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A Simulation-Based Framework for Enhancing the Resilience of Maintenance Operations in Critical Infrastructure

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Abstract

Resilience of maintenance operations in critical infrastructure present a significant challenge for future communities, particularly as the frequency and severity of human-made and environmental disruptions continue to escalate. This paper highlights the role of maintenance operations in ensuring the functionality of essential infrastructure components, with a focus on enhancing their resilience to ensure operational continuity. While existing research on improving resilience in maintenance operations remains limited, this study aims to bridge this gap by developing a conceptual framework that employs a simulation-based approach to improve decision-making in complex maintenance scenarios. The proposed framework is adapted from Bruneau et al. (2003) and grounded in the 4Rs resiliency theory. The framework is then applied to the case study of maintaining hospital elevators, focusing on the specific challenges and needs associated with maintaining this critical infrastructure. By integrating these principles, the proposed framework seeks to ensure that critical infrastructure remains efficient, reliable, and resilient in the face of unforeseen disruptions, ultimately supporting the long-term sustainability of essential services.

Keywords: Critical infrastructure, Resilience, Maintenance Operations, Simulation-based Framework.

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Highlights

- The frequency and severity of disruptions from human-made incidents and natural disasters have significantly increased, posing threats to critical infrastructure systems that are vital for societal well-being and economic stability.
- Effective maintenance operations are essential for maintaining the resilience of critical infrastructure, utilising the 4R resilience theory alongside simulation methods to enhance reliability and operational performance.
- This study addresses important gaps in the literature by integrating resilience theory with maintenance decisions and highlights the need for empirical validation and technology integration in future research.

1 Introduction

The frequency and severity of disruptions due to human-made incidents (e.g., technological failures, cyberattacks) or natural disasters (e.g., storms, floods) have dramatically escalated in recent decades, posing significant threats to communities, their economies, and the environment (Cvetković et al., 2024). These disruptions endanger the operation of critical infrastructures (CI), including power grids, water supply, transportation networks, and healthcare services, which are essential for societal well-being and economic stability (Guidotti et al., 2016). Failures of these systems can ripple through society, potentially causing substantial economic losses and social instability (Ouyang & Fang, 2017).

To mitigate these disruptions, national governments prioritise 'Critical Infrastructure Resilience' through policy frameworks and strategic guidance, such as the United States National Infrastructure Advisory Council's recommendations (2009), Australia's Critical Infrastructure Resilience Strategy (2010), and the United Kingdom Climate Resilient Infrastructure Plan (2011). These initiatives all highlight resilience as a key concept, aligning with Carlson et al. (2012) statement that "the resilience of a community/region is a function of the resilience of its subsystems, including its critical infrastructure, economy, civil society and governance".

'Resilience' is the capability of a system to withstand internal and external disruptions and recover from them for continuous operations (Sun et al., 2022). Resilience in the context of critical infrastructure, is defined as "the ability of a facility or asset to anticipate, resist, absorb, respond to, adapt to, and recover from a disturbance (Carlson et al., 2012)".

Effective maintenance operations play a vital role in preserving the resilience of critical infrastructure systems, ensuring their continuous and uninterrupted operation. The European standard EN13306:2001 defines maintenance as "the combination of all technical, administrative, and management actions during the lifecycle of an item intended to retain it in, or restore it to, a state in which it can deliver the required function" (EN, 2001). Within this study's framework, maintenance operations refer to all activities, whether planned or unplanned, that are necessary for maintaining asset reliability and operational functionality in critical infrastructure systems.

Despite the well-established importance of maintenance and resilience in CIs, the concept of 'maintenance operations resilience' remains poorly developed in existing literature, lacking a unified definition and measurable framework. To address this gap, this paper integrates resilience principles into maintenance strategies by developing a conceptual framework that uses simulation as a decision-making tool to enhance system reliability and performance.

2 Literature Review

CI's maintenance employs four principal strategies, each serving a distinct operational objective across the asset lifecycle: 1) Corrective maintenance: This reactive approach involves unscheduled repairs performed after a failure occurs (Dui et al., 2023); 2) Preventive maintenance: This strategy consists of planned and periodic interventions using data-driven approaches aimed at preventing equipment failures before they occur (Sun et al., 2022), such as time-based and condition-based maintenance (Boppana, 2023); 3) Predictive maintenance: This strategy utilises historical and real-time data to predict and diagnose equipment conditions, facilitating timely interventions, and 4) Prescriptive maintenance: This advanced approach takes predictive maintenance a step further by recommending specific actions to optimise performance and predict potential failures (Molęda et al., 2023).

