SUSTAINABILITY ANALYSIS: A STOCHASTIC FORMULATION FOR EVALUATING THE SUSTAINABILITY OF ENGINEERING SYSTEMS

BY

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THESIS

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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 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 work proposes a novel stochastic formulation, named Stochastic Life-cycle Sustainability Analysis (SLCSA), for evaluating the sustainability of engineering systems throughout their service lives. In the SLCSA, the sustainability of the system is evaluated for a fixed time horizon in terms of its environmental impact, which includes the impact of the construction, operation processes and recovery strategies that are associated with the various structural and mechanical 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. 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.

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CHAPTER 1: INTRODUCTION

In recent years, there has been an increasing attention toward the evaluation of the sustainability of engineering systems throughout their service lives. 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). In the context of disaster recovery, 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 as structural system/components (i.e., entire building or individual beams, columns and slabs) and mechanical components (i.e., fridge, AC unit and washing machine), and the effect of their interdependency on the environmental impact of the system. Third, they do not account for all the 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, in addition to the uncertainties in the extremal conditions, the capacity and demand models, etc…

This work proposes a formulation, named Stochastic Life-cycle Sustainability Analysis (SLCSA), for evaluating the sustainability of engineering systems throughout their service lives. 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. The proposed SLCSA provides a more comprehensive evaluation of the environmental impact of a system, by addressing the aforementioned limitations. First, we consider that any engineering system of interest consists of a structure and the mechanical components that are part of that structure. 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 structural components) and the mechanical components of the system. Accordingly, the environmental impacts from the structure and all the mechanical components defines then the total environmental impact of the entire system. Second, this work 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 (i.e., an environmental performance measure) of the system. By accounting for the various processes that affect the different components of an engineering system (i.e., structural and mechanical components), 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 structure or the structural system as a whole (i.e., bridge or building), 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) and recovery processes (Sharma et al. 2017) 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., structural system state) 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 state is modeled following Jia et al. (2017). Following the estimation of the structural and mechanical system states, the environmental performance can be determined. In particular, the time-varying quantity state variables for the system (which consists of the structure and the mechanical components) are first estimated as a direct function of the structural and mechanical system states. 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 described in the ISO 14040/14044 series. Third, to account for the relevant uncertainties in the assessment of the environmental impact of the system, the formulation adopts the simulation-based approach, such as the one developed by Jia and Gardoni (2018b), for the estimation of the stochastic performances. The simulation-based approach allows the propagation of the relevant uncertainties that result in a probabilistic output for the environmental impact of the system. The relevant uncertainties include those in the external conditions, such as environmental exposure and potential hazards, the system state models, and those in the environmental emissions, associated with the material and energy inputs.

Following this introduction, this thesis is organized as follows. Chapter 2 introduces the general background that is relevant for developing the SLCSA formulation. Chapter 3 presents the proposed SLCSA formulation. Chapter 4 presents the sustainability analysis of an example RC bridge, as an illustration of the proposed formulation. Finally, Chapter 5 presents some conclusions.

CHAPTER 2: BACKGROUND

2.1 Life-cycle Analysis

The life-cycle of an entire engineering system, a structure or a mechanical component consists of multiple phases in which the system is in use and down (Kumar and Gardoni 2014b; Jia et al. 2017), as illustrated in Figure 1. Within each cycle, the in use system is typically subject to various gradual and shock deterioration processes. These processes lead to the deterioration of the system state over time. The system state is described by the generic system performance measure $Q(t)$ (such as reliability, efficiency or probability of failure). When the system performance, $Q(t)$, is no longer acceptable, an intervention is triggered and the system is taken out of service/operation for repair, maintenance or replacement/reconstruction. With reference to Figure 1, an intervention is triggered when $Q(t)$ falls below the intervention threshold. In this case, $Q(t)$ can correspond to the reliability of a structure, or the efficiency of a mechanical component. If, for example, the probability of failure of a system is the performance measure of interest, then an intervention is triggered whenever the probability of failure exceeds a certain intervention threshold.

The repair, maintenance or replacement/reconstruction events, following an intervention, corresponds to the recovery process of the system, which consists of developing a specific recovery strategy that aims to restore the system to a target performance level (Kumar and Gardoni 2014b; Sharma et al. 2017). Whether the recovery strategy corresponds to a strategy of a repair, maintenance, or replacement/reconstruction depends on the intervention threshold, the system state at the time of intervention and the target state following the recovery process. These processes aim to prevent, mitigate or reverse the effects of the deterioration processes on the system and to increase the availability of the system. If the repair or maintenance strategies, following an intervention, do not succeed in restoring the damaged system to the desired state, then a replacement/reconstruction of the system is needed. In this thesis, we consider that a system can have multiple recovery processes during one cycle within the time horizon of interest. In particular, after a maintenance or a repair, the system is restored to a state that could be higher than the target performance level. In addition, a cycle ends whenever a replacement/reconstruction of the system is needed and a new cycle begins following the implementation of the replacement/reconstruction strategy. In this case, the system is restored to its initial target performance level, as illustrated in Figure 1.

