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Comparing the resilience of multi-hub supply chain networks under port disruption scenarios: a case study of Singapore, Port Klang and Tanjung Pelepas

Shengnan Zhao

James Cook University, Singapore, Singapore

zhao_shengnan2021@163.com

Abstract. Major transshipment hubs improve operational efficiency through cargo concentration but can transmit local disruptions across maritime supply chains. Existing research recognises network redundancy yet insufficiently distinguishes the presence of backup hubs from their deployable capacity. Using Singapore, Port Klang, and Tanjung Pelepas as a regional case, this study compares four network configurations across five disruption scenarios. A linear programming model allocates cargo flows while evaluating demand fulfillment and relative total cost; sensitivity analysis examines backup capacity assumptions. The findings show that additional hubs do not automatically generate resilience. Service continuity depends on whether deployable backup capacity covers the demand shortfall created by disruption at the primary hub. Under a 75% capacity loss at the Port of Singapore, the multi-hub configuration achieved a demand fulfillment rate of 57.76%, which was 32.76 percentage points higher than that of the single-hub configuration, while recording a lower relative total cost of 445.78 compared with 750.00. Dual-hub configurations also performed differently because alternative ports varied in usable capacity and rerouting costs. Overall, redundancy improved both service continuity and relative cost performance when the disruption losses it avoided exceeded the additional coordination and rerouting costs. This paper therefore offers a conditional theoretical interpretation for effective network redundancy and proposes the principle of capacity-matched selective diversification, which can guide the design of regional transshipment networks.

Keywords: maritime supply chain resilience, port disruption, transshipment multi-hub networks, network flow analysis, Southeast Asian ports

1. Introduction

Maritime supply chains rely on ports to connect transport networks, regional production, and cross-border trade. Large transshipment hubs improve daily operational efficiency through cargo flow concentration, liner connections, and economies of scale, but this also makes supply chains highly dependent on key nodes. Existing research shows that the systemic importance of ports cannot be measured solely by throughput, as their role in international trade and supply chain connections should also be considered [1]. The COVID-19 pandemic, widespread port congestion and shipping-network imbalances further demonstrate that local port operational failures can escalate into cross-regional service disruptions [2].

Faced with such risks, establishing alternative hubs is often proposed as a means of strengthening resilience. However, the presence of alternative ports represents only structural redundancy and does not reveal how much service the network can preserve following a disruption. Existing studies have paid considerable attention to network connectivity, adaptability and inter-organisational collaboration [3], as well as the relationships among topology, vulnerability and investment decisions [4]. Less is known about how these factors interact at the operational level: whether combined backup capacity remains sufficient as disruption intensifies, how displaced cargo should be allocated among alternative ports with different capacities and rerouting costs, and when the reduction in unmet demand justifies the additional cost of maintaining and using those alternatives. Without this capacity-and-cost perspective, the different performance of networks with similar levels of structural redundancy remains insufficiently explained. This study uses the Port of Singapore as the main hub, with Port Klang and the Port of Tanjung Pelepas as potential alternative nodes, comparing the performance of single-hub, two types of dual-hub, and multi-hub configurations under varying degrees of interruption. This study explores the capability and cost conditions under which nominal structural redundancy can be transformed into practical service resilience.

2. Literature review and analytical framework

2.1. Maritime supply chain resilience

Maritime supply chain resilience describes a system's capacity to sustain core functions under external shocks, adapt to operational disturbances and gradually restore services. Beyond physical infrastructure damage, it highlights interdependencies across ports, shipping routes, carriers and cargo-flow arrangements [3]. Existing maritime-network resilience research differentiates structural vulnerability, shock absorption, recovery pathways and investment trade-offs, demonstrating that network connectivity does not guarantee adequate service delivery for existing demand [4]. Based on this difference, this paper specifically limits resilience to the ability to repurpose cargo flows through alternative ports during disruptions, reduce unmet demand, and maintain service continuity. This definition focuses on shock absorption and service retention in the network, without factoring in recovery speed, vessel wait times, or long-term rebuilding capacity within unmeasured scopes.

2.2. Port disruptions and network vulnerability

Port disruptions feature prominent network spillover effects. Multiple studies illustrate that extreme weather, infrastructure failures and shipping-channel blockages can propagate shocks beyond individual port facilities and generate far-reaching logistics and trade-related economic consequences [5-7].

