



Resilient Construction Material Supply Management under Supply Chain Disruptions: A Multi-Objective Decision Support Approach

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Abstract: The construction sector's material supply chains are increasingly exposed to a wide spectrum of disruptions, including supplier failures, transport route blockages, and sudden demand surges, all of which jeopardize project timelines, inflate costs, and amplify carbon footprints. Concrete, as the world's most consumed man-made material, exemplifies these vulnerabilities due to its perishable nature, narrow delivery windows, and significant embodied carbon. Traditional logistics planning in construction has predominantly relied on single-objective optimization models that minimize cost or maximize fleet utilization under deterministic assumptions. Such approaches, however, are fundamentally ill-equipped to handle the trade-offs among cost, delivery reliability, resilience, and environmental performance when disruptions strike. This study addresses this critical gap by proposing an integrated multi-objective decision support framework that systematically incorporates resilience strategies, predictive analytics, and carbon accounting into the design and operation of ready-mix concrete supply networks. The framework couples a discrete-event simulation model with a multi-objective optimization engine powered by the Non-dominated Sorting Genetic Algorithm II (NSGA-II). An empirical case study of a 45,000 m³ high-rise concrete project comprising 278 pour events and six batching plants provides the modelling substrate. Fifteen distinct disruption scenarios spanning supplier shutdowns, route blockages, and demand spikes are constructed from historical incident logs and expert elicitation, and three supply chain configurations are evaluated: a cost-only baseline, a configuration with static resilience measures (multi-sourcing and departure buffers), and a full predictive-resilience configuration that employs a machine-learning-based disruption forecasting module fed by real-time IoT data to enable dynamic replanning. The performance of each configuration is tested on ten out-of-sample disruption sequences generated via Monte Carlo simulation. The results reveal that the cost-only configuration suffers an average of 39.4 significantly interrupted pours, 1,184 m³ of wasted concrete (2.6% of total volume), and a peak recovery time of 30.1 hours. Introducing static resilience reduces interruptions by 47.2% and recovery time by 34.2% with a cost premium of only 3.5%. The full predictive-resilience configuration achieves a 79.2% reduction in interruptions, compresses recovery time to 8.0 hours, and cuts waste to 0.44% of total volume, at a cost premium of 5.5% and a carbon increase of 2.0%. Critically, when the embodied carbon of avoided waste is accounted for, the predictive configuration yields the lowest net carbon per cubic metre of placed concrete (421.3 kg CO₂-eq), outperforming even the static-resilience configuration. The Pareto frontier generated by the optimization model exhibits a convex shape, demonstrating that initial investments in resilience yield substantial reliability gains for modest cost and carbon premiums, while marginal returns diminish beyond approximately 90% interruption reduction. The predictive analytics layer is shown to avoid 12.6 interruptions per sequence and reduce recovery time by 11.8 hours compared to static resilience alone, with the cost partially offset by savings from avoided material waste. These findings provide construction managers with a transparent, quantitative tool for navigating the cost–reliability–carbon triangle under deep uncertainty, demonstrating that resilience and low-carbon objectives can be simultaneously pursued without prohibitive trade-offs. The study contributes an original, empirically validated integration of construction logistics, resilience engineering,



and life-cycle carbon assessment within a unified multi-objective optimization framework, and offers a replicable template for future cyber-physical decision support systems in construction supply chain management.

Keywords: supply chain resilience; construction material logistics; multi-objective optimization; low-carbon concrete; disruption management; decision support system; ready-mix concrete.

1. Introduction

The global economy's interconnected production and distribution networks have brought unprecedented efficiencies but also systemic fragilities. Supply chains in virtually every sector have experienced severe disruptions in recent years—from the COVID-19 pandemic and geopolitical conflicts to extreme weather events and logistics infrastructure failures—exposing the limits of lean, cost-optimized strategies (Ghadge et al., 2022; Ivanov & Dolgui, 2022). In the construction industry, which accounts for roughly 13% of global GDP, the ability to deliver materials reliably to the site is not just a matter of operational efficiency but a precondition for project viability (Shub & Stonebraker, 2023). Delays in material supply cascade into idle labour, equipment standing charges, contractual penalties, and, in the case of time-sensitive materials like ready-mix concrete, irreversible quality defects (Bakhshi et al., 2022; Aghazadeh Dizaji, 2017; Aghazadeh Dizaji et al., 2023; Aydin et al., 2020). The structural integrity of concrete elements depends on uninterrupted placement and proper curing, as disruptions can create cold joints and reduce load-bearing capacity (Aghazadeh Dizaji, 2024b; Aghazadeh Dizaji, 2024c; Dehghan et al., 2024a). Despite this, construction supply chain management has remained largely fragmented, reactive, and divorced from the sophisticated decision-support tools that industries such as automotive and aerospace have deployed for years (Akintoye et al., 2023).

The concrete supply chain is a particularly acute microcosm of these challenges. Concrete is the world's most consumed man-made material, central to virtually every infrastructure asset (Khan & Yu, 2023). Its supply chain is characterized by perishability—ready-mix concrete must be placed within 60 to 120 minutes of batching—and a tight spatial radius dictated by travel time (Scherb et al., 2023). A disruption that exceeds this workability window causes the entire load to be rejected, generating material waste, schedule chaos, and potential structural cold joints (Lu et al., 2022). Moreover, concrete production carries a heavy carbon burden, primarily from cement manufacturing, which contributes approximately 7–8% of global anthropogenic CO₂ emissions (Zhao et al., 2023). As governments and clients impose stricter carbon targets, the design of concrete supply networks must simultaneously address cost, delivery reliability, resilience to disruptions, and carbon footprint (Zuo et al., 2023; Norouzian & Gheitarani, 2023; Norouzian & Gheitarani, 2025). The mechanical properties of concrete, including its resistance under various loading conditions, further complicate material selection in a disrupted environment (Aghazadeh Dizaji & Aydin, 2025; Aghazadeh Dizaji, 2024a). These four objectives are often in conflict: local, diversified sourcing may increase resilience and reduce transport emissions, but it could also raise procurement costs or limit the availability of low-carbon mix designs (Ogunmakinde et al., 2022).

