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Resilience-driven optimisation for cascading disruption adaptation across the European container shipping network

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Ports frequently face recurrent disruptive events associated with strikes, extreme weather, and regional conflicts. Recent disruptive events such as Red Sea crisis and Russia-Ukraine conflict have generated significant impact onto European ports. These shocks trigger cascading disruptions as cargo flows are redistributed to alternative ports, undermining network resilience and exposing the vulnerabilities of diverse stakeholders. To tackle this challenge, this study develops a resilience-driven multi-objective optimisation framework that supports actionable load redistribution during cascading disruptions. The framework jointly minimises time-related costs for shippers and carriers, alleviates port congestion, and preserves the structural integrity of the network. To enable a practical-scale implementation, a novel stepwise heuristic algorithm is designed to produce redistribution decisions at each stage of the disruption. By simulating full disruption propagation, the framework quantifies multidimensional resilience losses using economic, functional, and structural indicators. Applied to the European container shipping network (ECSN), a comprehensive assessment of failure scenarios across all 172 ports reveals pronounced heterogeneity in systemic importance across Europe. Using the Port of Hamburg as a case study, the proposed framework outperforms four widely used heuristics in mitigating the cascading disruptions triggered by port failure, delivering consistent gains in reduced cumulative costs, lower port congestion, and improved preservation of network connectivity.

Keywords: Resilience-driven optimisation, cascading failures, shipping networks.

1. Introduction

European container ports operate within a tightly coupled service network in which recurrent disruptive events (e.g., public incidents, extreme weather, infrastructure outages, and geopolitical conflicts) can rapidly propagate beyond the initially affected port (Cao et al., 2024). In such cases, when a port's handling capability or accessibility is impaired, load (e.g., cargo and vessel calls) needs to be redistributed to alternative ports, often concentrating surges on already busy hubs (Bai et al., 2023). Such redistribution behaviors thereby trigger cascading failures and expose heterogeneous resilience challenges. Shippers and carriers face schedule delay penalties and time-related costs, ports and terminal operators confront operational overload pressures, and public authorities must maintain essential trade connectivity while managing systemic structural integrity (Cao et al., 2025d).

Against this backdrop, analysing cascading failure propagation mechanisms and proposing effective mitigation strategies within container shipping networks are crucial to resilience and decision support for various shipping stakeholders to adapt disruptions. Currently, existing cascading failure studies in shipping networks typically operationalize two design choices: (i) how to identify feasible redistribution targets and (ii) how to determine redistributed volumes among those targets (Cao et al., 2025a). In the literature, target selection is often constrained using predefined conditions such as choosing neighbouring or downstream ports (Lu et al., 2024), applying distance or transit-time windows (Cao et al., 2025c), enforcing same role/country constraints (Bai et al., 2023), and requiring that candidate ports remain functional (Xu et al., 2024). Redistributed volumes are commonly defined via proportional calculation based on attributes such as capacity (Bai et al., 2023), degree, distance (Xu et al., 2024), or composite scores (Cao et al., 2025c). Although these studies have advanced post-event assessments and supported comparative analyses of propagation patterns, they still offer limited actionable decision support because these studies still focus on quantification of resilience losses by applying a pre-specified redistribution rule, rather than deriving interventions that are explicitly optimized to preserve resilience under cascading dynamics. This post-hoc perspective yields weak prescriptive guidance during unfolding disruptions. Moreover, many redistribution strategies remain effectively single-objective, which inadequately reflects the multi-stakeholder trade-offs among delay, port overload, and network-wide structural integrity.