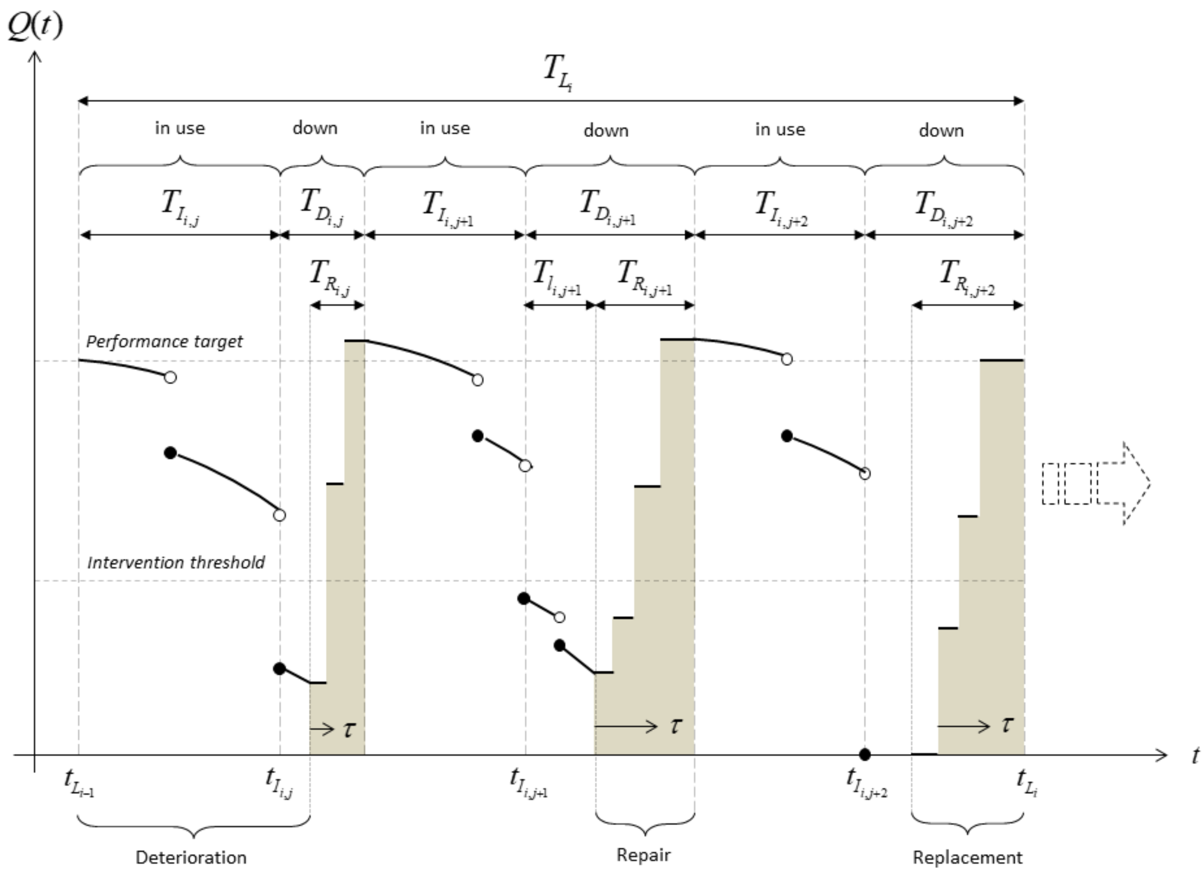

Figure 1: Illustration of the life-cycle performance of an engineering system.

In this thesis, the length of the ith cycle (in Figure 1) is denoted as T_{L_i} and can be written as $T_{L_i} = t_{L_i} - t_{L_{i-1}}$, where t_{L_i} is the end time of the ith cycle and $t_{L_{i-1}}$ is the end time of the $(i-1)$th cycle. An intervention event within the ith cycle is denoted as $I_{i,j}$. Following an intervention event $I_{i,j}$ at time $t_{I_{i,j}}$, there might be a lag period, denoted as $T_{l_{i,j}}$, between the time of intervention and the start of recovery. During the lag period (e.g., from $t_{I_{i,j}}$ to t_{I_i} to $t_{I_{i,j}} + T_{l_{i,j}}$), $Q(t)$ may further degrade, for example, due to the possible occurrence of aftershocks in case of deterioration due to seismic hazards. The subsequent recovery period is denoted as $T_{R_{i,j}}$, and the total period when the system is down (i.e., down time) following an intervention $I_{i,j}$, can be written as $T_{D_{i,j}} = T_{l_{i,j}} + T_{R_{i,j}}$.

During the time horizon of interest, every recovery strategy for the structure or a certain mechanical component has associated environmental impacts, in addition to the impacts resulting from the construction of the structure or manufacturing of the mechanical component. Besides these environmental impacts associated with both the structure and the mechanical components of the system, there are impacts specifically associated with the mechanical components during their use phase. When they are in use, mechanical components require materials and energy (i.e., water and electricity for a washing machine) for their operation. The operation of mechanical components can be modeled by specific operation processes that describe, for example, the energy use and consumption of these components. These operation processes result in additional environmental impacts during the life-cycle of these mechanical components, in particular, and the entire engineering system, in general. In this proposed formulation, we make the distinction between the operation and deterioration processes of mechanical components, even though these processes occur largely during the use phase of the mechanical components. With reference to

Figure 1, a mechanical component can still be subject to deterioration after it is removed from operation (during the lag phase of the down time). Accordingly, the additional deterioration of the component during the lag period would lead to a more elaborate recovery strategy, and subsequently a higher environmental impact associated with that strategy. On the other hand, once a component is removed from operation, there are no additional environmental impacts associated with the operation processes of that component. In all, the environmental impacts of the structure and all the mechanical components within that structure determine the environmental impact of the entire engineering system. The environmental impact associated with every process is evaluated using the life-cycle assessment approach, as described in the ISO 14040/14044 series. Additional life-cycle performance measures, such as the financial costs associated with these processes can also be evaluated to provide additional insight into the life-cycle performance of the system during the time horizon of interest (Gardoni et al. 2016).

CHAPTER 3: PROPOSED FORMULATION

Figure 2 shows the flowchart of the proposed SCLSA formulation for the evaluation of the environmental performance of the system over time, as a function of its structural and mechanical performance (Gharzouzi and Gardoni 2018a; 2018b). In the SLCSA formulation, the modeling of the structural and mechanical performance of the system follows a similar flow. The modeling of the different performance measures of the system is discussed next.