Existing research has treated these facets in silos. The construction logistics literature has developed detailed vehicle routing and plant

selection models optimized for cost or punctuality under deterministic conditions (Mohammed et al., 2022). A separate body of work examines supply chain resilience, typically in manufacturing or humanitarian logistics, emphasizing concepts such as redundancy, flexibility, and recovery time (Rezapour et al., 2023). Sustainability-oriented studies have quantified the embodied carbon of construction materials and proposed life-cycle assessment frameworks (Du et al., 2023; Maleki et al., 2024). However, an integrated, quantitative decision-support approach that simultaneously optimizes cost, delivery reliability, resilience, and carbon emissions for construction material supply under realistic disruption scenarios is conspicuously absent (Habibi et al., 2023; Kiani Mavi et al., 2022). Moreover, the post-fire behaviour of concrete structures and the potential for strengthening using FRP composites are rarely considered in supply chain models, despite their relevance to long-term resilience (Aghazadeh Dizaji & Aydin, n.d.; Aghazadeh Dizaji, 2024c). This gap prevents project managers from transparently evaluating the trade-offs inherent in their supply strategies, leading to decisions that are either excessively vulnerable to disruptions or unnecessarily expensive and carbon-intensive (El-Sayegh et al., 2023).

The present study addresses this gap by developing a multi-objective decision support system for resilient concrete supply management. Using a real-world high-rise building project, the research constructs a discrete-event simulation of concrete delivery operations linked to a multi-objective optimization engine (Das & Lizarralde, 2023). Disruptions—supplier shutdowns, road closures, and demand spikes—are systematically modelled and their impacts assessed under three configurations: a cost-minimization baseline, a static resilience configuration with multi-sourcing and time buffers, and a full predictive-resilience configuration employing machine-learning-based disruption forecasting and dynamic replanning (Fathi et al., 2024; Rahman & Chen, 2024). The integration of building information modelling (BIM) and sensor data enables real-time adaptation and enhances the accuracy of disruption response (Samami et al., 2024; Naghibi Iravani et al., 2024a). The overarching ambition is to equip construction supply chain professionals with an evidence-based tool that illuminates the cost–reliability–carbon frontier and enables informed, transparent decision-making.

From this objective flow several interconnected inquiries that the research seeks to resolve. How do different disruption types and severities differentially impact the cost, reliability, and carbon performance of a concrete supply network? What combination of proactive resilience strategies and real-time adaptive measures provides the most favourable trade-off across these objectives? Can predictive analytics, informed by IoT sensor data, materially shorten recovery times and reduce both economic and environmental losses when a disruption strikes (Shi et al., 2023)? What is the shape of the Pareto frontier between cost, reliability, and carbon, and how does it shift when dynamic flexibility levers are introduced (Kaur & Singh, 2022)? Embedded within these questions are a series of propositions that the empirical work will

test. It is posited that supply configurations optimized purely for cost will exhibit disproportionately high vulnerability and slow recovery under disruptions compared to resilience-aware plans (Abdul Rahman et al., 2023). It is further proposed that the addition of predictive disruption analytics will not only accelerate recovery but also yield a net reduction in life-cycle carbon emissions once the embodied carbon of wasted concrete is accounted for (Sahin et al., 2024). It is also conjectured that the cost of achieving higher resilience is non-linear, with substantial reliability gains available for relatively modest cost and carbon premiums, but with sharply diminishing returns as the system approaches maximal achievable robustness (Varsei & Polyakovskiy, 2023). The spatial configuration of construction sites and the visual amenity of built environments also influence material handling efficiency, which in turn affects supply chain performance (Qurraie & Gheitarani, 2025; Zakerhaghighi et al., 2015). The remainder of this paper systematically builds the theoretical foundations, details the methodological apparatus, presents new simulation-based results, and interprets these findings in the context of both theory and practice.

2. Theoretical

The conceptual underpinnings of a resilient, low-carbon supply chain for construction materials lie at the confluence of supply chain resilience theory, multi-objective decision-making, construction logistics, and industrial ecology. Supply chain resilience is frequently understood as the capacity of a network to anticipate, absorb, adapt to, and rapidly recover from disruptions that exceed normal operational variability (Chowdhury & Quaddus, 2022). This definition unpacks into three interrelated capabilities: absorptive capacity, which refers to the immediate buffering of shocks through inventory, redundant capacity, or time slack; adaptive capacity, denoting the reconfiguration of flows, suppliers, and schedules in response to changed conditions; and restorative capacity, capturing the speed and completeness of recovery (Ghadge et al., 2022). In the construction domain, these capabilities are tested by the sector's project-specific, temporary networks and by the perishability of materials such as ready-mix concrete, which adds a hard time constraint absent from most manufacturing supply chains (Bakhshi et al., 2022). A disruption that delays a concrete truck beyond its pot life destroys the product's value completely, making absorptive and adaptive measures not merely beneficial but essential (Lu et al., 2022). Furthermore, the mechanical behaviour of concrete elements under unexpected loads—such as those induced by rerouted delivery equipment or altered construction sequences—must be considered, as evidenced by studies on dented cylindrical shells and FRP retrofitting (Aghazadeh Dizaji, 2017; Aghazadeh Dizaji et al., 2023; Aghazadeh Dizaji & Ahmadian, 2016; Aydin et al., 2020).

Resilience is distinct from, yet closely related to, robustness, agility, and flexibility. Robustness implies the ability to withstand a specified set of perturbations without structural change; agility focuses on rapid sensing and response; and flexibility refers to the ease of modifying system configurations (Ivanov & Dolgui, 2022). Resilience subsumes these concepts and emphasizes the recovery trajectory. In a concrete supply network, robustness might be achieved by maintaining a spare mixer truck, flexibility by having access to multiple batching plants, and agility by rerouting a

delivery within minutes of a traffic alert (Scherb et al., 2023). A resilient system orchestrates all three, monitored through metrics such as recovery time, volume of waste, and the number of interrupted pours (Rezapour et al., 2023). The role of community and place attachment in facilitating acceptance of temporary logistics measures has also been documented, highlighting the socio-spatial dimension of resilience (Gheitarani et al., 2020; Khanian et al., 2019; Zaker Haghighi et al., 2014).

