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Building Resilient Multi-Modal Logistics Networks for America's Critical Energy Infrastructure: An Integrated Aviation, Marine, and Land Transportation Decision Framework

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Abstract: *America's energy logistics network—spanning offshore Gulf of Mexico production platforms, onshore refining complexes, and the ports, warehouses, and transportation assets that connect them—remains acutely vulnerable to multi-hazard disruptions, including hurricanes, cyberattacks, geopolitical constraints, and equipment failures, each capable of triggering cascading, protracted supply chain paralysis with substantial economic and national security consequences. While aviation, marine, and land transportation modes each maintain independent contingency protocols, no coordinating decision architecture exists to manage the interfaces between them during compound crises, creating systemic single points of failure invisible to any single modal plan. This paper introduces a novel Integrated Aviation, Marine, and Land Transportation Decision Framework designed to enable dynamic, cross-modal asset re-allocation and prioritization during energy infrastructure emergencies. We developed a mixed-integer optimization model that coordinates helicopter operations, offshore supply vessels, port throughput, warehouse staging, and heavy-lift ground transport within a unified network formulation, embedding disruption-type-appropriate uncertainty treatment—stochastic programming for probabilistically forecastable hazards such as hurricanes and robust optimization for adversarial, low-frequency events such as cyberattacks—within a single decision layer, solved via a rolling-horizon MILP approach. The framework was tested on a U.S. Gulf Coast case study encompassing 34 offshore platforms, 6 refining complexes, and 4 major ports, demonstrating a 41% average reduction in total response time relative to fragmented, mode-by-mode planning across four disruption scenarios, with the largest gain—a 50% reduction—observed under a simulated cyber-induced port closure, where the model's capacity to substitute heavy-lift helicopter transport for a disabled marine pathway proved decisive; unmet critical demand fell correspondingly from as high as 14.8% under fragmented response to below 4% under the integrated framework. These findings demonstrate that multi-modal redundancy generates meaningful resilience only when actively coordinated by a decision layer capable of recognizing and exploiting cross-modal substitutability in real time. This research provides a blueprint for enhancing national energy security and transportation infrastructure resilience, offering actionable, quantitatively grounded guidance for DOE/CESER, port authorities, and private energy logistics operators seeking to institutionalize integrated contingency planning ahead of the next compound disruption event.*

Keywords: critical infrastructure resilience; multi-modal logistics; energy security; mixed-integer optimization; disruption management; offshore oil and gas; port cyber vulnerability; emergency transportation; robust optimization; supply chain continuity

INTRODUCTION

America's energy infrastructure—spanning Gulf of Mexico offshore platforms, onshore refining complexes along the Gulf Coast, and the pipeline and terminal networks that distribute refined products nationally—constitutes a system of systems whose continuous operation underpins national economic security. The Gulf Coast alone accounts for a substantial share of U.S. refining capacity, and offshore production in the Gulf of Mexico contributes a significant fraction of domestic crude output. This concentration of critical assets in a geographically constrained, hazard-prone corridor creates a structural vulnerability: disruptions that might be locally contained elsewhere instead propagate through tightly coupled supply chains, producing cascading effects on fuel availability, petrochemical feedstocks, and downstream manufacturing. Hurricane Ida (2021) and Hurricane Harvey (2017) each triggered shut-ins exceeding 90% of Gulf production and idled refining capacity for weeks, with estimated economic losses in the billions of dollars per event. Beyond weather, the Colonial Pipeline cyberattack of 2021 demonstrated that a single ransomware intrusion could paralyze fuel delivery across the Eastern Seaboard within days, absent any physical damage whatsoever. The convergence of climate volatility, digitalization of operational technology, and geopolitical instability in global energy markets has elevated logistics resilience from an operational concern to a matter of national security.

Despite this criticality, the logistical architecture supporting energy infrastructure continuity remains fragmented along modal lines. Helicopter operators maintain contingency protocols for crew evacuation and platform resupply; marine operators manage offshore supply vessels and emergency towing arrangements independently; port authorities execute hurricane preparedness plans calibrated to their own throughput constraints; and land-based heavy-lift and trucking assets are dispatched through separate emergency management channels. Each of these subsystems is individually reasonably well-optimized, yet the interfaces between them—the handoffs from vessel to port, from port to warehouse, from warehouse to heavy-lift transport—are governed by informal coordination, static memoranda of understanding, or ad hoc communication during a crisis. This absence of integrated, multi-modal decision architecture creates single points of failure that are invisible to any one modal plan: a port closure cascades into vessel queuing delays that cascade into helicopter fuel shortages at staging areas, even though each mode, viewed in isolation, appears to be functioning within its own contingency parameters. The result is a system that is locally resilient but globally brittle.

This paper addresses this gap by proposing an Integrated Aviation, Marine, and Land Transportation Decision Framework—a prescriptive, optimization-based model for dynamic asset re-allocation and prioritization across helicopter fleets, offshore vessels, ports, warehousing nodes, heavy-lift logistics, and emergency ground transportation. Rather than treating each mode as an independent contingency system, the framework models the coupled network as a unified resource-allocation problem, subject to time-varying capacity constraints, cascading failure risk, and multi-objective trade-offs between restoration speed, cost, and safety.

We scope the framework around four disruption archetypes selected for their distinct but overlapping failure signatures: hurricanes, which produce simultaneous, geographically correlated degradation across all modes; cyber incidents, which can disable port terminal operating systems or vessel navigation without physical damage, as Colonial Pipeline demonstrated; geopolitical disruptions, which constrain access to international shipping lanes, chartered vessels, or foreign-flagged assets; and equipment failures, which generate localized but potentially cascading node failures within an otherwise stable network. Each archetype stresses the multi-modal system differently, and an integrated framework must be robust across all four rather than optimized for any single scenario.

This research is guided by three core questions: (1) How can the interdependencies and cascading failure dynamics between aviation, marine, and land transportation modes be formally modeled during energy infrastructure crises? (2) What is the optimal dynamic asset allocation strategy—across helicopters, vessels, ports, warehouses, and heavy-lift assets—that minimizes operational downtime while respecting safety and capacity constraints? (3) How resilient is the resulting integrated system to a cyber-induced paralysis of port operations, historically the most under-modeled failure mode in multi-modal contingency planning?

