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Resilient Logistics Flow Routing in Hyperconnected Networks

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Abstract: *Hyperconnected networks are prone to potentially wide variety of disruptions on daily basis that may impact their performance considerably. In this paper, we devise two combinatorial algorithms: a basic and an adaptive resilience-optimized algorithm to route commodities in large-scale hyperconnected networks that are robust against such disruptions. The basic resilience-optimized algorithm decomposes the total commodity routing based on each origin-destination (O-D) pair and then distributes this O-D commodity demand into multiple edge-disjoint paths. Alternatively, the adaptive resilience-optimized algorithm combinedly routes the commodity demand through multiple edge-disjoint paths without decomposing it separately for each O-D pair. Finally, we assess the efficiency and resiliency of routes obtained through resilience-optimized algorithms and benchmark them with routes generated through only considering efficiency on a hyperconnected network designed for finished vehicle logistics in Southeast USA. Benchmarking reveals enhanced capability of sustaining disruptions by the routes computed through the proposed algorithms as opposed to those generated through only efficiency consideration. Moreover, the results highlight the trade-off between efficiency and resilience in the generated routes.*

Keywords: *Hyperconnected Networks, Physical Internet, Resilience-Optimized Routing.*

Physical Internet (PI) Roadmap Fitness*: Select the most relevant area(s) for your paper according to the PI roadmaps adopted in Europe and Japan: ☐ PI Nodes (Customer Interfaces, Logistic Hubs, Deployment Centers, Factories), ☐ Transportation Equipment, ☒ PI Networks, ☒ System of Logistics Networks, ☐ Vertical Supply Consolidation, ☐ Horizontal Supply Chain Alignment, ☐ Logistics/Commercial Data Platform, ☐ Access and Adoption, ☐ Governance.*

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1 Introduction

The logistics and transport sectors, accounting for over one-third of global carbon dioxide emissions, stand as significant contributors and are at the forefront for the transition into a decarbonized future (IEA, 2022). Meeting global net-zero targets for 2030 necessitates a 20% reduction in emissions from this sector, urging an accelerated transition (Gould, 2023). While logistics service providers (LSPs) accept the responsibility of managing environmental impacts of their networks, the increased risk of disruptions and growing faster delivery expectations from customers may force some of them to drop their sustainable initiatives (Mari et al., 2014). Both individuals and businesses now want LSPs to provide higher level of transparency, flexibility and end-to-end digitization with aim for them to be resilient against disruptions. To address these changes and remain competitive, Montreuil (2011) suggests rethinking logistics and supply chain paradigms, leveraging the Physical Internet (PI). In principle, it notably means to move from closed logistic networks to more open networks with shared access to resources. Furthermore, by favoring shorter short-haul movement of modular containers between PI hubs for open consolidation, rather than direct long-haul drives as in traditional systems, PI effectively reduces driving distance, greenhouse gas emissions and improves the quality of life for truck drivers (Fazili et al., 2017). This approach paves way for hyperconnected logistics, encompassing multi-plane space structuring and multi-plane meshed networks, interconnecting hubs at multiple levels for efficient and sustainable logistics operations (Montreuil et al., 2018).

Hyperconnected Logistics promotes open sharing of existing assets such as logistic hubs and transportation services among stakeholders to achieve sustainability goals. For example, Naganawa et al. (2024) recently introduced a combinatorial optimization model achieving significant improvements in operational efficiency and a remarkable 52% reduction in CO_2 emissions by utilizing existing logistics facilities as nodes of PI without additional investments. However, they did not factor in the widespread disruptions daily faced by the PI network. Facing such disruptions unprepared induces service delays and increased freight-handling costs. Several works have tackled resilience in traditional supply chain and logistics networks under disruptions by employing strategies such as network topology optimization (Kim et al., 2015; Wang et al., 2023) and dynamic rerouting of commodities (Akyuz et al., 2023). Investigating how PI enabled freight transportation systems handle random disruptions, Yang et al. (2017) developed a multi-agent-based simulation model, focusing on fast-moving consumer goods (FMCGs) chains, highlighting superior performance of PI, even under significant capacity loss during worst-case disruptions. While these approaches enhance resilience, a significant portion of commodity flow remains to be impacted by disruptions. Moreover, the proposed solution approaches in these investigations work well in networks with limited degree of hyperconnectivity and fail to scale when applied to densely connected hyperconnected networks in large geographies. One way to tackle such a problem is to strategically route commodities within hyperconnected networks in the pre-disruption phase itself. Such an approach has the potential to ultimately reduce the portion of commodity flow susceptible to disruptions risks and provides an opportunity to improve operational resilience. As commodity routing tends to be challenging problems to solve, viewing it from a classical optimization lens provides approaches that lack practical scalability. To address such scalability concerns, although at a network design stage (Kulkarni et al., 2021; Kulkarni et al., 2022) proposed a modeling framework based on topology-based optimization. We leverage the core ideas from (Kulkarni et al., 2022) and devise commodity route generation approaches that reduce the commodity flow disruption risks and enhance operational resilience.

