Hyperconnected Logistics Hub Network Design Under Reliability and Adversarial Disruptions

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1 INTRODUCTION

The recent surge in e-commerce and world trade has led the parcel delivery industry to be one of the fastest growing industries. Due to efforts for quicker parcel delivery, the industry requires meticulous planning and proper execution. The planning phase involves strategic decision making such as logistics hub network design. Although the Hub-and-spoke configuration for logistics hub networks has been widely studied (Ben-Ayed, 2013), this topology does not perform well in high demand scenarios as it may cause congestion of parcels at hubs during peak delivery times (Tu & Montreuil, 2019). To improve the overall parcel delivery process and to overcome the current limitations, hyperconnected logistics networks have been proposed in the Physical Internet (PI). Hyperconnected logistics networks are multi-plane interconnected meshed networks that link open-access hubs present on multiple planes. Together they shape an open network of networks, termed a logistics web (Montreuil *et al.*, 2018).

Nevertheless, all logistics networks, including those shaping the PI's logistics web, face disruptions caused by frequent events such as power outages or major traffic jams, as well as low-probability high-impact events such as natural disasters, pandemics, and deliberate attacks. Such disruptions lead to delayed parcel deliveries, increased delivery costs, and excess pressure on functional network components. Some investigations consider disruptions at hubs and transportation edges to design a small-scale network (Zhalechian *et al.*, 2018). However, such a small network reveals little to an industry that aims to persistently deliver parcels across a wide geographical region. In (Kulkarni *et al.*, 2021), the authors propose solution approaches based on integer programs to design large-scale hyperconnected networks that can sustain random disruptions.

In this work, we formulate a tri-level stochastic optimization model to design a large-scale hyperconnected meshed logistics hub network that can sustain random and worst-case disruptions. To solve this problem, we first study an integer-programming-based heuristic algorithm that selects hubs so as to connect every origin-destination pair with multiple shortest edge-disjoint paths. We conduct non-adversarial and adversarial disruption experiments to compare the efficiency and resilience of the proposed solution against that of traditional lean logistics networks. Next, we aim to scale an exact solution approach based on the L-shaped method that leverages the structure of the problem to design optimally resilient hyperconnected logistics networks.

2 METHODOLOGY

We consider a logistics company or a group of such companies that seeks to design a resilient hyperconnected intercity logistics hub network to transport commodities between a set of Origin-Destination (O-D) pairs $\mathcal{P}$ by opening H logistics hubs among a predefined finite set of candidate locations. Each O-D pair $p \in \mathcal{P}$ is associated with a commodity demand of D_p units. Let $\mathcal{E}$ denote the set of directed edges (i, j) representing the available transportation links connecting locations

i and j. These edges induce hyperconnectivity by connecting any two locations that are within a specified travel time. For each edge (i, j), we denote τ_{ij} its traveling time in nominal situations.

However, traveling along these edges is prone to delays caused by disruptions. The logistics company has access to historical data regarding the travel times on each edge in $\mathcal{E}$. We suppose that these disruption events can be modeled using a representative finite set of scenarios Ω. Each scenario $\omega \in \Omega$ occurs with a probability π_ω and associates each edge (i, j) with a travel time τ_{ij}^ω. In addition, the network also experiences extreme disruption events, caused by natural disasters or adversarial attacks, for which the company has less data and cannot include in the set of scenarios Ω. Thus, the company also wants to ensure that the designed network is resilient against worst-case disruptions, which are assumed to occur with probability π_{wc}. Then, the goal is to select a subset of hub locations so that the network connects every O-D pair, is efficient in terms of transportation, and is resilient against random and worst-case edge disruptions.

To this end, we develop a tri-level optimization model. In the first stage, the logistics company selects which hubs to open. For each potential logistics hub candidate h, we define the binary variable y_h that is equal to 1 if hub h is open. The disruption scenario occurs during the second stage: With probability π_ω, scenario ω of random disruptions occurs, while with probability π_{wc}, a fictitious adversary with a disruption budget B allocates continuous delays x_{ij} to the network edges as to maximize the company's cost of operations. In the third stage, the company transports the commodities based on the realized disruption scenario. We model this stage using a flow formulation: For every O-D pair p and every edge (i, j), we define flow variables $f_{ij}^{p,\omega}$ and $f_{ij}^{p,wc}$ for each random disruption scenario ω and the worst-case disruption, respectively. These flow variables represent the amount of each commodity traveling along each edge under each disruption scenario. Commodities can only flow on transportation edges that connect logistics hubs opened in the first stage, and satisfy the flow conservation constraints.

