A Scenario-Based Robust Optimization Model for Warehouse Planning in Shipbuilding Supply Chains under Ripple Effects

Sis Ozgun Yamak Ormeci1,[1]*, Anna Shotadze[3], Murat Ozkok[2]

[1]Karadeniz Technical University, Graduate School of Natural and Applied Science, Türkiye

[2] Karadeniz Technical University, Surmene Faculty of Marine Sciences, Türkiye

[3] Batumi State Maritime Academy, Georgia

* Corresponding author: sisozgunyamak@ktu.edu.tr

Abstract. Shipbuilding supply chains (SSCs) are characterized by long production horizons and strong interdependencies among material flows. Disruptions affecting critical inputs such as steel plates, profiles, and pipes can rapidly propagate across multiple shipyards and parallel projects, generating ripple-effect-driven instability. Despite the relevance of this phenomenon, quantitative modeling efforts addressing ripple effects in shipbuilding logistics remain limited. This study develops a scenario-based robust optimization framework to support resilient material planning in shipbuilding supply chains under demand uncertainty. The supply network is modeled as a two-echelon structure in which material flows move from suppliers to candidate warehouses and subsequently to shipyards. Demand uncertainty is represented through discrete disruption scenarios reflecting increased material requirements. The proposed formulation focuses on evaluating system performance under adverse conditions by incorporating cost components associated with warehouse activation, material transportation, and unmet demand. The study presents an interpretable robust baseline model that evaluates warehouse activation and material flow decisions under progressively increasing disruption severity and also provides a structural basis for future stochastic extensions. Numerical results indicate that stable network configurations can be maintained as disruption severity increases, while system costs adjust in response to amplified material needs. Overall, the proposed framework provides an initial decision-support basis for analyzing warehouse configuration and material flow planning under ripple-effect conditions in shipbuilding supply chains. The findings show that a stable warehouse configuration can support resilient material planning, while operational flow adjustments absorb increasing demand pressure under ripple-effect conditions.

Keywords: Ripple effect, Shipbuilding supply chain, Robust optimization, Demand uncertainty, Warehouse configuration

1. Introduction

Global supply chains have become increasingly vulnerable to large-scale disruptions triggered by pandemics, geopolitical conflicts, natural disasters, and industrial crises. These disturbances propagate through interconnected supply networks, generating cascading failures in production, transportation, and distribution systems. This phenomenon, known as the ripple effect, amplifies localized disruptions into system-wide instability and has therefore become a central concept in resilience-oriented supply chain design (Dolgui et al., 2018; Hosseini & Ivanov, 2019; Ivanov et al., 2013).

Prior studies have examined ripple-effect propagation using probabilistic models, simulation approaches, and optimization-based decision frameworks, linking disruption dynamics with resilience, viability, and recovery planning. For instance, stochastic–robust optimization has been employed to mitigate cascading disruptions in healthcare and energy supply chains (Fattahi & Govindan, 2018; Yılmaz et al., 2023), while simulation studies have analyzed how epidemic outbreaks, warehouse disruptions, and coordinated routing decisions influence propagation patterns and recovery trajectories (Andoh & Yu, 2023; Ivanov, 2018; Luo et al., 2024). Additional research has explored the role of supplier flexibility, alternative routing, and regional coordination in limiting disruption spread across multi-tier networks (Kamalahmadi & Mellat-Parast, 2016). Despite these advances, the application of ripple-effect modeling to project-based industries remains limited. SSCs pose a unique challenge due to long production cycles and strong interdependencies among supply chain tiers, and reliance on a limited set of critical materials (particularly steel plates, profiles, and pipes) used in hull construction. Disruptions affecting these materials can rapidly propagate across parallel shipbuilding projects, leading to schedule delays, idle capacity, and substantial financial losses. Existing maritime and shipbuilding literature has predominantly focused on probabilistic risks, digital transformation, routing strategies, port-level resilience, and operational disruptions (Centobelli et al., 2023; Ferreira et al., 2018; Niu et al., 2026). Although some studies have modeled disruption propagation through Bayesian networks and stochastic shipment planning (Yazdani & Aouam, 2023; Zhang et al., 2026), he role of intermediate warehouses in buffering ripple effects by stabilizing material flows between suppliers and shipyards has not been explicitly investigated. In the Marmara Region (which hosts Tuzla and Yalova shipyard clusters), the strategic positioning of intermediate depots plays a critical role in sustaining production continuity under disruption-prone conditions. Motivated by this research gap, the present study proposes a scenario-based robust optimization framework for shipbuilding supply chains. The model focuses on the strategic activation of warehouses, and the allocation of material flows from suppliers to shipyards under ripple-effect-driven demand uncertainty. Rather than presenting a fully developed stochastic formulation, this study establishes a robust baseline structure that prioritizes feasibility under adverse demand scenarios. The proposed model minimizes the worst-case total supply chain cost, including warehouse activation costs, transportation costs, and penalty cost associated with unmet demand. By explicitly accounting for multiple demand scenarios, the formulation ensures that the resulting decisions remain viable even when material requirements at shipyards increase due to upstream or regional disruptions. The contribution of this study is threefold. First, it formulates a scenario-based robust optimization model for warehouse planning in shipbuilding supply chains under ripple-effect-driven demand uncertainty. Second, it provides a transparent numerical setting in which the response of warehouse activation, supplier engagement, and material flow decisions can be examined under gradually increasing disruption severity. Third, it offers managerial insight into how stable warehouse configurations can support resilient material planning in shipbuilding clusters where facility decisions are strategic and costly to revise.