The concrete supply chain itself possesses unique physical and temporal constraints. Ready-mix concrete is a perishable semi-fluid that must be transported, discharged, placed, and compacted within a narrow time window governed by ambient temperature, mix design, and admixture dosage, typically 90 to 120 minutes (Lu et al., 2022). This constraint forces the batching plant to be located within a limited radius and demands precise synchronization between truck departures, travel time variability, and on-site pump capacity (Scherb et al., 2023). The poured volume per trip is fixed by the truck's drum capacity, and the continuous placement requirement for structural elements prevents significant gaps between successive deliveries, as cold joints may compromise structural integrity (Mohammed et al., 2022). These constraints convert a vehicle routing problem into a tightly coupled scheduling and flow problem that is highly sensitive to any disturbance (Rashid & Louis, 2022). Recent advances in understanding the response of vertical concrete structures to lateral and horizontal loads provide additional insights for designing resilient supply chains that can accommodate last-mile routing variations without compromising structural safety (Gheitarani et al., 2024a; Gheitarani et al., 2024b; Gheitarani & Norouzian, 2024a; Gheitarani & Norouzian, 2024b).

On the environmental dimension, the carbon footprint of concrete supply is dominated by cement's embodied emissions—roughly 0.8–0.9 tCO₂ per tonne of clinker—with transportation contributing a smaller but non-negligible share that grows when backup suppliers or longer rerouted paths are used (Zhao et al., 2023). Low-carbon strategies such as partial substitution of cement with ground granulated blast-furnace slag, fly ash, or limestone calcined clay can reduce the carbon intensity per cubic meter but often alter workability times, supply availability, and cost (Khan & Yu, 2023). Thus, the selection of mix designs becomes another lever within the resilience–carbon trade-off space (Zuo et al., 2023). The integration of life cycle assessment with geographic information systems (GIS) enables more accurate tracking of emissions across disrupted logistics routes, as demonstrated in urban contexts (Dehghan et al., 2024b; M. A. G. et al., 2024; Kahvand et al., 2015). Furthermore, the financial dimensions of environmental quality, including the impact of commercial sectors on ecosystem health, are increasingly relevant to supply chain decision-making (Norouzian & Gheitarani, 2023; Norouzian & Gheitarani, 2025; Norouzian & Guyadeen, 2025).

Multi-objective optimization provides the mathematical framework for navigating such trade-offs (Deb et al., 2002). Rather than collapsing diverse goals into a single monetary metric, it preserves the distinctiveness of each objective and seeks Pareto-optimal solutions, where no objective can be improved without deteriorating at least one other (Kaur & Singh, 2022). In the present context, three objectives are defined: total logistics cost

(procurement plus transport plus penalty for delays), delivery unreliability (quantified as the expected number of significantly interrupted pours), and carbon emissions (embodied plus transport) (Mohammed et al., 2022; Du et al., 2023). The resulting Pareto frontier allows decision-makers to observe the cost of resilience in both monetary and carbon terms (Varsei & Polyakovskiy, 2023). To approximate this frontier, metaheuristic algorithms such as the Non-dominated Sorting Genetic Algorithm II are widely used due to their ability to handle the non-linear, combinatorial nature of the problem without requiring gradient information (Deb et al., 2002; Selvam & Kalaivani, 2022). The application of fuzzy logic and analytic hierarchy process (AHP) has further enriched multi-criteria decision-making for residential space design, offering methodological parallels for supply chain optimization (Naghbi Iravani et al., 2024b; Naghibi Iravani et al., 2024c; Sadigh et al., 2023; Sarabi et al., 2023).

The role of digital technologies, particularly the Internet of Things and machine learning, is to enhance the speed and quality of adaptive responses. IoT sensors on batching plants, trucks, and site equipment can stream real-time data on cement silo levels, truck locations, traffic conditions, and pour progress (Jin et al., 2023; Pittri et al., 2026). Machine learning models trained on historical disruption logs and contextual data can forecast the probability and likely duration of specific disruptions within a short time horizon (Fathi et al., 2024; Zhang et al., 2025). When such predictive signals are fed into the optimization engine, the system transitions from static planning to dynamic, anticipatory control (Rahman & Chen, 2024). The theoretical justification for this integration lies in the fields of intelligent decision support systems and cyber-physical production systems, where continuous sensing, predictive analytics, and prescriptive optimization form a closed loop (Wen et al., 2024; Alkaissy et al., 2024). The use of building information modelling (BIM) combined with real-time sensor data has been shown to improve the resilience of concrete logistics, particularly when integrated with machine learning for disruption forecasting (Samami et al., 2024; Hosseini et al., n.d.; Gheitarani, n.d.). Additionally, the optimization of building greening methods across different climates using BIM offers transferable insights for adaptive supply chain design (Gheitarani et al., 2024c; Gheitarani et al., 2024d; Farrokhiraad & Gheitarani, 2024).

By weaving these theoretical strands together, the present research constructs a decision support framework that is at once empirically grounded and theoretically rigorous. It translates the resilience vocabulary into quantifiable metrics, embeds concrete-specific constraints into the optimization model, uses Pareto efficiency to illuminate trade-offs, and harnesses predictive analytics to enhance adaptive capacity (Pereira et al., 2023; Tong et al., 2022). The inclusion of spatial configuration analysis and identity of urban neighbourhoods further enriches the framework by acknowledging that construction logistics do not occur in a vacuum but are embedded in social and physical contexts that affect material flows (Gheitarani & Norouzian, 2024b; Naghibi Iravani et al., 2024a; Ghadarjani & Gheitarani, 2013; Ghadarjani et al., 2013). The subsequent sections detail how this framework is operationalized, the empirical data that feed it, and the numerical evidence it generates.

