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On Decision Support for Sustainability and Resilience of Infrastructure

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Abstract: An overview of selected contributions across the different sciences to sustainability and resilience research is provided and discussed. A general framework for supporting decisions for sustainable and resilient design and management of societal infrastructures is then proposed taking basis in Bayesian decision analysis and probabilistic systems performance modelling.

A principal example for decision support at regulatory level is presented for a coupled system comprised of infrastructure, social, hazard and environmental subsystems. The infrastructure systems is modelled as multi-component Daniels system generating benefits over time after deduction of potential losses due to disturbance events. The societal system is represented in terms of the preparedness level with respect to respond, reorganize and rehabilitate functionality after disturbances and the environmental system is represented in terms of local and global scale constraints concerning acceptable emissions.

1 Introduction

1.1 Resilience research – a view across the sciences

In Pimm [17] and Holling [12]fundamental concepts ideas and insights regarding resilience of ecology systems are introduced. Resilience is introduced as as the ability of systems to sustain disturbances, and reduce the time it takes before the systems recover to their original states of functionality. Moreover, the magnitude of a disturbance, which is able to bring the system into another state of equilibrium with different functionality characteristics, is proposed as a measure of resilience. It is noted that not only the "strength" characteristics of systems with respect to disturbances play a role for resilience, but that "capacity building" is a key facilitator for "preparedness and recovery". Janssen and Anderies [1] discuss the relationship between systems robustness and resilience characteristics and underline that these are strongly dependent. Derissen et al. [6] conclude that system resilience is not necessarily a preferred state. One system may possess several states of equilibrium, which individually could be resilient; however, the benefits associated with the different possible resilient states may differ significantly. Anderies [2] addresses optimal allocation of available resources for the built environment and points at strategies for enhancing resilience in dependency of the magnitude and frequency of disturbances.

Cutter et al. [5] addresses resilience of social systems and provides indicators with explanatory power regarding their ability to sustain disturbances and to re-organize, adapt and re-establish functionality during and after disturbances.
In Kates et al. [15] it is recommended to explore and assess the relation between resilience and sustainability and decision support systems are proposed as a means to identify sustainable paths of societal developments. Building on the ideas and concepts relating to the Planetary Boundaries introduced by Steffen et al. [19] and Rockstrom [18], Hauschild [11] suggests to utilize quantitative sustainability assessments to assess the aggregate impacts of human activities at global level with respect to the main parameters controlling safe operating conditions for the planetary system, such as climate change and biodiversity. Thereby facilitating comparison of best available knowledge regarding the impacts associated with different possible societal development trajectories with the corresponding capacities of the planetary system.
Based on the aforementioned developments, new ideas on resilience modelling and quantification for systems relating to infrastructure are proposed in Faber et al. [8]. There a novel decision analytical approach to resilience modelling is taken and a probabilistic framework for the representation and quantification of resilience of interconnected systems is proposed. Resilience failure is represented as the event that a disturbance leads to a capacity loss of the system beyond its accumulated reserves and the probability and consequences associated with the event are modelled and analysed using approaches and techniques from modern structural reliability theory. Faber and Qin [10] extend the ideas of Faber et al. [8] to address also aspects of sustainability by considering material consumption and related CO2 emissions associated with construction, operation and failure of infrastructure systems providing first insights on how resilience, efficiency and sustainability relate to each other – and on how resilient is resilient enough.
In the present paper, following closely Faber et al. [8] and Faber and Qin [10], we outline and extend our previous works in order to investigate how to improve strategies for achieving resilient infrastructure systems in the face of both operational disturbances and disturbances originating from accidents, natural hazards or terrorist attacks by means of dedicated design provisions.

2 Decision analysis framework

2.1 Decision analytical systems representation

The considered system as illustrated in Figure 1 is comprised by the infrastructure system, the governance system, the geo-hazards system, the ecological/life support system and the regulatory system. As illustrated in Figure 1, it is assumed that the performances of the interlinked system evolve over time and the ultimate objective is to identify decisions on the design and governance of the interlinked system, which optimizes these performances in accordance with societal preferences. Typically, performances such as reliability, risk, efficiency, robustness, resilience and sustainability are of core interest. It is important to note that this system representation facilitates accounting for the temporal dependency in system performances over time – which is of special interest in resilience and sustainability modelling. In the example considered in Chapter 3 the temporal evolution of the system performances is accounted for through time-slicing, whereby the condition of the system is modelled e.g. on an annual basis and the condition of the system at one particular time depends on the system performance in the past.

