of variation. For this case study, the baseline confidence level therefore provides the most favorable balance between the operating cost component and cross-scenario variability among the settings examined.

4.6. Elasticity sensitivity analysis

To further investigate the behavior of the proposed model under different epidemic conditions, a two-dimensional parametric sensitivity analysis was conducted by varying the demand scale factor (λ_d) and the criticality threshold scale factor (λ_t). For the heatmap analysis, λ_d was varied from 0.2 to 1.8 with an increment of 0.20, while λ_t ranged from 0.3 to 1.9 with an increment of 0.20. The demand scale factor proportionally adjusts the epidemic-related demand parameters, whereas the threshold

scale factor proportionally modifies the critical node thresholds U_1 , U_2 , and U_3 . A smaller value of λ_i therefore represents a stricter criticality criterion, while a larger value corresponds to a more relaxed threshold. The analysis focuses on the robustness-related term OF_{12} , the critical node resilience penalty OF_2 , and the patient and material responsiveness indicators.

Figure 5 illustrates the variation in the robustness-related term OF_{12} under different combinations of demand and threshold scales. The dominant pattern is a strong increase in OF_{12} as λ_d rises. According to the current results, the mean robustness-related term increases from roughly 3.0×10^4 RMB under the lowest-demand conditions to close to 9.0×10^4 RMB under the highest-demand conditions. By comparison, changes in λ_i produce substantially smaller variation within a given demand level. This asymmetric response indicates that epidemic-related demand intensity is the primary driver of the robustness-related cost. Larger demand requires greater material flows and higher utilization of uncertain supply and capacity resources, thereby increasing the magnitude of the robustness terms in the RPP formulation. The criticality threshold primarily affects node classification and therefore has a comparatively limited direct effect on OF_{12} .

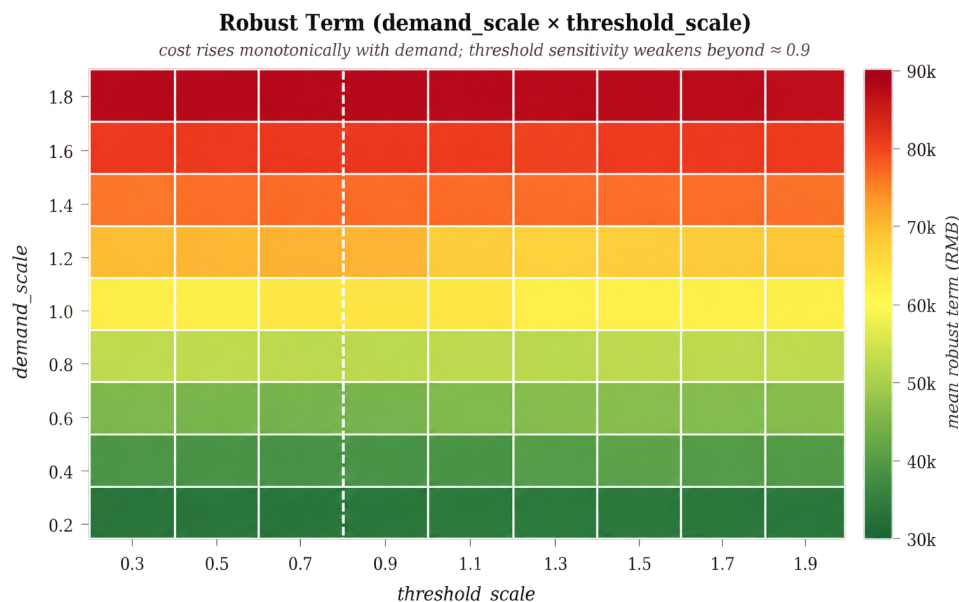


Figure 5. Heatmap of mean robust terms across demand and threshold scales.

Figure 6 presents the joint effect of the demand scale and the criticality threshold scale on the resilience penalty OF_2 . The penalty generally increases with λ_d because higher demand leads to larger material flows and increases the likelihood that suppliers and distribution centers will exceed their predefined criticality thresholds. In contrast, OF_2 decreases as λ_i increases because a larger threshold scale raises the criticality limits and makes activation of critical nodes less likely. Consequently, the largest penalties occur under the combination of high epidemic-related demand and relatively small threshold scales, whereas low demand combined with relaxed thresholds produces the smallest penalties. These results demonstrate that the resilience penalty is determined by the interaction between network loading and the threshold used to classify critical facilities.