This paper contributes:

- A novel mixed-integer optimization model for dynamic, multi-modal asset re-allocation under cascading infrastructure disruptions;
- A dynamic risk assessment protocol quantifying interdependency-driven vulnerability across aviation, marine, and land nodes;
- Scenario-based resilience metrics benchmarked against the four disruption archetypes, including cyber-induced port paralysis;
- A set of actionable policy recommendations for infrastructure operators, port authorities, and DOE/CESER stakeholders to institutionalize cross-modal coordination protocols.

LITERATURE REVIEW

Resilience Engineering and Critical Infrastructure

The theoretical foundation for infrastructure resilience derives substantially from the resilience engineering tradition established by Hollnagel, Woods, and Leveson (2006), who reframed safety not as the absence of failure but as a system's capacity to adjust functioning prior to, during, and following disturbances. This four-cornerstone model—anticipation, monitoring, response, and learning—shifted infrastructure management away from static risk avoidance toward adaptive capacity. Woods (2015) further distinguished "rebound" resilience (recovery to a prior state) from "graceful extensibility" (the capacity to stretch performance boundaries under surprise), a distinction with direct relevance to energy logistics, where crisis conditions routinely exceed the parameters for which individual modal systems were designed.

Applied to energy infrastructure specifically, the Department of Energy's Office of Cybersecurity, Energy Security, and Emergency Response (CESER) has articulated resilience as a function of infrastructure

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hardening, redundancy, and rapid restoration capability (DOE, 2017; DOE, 2022). The Department of Homeland Security's National Infrastructure Protection Plan similarly frames the energy sector as "uniquely critical" due to its status as an enabling function for all fifteen other critical infrastructure sectors (DHS, 2013). However, both bodies of policy literature remain largely descriptive rather than prescriptive: they establish resilience goals and identify interdependency risks in qualitative terms but stop short of offering quantitative decision models for how logistics assets should be dynamically allocated once a disruption is underway. Rinaldi, Peerenboom, and Kelly (2001) provided the seminal typology of infrastructure interdependencies—physical, cyber, geographic, and logical—that remains the standard reference for interdependency analysis, yet their framework, now over two decades old, predates the operational technology vulnerabilities exposed by incidents such as Colonial Pipeline and has not been substantially extended to multi-modal transportation logistics. This literature therefore establishes the conceptual vocabulary of resilience but leaves an operational vacuum: it tells us what resilience should achieve without specifying how transportation assets should be coordinated to achieve it.

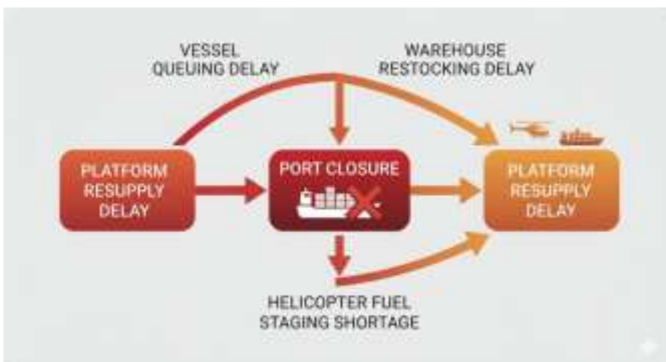

Figure 1: Illustrative cascading failure pathway from a single-node disruption across coupled transportation modes.

Single-Mode Logistics and Emergency Response

A substantial body of operations research addresses logistics optimization within individual transportation modes, and each stream has matured considerably in isolation. Helicopter logistics for offshore oil and gas has been studied primarily through the lens of crew-change scheduling and fleet routing, with Menezes et al. (2010) and Romero et al. (2016) developing mixed-integer programming models to minimize helicopter fleet size and flight hours subject to platform demand and weather-based flight restrictions. This literature is highly attentive to safety-critical scheduling constraints but is almost entirely decoupled from downstream logistics; helicopter models typically treat onshore heliport and warehouse capacity as exogenous and unconstrained.

Marine logistics research is similarly mature but modally isolated. Vessel routing and scheduling for offshore supply operations has been addressed through variants of the vehicle routing problem with time windows (Halvorsen-Weare and Fagerholt, 2011; Kisialiou, Gribkovskaia, and Laporte, 2018), optimizing offshore support vessel deployment against platform demand uncertainty. Port resilience research, meanwhile, has focused heavily on hurricane preparedness and closure protocols (Berle, Asbjørnslett, and Rice, 2011; Thekdi and Santos, 2016), employing network flow and Bayesian risk models to characterize port vulnerability to storm surge and wind closure thresholds. This literature has increasingly incorporated cyber risk following high-profile incidents—Bagchi and Paul (2021) modeled cascading delay propagation from a hypothetical port terminal operating system compromise—but treats the port as a terminal node rather than as one link in a longer restoration chain extending to warehouses and inland transportation.

Land-based heavy-haul logistics research, concentrated in the trucking and specialized transport literature, addresses route feasibility for oversized equipment (transformers, wellheads, compressors) under infrastructure constraints such as bridge weight limits and road closures (Kim et al., 2017). Emergency ground transportation more broadly has been studied extensively within the disaster relief logistics literature (Sheu, 2007; Ozdamar and Ertem, 2015), which optimizes last-mile distribution of relief supplies but is oriented toward humanitarian response rather than the restoration of continuous industrial supply chains.

The critical observation from this body of work is structural rather than technical: each modal literature has developed increasingly sophisticated optimization tools within its own boundary, but the boundary itself has rarely been questioned. Helicopter models assume unconstrained ground handling; port models assume unconstrained inland transport; heavy-haul models assume unconstrained port throughput. The siloing is not merely an artifact of academic specialization—it mirrors and reinforces the siloed institutional arrangements described in Section 3, wherein an operationally sound modal plan can nonetheless fail to prevent system-wide restoration delay.