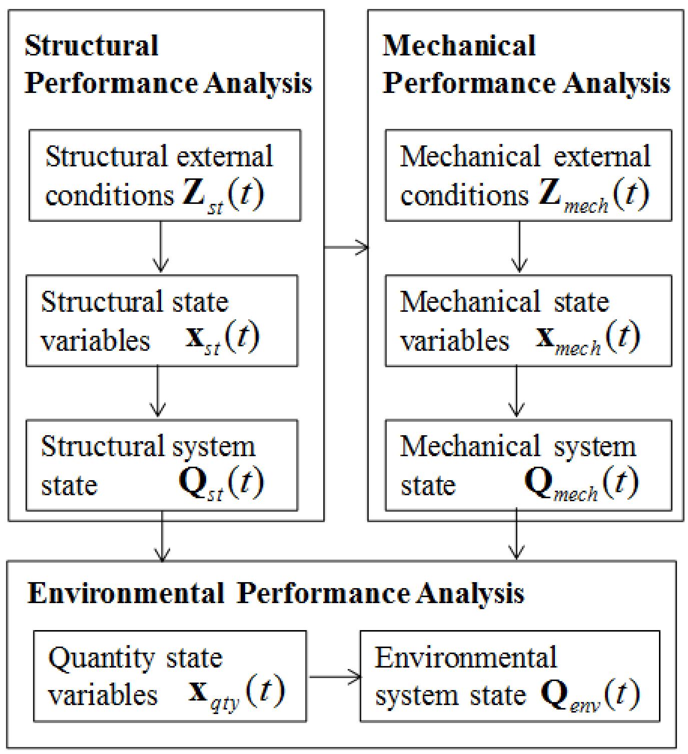

Figure 2: Overall flowchart for modeling the environmental performance of the system.

3.1 Structural Performance Analysis

3.1.1 Modeling of the Deterioration Processes and their Impact on the Structural State

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, atmospheric pressure 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 as a whole is subject to. Accordingly, the deterioration processes, that adversely affect the structure state, are influenced by these conditions (Jia and Gardoni 2018a). 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), the sequence $\{\mathbf{Z}_{st}(t)\}$ of the external conditions from 0 to t is used an input to the state-dependent stochastic models that model $\mathbf{x}_{st}(t)$. 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 or reconstruction 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. With reference to Figure 1, the reference time $t=0$ corresponds to the start of a new system cycle i, at time $t_{L_{i-1}}$, during the time horizon of interest. 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, where $t \in [t_{L_{i-1}}, t_{I_{i,j}} + T_{I_{i,j}}]$, as

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

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 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 (Jia and Gardoni 2018a). Since formulation is general, any model for the changes of $\mathbf{x}_{st}(t)$ can be incorporated. As an example, Jia and Gardoni (2018a) proposed a non-homogenous state-dependent Markov process model for evaluating the effect of gradual deterioration on $\mathbf{x}_{st}(t)$. Such model is able to capture time/age and state-dependence in modeling the changes in $\mathbf{x}_{st}(t)$ due to gradual deterioration. As for the models due to shock deteriorations, the random occurrence of shocks and their intensities is first modeled. As an example, homogeneous Poisson processes have been used to model the occurrence of shocks with constant occurrence rate (Kumar and Gardoni 2014b). Alternatively, non- homogeneous Poisson processes have been used to model the occurrence of shocks with time-varying occurrence rate (Kumar and Gardoni 2012). After modeling the shocks, the changes in $\mathbf{x}_{st}(t)$ due to a shock with a given intensity can be modeled, using for example, probabilistic predictive models as in Kumar and Gardoni (2012, 2014a).

The changes in $\mathbf{x}_{st}(t)$ lead to changes in the structural system state, denoted as $\mathbf{Q}_{st}(t)$. Note that this is a vector of structural performances which can include performance measures such as state of physical damage, reliability, instantaneous probability of failure and durability. We write the vector of structural system state as $\mathbf{Q}_{st}(t) = \mathbf{Q}_{st}[\mathbf{x}_{st}(t), \mathbf{\Theta}_{\mathbf{Q}_{st}}]$, where $\mathbf{\Theta}_{\mathbf{Q}_{st}}$ is the vector of unknown model parameters that need to be estimated. For instance, these model parameters 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).

3.1.2 Modeling of the Recovery Processes and their Impact on the Structural State

During the system life-cycle, a structural recovery occurs when the structure is taken out of service for repair, as a result of its structural performance, $\mathbf{Q}_{st}(t)$, falling no longer being acceptable. In this formulation, a structural recovery process characterizes a structural repair, structural maintenance or reconstruction, depending on the intervention threshold and the structural state at the time of intervention, and target state following the recovery process.

The key element of the recovery modeling is the development of a recovery schedule associate to a recovery strategy. The schedule should consist ideally of all of the recovery activities needed to restore the structure to a desired structural state. In this formulation, the recovery schedule, following any intervention $I_{i,j}$, has a duration of $T_{R_{i,j}}$, as illustrated in Figure 1. The structural state variables, $\mathbf{x}_{st}(t)$, change with the completion of recovery activities and possible disrupting shocks that could occur during the recovery process. The recovery activities that lead to a change in the structural state, $\mathbf{Q}_{st}(t)$, can be grouped into one recovery step. The disrupting shocks might lead to modifications in the structural state as well as the recovery schedule.

Sharma et al. (2017) 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.

Following Sharma et al. (2017), we can model the structural state variables during the implementation of the recovery strategy, at any time $\tau \in [0, T_{R_{i,j}}]$, as

$$\mathbf{x}_{st}\left(\tau\right) = \sum_{u=1}^{\infty} \mathbf{x}_{st}\left(\tau_{r,u-1}\right) \mathbf{1}_{\{\tau_{r,u-1} \le \tau < \tau_{r,u}\}} + \sum_{u,v=1}^{\infty} \Delta \mathbf{x}_{st}\left(\tau_{s,v}\right) \mathbf{1}_{\{\tau_{r,u-1} < \tau < \tau_{r,u}, \tau_{r,u-1} < \tau_{s,v} \le \tau\}} \tag{2}$$

where $\mathbf{x}_{st}(\tau)$ is the vector of structural state variables at relative time τ, measured from the beginning of the recovery process (i.e., the reference time $t = 0$ for the recovery schedule corresponds to $t = t_{I_{i,j}} + T_{I_{i,j}}$ following the intervention $I_{i,j}$ in the ith cycle in Figure 1), $\mathbf{x}_{st}(\tau_{r,u-1})$ is the vector of structural state variables after completing a recovery step at time $\tau_{r,u-1}$, $\mathbf{1}_{\{A\}}$ is an indicator function, defined such that $\mathbf{1}_{\{A\}} = 1$ if A is a true statement, and $\mathbf{1}_{\{A\}} = 0$, otherwise, and $\Delta \mathbf{x}_{st}(\tau_{s,v})$ is the change of the structural state change due to the occurrence of the vth disrupting shock at time $\tau_{s,v} \in [\tau_{r,u-1}, \tau_{r,u}]$. Note that probability distributions of $\mathbf{x}_{st}(\tau_{r,0})$ at the beginning of the recovery process can be obtained from the deterioration models.