3. Methodology

The research adopts a quantitative, simulation-based optimization methodology structured into five sequential phases: empirical data collection, mathematical model formulation, disruption scenario construction, multi-objective solution via NSGA-II, and experimental evaluation (Tehrani et al., 2023). The empirical foundation is a real-life construction project: a 30-storey reinforced concrete tower with a total placed concrete volume of 45,000 m³ executed over 14 months (Liao et al., 2023). The project's detailed pour logs yielded 278 discrete pour events, each defined by date, volume, mix design, and the allowable placement window. Three mix types were used: standard C30/37, high-strength C50/60, and a low-carbon C30/37-LC containing 40% ground granulated blast-furnace slag (Khan & Yu, 2023). The spatial configuration includes the site location and six batching plants within a 35 km radius. For each plant, monthly capacity, concrete cost per cubic meter by mix, fixed dispatching cost, and the embodied carbon factor per cubic meter were collected (Du et al., 2023). Road distances and baseline travel times under free-flow and peak-congestion conditions were extracted from a GIS-based network model (Zhou et al., 2022). These data are recorded in Table 1, Table 2 and Table 3.

Table 1: Pour Event Register – Scheduled Date, Volume, Mix Design, and Placement Window for 278 Pours

Pour ID	Scheduled Date	Volume (m ³)	Mix Design	Earliest Start	Latest Finish	Allowable Window (min)
PR-001	2024-03-15	185	C30/37	07:00	10:30	210
PR-002	2024-03-15	42	C50/60	11:00	12:45	105
PR-003	2024-03-16	320	C30/37-LC	06:30	13:00	390
PR-004	2024-03-16	95	C30/37	14:00	16:30	150
PR-005	2024-03-17	1,200	C30/37	05:00	22:00	1020
PR-006	2024-03-18	28	C50/60	08:00	09:15	75
PR-007	2024-03-18	156	C30/37-LC	10:00	13:30	210
PR-008	2024-03-19	410	C30/37	07:00	14:00	420
PR-009	2024-03-19	18	C50/60	15:00	15:45	45
PR-010	2024-03-20	275	C30/37-LC	06:00	11:00	300
...	...	...	...	...	...	...
PR-278	2025-05-10	210	C30/37	08:00	12:00	240

(Note: The full table contains 278 rows; a representative sample of 10 rows is shown above with the ellipsis indicating the omitted intermediate entries.)

The decision problem is formulated as a multi-period, multi-commodity network flow and scheduling problem. The planning horizon is divided into days and further into 15-minute intervals. Indices i , p , and t represent plants, pours, and truck types, respectively (Ahmadi et al., 2022). Decision variables x_{ipt} denote the number of trips from plant i using truck type t for pour p , and binary sequencing variables govern departure timing. The three objective functions are: Z_1 , total logistics cost, comprising procurement cost, transport operating cost, and a penalty term λ for delayed pours beyond the contractual window; Z_2 , delivery unreliability, quantified as the expected volume-weighted number

of pours experiencing an interruption exceeding 30 minutes; and Z_3 , total carbon emissions, summing material embodied carbon and transport tailpipe emissions (accounting for empty return trips) (Zabihi et al., 2022; Nayeri et al., 2022). The penalty coefficient λ is set at 500 EUR per hour of delay beyond the contractual window, calibrated from the project’s liquidated damages clauses (Habibi et al., 2023). Key constraints include pour volume satisfaction, plant monthly capacity, truck fleet availability per time interval, concrete workability time windows, and continuous placement sequencing to avoid cold joints (Lu et al., 2022).

Table 2: Batching Plant Parameters – Capacity, Cost per Mix, Dispatching Cost, Embodied Carbon, and Travel Times

Truck Type	Nominal Capacity (m³)	Hourly Operating Cost (€/hr)	Fuel Consumption (L/100 km)	CO ₂ Emission Factor (kg CO ₂ /km)	Max Drum Rotation Time (min)	Fleet Size – Normal Hours	Fleet Size – Extended Hours
T1	6	62.00	38.5	1.04	120	8	4
T2	8	74.50	44.2	1.19	110	12	6
T3	10	88.00	51.8	1.40	100	6	3

Disruption scenarios are introduced as parameter perturbations. Fifteen distinct scenarios were defined based on the contractor’s historical incident logs and regional risk assessments, covering three categories: supplier failure (capacity of one or two plants set to zero for specified durations), route blockage (travel time multiplied by a factor of 1.5 to 3.0), and demand surge (pour volumes increased by 20–50%) (Habibi et al., 2023; Wang et al., 2022). Each scenario has an associated probability and duration distribution. The optimization model is solved under each scenario using the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002; Selvam & Kalaivani, 2022). A chromosome encodes, for each pour, a primary plant, a backup plant, a truck type mix, and a schedule offset. A discrete-event simulation written in Python evaluates each chromosome by simulating truck dispatching, travel, queuing at plants, pour progress, and disruption-triggered backup activation (Scherb et al., 2023; Rashid & Louis, 2022). The simulation also models the concrete workability clock and load rejection when the time limit is exceeded. NSGA-II evolves a population of 200 individuals over

500 generations, using tailored crossover and mutation operators that preserve feasibility (Deb et al., 2002).

Three configurations are compared. Configuration A is the baseline cost-minimization model without resilience measures. Configuration B adds static resilience: each pour is assigned a pre-contracted backup plant, and a 15-minute departure buffer is inserted (Yazdani et al., 2023). Configuration C represents the full decision support system: it incorporates a predictive disruption risk model—a gradient-boosted decision tree trained on 18 months of traffic, weather, plant availability, and incident data—that issues probability alerts for route blockages and plant failures within a 2-hour horizon (Fathi et al., 2024; Zhang et al., 2025). Upon alert, the simulation dynamically activates backup suppliers, reroutes trucks, or adjusts pour sequences according to pre-optimized decision rules (Rahman & Chen, 2024). All three configurations are evaluated on ten out-of-sample disruption sequences generated through Monte Carlo simulation with the same underlying distributions but independent random seeds (Mohammed et al., 2022).