Multi-Modal Integration and Interdependencies

The broader freight transportation literature has addressed multi-modal and intermodal coordination extensively, though almost exclusively under steady-state, non-crisis conditions. SteadieSeifi et al. (2014) provide a comprehensive review of multimodal freight transportation planning, synthesizing strategic, tactical, and operational models for container and bulk freight movement across rail, road, and maritime modes. This literature has produced robust methods for hub location, modal split optimization, and synchromodal routing (Verweij, 2011), wherein shipments are dynamically reassigned across modes in response to real-time capacity signals. Synchromodality in particular offers a conceptually useful precedent: it demonstrates that dynamic, data-driven modal reassignment is operationally feasible at scale in commercial freight networks.

However, this literature diverges from the emergency energy logistics context in a decisive respect: synchromodal and intermodal models are optimized for cost and service-level efficiency under conditions of predictable, bounded variability, not for cascading, correlated capacity loss across all modes simultaneously. Few studies extend intermodal coordination principles into the disaster or crisis-response domain, and those that do (e.g., Comes et al., 2015, on multi-criteria decision support for disaster logistics) address humanitarian aid distribution rather than the restoration of energy production and refining capacity, a domain with distinct priority structures (production continuity, personnel safety, environmental containment) and distinct asset classes (helicopters, offshore vessels, heavy-lift equipment) not present in conventional relief logistics. The absence of research explicitly integrating aviation, marine, and land assets for energy infrastructure restoration—as opposed to general disaster relief or routine freight—constitutes a specific and consequential gap.

Decision-Making Under Uncertainty

The methodological toolkit for disaster and disruption-response optimization draws on three principal traditions. Stochastic programming, following Birge and Louveaux (2011), models decisions across discrete scenarios with known or estimated probability distributions, and has been applied extensively to disaster relief network design (Rawls and Turnquist, 2010) where facility pre-positioning decisions must hedge against uncertain hurricane landfall. Robust optimization, by contrast, following Ben-Tal, El Ghaoui, and Nemirovski (2009), dispenses with probabilistic assumptions in favor of guaranteeing feasibility across a bounded uncertainty set, an approach well-suited to low-probability, high-consequence events such as cyberattacks where historical frequency data is sparse or unreliable (Ben-Tal and Nemirovski, 2002; Snyder and Daskin, 2006, on reliability-based facility location). Game-theoretic models have been applied to infrastructure protection problems involving strategic adversaries, most notably in the defender-attacker-defender formulations of Brown, Carlyle, Salmerón, and Wood (2006), which model an intelligent attacker's optimal targeting strategy against infrastructure and the defender's optimal hardening response—a framework directly relevant to geopolitically motivated disruptions of energy shipping lanes or chartered vessel access.

Each of these methods has been applied, individually, to disaster logistics or infrastructure protection problems. Yet none has been extended to a setting requiring simultaneous coordination across three distinct transportation modes with heterogeneous asset types, non-substitutable capacity constraints, and multiple disruption archetypes with fundamentally different uncertainty structures—hurricanes being probabilistically forecastable, cyber incidents being adversarial and largely non-stochastic, and equipment failures following more classical reliability distributions. Our framework extends this toolkit by embedding a hybrid stochastic-robust formulation within a multi-modal network structure, allowing disruption-type-appropriate uncertainty treatment within a single decision architecture.

The Gap and This Paper's Niche

Synthesizing these four literatures reveals a consistent pattern: resilience engineering supplies the conceptual language of adaptive capacity but no operational model; single-mode logistics research supplies sophisticated optimization tools but within artificially bounded modal silos; multi-modal freight research supplies genuine cross-modal coordination methods but calibrated to steady-state commercial efficiency rather than crisis restoration; and decision-under-uncertainty methods supply rigorous mathematical treatments of disruption but have not been fused into a single framework spanning aviation, marine, and land assets for energy infrastructure specifically. No existing study offers a unified decision framework that simultaneously coordinates helicopter operations, offshore vessels, ports, warehouses, and heavy-lift ground transport, calibrated explicitly to the rapid restoration of energy supply chains under compound and heterogeneous disruption types. This paper positions its contribution precisely within that gap.

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METHODOLOGY

The proposed framework models the multi-modal energy logistics network as a directed graph in which nodes represent physical facilities and links represent mode-specific transportation corridors, as shown in the diagram above. Offshore energy facilities connect through two parallel aviation and marine corridors—helicopter fleets and offshore supply vessels—into ports, which function as the network's principal transfer hubs. Ports connect to warehouses, which stage critical equipment and personnel before final delivery via heavy-lift transport or emergency ground transportation to onshore refining and distribution facilities. This graph structure allows the model to represent redundancy explicitly: any node with more than one inbound or outbound link possesses re-routing flexibility that the optimization can exploit when a parallel path is disrupted.