These studies collectively demonstrate that the vulnerability of centralized networks stems from the high coupling between critical nodes and system functions. When freight flows lack alternative routes, the decline in main hub capacity is more likely to directly translate into demand losses; conversely, networks with alternative processing paths may retain some services after node damage. However, the structural presence of paths does not guarantee smooth transfer of goods; whether alternative nodes have callable capability is a key supplement to understanding network vulnerabilities.

2.3. Multi-hub networks and redundancy

The multi-hub network provides alternative space for damaged main hubs by dispersing cargo flow processing nodes. Current research has found that improving port route connectivity helps enhance overall network robustness [8]; load redistribution between ports and inland nodes can also slow the spread of local faults to the system [9]. However, these results do not mean that arbitrarily increasing nodes will proportionally improve resilience. There may be significant differences between node connectivity, callable processing capability, and cross-node coordination conditions.

Therefore, it is necessary to distinguish between "nominal redundancy" and "effective redundancy." Nominal redundancy refers to the presence of one or more backup nodes in the network; Effective redundancy means these nodes can truly be called under specific disruption scenarios and are sufficient to handle the freight flow that the main hub cannot handle. The former describes structural possibilities, while the latter determines whether service continuity can be achieved. The gap between the two means that the number of hubs is not a sufficient indicator of network resilience, and redundancy value must be evaluated in conjunction with capacity constraints and coordination costs.

2.4. Research gap and analytical framework

Existing literature has explained the importance of port network resilience from the perspectives of system risk, route optimization, and load redistribution, but rarely compares dual and multi-hub structures for single hubs or different alternative ports within the same region under unified demand, cost rules, and interruption scenarios. It is especially necessary to further explain why the same number of backup nodes produces different resilience results, and at what level of backup capacity structural redundancy can be converted into practical service assurance.

Based on this, this paper constructs a conditional analysis framework: network configuration determines which alternative nodes can enter the model, the callable capacity of alternative nodes determines the scale of freight flow that can be reallocated, and the results of reallocation collectively affect service continuity and relative total cost. The scale of main hub interruptions determines the service gaps that need to be filled, while the cost of coordination and rerouting determines the economic acceptability of redundant configurations. The core viewpoint of the study is that port network resilience depends on matching backup capacity with interruption gaps, rather than on the number of hubs; only when the loss of unmet demand avoided exceeds the additional organizational and rerouting costs can redundancy achieve both operational value and economic viability.

3. Research methodology

3.1. Case selection and network scope

This paper adopts a purposeful case selection, selecting the Port of Singapore, Port Klang, and the Port of Tanjung Pelepas as container transshipment nodes with potential substitution relationships within the same region. In 2024, the Port of Singapore handled 41.12 million TEU of containers [10], Port Klang about 14.64 million TEU [11], and Port Tanjung Pelepas 12.30 million TEU [12]. The three ports are all located in major Southeast Asian shipping regions, but differ in throughput scale, location, and shipping connectivity, making them suitable for comparing the impact of different alternative nodes on network resilience. Geographically, the Port of Tanjung Pelepas lies immediately west of Singapore, while Port Klang is located farther northwest along the Strait of Malacca. The coordinate-derived distance proxies are approximately 18.69 nautical miles between Singapore and Tanjung Pelepas, 179.53 nautical miles between Singapore and Port Klang, and 162.03 nautical miles between Port Klang and Tanjung Pelepas. The model sets the Port of Singapore as the main hub and the other two ports as potential backup nodes, using "network configuration—disruption scenario" as the unit of analysis. The scope of the study covers static cargo flow allocation at the port level, excluding origin, destination, inland transport, contract slots, and dynamic recovery processes. Therefore, this paper estimates the relative performance of different network structures under established assumptions, rather than the exact results after actual port disruptions. This analysis focuses on static port-level cargo-flow allocation under given disruption scenarios. Origin-destination cargo characteristics, inland hinterland transportation, carrier slot contracts, vessel queuing delays, port congestion induced by diverted cargo, multi-port simultaneous failures, and time-phased service recovery dynamics are excluded from the model.

