Stochastic Life-cycle Sustainability Analysis

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ABSTRACT: During their life-cycle, engineering systems typically suffer from deterioration due to regular operation and exposure to extreme events and harsh environmental conditions. As a result, regular or exceptional recovery strategies are often required to restore the system to a target safety and functionality level. There is a need to evaluate the associated impact of such strategies on the life-cycle sustainability of engineering systems. This paper proposes a novel stochastic formulation, named Stochastic Life-cycle Sustainability Analysis (SLCSA), for evaluating the sustainability of engineering systems throughout a time horizon of interest. In the SLCSA, the sustainability of the system is evaluated in terms of its environmental impact, which includes the impact of the construction, operation processes and recovery strategies that are associated with the various components of the system. The formulation proposes state-dependent stochastic models that capture the effects of gradual and shock deteriorations in the evaluation of the environmental impact of the system as well as the resilience of the system described by the recovery strategies. Moreover, the formulation accounts for the relevant uncertainties, such as those in the external conditions (e.g., environmental exposure and potential hazards), and those in the environmental emissions, associated with the materials and energy used throughout the system life-cycle. As an illustration, the proposed analysis is used to evaluate the life-cycle sustainability of a typical reinforced concrete (RC) bridge.

1. INTRODUCTION

In recent years, there has been an increasing attention toward the evaluation of the sustainability and resilience of engineering systems throughout their service lives (Gardoni 2019). Several researchers have developed frameworks and models to assess the sustainability of various infrastructure components like bridges (Tapia et al. 2011; Mara et al. 2013), pavements (Yu and Lu 2012; Yang and Al-Qadi 2017) and infrastructure systems (Seo and Hwang 2001; Ramesh et al. 2010; Biswas 2014; Abdallah and El-Rayes 2016). In these studies, sustainability is evaluated in terms of different performance measures that include environmental, economic, and social impacts of systems.

The interpretation and evaluation of sustainability depends on the context of the study. For example, in the context of modern building design, recent studies proposed frameworks that integrate the performance-based design with sustainability assessment to obtain a design that is both safe and sustainable (Welsh-Huggins and Leil 2016; Alibrandi and Mosalam 2017, 2019). In the context of disaster recovery of communities, Gardoni and Murphy (2008) conceptualized sustainable recovery in terms of capabilities as part of a Capabilities Approach to recovery.

When evaluating the sustainability of the system in terms of its environmental impact over a fixed time horizon, current studies have three important limitations. First, these studies do not consider the impacts on the sustainability associated with all the processes (i.e., construction, operation, and recovery processes) that are part of the system life-cycle. Second, they do not consider the various components within an engineering system, such structural system/components (i.e., entire building or individual beams, columns and slabs) and mechanical components associated with the structural system (i.e., refrigerator, AC unit and washing machine), and the effect of their interdependency on the environmental impact on the system. Third, they do not account for all relevant uncertainties in evaluating the sustainability of the system, such as the uncertainties in the environmental emissions associated with the material and energy needed during the system life-cycle, the uncertainties in the extremal conditions, and the uncertainties in the different models used for the assessment.

This paper proposes a formulation, named Stochastic Life-cycle Sustainability Analysis (SLCSA), for evaluating the sustainability of engineering systems throughout a time horizon of interest. The SLCSA assesses the sustainability of an engineering system in terms of its environmental impact (i.e., carbon footprint, ozone depletion or smog), for a fixed time horizon over which a system might be subject to multiple cycles of repair. The proposed SLCSA provides a more comprehensive evaluation of the environmental impact of a system, by addressing the aforementioned limitations.

First, we consider that an engineering system might consist of a structure as well as mechanical components. We make the distinction between an engineering system, a structure and a mechanical component to account for the environmental impacts associated with the structure as whole (which is composed of the structural components) and the mechanical components of the system. Accordingly, the environmental impacts from the structure and all the mechanical components together define the total environmental impact on the entire system.