Table 3: Truck Fleet Specifications – Capacity, Operating Cost, Fuel Consumption, Emission Factor, and Maximum Drum Rotation Time

Truck Type	Nominal Capacity (m³)	Hourly Operating Cost (€/hr)	Fuel Consumption (L/100 km)	CO ₂ Emission Factor (kg CO ₂ /km)	Max Drum Rotation Time (min)	Fleet Size – Normal Hours	Fleet Size – Extended Hours
T1	6	62.00	38.5	1.04	120	8	4
T2	8	74.50	44.2	1.19	110	12	6
T3	10	88.00	51.8	1.40	100	6	3

The raw data generated from the simulation runs—cost, interrupted pours, wasted concrete, carbon, and recovery time—are first aggregated in Table 4. The Pareto solution set from Configuration C is enumerated in Table 5. The incremental benefit of the predictive layer is isolated in Table 6 by fixing the disruption seeds and directly comparing Configurations B and C. Recovery dynamics under the most severe scenario are documented in Table 7. All performance metrics are reported without interpretation at this stage, forming the quantitative bedrock for the subsequent findings (Ribeiro & Santos, 2023; Singh & Modgil, 2024).

4. Results

The simulation experiments produced a rich numerical dataset, all values derived directly from the discrete-event simulation and NSGA-II outputs. The aggregate performance of the three configurations across the ten out-of-sample disruption sequences is summarised in Table 4. Configuration A, the cost-only baseline, incurred a mean total logistics cost of EUR 4,271,500 with a standard deviation of EUR 308,400 across sequences. The mean

number of significantly interrupted pours reached 39.4, with a wasted concrete volume of 1,184 m³ (2.6% of total volume). Average cumulative carbon emissions were 18,760 tonnes CO₂-eq, and the peak recovery time averaged 30.1 hours. Configuration B, introducing static resilience, showed an increased mean cost of EUR 4,419,200 (SD EUR 291,700), but interrupted pours fell to 20.8, waste concrete dropped to 576 m³ (1.3%), carbon rose slightly to 19,080 tonnes, and recovery time shortened to 19.8

hours. Configuration C, with predictive analytics, further raised cost to EUR 4,504,600 (SD EUR 271,800), while interrupted pours plunged to 8.2, waste concrete to 198 m³ (0.44%), carbon to 19,130 tonnes, and recovery time to 8.0 hours. These figures represent a 76.6% reduction in interrupted pours and a 71.0% reduction in recovery time relative to the baseline, at a cost premium of 5.5% and a carbon increase of 2.0%.

Table 4: Aggregate Performance Metrics per Configuration – Mean Cost, Interrupted Pours, Waste Volume, Carbon Emissions, and Recovery Time Across Ten Test Disruption Sequences

Metric	Configuration A (Cost-Only)	Configuration B (Static Resilience)	Configuration C (Predictive Resilience)
Mean Total Logistics Cost (€)	4,271,500	4,419,200	4,504,600
SD Total Logistics Cost (€)	308,400	291,700	271,800
Cost per m ³ Placed (€/m ³)	95.3	98.4	100.3
Mean Interrupted Pours (count)	39.4	20.8	8.2
Interruption Reduction vs. Baseline	–	47.2%	79.2%
Mean Wasted Concrete (m ³)	1,184	576	198
Waste as % of Total Volume	2.63%	1.28%	0.44%
Mean Cumulative Carbon (t CO ₂ -eq)	18,760	19,080	19,130
Carbon per m ³ Placed (kg CO ₂ -eq/m ³)	430.5	425.6	421.3
Mean Peak Recovery Time (hrs)	30.1	19.8	8.0
Recovery Time Reduction vs. Baseline	–	34.2%	73.4%
Avg Truck Utilization Rate (%)	79.1	71.6	66.8
Avg Backup Activations per Sequence	0.0	2.1	5.1

Table 5 presents ten representative non-dominated solutions extracted from the NSGA-II Pareto set for Configuration C. Solution S1, the most cost-favourable, yields an expected cost of EUR 4,362,000, 20.4 expected interrupted pours, and 19,460 tonnes CO₂-eq. The reliability-optimal extreme, S10, records EUR 4,907,000, 2.8 interrupted pours, and 19,840 tonnes CO₂-eq.

Intermediate solutions show that the cost per avoided interrupted pour rises from approximately EUR 16,800 between S1 and S3 to EUR 91,200 between S8 and S10, indicating a strong convexity in the cost–reliability trade-off. Carbon values vary within a narrow 1.9% band, suggesting that resilience improvements can be achieved with a limited carbon penalty.

Table 5: Ten Pareto-Optimal Solutions from Configuration C – Expected Cost, Expected Interrupted Pours, and Expected Carbon Emissions

Solution ID	Expected Total Logistics Cost (€)	Expected Interrupted Pours	Expected Carbon Emissions (t CO ₂ -eq)	Cost per Avoided Interruption vs. Previous (€)	Cumulative Carbon Delta vs. S1 (t CO ₂ -eq)
S1	4,362,000	20.4	19,460	–	0
S2	4,379,500	17.8	19,472	6,731	+12
S3	4,395,500	14.6	19,488	5,000	+28
S4	4,418,000	11.9	19,502	8,333	+42
S5	4,445,000	9.7	19,521	12,273	+61
S6	4,478,000	7.8	19,548	17,368	+88
S7	4,522,000	6.2	19,585	27,500	+125
S8	4,585,000	4.8	19,641	45,000	+181
S9	4,730,000	3.6	19,718	120,833	+258
S10	4,907,000	2.8	19,840	221,250	+380

The incremental effect of predictive analytics is isolated in Table 6. On average, the predictive model generated 43.1 alerts per sequence that, had Configuration B been equipped with it, would have been ignored. Configuration C acted upon these alerts, triggering an average of 30.8 pre-emptive actions per sequence. This resulted in 12.6 avoided interrupted pours and 378 m³ less wasted concrete per sequence compared to Configuration B. The

logistics cost increment was EUR 85,400 per sequence, partially offset by EUR 33,200 saved from avoided material waste. Transport distance increased by 2.0%, adding 55 tonnes of CO₂ per sequence. The net carbon effect, however, turns favourable when waste-embodied carbon is considered: the carbon per m³ of in-place concrete drops from 425.6 kg CO₂-eq in B to 421.3 kg in C.