2. Material and Method

2.1 Structure of the Shipbuilding Supply Chain Under Disruption Conditions

This study develops a robust optimization model to support strategic warehouse location and material flow decisions within the shipbuilding supply chain under ripple-effect-driven disruption conditions. The model is constructed as a scenario-based robust framework, serving as a preliminary structure for an extended two-stage stochastic formulation, which will be addressed in future work. The overall structure of the supply chain is illustrated in Figure 1 and consists of a two-echelon network in which critical inputs—such as steel plates, profiles, and pipes—are transported from suppliers to warehouses and subsequently distributed to shipyards. Within this network, the set of suppliers S, the set of candidate warehouses W, and the shipyards K constitute the main decision-making entities of the system. Demand at the shipyard level is exposed to significant variability during major disruptions, particularly when disturbances originating at upstream nodes propagate throughout the network. These ripple-effect conditions introduce uncertainty that directly affects material requirements and undermines traditional planning approaches. To capture this dynamic, the proposed model evaluates system performance under multiple demand scenarios, each corresponding to a distinct disruption severity level. In this structure, transportation links between suppliers, warehouses, and shipyards are assumed to be fixed, while demand parameters vary across scenarios to reflect the uncertain operating environment. The primary objective of the model is to minimize the total cost of the supply chain, including warehouse activation costs, transportation costs across both echelons, and penalty costs associated with unmet demand, while ensuring the robustness of decisions across all scenarios. By focusing on worst-case realizations, the model prioritizes solutions that remain feasible and cost-effective even when material requirements escalate unexpectedly due to upstream disruptions. This worst-case perspective enhances the resilience of the supply network and provides decision-makers with strategies that maintain service reliability under severe disruption conditions. To sustain analytical clarity, the model is formulated over a single planning period representing a typical procurement cycle in shipbuilding. Material attributes, capacity limits, costs, and distances are assumed to remain constant during this period. Uncertainty is introduced solely through shipyard demand, capturing the indirect ripple effects of disruptions occurring elsewhere in the regional supply network. Transportation routes between nodes are considered fixed throughout the planning horizon, emphasizing the impact of demand fluctuations rather than structural reconfiguration of the network. The numerical instance is intentionally kept compact to provide a transparent and traceable evaluation of the proposed robust formulation. Rather than representing a full-scale industrial case, it serves as a controlled test environment for observing how warehouse activation, supplier engagement, and material flow decisions respond to increasing disruption severity. This design allows the model behavior to be examined clearly before extending the framework to larger real-world shipbuilding networks.