Second, this paper proposes state-dependent stochastic models that capture the effects and the interaction of the various processes, such as deterioration, operation, and recovery processes, in the evaluation of the environmental impact of the system. By accounting for the various processes that affect the different components of an engineering system, the environmental performance can be determined as a function of the structural and mechanical performance of the system. Each of the time-varying structural and mechanical performances of the system is a function of a set of variables that characterize the system/component of interest (e.g., material properties, member dimensions, and imposed boundary conditions), called state variables. In this formulation, the structural state variables describe the structural system, whereas the mechanical state variables describe the mechanical components that are part of the engineering system. The change of these variables over time is estimated from the modeling of the relevant state-dependent stochastic processes. For instance, the modeling of the state-dependent structural deterioration (Jia and Gardoni 2018a, 2019) and recovery processes (Sharma et al. 2018) aims to estimate the time-varying structural state variables of the system. The estimates of these variables can be used to predict the structural performance of the system (i.e., that describes a certain state of the structure) over time (Choe et al. 2008, 2009; Simon et al. 2010; Zhong et al. 2012; Kumar et al. 2009; Kumar and Gardoni 2014a; Jia and Gardoni 2018a). The integration of the different stochastic processes, such as deterioration and recovery processes, and their effects on the system performance is modeled following Jia et al. (2017). Following the estimation of the structural and mechanical performance, the environmental performance can be determined. In particular, the quantity state variables are first estimated as a direct function of the structural and mechanical performance. In this formulation, the quantity state variables characterize the quantities of materials and energy used during the system life-cycle. These quantity state variables are then used as inputs to the models to estimate the environmental impact of the system over time. The environmental impact is estimated using the life-cycle assessment approach, as defined in ISO 14040/14044 (ISO 2006).

Third, to account for the relevant uncertainties in the assessment of the environmental impact of the system, the formulation adopts the simulation-based approach, developed by Jia and Gardoni (2018b). The simulation-based approach allows the propagation of the relevant uncertainties that result in a probabilistic output for the environmental impact of the system.

2. GENERAL FORMULATION

Figure 1 shows the flowchart of the proposed SCLSA formulation. In the SLCSA formulation, the modeling of the structural and mechanical performance of the system follows a similar flow. This formulation is based on the sustainability formulations proposed by Gharzouzi and Gardoni (2019a; 2019b). Next, we discuss the modeling of the different performance measures of the system.

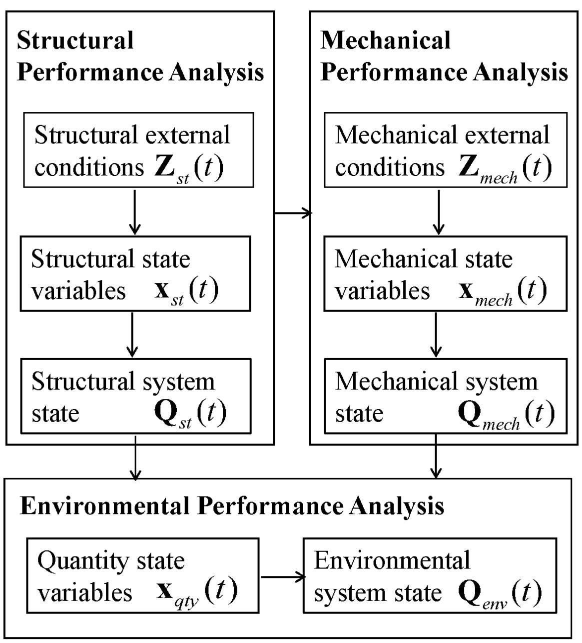

Figure 1: Overall flowchart for modeling the environmental performance of the system.

2.1. Structural performance analysis

Starting with the structural performance analysis, the vector of structural external conditions/variables, denoted as $\mathbf{Z}_{st}(t)$, is modeled first. The vector $\mathbf{Z}_{st}(t)$ consists of the vector of structural environmental conditions/variables (such as temperature and relative humidity), $\mathbf{E}_{st}(t)$, and the vector of structural shock intensity measures, $\mathbf{S}_{st}(t)$, where $\mathbf{Z}_{st}(t)=[\mathbf{E}_{st}(t),\mathbf{S}_{st}(t)]$. These vectors correspond to the external conditions that the structure is subject to. Accordingly, the deterioration processes, that adversely affect the structure state, are influenced by these conditions (Jia and Gardoni 2018a, 2019). Deterioration can occur both in the form of shocks due to extreme events such as earthquakes, hurricanes, floods, and blasts (i.e., shock deterioration processes), as well as gradually over time due harsh environments and regular use (i.e., gradual deterioration processes.) Jia and Gardoni (2018a) developed a general state-dependent stochastic formulation that models the change of the vector of structural state variables, $\mathbf{x}_{st}(t)$, over time due to deterioration processes using state-dependent stochastic models. These models can consider the likely interaction among different deterioration processes, such that their joint impact on the system state can become more significant than simply superimposing their individual impacts.