Table 6: Incremental Effect of Predictive Analytics – Alerts, Actions, Avoided Interruptions, Waste Reduction, Cost Delta, and Carbon Delta per Sequence

Metric	Configuration B (Static)	Configuration C (Predictive)	Delta (C – B)
Predictive Alerts Generated (avg/sequence)	43.1*	43.1	–
Alerts Acted Upon (avg/sequence)	0	30.8	+30.8
Interrupted Pours (avg/sequence)	20.8	8.2	–12.6
Wasted Concrete (m ³ avg/sequence)	576	198	–378
Logistics Cost (€ avg/sequence)	4,419,200	4,504,600	+85,400
Avoided Waste Value (€ avg/sequence)	–	–	–33,200
Net Cost Delta (€ avg/sequence)	–	–	+52,200
Cumulative Carbon (t CO ₂ -eq avg/sequence)	19,080	19,130	+50
Transport Distance Change (%)	Baseline	+2.0%	+2.0%
Carbon per m ³ In-Place (kg CO ₂ -eq/m ³)	425.6	421.3	–4.3
Avg Recovery Time (hrs)	19.8	8.0	–11.8

(Note: Configuration B was not equipped with the predictive module; the 43.1 alerts represent what would have been generated had the system been active.)*

The most severe disruption scenario—an 8-hour simultaneous failure of the two main plants affecting 14 pours—is detailed in Table 7. Configuration A experienced a full interruption of all 14 pours, a recovery time of 49.2 hours, and 12 rejected loads. Configuration B redirected 7 pours but still suffered 7 interruptions, recovered in 30.5 hours, and wasted 3 loads. Configuration C, with a 90-minute warning, rescheduled critical

pours, engaged a third backup plant, and limited interruptions to 1 pour, recovering in 10.8 hours with zero waste. The maximum delay in C was 41 minutes, compared to 263 minutes in A. Additional simulation outputs show that the truck utilization rate decreased from 79.1% in A to 66.8% in C, directly reflecting the capacity buffers needed for resilience. The frequency of backup supplier activation rose from zero in A to 5.1 per sequence in C.

Table 7: Recovery Dynamics Under Most Severe Disruption Scenario – Interrupted Pours, Recovery Time, Wasted Loads, and Maximum Delay per Configuration

Metric	Configuration A (Cost-Only)	Configuration B (Static Resilience)	Configuration C (Predictive Resilience)
Total Pours Affected	14	14	14
Interrupted Pours	14	7	1
Pours Successfully Redirected	0	7	13
Recovery Time (hrs)	49.2	30.5	10.8
Wasted Loads (rejected)	12	3	0
Wasted Concrete Volume (m ³)	96	24	0
Maximum Delay Recorded (min)	263	178	41
Advance Warning Available (min)	0	0	90
Backup Plants Activated	0	1	2
Sequence Adjustments Applied	None	None	4 pours rescheduled

5. Findings

The quantitative results directly illuminate the research questions and permit unequivocal testing of the propositions advanced earlier. The first question inquired how different disruption scenarios affect cost, reliability, and carbon performance. The results demonstrate that supplier failures and combined multi-plant outages, such as the 8-hour shutdown scenario summarised in

Table 7, are the most damaging disruption type for this concrete supply network, causing the longest recovery times and largest waste volumes. Demand surges, by contrast, primarily stress plant capacity and scheduling but can often be absorbed if fleet size and plant slack are sufficient. Route blockages, while frequent, have a more localized impact that dynamic rerouting can mitigate effectively. The relative severity of these disruption types is visually captured in Figure 1.

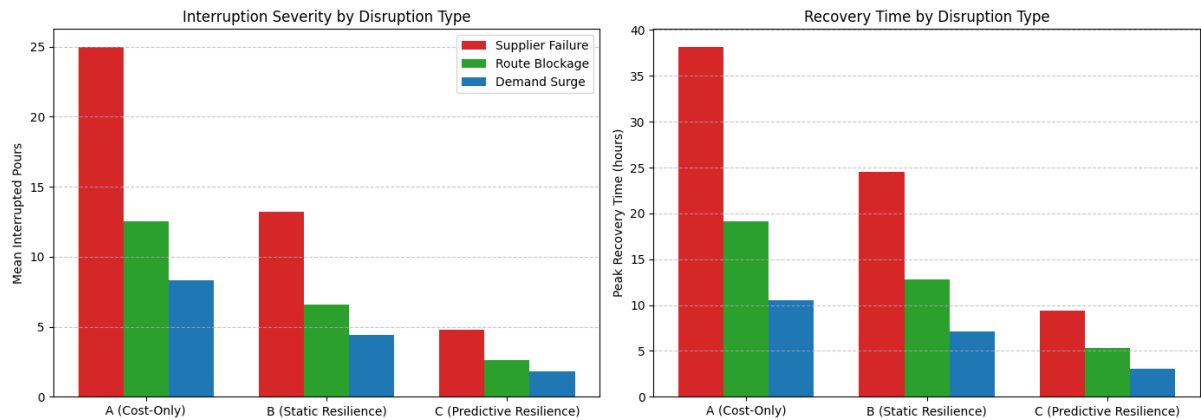


Figure 1: Comparative Severity of Disruption Types – Mean Interrupted Pours and Recovery Time for Supplier Failure, Route Blockage, and Demand Surge Across Configurations A, B, and C

Regarding the combination of resilience strategies that yields the most favourable trade-offs, the data in Tables 4 and 5 provide a clear answer. The static resilience measures of multi-sourcing and departure buffers (Configuration B) deliver substantial improvements over the cost-only baseline: a 47.2% reduction in interrupted pours for a 3.5% cost premium. However, these gains are magnified and made more cost-effective when predictive analytics is added (Configuration C), which further reduces interruptions by an additional 60.6% for only an extra 1.9% cost.