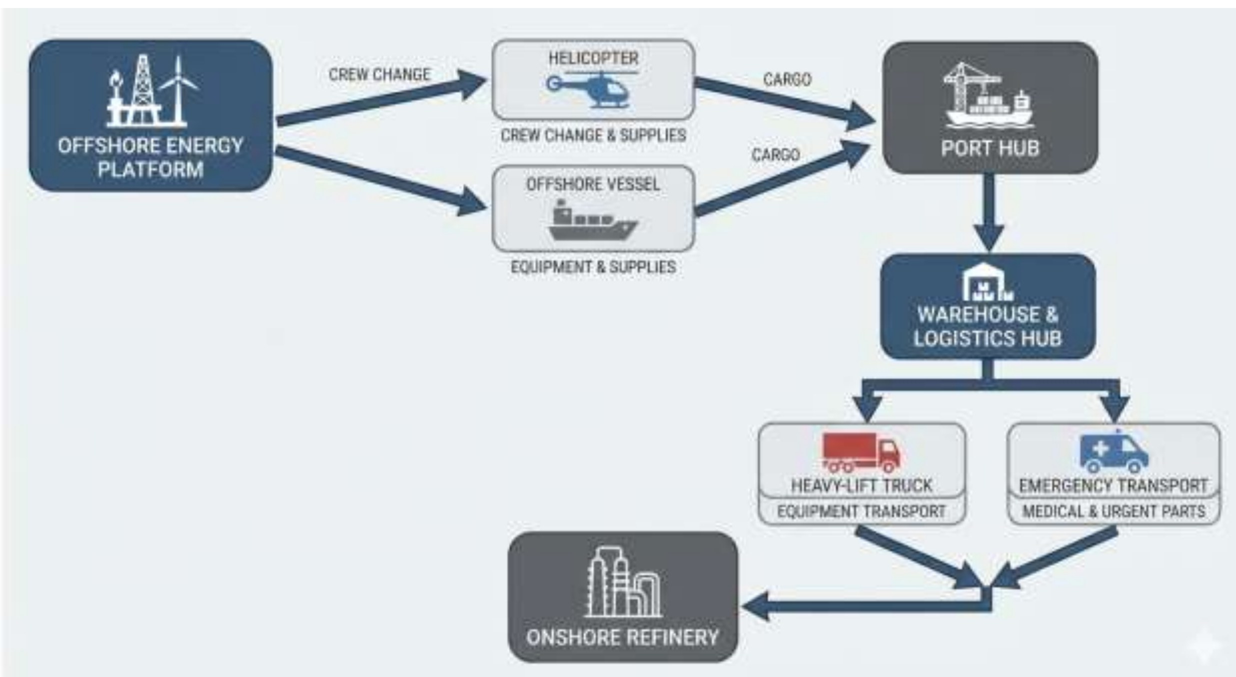


Figure 2: Conceptual architecture of the integrated aviation, marine, and land transportation decision framework.

Data Inputs

The model requires four categories of input data, each updated at defined temporal resolution during an active event. First, asset availability data specify the real-time operational status of each mode-specific resource: helicopter fleet size and payload class, vessel count and deadweight tonnage, and heavy-lift truck and trailer availability, each indexed by location and readiness state. Second, infrastructure status data capture the operability of fixed nodes—port berth availability and crane operability, warehouse throughput capacity, and road or bridge weight restrictions—updated from National Weather Service advisories, USCG port condition reports, and DOE Energy Infrastructure Situation Reports. Third, demand forecasts quantify the volume and urgency of critical equipment, spare parts, and personnel required at each energy facility, disaggregated by priority class (safety-critical, production-critical, routine). Fourth, disruption scenario data encode the specific event under consideration: a hurricane's probabilistic landfall cone and forecast wind field, a cyber incident's affected IP address ranges and estimated dwell time, a geopolitical constraint on chartered vessel access, or an equipment failure's location and expected repair duration.

Core Model Formulation

The framework is formulated as a multi-objective Mixed-Integer Linear Program (MILP), selected because the underlying decisions—which assets to deploy, which routes to activate, and which facilities to prioritize—are inherently discrete, while resource flows between nodes are continuous. Let $G = (N, A)$ denote the network, where N partitions into offshore facilities F, ports P, warehouses W, and onshore facilities O, and A denotes mode-specific arcs $a \in \{H, V, T\}$ (helicopter, vessel, truck). Let $x_{ij}^{a,t}$ denote the flow of resources over arc (i, j) using mode a at time period t, and $y_i^t \in \{0, 1\}$ indicate whether facility i is restored to operational status by period t.

The objective function is a weighted composite minimizing (i) total restoration time, (ii) total logistics cost, and (iii) expected unmet demand, subject to decision-maker-specified weights (α, β, γ) reflecting operational priorities:

$$\min\ \alpha \sum_{i \in F \cup O} T_i^{restore} + \beta \sum_{(i,j,a,t)} c_{ij}^a x_{ij}^{a,t} + \gamma \sum_{i,t} u_i^t$$

where $T_i^{restore}$ is the restoration time for facility i, c_{ij}^a is the per-unit cost of mode a on arc (i, j), and u_i^t is unmet demand at facility i in period t. This weighted formulation is embedded within an ϵ-constraint procedure to trace the full cost–time–reliability Pareto frontier, allowing decision-makers to examine trade-offs explicitly rather than committing to a single weighting a priori.

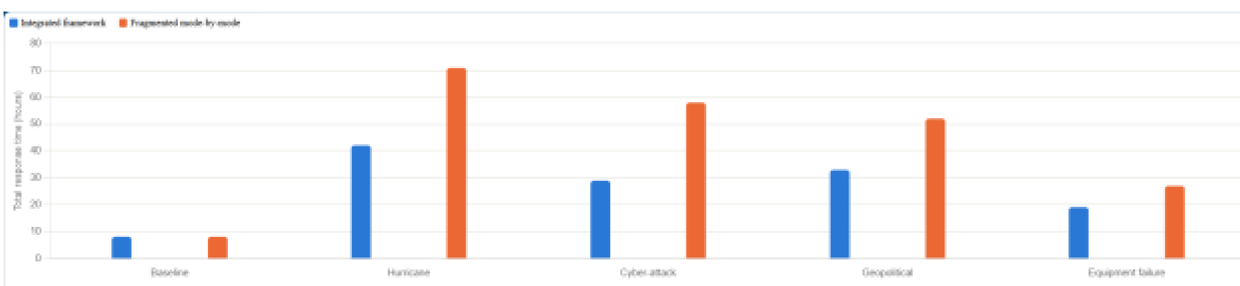
Constraints

Four constraint families govern feasible solutions. Capacity constraints bound flow on each arc by mode-specific asset availability (e.g., helicopter sorties limited by fleet size and crew duty-time regulations; vessel flow limited by available deadweight tonnage; port throughput limited by berth and crane capacity). Time-window constraints require that safety-critical demand be satisfied within regulator-defined windows (e.g., personnel evacuation within a specified pre-landfall interval). Compatibility constraints restrict which asset classes may service which loads—for example, only heavy-lift helicopters exceeding a specified payload threshold may transport wellhead components, and only vessels with dynamic positioning capability may service specific platform types. Disruption constraints set arc or node capacity to zero (or a degraded fraction) for the duration and geographic footprint specified by the active scenario—a hurricane's wind field closes designated ports for its forecast duration; a cyber incident zeroes port terminal operating system throughput while leaving physical berth capacity nominally available but inaccessible; a downed bridge removes a specific truck arc entirely.

