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Supply network disruption: A framework for assessing vulnerability and implementing resilience strategies

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ABSTRACT

Disruptions to food supply chains can have significant impacts on food security and economic stability. This study investigates the resilience of supply networks to such disruptions, focusing on the distribution of live fish between farms in England and Wales as a case study. A decision support framework is developed to assess network vulnerability and ensure operational continuity in the face of disruptions to the supply and demand balance. The framework incorporates a novel rewiring algorithm that dynamically reconfigures network connections to maintain the flow of goods. The algorithm predicts supply-demand pairs and adjusts connections to preserve functionality during disruptions. To evaluate the performance of the framework and algorithm, a combination of topological metrics, such as connectivity and redundancy, and operational measures, including supply fulfilment and distribution efficiency, is utilised. Through simulations of random and targeted node removals, the rewiring algorithm is shown to effectively mitigate the impact of disruptions, preserve network functionality, and help ensure a consistent supply of live fish. These findings offer valuable insights for managing disruptions in aquaculture supply chains and highlight the broader applicability of the framework to enhance the resilience of other supply networks.

1. Introduction

In today's interconnected world, supply chains—networks coordinating the flow of goods and services from origin to consumer—are the backbone of global commerce and vital to economic stability [1,2]. With rising globalisation and the growing emphasis on sustainability and responsiveness, effective supply chain management has gained critical importance [3]. Traditionally, supply chains were conceptualised as linear sequences of production and distribution. However, modern supply chains are better understood as complex networks, consisting of numerous interlinked entities such as manufacturers, suppliers, distributors, and consumers. These entities interact through multidirectional flows of materials, information, and capital and often include feedback loops and

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decentralised control [4–6]. Complex network analysis (CNA) is an area within network science that focuses on analysing systems characterised by structural properties such as scale-free degree distributions, high clustering, and small-world effects. CNA provides a method to model and understand the structure and behaviour of real-world systems like supply chains, which exhibit dynamic interdependencies and are susceptible to cascading disruptions [7,8]. Representing supply chains as complex networks, where entities such as suppliers and retailers are represented as nodes and the flows of goods or information as edges, enables the application of network analysis to identify critical nodes, bottlenecks, and vulnerabilities, thereby facilitating risk mitigation and the development of resilience strategies [9,10]. For instance, in the automotive industry, network analysis can optimise component flows and anticipate potential disruptions [8].

The coordination of elements within supply chains is often impeded by various disruptive events, both anticipated and unexpected. These disruptions may originate from various sources, including natural disasters, geopolitical instability, economic fluctuations, and operational issues [11,12]. History is replete with examples of such disruptions, culminating in the recent COVID-19 pandemic, which caused widespread disruptions across various industries [13,14]. Disruptions can be categorised as either random or targeted. Random disruptions occur unexpectedly and impact the network in a non-selective manner, often resulting from natural disasters, accidents, or unforeseen equipment failures [8,15]. For instance, the 2010 volcanic eruption in Iceland caused widespread air travel disruptions, affecting the transportation of goods by air [16]. In contrast, targeted disruptions are intentionally directed at specific nodes or edges within the network and may arise from malicious activities, including cyberattacks or market manipulation [17,18]. Understanding the characteristics and potential impacts of these distinct types of disruptions is essential for developing effective resilience strategies.

The aquaculture sector, which involves the holding and farming of fish and other aquatic animals, is not immune to the risks associated with supply chain disruptions. As one of the fastest-growing food production sectors globally, aquaculture is essential for addressing the increasing demand for fish as a source of protein [19]. The aquaculture supply chain is highly complex, with various components involved in addressing the demand for fish, from hatchery production and feed supply to processing, distribution, and retail. In particular, the distribution of live fish between fish farms is crucial for maintaining stock levels and ensuring continuous production. However, the logistics of transporting and distributing live fish are vulnerable to disruptions caused by various factors, including disease outbreaks that lead to control measures, environmental changes, and logistical failures [20]. For example, studies have shown that disease outbreaks such as infectious salmon anaemia (ISA) can rapidly spread through fish farms, resulting in production losses [21,22]. Such disruptions can propagate through the distribution of live fish, impacting multiple farms and leading to widespread losses. Despite the importance of resilience in the aquaculture supply chain, there is limited research on how disruptions propagate through the network and on implementing resilience strategies to mitigate their effects.

This study investigates the resilience of supply networks to disruptions, focusing on developing a framework for analysing network vulnerability and implementing resilience strategies. The framework utilises network analysis to understand disruption propagation and develops a novel rewiring algorithm for network optimisation in the face of disruptions. To demonstrate the effectiveness of this framework, we apply it to a specific case study: the distribution of live fish between farms in England and Wales. This sector was selected as a particularly relevant case study due to its inherent susceptibility to disruptions, including disease outbreaks and logistical challenges, which can have significant economic and ecological consequences. Furthermore, the availability of data collected by the Centre for Environment, Fisheries and Aquaculture Science (Cefas) provides a robust foundation for empirical analysis. By applying this framework to this specific case study, we investigate the impact of both random and targeted disruptions on this aquaculture supply chain. This study provides insights into disruption propagation, identifies critical nodes, and proposes resilience strategies to ensure operational continuity in this vital sector. The findings from this study contribute to the long-term sustainability of the aquaculture sector, addressing global food security challenges amid environmental and economic pressures. This need is further highlighted by the increasing demand for robust, data-driven tools to improve operational continuity in this sector.

2. Methodology

2.1. Complex network setup

Consider a network as a directed, weighted graph $G(V, E, w)$ where V is a set of nodes, E is the set of edges, and w is the weight assigned to each edge. The characteristics of the network are defined as:

1. $e_{(i,j)} \in E$ is a directed edge from node v_i to v_j ($v_i, v_j \in V$) where i and j are indices that denote specific nodes within the network.
2. The function $w : E \to \mathbb{R}^+$ assigns positive real numbers to each edge, representing the weights of the edges. In this study, the weights correspond to the distances between nodes. Unlike the standard approach where higher weights indicate stronger connections, in this case, higher weights represent weaker connections.
3. Each node v is characterised by its supply capacity (S_i), demand capacity (D_i) and net balance ($B_i = S_i - D_i$). The supply capacity represents the quantity of goods (e.g., live fish) a node can provide within a specific period, while the demand capacity denotes the quantity of goods required by the node within the same time frame. A node is classified as a supply node (V_S) if its net balance is positive ($B_i \geq 0$), indicating it sends more supplies than it demands. Conversely, a node is classified as a demand node (V_D) if its net balance is negative ($B_i < 0$), signifying that it receives more supplies than it sends.