Following Jia and Gardoni (2018a and 2019), the sequence $\{\mathbf{Z}_{st}(t)\}$ of the external conditions from 0 to t is used as an input to the state-dependent stochastic models of $\mathbf{x}_{st}(t)$. The vector of structural state variables is written as $\mathbf{x}_{st}(t)=\mathbf{x}_{st}[t,\mathbf{x}_{st,0},\{\mathbf{Z}_{st}(t)\},\mathbf{\Theta}_{\mathbf{x}_{st}}]$, where $\mathbf{x}_{st,0}$ is the vector of structural state variables at some reference time $t=0$, such as the time of the construction of the system (where $\mathbf{x}_{st,0}=\mathbf{x}_{st}(t=0)$), and $\mathbf{\Theta}_{\mathbf{x}_{st}}$ is the vector of unknown model parameters that need to be estimated. Because of deterioration processes, the vector of the structural state variables changes from $\mathbf{x}_{st,0}$ to $\mathbf{x}_{st}(t)$. Following Jia and Gardoni (2018a), we write the vector of the structural state variables at time t as

$$\mathbf{x}_{st}\left(t\right)=\mathbf{x}_{st,0}+\int_0^t \dot{\mathbf{x}}_{st}\left(\xi\right)d\xi \tag{1}$$

where $\dot{\mathbf{x}}_{st}(\xi)=\dot{\mathbf{x}}_{st}[\xi,\mathbf{x}_{st}(\xi^-),\mathbf{Z}(\xi),\mathbf{\Theta}_{\mathbf{x}_{st}}]$ denotes the rate of change of the structural state variables over time, and $\mathbf{x}_{st}(\xi^-)$ is the vector of vector of state variables immediately before time ξ.

To implement this formulation for modeling the effect of the structural deterioration processes on

$\mathbf{x}_{st}(t)$, specific models for the changes of $\mathbf{x}_{st}(t)$ need to be established and calibrated for each deterioration process. Since the formulation is general, any model for the changes of $\mathbf{x}_{st}(t)$ can be incorporated.

The changes in $\mathbf{x}_{st}(t)$ lead to changes in the state of the structural system, characterized by a vector of structural performance measures $\mathbf{Q}_{st}(t)$ that can include performance measures such as state of physical damage, reliability, resilience and durability. We write $\mathbf{Q}_{st}(t)$ as $\mathbf{Q}_{st}(t)=\mathbf{Q}_{st}[\mathbf{x}_{st}(t),\mathbf{\Theta}_{\mathbf{Q}_{st}}]$, where $\mathbf{\Theta}_{\mathbf{Q}_{st}}$ is a vector of unknown model parameters that need to be estimated. For instance, $\mathbf{Q}_{st}(t)$ can correspond to the capacity and demand models used to determine the time-varying fragility and corresponding reliability of the structure (Gardoni et al. 2002; 2003).

Recovery processes are the processes that characterize the recovery strategies of a system (Kumar and Gardoni 2014b; Sharma et al. 2018). During the system life-cycle, a structural recovery occurs, following an intervention, when the system is taken out of service for repair or reconstruction. The intervention is triggered when the structural performance of the system is no longer acceptable (in comparison to a set intervention threshold.) A key element of the recovery modeling is the development of a recovery schedule associate to a recovery strategy.

Sharma et al. (2018) proposed a stochastic formulation to model the recovery of a system incorporating the effect of recovery activities as well as possible disrupting shocks during the recovery process. As the recovery activities progress, the associated recovery steps might introduce additional structural state variables (e.g., describing new materials used for the repair) or replace a subset of existing ones. Ultimately, these updated structural state variables can be used to determine the new structural performance of the system during and after the recovery process.

2.2. Mechanical performance analysis

The modeling of the mechanical performance of the various mechanical components that are part of the system is similar to the modeling of the structural performance of the entire structure, as discussed in Section 2.1. In addition to the deterioration and recovery processes, we consider that mechanical components are subject to operation processes. In the SLCSA, the operation processes describe the operation of a certain component, in terms of, for example, the energy consumed for its operation.