3.2. Network construction and four network configurations

Let the port node set $V = S, K, T$, where S, K, and T represent the Port of Singapore, Port Klang, and the Port of Tanjung Pelepas, respectively. The binary variable $A(i, m)$ indicates whether port i is enabled in network configuration m: a value of 1 indicates it is eligible to participate in cargo flow allocation, and a value of 0 indicates that the node is unavailable. It is important to emphasize that enabling a node does not necessarily mean it will receive traffic; actual allocation still depends on disruption scenarios, effective capacity, and optimization goals.

Table 1. Network configurations and alternative-hub arrangements

Configuration	Enable vectors (S, K, T)	Structure	Alternative ports	Coordination cost index
N01	(1,0,0)	Single hub	None	0
N02	(1,1,0)	Dual hubs	Port Klang	2
N03	(1,0,1)	Dual hubs	Port Tanjung Pelepas	2
N04	(1,1,1)	Multi-hubs	Port Klang and Port Tanjung Pelepas	4

As shown in Table 1, N01 is the single-hub baseline in which only the Port of Singapore is active, and no coordination cost is added. N02 and N03 introduce Port Klang and the Port of Tanjung Pelepas as alternative hubs, respectively, with a coordination cost index of 2 for each configuration. N04 activates all three ports and allows both backup hubs to receive reallocated cargo, increasing the coordination cost index to 4. These configurations enable the effects of additional redundancy and alternative-port selection to be compared separately.

For each additional backup hub, the model increases the fixed coordination cost by 2 units to reflect the relative organizational burden of maintaining the backup link. The four configurations share the same requirements, port base capacity, interruption scenarios, and penalty parameters, allowing comparison of structural redundancy, alternative port heterogeneity, and the incremental effect of a second standby node respectively.

3.3. Network flow and multi-criteria analysis

The study adopts a method combining single-objective linear programming with post-event multi-indicator evaluation. Let $x(i, m, s)$ represent the allocation of cargo flow at port i in network configuration m and interruption scenario s, and $U(m, s)$ represent unmet demand. The effective handling capacity of a port is determined by the factors of base capacity, node activation status, scenario availability, and backup capacity:

$$Q(i,m,s) = B(i) \times A(i,m) \times Availability(i,s) \times CapacityFactor(i) \tag{1}$$

Where $B(i)$ is the Port Basic Capacity Index; $Availability(i,s)$ is the scenario availability; Capacity Factor is the proportion of capacity that can handle the cargo flow under the modeled conditions. The capacity factor for the Port of Singapore is 1, and the capacity factor for the two alternative ports in the baseline scenario is 0.5.

$$\begin{gathered} MinTC(m,s) = c(S) \times x(S,m,s) + c(K) \times x(K,m,s) \\ +c(T) \times x(T,m,s) + P \times U(m,s) + Ccoord(m) \end{gathered} \tag{2}$$

In the formula, $c(S)$, $c(K)$, and $c(T)$ are the unit rerouting cost indices for the three ports, P is the penalty for unmet demand, and $Ccoord(m)$ is the network coordination cost. Cargo flow allocation simultaneously meets port capacity constraints, demand balance constraints, and non-negative constraints:

$$0 \leq x(i,m,s) \leq Q(i,m,s) \tag{3}$$

$$x(S,m,s) + x(K,m,s) + x(T,m,s) + U(m,s) = D(s) \tag{4}$$

The model was solved using Microsoft Excel Solver's pure linear programming method. The results are compared by demand fulfillment rate with relative total cost, where demand fulfillment rate is defined as:

$$FulfilmentRate(m,s) = [D(s) - U(m,s)]/D(s) \times 100\% \tag{5}$$

To explain when structural redundancy can be converted into actual service continuity, this paper further calculates the demand gap and backup capacity coverage formed by the main hub based on existing model variables:

$$Gap(s) = max\{0, D(s) - Q(S,m,s)\} \tag{6}$$

$$Coverage(m,s) = [Q(K,m,s) + Q(T,m,s)]/Gap(s), Gap(s) > 0 \tag{7}$$

When coverage is not less than 1 and there are no additional transfer constraints outside the model, backup ports could fully fill the main hub gap; when coverage is below 1, unmet demand is inevitable.