4. V is the union of two non-overlapping subsets of V_D and V_S. An individual node cannot belong to both V_D and V_S at the same time, although its classification can change as supply and demand evolve.

$$V = V_D \cup V_S \text{ where } V_D \cap V_S = \emptyset \tag{1}$$

2.2. Network disruption

In this study, network disruptions were modelled by the removal of nodes (Fig. 1). The removal of a node also implicitly removed any edges connected to it. In G, when a node v_i was removed, its degree was reduced to zero. Disruptions to a network can be categorised as either random or targeted. For random disruptions, at probability p, a fraction $1 - p$ of the N nodes were randomly selected to simulate the disruption. To assess the network's robustness and adaptability under repeated disruptions, the iterative process of random node removal was repeated 300 times. Each iteration started from a randomly selected node and ended when the network collapsed or the iteration concluded. This approach captured a wide range of potential disruption patterns and provided a comprehensive evaluation of the network's resilience. After each instance of node removal and subsequent rewiring, network metrics were recalculated to evaluate the network's ability to maintain operational flows, including the continuity of supply-demand pairings and the stability of critical nodes and edges. The process terminated when a predetermined number of nodes had been removed or when the network was completely depleted of nodes or edges.

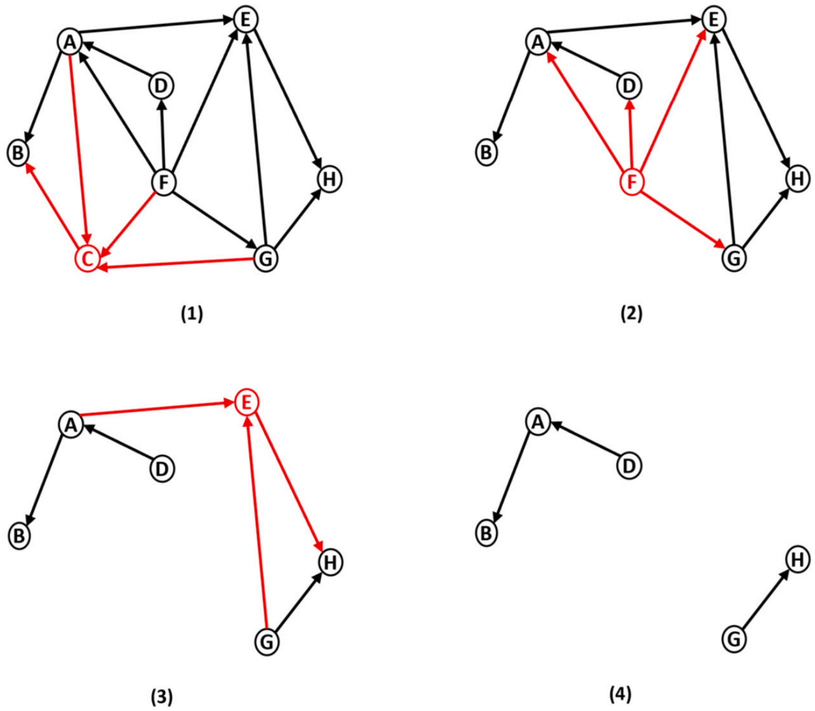

Fig. 1. Illustration of the progression (Steps 1–4) of disruptions to nodes and edges within the supply chain network. (1) The initial network configuration with all nodes and edges intact. (2) Disruption caused by the removal of node C and its associated edges (shown in red). (3) Further disruption resulting from the removal of node F and its connected edges (shown in red). (4) The final network state after the removal of nodes C, F, and E.

The findings from the random disruptions were grouped into best-case, worst-case, and typical scenarios to provide an overview of the network's performance. The best-case scenario identified the iteration where the network exhibited the highest resilience with minimal supply loss, keeping the total supply above zero and within a predefined buffer threshold θ, arbitrarily set to 10% for each simulation step. This provided a simple yet practical safeguard against the over-depletion of supply capacity during the rewiring process. In the absence of standardised thresholds specific to the live fish distribution context, this value was chosen as a conservative estimate to ensure that supply nodes retain a minimal reserve, maintaining operational viability and avoiding unrealistic resource exhaustion within the simulation framework. The worst-case scenario highlighted the iteration with the most significant impact on supply, showing the maximum loss for each simulation step. The typical scenario presented the mean values of the network metrics across all 300 iterations, providing a realistic understanding of how the network and the rewiring algorithm are likely to perform in practice, where disruptions can be unpredictable and varied.

In contrast, targeted disruptions involve selecting nodes for removal based on specific characteristics. In this study, supply nodes (V_S) were targeted for removal, thereby increasing the likelihood of cascading failures [23]. To simulate a disruption event with the highest likelihood of cascading failures, supply nodes were ranked and removed based on their supply capacity and balance. Nodes with the highest supply capacity and balance were removed first, simulating disruptions affecting key supply points in the network.

2.3. Network fragmentation

During a disruption of a supply-demand network, its ability to maintain operations and connectivity becomes crucial. Disruptions may lead to network fragmentation (Fig. 2), resulting in the network dividing into smaller, isolated components and thus impeding the efficient flow of goods. The robustness of a network is often measured using the size of the largest connected component (LCC), which is the largest group of interconnected nodes. However, the LCC does not account for the availability of supply [24]. To address this limitation, we used the concept of the largest functional subnetwork (LFS) [24]. The LFS is a subset of supply nodes within the larger network that maintains connectivity and includes at least one supply node with sufficient capacity to meet the demand of its directly connected neighbours, thereby ensuring operational continuity. This allows for a more accurate measure of a network's resilience and its ability to continue operating effectively in the face of disruptions. For network G, the largest functional subnetwork is defined as the node set V_{sub}, where the nodes in V_{sub} must satisfy the following conditions: 1) any two nodes within the subnetwork must have a path connecting them; and 2) every node within this subnetwork must be connected to at least one V_S.

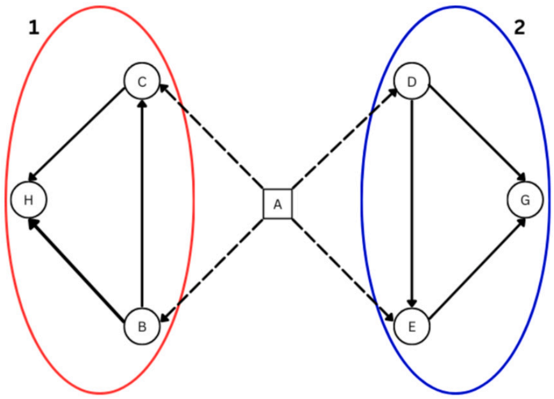

Fig. 2. Supply network disruption into fragments 1 (red) and 2 (blue) when the central supply node A is removed. The dotted arrows represent the edges connected to node A before removal. All other nodes (B, C, D, E, G, H) are demand nodes.

In addition to identifying the LFS, the average supply distance (ASD) for each V_S to a set of directly connected demand nodes was calculated. This provides insight into the average distance travelled between V_S and V_D, with lower ASD values indicating a well-positioned supplier capable of quickly meeting the demand of its neighbours. ASD is defined as:

$$ASD(v_i) = \frac{1}{|\Gamma(v_i)|} \sum d(v_i, v_j) \quad \text{for each } v_i \in V_s \tag{2}$$

where $|\Gamma(v_i)|$ is the number of nodes directly connected to $v_i \in V_s$, $d\left(v_i, v_j\right)$ is the shortest path distance between v_i and v_j defined as the sum of the weights (distances) along the shortest path.