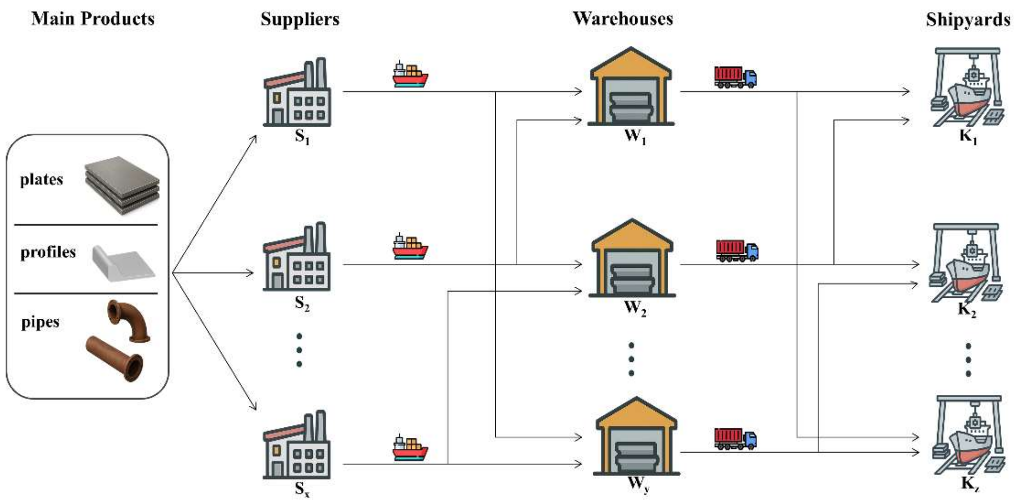

Figure 1. Structure of the proposed shipbuilding supply chain network under disruption conditions

2.2 Mathematical formulation of the robust model

This subsection introduces the notation and the complete mathematical formulation of the scenario-based robust shipbuilding supply chain model developed in this study. The network includes suppliers, candidate warehouses, and shipyards under multiple demand scenarios.

Sets and indices

S: set of suppliers, indexed by s
W: set of possible warehouses, indexed by w
K: set of shipyards, indexed by k
R: set of demand scenarios, indexed by r ($\boldsymbol{R} = \{\boldsymbol{r_1}, \boldsymbol{r_2}\}$)
L: set of uncertainty levels, indexed by l ($\boldsymbol{L} = \{\boldsymbol{0}, \boldsymbol{1}, \dots, \boldsymbol{10}\}$)

Parameters

cap$\boldsymbol{S_s}$*: capacity of supplier s*
cap$\boldsymbol{W_w}$*: capacity of warehouse w*
$\boldsymbol{d_k^0}$*: nominal demand of shipyark k*
$\boldsymbol{d_{kr}(l)}$*: demand of shipyark k in scenario r at uncertainty level l*
$\boldsymbol{f_w}$*: fixed opening cost of warehouse w*
$\boldsymbol{g_k}$*: penalty cost per unit of unmet demand at shipyard k*
$\boldsymbol{c_{sw}}$*: unit transportation cost from supplier s to warehouse w*
$\boldsymbol{c_{wk}}$*: unit transportation cost from warehouse w to shipyard k*
v: upper bound on total cost (budget limit)

Transportation costs are computed from distances and mode-specific unit costs as in the implementation

$\boldsymbol{c_{sw}}$*=costSea.dist*$\boldsymbol{SW_{sw}}$, $\boldsymbol{c_{wk}}$*=costRoad.dist*$\boldsymbol{WK_{wk}}$

Decision variables

$\boldsymbol{y_w} \in \{\boldsymbol{0}, \boldsymbol{1}\}$*: equals 1 if warehouse w is opened*
$\boldsymbol{x_{sw}^r} \geq \boldsymbol{0}$*: flow from supplier s to warehouse w under scenario r*
$\boldsymbol{x_{wk}^r} \geq \boldsymbol{0}$*: flow from warehouse w to shipyard k under scenario r*
$\boldsymbol{u_{kr}} \geq \boldsymbol{0}$*: unmet demand atshipyard k in scenario r*
$\boldsymbol{Cost_r} \geq \boldsymbol{0}$*: total cost in scenario r*