Specifically, this paper introduces a modeling framework tailored to enhance operational resilience and mitigate disruption impacts on commodity shipments within densely connected hyperconnected networks. We employ flow decomposition to build two combinatorial algorithms: basic resilience-optimized and adaptive resilience-optimized for commodity route generation. The underlying premise is that distributing commodity flow across multiple (edge-disjoint) paths, reduces the portion of flow impacted by disruptions while remaining efficient in nominal situations. Basic-resilience optimized restricts flow portions on each transportation arc to identify resilient commodity delivery paths and adaptive-resilience incorporates additional capacity constraints on arcs at a company level to select even-more resilient paths. Further, we evaluate the efficiency and resiliency of the generated commodity routes through a set of experiments performed on a case study of finished vehicle logistics in the Southeast USA. Especially, we focus on the freight flow at higher planes (inter-area and inter-regional hub networks), demonstrate the scalability of our algorithms, and showcase the efficacy of the generated routes by analyzing disrupted commodity flows.

The rest of the paper is organized as follows: Section 2 describes the problem setting and the proposed methodology in detail. Section 3 presents the set of experiments conducted with an illustrative case-study of car-hauling industry across Southeast USA. Section 4 provides concluding remarks and identifies promising areas of future research.

2 Resilient Route Generation

We consider a group of logistics companies that deliver commodities across a given geographical region. These companies are interested in devising commodity flow plans or routes that are both efficient in nominal operational conditions and resilient against a wide variety of disruptions.

Formally, we consider a set of locations $\mathcal{S}$ where the commodity demand originates and a set of locations $\mathcal{T}$ where the commodities are delivered. Let $\mathcal{P} \subseteq \mathcal{S} \times \mathcal{T}$ be the set of origin-destination (O-D) pairs of interest with each O-D pair $p \in \mathcal{P}$ having a commodity demand of D_p^1 units. As there are group of companies involved, let $\mathcal{B}$ be the set of these companies or company brands and $\mathcal{P}_{\mathscr{b}} \subseteq \mathcal{P}$ the set of O-D pairs of each brand b. So, for each brand b, its associated total commodity demand D_b^2 is then given by $\sum_{p \in \mathcal{P}_{\mathscr{b}}} D_p^1$ units.

These companies have together opened a set of logistics hub $\mathcal{H}$ at discrete locations which can be utilized to serve the O-D pairs. To this end, we consider the directed graph $\mathcal{G} = (\mathcal{S} \cup \mathcal{T} \cup \mathcal{H}, \mathcal{A})$, which represents a single plane of a hyperconnected network, where commodities are transported from origins $\mathcal{S}$ through logistics hubs $\mathcal{H}$ to finally be delivered at destinations $\mathcal{T}$ through available transportation arcs $\mathcal{A} \subseteq (\mathcal{S} \cup \mathcal{T} \cup \mathcal{H})^2$. Let Λ be the set of such paths which are used for commodity deliveries between these O-D pairs.

The logistics hubs $\mathcal{H}$ serve as locations where the commodities are sorted and shipped towards their respective destinations. As these commodities are not stored for a longer duration at these hubs, the hub capacities are not restrictive. So, we assume that hubs have sufficient capacities to sustain the logistics operations and satisfy the demand. Moreover, due to the huge volume of commodity flow that the network faces, the commodity flow costs can be approximated through linear flow function. So, we use transportation costs on each arc $(i, j) \in \mathcal{A}$ and assume it to be proportional to the travel distance of that arc (i, j).