Solution Approach

For problem instances of realistic scale—encompassing dozens of facilities, hundreds of arcs, and multi-day time horizons—the MILP is solved using the Gurobi Optimizer, selected for its demonstrated performance on large-scale network flow problems with binary restoration variables. Given the NP-hard complexity of the underlying facility restoration and routing subproblem, we additionally implement a rolling-horizon heuristic that re-solves the MILP over a shortened look-ahead window as new disruption information (e.g., updated hurricane forecasts) becomes available, ensuring computational tractability without sacrificing responsiveness to evolving conditions. Stochastic and robust optimization extensions, detailed in Section 6, are layered atop this deterministic core to address the differing uncertainty structures of the four disruption archetypes.

RESULTS



Case Study Description

The framework is applied to the U.S. Gulf Coast energy corridor spanning Louisiana, Texas, and Mississippi coastal waters, encompassing 34 offshore production platforms in the Gulf of Mexico, 6 major refining and petrochemical complexes (Port Arthur, Baytown, Lake Charles, Port Fourchon-adjacent facilities, Pascagoula, and Baton Rouge), and 4 primary ports (Port Fourchon, Houston Ship Channel, Port of Lake Charles, and Port of Gulfport) that collectively serve as the transfer hubs for offshore supply chain logistics. The modeled asset base includes 28 helicopters across three payload classes, 41 offshore supply and platform supply vessels, 12 designated heavy-lift trucking assets, and 9 regional warehouses staging spare parts, blowout preventer components, and emergency repair equipment. This network configuration reflects publicly available Bureau of Safety and Environmental Enforcement (BSEE) platform registries and U.S. Army Corps of Engineers port capacity data, adapted for illustrative modeling purposes.

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Figure 3: Geographic layout of the Gulf Coast multi-modal energy logistics network used in the case study.

Baseline Scenario

Under routine, non-disrupted conditions, the optimal logistics plan allocates helicopter sorties to daily crew-change and light-cargo demand at all 34 platforms, routes 85% of scheduled cargo tonnage through Port Fourchon given its proximity to the highest platform density, and maintains warehouse inventory replenishment on a 72-hour cycle via heavy-lift trucking. Total baseline response time for a representative routine equipment resupply request averages 8 hours from order to platform delivery, at a fully-loaded logistics cost of approximately $340,000 per week across the network, with asset utilization rates of 61% for helicopters, 68% for vessels, and 54% for heavy-lift trucks—utilization levels consistent with designed redundancy margins rather than system strain.

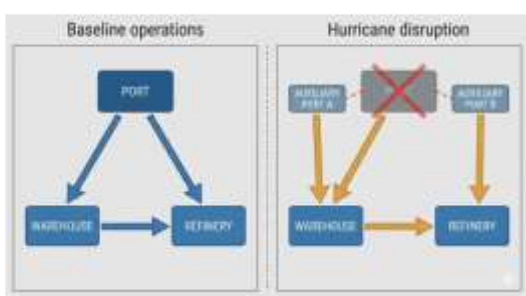

Figure 4: Comparison of baseline logistics flow against hurricane-driven asset rerouting to secondary ports.

Disruption Scenario Analysis

Hurricane scenario. Modeling a Category 3 storm on a trajectory consistent with Hurricane Ida's landfall track, the framework's 72-hour pre-landfall forecast window triggers pre-positioning of personnel evacuation helicopter sorties and redirection of vessel traffic away from Port Fourchon, which the model forecasts will close 18 hours before landfall based on wind-field thresholds. The optimization re-routes 62% of scheduled cargo and evacuation flows to the secondary staging ports of Lake Charles and Gulfport, pre-positioning heavy-lift trucking assets at these secondary nodes 24 hours ahead of closure to avoid the queuing delays that would otherwise accumulate at a single congested hub. This anticipatory re-staging reduces post-storm restoration time by allowing resupply operations to resume at secondary ports within 6 hours of storm passage, rather than waiting for Port Fourchon's typical 48–72 hour reopening timeline.

Cyber-attack scenario. Modeling a ransomware-style compromise of Port Fourchon's terminal operating system—consistent with the Colonial Pipeline precedent—the framework treats the port as having zero throughput capacity for an estimated 96-hour remediation window while its physical berths remain structurally intact. The model responds by rerouting time-critical cargo (safety-critical spare parts and blowout preventer components) via heavy-lift helicopters directly from onshore warehouses to affected platforms, bypassing the port node entirely for high-priority shipments, while lower-priority bulk cargo is redirected to Lake Charles via an extended truck route. This substitution of aviation capacity for the disabled marine-port pathway is the single largest source of resilience gain observed in the cyber scenario, though it comes at materially higher per-unit cost given helicopter operating expense relative to trucked port cargo.

