Lecture Notes in Civil Engineering

José C. Matos · Paulo B. Lourenço ·
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20th International Probabilistic Workshop

IPW 2024

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Preface

The imperative of managing uncertainty and facilitating informed decision-making renders evident the criticality of using probabilistic and reliability disciplines. This can be seen in the most recent advances in infrastructure maintenance and management, especially those related to safety under extreme events and security to non-conventional threats and dangers. Additionally, the escalating significance of climate change phenomena is incontrovertible, mostly affecting the likelihood and consequences of various natural hazards. Consequently, there is a need to develop deeper studies on probability and statistics for data science, as well as on its application to system analysis, combining these tools to face huge uncertainties.

The International Probabilistic Workshop (IPW) series started in 2003 as the Dresden Probabilistic Symposium at the Technical University of Dresden and repeated in 2004. In 2005, the 3rd edition held in Vienna was renamed as International Probabilistic Workshop. Subsequent IPWs took place in Berlin (2006), Ghent (2007), Darmstadt (2008), Delft (2009), Szcecin (2010), Braunschweig (2011), Stuttgart (2012), Brno (2013), Weimar (2014), Liverpool (2015), Ghent (2016), Dresden (2017), Vienna (2018), Edinburgh (2019) and Stellenbosch (2022).

The IPW 2020, planned to take place in September 2020 at the University of Minho, was postponed to May 2021 and transitioned to a digital format due to the global COVID-19 pandemic. IPW 2024 offers a renewed opportunity to gather the IPW Community in Guimarães, Portugal. Undoubtedly, IPW 2024 keeps the high-quality level of previous editions by bringing together high-calibre scientific contributions (51 papers spanning 22 countries) covering different applications and approaches to probabilistic-based methods.

The editors express their profound gratitude to all contributing authors, keynote speakers and attendees for their valuable contributions, to the members of the Scientific Committee for their meticulous work, and to the Workshop Secretariat for their dedicated teamwork.

May 2024

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Life-Cycle Probabilistic Multi-objective Optimum SHM Planning

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Abstract. Structural Health Monitoring (SHM) is widely utilized to detect potential damage and predict the structural performance of deteriorating structures. Timely damage detection and accurate structural performance prediction are crucial for ensuring structural safety and managing the service life of deteriorating structures. This paper addresses a life-cycle probabilistic multi-objective optimization for SHM planning. The life-cycle probabilistic multi-objective optimum SHM planning can be based on availability, damage detection, reliability, service life, life-cycle cost, and risk. When initial information is insufficient for reliable damage prediction, an availability-based objective is useful for optimum SHM planning. Otherwise, the damage detection delay, maintenance delay, reliability index, service life, life-cycle cost, and risk can be used for optimum SHM planning. They are formulated by integrating damage initiation and propagation, damage detection, and the effects of inspection and maintenance actions on service life, reliability, life-cycle cost, and risk. Approaches to solving the multi-objective optimization efficiently and multi-attribute decision-making to select the most appropriate solution among the Pareto optimal set are presented. Furthermore, an updating process incorporating information from SHM is outlined to enhance the accuracy of SHM planning.

Keywords: Availability · Damage Detection · Life-Cycle Cost · Maintenance · Multi-Objective Optimization · Reliability · Risk · Service Life · SHM planning

1 Introduction

Deteriorating structures demand maintenance interventions to sustain performance above the predefined threshold during their service life [1–3]. By implementing maintenance interventions, it's possible to delay the deterioration process, repair existing damage, enhance structural performance, and extend the service life of the structure [4–6]. For cost-effective maintenance, accurate assessment and prediction of the deterioration process and timely damage detection are crucial [7, 8]. However, they pose challenges for practical bridge management due to epistemic and aleatory uncertainties [9–11]. Consequently, the adoption of periodic inspections and maintenance has been a prevalent practice for several decades. To address the cost-effectiveness and uncertainty associated with management, it is necessary to adopt structural health monitoring (SHM) optimally [12–14].

