EXPLORING CAUSAL LOOPS IN RESILIENT MAINTENANCE OPERATIONS OF BUILT ASSETS: A LITERATURE REVIEW

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Abstract

Maintenance operations account for a significant portion of project lifecycle costs and are subject to disruptions. A potential solution to this problem is to develop resilient strategies to cope with disruptions, ensuring safe and reliable operation of assets. This paper intends to develop a causal loop diagram to depict system downtime causes among resilient maintenance operations of built assets and represent the complex nature of relationships between maintenance outcomes and disruptions. As a result, root causes of major disruption events to maintenance operations of built assets are mapped to inform technological advances that support predictive maintenance such as simulations.

Introduction

The operation and maintenance (O&M) phase is the "longest and costliest phase" of an asset's lifecycle (Chen and Tang, 2019), which can account for up to 80% of the total cost of the asset (Cavka et al., 2015). The cost of maintenance itself can constitute 25% of the overall operation and maintenance cost (Navas et al., 2020). Therefore, improving maintenance operations can significantly reduce the total cost of built assets. 'Maintenance operations' refers to what maintenance activities should be carried out on the asset, when and how the demand for this operation is activated (Gits, 1992). In this study, maintenance operations refer to activities to be undertaken to ensure the acceptable level of functionality of an asset. Maintenance operation is a complex process due to the requirement of incorporating a variety of disciplines, knowledge, human resources (e.g., maintenance crew), tools (diagnostics and predictive technologies), information technology systems (hardware and software), financial resources and physical resource (e.g., spare parts) (BS EN 15341:2019). This complex process can be affected by different sources of uncertainty and disruptions consequently leading to significant financial losses, threatening survival of asset and unserviceability of the assets (Osei-Kyei et al., 2021). In this regard, with the increase of disruption events (man-made and natural disasters) (Dianat, et al., 2021) there is an immediate need for a resilient strategy to improve responsiveness of the asset to the unexpected events and disruptions (Ali et al., 2017). As Hosseini et al. (2016) stated, improving resilience of systems significantly raised for researchers and industries. However, literature shows that there is a lack of clarity in the maintenance operation resilient definitions, concepts, and strategies (Ali et al, 2017, Burroughs, 2017). Simulation is one of the effective methods for modelling maintenance operations and analyzing the efficiency of various scenarios for improving resilience in response to disruptions. It can model the complexity and uncertainties of maintenance operations in a risk-free environment, allowing organizations to observe a system's behavior under various circumstances. The necessary first step to developing a decision-making model for this purpose is to look at the dynamic behavior of system and potential root causes of disruptions to analyze their interactions with each other and on the system and how they work to create the phenomenon (Dianat et al., 2021). In addition, there are some causes whose sources are independent of the system itself; however, the impacts of them amplify disruptions in the system. These interactions can be illustrated via causal loops using system dynamics (SD). The SD shows how components interact throughout the system by going beyond events and searching for behavior patterns (Khorshidi et al., 2023). It also captures, simulates, and estimates the effects of policies, parameters, and components that change dynamically over time on the whole system (Khorshidi et al., 2023) and demonstrates them in a causal loop diagram (CLD).

Methodology

This study is informed by a deductive approach where the qualitative data (pre-existing theory) is analyzed to anticipate certain core concepts. Thereby, an extensive literature review is conducted to identify root causes of disruptions to maintenance operations. In order to make full sense of the findings, a start list of priori categories was generated in line with previous research using the research questions (mentioned below). Data was deductively analyzed to develop clusters of disruption sources (internal to the organization, external to the organization but internal to the network, and external to the organization). Thereafter, a system dynamics approach was used to develop a novel causal loop diagram (CLD) for demonstrating the causality (causes and effects) and interrelationships between identified disruptions, their variables, and sources. CLD is one of the SD modeling that represents the complex and nonlinear relationships between components and can be developed through gaining knowledge about a system as well as discussing and brainstorming with experts (Khorshidi et al., 2023). The CLD helps the user communicate the feedback structure (root causes of a problem) and underlying assumptions (Sushil, 1993). According to Sterman (2000) CLD can *"1) quickly capture your hypotheses about the causes of dynamics, 2) eliciting and capturing the mental models of individuals or teams; and 3) communicating the important feedback, you believe are responsible for a problem."*

Research questions:

1) What are the root causes of major disruptions to the maintenance operation of assets?