As an overview, the modeling starts with the vector of mechanical external conditions/variables, $\mathbf{Z}_{mech}(t)$, which consists of the vector of mechanical environmental conditions/variables, $\mathbf{E}_{mech}(t)$, and the vector of structural shock intensity measures, $\mathbf{S}_{mech}(t)$. These vectors include the external conditions to which each mechanical component is subject. As for $\mathbf{x}_{st}(t)$, the sequence of $\{\mathbf{Z}_{mech}(t)\}$ is used to model $\mathbf{x}_{mech}(t)$. Accordingly, the $\mathbf{x}_{mech}(t)$ are used to model the vector of mechanical performance measures $\mathbf{Q}_{mech}(t)$, which can include the reliability and efficiency of the mechanical components. More details can be found in Gharzouzi and Gardoni (2019b).

2.3. Environmental performance analysis

With reference to Figure 1, the environmental performance analysis follows the modeling of both the structural and mechanical performance of the system. In particular, $\mathbf{Q}_{st}(t)$ and $\mathbf{Q}_{mech}(t)$ are used as inputs to model the change of the vector of the time-varying quantity state variables, $\mathbf{x}_{qty}(t)$. These variables describe the quantities of materials and energy used for all the processes associated with the engineering system over a fixed time horizon. For example, following a structural repair of the system, the quantities of old and new materials should be updated in accordance with the recovery strategy discussed in Section 2.1. These additional quantities used to restore the system to a target structural state, result in an environmental impact associated with the recovery process. As another example, the regular operation of a mechanical component results in a continuous use of energy which leads to a continuous environmental impact.

In this formulation, $\mathbf{x}_{qty}(t) \in \mathbb{R}_{\geq 0}^{n_q}$, where n_q is the total number of the materials and energy needed by the system over time. In the SLSCA, we write the vector of quantity state variables as $\mathbf{x}_{qty}(t) = \mathbf{x}_{qty}[t, \mathbf{x}_{qty,0}, \mathbf{Q}_{st}(t), \mathbf{Q}_{mech}(t)]$, where $\mathbf{x}_{qty,0}$ is the vector of quantity state variables at some reference time $t = 0$, such as the time of the construction of the system (where $\mathbf{x}_{qty,0} = \mathbf{x}_{qty}(t = 0)$.)

Due to the different processes that are part of the system life-cycle, the vector of the quantity state variables changes from $\mathbf{x}_{qty,0}$ to $\mathbf{x}_{qty}(t)$. We write the vector of the quantity state variables at time t as

$$\mathbf{x}_{qty}\left(t\right) = \mathbf{x}_{qty,0} + \int_0^t \dot{\mathbf{x}}_{qty}\left(\xi\right) d\xi \qquad (2)$$

where $\dot{\mathbf{x}}_{qty}(\xi) = \dot{\mathbf{x}}_{qty}[\xi, \mathbf{x}_{qty}(\xi), \mathbf{Q}_{st}(\xi), \mathbf{Q}_{mech}(\xi)]$ denotes the rate of change of the quantity state variables over time. Since the formulation is general, any model for the changes of $\mathbf{x}_{qty}(t)$ can be incorporated. More details on specific models for the changes $\mathbf{x}_{qty}(t)$ of can be found in Gharzouzi and Gardoni (2019a, 2019b).

The quantity state variables can then be used to estimate the time-varying environmental performance of the system $\mathbf{Q}_{env}(t)$, where the vector $\mathbf{Q}_{env}(t)$ includes various environmental impacts of interest such as carbon footprint, ozone depletion or smog. We write the vector of environmental performance measures as $\mathbf{Q}_{env}(t) = \mathbf{Q}_{env}[\mathbf{x}_{qty}(t), \mathbf{Y}_{qty}, \mathbf{W}_{qty}]$, where $\mathbf{Y}_{qty}$ is the matrix of environmental emissions associated with $\mathbf{x}_{qty}(t)$, and $\mathbf{W}_{qty}$ is the matrix of equivalency factors needed to determine the environmental impacts of interest based on the emissions in $\mathbf{Y}_{qty}$. Determining the matrices $\mathbf{Y}_{qty}$ and $\mathbf{W}_{qty}$ are two essential steps in evaluating the environmental impacts (EPA 2006; Heijungs and Suh 2002). In this formulation, the matrix $\mathbf{Y}_{qty} \in \mathbb{R}_{\geq 0}^{n_y \times n_q}$, where n_y is the number of the environmental emissions associated with $\mathbf{x}_{qty}(t)$, and the matrix $\mathbf{W}_{qty} \in \mathbb{R}_{\geq 0}^{n_y \times n_w}$, where n_w is the number of environmental impacts of interest associated with $\mathbf{Y}_{qty}$. Moreover, we can consider the environmental emissions and equivalency factors in $\mathbf{Y}_{qty}$ and $\mathbf{W}_{qty}$ as random variables to account for their uncertainty when estimating the environmental impacts of the system. Ultimately, we determine the environmental impacts of interest as