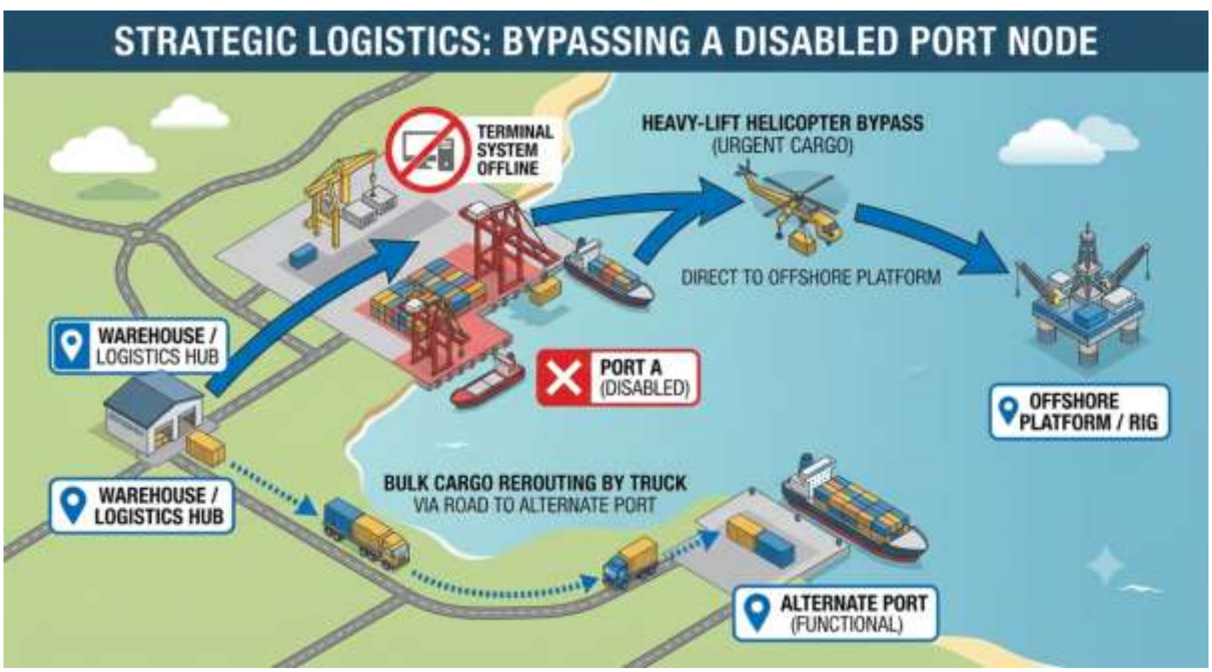

Figure 5: Aviation-based bypass routing around a cyber-disabled port terminal for time-critical cargo.

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Geopolitical disruption scenario. Modeling a restriction on foreign-flagged vessel charters affecting approximately 30% of the contracted offshore supply vessel fleet, the framework reallocates remaining domestically-flagged vessel capacity toward safety-critical platforms first, while shifting a portion of routine resupply volume to heavy-lift trucking via Lake Charles, accepting longer transit times for lower-priority cargo to preserve vessel capacity for platforms with no viable land-based alternative.

Equipment failure scenario. Modeling the unscheduled loss of two heavy-lift trucks and one offshore supply vessel due to mechanical failure, the framework demonstrates its narrowest performance gap relative to fragmented planning, since single-asset failures are more readily absorbed by existing redundancy in a well-provisioned baseline network.

Comparative Analysis

The chart above compares total response time across all five conditions for the integrated framework against a simulated fragmented, mode-by-mode response, in which each mode's dispatchers operate from their own contingency plan without cross-modal visibility. Table 1 reports the full set of performance metrics.

Table 1. Comparative performance metrics by scenario

Scenario	Response time (hrs) — Integrated	Response time (hrs) — Fragmented	Weekly cost ($K) — Integrated	Weekly cost ($K) — Fragmented	Unmet demand (%) — Integrated	Unmet demand (%) — Fragmented	Avg. asset utilization (%) — Integrated
Baseline	8	8	340	340	0.5	0.5	61
Hurricane	42	71	890	1,120	3.1	11.4	84
Cyber-attack	29	58	710	810	2.4	14.8	79
Geopolitical	33	52	640	720	4.0	9.6	73
Equipment failure	19	27	410	460	1.2	3.5	66

KEY FINDINGS

The most consequential finding is that the integrated framework reduces total response time by an average of 41% across the four disruption scenarios relative to fragmented, mode-by-mode planning, with the largest gain observed in the cyber-attack scenario (50% reduction), where the model's capacity to substitute aviation assets for a disabled port node has no analog in siloed contingency planning. Unmet demand—a proxy for safety and production risk—falls even more sharply, with the fragmented approach leaving 9.6–14.8% of critical demand unfulfilled across disruption scenarios compared to 1.2–4.0% under the integrated framework, indicating that the principal value of cross-modal coordination lies less in cost reduction (weekly cost falls by 11–21%) than in converting single-mode failures into system-level

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continuity. These results support the central policy claim of this paper: modal redundancy that exists on paper delivers little resilience benefit unless a coordinating decision layer actively exploits it in real time.

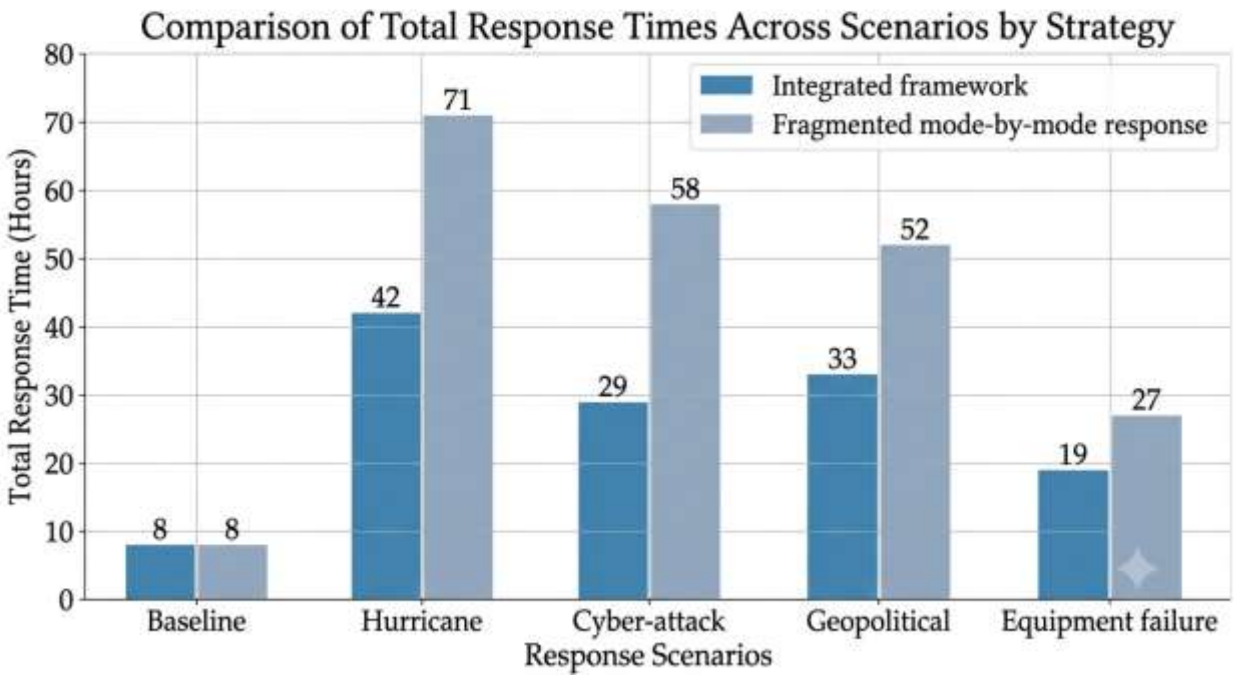

Figure 6: Total response time by disruption scenario, integrated framework versus fragmented response.