2) How do the identified events impact the maintenance operations (e.g., what aspects of maintenance operation are affected)?

3) How can the resilience of maintenance operations be improved (e.g., what capabilities are required to be improved to reduce the impact of disruptions)?

Literature review

Maintenance operation resilience

Resilience is the ability of a system to absorb, resist, adapt, and recover from disruptions (Osei-Kyei et al., 2021 and Durán et al., 2020) without interrupting the full performance of the system. If a system is substantially affected, its resilience gives it the ability to fully recover its function in the shortest possible time (Hosseini et al., 2016). In this paper, resilience of maintenance operations refers to the ability of the asset to continue its operations while subjected to disruptions. Bukowski and Werbińska-Wojciechowska (2021) developed a resilient-based maintenance support system with four subsystems including monitoring, responding, learning, and anticipating (as shown in Figure 1) to minimize the consequences of disruptions. The main task of the monitoring phase is to detect disruptive events. The response to disruptive events should be authorized, effective, and analyzed after the disruption. However, as resources (e.g., information, maintenance crew, materials, and tools) in organizations are not infinite, responses can only be prepared for a limited number of disruptive events or situations that occur frequently (Bukowski and Werbińska-Wojciechowska, 2021). The learning subsystem is based on the organization's behavior and actions in specific situations. The primary purpose of learning is to improve the organization's ability to respond, monitor, and anticipate disruption as well as changing values and criteria in the organization if required. The final phase is anticipation. The key purpose of this phase is to think and imagine outside the event horizon, conceive different possibilities, and predict what can happen in the future.

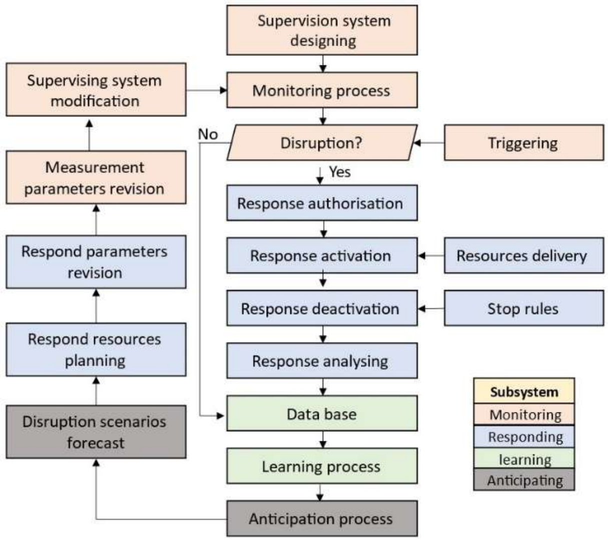

Figure 1: A functional diagram of a maintenance support system (after Bukowski and Werbińska-Wojciechowska. 2021)

Sun et al. (2022) examined another framework which is a resilience-based approach to maintenance asset and operational cost planning comprising three principal capacities: absorption, adaption, and restoration. As shown in Figure 2, 'Absorption' (R0) is the capacity of a system to withstand a disruption, absorb its consequences, and return to its original state. The strength of the absorption capacity is based on the structure of the system and the intensity of the interruption. A system with higher absorption capacity requires less effort to recover from a disruption (Sun et al., 2022). 'Adaption' (R1) is the ability of a system to recover a certain amount of lost performance without the need for external maintenance actions (Abimbola and Khan, 2019). And 'restoration' (R2) is the phase in which the system is restored to a new equilibrium state which can be lower, equal, or greater (green dotted line) than its original state by employing external maintenance actions.

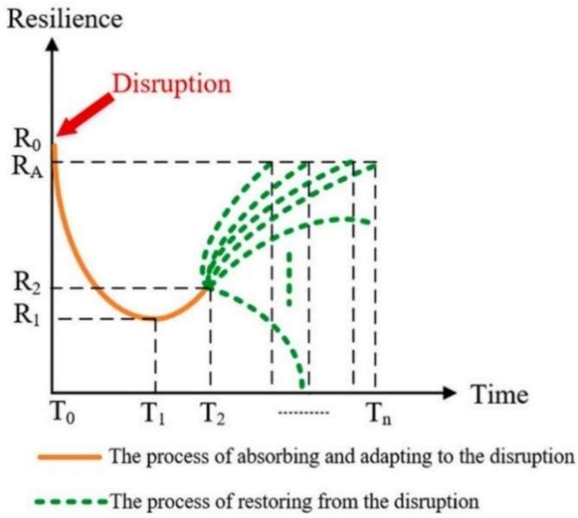

Figure 2: The resilience behaviour of a system subject to disruptions (after Sun et al., 2022)