The objective of the logistics company is to minimize the total cost of fulfilling the demand, assumed in this model to be proportional to the total distance traveled by commodities. Thus, the third-stage flow decision variables f are selected so as to minimize the route length for each commodity in each scenario. The fictitious adversary aims to maximize the length of the shortest route between each O-D pair. Finally, the logistics company selects the hubs to open in the first stage so as to minimize the total shortest path lengths, averaged across all disruption scenarios, including the worst-case scenario. The objective of the problem can be formulated as follows:

$$\min_{y} \left\{ \sum_{\omega \in \Omega} \pi_\omega \cdot \min_{f^\omega} \left\{ \sum_{p \in \mathcal{P}} \sum_{(i,j) \in \mathcal{E}} \tau_{ij}^\omega f_{ij}^{p,\omega} \right\} + \pi_{wc} \cdot \max_{x} \left\{ \min_{f^{wc}} \left\{ \sum_{p \in \mathcal{P}} \sum_{(i,j) \in \mathcal{E}} (\tau_{ij} + x_{ij}) f_{ij}^{p,wc} \right\} \right\} \right\}. \quad (1)$$

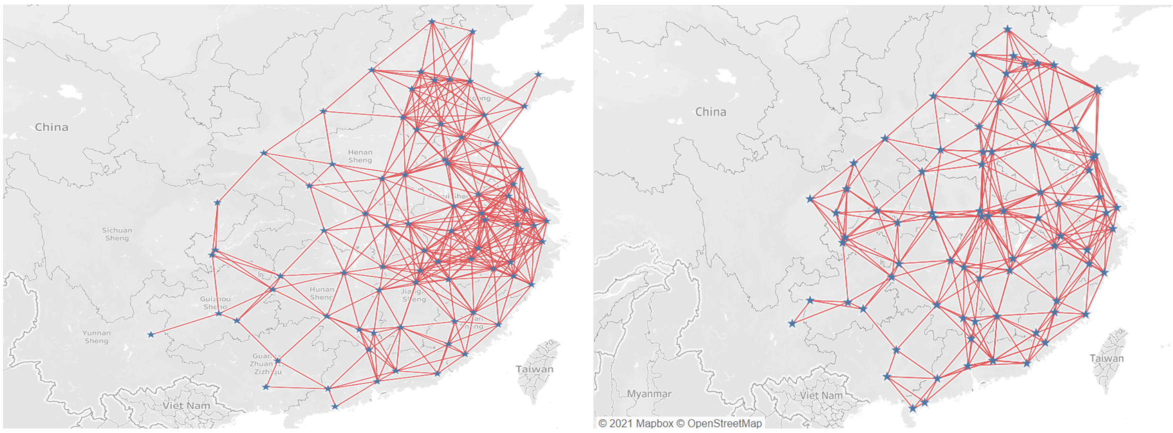
The problem defined above is challenging to solve for real-world instances due to the large number of random scenarios and potential combinations of opened hubs. In order to tackle this problem, we first propose a heuristic algorithm, which selects hubs to open using an integer program so as to connect every O-D pair with multiple shortest edge-disjoint paths. To evaluate the resilience of the network, the worst-case disruption scenario is determined by solving a linear program obtained by dualizing the third-stage flow problem, similarly to the single shortest path interdiction problem (Israeli & Wood, 2002). Secondly, we leverage the structure of the problem to propose an exact solution algorithm. In particular, we find that by sequentially dualizing the third and second stages, we obtain a large-scale mixed-integer program. Thus, we employ the L-shaped method (Slyke & Wets, 1969) to solve (1), where we split the decisions into two stages. We fix the first-stage decisions, then obtain a lower bound on the second stage value function and successively add cuts to better approximate the shape of the second-stage value function. Our ongoing efforts consist in scaling this algorithm to real-world instances.

3 CASE STUDY AND PRELIMINARY RESULTS

We apply the developed solution approaches to design a resilient hyperconnected intercity parcel logistics hub network to be the backbone infrastructure of China for ground transportation and consolidation of parcels. This network will form one tier in a PI-oriented multi-plane meshed network and could be leveraged by multiple parcel delivery companies to move numerous millions of parcels every day between Chinese cities. The network is to serve 184 O-D pairs in regions that house 91.88% of the Chinese population and are spread across 93.81% of the Chinese inhabitable land with 92.17% of total Chinese GDP (Li *et al.*, 2018).