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In this paper, a life-cycle probabilistic multi-objective optimization for SHM planning is presented. The life-cycle probabilistic optimum SHM planning can be based on multiple objectives considering availability, damage detection, maintenance, reliability, service life, life-cycle cost, and risk. When initial information is insufficient for reliable damage prediction, objectives based on the availability of monitoring data are useful for optimum SHM planning. Otherwise, optimum SHM planning can be based on objectives considering damage detection, reliability index, service life, life-cycle cost, and risk. Their formulations require integrating damage initiation and propagation, damage detection, and the effects of inspection and maintenance actions on service life, reliability, life-cycle cost, and risk. In addition to formulating objectives for optimal SHM planning, this study presents efficient approaches for solving multi-objective optimization and employing multi-attribute decision-making to select the most suitable solution from the Pareto-optimal set. Furthermore, an updating process that incorporates information from SHM is outlined to enhance the accuracy and reliability of SHM planning.

2 Framework for Life-Cycle Probabilistic Multi-objective Optimum SHM Planning

The framework for life-cycle probabilistic multi-objective optimum SHM planning consists of three parts: (a) formulations of the objectives, (b) multi-objective optimization and decision making, and (c) updating process with the monitored data, as shown in Fig. 1. Through the presented framework, the monitoring starting time and duration can be optimized. Through the multi-objective optimization process, multiple well-balanced solutions are obtained, which provide flexibility for managers in determining the best Pareto optimal solution. The monitored data is utilized to update the parameters related to the formulations of objectives, and thereby reducing the uncertainties associated with SHM planning. The three parts of the framework are iteratively applied throughout the life-cycle of deteriorating structures.

3 Objectives for Probabilistic Optimum SHM Planning

The formulation of objectives for optimum SHM planning considers the availability of monitoring data, damage detection, reliability index, service life, life-cycle cost, and risk [15]. The availability of monitoring data can be used when the initial information for damage initiation and propagation is insufficient. If there is sufficient information for damage initiation and propagation, the objectives based on damage detection, service life, reliability, life-cycle cost, and risk can be applied for SHM planning [4, 16]. Table 1 summarizes the nine objectives (i.e., O1 to O9) and required estimations for the formulations of objectives.

The availability-based objectives are O1 = maximization of expected availability of monitoring data and O2 = minimization of expected monetary loss. The damage detection-based objectives include O3 = minimization of expected damage detection delay (or minimization of expected damage detection time), O4 = maximization of probability of damage detection, and O5 = minimization of expected maintenance delay.

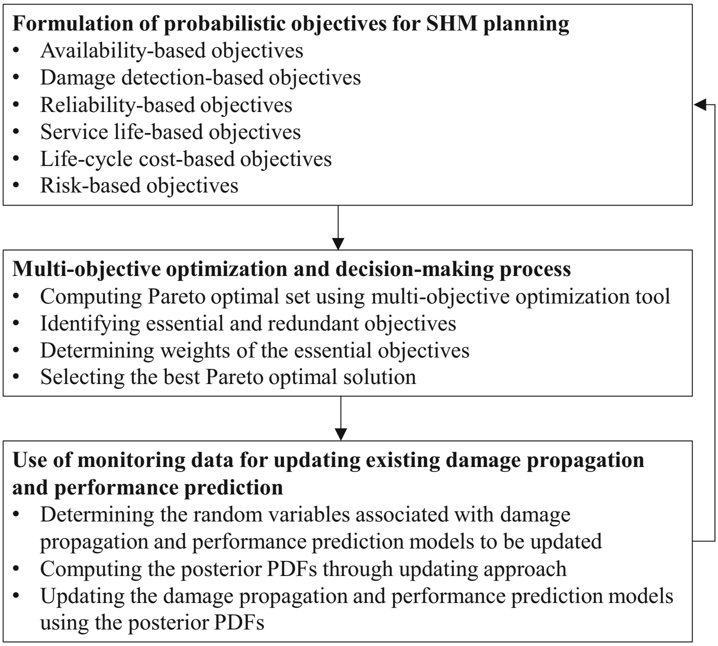

Fig. 1. Framework for life-cycle probabilistic multi-objective optimum SHM planning.

