TECHNICAL SCIENCES

SYSTEMS MODELING OF CONSTRUCTION ORGANIZATION UNDER WARTIME RISKS: NONLINEAR INTERDEPENDENCIES, FUNCTIONAL RESILIENCE, AND TRANSFORMATIVE RECOVERY SCENARIOS

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Abstract

The article develops a systems model for organizing the recovery of buildings, engineering structures and infrastructure facilities under wartime risks, in which structural readiness, engineering-service availability, site accessibility, resource sufficiency, logistics continuity and digital information readiness are treated as interdependent state variables rather than independent indicators. A nonlinear functionality model, a time-dependent recovery function, a functional-resilience index and an object-prioritization procedure are integrated into a scenario-based computational experiment covering twelve representative facility classes; the results show that linear aggregation can materially overestimate post-damage functionality, while function-priority and adaptive transformative recovery substantially reduce the time required to restore critical service levels. The proposed framework is intended for engineering and organizational decision support in reconstruction programs where repeated disruptive impacts, limited repair resources and cross-infrastructure dependencies require the simultaneous coordination of technical inspection, temporary stabilization, construction sequencing, logistics and modernization decisions.

Keywords: construction organization; civil engineering; wartime risks; infrastructure resilience; functional recovery; nonlinear interdependencies; reconstruction; recovery scheduling; engineering structures; digital twin

Introduction

The organization of construction and reconstruction under wartime conditions differs fundamentally from conventional project delivery because the object of management is not a stable construction site but a dynamically changing system of buildings, engineering structures, utility networks, access routes, temporary facilities and resource flows. Damage to one element can reduce the feasibility of work on other elements: a damaged power-distribution node can suspend dewatering or lifting operations; a blocked bridge can interrupt the delivery of structural components; a failure of water supply can constrain concrete works and sanitary operation; and restrictions on access can delay technical inspection even when construction resources are available. Consequently, the engineering problem is not exhausted by determining the physical degree of damage. It also requires modeling how the technical state of assets, availability of engineering services, site accessibility, logistics, repair resources and information support jointly determine the ability of a territorial construction system to restore functions over time.

The scale of this problem is particularly visible in Ukraine. The Fifth Rapid Damage and Needs Assessment (RDNA5), covering impacts through 31 December 2025, estimates direct damage at USD 195.1 billion, socioeconomic losses at USD 666.7 billion and recovery and reconstruction needs at USD 587.7 billion over a ten-year horizon; housing, transport and energy remain among the most affected sectors [1]. These figures are important not only as a measure of capital replacement requirements. They indicate that reconstruction must be organized as a multi-object, multi-network and resource-constrained engineering program in which the sequence of restoring individual facilities affects the recoverability of the entire built environment.

The theoretical basis for such analysis is provided by the engineering concept of resilience. Bruneau et al. [2] linked resilience to robustness, redundancy, resourcefulness and rapidity and showed that the performance of physical infrastructure must be considered together with organizational capabilities. Cimellaro, Reinhorn and Bruneau [3] formalized resilience through a time-dependent functionality trajectory, thereby shifting attention from a static loss estimate to the integral performance of a system during recovery. Hosseini, Barker and Ramirez-Marquez [4] demonstrated that resilience metrics differ substantially across engineering domains and that recoverability must be modeled explicitly. Francis and Bekera [5] proposed a framework based on absorptive, adaptive and restorative capacities, while Bocchini et al. [6] emphasized the need to connect resilience decisions with life-cycle and sustainability objectives in civil infrastructure. A second stream of research concerns the dynamic and stochastic behavior of infrastructure systems. Ouyang and Dueñas-Osorio [7] showed that resilience may display nonlinear time-dependent effects and that improvement measures effective in the short term do not necessarily produce the same effect over a longer horizon. Pant et al. [8] introduced stochastic recovery metrics that distinguish vulnerability from restoration speed. The PEOPLES framework further demonstrated that physical infrastructure should be interpreted within a multilayer system of functional dependencies rather than as an isolated asset [9]. These studies provide a strong conceptual basis for time-dependent recovery analysis, but their direct transfer to wartime construction organization requires additional representation of construction-site accessibility, temporary stabilization, repair-resource availability and repeated interference with construction operations. A third research direction addresses interdependent infrastructures and restoration optimization. Liu, Fang and Zio [10] integrated ex-ante and ex-post resilience strategies into a hierarchical optimization framework for interdependent critical infrastructures. Wu and Wang [11] formulated risk-averse post-disruption restoration under uncertainty by combining mixed-integer optimization with scenario-based stochastic programming. Bellè et al. [12] showed that the topology of coupling between critical infrastructures can materially influence resilience and that interface design can be treated as an optimization problem. At the operational level, Fan et al. [13] applied graph convolutional and deep reinforcement learning methods to road-network recovery, while Wang et al. [14] linked post-event road-network functionality to repair-order optimization. These contributions confirm that restoration sequencing is an engineering decision variable rather than merely an administrative schedule.