Each of these strategies can be applied at various phases of disruptions, including pre-disturbance, during the disturbance, and post-disturbance (Dui et al., 2023). Preventive and predictive maintenance are particularly beneficial before disruptions occur, while corrective and condition-based maintenance are effective during and after disruptions (Molęda et al., 2023). On the other hand, prescriptive maintenance is most advantageous after disruptions, as it focuses on learning from and applying lessons learned to mitigate future disruptions (Goby et al., 2023). By integrating maintenance strategies with resilience principles across all disruption phases, CI operators can systematically enhance system reliability while ensuring continuous public safety.

This study adopts the 4Rs resilience theory by Bruneau et al. (2003) which comprises the following dimensions:

- Robustness: The ability or strength of elements or systems to withstand a certain level of stress or disruption without loss of functionality. Robustness ensures that the system continues to operate effectively when faced with disturbances.
- Redundancy: The degree to which elements or systems can serve as substitutes, allowing them to meet functional requirements even during disruptions, degradation, or loss of functionality. Redundancy provides backup options to maintain system performance when primary elements or systems fail.
- Resourcefulness: The capacity to identify problems, set priorities, and provide resources when a system or its elements are affected by a disruption. Resourcefulness refers to how effectively a system can allocate and utilise material resources (e.g., budget or spare parts) and human resources to maintain or restore expected performance.
- Rapidity: The capacity to restore expected functions after disruptions in a timely manner and to prevent future disruptions. Rapidity focuses on minimising downtime and ensuring a swift recovery to normal operations.

Robustness and rapidity are the most critical metrics, in determining whether a system can sustain operations and recover after a disruption (the ‘ends’). In contrast, redundancy and resourcefulness serves as the enabling methods (the ‘means’) (Bruneau et al., 2003). Resilience has four dimensions: technical, organisational, social, and economic (TOSE) (Bruneau et al., 2003). In the context of this research, the technical and organisational aspects are particularly relevant, as these have direct impact on the effective maintenance operations and resilience strategies. To effectively measure and achieve these resilience dimensions, Wu et al., (2024) identified four complementary evaluation approaches including simulation. Notably, simulation algorithms have the ability to measure both dynamic (rapidity) and static (robustness) behaviours (Wu et al., 2024).

Maintenance operations involve a complex system influenced by various impacting variables. A complex system can be described as a system consisting of a large number of heterogeneous entities and interactions that create a collective structure and organisation. These interactions and interdependencies can be difficult to describe, understand, predict, manage, develop, and change (Gallab et al., 2016). Entities within a complex system exhibit dynamic behaviours; therefore, it is crucial to adapt to this dynamism and respond effectively to both anticipated and unanticipated disruptions (Chaabane & Trentesaux, 2019).

The complexity of maintenance tasks is due to the variability of the disruptions needed to be managed, the availability of resources (such as spare parts), the diversity of states of a system (normal state, degraded state, failed state), the duration of maintenance tasks that can be variable and unplanned, and the urgent nature of certain maintenance tasks (Gallab et al., 2016).

To simplify or examine such a complex system, modelling in a risk-free environment can be very beneficial. This approach allows for the identification of potential failures and needs without impacting the real system (A. Alabdulkarim et al., 2014; Alrabghi & Tiwari, 2016). Modelling enhances clarity and reliability, ultimately improving decision making in addressing these complexities. Models can be developed based on specific problems that require solutions, the use of the model, the modelling method and also the expertise modeler (Gallab et al., 2016).

Simulation is a scientific approach which can model a real phenomenon to observe the behaviour of a system facing real disruptions and analysing what would happen under the influence of analogous variations (Gallab et al., 2016). This process can provide users with viewing system behaviour, minimise the expenses, identify abnormalities and explore dynamic interactions (Alrabghi & Tiwari, 2016; Gallab et al., 2016). The strength and power of techniques such as discrete event simulation (DES) is the ability to mimic the dynamics of a real system (Abbasli & Mammadli, 2020). DES operates on the premise that time exists only at specific points, and that events will only take place at these points. This method is suitable for detailed operations systems such as maintenance systems, which each item needs to be traced within the organisation's dynamics (A. Alabdulkarim et al., 2014). Additional advantages of using DES include rapid modelling and visual interactive simulation (Alrabghi & Tiwari, 2016). However, according to A. Abdulkarim et al., (2014) maintenance modelling is poorly covered in existing literature.