3.4. Data, indicators and disruption scenarios

The study uses publicly available port data from 2024. Liner Transport Connectivity refers to the Port Liner Connectivity Index published by the United Nations Conference on Trade and Development [13], port performance references the Container Port Performance Index published by the World Bank and S&P Global Market Intelligence [14], and port coordinates are sourced from the UN Trade Location Code database [15].

The baseline demand is set at 100 standardized cargo flow units, and the base capacity of the Port of Singapore is set at 100. The base capacity of the two alternative ports is calculated based on the ratio of 2024 throughput to the Port of Singapore's throughput:

$B(K)$ = 14.64 / 41.12 × 100 = 35.603

$B(T)$ = 12.30 / 41.12 × 100 = 29.912

The unit rerouting cost is based on the large circular distance calculated from port coordinates as the proxy variable, and the maximum normalization method is used to convert it into a relative cost index:

$$CostIndex(r) = DistanceProxy(r) \div MAX[DistanceProxy] \tag{8}$$

Among the three port-to-port routes, the distance agent value for the Port of Singapore to Port Klang is the largest, so its normalized cost index is 1; The cost index for the Port of Singapore to the Port of Tanjung Pelepas is 0.10410468; The cost index for Port Klang to the Port of Tanjung Pelepas is 0.90256625. (These values only represent the relative distance cost relationships between routes and do not represent actual route distance, market rates, or total logistics costs.)

The base analysis sets five Port of Singapore capacity loss scenarios at 0%, 25%, 50%, 75%, and 100%; the two backup ports remained available in the baseline scenario, with a backup capacity factor set at 50%. The unit penalty for unmet demand was set at 10, higher than the unit cost of the two alternative paths. The four networks combined with five interruption levels formed 20 base simulations. Sensitivity analysis further fixed the main port capacity loss at 75%, adjusting the backup capacity factor to 25%, 50%, 75%, and 100%, forming 16 supplementary simulations to test the different effects of "node count" and "callable capacity" on resilience.

4. Results and comparative analysis

4.1. Performance under normal conditions

During normal operation, all four networks can meet all demand, with cargo flow handled independently by the Port of Singapore. Although the backup ports are enabled in dual and multi-hub structures, they do not provide additional fulfillment benefits under normal conditions because the main hub is already capable of covering all demand. The differences between configurations mainly manifest in the coordination cost set by the model: the total cost indices for single-, dual-, and multi-hub configurations are 0, 2, and 4 respectively. The results show that under the uninterrupted scenario, the handling capacity of the Port of Singapore is sufficient to meet all demand, so enabling a standby port does not further improve demand fulfillment rates but rather increases the fixed coordination costs set by the model. From this perspective, single-hub networks have higher cost efficiency during normal operation. However, this advantage only reflects static performance without impact and does not directly represent overall performance in port disruption scenarios. The additional coordination costs borne by dual-hub and multi-hub networks are the preparatory inputs required to maintain backup port relationships and cargo flow transfer capacity. Whether these inputs generate resilience benefits requires further judgment based on demand fulfillment rates, unmet demand, and total costs at different levels of interruption.

4.2. Performance under moderate disruption

After the main hub experiences mild to moderate shocks, network differences no longer depend on the presence of backup nodes, but on whether their processing capacity covers service gaps. When the Port of Singapore loses 25% capacity, the multi-hub network maintains a 100% demand fulfillment rate, while the single hub maintains only 75%, while the two dual hubs have rates of 92.80% and 89.96%, respectively. When capacity loss expands to 50%, the fulfillment rate of the multi-hub drops to 82.76%, indicating that even with two backup nodes, the actual callable capacity is still insufficient to fully offset the larger primary port loss. From the model's cargo flow allocation results, the above differences mainly come from the backup processing capacity that different networks can call. Under the condition of a backup capacity factor of 0.5, Port Klang and the Port of Tanjung Pelepas can handle about 17.80 and 14.96 standardized cargo flow units, respectively. Therefore, when the Port of Singapore loses 25 units of processing capacity, no single backup port alone can fill the entire gap, while the multi-hub network can integrate the total processing capacity of about 32.76 units from two backup ports, continuing to meet all demand. When the capacity loss reaches 50%, the fulfillment rate of the multi-hub network falls to 82.76%, indicating that even the combined capacity of two backup nodes is insufficient to fully offset the larger loss at the primary port (Figure 1). This indicates that the advantage of the multi-hub network does not simply come from increasing the number of ports, but from integrating more available capacity; when the capacity gap caused by disruptions exceeds the combined capacity of the backup ports, unmet demand still occurs.