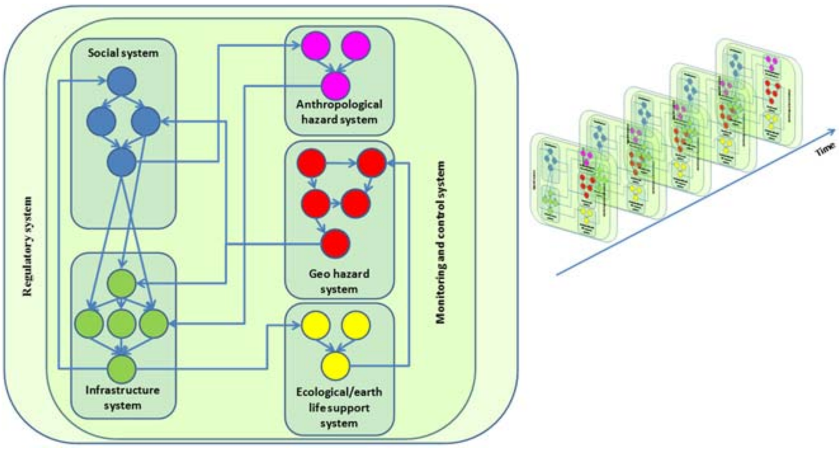


Figure 1: Illustration of interlinked system with time slicing over time (extended from Faber et al. [9])

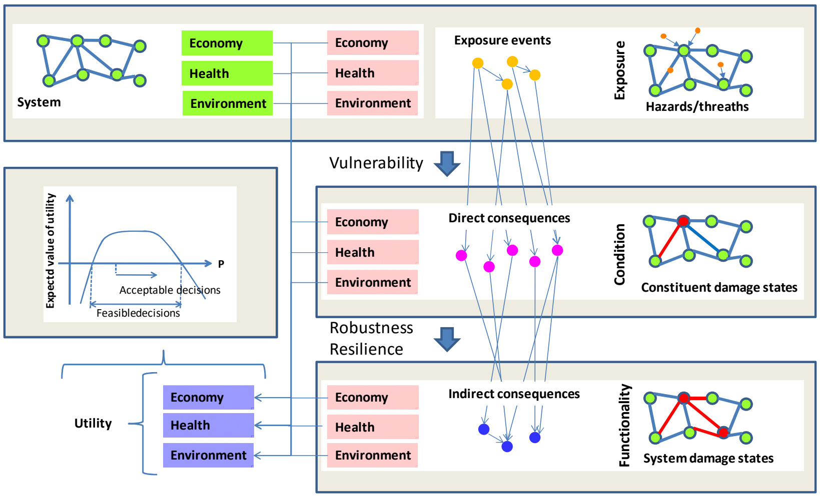


Figure 2: Illustration of systems modeling framework (Faber et al. [9])

The performances of the interlinked system (see Figure 1) may be assessed from the principal model illustrated in Figure 2 which applied in accordance with Bayesian decision analysis facilitates consistent book-keeping of benefits and losses associated with different decision alternatives and with due consideration of uncertainties and/or lack of knowledge.

2.2 Modelling of resilience failure

Different propositions for the modelling and quantification of systems resilience are available in the literature, see e.g. Cimellaro et al. [4]and Linkov et al. [16]. Typically, focus is directed on the short-term representation of the ability of the system to sustain and recover from disturbances, fast and without substantial loss of functionality. Hazard and disturbance events are generally specified in terms of type and intensity. The ability to sustain and recover from disturbances is modelled through the social, organisational and adaptive capacities together with traditional characteristics of technical systems such as strength, ductility, brittleness, redundancy, segmentation and diversity, see e.g. Derissen et a. [6]and Pimm [17].

Following Faber [7], we propose a life-cycle oriented model of systems resilience in which scenarios of benefit generation and losses are modelled and analysed over time and where insufficient resilience or systems resilience failure is defined as exhaustion of system capacity (social, economical and/or environmental). Resilience, in the same manner as robustness is thereby a system characteristic of a random nature and requirements to resilience may only be specified meaningfully in probabilistic terms; e.g. in terms of an acceptable annual probability of resilience failure.