The overall supply distance (OSD), an indicator of the overall distance for supplying demand nodes, is calculated as follows:

$$\text{OSD} = \frac{1}{|V_S|} \sum_{v_i \in V_S} \text{ASD}(v_i) \tag{3}$$

A lower OSD value indicates a more efficient network where supply nodes are, on average, closer to the demand nodes they serve.

2.4. Simulation

We propose a network rewiring approach designed to adaptively maintain connectivity in a disrupted supply-demand network, through a structured, iterative process of node removal and edge rewiring (Fig. 3). Nodes were iteratively removed, either randomly or based on specific criteria, to simulate disruptions within the network.

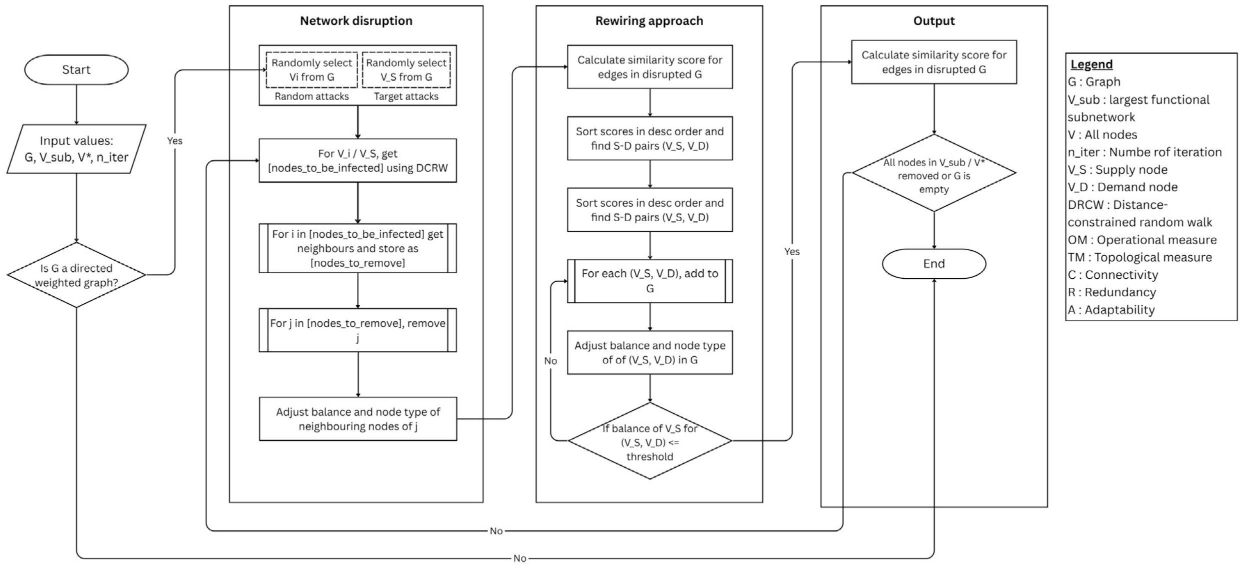

Fig. 3. Flowchart of the rewiring simulation.

2.4.1. *Distance-constrained random walk*

Before removing a node, the algorithm initiated a distance-constrained random walk originating from the node identified to be removed. This step identified nodes that fall within a specified distance threshold, OSD, and are impacted by the removal. The random walk only considered nodes that have not already been traversed in the current iteration and remain reachable within the cumulative distance threshold. Mathematically, the distance threshold is represented by the inequality:

$$d(v_i, v_{i+1}) + \sum_{j=1}^{i} d(v_{j-1}, v_j) \leq OSD \tag{4}$$

where $d(v_i, v_{i+1})$ is the distance between consecutively visited nodes. The walk stopped when the cumulative distance exceeds the OSD.

2.4.2. *Adjusting balances and updating node type*

For each node identified as affected by the disruption, the algorithm adjusted the balance of its neighbours based on the node's type. If the removed node was a supply node, the balance of its connected nodes was proportionally adjusted based on the demand of each connected node relative to the total demand of all connected nodes. Conversely, if a demand node was removed, neighbouring supply nodes adjusted their balances to account for the lost demand. This balance update preserved the network's functional integrity, as it recalibrated the distribution across the network. Following these adjustments, a supply node may become a demand node and vice versa, depending on the updated balance. This ensures that the network remains dynamically represented as disruptions and rewiring occur, maintaining an accurate reflection of the network's evolving state.

2.4.3. *Rewiring algorithm*

With the updated balances, Algorithm 1 identified new potential connections between supply and demand nodes using the Edge Weighted Katz Index (EWKI) [25]. This metric is an adaptation of the traditional Katz index and is specifically tailored for spatially embedded networks, incorporating the distance between nodes as an exponential weight. The EWKI scores were computed for all existing edges and compared against an empirically derived threshold score, calculated as the mean of existing edge scores. Potential connections that exceeded this threshold were considered viable for new edges. EWKI is given by

$$\text{EWKI}_{(i,j)} = \omega_{(i,j)} \cdot \sum_{l=1}^{\infty} \beta^l |\text{walks}^{\langle l \rangle}_{(i,j)}| \tag{5}$$

$$\omega_{(i,j)} = e^{-\gamma \times d_{(i,j)}} \tag{6}$$

where $d_{(i,j)}$ represents the distance between nodes i and j, γ is a constant that modulates the decay of links with distance. As the distance between nodes increases, the probability of link formation decreases exponentially.

The algorithm then identified supply-demand pairs for rewiring based on EWKI scores, OSD, and balance conditions. For each demand node $v_i \in V_D$ in the neighbourhood of the removed node, the function iterated through available supply nodes $v_j \in V_S$, verifying that v_j's balance can meet v_i's demand. If a pair met these criteria, a new edge was formed, effectively re-establishing disrupted supply routes. To prevent excessive depletion of a supply node's balance during the rewiring process, the algorithm incorporated a user-specified buffer threshold θ. This threshold defined the minimum percentage of a supply node's original balance that must be maintained. If the supply node's balance fell below θ of its initial level, it was excluded from further resource reallocation and the rewiring process. This condition ensured that the supply node retained a minimum reserve of resources, avoiding situations where a supply node's balance would become critically low, potentially destabilising the network.