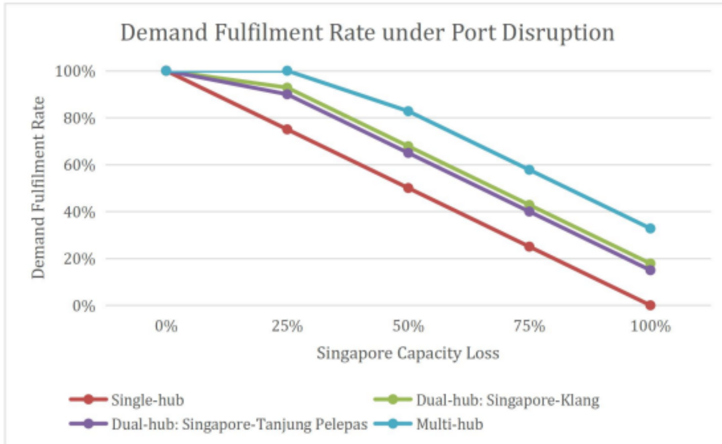

Figure 1. Demand fulfilment rate under different levels of port disruption

A comparison of the two dual hubs further shows that having the same structural form does not necessarily mean the same resilience. The Port of Tanjung Pelepas has lower unit rerouting costs, but Port Klang offers greater effective capacity. Therefore, in a benchmark model with higher penalties for unmet demand, the dual hubs configured at Port Klang maintain higher service levels and achieve lower relative total costs. This indicates that the selection of backup nodes should not be based solely on the number of hubs or geographic distance, but also on the main port gap, available capacity, and losses caused by unmet demand.

4.3. Performance under severe disruption

Severe disruption scenarios further show that the main role of network redundancy is not to eliminate the impact of interruptions, but to mitigate the direct transmission of main hub capacity loss to overall service levels. In a single-hub structure, the decline in the Port of Singapore's capacity directly translates into unmet demand; in dual-hub and multi-hub structures, some cargo flow can be transferred to backup ports. When Singapore Port loses 75% of its processing capacity, the multi-hub network can still maintain a demand fulfillment rate of 57.76%, significantly higher than the 25% of the single-hub network. Even if the Port of Singapore is completely disrupted, the multi-hub network can still maintain some cargo flow through two backup ports, indicating that replacement nodes can prevent the network service capacity from being completely lost due to the main hub's failure.

However, multi-hub structures can only buffer interruptions and cannot absorb shocks indefinitely. As capacity loss at Singapore Port continues to grow, the volume of cargo to be transferred gradually exceeds the effective handling capacity of the backup port under the model, and unmet demand will still arise. Therefore, having multiple ports in the network does not mean the network can continuously meet all demand. The actual performance under severe disruptions depends on how much transferred cargo the backup ports can jointly handle. This shows that network resilience depends not only on the presence of alternative nodes but also on whether backup capacity matches the expected scale of outages.

Figure 2 further shows that disruptions change the cost ranking between different network structures. A single-hub network has the lowest cost under normal conditions, but during severe disruptions, the cost of unmet demand quickly increases. Although multi-hub networks bear higher coordination and rerouting costs, they can reduce the total cost of modeling by reducing unmet demand. The differences between the two dual-hub structures also indicate that alternative ports that are closer or have lower unit rerouting costs do not necessarily result in lower total costs; under conditions of high penalties for unmet demand, the scale of cargo capacity that backup ports can handle may be more important than the unit rerouting cost. Therefore, network selection during severe disruptions should not only compare to normal operating costs but also consider how much backup capacity can reduce service losses.