Z: worst-case scenario cost

Min-max robust formulation:

$$min_{y,x,u} max_{r\in R}\left\{\sum_{w\in W} f_w y_w + \sum_{s\in S}\sum_{w\in W} c_{sw}x_{sw}^r + \sum_{w\in W}\sum_{k\in K} c_{wk}x_{wk}^r + \sum_{k\in K} g_k u_{kr}\right\} \quad (1)$$

$$Cost_r(y,x,u) \sum_{w\in W} f_w y_w + \sum_{s\in S}\sum_{w\in W} c_{sw}x_{sw}^r + \sum_{w\in W}\sum_{k\in K} c_{wk}x_{wk}^r + \sum_{k\in K} g_k u_{kr}, \forall r\in R \quad (2)$$

Subject to:

$$\sum_{w\in W} x_{sw}^r \le capS_s, \forall s\in S, \forall r\in R \quad (3)$$

$$\sum_{s\in S} x_{sw}^r \le W_w y_w, \forall w\in W, \forall r\in R \quad (4)$$

$$\sum_{s\in S} x_{sw}^r = \sum_{k\in K} x_{wk}^r, \forall w\in W, \forall r\in R \quad (5)$$

$$\sum_{w\in W} (x_{wk}^r + u_{kr}) = d_{kr}(l), \forall k\in K, \forall r\in R \quad (6)$$

$$Cost_r(y,x,u) \le v, \forall r\in R \quad (7)$$

$$x_{sw}^r \ge 0, x_{wk}^r \ge 0, u_{kr} \ge 0, \forall s\in S, \forall w\in W, \forall k\in K, \forall r\in R \quad (8)$$

$$y_w \in \{0,1\}, \forall r\in R \quad (9)$$

$$Z \ge Cost_r(y,x,u), \forall r\in R \quad (10)$$

Equation (1) defines the min-max objective, through which the model seeks to minimize the worst-case total cost across all disruption scenarios. Equation (2) specifies the scenario-dependent total cost structure, which aggregates warehouse activation costs, transportation costs, and penalty costs associated with unmet shipyard demand. Equation (3) enforces supplier capacity limits, while Equation (4) imposes capacity constraints on warehouses that are activated in the network. Equation (5) enforces flow conservation at each warehouse by ensuring that the total inbound flow from suppliers equals the total outbound flow to shipyards in each scenario. Equation (6) ensures the satisfaction of scenario-based shipyard demand through inbound shipments or unmet-demand quantities. Equation (7) constrains total cost in each scenario to remain within a predefined allowable budget. In the numerical study, v is used as a sufficiently large feasibility-oriented upper bound and does not act as a binding budget constraint in the reported solutions. Equation (8) establishes the robust requirement by forcing the objective variable to dominate all scenario costs, ensuring that the final solution corresponds to the worst-case outcome. Equation (9) defines the binary nature of warehouse activation decisions, and Equation (10) connects the robust objective to scenario costs through the min–max structure.

Demand uncertainty is represented through two discrete demand scenarios, r_1 and r_2, and an uncertainty level $l \in \{0,1,\ldots,10\}$. For each shipyard k, d_k^0 denotes the nominal demand. Scenario-specific demand levels are generated as follows:

$$d_{kr_1}(l) = d_k^0, \forall k \in K, \forall l \in \{0, \dots, 10\} \tag{11}$$

$$d_{kr_2}(l) = (1 + 0{,}002l) d_k^0, \forall k \in K, \forall l \in \{0, \dots, 10\} \tag{12}$$

Robust counterpart explanation

The robust counterpart of the proposed model is constructed by embedding scenario-based demand uncertainty directly into the nominal deterministic formulation. In the nominal structure, Equation (2) defines the total cost under a single deterministic demand realization. However, shipyard demand is not constant under ripple-effect conditions, and therefore a single deterministic constraint is insufficient to ensure feasibility and reliable performance when the system is exposed to disruptions. To address this limitation, additional constraints representing alternative demand realizations are introduced, and the total cost expression is evaluated independently for each scenario.