Ultimately, these updated structural state variables can be used to determine the new structural performance of the system during and after the recovery process, as described in Section

3.1.1. As an example, the probabilistic capacity and demand models for FRP-retrofitted RC bridges, developed by Tabandeh and Gardoni (2014; 2015) can be used to determine $\mathbf{Q}_{st}(\tau)$.

3.2 Mechanical Performance Analysis

The modeling of the mechanical performance of the various mechanical components, that are part of the entire engineering system, is similar to the modeling of the structural performance of the structure, as discussed in Section 3.1. The mechanical components are subject to mechanical deterioration which are followed needed mechanical recovery processes when the performance is no longer acceptable. In this formulation, we assume that there are no interactions between the mechanical components. This means that the performance of a certain mechanical component does not depend on the performance of another mechanical component. Moreover, we consider that the mechanical performance of a certain component is affected by the structural performance of the structure. Note that the detailed modeling of the mechanical performance and the dependency of the mechanical performance on the structural performance is not part of the scope of this thesis. In this section, we present an overview of the modeling of the performance of a mechanical component k, where $k = 0,...,n_m$ and n_m is the total number of mechanical components considered as part of the engineering system.

As an overview, the modeling starts with the vector of mechanical external conditions/variables relevant to the kth mechanical component, $\mathbf{Z}_{mech,k}(t)$, which consists of the vector of mechanical environmental conditions/variables, $\mathbf{E}_{mech,k}(t)$, and the vector of structural shock intensity measures, $\mathbf{S}_{mech,k}(t)$. These vectors correspond to the external conditions that each mechanical component is subject to. Similarly to $\mathbf{x}_{st}(t)$, the sequence of $\{\mathbf{Z}_{mech,k}(t)\}$ is used to model $\mathbf{x}_{mech,k}(t)$. Accordingly, the $\mathbf{x}_{mech,k}(t)$ are used to model the vector of mechanical performance measures $\mathbf{Q}_{mech,k}(t)$, which can include the reliability and efficiency of the kth mechanical component. The mechanical performance measures, at any time t, for all the mechanical components in the system can be grouped in the matrix $\mathbf{Q}_{mech}(t)$ where $\mathbf{Q}_{mech}(t) = (\mathbf{Q}_{mech,1}(t), \ldots, \mathbf{Q}_{mech,n_m}(t))$.

3.3 Environmental Performance Analysis

With reference to Figure 2, the environmental performance analysis of the system follows the modeling of the structural and mechanical performances for the structure and the mechanical components, respectively. The evaluation of the environmental performance of the engineering system begins with modeling the change of the vector of the time-varying quantity state variables, $\mathbf{x}_{qty}(t)$, that describes the quantities of the materials and energy used for all the processes (i.e., construction, recovery and operation processes) associated with the engineering system over a fixed time horizon. Accordingly the vector $\mathbf{x}_{qty}(t)$ incorporates all the quantities needed by the structure and the mechanical components over time. In this formulation, $\mathbf{x}_{qty}(t) \in \mathbb{R}^{n_q}_{\geq 0}$, where n_q is the total number of the materials and energy used during the life-cycle of the system.

In the SLCSA, $\mathbf{Q}_{st}(t)$ and $\mathbf{Q}_{mech}(t)$ are used as inputs to the state-dependent stochastic models that model $\mathbf{x}_{qty}(t)$. The vector of quantity state variables is written 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 structure or the manufacturing of the mechanical components (where $\mathbf{x}_{qty,0} = \mathbf{x}_{qty}(t=0)$). Note there are no explicit models parameters in the expression of $\mathbf{x}_{qty}(t)$, as the models account for the propagation of uncertainties from $\mathbf{Q}_{st}(t)$ and $\mathbf{Q}_{mech}(t)$. The estimated quantities of materials and energy in $\mathbf{x}_{qty}(t)$ can be considered as random variables in the evaluation of the environmental performance of the system. Because of the various processes (i.e., construction, recovery and operation processes) during the time horizon of interest, the vector of the structural state variables changes from $\mathbf{x}_{qty,0}$ to $\mathbf{x}_{qty}(t)$. In this formulation, we consider two main cases in modeling the change of $\mathbf{x}_{qty}(t)$: (i) the change of $\mathbf{x}_{qty}(t)$ due to the operation processes of the mechanical components (i.e., when these components are in use); and (ii) the change of $\mathbf{x}_{qty}(t)$ due to the recovery processes of the structure and the mechanical components (i.e., when they are down and out of service/operation).