Digital information technologies are increasingly important for such decisions. Pregnolato et al. [15] proposed a workflow for digital twins of existing civil infrastructure and demonstrated its applicability to bridge management. Guo and Fang [16] developed lifecycle digital-twin modeling for cable-stayed bridges, while He et al. [17] showed how reduced-order modeling can accelerate the state estimation of engineering structures. Lünnemann, Lindow and Goßlau [18] emphasized that digital twins for existing infrastructure should be built around functional user requirements. For wartime reconstruction, this is relevant because the value of BIM, GIS, monitoring and digital-twin technologies lies not only in visualization but also in the ability to maintain a synchronized representation of damage, work fronts, access restrictions, temporary states and restoration priorities.

Research focused directly on reconstruction also points to this convergence of civil engineering and digital decision support. Demian et al. [19] identified the potential and institutional barriers of BIM implementation in the post-war reconstruction of Ukraine. Rawat et al. [20] systematized the role of GIS, BIM, UAVs, artificial intelligence and related digital technologies in post-disaster reconstruction, and Li, Yu and Deng [21] showed that resilience research in the construction industry remains fragmented across objects, organizational levels and uncertain impacts. At building scale, Zhao and Takahashi [22] demonstrated the importance of explicitly modeling repair scheduling in functional-recovery assessment. Recent infrastructure performance research also confirms that resilience indicators need to be embedded in practical project-assessment tools rather than treated as descriptive attributes [23], while digital-twin and AI studies increasingly move toward federated, multi-scale infrastructure models [24]. The nexus perspective of Erfani et al. [25] further supports consideration of infrastructure as a system of interdependent services and resource flows.

Despite these advances, three methodological gaps remain important for construction organization under wartime risks. First, many models aggregate performance indicators linearly and therefore underrepresent bottleneck effects: moderate deficits in power, access and logistics can interact and produce a much larger decline in feasible construction output than the arithmetic mean suggests. Second, structural or network resilience is frequently modeled separately from the organization of repair works, although inspection, stabilization, resource mobilization, construction sequencing and commissioning determine the actual recovery trajectory. Third, conventional recovery models often assume restoration to the pre-event state, whereas reconstruction programs may deliberately increase redundancy, modularity, energy autonomy, maintainability, monitoring capability and environmental safety beyond the original baseline.

Accordingly, the aim of this study is to develop and test a systems model for organizing the recovery of buildings, structures and infrastructure facilities under wartime risks, with explicit representation of nonlinear interdependencies, functional resilience and alternative recovery-transformation scenarios. The study has four objectives: (1) to formalize a state vector linking physical, engineering, logistical, resource and digital conditions; (2) to construct a nonlinear functionality function sensitive to simultaneous deficits and cross-system coupling; (3) to integrate functionality with recovery dynamics, object prioritization and resource constraints; and (4) to compare restorative, function-priority and adaptive transformative recovery scenarios using a reproducible computational experiment.

Materials and methods

The methodological approach combines systems analysis, nonlinear aggregation, time-dependent recovery modeling, priority ranking and scenario simulation. The unit of analysis is a territorial or program-level set of construction objects that may include residential and public buildings, bridges, road sections, energy facilities, water and wastewater infrastructure, district-heating nodes, shelters and logistics facilities. The model is intended for the organization stage after rapid engineering assessment has established that work can proceed subject to specified safety restrictions. It does not replace structural calculation, forensic examination, explosive-hazard clearance or statutory decisions on demolition and reconstruction; rather, it connects the outputs of those procedures to construction-sequencing decisions. RDNA5 [1] is used as the contextual source for the scale and sectoral composition of recovery needs. The numerical experiment presented below is a methodological scenario test, not a damage inventory of named Ukrainian facilities. Normalized inputs were assigned to twelve representative object classes to reproduce combinations of criticality, functional deficit, network centrality, repair duration and resource intensity that are typical of multi-object recovery programs. This distinction is essential: the purpose of the experiment is to test the behavior and decision logic of the model, while project application requires replacement of normalized inputs with data from technical inspection reports, BIM/GIS models, bills of quantities, network operators, construction schedules and field monitoring. For each recovery program, the construction system at time t is represented by a normalized state vector containing six variables. Their engineering interpretation and practical sources are summarized in Table 1. All variables are scaled to the interval [0, 1], where 1 denotes the target state required for full planned functionality. Because these states are mutually dependent, the model does not interpret a high value of one variable as fully compensating for a critical deficit in another.