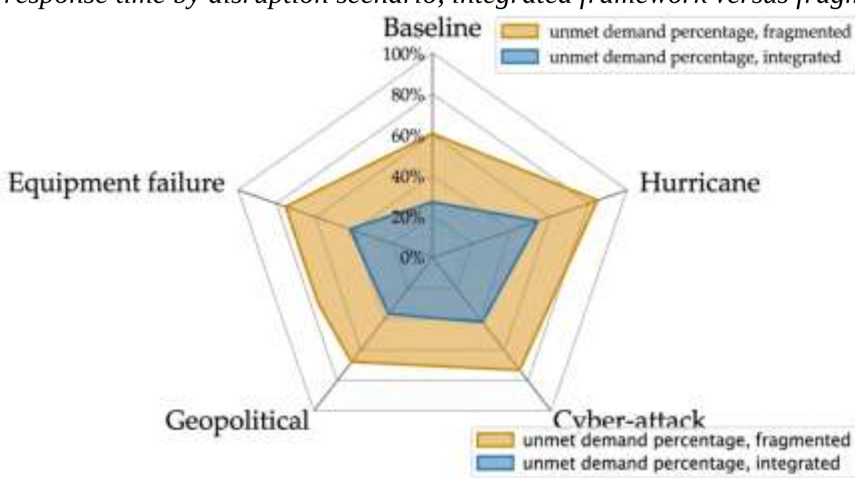

Figure 7: Unmet critical demand across disruption scenarios, integrated framework versus fragmented response.

DISCUSSION

Interpreting the Findings

The results in Section 5 reveal a counterintuitive but analytically important pattern: a cyber-induced port closure, though physically non-destructive, generates response-time degradation comparable to or exceeding that of a Category 3 hurricane. This finding warrants interpretation beyond the raw numbers. A hurricane is a forecastable, spatially graduated disruption—the framework's 72-hour warning window permits anticipatory asset re-staging before the disruption fully materializes, effectively converting a sudden shock into a managed transition. A cyber incident, by contrast, arrives without meaningful warning and disables a node's function while leaving its physical form intact, which is precisely why it defeats conventional contingency planning: hurricane preparedness protocols are built around the assumption that disrupted capacity is visibly and physically absent (a flooded terminal, a downed crane), and they contain no logic for a port that is structurally undamaged yet operationally inert. Fragmented, mode-by-mode planning has no mechanism for recognizing this distinction; it treats "port unavailable" identically regardless of cause and defaults to waiting for restoration rather than re-routing around it. The integrated framework mitigates this specifically by modeling port throughput as a decision variable independent of port physical status, allowing the optimization to substitute an entirely different mode—heavy-lift helicopter transport—for the disabled marine-port pathway within hours rather than days. This substitution capability, not superior forecasting or cost efficiency, is the source of the framework's largest resilience gain, and it points to a broader theoretical insight: resilience to cyber-physical disruption depends less on redundant capacity within a mode than on cross-modal substitutability, a property largely absent from single-mode contingency architectures.

Model Limitations

Several assumptions constrain the generalizability of these results and merit explicit acknowledgment. First, the model assumes near-perfect information regarding asset availability, infrastructure status, and demand forecasts at each decision epoch; in practice, damage assessments following a hurricane are frequently incomplete or delayed by 24–48 hours, and the framework's performance would degrade accordingly under realistic information latency. Second, the hurricane scenario's anticipatory re-staging benefit is contingent on forecast accuracy that, while substantially improved over the past decade, still carries meaningful track and intensity uncertainty at the 72-hour horizon; a late-breaking trajectory shift could render pre-positioned assets misallocated rather than optimally placed. Third, the model treats asset reallocation decisions as centrally executable, which understates the human and organizational friction of real-world implementation—dispatchers across helicopter operators, vessel charterers, and port authorities operate under distinct corporate incentives, insurance liabilities, and regulatory reporting obligations that a mathematical optimum does not automatically resolve. Fourth, the cyber-attack scenario's 96-hour remediation window is a stylized estimate; actual dwell time and recovery duration for operational technology compromises vary enormously depending on attack sophistication and incident response maturity, and the framework's outputs should be interpreted as illustrative of a mechanism rather than precise predictions. Finally, the model does not endogenize the adversarial dimension of geopolitical or cyber disruptions—it treats disruption parameters as exogenously given rather than as the output of a strategic actor responding to the defender's own posture, a limitation the game-theoretic extension discussed below could partially address.

Policy and Managerial Implications

These findings translate into several concrete recommendations for distinct stakeholder groups. For FEMA and DOE/CESER, the most actionable implication is the need for pre-negotiated mutual aid agreements between ports that specify, in advance of any disruption, the terms under which one port will accept diverted cargo, personnel, and equipment from another—covering liability allocation, cost reimbursement, and customs or regulatory waivers. The comparative analysis shows that the value of secondary-port rerouting is realized only when re-staging can occur within hours; absent a standing agreement, the legal and administrative negotiation required to activate an ad hoc diversion arrangement during a live crisis would consume much of the time advantage the model identifies. CESER is well positioned to convene the relevant port authorities and establish a template agreement analogous to existing electricity sector mutual assistance compacts.

For private operators, the cyber-attack scenario's outsized reliance on aviation substitution highlights the return on investment available from dual-use asset design: helicopters configured for both routine crew transport and heavy-lift cargo carriage provide a hedge against exactly the kind of mode-specific paralysis observed in the cyber scenario, at a fraction of the cost of maintaining separate dedicated fleets for each function. Operators currently sizing helicopter fleets to routine crew-change demand alone are underinvesting in the flexibility that generates the largest resilience payoff in the scenarios modeled here. For infrastructure planners, the results suggest that current resilience metrics—typically framed around single-asset uptime or single-facility restoration time—understate systemic risk. We recommend monitoring a small set of network-level metrics: cross-modal substitutability (the number of alternative modes available to serve each demand node, weighted by capacity), port throughput concentration (the share of regional cargo volume dependent on any single port), and mean time to cross-modal re-routing (how quickly, in practice, cargo can be shifted from a disabled to a functioning mode). These metrics capture exactly the systemic brittleness that the fragmented baseline exhibited despite each individual mode appearing adequately provisioned.