To design the network, we consider 807 candidate locations for intercity hubs that are either major highway intersections and/or existing city-based hubs (inbound/outbound). In addition, due to regulations imposed by the Chinese government, a truck driver can drive for 11 hours per day and hence, we limit the transportation edges $(i, j) \in \mathcal{E}$ to up to 5.5 hours' drive time between locations to enable truck drivers to return home daily while the parcels keep moving toward their destinations. The resulting graph contains 44,330 directed edges.

In this preliminary work, we design a resilient logistics hub network by using the above-mentioned integer-programming-based heuristic. Specifically, we opened 80 hubs to connect each O-D pair – with identical demand – by four edge-disjoint paths. To compare the proposed resilient network with a lean meshed network, we also designed a lean network by selecting 80 hubs to open with the goal of minimizing the (single) shortest path length between each O-D pair. Similarly, the transportation edges were limited to 5.5 hours' drive. Figure 1 illustrates the resulting networks.



(a) *Lean network* (b) *Resilient network*

Figure 1 – *Hyperconnected logistics meshed networks with 80 hubs. Blue asterisks represent opened hubs, and red lines represent transportation edges connecting hubs within 5.5 hours' drive.*

We validate the performance and resilience of the proposed network by analyzing the impact of non-adversarial and adversarial disruptions. We conduct two sets of experiments: (i) random disruptions, where each disruption scenario increases the travel time on a single edge by a certain percentage; and (ii) worst-case disruptions, where a fictitious adversary has a delay budget to allocate across edges so as to maximize the total shortest path lengths across all commodities.

In the random edge disruption experiment, it can be observed that the increase in disruption strength has little impact on the average shortest path length between O-D pairs in the proposed network whereas the effect is quite significant in the lean logistics network. Table 1 bolsters this claim and shows that the the average increase in shortest path length in the proposed network is 10 times lower than that of the lean logistics network.

Table 1 – *Average increase in shortest path length (hours) during the random edge disruption experiment for networks of size* $H = 80$.

Increase in Edge Length	**Lean Logistics Meshed Network**	**Resilient Hyperconnected Logistics Meshed Network**
50%	1.97	0.202
100%	3.08	0.256
150%	4.05	0.296
200%	4.95	0.481

In case of adversarial disruptions, it can be seen in Figure 2 that the lean logistics network worsens at a higher rate compared to the proposed network as the disruptive impact increases. Interestingly, the performance in nominal situations (when the total delay available to the adversary is 0) of the lean network is better than that of the resilient network but comparable. With this marginal compromise in performance in the absence of disruptions, the proposed network achieves a significantly higher capability to sustain adversarial disruptions in comparison to the lean network. Thus, our study illustrates the value of optimization and the Physical Internet in designing hyperconnected meshed logistics network that are efficient and resilient.

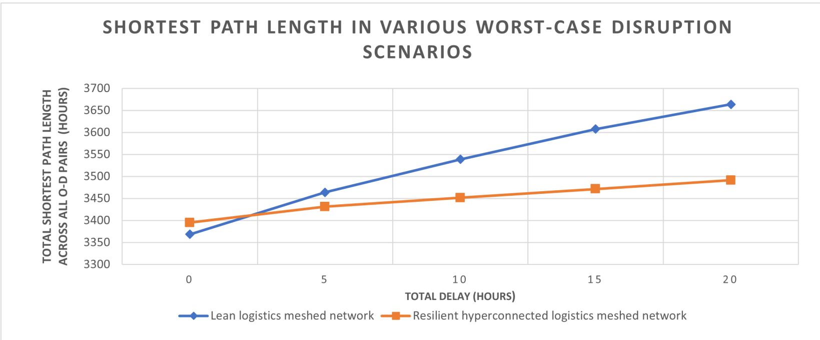


Figure 2 – *Worst-case disruption experiment for networks of size* $H = 80$.

In the presentation, we intend to depict network designs obtained through the scaled L-shaped algorithm to optimally solve the tri-level optimization problem (1) exactly for real-world instances, and compare its performance with heuristically generated network designs. We plan to illustrate the trade-off between efficiency and resilience capabilities among these networks in a nuanced manner through simulations under real-world disruption scenarios. We will also show the effect of hub capacity constraints on network designs and chalk out future research avenues.

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