Table 1. Objectives and required estimations for their formulations

Objectives	Required estimations
O1 = maximization of expected availability of monitoring data	RE1
O2 = minimization of expected monetary loss	RE1 + RE2
O3 = minimization of expected damage detection delay (or minimization of expected damage detection time)	RE3
O4 = maximization of probability of damage detection	RE3
O5 = minimization of expected maintenance delay	RE3 + RE4
O6 = maximization of expected extended service life (or expected service life extension)	RE3 + RE4 + RE5
O7 = maximization of reliability	RE3 + RE4 + RE5
O8 = minimization of expected total life-cycle cost	RE3 + RE4 + RE5
O9 = minimization of risk	RE3 + RE4 + RE5 + RE6

Note: RE1 = monitoring cost during a given monitoring period; RE2 = monetary loss due to unavailable monitoring data; RE3 = damage initiation and propagation; RE4 = relation between the degree of damage and probability of maintenance; RE5 = effects of damage detection and maintenance application on reliability, service life, and life-cycle cost; RE6 = direct and indirect monetary loss due to structural failure

The objectives O6, O7, and O8 are based on service life, reliability, and life-cycle cost, respectively. Optimum SHM planning can also be based on O9 = minimization of risk. The detailed formulations of O1 – O8 are available in Kim & Frangopol [15] and Frangopol & Kim [4, 16].

The risk is the probabilistic performance indicator to integrate the occurrence probability of an adverse event (e.g., structural failure, malfunction) and the resulting monetary loss [17]. The risk due to the failure of the ith component of a system RS_i is expressed as [17, 18]

$$RS_i = RS_{dir,i} + RS_{ind,i} \tag{1}$$

The direct risk $RS_{dir,i}$ and indirect risk $RS_{ind,i}$ in Eq. (1) are estimated, respectively, as

$$RS_{dir,i} = p_{f,i} \cdot C_{dir,i} \tag{2a}$$

$$RS_{ind,i} = p_{f,i} \cdot p_{f,sub|i} \cdot C_{ind,i} \tag{2b}$$

where $p_{f,i}$ = probability of failure of the ith component; $p_{f,sub|i}$ = probability of system failure caused by the failure of the ith component; $C_{dir,i}$ = direct monetary loss; and $C_{ind,i}$ = indirect monetary loss. Using the damage detection time t_{det}, the probability of failure of the ith component $p_{f,i}$ can be computed as [4, 16]

$$p_{f,i} = P\left(t_{crt,i} - t_{det,i} < 0\right) \tag{3}$$

where $t_{crt,i}$ is the time to reach the critical degree of damage of the ith component, and $t_{det,i}$ is the damage detection time. Since the damage initiation and propagation are uncertain, $t_{crt,i,}$ and $t_{det,i}$ can be treated as random variables. The damage detection time $t_{det,i}$ is estimated considering the relation among the damage initiation/propagation, monitoring starting time, and monitoring duration [4, 15, 16]. The direct monetary loss $C_{dir,i}$ is the required cost for the replacement of the ith component. The indirect monetary loss $C_{ind,i}$ includes operating cost, time-loss cost, and accident cost [17, 19]. The SHM planning can be optimized to minimize the risk caused by the failure of the monitored components.

4 Multi-objective Optimization and Decision Making

When more than two objectives for optimum SHM planning are considered simultaneously, the multiple-objective optimization problem can be solved using various methods such as genetic algorithms (GA), weight sum method, lexicographic method, and bounded objective, among others [20]. As a result, the Pareto optimal solutions can be obtained. The GA is widely used to find all Pareto optimal solutions regardless of the continuity or differentiability of the objective functions [16, 20]. The general formulation of the multi-objective optimization for SHM planning can be expressed as

$$\begin{aligned} \text{Find} \quad \mathbf{t_{ms}} &= \left\{t_{ms,1}, t_{ms,2}, \ldots, t_{ms,Nmon}\right\} \\ \mathbf{t_{md}} &= \left\{t_{md,1}, t_{md,2}, \ldots, t_{md,Nmon}\right\} \end{aligned} \tag{4a}$$

$$\begin{aligned}&\text{which minimizes } \Omega^{(-)} = \{O2, O3, O5, O8, O9\}\\ &\text{and/or maximizes } \Omega^{(+)} = \{O1, O4, O6, O7\}\end{aligned} \tag{4b}$$

$$\text{subject to } g_k(\mathbf{t_{ms}}, \mathbf{t_{md}}) \leq 0 \quad k = 1, 2, \ldots n_c \tag{4c}$$

$$\mathbf{t}^-_{\mathbf{ms}} \leq \mathbf{t_{ms}} \leq \mathbf{t}^+_{\mathbf{ms}} \text{ and/or } \mathbf{t}^-_{\mathbf{md}} \leq \mathbf{t_{md}} \leq \mathbf{t}^+_{\mathbf{md}} \tag{4d}$$