Equation (11) corresponds to the nominal demand case and reflects the baseline material requirement of each shipyard. Equation (12) represents the disrupted case, where demand is scaled proportionally according to the uncertainty level l. For each uncertainty level, the demand of scenario r_2 is generated by applying a controlled amplification rate of 2% per level, reaching up to a maximum increase of 20% when l = 10. This structure enables the model to evaluate the system under a sequence of progressively deteriorating conditions, capturing the escalation effect that is typical of ripple-effect propagation. The 2% incremental demand increase is used as a controlled stress-testing mechanism rather than as an empirically estimated disruption probability. This setting allows the model response to be observed under gradually worsening demand conditions, from the nominal case to a 20% demand increase. The two-scenario structure is selected to maintain transparency in the baseline formulation: r_1 represents normal operating conditions, whereas r_2 represents a disrupted demand state. This structure can be expanded by adding more scenarios when real shipyard data become available. In the robust formulation, the min-max objective in Equation (1) is activated by replacing the single deterministic cost expression with the scenario-dependent cost structure of Equation (2) and by imposing the robust bound in Equation (8). This constraint forces the objective variable Z to dominate all scenario-specific costs, thereby ensuring that the worst-case total cost governs the final solution. By adopting this structure, the model protects against systematic underestimation of demand and preserves feasibility across multiple disruption scenarios. Unlike classical robust optimization approaches that require additional auxiliary variables or an explicit uncertainty budget, the proposed formulation achieves robustness exclusively via alternative scenario costs and a dominating objective variable. As a result, the model delivers a conservative yet computationally tractable protection mechanism without introducing additional combinatorial complexity. The resulting robust counterpart therefore evaluates supplier–warehouse–shipyard flows under both nominal and stressed demand conditions and identifies warehouse activation and material flow decisions that remain stable and feasible across all demand realizations considered.

Overall, the robust counterpart integrates uncertainty into the model by substituting the deterministic demand constraint with scenario-specific demand values and by enforcing a worst-case protection mechanism through the min-max structure. This integration ensures that the network design remains feasible and cost-effective even when shipyard demand intensifies due to disruptions, thereby representing the cost of robustness embedded within the optimal solution.

3. Results

The numerical analysis is conducted using the illustrative shipbuilding supply chain instance defined in Section 2. The test network consists of three suppliers, three candidate warehouses, and eight shipyards. The parameter values are selected to create a balanced test setting in which capacity, transportation cost, warehouse activation cost, and unmet-demand penalty jointly influence the solution. Supplier capacities are set to 40, 45, and 50 units, respectively, while each warehouse has a capacity of 60 units. These values prevent the network from becoming either trivially feasible or infeasible under increasing demand. Warehouse activation costs are defined as 100, 110, and 120 to represent cost heterogeneity among candidate locations. The unmet-demand penalty is set to 100 per unit to discourage shortages when feasible shipment alternatives exist. Transportation costs are distance-based and computed as 0.8 × distSW for supplier–warehouse flows and 1.2 × distWK for warehouse–shipyard flows. Baseline shipyard demand is fixed at 10 units, except for k_1 and k_2, where nominal demand is set to 12 and 14 units, respectively. All tests are performed in GAMS with the CPLEX solver, and the performance of the robust model is evaluated across uncertainty levels ranging from 0 to 10. The results indicate that the worst-case objective value rises steadily as the uncertainty level increases. This trend directly reflects the growing material requirements at the shipyards: higher scenario demand leads to additional transportation activity and larger unmet-demand penalties, which collectively raise the cost captured by the robust objective value. A detailed summary of these outputs across all uncertainty steps is provided in Table 1, which reports the progression of worst-case costs together with the corresponding warehouse activation patterns and supplier engagement decisions. Across all uncertainty settings, the model consistently activates the same two warehouses and utilizes all three suppliers. This stable configuration suggests that, within the scope of the illustrative instance, the robust solution does not rely on repeated changes in facility activation decisions. Instead, the model absorbs increasing demand pressure through operational adjustments in shipment quantities and unmet-demand levels. Therefore, the predictable increase in the worst-case cost should not be interpreted as a weak result, but as the expected cost of maintaining feasibility under progressively severe demand conditions. In this sense, the increase in Z represents the price of robustness embedded in the min–max structure. For shipbuilding clusters such as Tuzla and Yalova, this finding is practically relevant because warehouse activation is a strategic decision, whereas shipment quantities can be adjusted more flexibly during disruption periods.