3.3.1 Modeling the Change of the Quantity State Variables due to the Operation Processes

For the change of $\mathbf{x}_{qty}(t)$ due to the operation processes of the mechanical components, we write the change of the quantity state variables associated with any mechanical component, since we assume that there are no interactions between the mechanical components (as discussed Section 3.2). Note that in the following expression, we use the index h, where $h=0,...,n_m+1$, to refer the mechanical components (with a total number n_m), in addition to the structure (for $h=n_m+1$). Accordingly, we write the vector of quantity state variables for the hth mechanical component, $\mathbf{x}_{qty,h}(t)$, at time t where $t\in[t_{L_{i-1}},t_{I_{i,j}}]$, as

$$\mathbf{x}_{qty,h}\left(t\right)=\mathbf{x}_{qty,h0}+\int_0^t\dot{\mathbf{x}}_{qty,h}\left(\xi\right)d\xi \tag{3}$$

where $\dot{\mathbf{x}}_{qty,h}(\xi)=\dot{\mathbf{x}}_{qty,h}[\xi,\mathbf{x}_{qty,h}(\xi),\mathbf{Q}_{op,h}(\xi)]$ denotes the rate of change of the quantity state variables over time, for the hth mechanical component, and $\mathbf{Q}_{op,h}(\xi)=\mathbf{Q}_{op,h}[\mathbf{Q}_{st}(\xi),\mathbf{Q}_{mech,h}(\xi),\mathbf{\Theta}_{\mathbf{Q}_{op,h}}]$ is the vector of operational performance measures of the hth mechanical component, with $\mathbf{\Theta}_{\mathbf{Q}_{op,h}}$ being the vector of unknown model parameters that need to be estimated. The vector $\mathbf{Q}_{op,h}(\xi)$ can include the quantities of material inputs and energy used by a mechanical component required for its operation during its in use phase, as discussed in Section 2.1. The detailed modeling of the operation processes and the associated gradual/continuous change of quantity state variables is out of scope of this thesis, since these processes are related to the mechanical components of the system.

Following the modeling of $\mathbf{x}_{qty,h}(t)$, the entire vector $\mathbf{x}_{qty}(t)$ due to the operation processes of all the mechanical components can be determined by

$$\mathbf{x}_{qty}(t) = \sum_{h=1}^{n_m} \mathbf{x}_{qty,h}(t) \tag{4}$$

The rate of change $\dot{\mathbf{x}}_{qty}(t)$ is incremental over time. Accordingly, $\mathbf{x}_{qty}(t)$ includes the cumulative quantities of materials and energy used up to time t.

3.3.2 Modeling the Change of the Quantity State Variables due to the Recovery Processes

For the change of the quantity state variables due to the recovery processes of the structure or any mechanical component, h, of the system, we write $\Delta\mathbf{x}_{qty,h}(\tau)$ during the implementation of the corresponding recovery strategy, at any time $\tau \in [0, T_{R_{i,j}}]$, as

$$\Delta\mathbf{x}_{qty,h}\left(\tau\right) = \sum_{u=1}^{n_{rh}} \Delta\mathbf{x}_{qty,h}\left(\tau_{rh,u}\right)\mathbf{1}_{\left\{\tau_{rh,u-1}<\tau\le\tau_{rh,u}\right\}} \tag{5}$$

where $\Delta\mathbf{x}_{qty,h}(\tau_{rh,u})$ is the change of the quantity state variables after the completion of the recovery step at time $\tau_{rh,u}$, and n_{rh} is the number of recovery steps needed to restore the structure or the hth mechanical component to a target performance level. From the modeling of the recovery process, discussed in Section 3.1.2, we can obtain the number of recovery steps, n_{rh}, for the structure or the hth mechanical component. Note that n_{rh} is a random number which makes the sum in Eq.

(5) a random sum. Moreover, the change of the quantity state variables at the beginning of the recovery process, $\Delta\mathbf{x}_{qty,h}(\tau_{rh,0})$, is considered to be zero.

In this formulation, $\Delta\mathbf{x}_{qty,h}(\tau_{rh,u})$ reflects the incremental increase in the quantities associated with the structural or mechanical state variables introduced or updated during the recovery process. Accordingly, we can write the change of the quantity state variables, after the completion of the uth recovery step at time $\tau_{rh,u}$, as

$$\Delta\mathbf{x}_{qty,h}\left(\tau_{rh,u}\right) = \Delta\mathbf{x}_{qty,h}\left[\mathbf{x}_{qty,h}\left(\tau_{rh,u-1}\right), \mathbf{Q}_{st}\left(\tau_{rh,u}\right), \mathbf{Q}_{mech,h}\left(\tau_{rh,u}\right)\right] \tag{6}$$

where $\Delta\mathbf{x}_{qty,h}[\mathbf{x}_{qty,h}(\tau_{rh,u-1}), \mathbf{Q}_{st}(\tau_{rh,u}), \mathbf{Q}_{mech,h}(\tau_{rh,u})] = \mathbf{x}_{qty,h}(\tau_{rh,u}) - \mathbf{x}_{qty,h}(\tau_{rh,u-1})$ is the change of the quantity state variables between recovery steps $(u-1)$ and u, $\mathbf{x}_{qty,h}(\tau_{rh,u-1})$ represents the values of the quantity state variables at the $(u-1)$th recovery step, $\mathbf{Q}_{st}(\tau_{rh,u})$ represents the target structural performance after completing the uth recovery step, and $\mathbf{Q}_{mech,h}(\tau_{rh,u})$ represents the target mechanical performance of the hth component after the uth recovery step. Because of the dependency of the mechanical performance on the structural performance, $\mathbf{Q}_{st}(\tau_{rh,u})$ is included in the expression for evaluating $\Delta\mathbf{x}_{qty,h}(\tau_{rh,u})$ for the hth mechanical component. When we evaluate $\Delta\mathbf{x}_{qty,h}(\tau_{rh,u})$ for the structure (i.e., $h = n_m + 1$), then we consider that $\mathbf{Q}_{mech,h}(\tau_{rh,u})$ does not affect $\Delta\mathbf{x}_{qty,n_m+1}(\tau_{r(n_m+1),u})$ (i.e., $\mathbf{Q}_{mech,n_m+1}(\tau_{r(n_m+1),u}) = 0$).

Following the modeling of $\Delta\mathbf{x}_{qty,h}(\tau)$, the total change of quantity state variables, $\Delta\mathbf{x}_{qty,h}(\tau)$, due to the recovery processes of the structure and all the mechanical components can be determined by

$$\Delta\mathbf{x}_{qty}(\tau) = \sum_{h=1}^{n_m+1} \Delta\mathbf{x}_{qty,h}(\tau) \tag{7}$$

Similarly, $\mathbf{x}_{qty}(\tau)$ during the recovery period is cumulative, since $\Delta\mathbf{x}_{qty}(\tau)$ corresponds to an incremental change of the quantity state variables.