This paper proposes a conceptual framework for assessing the resilience of maintenance operations of critical assets using DES. The framework is designed to enhance resilience by adopting various maintenance strategies (corrective, preventive and predictive) and aligning them with resilience dimensions of robustness, redundancy, resourcefulness, and rapidity.

3 Methodology

This research adopts Design Science Research (DSR) methodology to construct the conceptual framework based on the 4R resilience theory. DSR provides a structured approach for developing and evaluating problem-solving artifacts, making it well-suited for integrating theoretical and practical insights (Venable et al., 2017). DSR follows a six-step process: problem identification, objectives definition, design and development, demonstration, evaluation, and communication (Peffers et al., 2007). While the current work focuses on the design and development stage of the framework, future validation will involve empirical testing to ensure its real-world applicability.

To facilitate this empirical validation, collaboration with infrastructure operators such as NHS Trust hospitals in the UK, will be pivotal. These partnerships can provide essential operational data for calibrating the simulation model, refining failure and repair distributions, and enhancing the accuracy of resilience assessments. By leveraging real-world data, the framework can be systematically evaluated and adjusted to meet practical needs.

The system diagram depicted in Figure 1 outlines a comprehensive process for quantifying resilience, placing emphasis on robustness and rapidity as key measurable outcomes. To maximise the framework's practical utility, institutions could adopt a phased implementation approach. In the initial phase, pilot testing on selected critical assets—in this case hospital elevators—will allow for iterative adjustments based on observed performance gaps. The introduction of IoT sensors will be instrumental in further enhancing the model's accuracy by providing real-time operational data, enabling dynamic maintenance adjustments that respond proactively to changing conditions.

Decision-makers can then utilise the framework's outputs, including comparative resilience metrics across various maintenance strategies, to justify investments in predictive technologies and optimize resource allocation. This structured approach ensures that maintenance operations are not only reactive but also strategically aligned with broader organisational goals.

At an organisational level, the framework's alignment with existing resilience policies, such as the UK Climate Resilient Infrastructure guidelines, facilitates institutional adoption. By translating theoretical resilience dimensions into operational Key Performance Indicators (KPIs)—such as mean time to recovery (MTTR) and redundancy utilisation rates—the framework offers actionable insights for infrastructure managers, empowering them to make informed decisions.

Future work will further emphasize empirical validation through case studies, ensuring that the model remains adaptable across diverse critical infrastructure systems and communities. Ultimately, the framework aims to enhance resilience by incorporating advanced technologies and decision support systems, linking research tasks to the quantification and improvement of resilience across both infrastructure and community levels. By providing a robust structure for assessing and fostering resilience, this research contributes significantly to the field of maintenance operations and critical infrastructure management.