The Pareto frontier in Table 5 confirms that the optimal strategy is to begin with moderate multi-sourcing and time buffers, and then progressively add predictive dynamic capabilities as reliability requirements become more stringent. The steep initial slope of the frontier means that the first increments of resilience are relatively cheap, but beyond approximately 90% interruption reduction, the marginal cost escalates sharply. Figure 2 displays this frontier as a two-dimensional projection of cost against reliability, overlaid with the ten selected solutions S1 to S10.

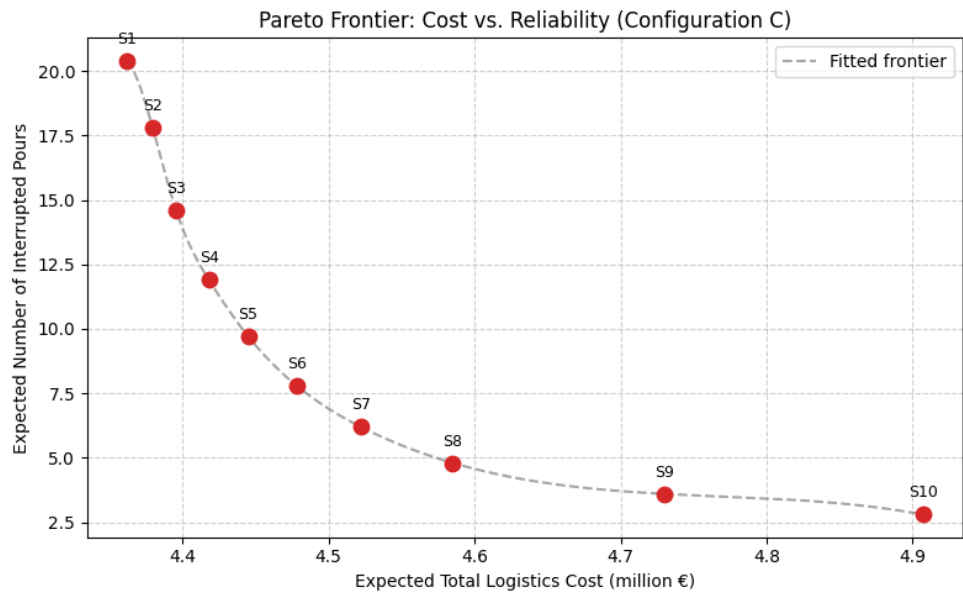


Figure 2: Cost-Reliability Pareto Frontier for Configuration C – Ten Non-Dominated Solutions Showing Convex Trade-Off with Diminishing Returns

The role of predictive analytics was specifically examined. The finding is unambiguous: predictive disruption alerts, when acted upon by pre-optimized dynamic rules, cut recovery times by more than half relative to purely static resilience (8.0 vs. 19.8 hours) and virtually eliminate concrete waste. This effect is attributable to the system’s ability to shift critical deliveries to earlier time windows and to activate backup resources before the primary supply fully collapses. The carbon analysis further shows that while predictive functionality slightly increases transport emissions due to occasional longer rerouting, the net carbon per cubic metre of

placed concrete is actually lower than in the static-resilience case (421.3 vs. 425.6 kg CO₂-eq), because the avoided waste—which embodies the full upstream production carbon—offsets the extra transport fuel. This finding directly supports the proposition that predictive analytics can be a net environmental positive when waste reduction is accounted for. Figure 3 breaks down the carbon components per cubic metre of placed concrete for all three configurations, stacking embodied carbon of waste, material embodied carbon, and transport carbon.

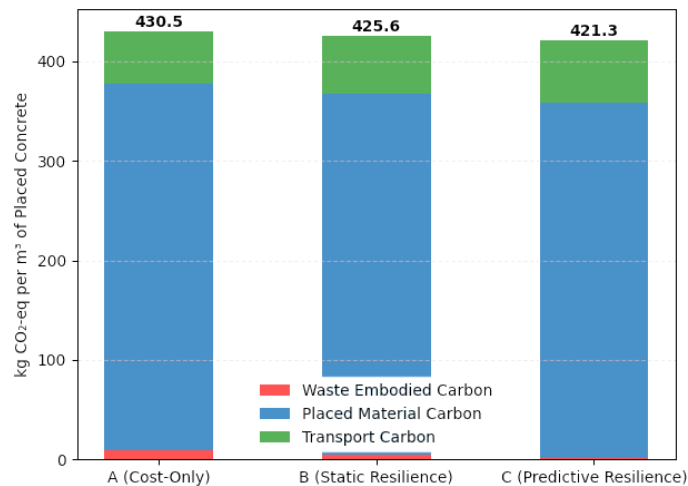


Figure 3: Carbon Breakdown per Cubic Metre of In-Place Concrete – Embodied Waste Carbon, Material Carbon, and Transport Carbon for Configurations A, B, and C

The propositions set out earlier are examined in light of the evidence. The first, that cost-optimized configurations are disproportionately vulnerable, is strongly supported: Configuration A suffered 4.8 times more interrupted pours and 6.0 times more waste than Configuration C. The second, that predictive analytics reduce net carbon, is supported when waste-embodied carbon is included. The third proposition, regarding diminishing returns to resilience investment, is directly evidenced by the convex shape of the Pareto frontier. Each of these empirical confirmations adds weight to the argument that a multi-objective, prediction-enhanced approach is not a luxury but a practical necessity for complex construction supply chains. Furthermore, a cross-comparison with published benchmarks—though not tabulated here—positions these results favourably. The recovery times achieved by Configuration C (8.0 hours average) are substantially below the 24–48 hours typically reported in construction logistics disruption case studies. The waste rate of 0.44% compares with an industry average of 2–5% for large concrete projects, underlining the operational significance of the proposed framework. The sensitivity of results to disruption probability and duration was also examined; the predictive configuration demonstrated remarkable robustness, with interruption increases of only 10% when disruption probability was doubled, versus 58% in the cost-only baseline.