3.3.3 Modeling the Environmental Impact of the System

After modeling the quantity state variables over time, $\mathbf{x}_{qty}(t)$, these variables can then be used to estimate the time-varying environmental performance of the entire engineering 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 system state 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 using the life-cycle assessment approach, according to the U.S. Environmental Protection Agency (EPA) (2006) and Heijungs and Suh (2002). In this formulation, the matrix $\mathbf{Y}_{qty} \in \mathbb{R}^{n_y}_{\geq 0} \times \mathbb{R}^{n_q}_{\geq 0}$, where n_y is the number of the environmental emissions associated with $\mathbf{x}_{qty}(t)$, and the matrix $\mathbf{W}_{qty} \in \mathbb{R}^{n_y}_{\geq 0} \times \mathbb{R}^{n_w}_{\geq 0}$, where n_w is the number of environmental impacts of interest associated with $\mathbf{Y}_{qty}$.

In this formulation, 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

$$\mathbf{Q}_{env}(t) = \mathbf{x}^T_{qty}(t) \cdot \mathbf{Y}^T_{qty} \cdot \mathbf{W}_{qty} \tag{8}$$

Using Eq. (9), we can determine the cumulative environmental impact of the system up to time t during the time horizon of interest. The expression in Eq. (9) is a generic expression to evaluate $\mathbf{Q}_{env}(t)$, following Heijungs and Suh (2002). This expression allows us to compute the environmental impacts of a system and obtain similar impacts as the ones evaluated from commercially available software for life-cycle assessment.

CHAPTER 4: EXAMPLE

As an illustration of the proposed formulation, we model the environmental performance of an example RC bridge. We consider the RC bridge with one-single column bent in Kumar and Gardoni (2014b) and Jia et al. (2017). The bridge is subject to gradual deterioration due to corrosion, and to shock deterioration due seismic excitations. Figure 3 shows the bridge configuration in addition to a schematic layout of the hypothetical seismic site of the bridge. The structural properties of the bridge can be found in Kumar and Gardoni (2014b) and Jia et al. (2017). In this example, we evaluate the environmental performance of the bridge in terms of its carbon footprint over a time 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 associated with the system of interest. These greenhouse gases are due to the different processes associated with the bridge throughout these 75 years. Since the carbon dioxide equivalent is evaluated over time, in this example, we express the carbon footprint as $CO_2eq(t)$.

In this example, we make some simplifying assumptions, since the purpose of this example is to show how the proposed formulation works. For the evaluation of the $CO_2eq(t)$ of the bridge, we only consider the environmental impact due to the bridge (i.e., the structure), as the detailed modeling of the mechanical performance is not part of the scope of this thesis. For the evaluation of the structural performance of the bridge, we use the reliability index, $\beta(t)$, and an intervention threshold of 3.09 to determine when a recovery of the bridge is needed (i.e., when $\beta(t) \leq 3.09$). For the purpose of illustration, we simulate one scenario of the change of $\beta(t)$, due to corrosion and seismic excitations, and the subsequent effect on $CO_2eq(t)$, over 75 years. Accordingly, the scope of evaluating $CO_2eq(t)$ includes the contribution of the construction of the bridge and the required recovery processes over the period of interest.

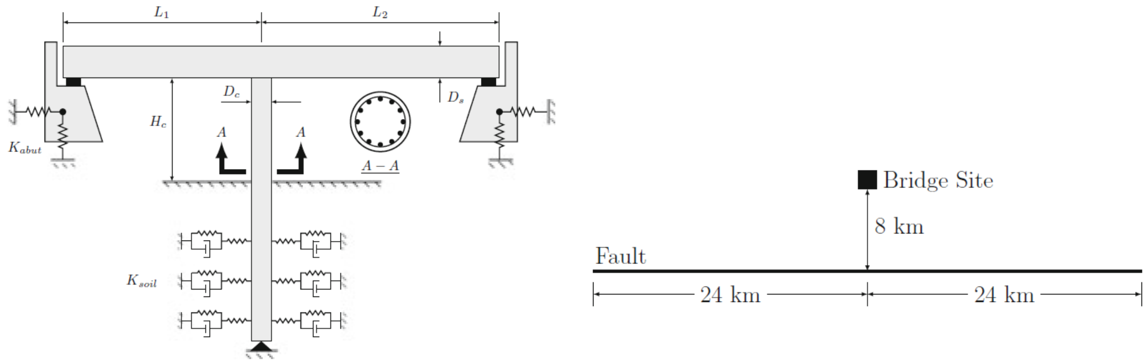

Figure 3: The considered RC bridge and its hypothetical site.

4.1 Structural Performance Analysis

The modeling of the gradual and shock deterioration processes and their impact on $\mathbf{x}_{st}(t)$ follows Jia et al. (2017). After determining $\mathbf{x}_{st}(t)$ for the simulated scenario, we first evaluate the instantaneous probability of failure, $P_f(t)$, similarly to Jia et al. (2017). Then, we can evaluate $\beta(t)$ as

$$\beta(t) = \Phi^{-1}\left[1 - P_f(t)\right] \tag{9}$$

where $\Phi^{-1}(\cdot)$ is the inverse of the standard normal cumulative distribution function (Ditlevsen and Madsen 1996; Gardoni 2017).