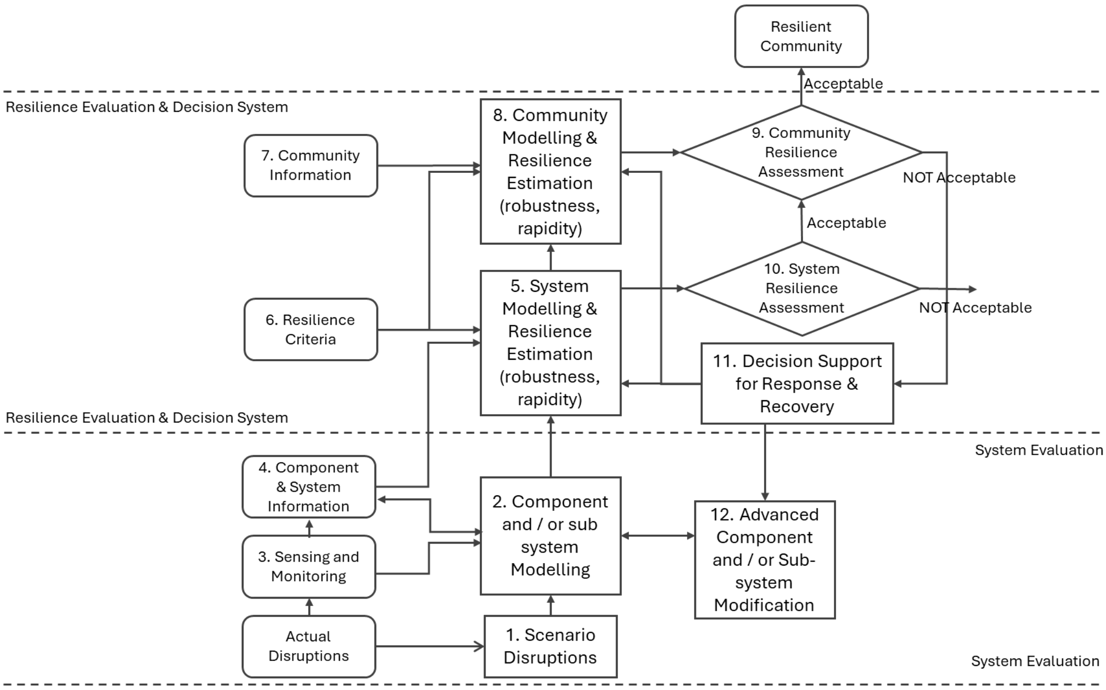

Figure 1. System diagram by Bruneau et al (2003)

4 Simulation-based Conceptual Framework

The system diagram in Figure 2 identifies the key steps required to quantify infrastructure systems resilience. It outlines how the previously introduced performance criteria (robustness and rapidity as the two desired 'ends' and resourcefulness and redundancy as the 'means') can be applied to assess the resilience of a system. At the community level, technical, organisational, social and economic resilience can be evaluated analogously for various types of physical and organisational systems.

Step 1: System definition and performance measures: This step aims to establish the asset's baseline configuration along with its key performance indicators. This involves clearly articulating the asset's configuration and functionalities while defining vital performance metrics—such as uptime and service levels—that serve as benchmarks for assessing system performance. By doing so, a comprehensive description of the system is created, providing an essential foundation for analysing performance declines during failures in subsequent stages of the research.

Step 2: Identify failure modes and maintenance strategies: Typical failure modes of assets include mechanical breakdowns, power failures, or control system errors. Other necessary details include failure type (based on availability or downtime), frequency or probability distribution, Mean Time Between Failures (MTBF), diagnosis time (for reactive maintenance only), repair time, and prognostics (time in advance when an asset provides feedback on a failure) (Alabdulkarim et al., 2015). Additionally, choose appropriate maintenance strategies. For each strategy, detail its rules: for reactive maintenance, note the repair initiation after failure; for preventive maintenance, specify the interval or condition for service (e.g. inspect every 100 operating hours); for predictive maintenance, specify the condition triggers. These strategies can be drawn from real critical assets maintenance protocols or hypothetical what-if scenarios. At this stage, also determine the resources required for maintenance, such as the number of available technicians, what the typical repair time is (distribution of MTTR), and if spare parts supply is a constraint. This information forms the failure/maintenance model input to the simulation (Abbasli & Mammadli, 2020).