where $\mathbf{t_{ms}}$ and $\mathbf{t_{md}}$ are the vectors of design variables (i.e., monitoring starting times $t_{ms,i}$ and monitoring duration $t_{md,i}$), N_{mon} is the number of monitorings, $\Omega^{(-)}$ and $\Omega^{(+)}$ indicate the objective sets to be minimized and to be maximized, respectively, $g_k(\mathbf{t_{ms}}, \mathbf{t_{md}})$ is the kth inequality constraint among n_c constraints, and $\mathbf{t}^-$ and t^+ are the vectors of lower and upper bounds of the design variable $\mathbf{t}$.

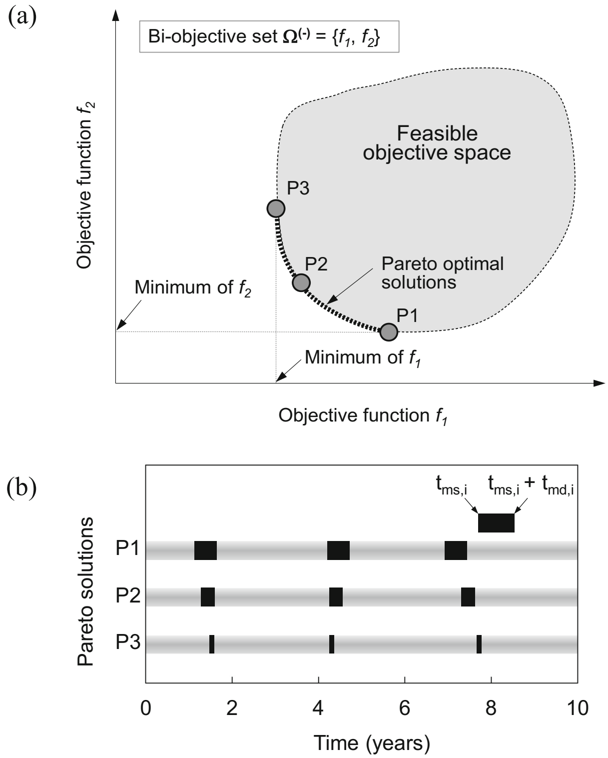

Fig. 2. Bi-objective optimization for SHM planning: (a) feasible objective space and Pareto optimal solutions; and (b) monitoring starting times and monitoring durations for the Pareto solutions P1, P2 and P3 presented in (a).

Figure 2(a) shows the feasible objective space and Pareto optimal solutions when two objectives to be minimized are considered. Any solution among the Pareto optimal solutions can be used for the optimum SHM planning. The monitoring starting times and monitoring durations of the representative Pareto solutions P1, P2 and P3 in Fig. 2(a) are illustrated in Fig. 2(b).

Decision making is the process to select the best solution from the computed Pareto optimal set, which determines the weight of the essential objectives, and estimates the overall assessment value of the Pareto optimal solutions [4, 15, 16]. The essential objective set indicates the minimal set of objectives that generates an equivalent Pareto front of the multi-objective optimization when compared to the original objective set. Through the dominance relation-based approach [21], the essential objective set can be identified. When depicting Pareto optimal solutions in multi-objective optimization with fewer than four objectives, the Cartesian coordinate system is useful. However, visualizing solutions with more than three objectives becomes challenging. To address this, the parallel coordinate system can be employed for the effective representation of Pareto optimal solutions. As shown in Fig. 3, in the parallel coordinate system, the vertical axes denote the values of the objective, and each Pareto solution is represented by a polyline connecting the corresponding values along the vertical axes.