Algorithm 1: Find Supply-Demand Pairs.

```
Input: G, neighbours, OSD, ewki_scores, score_threshold
Output: List of pairs with valid supply-demand pairs
Initialize pairs ← [];
/* neighbours is a list of nodes that are directly connected to the node being removed in the network G */
for each node v_i in neighbours do
    if v_i ∈ G.nodes() and G.nodes[v_i]['desc'] is "Demand" then
        demand_balance ← G.nodes[v_i]['Balance'];
        for each node v_j in G.nodes do
            if v_j ≠ v_i and G.nodes[v_j]['desc'] is "Supply" then
                supply_balance ← G.nodes[v_j]['Balance'];
                if supply_balance > demand_balance and path exists from v_j to v_i then
                    dist ← shortest path length from v_j to v_i in G;
                    if dist ≤ OSD and G does not have an edge between v_j and v_i then
                        score ← ewki_scores_dict[(v_j, v_i)] if it exists;
                        if score ≠ None and score ≥ score_threshold then
                            Append ((v_j, v_i), dist, score) to pairs;
    else
        if v_i ∈ G.nodes() and G.nodes[v_i]['desc'] is "Supply" then
            supply_balance ← G.nodes[v_i]['Balance'];
            for each node v_j in G.nodes do
                if v_j ≠ v_i and G.nodes[v_j]['desc'] is "Demand" then
                    demand_balance ← G.nodes[v_j]['Balance'];
                    if supply_balance > demand_balance and path exists from v_i to v_j then
                        dist ← shortest path length from v_i to v_j in G;
                        if dist ≤ OSD and G does not have an edge between v_i and v_j then
                            score ← ewki_scores_dict[(v_i, v_j)] if it exists;
                            if score ≠ None and score ≥ score_threshold then
                                Append ((v_i, v_j), dist, score) to pairs;
return pairs;
```

2.5. Evaluation metrics

Following the removal and rewiring of nodes, this study employed a suite of topological and operational metrics to evaluate the resilience and efficiency of the supply-demand network. These metrics captured different facets of network robustness and provided a quantitative basis for assessing the impact of disruptions and the effectiveness of the rewiring strategy. Operational measures track changes in the quantities of supply, demand, and balance within the network for each simulation. Specifically, these measures quantify total supply capacity, total demand, and the balance between the two. This allows for an assessment of the immediate operational impact of disruptions, such as reductions in supply or increases in unmet demand, and the effectiveness of subsequent rewiring efforts in restoring balance and functionality to the system.

Topological measures provide insights into the structural characteristics of the network, quantifying its resilience under disruption and rewiring scenarios. These measures focus on inherent properties of the network, including connectivity, redundancy, and adaptability. Connectivity is measured using the average degree of nodes. Redundancy is assessed with the clustering coefficient, and adaptability is evaluated using betweenness centrality. These measures provide quantitative insights into the structural and functional characteristics of the network, enabling an assessment of how the network responds and adapts to disruptions.

1. Connectivity (C): This component quantifies the extent to which nodes in the network are interconnected, specifically measuring the degree to which each node maintains its connections relative to the maximum possible connections within the network. Mathematically, connectivity is calculated as:

$$C = \frac{1}{|V|} \sum_{v \in V} \frac{\text{degree}(v)}{\text{max degree in } G} \tag{7}$$

where $|V|$ is the total number of nodes in the network, and degree (v) represents the number of connections of node v. Connectivity values range between 0 and 1.

2. Redundancy (R): Redundancy captures the availability of alternative paths within the network, enabling the re-routing of flow in case of disruptions. This study used the clustering coefficient as a proxy for redundancy. The clustering coefficient quantifies the extent to which a node's neighbours are also connected to each other. Higher clustering coefficients imply a greater number of redundant paths, increasing the network's resilience to node or edge failures. The values for redundancy range between 0 and 1 and are calculated as:

$$R = \frac{1}{|V|} \sum_{v \in V} \frac{\text{clustering coefficient}(v)}{\text{max clustering coefficient in } G} \tag{8}$$

3. Adaptability (A): Adaptability reflects the network's capacity to respond to changes and disruptions by re-routing flow through alternative paths. Betweenness centrality, a metric that identifies nodes critical for maintaining network connectivity, is used to assess adaptability. Nodes with high betweenness centrality act as bridges between different parts of the network. A network with well-distributed betweenness centrality (higher A value) better adapts to disruptions. Adaptability also ranges between 0 and 1. It is calculated as:

$$A = \frac{1}{|V|} \sum_{v \in V} \frac{\text{betweenness centrality}(v)}{\text{max betweenness centrality in } G} \tag{9}$$

To provide a measure of network resilience, we used the network resilience index (NRI), a composite index that averaged the three topological measures. While a weighted average could be considered, we opted for a simple average to provide an initial, unweighted assessment of overall network resilience. The NRI is calculated as:

$$NRI = \frac{C + R + A}{3} \tag{10}$$

2.5.1. Rate of collapse (RoC)

The Rate of collapse (RoC) measures the network's ability to maintain operational capacity before and after a disruption event by assessing the change in its ability to connect supply nodes to demand nodes. The RoC is determined through a two-step process that begins with calculating the Proportional connectedness (PC), the fraction of demand nodes reached from at least one supply node:

$$PC = \frac{\sum_{i \in V_D} \min(1, \sum_{j \in V_S} \text{path}_{i,j})}{|V_D|} \tag{11}$$

The RoC is then calculated by comparing the PC before and after the disruption and rewiring as:

$$RoC = \frac{PC_{\text{before}} - PC_{\text{after}}}{PC_{\text{before}}} \tag{12}$$

A higher RoC indicates a greater loss in connectivity and, therefore, a more severe impact of the disruption on the network's ability to meet demand. A negative RoC value would indicate that the rewiring strategy has improved the network's ability to connect supply nodes to demand nodes after a disruption.

2.6. Case study: live fish distribution network

The methodology was applied to a case study on the live fish distribution network across England and Wales, which involves the movement of live fish between farms and fisheries. The dataset includes detailed records of live fish movements from January 1, 2021, to December 31, 2023, with each record containing the date of movement, source and destination fish holdings, and their geographical coordinates. The haversine distance was calculated using these coordinates to represent the weighted edges of the network.

3. Results & discussion

3.1. Initial network characteristics

Prior to simulating disruptions and implementing the rewiring approach, we conducted a baseline analysis of the initial aquaculture network to characterise its structure and resilience. This analysis showed that the network had a higher proportion of demand nodes, with a total of 603 demand nodes and 64 supply nodes. The total supply capacity of the network, quantified at 173,206,148 fish, slightly exceeded the total demand of 169,079,822 fish, resulting in an overall positive balance of 4,126,326 fish. This surplus indicated a degree of resilience within the network, suggesting the potential to absorb minor fluctuations in supply or demand. However, the network exhibited low connectivity, with a connectivity value (Equation (7)) of 4%. This finding suggested that the network was sparsely connected, with limited alternative routes for fish distribution. While such low connectivity may be typical for aquaculture networks due to factors such as geographical constraints and biosecurity considerations, it increases the network's vulnerability to disruptions, as the removal of key nodes or edges could significantly impede the flow of live fish. Similarly, the redundancy of the network (Equation (8)), measured at 13%, was also low. The reliance on a limited number of supply routes contributes to this low redundancy, further increasing the risk of cascading failures in the event of disruptions. The adaptability of the network was measured at 1% (Equation (9)), indicating a high dependence on a small subset of central nodes to maintain overall