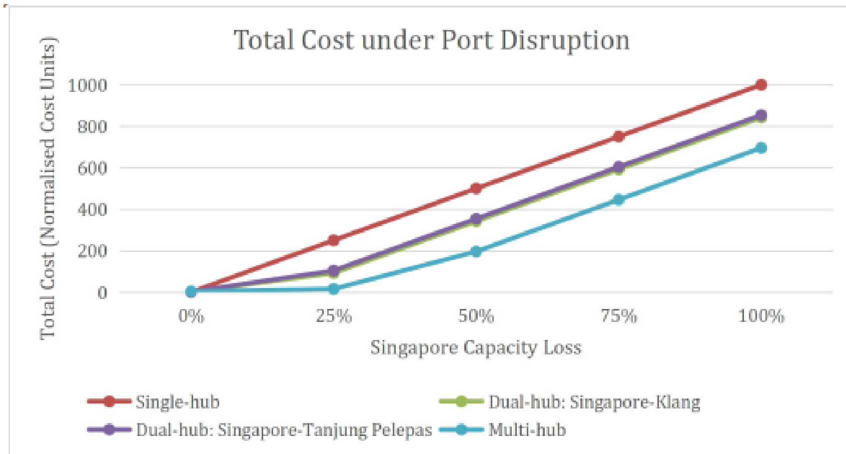

Figure 2. Relative total cost under different levels of port disruption

4.4. Overall comparison of network resilience

No network configuration universally outperforms others across all scenarios. Network structure defines whether rerouting pathways exist, yet achievable service continuity is jointly constrained by the deployable handling capacity of available backup ports. Heterogeneity among alternative ports further implies that configurations with identical hub quantities can deliver divergent resilience outcomes. Multi-hub designs provide broader cargo-flow adjustment space but incur higher coordination overheads. The sensitivity analysis in Figure 3 further shows that structural backup nodes can only be effective when they have sufficient processing power. Under conditions of severe disruption at the Port of Singapore, increasing the backup capacity factor will not change the performance of the single-hub network, as the structure lacks backup ports capable of participating in cargo flow transfers. In contrast, the demand fulfillment rate for dual-hub and multi-hub networks increases as backup capacity increases, with the most significant improvements in multi-hub networks. This suggests that network structures offer potential alternatives rather than automatically formed resilience outcomes. If backup ports can only handle a small amount of cargo flow, even if there are multiple alternative routes in the network, their service improvements remain limited; when more backup capacity can be used for freight flow transfer, the same network structure will demonstrate stronger interruption absorption capacity. However, increasing backup capacity does not infinitely improve network performance. Even if the capacity factor of the two backup ports is raised to 100%, the multi-hub network still cannot fully cover the full capacity gap created by the severe disruption at Singapore Port. This indicates that each network configuration has a service ceiling determined by the overall processing capacity of the backup ports. Therefore, network resilience planning should not simply pursue more ports or more complex structures but should allocate sufficient backup capacity based on the expected disruption scale and target service levels. Redundant allocations only have real value when backup capacity can cover the freight flow gap in major risk scenarios, and the reduced unmet demand costs are sufficient to offset the additional coordination and rerouting costs.

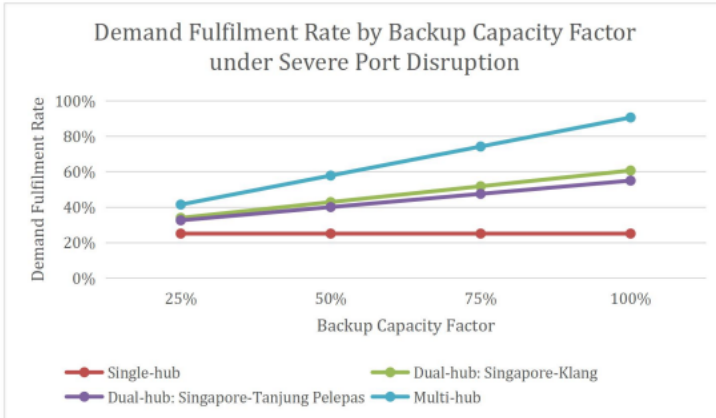

Figure 3. Demand fulfillment under different backup capacity factors

The simulation results reveal clear cost-service-level trade-offs conditional on disruption severity. Under minor disruptions, single-hub configurations deliver the lowest total cost, since the extra coordination costs of dual-hub and multi-hub networks cannot be offset by limited avoided disruption losses. Under moderate disruptions, multi-hub networks achieve superior demand fulfillment.