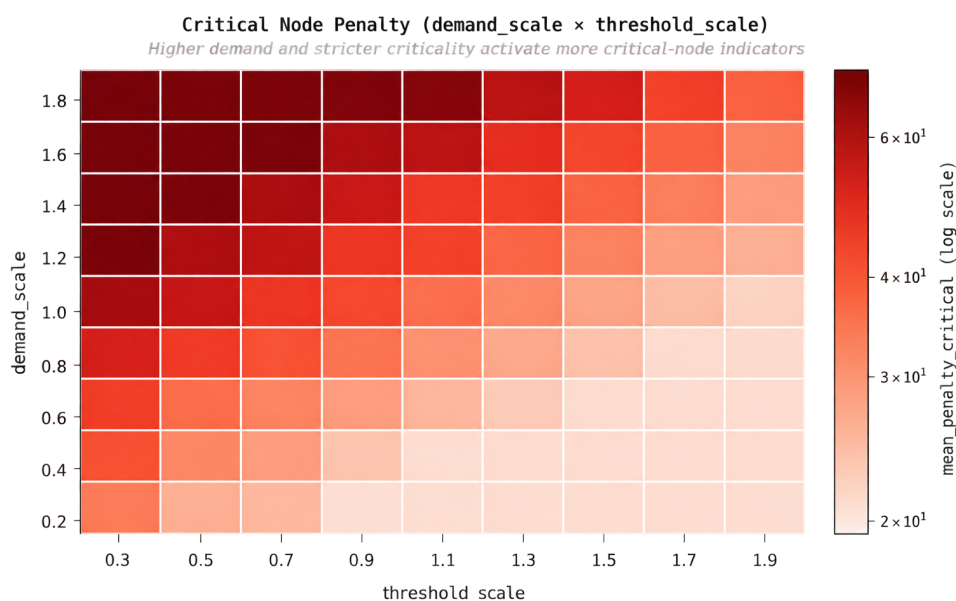


Figure 6. Heatmap of the mean critical node penalty across demand and threshold scales.

Figure 7 shows that patient and material responsiveness follow different trajectories as the epidemic-related demand increases. Patient responsiveness initially rises from approximately 0.66 under the lowest-demand condition and reaches its highest level of approximately 0.88 in the high-demand region before declining to approximately 0.75 at the upper end of the examined range. This nonmonotonic pattern suggests that patient transportation and hospital resources are utilized more intensively as demand increases, but the ability to maintain the same level of patient service becomes constrained when the system approaches its capacity limits.

Material responsiveness exhibits a markedly different pattern. It decreases almost monotonically from approximately 0.90 under low-demand conditions to approximately 0.52 at the highest demand level. This decline indicates that material supply and distribution capacities become progressively more restrictive as epidemic-related demand grows. The model therefore has increasing difficulty maintaining the minimum material fulfillment ratio across all relevant demand nodes.

The two responsiveness curves become comparable between approximately $\lambda_d = 1.0$ and 1.2 , rather than near $\lambda_d = 1.5$. This region indicates a shift in the relative importance of the two operational bottlenecks. Under relatively low demand, material availability is sufficient and patient allocation remains an important operational consideration. As demand increases, material supply and distribution become increasingly restrictive, causing material responsiveness to fall below patient responsiveness. These results suggest that emergency response priorities should evolve with the epidemic's severity rather than remain fixed throughout the response period.

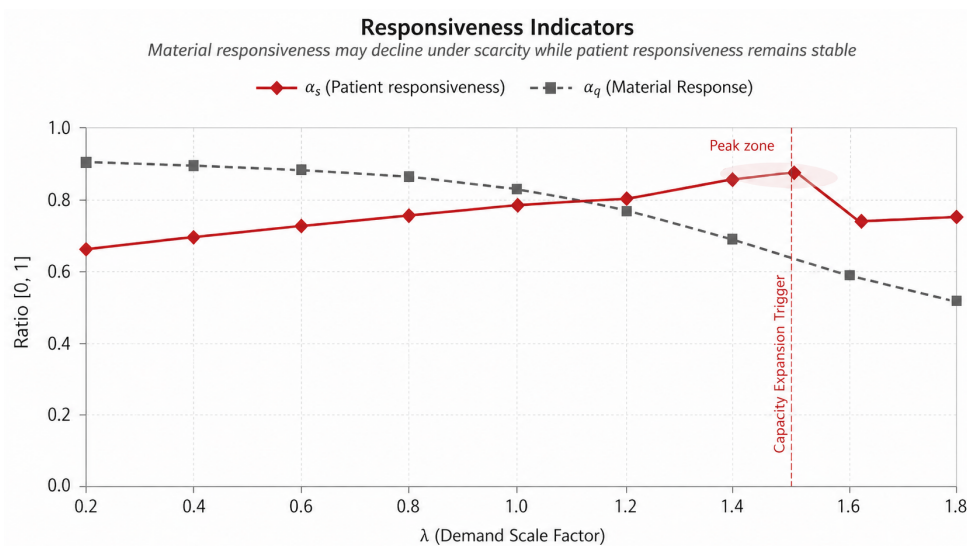


Figure 7. Two responsiveness indicators versus the demand scale factor.