In Figure 4 this idea is illustrated for the simple case of a system for which the only explicitly considered capacity is a financial reserve collected as a fixed percentage of the annual benefit generated by the system over time.

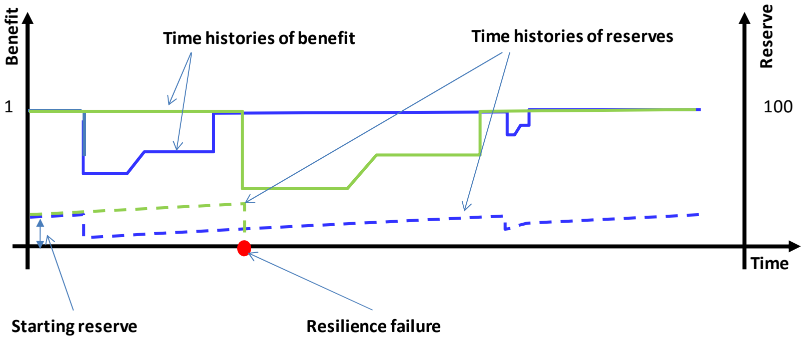


Figure 4: The proposed resilience model in terms of time histories of benefit generation and corresponding time histories of accumulated economic reserves [8].

The general shape of the benefit loss curves in the aftermath of disturbances reflects, that a certain time is required before the functionality can be re-established; first only up to a certain level, reflecting that interim solutions are foreseen, implemented and operated while waiting for the preparation and implementation of full and possibly even improved system rehabilitation. In Figure 4 two pairs of time histories of benefit generation and accumulated economic reserves are illustrated and it is seen how disturbance events may both reduce the benefit generation as well as the reserves. In the time history illustrated with a green line it is seen that a disturbance event exhausts the accumulated reserves and causes a resilience failure.

The probability of resilience failure $P_{RF}(t,\mathbf{a})$ may in this manner be represented and assessed probabilistically as (see Faber and Qin [10]):

$$P_{RF}(t,\mathbf{a}) = P\left[r_r(\mathbf{X}(t),\mathbf{a}) - s_r(\mathbf{X}(t),\mathbf{a}) \le 0\right] \tag{1}$$

where $r_r(\mathbf{X}(t),\mathbf{a})$ is a function representing a given capacity of the system at time t and $s_r(\mathbf{X}(t),\mathbf{a})$ is a function representing the stress on the system caused by a disturbance event at time t. $\mathbf{X}(t)$ is a vector of random variables which may depend on time and $\mathbf{a}$ is a vector containing all decision alternatives which may affect the resilience performance of the system. It is seen that the problem of assessing the probability of resilience failure is a first excursion problem. Conditional resilience may be modelled and assessed utilizing the scenario based life-cycle oriented approach. Conditioning on hazard events of given characteristics, the resilience can be defined as recovery within a given time horizon without exceeding available reserves.

Examination of Figure 4 reveals that the first immediate drop in the benefit rate (or functionality) after a disturbance event relates directly to the systems robustness. Even with moderate assumptions concerning the contribution of indirect consequences to total consequences it is apparent that cascading failures and loss of functionality plays a significant role for the resilience of the system. Moreover, it is seen in Figure 4 that a starting capital or reserve is assumed available at time $t = 0$. In a normative perspective, such a reserve is indeed possible, provided that the portfolio of assets in the considered system is sufficiently large. In the design and management of systems, however, sufficient resilience critically depends on the maintenance of this reserve as illustrated in the example presented in Chapter 3.

2.3 Modelling of sustainability failure

The framework presented in the foregoing facilitates for a joint consideration of impacts to the environment, health and welfare of people, economy and exhaustion of natural resources from the perspective of intergenerational and temporal equity. However, in the following, only impacts of CO2 emissions to the stability of the planetary system are considered – the Earth Life Support System (ELSS). According to Steffen et al. [19] the ELSS may become unstable if its capacities to cope with emissions and other disturbances caused or influenced by human activities are exhausted. Research is still ongoing with respect to understanding and assessing the capacities of the ELSS with respect to CO2 emissions, acidification of the oceans, extinction of species, fresh water use etc. However, it may be assumed that for each of the presently identified 11 critical boundary variables it is (or will soon be) possible to formulate criteria of the form:

$$r_i(\mathbf{x},\mathbf{a},t) - s_i(\mathbf{x},\mathbf{a},t) \le 0, \qquad i = 1,2,..n_B \tag{2}$$

where $r_i(\mathbf{x},\mathbf{a},t)$ and $s_i(\mathbf{x},\mathbf{a},t)$ are complex functions describing the capacities and the stresses acting on the ELSS with respect to its n_B boundary variables at a given point in time t. $\mathbf{x}$ is a vector of variables entering the functions and $\mathbf{a}$ is a vector of decision alternatives which may influence both the capacities and the stresses. Assuming that the variables $\mathbf{x}$ are associated with uncertainty we may assess system sustainability probabilistically along the same lines as system resilience failure through:

$$P_{SF,i}(\mathbf{a},t) = P\left[r_i(\mathbf{x},\mathbf{a},t) - s_i(\mathbf{x},\mathbf{a},t) \le 0\right], \qquad i = 1,2,..n_B \tag{3}$$

The probability of sustainability failure $P_{SF,i}(\mathbf{a},t)$ may, as for the case of resilience failure, be assessed as a first excursion problem. In the general case where all n_B planetary boundary variables are considered, this becomes a vector valued first excursion problem. As stated earlier, however in the present paper only CO2 emission environmental impacts are considered. These impacts are assumed to be directly related to the material consumption implied by the construction and operation of the societal infrastructure, with due account to maintenance and reconstruction after disturbance events as well as renewals due to obsolesce.

3 Example

3.1 Infrastructure system representation

In the present example, we address how accounting for differentiated perspective to the reliability of systems constituents into the design of systems may enhance their performance in terms of resilience with respect to different hazard types. The example extends on examples given in Faber et al. [8] and Faber and Qin [10] outlined in the following.

The infrastructure system considered is represented by a Daniels system comprised of n_C constituents, see Figure 5. The system performances are modelled over time histories of 100 years. Each constituent is represented by a resistance R with respect to operational annual maximum loading L, and a resistance η with respect to geo-hazard disturbances H.

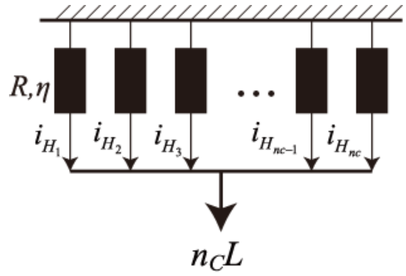


Figure 5: Illustration of the n_c-constituent Daniels system

The resistances of the infrastructure system R and η, are assumed correlated with correlation coefficient $\rho[R,\eta]=0.8$, and are both represented by log-normal distributed random variables with expected values equal to 1 and coefficients of variation (CoV) equal to 0.2 and 0.3 respectively. The operational annual maximum loading L is modeled by a Gumbel distributed random variable with expected value equal to 1 and CoV equal to 0.3. The daily maximum operational load is modeled by a Weibull distribution (to ensure non-negative realizations) which is fitted such that it provides the same annual failure probability as the Gumbel distribution for the annual maximum. The daily maximum operational load is relevant in the case where part of the infrastructure system is damaged and the further progression of system damage is assessed subject to redistribution of operational load, i.e. $n_C L$. The constituents of the infrastructure system are assumed to behave brittle at failure, implying that they lose their load carrying capacity completely after their capacity limit is reached.

The natural hazard disturbance events are assumed to follow a Poisson counting process with annual occurrence rate λ_H. The intensity of disturbance events acting on each constituent I_H is assumed to follow log-normal distribution, whose expected value $E[I_H]$ varies with the annual occurrence rate and coefficient of variation $COV[I_H]$ is equal to 0.4. The realizations of the intensities are assumed independent from time to time but the disturbances acting on the constituents at a given time are assumed correlated with correlation coefficient $\rho_{I_H} = 0.8$.

The limit state functions representing failure of the individual constituents with respect to operational annual maximum loads and the disturbances from the geo-hazard system are given as:

$$\begin{cases} g_O(\mathbf{x}) = z_1 r - l \\ g_H(\mathbf{x}) = z_2 \eta - i_H \end{cases} \tag{4}$$

where z_1 and z_2 are design parameters depending on the target probabilities of constituent failure which should comply with the requirements of the regulatory system. The material consumption M_C is also introduced here, which is considered proportional to the design parameters z_1 and z_2 together with the total number of constituents. Here for simplicity, the initial material consumption is represented by $z_1 n_C$.