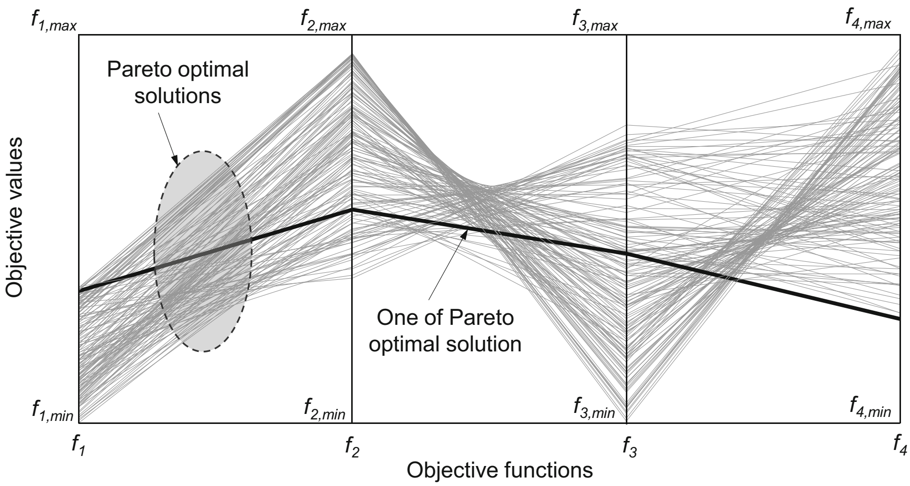

Fig. 3. Pareto solutions of a multi-objective optimization problem with four objectives in the parallel coordinate system.

The weights for essential objectives are calculated using various objective weight determination methods such as the standard deviation (SD) [22], criteria importance through the inter-criteria correlation (CRITIC) [23], and correlation coefficient and standard deviation (CCSD) [24] methods. Subsequently, multiple attribute decision-making approaches, including simple additive weighting (SAW) [25], technique for order preference by similarity to ideal solution (TOPSIS) [26], and elimination and choice expressing the reality (ELECTRE) [27] methods, are applied to estimate the overall assessment values of Pareto optimal solutions with the computed weights of essential objectives. The best optimal solution results in the largest overall assessment value.

5 Updating with Monitored Data

The optimum SHM planning is based on the multiple objectives considering damage propagation prediction, as shown in Table 1. Therefore, improving the accuracy of damage propagation prediction is crucial for enhancing the effectiveness of SHM planning. It can be achieved through the updating the damage propagation prediction with monitoring data [7, 8, 10, 16]. During the last two decades, various approaches for use of the monitoring data to update the damage propagation and structural performance prediction have been developed [4, 15, 16]. Most of updating approaches are based on the Bayesian theorem, which is generally expressed as [28]

$$f''_{\Theta}(\theta) = k \cdot L(\theta) \cdot f'_{\Theta}(\theta) \tag{5}$$

where $f''_{\Theta}(\theta)$ = updated probability density function (PDF) of the parameter θ; k = normalizing constant; $L(\theta)$ = likelihood function; and $f'_{\Theta}(\theta)$ = initial PDF of the parameter θ. The parameter θ is the involved in the PDF $f_X(x)$ of a random variable X. The likelihood function $L(\theta)$ with n monitored data associated with the underlying random variable X is expressed as

$$L(\theta) = \prod_{i=1}^{n} f_X(x_i|\theta) \tag{6}$$

The updated PDF of the underlying random variable X can be obtained as [29]

$$f''_X(x) = \int_{-\infty}^{\infty} f_X(x|\theta) \cdot f''_{\Theta}(\theta) d\theta \tag{7}$$

Markov Chain Monte Carlo (MCMC) methods are widely used in Bayesian statistics, particularly for updating posterior distributions with new information [31]. In the context of SHM, these methods allow for the integration of monitoring data to update the structural performance and SHM planning. One of the main strengths of MCMC methods is their ability to sample from complex, high-dimensional posterior distribution. It is useful in cases where direct computation of the posterior distribution is impractical or impossible due to its complexity [32]. MCMC methods generate a Markov chain that converges to the target distribution as the number of iterations increases. They are suitable for updating the parameters of complex damage propagation prediction. The accuracy and reliability of the updating can improve as the Markov chain converges to the true underlying distribution [33, 34]. Metropolis–Hastings, Slice Sampling, and Gibbs Sampling are well-known MCMC methods [35]. Metropolis–Hastings is a general algorithm applicable in various contexts, including those with high-dimensional spaces. Gibbs sampling is useful when dealing with multivariate distributions and can simplify computations. Slice sampling is a technique that can be effective when dealing with unnormalized distributions. The MCMC techniques allow for the sequential updating of the damage propagation, performance prediction, and optimum SHM planning as new SHM data becomes available [4, 8, 15, 16, 30].