Table 1.

State variables of the construction-recovery system

Symbol / state	Engineering interpretation	Typical project data	Scale
S(t)	Structural and physical readiness	Inspection category, stability, temporary strengthening, work-front readiness	0-1
E(t)	Availability of engineering services	Power, water, heat, drainage, communications needed for works and operation	0-1
A(t)	Site and network accessibility	Road access, bridge passability, safe zones, lifting and staging access	0-1
R(t)	Construction-resource sufficiency	Crews, machinery, materials, temporary systems, specialist contractors	0-1
L(t)	Logistics continuity	Delivery reliability, route redundancy, storage and transfer capacity	0-1
D(t)	Digital information readiness	BIM/GIS completeness, georeferenced inspection data, CDE and monitoring updates	0-1

Source: developed by the authors.

The state vector is written as:

$$\mathbf{z}(t) = [S(t), E(t), A(t), R(t), L(t), D(t)]^T \quad (1)$$

where each component $z_j(t) \in [0,1]$. The weights used in the experiment were w = (0.22, 0.21, 0.16, 0.15, 0.14, 0.12), with the largest shares assigned to structural readiness and engineering-service availability. The weighting structure is deliberately transparent and can be recalibrated for a specific reconstruction program by expert judgment, entropy weighting, Bayesian updating or statistical learning from completed work packages.

To avoid the compensatory bias of a weighted arithmetic mean, the system functionality Q(t) is defined as a weighted geometric state multiplied by a nonlinear interdependency term:

$$Q(t) = \left[\prod_{j=1}^{m} z_j(t)^{w_j}\right]\left\{1 - \sum_{(i,j)\in\Omega} \gamma_{ij}\,[1 - z_i(t)][1 - z_j(t)]\right\}, \quad \sum_{j=1}^{m} w_j = 1 \quad (2)$$

where Ω is the set of material interdependencies and $\gamma_{ij} \geq 0$ is the interaction coefficient. In the computational experiment, four dominant couplings were retained: engineering services-accessibility, engineering services-resources, accessibility-logistics and resources-logistics. The expression in braces is bounded to the interval [0,1]. This form has two useful properties for construction engineering: a severe deficit in one component cannot be fully offset by high values elsewhere, and simultaneous deficits in dependent components cause an additional loss of functionality.

The recovery trajectory for state variable j under scenario s is represented by a generalized saturation function:

$$z_{j,s}(t) = z_{j,0} + (z_{j,s}^{\infty} - z_{j,0})\{1 - \exp[-(k_{j,s}t)^{p_{j,s}}]\}, \quad t \geq 0 \quad (3)$$

where $z_{j,0}$ is the post-damage state, $z_{j,s}^{\infty}$ is the scenario target, $k_{j,s}$ is the recovery-rate parameter and $p_{j,s}$ controls the curvature of mobilization and commissioning. Values $p > 1$ represent an initially constrained period followed by accelerated recovery after access, design, procurement or enabling infrastructure is established. This is relevant to wartime reconstruction, where early progress can be limited by inspection and stabilization even when later construction production is comparatively rapid.

For comparison across scenarios, functionality is normalized by the pre-event reference Q_{pre}:

$$q_s(t) = \frac{Q_s(t)}{Q_{\text{pre}}} \quad (4)$$

The conventional resilience index over planning horizon T is defined as the area under the normalized functionality curve capped at the original baseline:

$$R_s(T) = \frac{1}{T}\int_0^T \min\,[1, q_s(t)]\,dt \quad (5)$$

Because reconstruction may intentionally improve performance above the original state, an additional transformation-adjusted index is used:

$$R_s^{\mathrm{tr}}(T) = \frac{1}{T}\int_0^T q_s\,(t)\,dt, \qquad G_s(T) = q_s(T) - 1 \tag{6}$$

Here $G_s(T)$ measures the terminal transformation gain relative to the pre-event baseline. A positive value does not imply unlimited capacity; it denotes that the selected functional criteria, such as redundancy, service availability, maintainability or information readiness, exceed their pre-event reference values.