Shekarian and Mellat Parast (2021) defined four resilience enhancers (flexibility, agility, collaboration, and redundancy) and examined the effect of each enhancer on five types of disruptions to a network (demand, supply, process, control, and environmental disruptions) and realized that adopting appropriate enhancers has great impacts on organizational performance while being affected by disruptions. To improve resilience in an organization, all the affective variables are required to be identified. In this regard, disruptions and their root causes to the maintenance operations categorized are discussed below.

Disruption to maintenance operation

Sources of disruptions to a system can be categorized into three types: 1) internal to the organization, 2) external to the organization but internal to the network, and 3) external to the network (Shekarian and Mellat Parast, 2021, Sun et al., 2022). Shekarian and Mellat Parast (2021) defined five types of disruptions to a network including process and control risks (internal to the firm), demand and supply risks (external to the firm but internal to the network) and environmental risks (external to the network) and classified supply chain disruptions into these categories as shown in Figure 3 below.

The following section discusses the sources of disruptions to the maintenance operation of built assets based on the identified categories discussed.

Maintenance process risks: process risks involve potential deviations from producing the desired quality and quantity at the right time (Shekarian and Mellat Parast, 2021). Root causes of maintenance operations process risks can be referred to lack of maintenance crews or skilled workers (e.g., labor strikes), lack of spare parts (caused by deficiency in inventory management and logistic network), adequate budgetary resources for maintenance costs, lack of diagnostic and preventive technologies tools, and interruptions to information communication technology (ICT). For example, cyber-attacks are one type of ICT disruption. In recent years, the development of digital platforms for the operation and maintenance of assets to exchange and store data has benefited organizations but it has also made them more vulnerable to cyber-attacks (Ghadiminia et al., 2022).

There are some additional sources of process risks depending on the maintenance approach adapted in the organization, such as failure in the data transmission network (failures in sensors and IoT networks), breakdown of external or internal IT infrastructure, insufficient maintenance records, inaccessibility to data in real time, and lack of decision support systems.

Control risks: "control risk or network risk involves the assumptions, rules, systems, and procedures that govern how an organization exerts control over its processes" (Shekarian and Mellat Parast, 2021). Various maintenance approaches, including corrective maintenance (unscheduled and event-driven tasks) and proactive maintenance (time-based or planned preventative maintenance, and condition-based maintenance) have different maintenance standards, regulations, and legislation (Miles et al., 2019). However, many maintenance standards have been developed in a way that they provide a common ground for a harmonized maintenance approach (Miles et al., 2019). These legislation and regulations outline the general requirements for defining all types of maintenance (e.g., EN 13306), present general recommendations for the technical documentation of maintenance (e.g., EN 13460), provide generic descriptions of maintenance process (e.g., EN 17007) among others but they lack local legislation to mitigate health, safety, and environmental (HSE) risks (Miles et al., 2019). On the other hand, compliance with such requirements is typically governed and managed by experienced system experts in the organization; therefore, lack of interorganizational policies to embed these rules is another source of control risk. Other examples of sources of this type of risk are lack of safety policies and asset management policies.

Demand risks: this type of risk involves any possible gap between actual and anticipated demand and any potential disruptions in the flow of material and information within the network or between the focal firms and the market (Shekarian and Mellat Parast, 2021).

Demand forecasting is a challenging task as the demand is intermittent and lumpy. From maintenance operations perspective, unanticipated demands (e.g., skilled workers), high demand services, uncertain maintenance demands, and insufficient information for forecasting demands are examples of demand risks.

Supply risks: these risks entail: 1) failure to supply spare parts in terms of time, quantity, and quality; and 2) disruptions to the flow of products and information within or outside the organization. Turan et al. (2020) stated that unavailability of spare parts accounts for up to 80% of all system downtime in the maintenance operations. Sources of supply risk associated with maintenance operations can be referred to insufficient logistics networks (failures in nodes (facilities) or links), poor inventory planning, and lack of outsourcing and globalization.