To address these gaps, this paper develops a resilience-driven, multi-objective optimization framework for cascading disruption adaptation. The framework formalizes load redistribution as a tri-objective optimization problem aligned with stakeholder priorities, i.e., minimizing time-related cost impacts for shippers and carriers, reducing overload stress for port and terminal operators, and preserving network-level structural integrity for public authorities. To solve the resulting problem at a practical scale, a stepwise heuristic algorithm is designed that integrates elite target selection, an iterative load calculation, and an evolutionary search. This combination maintains Pareto solution diversity while controlling computational burden, thereby supporting decision-making contexts in which multiple trade-off solutions are needed. Application to the European container shipping network (ECSN) further demonstrates the framework's superiority in mitigating disruption impacts relative to benchmark strategies, providing evidence of its operational relevance for emergency response and resilience enhancement.

The remainder of this paper is organized as follows. Section 2 presents the resilience-driven multi-objective optimization framework for cascading disruption adaptation. Section 3 reports the numerical experiments. Section 4 concludes the paper.

2. Methodological Framework

This section proposes the resilience-driven optimisation framework used to model load redistribution under cascading disruptions. Section 2.1 introduces the network representation and the cascading disruption mechanism. Section 2.2 formulates the multi-objective optimisation problem. Section 2.3 develops the stepwise heuristic solution algorithm. Section 2.4 introduces the decision method, and Section 2.5 introduces the resilience evaluation indicators.

2.1. *Network Representation and Cascading Disruption Mechanism*

The container shipping network is represented as a directed and weighted graph $G = (V, E)$, where each node $i \in V$ denotes a port belonging to the port set V and each directed link $(i, j) \in E$ denotes an available port-to-port service connection belonging to the set E. For each link (i, j), it is characterised by a flow weight w_{ij} (e.g., approximated by deployed cargo volume) and a sailing time T_{ij} (unit: days). Based on these link weights, the initial operational (baseline) load of port i is defined as its aggregated outbound flow:

$$W_i = \sum_{j \in V, i \neq j} w_{ij} \tag{1}$$

Following the classical load–capacity setting proposed by Motter and Lai (2002), each port's handling capacity, C_i, is assumed to be proportional to its baseline load, i.e.,

$$C_i = \lambda W_i \quad (2)$$

where λ is a capacity multiplier that captures the level of spare capacity (i.e., redundancy) under normal operations, $\lambda \geq 1$.

Within the network G, disruptive events may reduce a port's effective functionality and trigger load redistribution to alternative ports. Such redistribution can concentrate additional load on already busy ports, potentially causing overloads and thereby propagating failures through the network. In this study, cascading disruption is initiated by a port failure at $t = 0$. To represent a worst-case shock, the initially failed port is assumed to redistribute its entire current load. For subsequent rounds $t > 0$, whenever a port becomes overloaded, only the excess load above its capacity is redistributed. Mathematically, the volume redistributed from port i at round t is defined as:

$$\Delta L_i(t) = \begin{cases} L_i(t) & t = 0, \\ L_i(t) - C_i & t > 0, \end{cases} \quad (3)$$

where $L_i(t)$ is the existing load of port i at round t. Before any cascading redistribution occurs, the load at port i equals its original weight, i.e., $L_i(0) = W_i$. The redistribution may overload additional ports, triggering further rounds until no new overload occurs.

2.2. *Tri-objective Formulation*

To mitigate the impact of cascading disruptions to the least severity, this section formulates the objectives of different stakeholders and defines the corresponding optimisation problem. Specifically, at each redistribution round t, the framework determines (i) which ports are selected as redistribution targets and (ii) how much load is redistributed to each selected target. Mathematically, let $\varepsilon_{ij} \in \{0,1\}$ indicate whether port j is selected as a redistribution target for the redistributing port i, and let $\Delta L_{ij}(t)$ denote the load volume redistributed from ports i to j at round t. The set of selected targets is $S = \{j \mid \varepsilon_{ij} = 1\}$. The optimal decision $\left(\varepsilon_{ij}^*, \Delta L_{ij}^*(t)\right)$ is identified by jointly minimising three objectives that reflect stakeholder priorities from micro- to macro-level perspectives (Cao et al., 2025d).