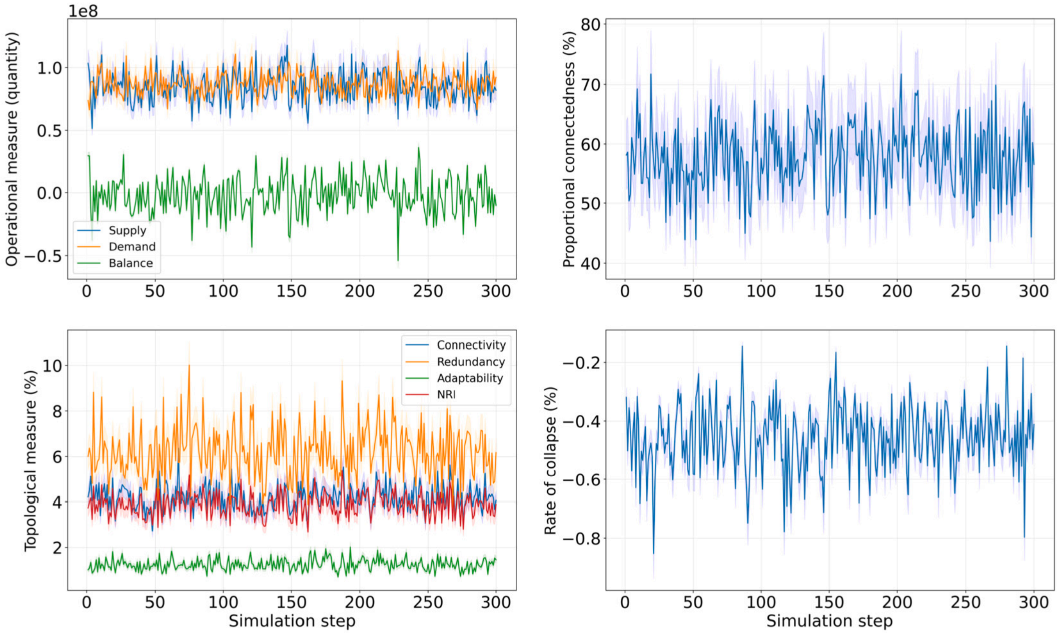

Fig. 4. Simulation results for the typical scenario. The top row shows the change in 1) operational quantity (left) and 2) proportional connectedness over time. The bottom row shows the changes in the 1) topological measure (left) and 2) rate of collapse (right). Shaded regions represent a ±10% band around the value of each metric.

Table 1
Random disruptions under the typical scenario. A negative value for the rate of collapse indicates improvements, while a negative value for balance indicates a deficit.

Metric	Average measure	Average rate of change
Supply	84,733,437	2.05%
Demand	86,859,614	0.88%
Balance	-2,126,177	12.26%
Connectivity	4.18%	1.59%
Redundancy	6.21%	3.27%
Adaptability	1.25%	4.02%
NRI	3.88%	1.57%
Proportional connectedness	57.76%	-
Rate of collapse	-0.46%	-

connectivity. Such dependence heightens the network's susceptibility to targeted disruptions, as the removal of these critical nodes can rapidly fragment the network. The overall NRI was 6%, highlighting the combined effects of low connectivity, redundancy, and adaptability. Despite these vulnerabilities, the initial network demonstrated a high PC of 100%. This indicated that, in its undisturbed state, all demand nodes could be reached from at least one supply node, ensuring complete fulfilment of demand.

3.2. Random disruption and rewiring

The typical scenario, as presented in Fig. 4 and Table 1, provides a view of the network's response to disruptions across 300 iterations. This analysis revealed the interplay between node removal effects on the supply-demand balance and the positive influence of the rewiring algorithm on network connectivity and adaptability. An oscillatory trend was observed across all metrics. The average supply decreased by 2.05%, while demand decreased by 0.88%, resulting in about 55% of the iterations having a negative balance on average. This translated to an average deficit of 2,126,177 units, implying that the network faced challenges in maintaining sufficient supply to meet demand under disruption scenarios. This negative balance caused by node removals reduced the overall supply capacity of the network. While the rewiring algorithm attempted to redistribute the lost supply by creating new connections, it may not always fully compensate. A similar challenge was observed in the trends for connectivity, redundancy, and adaptability. The average RoC was 0.46%, and the average PC was 57.76%. While the rewiring algorithm may not restore the network's original structure, it managed to establish new connections to maintain a reasonable level of connectivity between supply and demand nodes.

The findings showed important trends in the network's ability to adapt (Fig. 5 and Table 2). In the best-case scenario, the network maintained a stable relationship between supply and demand, with an average reduction in supply of 0.37% and a slightly higher average reduction in demand of 0.53%. This observation indicated that, while both supply and demand decreased as nodes were

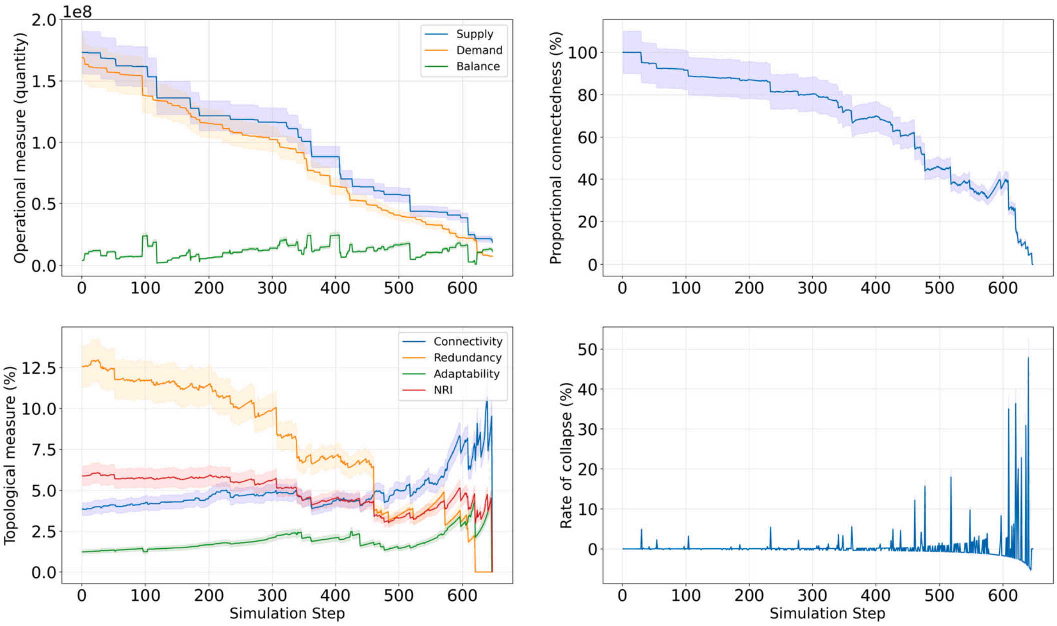

Fig. 5. Simulation results for the best-case scenario. The top row shows the change in 1) operational quantity (left) and 2) proportional connectedness over time. The bottom row shows the changes in the 1) topological measure (left) and 2) rate of collapse (right). Shaded regions represent a ±10% band around the value of each metric.

Table 2
Random disruptions under the best-case scenario. A negative value for the rate of collapse indicates improvements, while a negative value for balance indicates a deficit.