Table 2.

Recovery scenarios used in the computational experiment

Scenario	Construction-organization principle	Target state
S1 Restorative repair	Object-by-object repair; limited reprioritization; restoration mainly to pre-event configuration	Return to baseline functionality
S2 Function-priority recovery	Priority to enabling infrastructure and shared services; temporary solutions; rolling resource reallocation	Fast restoration with selective improvement
S3 Adaptive transformative recovery	Function-priority sequencing plus redundancy, modularity, digital monitoring and maintainability upgrades	Recovery above baseline where justified

Source: developed by the authors.

Construction sequencing is determined by a priority score for object i. In the demonstrative case, the score combines facility criticality C_i, initial functional deficit $(1 - F_{i0})$, network centrality N_i, safety and social significance S_i, expected repair duration T_i and normalized resource intensity R_i:

$$P_i = \frac{C_i^{0.30}(1 - F_{i0})^{0.25} N_i^{0.20} S_i^{0.15}}{(T_i/10)^{0.06} R_i^{0.04}} \tag{7}$$

The exponents are normalized decision weights for the methodological experiment; they are not proposed as universal constants. Their role is to ensure that objects with high systemic criticality, large functional deficits and strong enabling effects can outrank assets that are easier to repair but less important for the recovery of the whole system.

At any planning interval, the selected work fronts must satisfy resource-capacity constraints:

$$\sum_i a_{ir}\, x_i(t) \le B_r(t), \qquad r = 1, \dots, R \tag{8}$$

where a_{ir} is the requirement of object i for resource r, $x_i(t)$ indicates whether the corresponding work package is active, and $B_r(t)$ is the available capacity of crews, machinery, materials or specialized services. When a new disruption or a material change in access occurs, z(t), P_i and $B_r(t)$ are updated and the schedule is recalculated on a rolling horizon.

A conventional linear comparator was also calculated:

$$Q_{\mathrm{lin}}(t) = \sum_{j=1}^{m} w_j\, z_j(t) \tag{9}$$

The difference between Q_{lin} and the nonlinear Q provides a direct measure of the extent to which a conventional compensatory index may overstate actual construction feasibility under simultaneous constraints.

The recovery parameters were selected to reproduce three distinct organizational logics rather than to fit a particular named object. S1 uses slower and nearly exponential recovery rates and returns states to their pre-event levels. S2 accelerates engineering-service, access, resource and logistics restoration and allows modest improvements in selected states. S3 applies nonlinear mobilization with higher target states reflecting redundancy, modularity, monitoring and maintainability improvements. The simulation horizon is 120 days. In addition to the deterministic run, a Monte Carlo sensitivity experiment with 5,000 realizations was performed. Recovery-rate multipliers were sampled with a standard deviation of 12%, and interaction coefficients with a standard deviation of 18%, with truncated ranges to prevent physically implausible values.

Table 3.

Normalized characteristics and calculated priority of representative recovery objects

Object class	C	F0	N	S	T, d	R	P	Rank
Power distribution substation	0.98	0.35	0.95	0.90	14	0.80	0.860	1
Water pumping station	0.96	0.40	0.92	0.92	12	0.75	0.845	2
Bridge crossing	0.93	0.30	0.94	0.88	26	0.95	0.821	3
Hospital building	0.95	0.42	0.90	0.95	18	0.85	0.811	4
District-heating node	0.88	0.48	0.82	0.85	10	0.68	0.778	5
Civil-protection shelter	0.90	0.62	0.70	0.98	8	0.55	0.733	6
Sewer collector	0.84	0.50	0.80	0.82	16	0.77	0.728	7
Urban arterial road section	0.86	0.55	0.88	0.78	20	0.72	0.715	8
Logistics hub	0.82	0.52	0.78	0.70	18	0.73	0.691	9
Residential building cluster	0.78	0.58	0.60	0.80	24	0.88	0.622	10
School building	0.72	0.60	0.55	0.74	15	0.60	0.609	11
Municipal service building	0.68	0.66	0.50	0.65	11	0.48	0.568	12

Source: authors' scenario dataset and calculations. C - criticality; F0 - initial functionality; N - network centrality; S - safety/social significance; T - expected repair duration; R - resource intensity; P - priority score.