Failure of the Daniels system takes place either due to annual operational maximum loads exceeding the capacities of the constituents with possible subsequent cascading failure scenarios, or by constituent failures due to natural hazard events, which then further due to daily maximum operational loads may lead to cascading constituent failure scenarios for the system. The infrastructure system represented by the Daniels system provides generation of benefit which is assumed constant in time as long as the system is undisturbed. In case of disturbances due to operational or geo-hazard disturbance events the generation of benefit is reduced or lost. It is further assumed that the replacement costs in a given event scenario of failures C_F are directly proportional to the number of failed constituents in that event scenario n_f, i.e. $C_F = 10 n_f / n_C$. Correspondingly, the material consumption is $z_1 n_f$.

The main function of the governance system is here simply to respond to failures of the infrastructure caused by disturbances. It is assumed, that the governance system can be represented by the functionality disturbance and recovery curve illustrated in Figure 6.

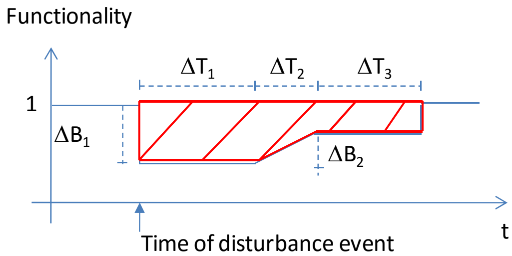


Figure 6: Illustration of the main function of the governance system with respect to recovery of infrastructure functionality under disturbances (Faber et al. [8])

Details on the probabilistic modeling of benefit loss and recovery curve shown in Figure 6 are given in Faber et al. [8]

It is assumed that the governance system maintains a reserve capital to be available over the life cycle of the infrastructure system for covering the cost of replacement of system constituents, which may fail over time due to disturbance events. At time $t = 0$ the starting capital reserve R_S is modeled as a percentage χ% of the expected value of the accumulated benefits over the life cycle $E[B_L]$ minus the construction cost of the system, i.e. C_C, which is assumed to be proportional to the design parameter z_2 here, i.e. $R_S = \chi\% \times E[B_L] - C_C = \chi\% \times E[B_L] - 2.473 z_2$.

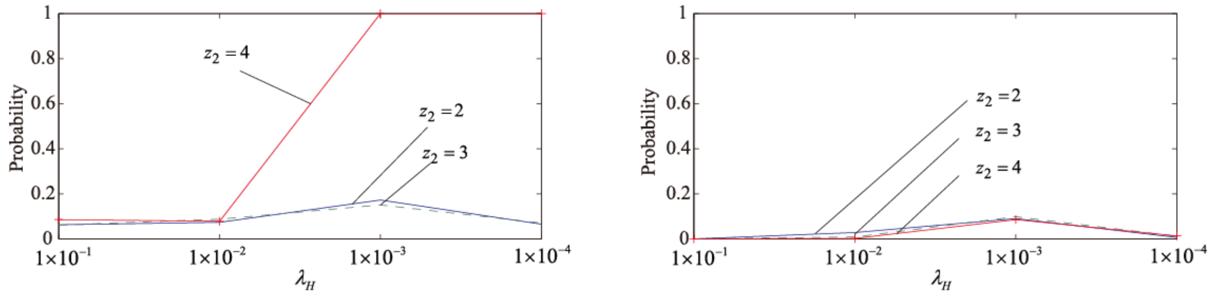
The regulatory system is formulated here to manage the performance of the infrastructure system subject to the operational loads and the geo-hazard system on behalf of the governance system through the calibration of the design parameters z_1 and z_2 and the percentage χ%.

3.2 Discussion of results

The resilience performance and the corresponding environmental impact of infrastructure systems are investigated as function of the reliability of the system constituents with respect to the geo-hazard system and the social preparedness level, taking basis in an example considering a n_c-constituent Daniels system.