6 Conclusions

This study presents a comprehensive framework for life-cycle probabilistic multi-objective optimum SHM planning. The framework effectively integrates various objectives based on availability, damage detection, maintenance, reliability, service life, life-cycle cost, and risk. Multi-objective optimization techniques can be utilized to efficiently identify Pareto optimal solutions. In the decision-making process, multi-attribute methods are employed to select the best SHM planning from the computed Pareto optimal solutions. Furthermore, the incorporation of SHM data updates the planning process, thereby enhancing its accuracy and reliability throughout the life cycle of the monitored structures. This presented framework can lead to improving structural safety but significant economic benefits by efficiently managing risks.

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Toward a More Resilient Road Infrastructure

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Abstract. The transportation infrastructure serves as a cornerstone for economic prosperity, enabling market expansion and fostering a more efficient division of labor. Ensuring its continued functionality in the face of disruptive events is imperative. This paper introduces a practical method for assessing the functionality of road networks and outlines a procedure for estimating their resilience. While many of these disruptive events are stochastic in nature, such as natural hazards, planned maintenance interventions can also significantly impact the functionality of high-volume road networks. The proposed framework for resilience evaluation takes into account both stochastic events and planned interventions. It specifically examines the impact of recovery time on resilience, particularly in cases of stochastic disruptive events. Furthermore, the framework also separates resilience from the overall costs that are associated with achieving a certain level of resilience, facilitating a comparison between resilience levels and corresponding costs in decision-making processes. Additionally, the paper explores measures that target different aspects of resilience.

Keywords: Resilience · Road Infrastructure · Stochastic processes · Functionality · Disruptive event · Maintenance

1 Introduction

The term "resilient" can be traced back to as early as 1674, although its usage likely predates this. It originates from the Latin verb "resilire," which conveys the idea of rebounding or recoiling. In accordance with this definition, the adjective "resilient' emerged to describe an object's ability to endure a disturbance without suffering permanent deformation or rupture. The noun resilience has the same meaning as a property of objects to recover from deformation caused by mechanical forces.

The modern application of the term "resilience" gained prominence in the 1970 and 1980 by psychologist Emmy Werner. She conducted a 40-year study of 698 infants, the entire multiethnic birth cohort for the year 1955 on the Hawaiian island of Kauai. In her work [1] Werner employed the term "resilience" to describe "three kinds of phenomena: good development outcomes despite high-risk status, sustained competence under stress and recovery from trauma". The high-risk status means that these children were born in chronic poverty, had experienced perinatal stress and lived in a family environment

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troubled by chronic discord, divorce, or parental psychopathology. By the age 10, two thirds of children have indeed developed serious learning and behavior problems or had delinquency records and mental health problems by the age of 18. However, one third of the children who had experienced four or more such risk factors defied the odds and matured into competent, confident and caring adults. Emmy Werner used the term "resilient" for these children.

The term "resilience" entered the engineering realm firstly in ecology [2], and then in structural engineering [3]. It quickly spread into fields of infrastructure and transportation Engineering. However, its rapid popularization also had a downside as it led to the emergence of multiple competing definitions. A clear delimitation to other related terms such as robustness, resistance, reliability and risk is missing.

World Road Association (PIARC) defines the resilience as follows [3]:

> *The ability of a system or systems to survive and thrive in the face of a complex, uncertain and ever-changing future.*

This is a quite generic definition applicable to all kinds of systems that need to be explained in detail to be useful in practice. Drawing from its usage in psychology, it's intuitively clear that resilient infrastructure can maintain its function during or restore its function after disruptive events. However, there's a significant difference compared to biological and ecological systems, where recovery from disruptive events occurs within the system itself. In the case of non-living matter such as road infrastructure, recovery after a disruptive event happens through deliberate action by society. Therefore, it's necessary to extend the system boundary for resilience evaluation to include the organization responsible for maintaining the functioning of the infrastructure.

In this paper the practice-oriented resilience evaluation for road infrastructure and the measures to improve the resilience of road infrastructure are discussed.

2 The Benefit of Transportation Infrastructure

The effect of road infrastructure or more generally of transportation infrastructure on economic prosperity was already recognized in the eighteenth century by Adam Smith [4]. He astutely identifies the division of labor or specialization as a key productivity driver and therefore essential for economic prosperity. Adam Smith recognized that the division of labor results in production surpassing the needs of the producer, leading to a surplus that must be traded for other goods. He emphasized that

> *"… it is the power of exchanging that gives occasion to the division of labour, so the extent of this division must always be limited by the extent of that power, or, in other words, by the extent of the market."*

Adam Smith found it self-evident that the extent of the market is determined by the capacity to transport products. Given the era in which he lived, he identified water transport as a means to expand the market.