The recovery processes as result of the deterioration of $\beta(t)$ also follows Jia et al. (2017). We consider a repair strategy that consists of applying fiber reinforced polymer (FRP) to repair the bridge and restore it to a desired target state. We consider the reliability index at the time of construction (at $t = 0$), β_0, as the target performance level, where $\beta_0 = 3.689$. The recovery strategy is modeled with the FRP application as being the sole recovery step. This means that the reliability of the bridge only improves once the FRP is applied to the bridge column. In this example, we consider a lag period, T_l, of 3 months, and a recovery time, T_R, of 1 month. Based on this repair strategy, new structural state variables that characterize the FRP and its properties are introduced to $\mathbf{x}_{st}(t)$ during the recovery process. In this example, we choose a carbon fiber reinforced polymer (CFRP) with a composite nominal strength of 3465 MPa, and a tensile modulus of 231 GPa for retrofitting the column of the bridge. Following the CFRP retrofit of the bridge, we do not consider the deterioration of the added CFRP, due to the lack of available models in the literature. As such, we might be overestimating the deterioration of $\beta(t)$ after a recovery process.

In case the application of FRP did not sufficiently improve the reliability of the bridge (due to accumulation of damage), then we consider a reconstruction of the bridge. This corresponds to the start of a new cycle for the bridge during the 75 years. For the reconstruction of the bridge, we consider a reconstruction time of 2 years.

4.2 Environmental Performance Analysis

To evaluate $CO_2eq(t)$ of the bridge, we first need to determine $\mathbf{x}_{qty}(t)$ associated with the recovery processes, in addition to $\mathbf{x}_{qty,0}$ due to the construction of the bridge at $t=0$. In determining $\mathbf{x}_{qty}(t)$, we make some simplifying assumptions based on the available information.

For the construction of the bridge, $\mathbf{x}_{qty,0}$ is determined based on the initial bridge dimensions and material properties. To obtain $\mathbf{x}_{qty,0}$, we mainly focus on the materials and energy used for the construction of column of the bridge. That is because, in this example, we assume that the environmental impact due the construction the bridge deck remains constant throughout the 75 years of interest, since the repair strategy using CFRP mainly targets the column of the bridge (the CFRP is applied in the plastic hinge region of the column). We evaluate the volumes of concrete and steel, as well as the diesel used for the site operations and for the transportation of material to and from the site. Table 1 shows the quantities of materials and energy used for the construction of the bridge. For $\mathbf{x}_{qty}(t)$ associated with the recovery processes, we mainly determine the CFRP quantities needed to restore $\beta(t)$ to β_0. We consider a composite consisting of 65% fibers and 35% resin. In the case where a reconstruction is needed, then the additional material and energy requirements for the demolition of the bridge before its reconstruction are included in $\mathbf{x}_{qty}(t)$.

Table 1: The quantities of materials and energy used for the construction of the bridge

Material and Energy	Quantity	Unit
Concrete	15	m^3
Steel	0.4657	m^3
Diesel (on site operations)	8	h
Diesel (transportation and hauling)	8.7632	h

After determining $\mathbf{x}_{qty}(t)$, we can obtain $\mathbf{Y}_{qty}$ and $\mathbf{W}_{qty}$, as discussed in Section 3.3.3. In this example, $\mathbf{W}_{qty}$ is a vector since we are only determining the $CO_2eq(t)$ of the bridge. Using the databases in the LCA software, SimaPro (Pre Consultants 2016), we obtain $\mathbf{Y}_{qty}(t)$. The vector of $\mathbf{W}_{qty}(t)$ 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 environmental emissions in $\mathbf{Y}_{qty}$ are random variables and follow a lognormal distribution where each environmental emission has a mean corresponding to their value in $\mathbf{Y}_{qty}$ and a COV equal to

0.3 as a measure of the dispersion of each distribution. The simulation-based approach, from Jia and Gardoni (2018b), was used to probabilistically estimate the $CO_2eq(t)$ of the bridge for the simulated scenario over 75 years.

4.3 Results

Figure 4 shows the variation of $\beta(t)$ of the bridge due to corrosion and seismic excitations. In the simulated scenario over 75 years, we observe that a total of four intervention where needed when $\beta(t) \leq 3.09$.