In order to design commodity flow routes that are both efficient and resilient, we aim to distribute the commodity flow between each O-D pair among multiple paths. The underlying idea is that when a disruption occurs and renders a path unavailable for commodity delivery, only a fraction of total commodity demand is affected and majority of commodity demand gets delivered (Kulkarni et al., 2023). At its core, such a way of commodity flow routing will spread the risks of commodity flow being disrupted and in turn increase the chances of larger fraction of commodity demand fulfillment in timely manner. So, in this section, we present two algorithms (Algorithm 1 and 2) that generate such resilience-optimized commodity delivery routes on the hyperconnected network $\mathcal{G}$. Moreover, these algorithms also determine the commodity flow distribution on these routes for fulfilling the commodity demand D_p^1 between each O-D pair $p \in \mathcal{P}$.

2.1 Basic Resilience-Optimized Route Generation Algorithm

In order to devise such resilience-optimized commodity flow routes, we employ the principle of distributing the commodity flow across multiple edge-disjoint paths (Kulkarni et al., 2021). Whenever a transportation arc is disrupted which belonged to one of the commodity delivery paths, the above-described approach will guarantee the existence of an alternate commodity delivery path that doesn't utilize the disrupted arc at all.

Let $M_p \in [0,100]$ be the maximum allowable proportion of commodity flow between O-D pair $p \in \mathcal{P}$ on each transportation arc. Then, the aim here is to devise $k_p = \lceil 100/M_p \rceil$ edge-disjoint path for commodity flow of O-D pair $p \in \mathcal{P}$. Due to absence of hub capacity restrictions, the task of finding k_p edge-disjoint paths can be computed independently for each O-D pair $p \in \mathcal{P}$. Rather than formulating an optimization problem that finds k_p edge-disjoint paths, we utilize a combinatorial algorithm instead. One of the major benefits of this choice is its vast scalability, especially in very dense networks such as hyperconnected networks. The detailed pseudocode for this basic resilience-optimized route generation algorithm is provided in Algorithm 1.

Algorithm 1: Basic Resilience-Optimized Route Generation

Input : Original Graph $\mathcal{G} = (\mathcal{S} \cup \mathcal{H} \cup \mathcal{T}, \mathcal{A})$, Set of O-D Pairs $\mathcal{P}$, Commodity demand $(D^1)_{p\in\mathcal{P}}$, Maximum allowable proportion of commodity flow on each arc $(M)_{p\in\mathcal{P}}$

Output : Vector of flow on each arc for each commodity $(\boldsymbol{f})_{(i,j)\in\mathcal{A},p\in\mathcal{P}}$

Initialize: Vector of flow $\boldsymbol{f} \leftarrow \{0\}^{|\mathcal{A}|\times|\mathcal{P}|}$, # of edge-disjoint paths $(k_p \leftarrow \frac{100}{M_p})_{p\in\mathcal{P}}$;
for every $p \in \mathcal{P}$ **do**
  Initialize: $\ell_p \leftarrow 0$, $\mathcal{G}_p \leftarrow$ Copy of graph $\mathcal{G}$;
  while $\ell_p \leq k_p$ **do**
    $\lambda_{\ell_p} \leftarrow$ Shortest path on $\mathcal{G}_p$ using Dijkstra's Algorithm ;
    for every $(i,j) \in \lambda_{\ell_p}$ **do**
      $f^p_{i,j} \leftarrow M_p \cdot D_p$, $\mathcal{A}_p \leftarrow \mathcal{A}_p \setminus \{(i,j)\}$;
    $\ell_p \leftarrow \ell_p + 1$;
return $\boldsymbol{f}$

Algorithm 1 distributes the commodity demand into multiple edge-disjoint paths effectively. However, in practice, a transportation arc capacity for each O-D pair is not sufficient. A company (or company brand $b \in \mathcal{B}$) usually has a transportation arc restriction for all its O-D pairs ($\mathcal{P}_b$) together because of the associated contracts with truckers for their travel on each arc. Such a caveat is not captured by Algorithm 1. Hence, next we modify Algorithm 1 to capture such technicality more realistically.