Firstly, shippers and carriers typically prioritise timely delivery. Under disruption, redistribution often implies longer sailing distances and transhipment detours, which translate into higher time-related costs and delay penalties. To reflect this, the first objective is defined to minimise the total time-weighted redistributed volume at round t:

$$\min\ F_1(t) = \sum_{j \in V, i \neq j} T_{ij} \Delta L_{ij}(t) \quad (4)$$

This formulation captures the economic implication to redistribute more volume to nearer ports (i.e., lower T_{ij}), in order to reduce the aggregate delay exposure.

Secondly, from a port/terminal perspective, excessive overloading leads to queueing, yard congestion, safety and environmental pressures, and loss of competitiveness. For each port participating as a redistribution target, their primary concern is to minimize their overloading level as much as possible. Given this, the second objective is formulated to minimise the average post-redistribution load-to-capacity ratio across the selected targets:

$$\min\ F_2(t) = \left[\sum_{j \in V, i \neq j} \frac{L_j(t-1) + \Delta L_{ij}(t)}{C_j}\right] \Big/ \left(\sum_{j \in V, i \neq j} \varepsilon_{ij}\right) \quad (5)$$

where $L_j(t-1)$ is the load at port j at round $t-1$, and $\sum_{j \in V, i \neq j} \varepsilon_{ij}$ is the number of selected targets. This objective operationalizes two practical principles: (i) avoid concentrating redistribution on a single hub, and (ii) prefer targets with larger effective redundancy (higher C_j relative to $L_j(t-1)$), thereby reducing the probability that a target becomes a new cascade source. In particular, when a target becomes overloaded after receiving redistributed load, i.e., $(L_j(t-1) + \Delta L_{ij}(t))/C_j > 1$, lowering this ratio directly mitigates congestion severity and facilitates faster system stabilisation

Thirdly, at the system level, cascading impacts are most directly reflected in how widely overload propagates across the network. Each additional overloaded port may exacerbate loss of local functionality, increase likelihood of subsequent redistribution rounds, and affect network connectivity. Accordingly, the third objective is formulated to minimise the number of overloaded ports at round t:

$$\min\ F_3(t) = N_o(t) \tag{6}$$

where $N_o(t)$ is the number of overloaded ports at round t, serving as a direct proxy for systemic disruption and structural integrity loss.

Taken together, the optimisation at each redistribution round is:

$$\min \boldsymbol{F}(t) = \left(F_1(t), F_2(t), F_3(t)\right) \tag{7}$$

subject to the following constraints:

$$\Delta L_i(t) = \sum_j \Delta L_{ij}(t)\,, \forall i,j \in V, i \neq j, t \in \{0, \mathbb{N}^+\} \tag{8}$$

$$\varepsilon_{ij} = \{0,1\}, \forall i,j \in V, i \neq j \tag{9}$$

$$0 \leq \Delta L_{ij}(t) \leq \Delta L_i(t)\,, \forall i,j \in V, t \in \{0, \mathbb{N}^+\}, i \neq j \tag{10}$$

$$L_i(t) \geq W_i, \forall i \in V, t \in \{0, \mathbb{N}^+\} \tag{11}$$

where constraint (8) enforces load conservation between the redistributing port and its selected targets. Constraint (9) defines the binary selection decision. Constraint (10) ensures feasibility by requiring redistributed volumes to be non-negative and not exceed the total load to be redistributed from port i. Constraint (11) bounds the dynamic load at each port by its baseline level, preventing over-redistribution.

2.3. *A Stepwise Heuristic Solution Algorithm (SHSA)*

As introduced before, cascading disruptions are typically triggered by an initial port disruption and then propagate through repeated rounds of load redistribution. Reasonable load redistribution strategies need to reduce resilience losses and protect stakeholder interests. To achieve this goal, this study proposes the SHSA that seeks to minimise all three objectives at each redistribution round. The SHSA consists of three modules: elite target selection, equilibrium load calculation, and evolutionary filtering.