Environmental risks: these are risks external to the organization and are beyond the control of organizations. One of the examples of sources of environmental risk is natural disasters. As a result of climate change, natural disasters, such as floods, have occurred more frequently and intensively in the past decades (Song et al., 2016 and Feldmeyer et al., 2020). In fact, a 2% rise in the annual incidence of natural disaster was documented during the past 15 years and built assets are one of the most vulnerable areas to be affected by natural disasters (Bang and Burton, 2021). Other examples include war, epidemics (e.g., COVID-19), and political instability.

In addition to the previously described disruptions, evaluating 'co-occurring' or 'compounding failures' (when two or more sources of disruption occur

Supply chain sources of risks				
Internal to the firm		External to the firm but internal to the supply chain network		External to the network
Process risk	**Control risk**	**Demand risk**	**Supply risk**	**Environment risk**
Machine failure	Lack of collaborative planning	Volatile demand	Outsourcing and globalisation	Natural disaster
Labor strike	Asset management policy	Market changes	Sudden hike in costs	Terrorism and war
Product quality problem	Safety stock policy	Innovation competitors	Supplier commitment	Political instability
Equipment unreliability	Batch size or order quantity policy	Unanticipated demand	Supplier insolvency	Social and political grievance
Operator unavailability	Transportation management policy	Unusual customer payment delays	Variability of replenishment lead time	Technology changes
Bottleneck or inflexible process		Competition changes	Supplier quality problem	Diseases or epidemics
Breakdown of external or internal IT infrastructure	Asymmetric power relationships	Forecasting errors	Supplier bankruptcy	Economic downturn
			Sudden supplier demise	
Reliability of supporting communication system	Poor visibility along the supply chain	Insufficient information from customer order	Poor logistics performance of suppliers	
			Capacity fluctuations or shortage in supply market	

Figure 3: Supply chain sources of risks and disruptions (after Shekarian and Mellat Parast, 2020)

concurrently) and ‘cascading failures’ (when a disruption happens after the initial failure (horizontal-correlated cascading failures) or when a disruption can cause failure at the upper layers of the system (vertical-correlated cascading failures) (Moffatt et al., 2021) is crucial because they have high impacts on the maintenance operations and are more difficult to fix.

Due to the variety of sources of disruptions to the maintenance operations, developing strategies to mitigate disruptions by making the maintenance operations more resilient and responsive is crucial. Access to reliable and quality data is critical for achieving this aim and developing a simulation-based decision support system.

Technologies and disruptions

There are two types of disruptions to maintenance operations: 1) ‘anticipated’ disruptions, like demand risks, which can be predicted based on historical data related to their nature, range, and frequency, and 2) ‘unanticipated’ disruptions like environmental disruptions, which are not dependable or consistent with historical data (Tsiamas and Rahimifard, 2021).

In recent years, integrating BIM (building information modeling), GIS (geographic information system), IoT (Internet of Things) and computerized maintenance management system (CMMS) such as IBM Maximo, ARCHIBUS, EcoDomus, FM Systems, AssetWorks, or eMaint among others has supported maintenance operations by improving decision-making (Ma et al., 2020). These approaches use asset life-cycle data and maintenance records to detect possible failures (Moradi et al., 2021). For example, BIM can be used to minimize maintenance processes and supply disruptions by providing equipment location data, equipment maintenance data, cost data, and historical maintenance records. Also, it can be adopted to deal with control disruptions by increasing collaboration between participants and identifying potential risks. IoT and machine learning tools can be adapted to minimize supply and maintenance process disruptions, as they can predict when an asset or equipment requires maintenance actions (before breakdown point) and provide an accurate assessment of equipment health conditions based on data collected by sensors (Shamayleh et al., 2020).

Digital twins, through the synergy of several technologies including IoT, artificial intelligence (AI) and BIM integrate multi-source data into one single system to support decision-making for maintenance processes. AI can be adapted to improve maintenance demand planning with identification of demand pattern, market trend, and efficient forecasting. However, in order to take advantage of AI, clean and quality data, sufficient technological infrastructure, resource availability, and area experts are necessary. This will include supplying spare parts.