Results and Discussion

The first result concerns the effect of nonlinearity on the assessment of immediate post-damage functionality. For the reference state used in the computational experiment, the normalized post-damage vector was S = 0.62, E = 0.46, A = 0.58, R = 0.52, L = 0.55 and D = 0.72. When these values were aggregated with the same weights by a conventional weighted sum, normalized functionality was 0.615 relative to the pre-event state. The proposed nonlinear model produced 0.520. Thus, linear aggregation overestimated feasible functionality by 15.5%. The difference is generated by simultaneous deficits in engineering systems, accessibility, resources and logistics, which are precisely the conditions under which construction organization is constrained by bottlenecks rather than by average performance.

This result has a direct civil-engineering interpretation. A building may preserve a substantial part of its load-bearing capacity, yet restoration works cannot proceed at a proportional rate if the site lacks safe access, electricity for equipment, water for technological processes, cranes or transport routes. Conversely, the restoration of a substation or bridge can create a system-wide gain because it removes constraints from several downstream work fronts. The nonlinear term therefore functions as an engineering representation of coupled feasibility rather than as a purely mathematical penalty. Its value should be calibrated for a specific territory or project portfolio using observed dependencies, network topology, construction-method statements and expert elicitation.

The object-priority calculation is presented in Table 3. The highest priorities are assigned to the power-distribution substation, water pumping station, bridge crossing and hospital building. This ordering differs from a simple ranking by physical damage. The bridge, for example, has a comparatively long repair duration and high resource intensity, but its network centrality and large functional deficit increase its system value. The civil-protection shelter has a shorter repair duration and high safety significance, which moves it above several larger assets. Residential and school buildings remain important, but in the modeled first recovery wave their lower network centrality means that earlier restoration of enabling infrastructure can create better conditions for their subsequent reconstruction.

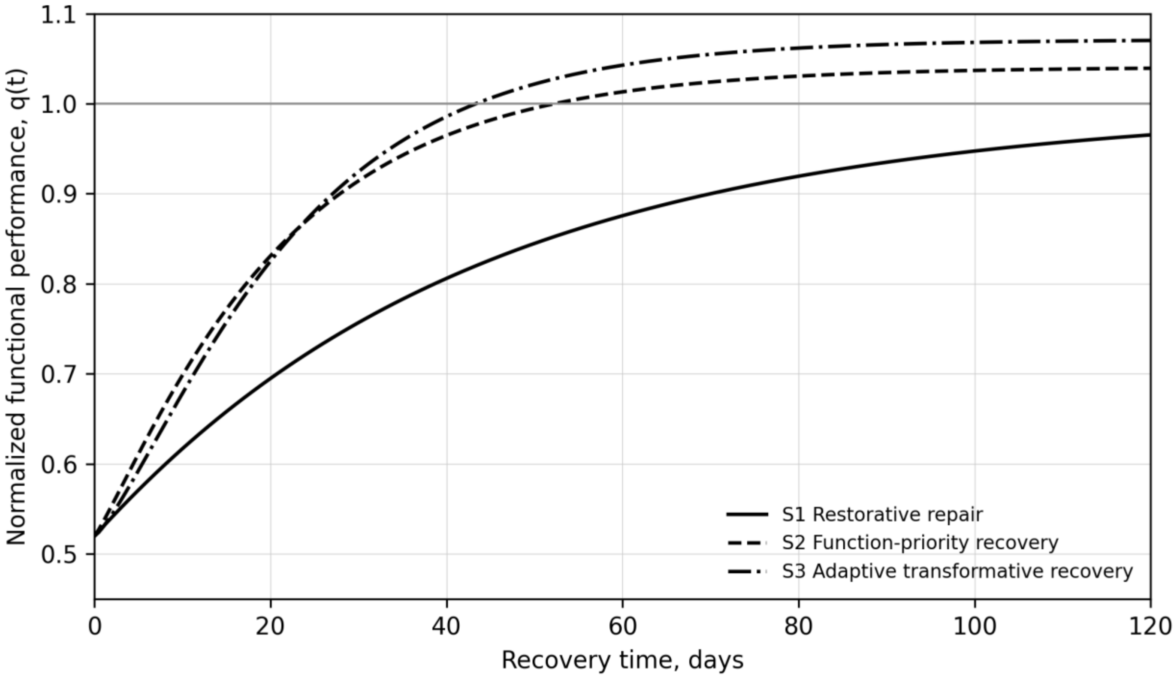

Fig. 1. Modeled functional recovery trajectories for three construction-organization scenarios

Source: developed by the authors using Eqs. (2)-(6).