2.2 Adaptive Resilience-Optimized Route Generation Algorithm

Let N_b be the maximum allowable proportion of brand-based commodity flow on each transportation arc for each company brand $b \in \mathcal{B}$. Due to this brand-based arc capacity restriction, the independence of devising commodity delivery routes for each O-D pair separately is not present anymore, although exists at each brand level. So, we compute the commodity delivery routes (through utilizing a combinatorial algorithm) of all the O-D pairs $\mathcal{P}_b$ that belong to a brand $b \in \mathcal{B}$ together. Precisely, we process the O-D pairs $p \in \mathcal{P}_b$ in decreasing order of their associated demand D^1_p. The detailed pseudocode for such adaptive resilience-optimized route generation algorithm is provided in Algorithm 2.

We note that one of the major advantages of adaptive resilience-optimized route generation for commodity delivery other than it able to capture the logistics operational constraints more realistically is that it provides more resilient commodity delivery paths than the basic resilience-optimized algorithm. This happens because of an additional capacity restriction on each transportation arc which leads to distribution of commodity flow to even larger number of (edge-disjoint) paths.

Algorithm 2: Adaptive Resilience-Optimized Route Generation

Input : Original Graph $\mathcal{G} = (\mathcal{S} \cup \mathcal{H} \cup \mathcal{T}, \mathcal{A})$, Set of O-D Pairs $\mathcal{P}$, Set of Brands $\mathcal{B}$, Set of O-D pairs in each brand $(\mathcal{P}_b)_{b\in\mathcal{B}}$, Commodity demand $(D^1)_{p\in\mathcal{P}}$, Maximum allowable proportion of commodity flow on each arc $(M)_{p\in\mathcal{P}}$, Maximum allowable proportion of brand-based commodity flow on each arc $(N)_{b\in\mathcal{B}}$

Output : Vector of flow on each arc for each commodity $(\boldsymbol{f})_{(i,j)\in\mathcal{A},p\in\mathcal{P}}$

Initialize: Vector of flow $\boldsymbol{f} \leftarrow \{0\}^{|\mathcal{A}|\times|\mathcal{P}|}$, Brand-based Commodity demand $D_b^2 \leftarrow \sum_{p\in\mathcal{P}_b} D_p^1$;
for every $b \in \mathcal{B}$ **do**
  Sort $\mathcal{P}_b$ based on decreasing of D^1, $\mathcal{G}_b \leftarrow$ Copy of graph $\mathcal{G}$, Brand-based arc capacity $(C^b \leftarrow N_b \cdot D_b^2)_{(i,j)\in\mathcal{A}}$;
  for every $p \in \mathcal{P}_b$ **do**
    Initialize: $\mathcal{G}_p \leftarrow$ Copy of graph $\mathcal{G}_b$, Commodity flow yet to be routed $R_p \leftarrow D_p^1$, O-D pair-based arc capacity $(C^p \leftarrow M_p \cdot D_p^1)_{(i,j)\in\mathcal{A}}$, $\ell_p \leftarrow 0$;
    while $R_p > 0$ **do**
      $\lambda_{\ell_p} \leftarrow$ Shortest path on $\mathcal{G}_p$ using Dijkstra's Algorithm ;
      $q_p \leftarrow \min_{(i,j)\in\lambda_{\ell_p}} \left\{ \min\{R_p\,,\, C_{i,j}^p\,,\, C_{i,j}^b\} \right\}$;
      for every $(i,j) \in \lambda_{\ell_p}$ **do**
        $f_{i,j}^p \leftarrow q_p$, $C_{i,j}^p \leftarrow C_{i,j}^p - q_p$, $C_{i,j}^b \leftarrow N_b \cdot D_b^2 - \sum_{p\in\mathcal{P}_b} f_{i,j}^p$;
        if $C_{i,j}^p = 0$ **then**
          $\mathcal{A}_p \leftarrow \mathcal{A}_p \setminus \{(i,j)\}$;
        if $C_{i,j}^b = 0$ **then**
          $\mathcal{A}_b \leftarrow \mathcal{A}_b \setminus \{(i,j)\}$;
      $\ell_p \leftarrow \ell_p + 1$;
return $\boldsymbol{f}$

3 Computational Study

3.1 Case Study

In this section, we design commodity flow routes within hyperconnected hub network for finished vehicle logistics across US Southeast through proposed algorithms and assess their efficiency and resiliency. The hyperconnected network is designed through principles mentioned in (Montreuil, 2011; Kulkarni et al., 2024).