(1) Elite selection of feasible target ports.

Firstly, when port i needs to redistribute load, both the set of feasible targets and the number of targets are uncertain. To enable feasibility, downstream ports of i are first screened by excluding ports that are already disrupted or overloaded. Then, candidates are ranked by capacity and proximity (via sailing time), and the top-d ports under each criterion are retained as elite candidates, forming a candidate set of size D (typically limited to a small local subset). Feasible redistribution target sets are then generated by selecting K ports from these D candidates, producing combinations that represent different diversification levels.

(2) Equilibrium calculation of redistributed load volumes.

Given a candidate target set with fixed targets, the next step is to determine the redistributed volumes assigned to each target. Here, a modified Method of Successive Averages (MSA) procedure is employed (Xu et al., 2024). Specifically, within a target set, each target is first assigned a normalized cost constant based on the sailing time attribute (i.e., T_{ij}). An iterative update then constructs a generalised cost function that incorporates both (i) the current redistributed load and (ii) time-related cost. A logit-based model further allocates interim flows based on the updated costs, and MSA averaging updates the actual redistribution volumes until convergence under a small threshold. This produces an equilibrium redistribution across selected targets rather than an ad hoc proportional split.

(3) Gradient-based evolutionary filtering

Although each redistribution solution can be fully specified by its selected targets and redistributed volumes, the number of feasible target combinations increases exponentially with the size of the candidate set, making exhaustive enumeration computationally expensive. To improve scalability, this study introduces a gradient-based evolutionary filtering scheme that controls combinatorial complexity while preserving solution quality and diversity. Specifically, candidate solutions are first grouped into gradients by the number of selected target ports, ranging from one-target to multi-target diversifications. Starting from the simplest gradient, the algorithm evaluates solutions, computes (F_1, F_2, F_3), and retains non-dominated solutions in an external archive. The procedure advances to higher gradients only if the archive is updated, otherwise, it terminates early to avoid unnecessary computation. To this end, the final converged archive constitutes the Pareto front.

2.4. *Trade-off Selection for Implementation*

Although all archived solutions are feasible and represent different trade-offs among the three objectives, practical implementation requires selecting a single actionable decision. The Technique for Order Preference by Similarity to

Ideal Solution (TOPSIS) is therefore used to identify the solution closest to the ideal point across objectives (Cao et al., 2025d). The selected redistribution is applied to update port loads. If new overloads arise, the algorithm repeats for the newly overloaded ports until propagation ceases.

2.5. *Resilience Assessment Indicators*

Once the cascading process terminates (i.e., no additional ports become overloaded), network resilience is evaluated along three complementary dimensions, i.e., economic, functional, and structural, using indicators that are directly aligned with the three optimization objectives.

To quantify the economic impact of cascading disruptions, the framework uses the total Time Cost (TC) accumulated by all redistributed load throughout the entire cascade. Formally, TC aggregates the time-related cost of every redistribution movement across all rounds and all redistributing ports. It therefore serves as a system-level proxy for cumulative delay and cost exposure for shippers and carriers during cascading propagation:

$$TC = \sum_t \sum_i \sum_j T_{ij} \, \Delta L_{ij}(t) \tag{12}$$

To measure functional resilience from the perspective of port operations, the framework introduces the total Overloading Level (OL) as a cumulative indicator of port-level stress induced by redistributed load. Mathematically, OL is defined as the cumulative sum of F_2 over all redistribution rounds and all redistributing ports, i.e., the sum of post-redistribution load-to-capacity ratios averaged over all participated targets:

$$OL = \sum_t \sum_i \frac{\left[\sum_{j\in V, i\neq j} \frac{L_j(t-1)+\Delta L_{ij}(t)}{C_j}\right]}{\left(\sum_{j\in V, i\neq j} \varepsilon_{ij}\right)} \tag{13}$$

where a high OL indicates that the redistribution decisions repeatedly push target ports close to, or beyond, capacity, which is associated with increased congestion risk, queueing, yard pressure, and reduced operational feasibility.