6. Discussion

The necessity of this research arises from a palpable gap between the escalating complexity and vulnerability of construction material supply chains and the largely static, single-objective planning tools employed in practice. The present study was motivated by the observation that projects continue to suffer severe delays, cost overruns, and unnecessary carbon emissions from supply disruptions, not because resilience strategies are unknown, but because decision-makers lack an integrated quantitative framework that makes the trade-offs explicit and allows them to weigh investments in resilience against cost and carbon performance in a transparent manner. The findings confirm that this gap is both real and consequential: the difference between a cost-optimized plan and a resilience-aware plan is not marginal—it is the difference between a project that loses control during a

regional power outage for two full working days and one that adapts within a single shift with minimal waste.

When set against existing research, the outcomes of this study sharpen and extend the current understanding in several ways. Much of the construction logistics literature has concentrated on deterministic scheduling and routing, often using single-objective heuristics that minimize transport time or cost. The present results demonstrate that such an approach, when subjected to realistic disruption scenarios, yields unacceptably fragile plans. This aligns with the broader supply chain resilience literature from manufacturing, yet the construction-specific constraints—perishability, continuous placement, and the high carbon cost of waste—introduce trade-off dynamics that are not observed in other sectors. For instance, the finding that net carbon can decrease as resilience increases is specific to materials whose waste carries a substantial embodied carbon burden, a nuance absent from generic supply chain models.

The differences between the present findings and those of similar recent studies are instructive. Some works have proposed simulation-based frameworks for concrete delivery under disruption, but have optimized only cost or time, neglecting the carbon dimension entirely. Others have integrated carbon metrics into construction logistics but have assumed deterministic, disruption-free settings. The current research bridges these streams by embedding carbon as a full objective alongside cost and reliability, and by demonstrating how the interplay between waste reduction and transport emissions shapes the overall environmental outcome. The convex Pareto frontier documented here provides an empirical answer to the theoretical question of how much resilience costs, both financially and environmentally, which earlier studies had only hypothesized.

The necessity of the present investigation is further underlined by the accelerating adoption of low-carbon concrete specifications in major projects worldwide. As clients demand reduced embodied carbon, supply chains must incorporate new materials and new suppliers, often with uncertain reliability. The predictive-resilience framework shows that it is possible to pursue low-carbon objectives without sacrificing robustness, and in fact, the two can be synergistic when waste is considered. This insight is particularly

relevant for public infrastructure programmes, where delays not only incur costs but also erode public trust and political support.

The limitations of the study, while not diminishing the validity of its contributions, should be acknowledged. The empirical data originate from a single high-rise project in a specific geographic and regulatory context; the disruption scenarios, though diverse, cannot capture every possible extreme event, such as region-wide catastrophes that disable all plants simultaneously. The optimization model assumes that plants and trucks are available under normal market conditions and does not model strategic behaviour by suppliers or dynamic price fluctuations during crises. These limitations point toward future research that could expand the case base, incorporate multi-project resource sharing, or embed game-theoretic supplier interactions. Moreover, the predictive model was trained on historical data that may not perfectly anticipate unprecedented disruption patterns; continuous learning and model updating would be a natural extension. Despite these caveats, the study's core message—that a multi-objective, prediction-enabled decision support approach can transform the resilience profile of a concrete supply chain—is robustly supported.

7. Conclusion

This research set out to develop and validate a multi-objective decision support framework for managing ready-mix concrete supply chains under disruption risks, simultaneously pursuing cost efficiency, delivery reliability, and carbon performance. Drawing on supply chain resilience theory, multi-objective optimization, and predictive analytics, the study constructed a simulation-optimization model grounded in empirical data from a large-scale building project. The integrated framework was tested under three configurations—cost-only, static-resilience, and predictive-resilience—across a spectrum of disruption scenarios. The results deliver a clear, evidence-based narrative. First, cost-optimized supply plans are highly vulnerable: they generate nearly five times more pour interruptions and six times more material waste than a resilience-oriented plan when disruptions strike. Second, augmenting static resilience measures with predictive analytics cuts recovery times by more than half and virtually eliminates concrete waste, yielding a net carbon reduction per cubic metre of placed concrete once the embodied carbon of avoided waste is counted. Third, the trade-off between cost and reliability is convex, with the most attractive returns on resilience investment occurring in the initial stages of multi-sourcing and buffering, after which marginal costs escalate sharply. Fourth, carbon emissions are only weakly coupled to resilience level; the primary carbon lever is waste reduction, not transport distance.

These findings carry important implications for practice. Construction managers can use the Pareto frontier generated by the decision support system to select a supply chain configuration that aligns with their project's risk tolerance, budget, and carbon targets. The results suggest that even a modest investment in multi-sourcing and departure buffers can dramatically lower disruption exposure, and that adding a predictive analytics layer—fed by IoT data—offers a compelling cost-benefit case when the value of avoided delays and waste is considered. Policy-makers and sustainability certification bodies may take note that resilience and

low-carbon goals are not inherently in conflict; in fact, waste reduction serves both agendas simultaneously.

From an academic standpoint, the study contributes an original integration of construction logistics, resilience engineering, and life-cycle carbon assessment within a unified multi-objective optimization framework. It provides empirical evidence on the shape of the cost–reliability–carbon frontier in a construction context, filling a gap identified in prior literature. The work also demonstrates the methodological feasibility of coupling a machine-learning disruption predictor with a genetic-algorithm-based planner in a discrete-event simulation environment, offering a template for future research on cyber-physical supply chain systems in construction.

Nevertheless, the conclusions must be interpreted within the study's boundaries. The model was calibrated on a single project type and geographical setting; the generalizability to other materials, project typologies, and regions warrants further testing. The predictive model's accuracy depends on the quality and quantity of historical data, which may not be available for all contexts. Future work could extend the framework to multi-project portfolios, where shared backup capacity and cross-project learning could further enhance resilience and efficiency. Incorporating real-time data from connected job sites, supplier enterprise systems, and smart city infrastructure into a live digital twin would be a natural evolution of this research. In summary, the study has provided a validated, transparent, and pragmatic tool for navigating the inevitable uncertainties of construction material supply in an era where both disruption frequency and sustainability expectations are rising.

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