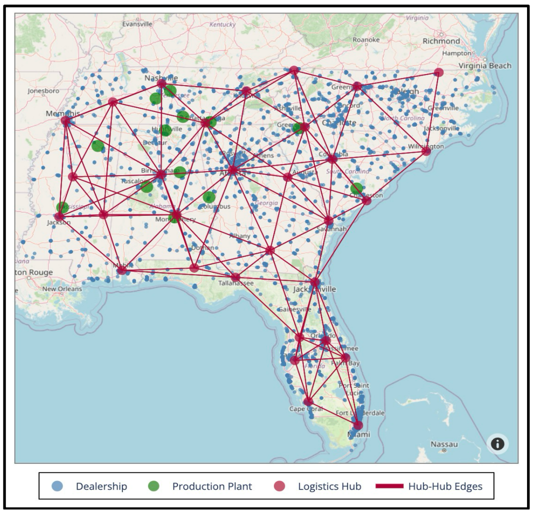

Figure 1: Hyperconnected Hub Network for finished vehicle logistics in the Southeast USA.

Figure 1 represents the hyperconnected network utilized for computational purposes. Here, each node in the network represents the centroid of a cluster of hubs located around the sites with logistics significance such as those having an easy access to boulevards, highways, airports, railway infrastructures, and waterways (Grover et al., 2023). Aligning with the core idea of hyperconnected logistics underpinning the Physical Internet, these hub networks are shared by multiple brands to move thousands of finished vehicles from their production plants to partnered dealerships over large regions. In the interest of this case study, we purposefully assume that these hubs are only used for transporting finished vehicles while it can be utilized by logistics service provides to move other types of freight. In compliance with the regulations imposed by the government stipulating a maximum driving time of 11 hours per day for a truck driver, we restrict the transportation arcs in the network to be within 5.5 hours of drive time. This policy ensures that the drivers can conclude their journeys and return home daily without violating their daily driving limit. Additionally, it's presumed that production plants employ hub network for shipments to dealerships situated more than 5.5 hours away in terms of travel time. This strategic decision aims at capitalizing the advantages of consolidation at hubs for shipments requiring longer travel, thereby achieving greater economies of scale.

3.2 Computational Results

The proposed algorithms and network simulations are implemented in Python v3.11.4 on a laptop with Apple M2 Pro chip (Apple, Cupertino, CA, USA) with 10-core CPU and 16GB unified memory.

First, we generated resilience-optimized flow routes through hyperconnected network for each O-D pair using basic resilience-optimized route generation algorithm as described in Section 2.1. Particularly, by setting the maximum proportion of commodity flow per O-D pair on each transportation arc $M_p = 50\%$, we decomposed the flow through two edge-disjoint paths. Next, we also generated commodity flow routes through adaptive resilience-optimized algorithms by setting maximum allowable proportion of brand-based commodity flow on each transportation arc $N_b = 20\%$ for each brand $b \in \mathcal{B}$ in addition to setting $M_p = 50\%$. To benchmark the efficiency and resiliency of the computed commodity flow routes, we also calculated efficiency-optimized routes for each O-D pair through hub network. The underlying reasoning for computing such routes is that they follow the minimum cost-paths which in turn minimizes the operational expenses in the absence of disruptions.

Figure 2 (a), (b) and (c) presents the commodity flow routes generated using the three algorithms for shipments from a plant located in Mississippi to a dealership in Georgia. Efficiency-optimized methodology select the shortest path via the hub in Birmingham to route the associated O-D flow while resilience-optimized algorithms select two edge-disjoint paths based on set parameters. One interesting observation is that the two edge-disjoint flow routes generated in basic and adaptive resilience-optimized algorithms are different. Basic resilience optimized methodology chooses first two minimum-cost edge-disjoint paths by independently solving for each O-D pair. However, since the adaptive resilience-optimized methodology restricts flow on arc based on brand and solves O-D pairs within brand together in decreasing order of flow, the arc from plant to Birmingham and Montgomery are allocated to O-D pairs with higher flow.