Metric	Average measure	Average rate of change
Supply	99,584,304	0.37%
Demand	87,884,007	0.53%
Balance	11,700,297	2.84%
Connectivity	4.90%	-0.10%
Redundancy	7.89%	0.36%
Adaptability	1.88%	-0.12%
NRI	4.89%	0.16%
Proportional connectedness	68.54%	-
Rate of collapse	-0.52%	-

removed, the network adapted more effectively to the loss of demand by re-routing supply to the remaining demand nodes. Consequently, the network balance was reduced by an average of 2.84%. The average PC of 68.54% indicated that, despite disruptions, the algorithm ensured that a significant portion of demand nodes remained connected to the network. This finding was further reinforced by an average RoC of 0.52%. This improvement suggested that the algorithm effectively identified and established new connections to compensate for disrupted routes, leading to a more robust and resilient network.

Examining the network resilience metrics, we observed an average improvement in connectivity of 0.10% per iteration, indicating that the rewiring algorithm not only maintained but slightly enhanced the overall interconnectedness of the network despite ongoing node removals. This suggested that the algorithm effectively compensated for lost connections by creating new routes, potentially leading to a more robust network structure. Redundancy decreased by an average of 0.36% per iteration. This gradual erosion of alternative routes indicated that while the algorithm prioritised maintaining connectivity, the network's re-routing options became increasingly limited as disruptions accumulated. Adaptability also demonstrated an average improvement of 0.12% per iteration, indicating that the network's capacity to adjust and respond to disruptions was gradually enhanced. Overall, the average NRI of 5% throughout the simulation illustrated that the algorithm balanced these competing factors to maintain overall network resilience.

Towards the end of the simulation, notable peaks and valleys were observed in several metrics, particularly connectivity, adaptability, rate of collapse, and NRI. These fluctuations resulted from the interaction between node removals and the adaptive rewiring process. As nodes are removed, the total number of nodes decreases, potentially increasing connectivity, especially if the removed nodes were not highly connected. However, node removal also disrupts existing connections, impacting metrics such as redundancy and adaptability. The rewiring algorithm counteracts this by forming new connections between supply and demand nodes. This rewiring can enhance the connectivity of certain supply nodes, contributing to improved overall network connectivity and adaptability. If the algorithm cannot establish new connections due to constraints such as distance or insufficient supply, the metrics may

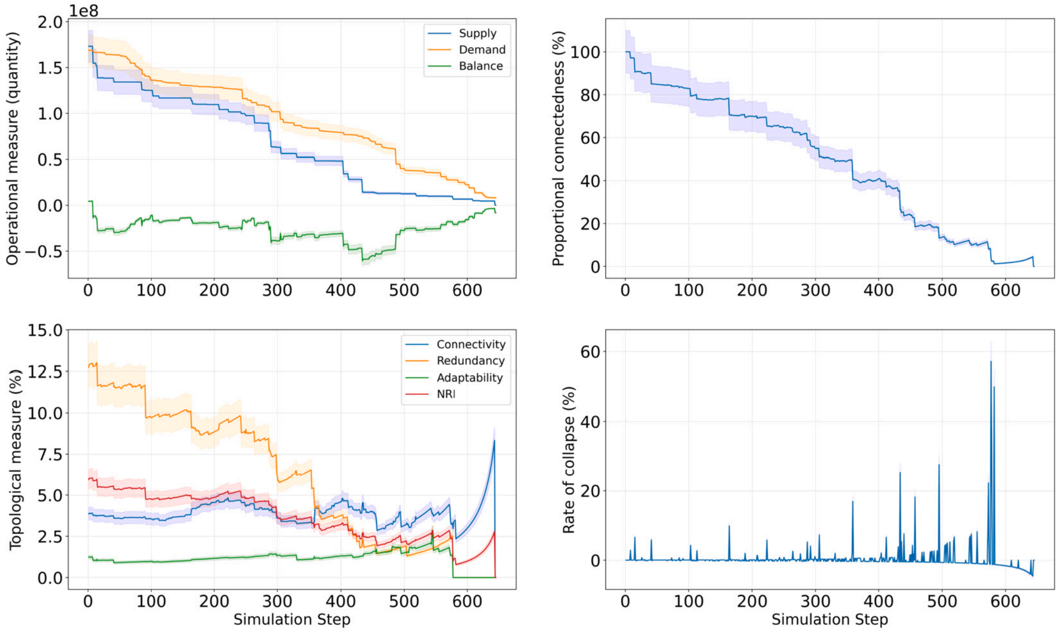

Fig. 6. Simulation results for the worst-case scenario. The top row shows the change in 1) operational quantity (left) and 2) proportional connectedness over time. The bottom row shows the changes in the 1) topological measure (left) and 2) rate of collapse (right). Shaded regions represent a ±10% band around the value of each metric.

Table 3
Random disruptions under the worst-case scenario. A negative value for the rate of collapse indicates improvements, while a negative value for balance indicates a deficit.

Metric	Average measure	Average rate of change
Supply	66,668,637	0.66%
Demand	92,606,280	0.50%
Balance	-25,937,644	0.26%
Connectivity	3.89%	-0.07%
Redundancy	5.97%	0.35%
Adaptability	1.14%	0.06%
NRI	3.66%	0.24%
Proportional connectedness	47.92%	-
Rate of collapse	-0.52%	-

remain unchanged or decrease, leading to valleys in the plots. Furthermore, the removal of certain nodes triggered a threshold effect, causing a significant change in the network structure. This occurs when highly connected nodes are removed, forcing the rewiring algorithm to create new connections to compensate. This compensation can result in a sharp increase in connectivity, as observed around simulation step 600.

Unlike the stable supply observed in the best-case scenario, the worst-case scenario was characterised by a pronounced decline in supply capacity (Fig. 6). The average reduction in supply was 0.66% (Table 3), significantly higher than the 0.37% observed in the best-case scenario. Concurrently, the average reduction in demand was 0.50%, slightly lower than the 0.53% in the best-case scenario. This disparity between supply and demand reductions led to an average balance of -25,937,644 units in the worst-case scenario, compared to a positive balance of 11,700,297 units in the best-case scenario. The negative balance in the worst-case scenario signified a severe resource deficit, highlighting the network's inability to meet demand effectively as disruptions accumulated. The worst-case scenario also exhibited a lower PC of 47.92%, compared to 68.54% in the best-case scenario. This reduced PC indicated a more fragmented network, where fewer demand nodes remained connected to supply nodes after disruptions. Although the rewiring algorithm partially mitigated connectivity losses, the lower PC underscores the network's reduced efficiency in maintaining functional routes for resource distribution in the worst-case scenario.