5. Discussion

Existing studies on maritime supply chain resilience usually explain port systems' ability to cope with disruptions from the perspectives of network topology, infrastructure reliability, organizational adaptation, and post-disaster recovery [3, 4]. Route optimization and load redistribution studies also show that alternative routes and nodes can reduce the impact of local failures on the overall network [8, 9]. The results of this paper support this basic understanding but also indicate that providing alternative port access to the network only means cargo flow can be transferred, not that all cargo affected by interruptions can be handled. Network connectivity determines whether alternative paths exist, while the effective processing capacity of backup ports under the model determines how much service those paths can sustain. Therefore, port network resilience cannot be judged solely by the number of hubs or connection relationships; the relationship between backup capacity and the main hub service gap must also be considered.

The two dual-hub configurations have the same number of nodes but show different demand fulfillment rates and total costs, further indicating that network topology alone is insufficient to explain resilience differences. Backup ports have different characteristics in terms of relative processing scale and rerouting costs, so not all replacement nodes can play the same role. Under the model conditions discussed in this paper, larger effective processing capacity can reduce more unmet demand, and its impact may even outweigh the difference in unit rerouting costs. Thus, the evaluation of backup ports should not be based solely on geographic distance or nominal throughput scale but should consider the amount of cargo they can handle under specific disruption scenarios and the corresponding reconfiguration costs.

Based on these results, this paper advances the interpretation of port network redundancy from the structural level to the operational level. Network structure determines which backup nodes can participate in cargo flow allocation; the effective handling capacity of backup ports determines the upper limit of transferable cargo flow; the degree of disruption at the main hub determines the service gaps that need to be filled; and the final redistribution of cargo flow collectively affects demand fulfillment rates and total costs.

This process indicates that structural redundancy can only be converted into observable resilience benefits when backup capacity can fill service gaps.

The research also shows that the relationship between efficiency and resilience changes with network operating conditions. Under normal conditions, standby ports do not participate in cargo flow processing, and coordination costs manifest as additional expenditures; after interruptions, standby ports reduce unmet demand by taking on transferred cargo flows, turning these upfront investments into real value. As disruption levels increase, networks with greater backup capacity can avoid more service losses, and their total cost may be lower than centralized networks lacking replacement capacity. The differences between the two dual-hub configurations also indicate that when unmet demand losses are high, the additional processing capacity of backup ports can offset higher unit rerouting costs. Therefore, the economic performance of network architecture depends on the combined effect of normal operating costs, backup processing capacity, and service losses caused by interruptions.

For practical network planning, managers should first define target service levels under plausible disruption scenarios and quantify potential service gaps of primary hubs when configuring backup resources. Backup-port selection should jointly consider deployable handling capacity and rerouting costs. Under severe disruptions, sufficient usable capacity may outweigh the advantage of low unit rerouting expenses.

6. Conclusion

By comparing the performance of four network configurations under varying degrees of disruption, the study found that network architecture significantly changes how port supply chains absorb disruptions. A single-hub network can maintain low costs during normal operation, but its service level rapidly weakens as the Port of Singapore's capacity declines; dual-hub and multi-hub networks can reallocate cargo flow through Port Klang and the Port of Tanjung Pelepas, reducing the impact of main hub disruptions on overall service. Multi-hub networks typically maintain higher demand fulfillment rates, but this advantage is not simply due to the increase in port numbers. What truly determines network resilience is whether the effective processing capacity provided by backup ports matches the service gaps of the main hub. The different outcomes produced by the two dual-hub configurations also indicate that the processing scale and rerouting costs of backup ports jointly affect network performance.

Annual throughput reflects the relative processing scale among the three ports but does not fully represent the remaining capacity immediately available to receive transferred cargo flow when disruptions occur; Standardized distance and cost parameters also simplify real-world freight rates, berths, routes, and coordination arrangements. At the same time, the model keeps demand at a fixed level and focuses on scenarios of disruption at Singapore, without showing more complex changes such as backup port congestion, simultaneous disruptions at multiple ports, or cargo flow adjustments over time. These settings allow different networks to be compared under the same conditions, but simulation results are mainly used to explain the relationships between network structure, backup capacity, and continuity.

Future research can further replace current agent parameters with terminal operation records, shipping company cargo flows, actual freight rates, and contingency capacity agreements, incorporating vessel waiting, port congestion, related disruptions, and phased recovery processes through dynamic or random optimization.

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