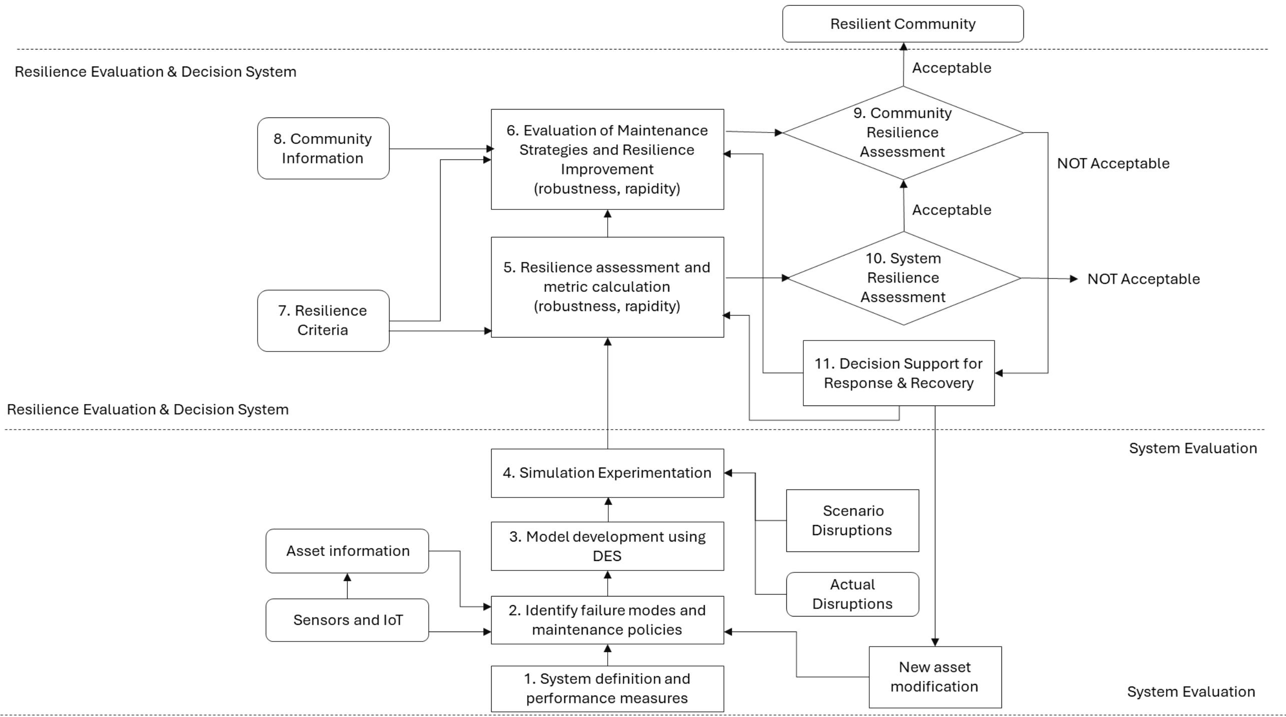

Figure 2 Conceptual Framework for Resilient Maintenance Operations of an Asset Using DES

Step 3: Model construction (DES implementation): The objective of this stage is to build a discrete event simulation (DES) model that mimics real-world operational dynamics. To accomplish this, the process begins by developing a set of state variables that capture key operational conditions, such as "working", "under maintenance", and "failed." Simultaneously, event triggers are programmed into the model to represent asset failure and subsequent repair interventions. The outcome is a robust simulation model that accurately represents the lifecycle of asset operation under various conditions, enabling detailed analysis of system performance in different scenarios.

Step 4: Simulation experimentation: With the DES model in place, design simulation experiments to stress-test the system's resilience. This typically involves running multiple replications of the simulation under various scenarios: (a) Baseline normal operation (no major failures beyond routine, to establish the steady performance); (b) Disruption scenarios, such as an asset failure, or multiple simultaneous failures if exploring extreme cases. For each maintenance strategy, execute each scenario multiple times using Monte Carlo simulation to account for randomness and gather statistical results. Ensure that the simulation runs long enough to capture the recovery phase after disruptions – e.g., continue the simulation until all backlogs are cleared and performance returns to normal to measure how long thit takes (as a direct observation of rapidity). The output of this step will be a dataset of performance metrics under each combination of scenario and maintenance strategy.

Step 5: Resilience assessment and metric calculation: Analyse the simulation output to evaluate resilience. This involves quantifying the four resilience factors with suitable metrics derived from the results. For robustness, observe how much the performance metric degrades upon a failure. Redundancy can be quantified by the spare capacity that was utilised during the failure, for instance if the system has N assets and one fails, a fully redundant system might still operate at (N-1)/N×100% of its capacity. Resourcefulness is a bit less direct to quantify via simulation but can be inferred from how the maintenance and operations responded: for example, if the model includes the dispatch of repair crews, resourcefulness can be measured by the mobilisation time (how quickly repair began after failure) or whether alternative actions were taken. Finally, rapidity is directly measured by the time to recovery: how long did it take from the moment of failure until the system restored normal performance?

Step 6: Evaluation of Maintenance Strategies and Resilience Improvement: Compare the resilience metrics across different strategies or design options. The framework's ultimate goal is to identify how resilient the asset is and how it can be improved. Through simulation, it can be quantified whether a preventive maintenance schedule provides better overall resilience compared to a corrective approach. For instance, the preventive maintenance may result in 50% reduction in breakdown events over the simulation period, significantly enhancing robustness.