To capture structural disruption, i.e., how widely cascading overload propagates across the network, the framework uses the Number of Overloaded Ports (NOP), defined as the cumulative total of overloaded ports across all redistribution rounds:

$$NOP = \sum_t N_o(t) \tag{14}$$

Here, NOP quantifies the spatial extent and persistence of cascade spread. A larger NOP indicates the systemic propagating across the network.

Together, TC, OL, and NOP provide a coherent, three-dimensional resilience evaluation that maps directly onto the tri-objective optimisation design. This one-to-one correspondence ensures that solution trade-offs observed in the Pareto front remain interpretable in resilience terms and can be communicated transparently to different stakeholder groups.

3. Numerical Experiments

This section applies the proposed framework to the ECSN. Section 3.1 introduces the datasets and reports the resilience assessment results. Section 3.2 delivers a detailed case study.

3.1. *Resilience Assessment of the ECSN*

This study establishes the ECSN to evaluate its resilience to cascading disruptions. The network is constructed using service route data obtained from the BlueWater Reporting Application Server (https://www.bluewaterreporting.com) as input to the proposed framework (Cao et al., 2025b). In total, 913 service route records spanning 2020 to 2023 are used to build the ECSN, which comprises 172 European ports.

A systematic stress test is then conducted under a fixed redundancy setting. Specifically, the capacity multiplier is set to $\lambda = 1.3$, meaning that each port's operational capacity is defined as 1.3 times its baseline load (Bai et al., 2023). Under this setting, each of the 172 ports is, in turn, specified as the initial failure node. The failure of a port triggers load redistribution under the proposed framework until no further overloads occur. For each initial failure scenario, three resilience indicators, namely TC, OL, and NOP, are recorded to quantify cascading impacts from economic, operational, and structural perspectives, respectively.

Table 1 reports the ten ports that generate the most severe cascading consequences under each indicator. The results reveal pronounced heterogeneity in systemic importance across Europe. From an economic perspective, measured by TC, major hub ports such as Rotterdam (NLRTM), Hamburg (DEHAM), Valencia (ESVLC), and Antwerp (BEANR) dominate the ranking, indicating that disruptions at these ports induce substantial detours and time penalties. In contrast, the structural cascade indicator NOP exhibits a different pattern. Valencia (ESVLC) produces the largest cascade spread, with 14 overloaded ports, substantially exceeding other scenarios, while Marsaxlokk (MTMAR) and Gdansk (PLGDN) also trigger comparatively broad overload propagation. The operational stress indicator OL similarly highlights the prominence of Valencia (ESVLC) and Marsaxlokk (MTMAR), suggesting that disruptions at these ports not only spread widely but also impose severe utilisation pressures on receiving hubs. Overall, the top-ten lists show that ports associated with high delay impacts do not necessarily coincide with those that maximise cascade spread or overload severity, reinforcing the need for multidimensional resilience assessment and multi-objective adaptation strategies.

Table 1. Top 10 ports with the greatest cascading impacts under $\lambda = 1.3$ (ranked separately by TC, NOP, and OL).

No.	Initial failure	TC	No.	Initial failure	OL	No.	Initial failure	NOP
1	NLRTM	712054.0	1	ESVLC	11.21	1	ESVLC	14
2	DEHAM	700668.1	2	MTMAR	9.90	2	MTMAR	6
3	ESVLC	700122.1	3	DEHAM	9.53	3	PLGDN	5
4	BEANR	548396.4	4	ITGOA	8.82	4	ITTRS	5
5	ITGOA	338871.8	5	DKAAR	8.72	5	NLRTM	4
6	GRPIR	273611.7	6	PLGDN	8.12	6	DEHAM	4
7	MAPTM	199293.2	7	ITTRS	6.94	7	ITGOA	4
8	ESALG	185101.7	8	ESBCN	6.90	8	GRPIR	4
9	ESBCN	176056.1	9	NLRTM	6.75	9	ESBCN	4
10	MTMAR	172410.1	10	NOOSL	5.82	10	NOOSL	4