Overall, the parametric sensitivity analysis shows that the examined performance measures respond differently to changes in the epidemic's severity and criticality settings. Epidemic-related demand has a substantially stronger influence on the robustness-related term OF_{12} than the criticality threshold scale, whereas the resilience penalty OF_2 is jointly determined by demand intensity and threshold calibration. Patient and material responsiveness also exhibit different trajectories as demand increases, with material availability becoming an increasingly important bottleneck under severe epidemic conditions. These findings indicate that criticality thresholds, resource allocation priorities, and capacity management strategies should be adapted to the epidemic's severity rather than applying a uniform operating policy across all response conditions.

5. Conclusions

This study developed an integrated multiobjective healthcare supply chain network design model for a vector-borne disease response under uncertainty. The proposed framework simultaneously considers material distribution, patient transportation, resilience, and responsiveness within a unified optimization model. To address uncertainty in epidemic demand, transportation costs, and facility capacities, the established RPP approach was incorporated into the proposed model, while the AEC method was used to generate Pareto-optimal solutions.

The proposed framework was validated through a real-world case study based on the 2025 Chikungunya fever outbreak in Shunde District, Foshan, China. The computational results demonstrate that the proposed model is capable of generating coordinated resource allocation strategies for suppliers, distribution centers, VCU, communities, and hospitals under uncertain epidemic conditions. The Pareto analysis reveals clear trade-offs among the robust total objective, resilience, and responsiveness. In particular, the results show that responsiveness exhibits diminishing marginal returns with increasing investment, resilience penalties gradually stabilize after sufficient facility activation, and the robustness-related component OF_{12} contributes structurally to the first objective under uncertainty. The uncertainty sensitivity analysis further shows that, at the matched baseline

confidence level $\alpha = \beta = 0.5$, incorporating the robustness-related term reduces the cross-scenario variability of the reoptimized operating-cost outcomes. Among the three RPP confidence levels examined, $\alpha = \beta = 0.5$ yields the lowest standard deviation and coefficient of variation.

From a practical perspective, the proposed framework provides quantitative decision support for healthcare administrators facing different epidemic scenarios. The Pareto frontier enables decision-makers to select resource allocation strategies according to the available budgets and the epidemic's severity, while the elasticity analysis illustrates how demand growth and criticality thresholds jointly influence resilience, robustness, and responsiveness. These findings may assist public health authorities in developing more adaptive healthcare supply chain strategies for future vector-borne disease outbreaks.

Several limitations should be acknowledged. First, the current model considers a single-period planning problem, whereas an epidemic response is inherently dynamic. Second, the fuzzy parameters were calibrated using data from a single regional outbreak, and additional case studies are required to further examine the generalizability of the proposed framework. Third, the current model assumes a fixed healthcare network structure and does not consider endogenous network reconfiguration following facility disruption or failure of the infrastructure. Finally, patient heterogeneity is simplified by treating hospitalized patients as a homogeneous group.

Future research may extend the proposed framework in several directions. Incorporating multiperiod epidemic evolution and data-driven demand forecasting would improve the dynamic adaptability of the model. Integrating epidemiological transmission models with healthcare supply chain optimization would provide stronger decision support for epidemic control. In addition, developing decomposition algorithms or metaheuristic solution approaches for large-scale applications and incorporating equity- or sustainability-oriented objectives would further enhance the practical applicability of the proposed framework.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Acknowledgments

The authors would like to express their thanks to the anonymous referees for their constructive comments on the paper, which have greatly improved its presentation.

Funding statement

Shuai Huang was supported by the Guangdong Basic and Applied Basic Research Foundation (Grant No. 2022A1515110315) and the Natural Science Foundation of China (Grant No. 42274058). Pei Wang was supported by the Science and Technology Projects of Guangzhou (Grant No. 2025A04J3386). Jing Zhang was supported by the 2023 Teaching Quality and Teaching Reform Engineering Project of Guangdong University of Foreign Studies.

Conflict of interest

The authors declare that there is no conflict of interest.

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