Table 4.

Deterministic recovery-performance indicators

Scenario	q(0+)	q(120)	R120	Rtr,120	T80, d	T95, d	T100, d
S1	0.520	0.965	0.834	0.834	39.0	102.5	-
S2	0.520	1.039	0.931	0.948	17.5	37.0	52.5
S3	0.520	1.070	0.932	0.967	18.5	34.0	43.5

Source: authors' calculations. R120 is capped at the pre-event baseline; Rtr,120 retains performance above baseline.

The scenario trajectories are shown in Fig. 1 and the numerical outcomes are summarized in Table 4. Under S1, restorative repair gradually returns individual state variables toward the pre-event configuration, but the slow recovery of engineering services, resource sufficiency and digital coordination keeps the system below its original normalized functionality even after 120 days (q(120) = 0.965). The 120-day conventional resilience index is 0.834, and the modeled time to reach 95% functionality is 102.5 days. This scenario represents a technically feasible but sequentially fragmented approach in which each asset is largely repaired as an independent construction object.

S2 changes the organization principle: objects that restore enabling services and accessibility are moved forward, temporary engineering solutions are used to open downstream work fronts, and resource allocation is updated according to functional priority. As a result, 95% functionality is achieved after 37.0 days, which is 63.9% faster than in S1. The conventional 120-day resilience index increases to 0.931, an improvement of approximately 11.7%. The terminal functionality reaches 1.039 because selected components are not merely repaired but modestly upgraded, for example through backup power connections, improved routing or more reliable temporary-to-permanent engineering interfaces.

S3 combines function-priority recovery with transformation measures introduced during reconstruction. These measures may include modular replacement, local redundancy, decentralized energy backup, standardized connection nodes, enhanced monitoring, BIM/GIS-based asset information and construction solutions that improve maintainability and future repairability. In the simulation, S3 reaches 95% functionality after 34.0 days and the original baseline after 43.5 days. The conventional resilience index is close to S2 because this index is capped at the pre-event level; however, the transformation-adjusted integral increases to 0.967 and q(120) reaches 1.070. This demonstrates why a conventional resilience metric alone can conceal the long-term value of rebuilding to a functionally improved state.

The comparison between S2 and S3 is also important. S3 does not dominate S2 at every instant: additional design coordination, modular interfaces and modernization can slightly delay some early work packages. In the model, S2 reaches 80% functionality in 17.5 days, compared with 18.5 days for S3. Nevertheless, S3 reaches 95% and 100% thresholds sooner and provides a higher terminal state. This pattern is realistic for construction practice because transformation measures can impose an initial planning and procurement burden while reducing later commissioning constraints and increasing the capacity of the recovered system.

Table 5.

Monte Carlo sensitivity results (5,000 realizations)

Scenario	Median R120	10th-90th percentile R120	Median T95, d	10th-90th percentile T95, d
S1	0.833	0.822-0.842	104	97-112
S2	0.931	0.925-0.936	37	35-40
S3	0.932	0.926-0.936	34	32-36.5

Source: authors' calculations with uncertain recovery rates and interaction coefficients.

A 5,000-run Monte Carlo sensitivity experiment was additionally performed by varying recovery-rate parameters with a standard deviation of 12% and interaction coefficients with a standard deviation of 18%, subject to truncation limits. The median conventional resilience indices were 0.833 for S1, 0.931 for S2 and 0.932 for S3. The 10th-90th percentile ranges were 0.822-0.842, 0.925-0.936 and 0.926-0.936, respectively. Median times to 95% functionality were 104, 37 and 34 days; the corresponding 10th-90th percentile ranges were 97-112, 35-40 and 32-36.5 days. The ranking of the scenarios therefore remained stable under moderate parameter uncertainty, although the absolute duration of restorative repair was substantially more variable because it was more sensitive to slow components and interaction penalties.