Under the scenario that the transportation arc from plant to Montgomery is disrupted, the entire O-D flow is impacted in efficiency-optimized while 50% flow reaches the dealership on time in case of basic resilience-optimized and 100% flow delivered on time in case of adaptive resilience-optimized. This clearly showcases that the adaptive resilience-optimized can distribute flow to wider range of edge-disjoint paths, leading to generating more resilient flow routes for commodity shipments. In next subsections, we compare the efficiency and resiliency of routes generated by resilience-optimized methodologies by setting $M_p = 33.4\%$ and $N_b = 20\%$ for each brand $b \in \mathcal{B}$, to decompose flow into 3 edge disjoint paths for each O-D pair.

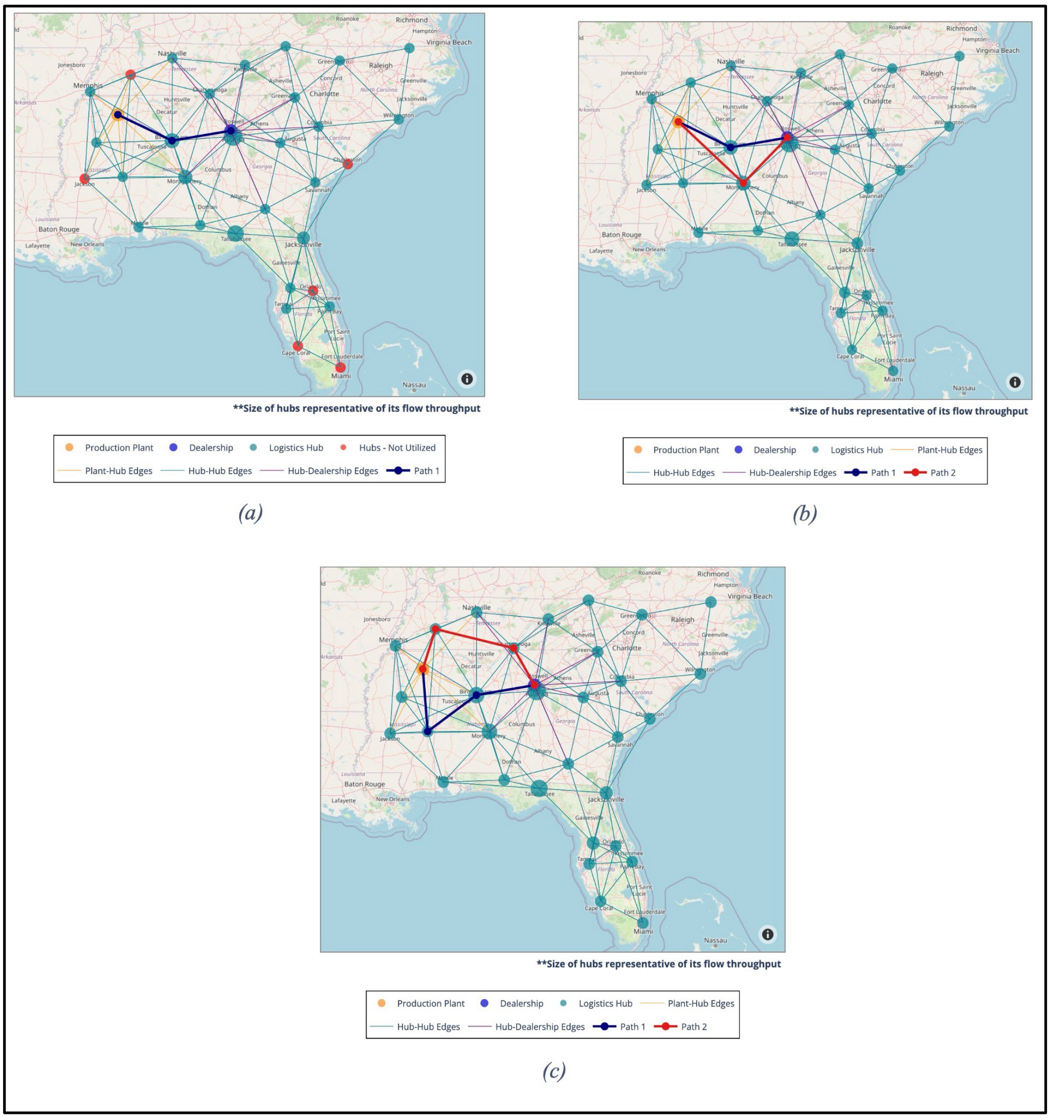

Figure 2: Flow Routes generated for an O-D pair by: (a) Efficiency-Optimized (b) Basic Resilience-Optimized (c) Adaptive Resilience-Optimized algorithms