Efficient utilization of transportation infrastructure facilitates market expansion and enhances the division of labor. Affordable transportation of goods enables the concentration of production facilities, leading to higher productivity. Additionally, it stimulates demand for niche products that require further specialization, thereby increasing productivity. These effects unfold gradually as the economy adjusts to improved transportation capabilities.

However, it's important to note that increased productivity isn't solely attributable to readily available transportation infrastructure. It is also influenced by factors such as technological innovation, education, and political stability. Therefore, accurately evaluating the long-term benefits of transportation infrastructure, akin to the benefits of education and political stability, is complex and multifaceted.

The lower limit of annual macroeconomic benefit of road traffic can be estimated by the contribution of road traffic to the Gross Domestic Product (GDP). It lies between 4% [5] and 10% [6] and [7], of Gross Domestic Product (GDP). The inconsistency in the contribution of road transportation to GDP stems from the differences in financing and accounting practices in different countries, as discussed in [8]. Apart from purely economic benefit, road infrastructure enables road users to be involved in various activities that yield other private, public, and social benefits [9] and [10]. In addition to these beneficial externalities, road traffic and indirectly the road infrastructure also have negative health, societal and environmental impact (e.g. accidents, noise, pollution), which is mostly difficult to ponder against the benefits. However, despite these detrimental externalities, which are indeed significant, they do not substantially diminish the overall benefit of mobility and, consequently, of road infrastructure to society.

It appears that measuring resilience based on the benefits of road transport, as proposed in [11] would be the most logical choice consistent with the preceding discussion. However, even if the benefit of road transport could be evaluated in sufficient granularity the portion attributable to road infrastructure is nearly impossible to estimate. Therefore, one resorts to proxies that serve as resilience measure.

3 Measuring Resilience

3.1 Functionality

One can assume that the benefit of road infrastructure, even if unknown, is fully exploited if the road network doesn't impose any impediments to the free flow of traffic, which is the primary purpose of road infrastructure. In the literature one associates this situation with a functionality[1] level of 100%. However, evaluating the functionality following a disruptive event, i.e., the reduction from 100%, is not straightforward. It is intuitively clear that this reduction is associated with network topology, traffic volume, and traffic composition. In the literature, there are suggestions to use network (or graph) properties such as connectivity [12] and centrality [13] as functionality measures. While these measures are quite useful, they do not adequately model the loss of benefit due to a disruptive event.

On the other hand, traffic-related models can capture the disbenefit of a disruptive event. For example, the disruption in the network, such as the loss of a road link between two junctions, will lead to a redistribution of traffic. The new traffic patterns can be determined using macroscopic or microscopic simulations, which are widely used in

[1] The terms "level of service" and "performance level" are also used with the same meaning.

practice for transport planning. Macroscopic simulations provide traffic equilibrium solutions before and after the disruption [14]. Assuming that the origins and destinations of road users remain unchanged, one can evaluate the additional travel time i.e. the difference between cumulative travel time before T_0 and after disruption T_{dis} for all vehicle categories.

This approach allows for the estimation of the throughput time for each origin and destination pair, as well as for each vehicle type, which can be compared between undisrupted and disrupted networks. The difference, i.e., the reduction in functionality, is illustrated in Fig. 1. The integral of the functionality reduction over time, depicted by the light grey area in Fig. 1, represents the loss of resilience.

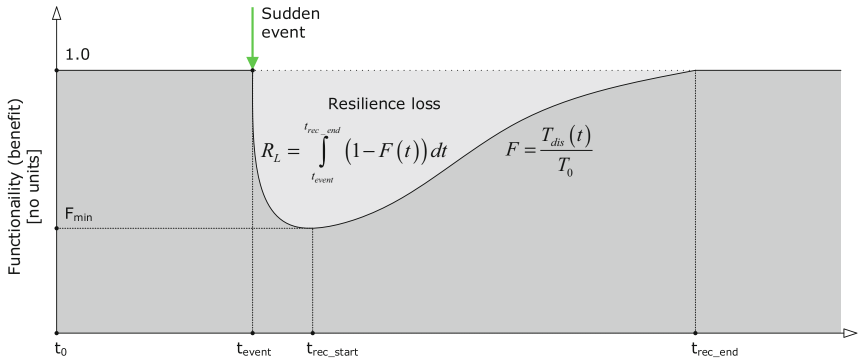

Fig. 1. Resilience on the basis of functionality.