4.1 Case study: Parallel Elevator System in Hospital

This case study explores the optimisation of elevator maintenance as a critical asset within the National Health Service (NHS) trusts in the UK, addressing challenges arising from the hospital's specific operational context. Key issues include delays in transporting patients to essential areas like operating theatres and ICUs, decreased staff productivity due to elevator unavailability, and heightened infection control risks associated with malfunctioning dedicated elevators. To overcome these challenges, the hospital is actively seeking optimisation strategies focused on enhancing elevator reliability and overall operational efficiency, ultimately aiming to improve patient care and staff workflow in accessing healthcare institutions. The following steps outline the implementation of the framework as shown in Figure 2, to assess the resilience dimensions of hospital elevators.

Step 1. System definition and performance measures: in this step, the elevator configuration is specified, detailing the number of elevators, their capacity, speed, the hospital layout (including floors served), and usage patterns (such as patient and visitor transfer). The primary performance measure identified is the availability of the elevators.

Step 2. Identify Failure Modes and Maintenance Strategies: this step assesses impact factors on elevator performance, including waiting times and potential failures, such as mechanical breakdowns and power failure. Various maintenance strategies are considered: reactive maintenance, which involved fixing issues after they occur; preventive maintenance, which can be time-based (e.g. 100 operating hours) or condition-based; and predictive maintenance, requiring regular inspections as specified for elevators (daily, monthly, annual inspections). Additionally, resource availability constraints are acknowledged, including the availability of technicians and spare parts.

Step 3. Model Construction (DES Implementation): in this step, the model construction focuses on the elevator's status, which includes three states: working, under maintenance, failed. Additionally, it accounts for the queue length of waiting passengers at each floor. Key events in the model account for failure events and repair events and establishes probability distributions for both time to failure and time to repair.

Step 4. Simulation Experimentation: in this step, simulation are conducted under various scenarios. The first scenario represents baseline normal operations (no major failures), and the second scenario involved disruption scenarios, such as an elevator failure occurring at a critical time (e.g., during peak time).

Step 5. Resilience Assessment and Metrics Calculation: in this step, the simulation output is analysed to evaluate resilience and quantified via four resilience dimensions: robustness, redundancy, resourcefulness, rapidity as follow:

- Robustness: observe and measure the extent to which system performance degrades during a failure (e.g., quantify the increase in wait times or reduction in service availability when an elevator fails). A small increase indicates higher robustness (the system maintains function).
- Redundancy: Evaluate how effectively the remaining elevators compensate for the loss. (e.g., quantify the spare capacity utilised by the remaining elevators to handle the additional load during the failure).
- Resourcefulness: resourcefulness can be examined by the alternative actions to evaluate the system' s performance in the absence of sources such as maintenance crew.
- Rapidity: Measure the time to recovery, which is the duration from the moment of failure until the system restores normal performance. (e.g. how long did it take from the moment of failure until the system restored normal performance?)

Step 6. Evaluation of maintenance strategies and resilience improvements: in this step, the resilience metrics are compared across various maintenance strategies. The ultimate goal of the framework is to assess the current resilience of the elevator system and identify opportunities for improvement.

5 Discussion

This research develops a novel simulation-based framework for improving maintenance operations resilience, specifically focusing on elevators as a critical asset in hospital infrastructure. This case study, reported by the National Health Services (NHS) of the UK, aims to address the challenges associated with elevator reliability and maintenance. The framework integrates 4R resilience theory, with DES to model and evaluate maintenance strategies under disruptions. Unlike traditional static resilience assessment (Carlson et al., 2012), the proposed framework adopts a dynamic modelling approach (Sun et al., 2022) that: 1) simulates real-time disruptions and their cascading effects in complex systems (Gallab et al., 2016), 2) quantifies resilience metrics, including robustness (measured as performance degradation during failures) and rapidity (captured via mean-time-to-recovery (MTTR) distribution (Alabdulkarim et al., 2015)), and 3) predictive capability such as redundancy (backup capacity) and resourcefulness (e.g., spare part availability and technician allocation).

The NHS faces significant challenges with maintenance backlogs that can hinder the operational efficiency of critical assets. As of recent reports by NHS Estates Returns Information Collection (ERIC), the maintenance backlog within NHS facilities has reached £13.8 billion in 2023/24, impacting the timely response to maintenance needs and exacerbating issues related to equipment reliability. This backlog can lead to prolonged downtime, which directly affects patient care and operational workflows. Addressing this backlog is essential for enhancing the resilience of maintenance operations, as effective strategies must be implemented to prioritize repairs and maintenance tasks in order to mitigate risks and improve overall service delivery.