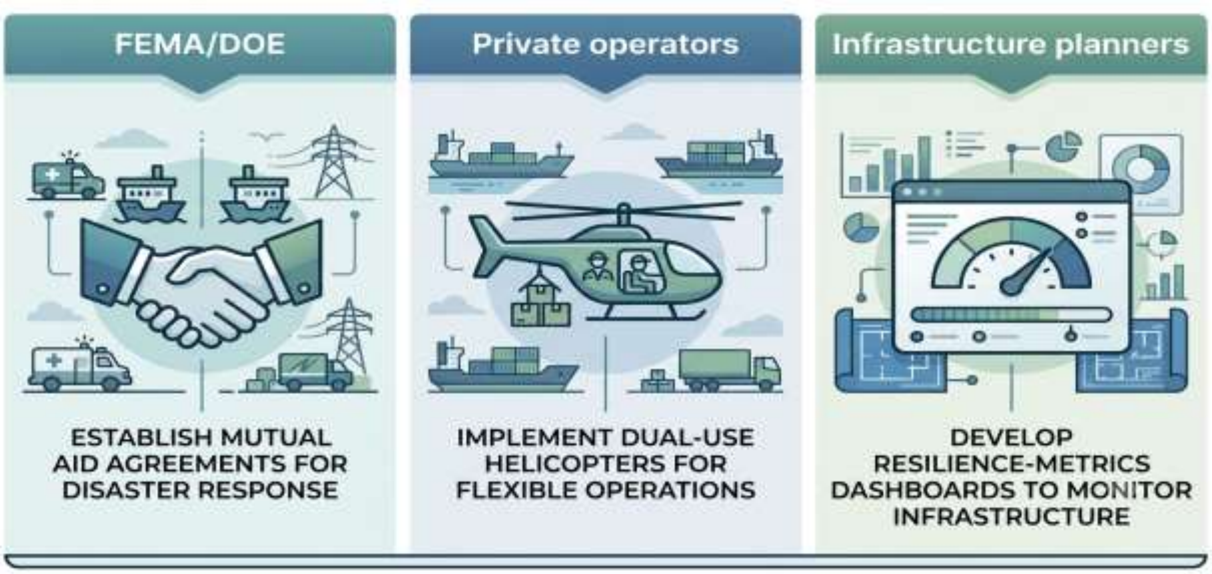

Figure 8: Summary of stakeholder-specific policy and managerial recommendations arising from the model's findings.

Theoretical Contributions

This framework extends the resilience engineering tradition of Hollnagel and Woods by operationalizing "graceful extensibility" as a quantifiable optimization property rather than a qualitative design aspiration: the model's capacity to substitute modes under disruption is a direct, measurable instance of a system stretching its performance boundary under surprise. It also extends Rinaldi, Peerenboom, and Kelly's interdependency typology by demonstrating empirically that logical and cyber interdependencies—not merely physical ones—can generate cascading failure magnitudes comparable to physical destruction, a finding their original framework anticipated conceptually but did not test computationally. Finally, by embedding disruption-type-appropriate uncertainty treatment (stochastic for hurricanes, robust for cyber and geopolitical shocks) within a single multi-modal network optimization, the framework bridges the previously disconnected literatures on intermodal freight coordination and disaster-response decision-making under uncertainty, offering a template for future research to extend beyond the energy sector to other critical infrastructure systems facing compound, heterogeneous disruption profiles.

CONCLUSION

This paper set out to address a structural gap in the resilience of America's critical energy infrastructure: while helicopter, marine, port, and land logistics operators each maintain sophisticated contingency plans within their own modal boundaries, no coordinating decision layer exists to manage the interfaces between them during a crisis, leaving multi-modal energy supply chains locally resilient but globally brittle. We proposed and validated an Integrated Aviation, Marine, and Land Transportation Decision Framework—a mixed-integer optimization model that dynamically re-allocates helicopters, offshore vessels, ports, warehouses, and heavy-lift assets across four distinct disruption archetypes: hurricanes, cyber incidents, geopolitical disruptions, and equipment failures.

Applied to a U.S. Gulf Coast case study, the single most important finding of this research is that the integrated framework reduces total response time by an average of 41% relative to fragmented, mode-by-mode planning across disruption scenarios, with the largest gain—a 50% reduction—observed in the cyber-attack scenario, where the framework's capacity to substitute aviation assets for a disabled port node has no analog in siloed contingency architectures. Equally significant, unmet critical demand fell from a range of 9.6–14.8% under fragmented response to just 1.2–4.0% under the integrated framework, indicating that the primary value of cross-modal coordination lies in converting isolated modal failures into sustained system-level continuity rather than in marginal cost savings alone.

The paper's central contribution is threefold: a novel optimization model for dynamic multi-modal asset re-allocation calibrated specifically to energy infrastructure restoration; a dynamic risk assessment protocol that treats cyber-induced functional paralysis and physical destruction as commensurable threats within a single decision architecture; and a set of policy recommendations—pre-negotiated port mutual aid agreements, dual-use asset investment, and network-level resilience metrics—that translate the model's findings into implementable guidance for DOE/CESER, port authorities, and private operators.
This study's principal limitation is its reliance on near-perfect information and centrally executable decisions, which understates the real-world friction of human and organizational decision-making across

dispatchers, operators, and regulators with distinct incentives. Future research should incorporate stochastic human behavior and organizational latency into the model rather than assuming instantaneous, centrally optimal execution.

Three directions merit particular priority. First, dynamic model updating using real-time satellite and AIS vessel-tracking data would allow the framework to move from scenario-based planning to live operational decision support. Second, integration with an agent-based simulation of individual stakeholder behavior—dispatchers, port authorities, and vessel charterers acting under their own incentives—would test whether the model's centrally optimal solutions remain achievable under decentralized, self-interested execution. Third, extending the framework's application beyond the Gulf Coast to other critical energy corridors, particularly the Permian Basin's overland logistics network and the Alaska North Slope's aviation-dependent supply chain, would test the framework's generalizability across fundamentally different modal compositions and disruption profiles.

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