The average RoC was consistently 0.52% across both scenarios, demonstrating that the rewiring algorithm was able to enhance the network's ability to connect supply and demand nodes even under severe disruptions. In the worst-case scenario, connectivity showed a slight average improvement of 0.07% per iteration, compared to 0.10% in the best-case scenario. While this indicated that the algorithm maintained interconnectedness to some degree, the lower average connectivity of 3.89% (compared to 4.90% in the best-case scenario) highlights the challenges of preserving network structure when critical supply nodes are removed. Redundancy in the worst-case scenario decreased at an average rate of 0.35% per iteration. This reflected a gradual reduction in alternative routes

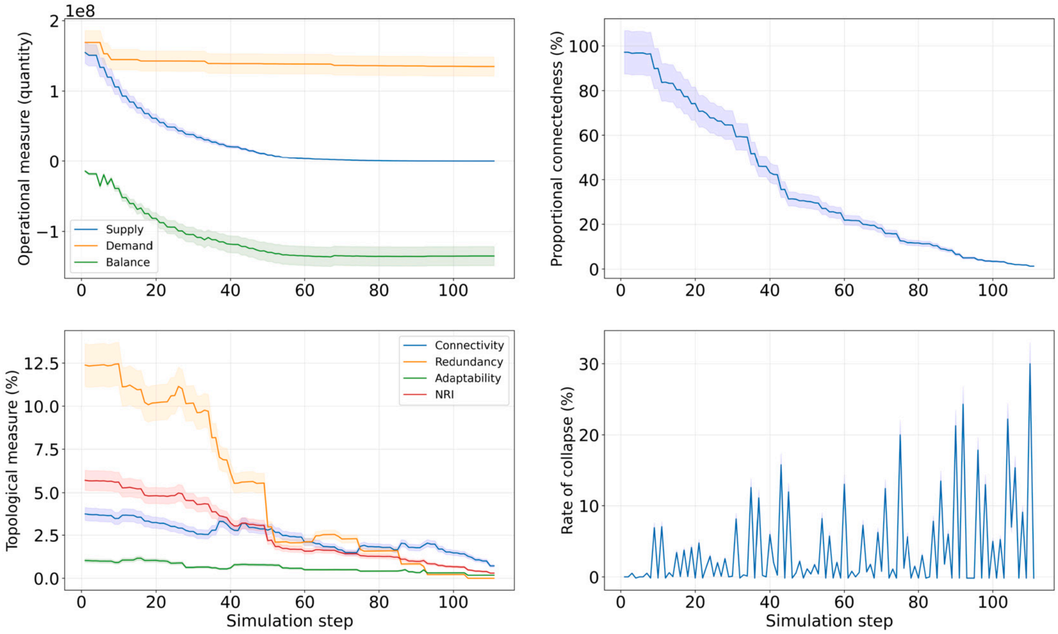

Fig. 7. Simulation results for best-case scenario for target disruption and rewiring. The top row shows the change in 1) operational quantity (left) and 2) proportional connectedness over time. The bottom row shows the changes in the 1) topological measure (left) and 2) rate of collapse (right). Shaded regions represent a ±10% band around the value of each metric.

Table 4
Findings from target disruptions, where negative values for the rate of collapse indicate improvements, and negative values for balance represent deficits.

Metric	Average measure	Average rate of change
Supply	27,628,994	13.13%
Demand	140,170,056	21.00%
Balance	-112,541,062	3.36%
Connectivity	2.41%	1.17%
Redundancy	4.97%	5.72%
Adaptability	0.62%	2.19%
NRI	2.66%	2.92%
Proportional connectedness	36.56%	-
Rate of collapse	3.62%	-

as the network became more fragmented. The adaptability metric showed an average decrease of 0.06% in the worst-case scenario. This suggested that the network struggled to adapt effectively to disruptions in the worst-case scenario, as the rewiring algorithm was less successful in reconfiguring the topology to respond to node removals. The NRI showed a faster decline of 0.24% per iteration, slightly higher than the 0.16% observed in the best-case scenario. This was further supported by the average NRI of 3.66%, compared to 4.89% in the best-case scenario.

3.3. Targeted disruptions and rewiring

Fig. 7 and Table 4 illustrate the network's response to targeted disruptions, in which supply nodes were ranked by capacity and balance and then removed sequentially, starting with those that had the highest values. The results of the targeted disruption simulation revealed a stark contrast to the random disruption scenario. Supply dropped drastically from approximately 154,742,701 in the initial steps to 1,310 by the end of the simulation, reflecting an average decline of 13% in supply. This reduction in supply, coupled with a negligible 0% reduction in demand, resulted in a severe deficit in overall balance, averaging -112,541,062 units. This indicated that the targeted removal of supply nodes severely compromised the network's ability to meet demand, leading to a collapse in the distribution of live fish between farms. Similarly, proportional connectedness decreased from an initial value of 97% to just 1% by the simulation's conclusion, indicating severe fragmentation and inefficiency in resource distribution as the network failed to adapt to the loss of key nodes.

Connectivity, redundancy, adaptability, and NRI also showed sharp declines throughout the disruption process. Connectivity decreased from 4% at the start to 1% by the end of the simulation, reflecting the network's inability to maintain interconnections. Redundancy fell from 12% to nearly 0%, indicating a loss of alternative routes that could compensate for the disrupted nodes.

Adaptability and NRI, which began at 1% and 6% respectively, dropped to negligible values by the end of the simulation, highlighting the network's limited capacity to respond to targeted disruptions. Examining the network resilience metrics, we observed a 1.17% average decrease in connectivity, a 5.72% average decrease in redundancy, and a 2.19% average decrease in adaptability. These declines suggested that the targeted removal of supply nodes weakened the network's overall structure and its ability to adapt to disruptions.

Despite these challenges, the rewiring algorithm demonstrated some success in mitigating the impact of targeted disruptions. The average PC was 36.56%, suggesting that the algorithm could maintain a degree of connectivity between supply and demand nodes, even when large suppliers were removed. However, the RoC showed an average collapse of 3.62%, indicating that the network faced rapid structural breakdown as cascading failures propagated through the system.

3.4. Impact on distribution of live fish between fish farms

The comparative analysis of random and targeted disruptions showed that the nature of node removal significantly influenced the network's distributional resilience. Random disruptions typically affect non-critical nodes, allowing the network to maintain alternative supply routes. Thus, even in the event of significant node loss, alternative paths could sustain fish distribution across the network. In contrast, targeted disruptions exposed the network's vulnerability to centralised dependency. The sequential removal of supply nodes in the order of their supply capacity and balance creates a situation where the network is unable to compensate for lost supply channels, resulting in a rapid and irrecoverable loss of connectivity. These results suggested that network decentralisation and multi-source supply chains enhanced resilience against targeted disruptions. However, achieving such decentralisation in practice can be challenging due to the physical nature of the networks and the geographical constraints involved in fish farming. By reducing reliance on high-centrality nodes, aquaculture managers can increase the stability of fish distribution even when critical nodes are compromised.

Rewiring is pivotal in determining the network's response to disruptions. In the optimal scenarios, effective and adaptive rewiring ensured that the network retained sufficient redundancy and alternative supply routes, so the flow of live fish continued with minimal interruptions. The efficiency of rewiring strategies was especially evident under random disruptions, where non-critical nodes can be replaced or rerouted with less impact on the overall supply chain. In these cases, the balance metric remained relatively stable, with the network consistently adjusting to maintain PC and avoid drastic losses in fish distribution to individual farms. However, the network's vulnerability to disruption and the limitations of rewiring became apparent under targeted disruptions. When multiple high-betweenness nodes were removed, the network's structural integrity declined faster than rewiring could compensate.