Results and discussion

The initial contribution to this research is to define the sources of disruptions to the maintenance operations and propose a classification based on these criteria. The classification includes ‘Internal disruptions’ (process risk, control risks), ‘External to the organization but internal to the network’ (demand risks, supply risks) and ‘External disruptions’ (environmental risks) to the maintenance operations. The connections between sources of disruptions and their root causes to improve organizational responses are mapped. To achieve this, SD is adapted due to its capability of capturing the dynamic behavior of complex systems and depicting the dynamic interactions of maintenance operations in different areas such as economic, risks, humanity, environmental, and supply chain. Causal loop diagrams in SD are employed for developing a hypothetical and knowledge based CLD (see Figure 4) to demonstrate maintenance operation system structure, complexity, and feedback processes.

In CLD, each box is a variable and causal relationships between each variable are represented as arrows with polarities (positive and negative signs). In this context, a positive sign means that a change in one variable led to a change in the same direction, and a negative sign led to a change in the opposite direction. The causal loops can be positive (reinforcing) or negative (balancing). “A positive loop is associated with exponential growth. However, a

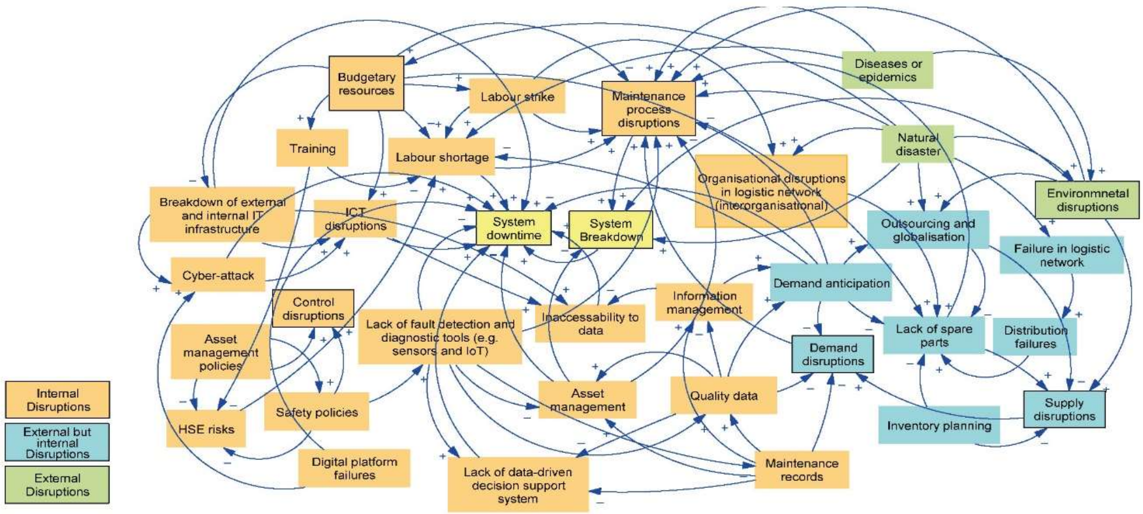

Figure 4: Causal loop diagram - root causes of disruptions to the maintenance operations.

negative loop tends to reach a balance point" (Khorshidi et al., 2023). Color coding is adapted to distinguish different types of disruptions (internal, external, external but internal) and their interconnected factors.

The advantage of CLD is that it can connect non-linear relationships between different sources and varieties and present casualty of system breakdown or system downtime. As it can be seen in Figure 4, the relationship between maintenance process disruptions and training is not a linear relationship. For example, budgetary resources have a positive impact on training; the higher the budget, the more training is conducted. So, training has a negative impact on maintenance process disruptions through budgetary resources, which is a dynamic variable.

The proposed CLD requires it to be tested empirically and validated by experts in the future. Once the CLD is validated, it can be transformed and formulated for the model and run for results. By adopting simulation, different recovery strategies on maintenance operations performance affected by disruptions can be analyzed. To achieve this, different scenarios in terms of the presence or absence disturbances and presence or absence of a mitigation strategy can be examined. The impact of mitigation strategies will be analyzed in regard to time and cost of recovery.

The CLD aims to provide a base for the development of accurate simulation models in the context of maintenance disruptions. In this context, the CLD can be used to ensure that the all the relevant and impactful data on the simulated variable is considered in the simulation. For example, let's envision creating a simulation model that aims to determine the impact of disruptions on 'spare parts supply chain'. Following the CLD across the multiple links that connect 'Supply Disruptions' with the rest of the variables, one can ensure that all the relevant variables are included in the model. On the first instance, 'outsourcing and globalization', 'logistic networks', 'lack of spare parts', 'inventory planning' and 'environmental disruptions' are connected, then the variables linked to those need to be considered and so on. With the CLD in mind, a comprehensive list of variables required to accurately simulate an outcome from a major disruption is given. However, the importance and impact of each variable on the outcome is not provided on the CLD and simplification of simulation models from the initial list of variables is a work in progress.