3.2.1 Efficiency Comparison

To compare the efficiency of proposed algorithms, we calculate an efficiency metric as the ratio of sum of travel times in path weighted by its associated flow to the sum of travel times in minimum cost path weighted by its associated path-flow and shown in Figure 33. In case of routes generated through basic resilience-optimized algorithm, we observe that the induced travel time for all O-D pairs is not more than 20% as that of the routes obtained from efficiency-optimized routes. This depicts the strong hyperconnectivity in hub network and showcases that the resilience-optimized routes generated by basic resilience algorithm are highly efficient under nominal operating situations.

However, in case of routes obtained from the adaptive resilience-optimized algorithm, we find that ~13% of O-D pairs have an induced travel time of greater than 20% and 3% of O-D pairs taking more than 40% than the efficiency-optimized routes. One potential reason for such occurrence lies in the fact that Algorithm 2 prioritizes O-D pairs with higher flows within each brand, and consequently, the O-D pairs with lower commodity demand have to take considerably longer routes.

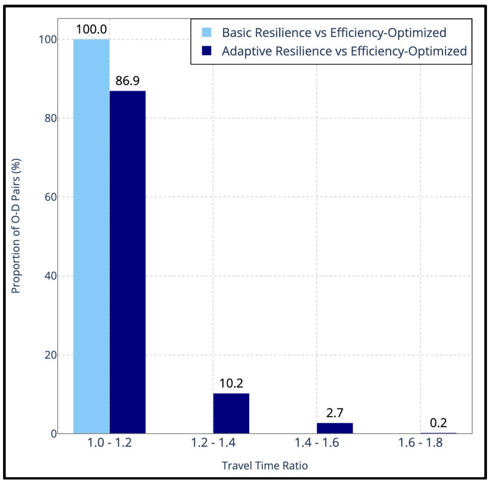

Figure 33: Travel Time Ratio of proposed algorithms with Efficiency-optimized routes

3.2.2 Resiliency Comparison

To assess the resilience of the routes generated by resilience-optimized algorithms against efficiency-optimized ones, we conduct two types of worst-case disruption experiments where we disrupt either a single edge or a single hub randomly. By “worst-case disruptions”, we refer specifically to disruption of transportation arcs (or) hubs that are employed for routing the flow from plants to dealerships under different algorithms (Kulkarni et al., 2023). For these disruption experiments, we suppose that the consolidation plans are fixed a priori and cannot be substantially changed upon the realization of a disruption scenario.

The results from the random 1-edge disruptions are shown in Figure 44(a). In the case of efficiency-optimized routes, the distribution of flow for all O-D pairs in network is highly concentrated on a fewer number of critical edges. These edges are critical in nature as they are being utilized to route associated demand of a large proportion of O-D pairs. When they are disrupted, a substantial flow is affected, leading to a significant increase in freight operational expenses and delayed deliveries for a larger proportion of total flow. On the contrary, in resilience-optimized algorithms, the proportion of flow is well-distributed across the transportation edges and any disruption in these edges affects a lesser proportion of overall flow, thereby depicting higher operational resilience. In particular, the flow is evenly distributed to multiple edges in adaptive resilience-optimized routes enabling a major proportion of flow to reach destination on time even under such worst-case disruptions.

Next, we randomly disrupt 1-hub and the results regarding the disrupted flow are shown in Figure 44(b). Similar to the trend observed in 1-edge disruptions, distribution of flow is more concentrated on a few hubs in efficiency-optimized methodology, with almost 40% flowing through one hub. This hub is consistently utilized for over 30% of flow in resilience-optimized cases, indicating its criticality in the network. Moreover, in the case of efficiency-optimized, more than 50% of the hubs have higher throughput flow compared to resilience-optimized, signifying that on an average higher proportion of O-D flow is likely to be affected under worst-case hub disruptions.