The findings highlighted the importance of redundancy and alternative routing in maintaining distributional stability. Fish farms that rely heavily on a single supply source face a heightened risk of severe shortages during disruptions, particularly when key nodes are targeted. Diversifying the supply chain by establishing multiple independent routes for the distribution of live fish can mitigate these risks and provide a buffer against unexpected disruptions. For instance, the supply of eggs and fingerlings for on-growing operations often depends on a small number of specialist sites, such as hatcheries, which are, by necessity, highly connected nodes and may be more difficult to substitute. Furthermore, the importance of network adaptability through efficient rewiring was evident in the differences observed between best- and worst-case scenarios. For fish farms, this adaptability translates to the ability to identify and secure alternative supply sources in the event of disruptions. This proactive approach to risk management, where farmers anticipate potential disruptions and establish contingency plans with alternative suppliers, can significantly enhance their resilience and operational continuity.

3.5. Comparison with existing methods

Our proposed rewiring algorithm distinguishes itself from conventional network resilience strategies by addressing both structural and operational dynamics within the supply network. Conventional methods often rely on techniques such as shortest-path re-routing, which focuses on identifying the most efficient route between two points after a disruption [26], or greedy heuristics, which make locally optimal choices at each step without considering the global network impact [27]. These approaches often assume a static network configuration and overlook the broader systemic implications of node removal, such as cascading failures or fluctuating supply-demand balances. Static redundancy-based models, conversely, pre-designate backup connections to mitigate failures, lacking the adaptability to respond to unforeseen disruption patterns [28]. Our algorithm, however, offers a more dynamic and nuanced approach.

Crucially, the rewiring process extends beyond mere simulation and analysis of random or targeted node removal. It explicitly integrates the pivotal real-world constraint of distance in the movement of goods between farms. This consideration is central to the distance-constrained random walk component of the algorithm, which identifies affected nodes within a permissible distance threshold and guides the formation of new connections while adhering to realistic spatial limitations. This mechanism reflects the practical limitations of transporting live aquatic stock, where longer routes may not be viable due to biosecurity risks or physiological stress on the stock [14]. By embedding distance constraints into the simulation process, the algorithm offers a more realistic assessment of potential re-routing options during disruptions.

Furthermore, the algorithm incorporates a mechanism for dynamic balance adjustment. Unlike static models, the rewiring algorithm updates the supply-demand balance of nodes as disruptions occur, reflecting the fluctuating conditions observed in real-world supply chains, where trade volumes and roles within the network can shift over time [3].

Finally, a key distinguishing feature is the algorithm's iterative nature and its use of an EWKI to predict potential connections not only based on structural feasibility but also on geographic proximity. This predictive capacity enables the proactive identification of connections that can ensure the continuous flow of goods, rather than simply reacting to disruptions after they occur. By iteratively refining the network structure based on these predictions, the algorithm fosters a more resilient and adaptable system compared to reactive or pre-determined strategies.

Overall, the integration of spatial constraints, dynamic balance recalibration, and an iterative rewiring mechanism makes the proposed method more adaptable and representative of real-world supply networks than many existing techniques.

4. Conclusion and future work

This study introduced and evaluated a rewiring approach to enhance the resilience of supply networks against disruptions. The proposed algorithm adaptively re-establishes connections within the network by identifying alternative supply-demand routes following node or edge removals. This approach provides a systematic framework for mitigating the impact of random and targeted disruptions, ensuring the continuity of resource distribution even under severe network fragmentation. The simulations conducted demonstrated the effectiveness of this rewiring mechanism in restoring network functionality and preventing catastrophic failures, making it a valuable tool for improving the robustness of supply systems across various contexts.

The aquaculture network, used as a case study to evaluate the proposed algorithm, highlights the practical application and significance of this approach. The simulations focused on the distribution of live fish between farms, revealing the critical role of network structure and node composition in determining resilience. In the aquaculture network, characterised by low initial connectivity, redundancy, and adaptability, random disruptions were effectively mitigated by the rewiring algorithm. The algorithm preserved a relatively stable supply-demand balance by dynamically reallocating resources and restructuring the network. However, the case study also underscored the limitations of the approach under targeted disruptions. The removal of critical supply nodes significantly impaired the network's ability to recover, resulting in reduced connectivity and cascading failures. These findings emphasise the importance of protecting high-centrality nodes and diversifying supply sources in networks where such nodes play an outsized role.

The results of the aquaculture network analysis provide valuable insights for enhancing resilience in similar systems. The dominance of demand nodes over supply nodes in the case study created a structural vulnerability where the loss of even a few supply nodes could severely disrupt operations. While increasing the number of supply nodes may not always be feasible, diversifying supply chains and identifying alternative suppliers can significantly enhance network resilience. This aligns with the broader principles of network science, which suggest that decentralised and redundant networks are more robust against disruptions [6,28].

Furthermore, the case study demonstrated the effectiveness of adaptive rewiring as a practical strategy for maintaining operational stability in supply chains. The algorithm's ability to reconfigure the network in response to disruptions highlights its potential for broader application in sectors such as logistics, energy, and critical infrastructure. However, the successful adaptation of the algorithm to these diverse contexts requires careful consideration of their unique operational characteristics. For example, in energy grids, rewiring could represent the reallocation of energy flows across substations or nodes, with constraints based on the capacity and transmission distance. In healthcare logistics, the framework could support the redistribution of medical supplies across hospitals or distribution hubs during emergencies, accounting for urgency and proximity. These considerations are particularly relevant, necessitating modifications to the distance-constrained random walk to incorporate these factors. The types of data needed would also vary; while supply chain analysis often relies on inventory and flow data, energy grids might require real-time load and generation data, and healthcare logistics would incorporate patient flow and resource availability information. Consequently, sector-specific modifications to the algorithm may be required. Nevertheless, the underlying principle of adaptive rewiring offers a valuable foundation for enhancing resilience across a range of interconnected systems.

The aquaculture network model did not incorporate all operational complexities, such as species-specific requirements or seasonal variability, which could influence network resilience. Future research should aim to integrate these factors to provide a more comprehensive analysis. Additionally, while the focus of this study was on topological and operational metrics, the socio-economic implications of network disruptions warrant further exploration. Understanding the economic and social impacts of disruptions on stakeholders across the supply chain will support the design of equitable and sustainable resilience strategies [29,30].

In conclusion, this study contributes to the growing body of knowledge on supply network resilience by developing and evaluating a rewiring framework that adaptively mitigates disruptions. Using the aquaculture network as a case study, the findings illustrate the potential of the framework to enhance connectivity and maintain supply flows under varying disruption scenarios. While the framework demonstrates its capacity to restore network function, the results also reveal sector-specific constraints that could limit its practical implementation. These insights highlight the broader applicability of the approach to other networked systems, offering valuable guidance for strengthening supply chain resilience across diverse contexts.

CRediT authorship contribution statement

Michael-Sam Vidza: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Marcin Budka:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Conceptualization. **Wei Koong Chai:** Writing – review & editing, Validation, Supervision, Project administration, Conceptualization. **Mark Thrush:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation. **Mickaël Teixeira Alves:** Writing – review & editing, Validation, Supervision, Investigation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Michael-Sam Vidza reports financial support was provided by United Kingdom Department for Environment Food and Rural Affairs. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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