3.2. *Resilience Assessment of the ECSN*

To demonstrate the behavioral realism and mitigation effectiveness of the proposed optimization framework, this study selects Hamburg (DEHAM) as a representative European hub and analyses the cascading impacts triggered by its disruption. The proposed SHSA is benchmarked against four cascading simulation rules in the literature, i.e., Network Structure Load Redistribution (NSLD) (Lu et al., 2024), Breadth-First Redistribution Rule (BFRR) (Cao et al., 2025a), MSA-based redistribution (Xu et al., 2024), and Local Weighted Flow Redistribution Rule (LWFRR) (Bai et al., 2023). All benchmark methods adopt the classical Motter-Lai model in which port capacity is proportional to baseline load via a capacity multiplier λ. Consistent with standard practice, λ is varied over [1.1, 2.0] to represent increasing levels of spare capacity (redundancy), and disruption propagation is simulated through continuous redistribution rounds until no further overloads occur. Figures 1–3 show the resulting TC, OL, and NOP for the five methods as λ increases. Three consistent patterns emerge.

First, for all methods, increasing λ reduces cascade severity, confirming that greater redundancy materially suppresses overload propagation and mitigates economic and operational losses. Second, the proposed SHSA outperforms the benchmarks across the most λ ranges, achieving markedly lower TC, substantially reduced OL, and less NOP. This reflects the core advantage of the proposed framework, where redistribution decisions are not defined by a single rule, but are explicitly optimised against stakeholder objectives at each cascade round, yielding stronger operational relevance. Third, all benchmark rules exhibit clear limitations in managing multi-stakeholder trade-offs. On the one hand, topology-driven rules (e.g., BFRR/LWFRR/NSLD) can reduce pressures on single port but frequently shift excessive burdens to more neighbouring ports, which sustains a higher NOP with a small λ. On the other hand, while the MSA-based approach generally outperforms three topology-driven rules, it still shows weaker economic performance when λ is small, where the feasible set is tight and poor early redistributions compound through subsequent rounds.

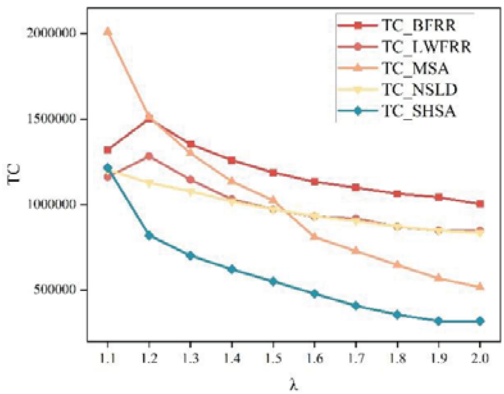

Figure 1 Comparison of TC under five cascading failure models for the Port of Hamburg (DEHAM) initial failure scenario.

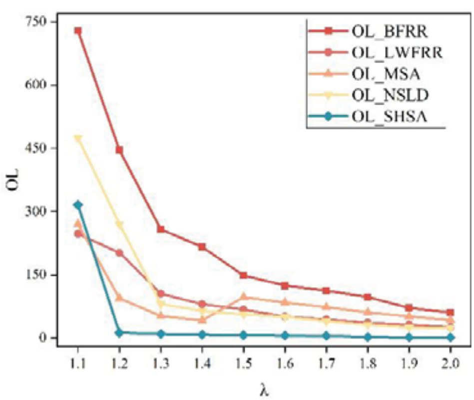

Figure 2 Comparison of OL under five cascading failure models for the Port of Hamburg (DEHAM) initial failure scenario.