A comparison of scenario-based costs shows that the inflated scenario (r_2) always produces higher total costs than the nominal scenario (r_1), and the gap between the two scenarios widens as uncertainty increases. This behavior illustrates how increasing disruption severity amplifies downstream demand pressure and progressively pushes the system toward its capacity limits.

At each uncertainty level, the robust objective value coincides with the r_2 outcome, confirming that the model correctly identifies and protects against the most adverse cost scenario. Overall, the numerical findings demonstrate that the proposed framework maintains a balanced trade-off between feasibility and resilience. While the network structure remains unchanged, the system responds predictably to increasing disruption intensity, and the steady progression of worst-case costs highlights that robust planning inherently requires accepting higher operational expenditures as protection levels increase. These insights confirm that the proposed model effectively supports strategic decisions on warehouse activation and material flow allocation under ripple-effect conditions in shipbuilding supply chains.

To further examine the stability of the warehouse activation decision, a limited sensitivity analysis is conducted for the unmet-demand penalty at the highest uncertainty level (*l=10*). As shown in Table 2, the lower penalty value leads the model to activate only warehouse 1 and accept unmet demand in the disrupted scenario. In contrast, the base and higher penalty values result in the selection of warehouses 1 and 2, the use of all three suppliers, and zero unmet demand in the disrupted scenario. This finding indicates that the selected warehouse configuration becomes more robust when shortage avoidance is prioritized.

Table 1. Numerical results

Uncertainty level *(l)*	Worst-case cost *(Z)*	Selected warehouses *(W)*	Active suppliers *(S)*
0	6002.80	1,2	1,2,3
1	6130.02	1,2	1,2,3
2	6257.23	1,2	1,2,3
3	6384.45	1,2	1,2,3
4	6511.66	1,2	1,2,3
5	6638.88	1,2	1,2,3
6	6766.10	1,2	1,2,3
7	6893.31	1,2	1,2,3
8	7020.53	1,2	1,2,3
9	7147.74	1,2	1,2,3
10	7274.96	1,2	1,2,3

Table 2. Sensitivity analysis for unmet-demand penalty al *l=10*

Penalty cost	Worst-case cost	Selected warehouses	Active suppliers	Unmet demand in disrupted scenario
80	7173.60	1	1,2	43.20
100	7274.96	1,2	1,2,3	0.00
120	7274.96	1,2	1,2,3	0.00

4. Conclusion

This study presents a scenario-based robust optimization model designed as a preliminary step toward a two-stage stochastic optimization framework for shipbuilding supply chains. The proposed model captures demand uncertainty under disruption conditions and aims to establish a structurally stable and reliable network configuration before introducing more advanced stochastic decision layers.

The formulation represents a two-echelon material flow network from suppliers to intermediate warehouses and subsequently to shipyards. Demand uncertainty is incorporated through discrete scenarios, and robustness is ensured by minimizing the worst-case total system cost. This structure allows the supply chain to remain feasible under elevated demand levels without the need for scenario-specific recourse decisions.

Numerical results show that the worst-case cost increases gradually as demand uncertainty intensifies, reflecting higher material requirements and the associated growth in transportation and shortage penalty costs. Despite this increase, the set of activated warehouses and engaged suppliers remains invariant across all uncertainty levels. This outcome indicates that the robust structure primarily adapts through adjustments in material flow quantities rather than changes in the facility configuration.

The worst-case objective value consistently aligns with the most severe demand scenario, confirming that the min–max formulation effectively captures the system's exposure to disruption risk. Overall, the findings demonstrate that a stable, interpretable, and computationally tractable robust baseline can be established for shipbuilding supply chains operating under ripple-effect conditions.

This robust model constitutes the foundational modeling layer of an ongoing two-stage stochastic optimization study. Although the numerical instance is illustrative and intentionally compact, it provides a transparent basis for examining the behavior of the proposed robust formulation. Future research will extend this structure using real shipyard data, larger regional networks, additional disruption scenarios, and two-stage stochastic recourse decisions.

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