$$\mathbf{Q}_{env}\left(t\right) = \mathbf{x}_{qty}^T\left(t\right) \cdot \mathbf{Y}_{qty}^T \cdot \mathbf{W}_{qty} \qquad (3)$$

Using Eq. (3), we can determine the cumulative environmental impact of the system up to time t during the time horizon of interest.

3. EXAMPLE

As an illustration of the proposed formulation, we consider the RC bridge with one-single column bent in Kumar and Gardoni (2014b) and Jia et al. (2017) potentially subject to an earthquake excitation. Figure 2 shows the bridge configuration in addition to a schematic layout of the hypothetical seismic site of the bridge.

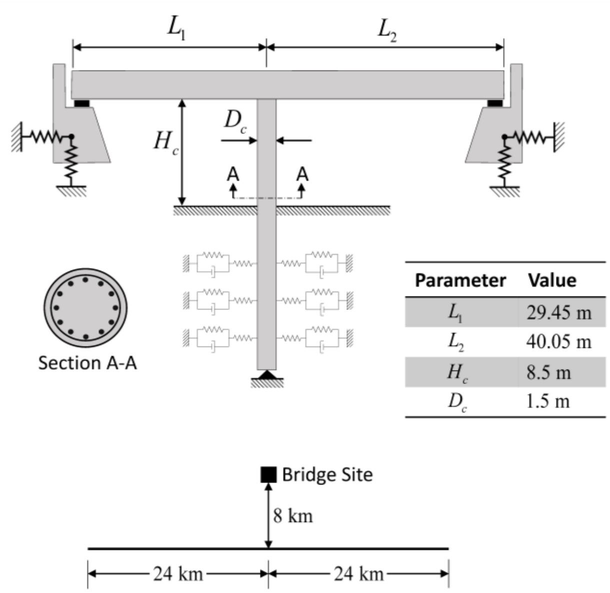

Figure 2: The RC bridge and the hypothetical site (adapted from Jia et al. 2017).

We evaluate the environmental performance of the bridge in terms of its carbon footprint over a set horizon of 75 years. The carbon footprint represents the total amount of carbon dioxide equivalent (CO_2eq), in kilogram (kg), as a result of all the greenhouse gases due to different processes associated with the bridge throughout the 75 years. Since the carbon dioxide equivalent is evaluated over time, we express the carbon footprint in this example as $CO_2eq(t)$.

In this example, we focus on the structural state variables and their changes due to corrosion (gradual deterioration), due to seismic excitations (shock deterioration), and the subsequent recovery processes. The modeling of the deterioration and recovery processes and their impact on $\mathbf{x}_{st}(t)$ follows Jia et al. (2017).

For the evaluation of the structural performance of the bridge, we use the generalized reliability index, $\beta(t)$, and an intervention threshold of 3.09 (which corresponds to a probability of failure, $P_f(t)$, of 0.001) to determine when a recovery of the bridge is needed (i.e., when $\beta(t) \leq 3.09$). We consider a retrofit scheme that consists on applying carbon fiber reinforced polymer (CFRP) to repair the bridge and restore it to a desired target state. The repair strategy and repair time are modeled with the CFRP application as being the sole recovery step. This means that the reliability of the bridge only improves once the CFRP is applied to the bridge column. In case the application of CFRP did not sufficiently improve the reliability of the bridge i.e., the bridge is not restored to the target performance level of its initial reliability $\beta_0 = \beta(t=0) = 3.196$ then we consider a reconstruction of the bridge. Following Gardoni and Gharzouzi (2019a), we consider a lag period of 3 months (before repair or reconstruction starts), a repair period of 1 month, and a reconstruction time of 1.5 years.