Expanding upon the traffic composition, one can also assign monetary values to these additional travel times, resulting in a monetary disbenefit due to disruptions in the road network. Following this rationale, it can be argued that reintroducing the same link would result in an increased benefit equal to the disbenefit caused by the lost link. Therefore, this value can be assumed as the benefit of the said link [15].

Similarly, this reasoning applies if multiple links are affected simultaneously. However, it's crucial to note that this approach cannot be applied if the disruptive event severs the existing network into disconnected networks. In such cases, other transport modes need to be considered, or as a last resort, a macroeconomic analysis of the disconnected region needs to be conducted.

The functionality as defined in this chapter, is constrained to traffic throughput times, which may or may not be monetized. While this definition aligns with the concept of functionality, it raises questions about whether this should be the sole criterion when evaluating resilience.

3.2 Safety and Environmental Impact During Recovery

The redistribution of traffic due to disruptive event can in certain cases lead to change in accident rates. The detour on two-lane two-way roads with increased traffic density can lead to higher accident rates. Conversely, in some cases, slower traffic may result in lower or less severe accident rates. Considering that safety is one of the most critical performance indicators in Asset Management, the impact of safety should be included in resilience evaluations.

The same principle applies to environmental impact, as traffic redistribution resulting from disruptive events can lead to longer travel times, including congestion and higher gas consumption, thus contributing to negative environmental impacts. Similar to safety, environmental impact is an important performance indicator in Asset Management that should be included in resilience evaluations.

Evidently, once full functionality is restored, the original traffic regime, along with associated accident rates and environmental impacts, are also restored. If necessary, these effects can be monetized and added to monetized functionality.

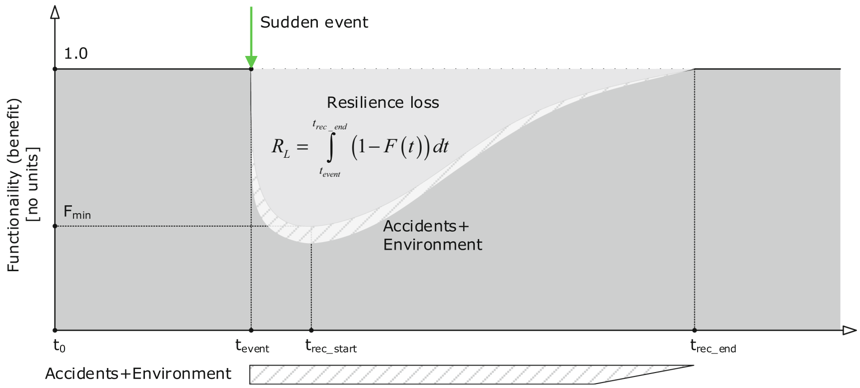

Fig. 2. Alternative consideration of safety and environmental impact.

Alternatively, in accordance with the chosen evaluation and decision-making framework, safety and environmental impact can be integrated into costs (see Sect. 3.5). Both alternatives are illustrated in Fig. 2. Accidents and environmental impact can be treated as the reduction of functionality (area with striped area in the upper part of the figure) or as separate performance indicator (striped area in the lower part of the figure).

3.3 Consequences of Disruptive Event

Disruptive events such as flooding or earthquakes not only abruptly alter the functionality of the road network but also have unrecoverable consequences. Loss of life, physical injuries, and damage to cultural heritage are examples of such consequences. While these consequences are typically considered in risk analysis [16], they are seldom included in resilience assessments due to their irrecoverable nature. These unrecoverable losses are depicted as a separate performance indicator in Fig. 3.

There are also consequences of disruptive events that generally can be alleviated or even eliminated, but the costs of doing so are disproportionally high. In rare cases, even the affected infrastructure can be abandoned altogether. A tragic example is the Lower Ninth Ward in New Orleans, which now has less than 35% of its pre-Hurricane Katrina