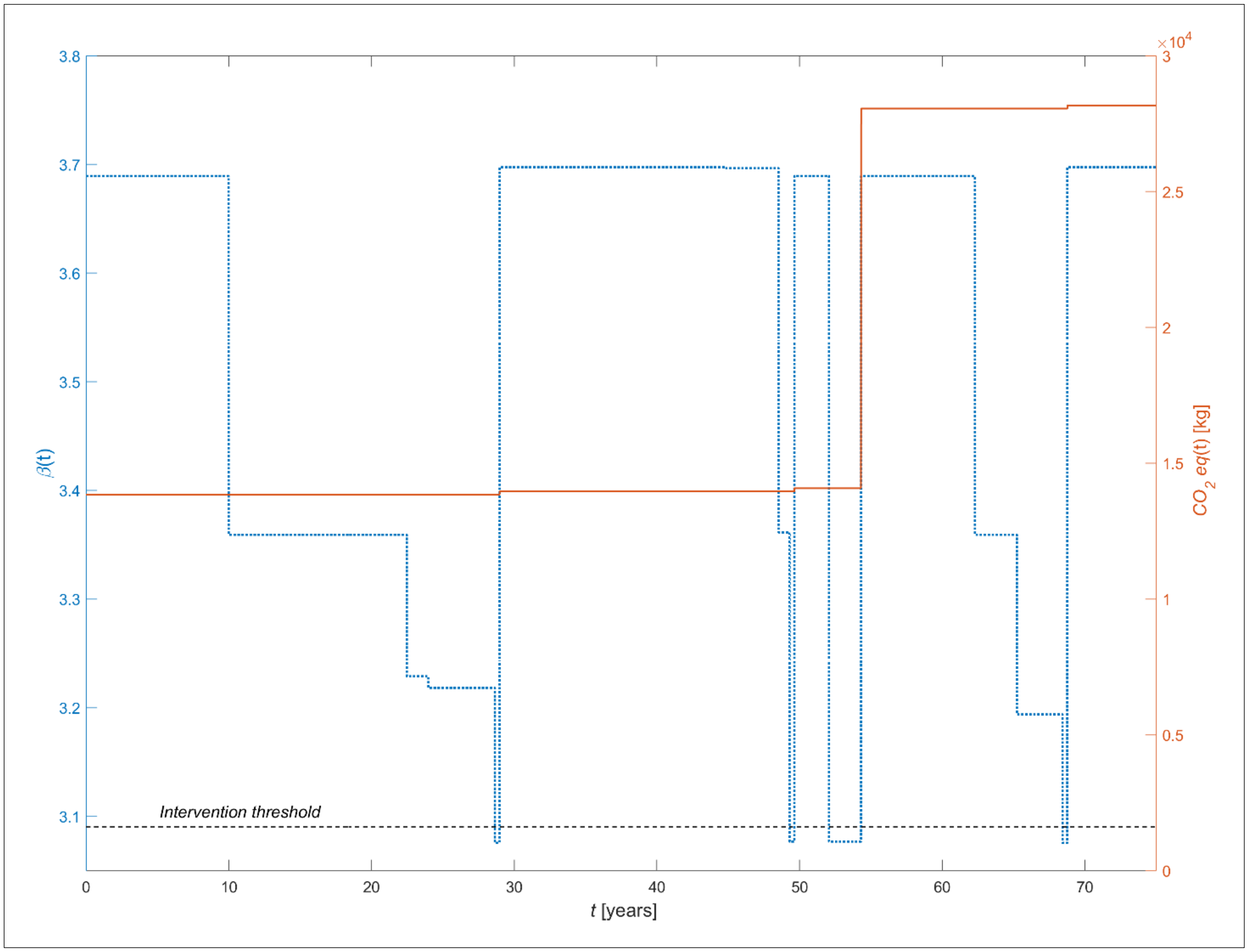

Figure 4: A scenario of the change of the bridge reliability (dashed blue line with respect to the left y-axis) and its carbon footprint (solid orange line with respect to the right y-axis) during 75 years.

At years 29, 50 and 69, a repair strategy using CFRP required. We notice that, following the first repair strategy at year 29, the bridge is restored to a higher state than β_0. However, with the second repair strategy at year 50, the bridge was restored to a slightly lower level than the target reliability. That is due to the accumulation of damage up to year 50. In addition, one can argue that a repair strategy using CFRP was sufficient to restore the bridge to the desired level at a relatively early time in the bridge life-cycle (at year 29). However, at year 50, additional repair and retrofitting schemes could be added to the repair strategy to further improve the structural performance of the bridge. Before discussing the last intervention at year 69, we notice that the bridge was reconstructed at year 52. This corresponds to the third intervention, which was required shortly after the second intervention. The short interval of time between the successive repairs needed at years 50 and 52 indicates that the bridge is deteriorating rapidly at this point and that the CFRP applied is not sufficient to counteract the effects of the damage accumulated from the deterioration processes up to that time. Following the reconstruction of the system, a new cycle begins during the time horizon of 75 years. Subsequently, the fourth intervention restores the bridge to a higher state than β_0.

For $CO_2eq(t)$ due to the construction and the recovery processes, we first observe, in Figure 4, the carbon footprint due to the construction at $t=0$, CO_2eq_0. The increase in $CO_2eq(t)$ at years 29, 50 and 69 is of similar magnitude due to the application of a similar amount of CFRP at each intervention. CFRP with thicknesses 1.25 mm, 1.35 mm, and 1.25 mm are required around the plastic hinge for the repair strategies at year 29, 50 and 69, respectively. In addition, the small magnitude of the $CO_2eq(t)$ due to these repair strategies, compared to CO_2eq_0, reflects the difference between the contribution between the construction and each repair strategy with respect to the overall $CO_2eq(t)$. However, we can observe the significant increase in $CO_2eq(t)$ due to the reconstruction of the bridge at year 52. This means that the $CO_2eq(t)$ due to the multitude of recovery strategies required during these 75 years exceeds the impact of the CO_2eq_0 due to the bridge construction at $t=0$. Accordingly, this reflects the importance of considering the deterioration of the bridge in evaluating its environmental performance, since the deterioration processes ultimately lead to the recovery processes which result in an increase of the $CO_2eq(t)$ of the bridge over time. From the simulation-based approach, we obtain a probabilistic output of the $CO_2eq(t)$ due to the construction of the bridge and the four recovery processes, as presented in Table 2, which shows the mean and standard deviation of the $CO_2eq(t)$ during 75 years.

Table 2: 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)	Standard Deviation (kgCO2eq)
0	13844.35	2528.96
29	117.66	26.14
50	117.77	25.55
52	13979.29	2548.04
69	118.11	25.9

CHAPTER 5: CONCLUSIONS

This work proposed a stochastic formulation for the evaluation of the life-cycle sustainability of engineering systems, named Stochastic Life-cycle Sustainability Analysis (SLCSA). In the SLCSA, the sustainability of the system is evaluated in terms of its environmental impact over a fixed time horizon. The formulation provides a more comprehensive approach to estimate the environmental impact of a system, by considering the environmental impacts due to the various processes (such as construction, recovery and operation processes) associated with the structure and the mechanical components of an engineering system. Moreover, the proposed formulation accounts for the relevant uncertainties, such as those in the external conditions, and those in the environmental emissions associated with the materials and energy processes used during the time horizon of interest, in determining the environmental impact of the system.

As an illustration, the life-cycle sustainability evaluation of an example RC bridge, subject to corrosion and seismic excitations, is presented. In the example, the carbon footprint due to construction of the bridge and four recovery processes is evaluated. Based on the simulated scenario of the bridge deterioration, the results indicated that the cumulative carbon footprint from the recovery processes can exceed the initial footprint due to construction. This particularly the case when a repair strategy (such CFRP retrofit scheme) is not sufficient to restore the structure to a target state, and a reconstruction of the bridge is thus needed. The example shows the importance of considering the deterioration of engineering systems when evaluating their sustainability over a time horizon of interest. Subsequently, the estimated environmental impacts can be used in a multi-criteria optimization problem for the design and management of reliable and environmentally friendly engineering systems.

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