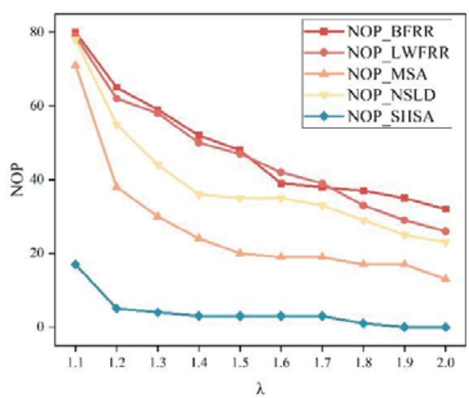

Figure 3 Comparison of NOP under five cascading failure models for the Port of Hamburg (DEHAM) initial failure scenario.

Having established the superiority of SHSA, the redistribution map (Figure 4) further visualises how the failure of DEHAM is absorbed and stabilised through multi-round redistributions. Figure 4 shows that, in the initial rounds, load is redistributed primarily to major nearby North Sea ports through single-target redistributions (e.g., DEBRV, DEWVN, and BEZEE), leveraging dense connectivity and proximity to limit immediate time penalties. In later rounds, secondary redistributions are triggered and the strategy becomes more decentralised, moving load to additional feasible ports through multi-target redistributions (e.g., NLRTM, BEANR, GBLGP, and GBFXT) to avoid creating new congestion bottlenecks and to reduce the risk of cascade amplification.

To make the optimisation logic more transparent, a representative redistribution decision from DEHAM to DEBRV is further illustrated in Figure 5. Here, each point corresponds to a redistribution solution for this round, encoding a distinct combination of redistribution destinations and load volumes, where its location in the objective space directly reflects the performance implications across all three dimensions. The Pareto front characterises the non-dominated solution set, from which a single implementable trade-off solution is selected using the TOPSIS-based decision module. Relative to other solutions within the Pareto front, the selected solution performs well across all three objectives, especially lowering time-related costs. In this sense, the selected solution ensures that the adopted action is both performance-robust and operationally interpretable for practitioners.

Figure 4 Visualisation of cascade propagation and multi-round redistributions triggered by the Port of Hamburg (DEHAM) disruption.

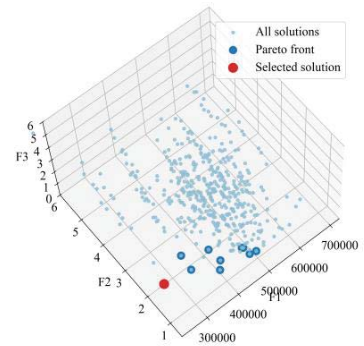

Figure 5 Pareto trade-offs for the redistribution decision from DEHAM to DEBRV.

4. Conclusions

This study develops a resilience-driven multi-objective optimization framework to support cascading disruption adaptation in the ECSN. By modelling disruption propagation through a tri-objective structure and solving the resulting problem by the proposed SHSA, this study moves beyond rule-based, single-objective redistribution logic, providing more actionable decision support for stakeholders seeking to minimise the impacts of cascading disruptions. Numerical experiments on the ECSN with 172 ports show substantial heterogeneity in port-triggered cascade impacts. Benchmarking against four established cascading redistribution rules further demonstrates that the proposed approach delivers consistently improved resilience outcomes across different redundancy settings, particularly by avoiding repeated concentration of load on a small set of already-stressed ports and by containing cascade amplification through balanced, trade-off-aware decisions.

Looking forward, two future research directions are promising. First, disruption environments are inherently uncertain. Extending the framework to incorporate stochastic disruption duration, partial capacity loss, demand volatility, and information delays would support more robust, risk-aware redistribution policies. Second, practical deployment would benefit from coupling the optimization with real-time data (e.g., AIS data, terminal operating indicators, and weather/traffic forecasts) to support adaptive decision-making during evolving disruptions.

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