We note an interesting aspect which lies in the context of adaptive resilience-optimized routes. Despite achieving higher resilience under edge disruptions by limiting the proportion of flow on edges by brand, it introduces a trade-off. The selected edge-disjoint paths exhibit more intersections of nodes, rendering the system less resilient under hub disruptions compared to the basic-resilience optimized algorithm.

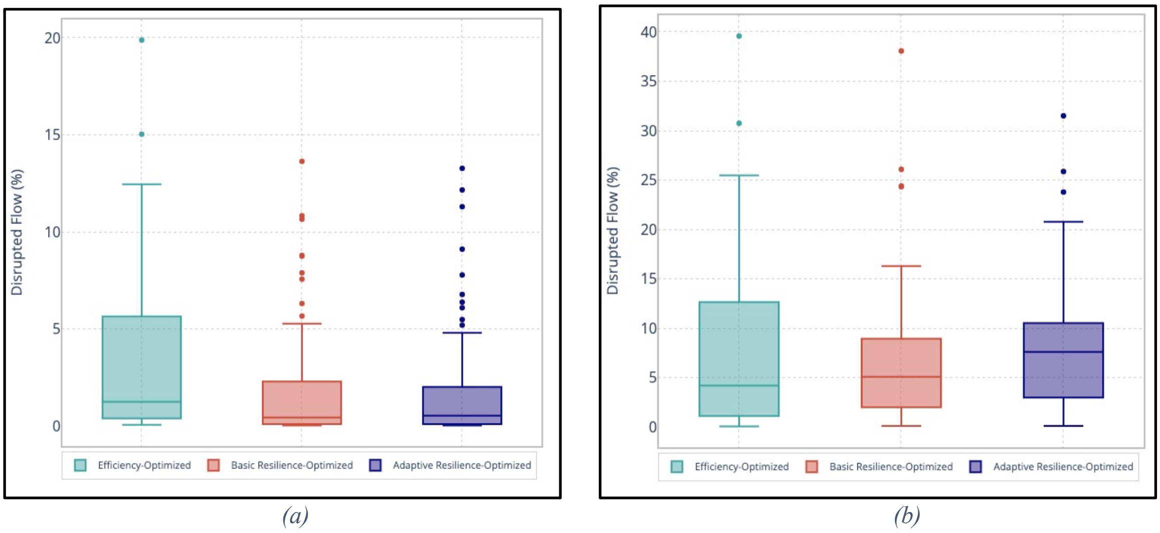

Figure 44: Comparison of disrupted flow % across methodologies under random (a) 1-Edge Disruption (b) 1-Hub Disruption

4 Conclusion

In this article, we ascertained the need for and importance of devising commodity delivery paths across hyperconnected networks that are both efficient in the absence of disruptions and resilient to sustain a wide variety of disruptions. To this end, we devised two algorithms: basic and adaptive resilience-optimized for commodity route generation. These algorithms distribute commodity flow smartly across multiple (edge-disjoint) paths while respecting the constraints of logistics operations realistically. Comparison results depicted enhanced capability of sustaining disruptions by the routes computed through proposed algorithms as opposed to that generated through only efficiency considerations. We observed that the routes generated through basic resilience-optimized were more efficient than those of adaptive resilience-optimized algorithm. In terms of resiliency, we witnessed the opposite trend of that observed for efficiency comparison. Overall, a classic trade-off between efficiency and resiliency is observed in all the routes generated through the proposed algorithms.

The current work opens multiple avenues of research. These algorithms, although scalable, are still heuristic ways to devise resilience-optimized commodity delivery routes. The first avenue is to explore optimization-based modeling framework for the same problem and devise exact solution approaches for it. Second, instead of devising edge-disjoint commodity delivery paths, non-edge-disjoint paths can be computed. Such an approach, although less capable of sustaining disruptions, is indeed more efficient in nominal operating conditions. This will require exponential-sized optimization models and sophisticated solution techniques such as column generation to devise good quality routes. Finally, regarding evaluation of such routes, a more comprehensive set of disruption experiments can be conducted. This could involve simulating other types of disruption scenarios such as multiple edge and hub disruptions, localized disruptions, and adversarial type of disruptions.

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