The time-varying environmental impact is estimated using Eq. (3). The quantities of material and energy used for construction, $\mathbf{x}_{qty,0}$, are determined based on the initial bridge dimensions and material properties. The $\mathbf{x}_{qty}(t)$ associated with the recovery processes are mainly determined based on the CFRP quantities needed during the recovery period. More details on the assumed quantities of materials and energy can be found in Gharzouzi and Gardoni (2019a).

Using the databases in the software, SimaPro (Pre Consultants 2016), we then obtain $\mathbf{Y}_{qty}(t)$ associated with $\mathbf{x}_{qty}(t)$. The vector $\mathbf{W}_{qty}(t)$ is obtained using the Tool for the Reduction and Assessment of Chemical and Other Environmental Impacts (TRACI v2.1) from the EPA. In this example, we assume that the only environmental emissions follow a lognormal distribution with a COV equal to 0.3 as a measure of the dispersion of each distribution. Finally, the simulation-based approach from Jia and Gardoni (2018b) is used to probabilistically estimate $CO_2eq(t)$.

Figure 3 shows one realization of the change in $\beta(t)$ and the associated change in the expected value of $CO_2eq(t)$, denoted as $\mathrm{E}[CO_2eq(t)]$. Table 1 shows the mean and standard deviation of the carbon footprint associated with the construction of the bridge, as well as the needed three recovery processes at the different intervention times during the 75 years.

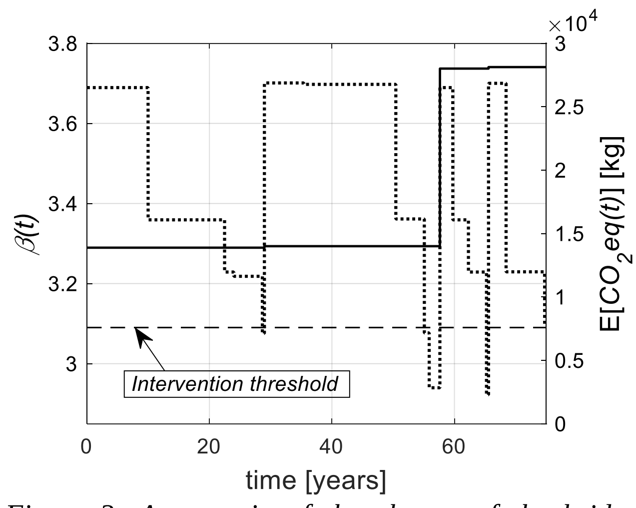

Figure 3: A scenario of the change of the bridge reliability (dotted line) and its carbon footprint (solid line) during 75 years.

Table 1: Mean and standard deviation of the carbon footprint of the bridge due to construction and the recovery processes during 75 years.

Time (years)	*Mean (kgCO2eq)*	*St. Dev. (kgCO2eq)*
0	*13883.22*	*2572.42*
29	*117.49*	*25.87*
57.6	*14005.27*	*2535.85*
65.6	*118.08*	*25.81*

We observe that the increase in the carbon footprint at years 29 and 65.6, due to repairs, is of similar magnitude. That is because a similar amount of CFRP is applied to restore the bridge to β_0 as indicated in Table 1. However, at year 57.6, we notice that a reconstruction was needed due to the failure of the recovery strategy to restore the bridge to the desired level of structural performance. This could be due to the accumulated damage on the bridge as a result of the deterioration processes that the bridge is subject to. And despite the first repair at year 29, the bridge could be significantly affected by deterioration processes occurring prior to and following the first repair, which might justify the need for reconstruction during the second recovery process.

4. CONCLUSIONS

This paper proposed a general stochastic formulation for the evaluation of the environmental impacts of an engineering system over a fixed time horizon. The formulation provides a more comprehensive approach to estimate the environmental performance of a system, by addressing several limitations in the current literature. As illustrated in an example, the evaluation of the carbon footprint of a system provides valuable insights on the relation between the reliability and resilience of the system and its sustainability. Moreover, the estimated environmental impacts can be used in an optimization problem for resilient and sustainable engineering systems.

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