In the following we model and assess the annual probability of resilience failure for different assumptions regarding the parameters defining the considered system. More specifically the system is analyzed with the annual occurrence rate λ_H=1x10^{-1}, 1x10^{-2}, 1x10^{-3} and 1x10^{-4} (the mean of the intensity $E[I_H]$ takes the values 0.1, 1, 10 and 100 correspondingly), the design parameter z_2 = 2, 3 and 4, low and high levels of social preparedness. The number of the constituents n_C is 10. The design parameter z_1 is here defined to be 3.5 corresponding to an annual probability $p_{f,O}$ close to 2×10^{-4}. The percentage χ% is set to be relatively low 10% so that the influence of the geo-hazard subsystem and the social preparedness system may be assessed with moderate computational efforts.

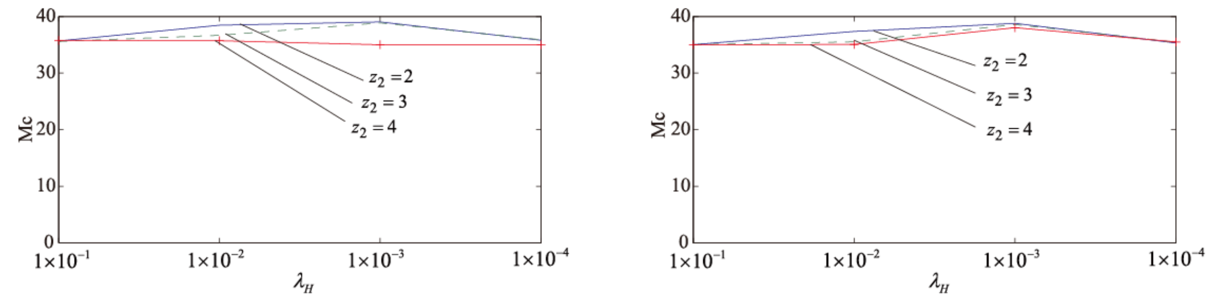
The value of λ_H then varied to investigate the influence of the design target with respect to the natural hazard disturbances on the systems resilience and material consumption. The results are shown in Figure 8 and Figure 9 respectively. It is seen that for the rare disturbances with high intensities the increase of the design parameter z_2 will not necessarily improve the system resilience. The increase of z_2 increases the initial construction cost and correspondingly reduce the starting reserves. For the system with small percentage $\chi\,\%$ and large z_2, the starting reserve R_S diminishes and even small disturbance from the operational load or the geo-hazard subsystem may result in exhaustion of the reserve. Nevertheless, the high level of preparedness maintains the probability of the resilience failure at a relatively low level.



(1) Low preparedness (2) High preparedness

Figure 8 : Probability of resilience failure of the infrastructure system for different values of λ_H given the design parameter z_2 and the level of preparedness

The expected value of total material consumption of the system considering the initial construction and further reconstruction due to the damage caused by the disturbances is calculated and provided in Figure 9. It is seen that compared with systems with low level of preparedness, the systems with high levels of preparedness, which keep the probability of resilience failure low, does not increase the consumption significantly. Meanwhile, the increase of the design parameter i.e. z_2 results in larger initial material consumption but also reduces the probability of renewals during the service life.



(1) Low preparedness (2) High preparedness

Figure 9 : Expected value of material consumption of the infrastructure system for different values of λ_H given the design parameter z_2 and the level of preparedness

4 Conclusions

The present paper proposes a general framework for supporting decisions on sustainable and resilient design and management of societal infrastructures closely following Faber et al. [8] and Faber and Qin [10]. An interlinked system comprised by infrastructure, social, hazard and environmental subsystems is presented and analyzed. From the analysis, the trade-offs between reliability, resilience, sustainability and reliability may be assessed. The example shows that for the considered systems, especially those faced with rare natural hazard disturbances with high intensities, a high resilience performance necessitates the availability of an adequate financial reserve rather than a high target reliability for the constituents of the considered system;

moreover these two factors do not significantly influence the material consumption. A high target reliability for the individual constituents generally increase the initial material consumption but the subsequent consumption is reduced. On the other side, a high level of preparedness, which improves the resilience performance substantially, does not lead to significant addition material consumption.
The modeling and investigations presented provide a holistic and consistent framework for balancing tradeoffs between system performance characteristics such as robustness, resilience and sustainability. Future research is needed to develop the framework further to better capture the interdependencies between impacts to human health, economy, social capacity and emissions and other damages and impacts to the qualities of the environment.

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