The framework's potential is further enhanced through integration with emerging technologies. IoT connectivity can feed real-time operation data into the simulation model, creating a continuous feedback loop that improves prediction accuracy. The Decision Support for Response & Recovery component (box 11) represents a significant advancement in adaptive maintenance management by dynamically adjusting recovery strategies based on real-time system status and learning from historical disruption patterns to optimise future responses.

Focusing on elevators, their reliability is crucial to avoiding delays in transporting patients to critical areas, such as operating theatres or ICUs, thereby minimising impacts on patient flow for less critical conditions. Reliable elevators also enhance staff productivity compared to using stairs and help reduce infection control risks when dedicated elevators are used for patients. Furthermore, consistent elevator performance is essential for transporting visitors and equipment. However, the impact of elevator reliability on patients and staff is often not fully understood or quantified in many hospital environments. While Engineering and Facility Management (EFM) staff may track outage times, they generally do not assess the broader 'business impact' on both staff and patients.

To optimise elevator maintenance, several areas must be considered including planned maintenance regimes that adhere to time-based job plans and compliance with health and safety guidelines of the UK, such as HTM's SFG20 or OEM recommendations. The quality of executed inspections and maintenance routine should also be evaluated to ensure they meet certification standards and completed within Service Level Agreements (SLAs). Implementing predictive and preventive maintenance strategies that maximise sensor data for trend analysis can help trigger events, generate comparative analytics, and provide insights from multiple elevators. Additionally, automating maintenance process- such as event triggers, intervention management (resource allocation, timings, compliance) and incident closure and reporting- can enhance EFM productivity and reduce elevator downtime.

Capturing key incident information during maintenance interventions, including details about component failures, electrical issues, vandalism and damage caused by beds, bins, or equipment transport, is essential. Finally, interpreting the 'business impact' of elevator outages is crucial to ensuring that incidents are appropriately prioritised for maintenance interventions.

Ultimately, optimising maintenance operations is directly linked to enhancing the resilience of those operations, as effective maintenance strategies enable elevators to function reliably, thereby minimising disruptions and improving overall service delivery in hospital environments.

6 Conclusions

This study presents a simulation-based framework designed to enhance the resilience of maintenance operations in critical infrastructure, using hospital elevator systems as a representative case study. By integrating the 4R resilience theory with the discrete event simulation (DES) approach, the framework successfully bridges theoretical constructs and practical applications, allowing for an in-depth analysis of how various maintenance strategies affect system performance under diverse disruption scenarios.

The framework provides a comprehensive methodology—from system definition and failure mode identification to model construction, simulation experimentation, and resilience metric evaluation—enabling a robust assessment of key resilience dimensions, namely robustness, redundancy, resourcefulness, and rapidity. The case study exemplifies how the framework could be employed to quantify the impact of different maintenance strategies, revealing insights such as the potential benefits of preventive maintenance over corrective methods in reducing failure events and enhancing operational resilience.

Moreover, the simulation experiments underscore the framework's versatility and its capacity to offer actionable recommendations for improving maintenance practices. Although the current research focuses on the design and development phase, it establishes a solid foundation for future studies that will further evaluate and refine the framework through real-world data validation and sensitivity analyses. Ultimately, the proposed framework not only enhances decision-making in maintenance operations but also contributes significantly to ensuring the long-term sustainability and reliability of critical infrastructure systems.

Research gap

This study addresses three research gaps in maintenance operations resilience literature; 1) the lack of dynamic assessment tools bridging Bruneau et al.'s 4R theory with operational maintenance decisions (Sun et al., 2022), 2) the absence of quantifiable metrics for evaluating resilience in complex, interdependent infrastructure systems (Gallab et al., 2016), 3) limited integration of simulation-based predictive capabilities with real-time maintenance optimisation (Alabdulkarim et al., 2015).

Future studies

Building on this framework, several future research directions emerge: 1) Empirical performance benchmarking with real-world operational data, such as maintenance logs, to statically validate the framework, 2) Technology integration, such as IoT-enabled digital twins, to assess the framework's predictive accuracy; and 3) policy integration for resilience benchmarking aligned with national infrastructure strategies.

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