The findings are consistent with the broader resilience literature, which treats recovery speed and interdependence as central determinants of system performance [3, 7, 10-14]. Their contribution to construction engineering lies in translating these concepts into a state vector and scheduling logic that can be populated from project data. The model is particularly suitable for portfolios where technical inspection identifies many repairable objects but the simultaneous availability of crews, lifting equipment, specialized materials, access routes and engineering services is limited. In such settings, a schedule optimized only for individual project duration can be inferior to a schedule that restores shared enabling functions first.

The proposed model also clarifies the role of digitalization. Digital twins and BIM do not directly create resilience; their effect enters through D(t) and through improved estimation of the other state variables. A synchronized information environment can shorten the time between inspection and design, reduce inconsistency between damage records and work packages, support geospatial coordination of access restrictions, and permit faster updating of quantities and resource needs [15-20, 24]. In practical implementation, D(t) may be measured through the completeness and currency of the common data environment, the share of assets with georeferenced inspection data, model-to-field synchronization frequency, or the availability of sensor and network-operator data.

Environmental and safety constraints should be integrated in the same decision loop. Recovery sequencing must account for debris handling, hazardous materials, damaged utility lines, contaminated areas, unstable elements and restrictions associated with explosive hazards. In the proposed framework these factors can be represented either as hard feasibility constraints on A(t) and S(t) or as separate state variables when environmental risk is a dominant characteristic of the program. This is consistent with the view that resilient infrastructure planning should consider interacting technological, environmental and resource systems rather than isolated assets [23, 25].

For practical application, the model can be implemented as a rolling-horizon procedure. After each inspection cycle or significant change in conditions, the state vector is updated; q(t), object priorities and resource constraints are recalculated; and the next set of work fronts is selected. The planning horizon may range from days for emergency stabilization to weeks or months for reconstruction. Such recalculation is especially important under wartime risks, where access, labor availability, energy supply and damage conditions may change faster than a conventional baseline schedule can be formally revised.

Several limitations should be recognized. First, the computational experiment uses normalized scenario data rather than observations from a single documented recovery program; therefore, the numerical thresholds should not be interpreted as universal engineering constants. Second, the interaction structure Ω is deliberately sparse for transparency, whereas real infrastructure networks may require graph-based or multilayer network representations. Third, the current recovery function is monotonic; repeated disruptive impacts would require piecewise state transitions or a stochastic jump process. Fourth, the priority function does not yet include explicit cost, carbon or contractual constraints. These limitations define the next stage of development rather than invalidate the proposed logic. Calibration on monitored reconstruction projects would allow interaction coefficients, recovery exponents and priority weights to be estimated statistically and linked to specific facility types.

Conclusions

The study developed a systems model for construction organization in recovery programs where buildings, engineering structures and infrastructure facilities are functionally interdependent and recovery resources are constrained. The central methodological result is the replacement of independent linear indicators by a nonlinear functionality function that combines a weighted geometric state with explicit interaction penalties. In the test case, the linear model overestimated immediate normalized functionality by 15.5%, demonstrating that concurrent deficits in engineering services, access, resources and logistics cannot be treated as mutually compensating. The second result is the integration of facility condition with construction sequencing. The proposed priority score links criticality, functional deficit, network centrality, safety significance, repair duration and resource intensity, allowing enabling infrastructure to be advanced when its restoration opens multiple downstream work fronts. This converts resilience from a descriptive property into an operational criterion for selecting the sequence of inspection, stabilization, repair, reconstruction and commissioning activities. The third result is the differentiation between restorative and transformative recovery. In the computational experiment, function-priority and adaptive transformative scenarios reduced the modeled time to 95% functionality from 102.5 days to 37.0 and 34.0 days, respectively. The transformative scenario also produced a terminal functional level above the pre-event baseline, indicating that reconstruction decisions can simultaneously restore service and reduce future dependence on vulnerable interfaces.

For civil-engineering practice, the framework can serve as the analytical core of a BIM/GIS-enabled rolling-horizon decision-support system for multi-object reconstruction. Its further development should focus on calibration with field data from damaged buildings and infrastructure, graph-based representation of energy-water-transport dependencies, stochastic modeling of repeated wartime disruptions, integration of structural-health-monitoring data, and multi-criteria optimization that jointly considers functional recovery time, construction cost, resource scarcity, environmental safety and life-cycle performance.

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