Conclusion and further study

This study presents a review of the literature to explore potential root causes of disruptions to the maintenance operations of built assets to improve maintenance operations resilience. Due to the dynamic nature of this system, system dynamics theory is used to demonstrate relationships and feedback loops between related factors to enhance understanding of the system complexity and non-linear causality. It also shows the need of multidisciplinary resilience approaches (current research gap). As a result, academics and practitioners are better equipped with the technological advances that support predictive maintenance, such as simulations, for improving resilience of maintenance operations in the practices. It is mentionable that practices required some practical changes for adopting resilience policies that necessitated a rethinking and adaptation of new governance approaches.

The limitations for this study are: 1) there is not much available literature about disruptions to maintenance operations as well as improving resilience in maintenance operations (research gap); and 2) the literature review is secondary data, not primary data: therefore, quality and accuracy of data is limited.

By understanding the current gaps, future research will develop a digital simulation-based decision-support system (based on the proposed CLD) to improve resilience of maintenance operations of built assets. Survey research including expert interviews will be conducted to 1) analyze the intensity and frequency of experienced disruptions in the medium-to-large size organizations, 2) explore organizational mitigation plans to recover from the disruptions, 3) evaluate the efficiency of the mitigation strategies adapted, 4) evaluate resilient capabilities in the organization absorption, adaption, and restoration.

Also, given that most of the research has focused on the pre-disruption stage, future studies are recommended that also investigate the post-disruption stage and its management.

References

Abimbola, M., & Khan, F. (2019). Resilience modeling of engineering systems using dynamic object-oriented Bayesian network approach. Computers & Industrial Engineering, 130, 108-118. https://doi.org/10.1016/j.cie.2019.02.022

Ali, A., Mahfouz, A., & Arisha, A. (2017). Analysing supply chain resilience: Integrating the constructs in a concept mapping framework via a systematic literature review. Supply Chain Management: An International Journal, 22(1), 16-39. https://doi.org/10.1108/scm-06-2016-0197

Bukowski, L., & Werbińska-Wojciechowska, S. (2021). Using fuzzy logic to support maintenance decisions according to resilience-based maintenance concept. Eksploatacja i Niezawodność – Maintenance and Reliability, 23(2), 294-307. https://doi.org/10.17531/ein.2021.2.9

Burroughs, S. (2017). Development of a tool for assessing commercial building resilience. Procedia Engineering, 180, 1034-1043. https://doi.org/10.1016/j.proeng.2017.04.263

Cavka, H., Staub-French, S., & Pottinger, R. (2015). Evaluating the alignment of organizational and project contexts for BIM adoption: A case study of a large owner organization. Buildings, 5(4), 1265-1300. https://doi.org/10.3390/buildings5041265

Chen, C., & Tang, L. (2019). BIM-based integrated management workflow design for schedule and cost planning of building fabric maintenance. Automation in Construction, 107, 102944. https://doi.org/10.1016/j.autcon.2019.102944

Dianat, H., Wilkinson, S., Williams, P., & Khatibi, H. (2021). Planning the resilient city: Investigations into using “causal loop diagram” in combination with “UNISDR scorecard” for making cities more resilient. International Journal of Disaster Risk Reduction, 65, 102561. https://doi.org/10.1016/j.ijdrr.2021.102561

Durán, O., Aguilar, J., Capaldo, A., & Arata, A. (2020). Fleet resilience: Evaluating maintenance strategies in critical equipment. Applied Sciences, 11(1), 38. https://doi.org/10.3390/app11010038

Feldmeyer, D., Wilden, D., Jamshed, A., & Birkmann, J. (2020). Regional climate resilience index: A novel multimethod comparative approach for indicator development, empirical validation and implementation. Ecological Indicators, 119, 106861. https://doi.org/10.1016/j.ecolind.2020.106861

Ghadiminia, N., Mayouf, M., Cox, S., & Krasniewicz, J. (2021). BIM-enabled facilities management (FM): A scrutiny of risks resulting from cyber attacks. Journal of Facilities Management, 20(3), 326-349. https://doi.org/10.1108/jfm-01-2021-0001

Gits, C. (1992). Design of maintenance concepts. International Journal of Production Economics, 24(3), 217-226. https://doi.org/10.1016/0925-5273(92)90133-r

Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. Reliability Engineering & System Safety, 145, 47-61. https://doi.org/10.1016/j.ress.2015.08.006

Khorshidi, H. A., Marshall, D., Goranitis, I., Schroeder, B., & IJzerman, M. (2023). System dynamics simulation for evaluating implementation strategies of genomic sequencing: Tutorial and conceptual model. Expert Review of Pharmacoeconomics & Outcomes Research, 24(1), 37-47. https://doi.org/10.1080/14737167.2023.2267764

Ma, Z., Ren, Y., Xiang, X., & Turk, Z. (2020). Data-driven decision-making for equipment maintenance. Automation in Construction, 112, 103103. https://doi.org/10.1016/j.autcon.2020.103103

Maintenance process and associated indicators. (n.d.). https://doi.org/10.3403/30340662

Maintenance. Documentation for maintenance. (n.d.). https://doi.org/10.3403/30163968

Maintenance. Maintenance key performance indicators. (n.d.). https://doi.org/10.3403/30140422

Maintenance. Maintenance terminology. (n.d.). https://doi.org/10.3403/30187553

Moffatt, J., Zaitouny, A., Hodkiewicz, M. R., & Small, M. (2021). Detecting asset cascading failures using complex network analysis. IEEE Access, 9, 120624-120637. https://doi.org/10.1109/access.2021.3108427

Moradi, P., Asadi, M. J., Ebrahimzadeh, N., & Yarahmadi, B. (2021). Ilam tunnels inspection, maintenance, and rehabilitation: A case study. Tunnelling and Underground Space Technology, 110, 103814. https://doi.org/10.1016/j.tust.2021.103814

Navas, M. A., Sancho, C., & Carpio, J. (2020). Disruptive maintenance engineering 4.0. International Journal of Quality & Reliability Management, 37(6/7), 853-871. https://doi.org/10.1108/ijqrm-09-2019-0304

Ngenyam Bang, H., & Church Burton, N. (2021). Contemporary flood risk perceptions in England: Implications for flood risk management foresight. Climate Risk Management, 32, 100317. https://doi.org/10.1016/j.crm.2021.100317

Osei-Kyei, R., Tam, V., Ma, M., & Mashiri, F. (2021). Critical review of the threats affecting the building of critical infrastructure resilience. International Journal of Disaster Risk Reduction, 60, 102316. https://doi.org/10.1016/j.ijdrr.2021.102316

Shamayleh, A., Awad, M., & Farhat, J. (2020). IoT based predictive maintenance management of medical equipment. Journal of Medical Systems, 44(4). https://doi.org/10.1007/s10916-020-1534-8

Shekarian, M., & Mellat Parast, M. (2020). An integrative approach to supply chain disruption risk and resilience management: A literature review. International Journal of Logistics Research and Applications, 24(5), 427-455. https://doi.org/10.1080/13675567.2020.1763935

Song, X., Zhang, Q., Sekimoto, Y., Shibasaki, R., Yuan, N. J., & Xie, X. (2016). Prediction and simulation of human mobility following natural disasters. ACM Transactions on Intelligent Systems and Technology, 8(2), 1-23. https://doi.org/10.1145/2970819

Sun, H., Yang, M., & Wang, H. (2022). Resilience-based approach to maintenance asset and operational cost planning. Process Safety and Environmental Protection, 162, 987-997. https://doi.org/10.1016/j.psep.2022.05.002

Tsiamas, K., & Rahimifard, S. (2021). A simulation-based decision support system to improve the resilience of the food supply chain. International Journal of Computer Integrated Manufacturing, 34(9), 996-1010. https://doi.org/10.1080/0951192x.2021.1946859

Turan, H. H., Atmis, M., Kosanoglu, F., Elsawah, S., & Ryan, M. J. (2020). A risk-averse simulation-based approach for a joint optimization of workforce capacity, spare part stocks and scheduling priorities in maintenance planning. Reliability Engineering & System Safety, 204, 107199. https://doi.org/10.1016/j.ress.2020.10719