Resilience of systems by value of information and SHM

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Abstract: Critical infrastructure systems such energy provision and distribution systems, transport systems and the built environment in general are subject to and sensitive to deterioration processes. Structural Health Monitoring (SHM) strategies have been increasingly employed as a means to detect deterioration, facilitate timely and efficient interventions – and thereby to enhance resilience of critical infrastructure. However, in specific situations, it is generally not obvious if and to what degree different SHM strategies are efficient and sufficient for enhancing the resilience of critical infrastructure systems. In response to this challenge, the present contribution puts forwards a novel approach, taking basis in the concept of value of information analysis from Bayesian pre-posterior decision. Utilizing a principal model framework we show how the proposed approach is implemented with due consideration of the resilience governing characteristics and interdependencies between infrastructure systems, social/organisational systems, regulatory systems, ecological systems as well as anthropological and geological hazard systems.

1 Introduction

The resilience performance of critical infrastructure systems subject to disturbance events strongly depends on the degree and type of interaction among its components and their condition state at the time the disturbances occur. In order to gain more knowledge and thereby reduce uncertainty associated with the state of degradation of the system components, structural health monitoring is widely applied; see e.g. [7], [21]. The use of SHM facilitates the observation and assessment over time of the condition of system components providing valuable information in the context of asset integrity management. Based on information collected in the future, relevant and optimal remedial activities may be identified. When considering system performance in the context of resilience assessment, not only the performance of the infrastructure system with respect to disturbance events is in focus but very importantly also the interactions between the infrastructure system and the other systems defining its context. Indeed, in the context of resilience assessment critical infrastructure must be seen as complex systems comprised by interacting and interdependent sub-systems including, regulatory authorities, owner and operator organisations, the free market, monitoring and control systems, ecological systems, natural resources and the qualities of the environment in general. Those interactions represent the context of the infrastructure systems, i.e. the dynamic interrelations between the services provided by the infrastructure systems, the natural resources facilitating the provision of the services, the organisations and the market mechanisms providing for the development, operation, maintenance and renewals of the infrastructures, the environmental qualities affected by the service provision, together with the anthropological hazards and the geo-hazards, which may cause disturbances. Moreover, it should be noted that severe disturbance events cause damages not just to the physical infrastructures, but also generate damages and associated losses to any of the other interacting sub-systems ([3], [9]).

The term resilience has been widely used in different disciplines starting from psychology and anthropology to system dynamics, biology and engineering systems [1]. A milestone was set by Holling [13] for the definition and understanding of system resilience as the ability of those 'relationships governing the ecosystems to persist after disturbance'.

Different research activities are targeting the quantitative assessment of resilience at infrastructural and community level, identifying robustness, redundancy, resourcefulness and rapidity of response as key performance indicators of the infrastructure system (e.g. [4], [10]), mostly considering only structural and functional performances and no interactions with interrelated sub-systems. As highlighted in the foregoing, this perspective is very narrow and leads to over simplification of reality. Resilience modelling and assessments must take basis in a representation of infrastructure systems in their context. Moreover, resilience targets should be set in coordination with all the involved stakeholders to enhance the restorative ability of the built environment [10].

In Faber et al. ([8], [9]), a holistic approach to system representation and resilience quantification is presented, showing how resilience should be seen as an integral property of the built environment modelled as an interlinked system built on five components, namely geo-hazard, infrastructure, governance, regulatory and earth life supporting system. The resilience of the system is modelled in terms of the temporal evolution of the system service provision depending on the geo-hazard, losses and preparedness of the governance system which in turn is related to the societal level of development (see [9]).

Therefore, structural health monitoring alone is not enough in the context of resilience and the monitoring framework should be extended to all sub-systems, which affect the service provision of the infrastructure systems.

To this aim, based on [9], the concept of value of information analysis is proposed as a consistent methodical framework to assess the value associated with different strategies for collecting new information regarding any of the sub-systems governing resilience of critical infrastructure systems, including the physical infrastructure systems themselves.

2 Value of Information in systems resilience modelling

2.1 Definition of value of information

Based on prior information (probabilistic models) the Bayesian a-priori decision analysis is readily utilized to rank possible decision alternatives in accordance with the associated expected values of utility, see e.g. Raiffa and Schlaifer [19]. If new information is available, this may be taken into account as support for the ranking of decision alternatives by means of Bayesian updating. The prior probabilistic models are updated using the new information and an a-posteriori decision analysis is conducted in exactly the same manner as the a-priori decision analysis. It is typical that the ranking of decision alternatives changes after new information is utilized. The idea behind the concept of value (VoI) is that even if new information is only available in a probabilistic sense, the expected value of utility associated with the new information can be assessed by accounting for the changes (a-posteriori) in the ranking of possible decision alternatives that the possible realizations (a-posteriori) of the new information would imply.

Information comes at a cost and the decision maker needs to assess the benefit she can derive from buying this ([7],[17]). Indeed, the decision maker can typically choose among different strategies for collecting new information and the application of VoI greatly their optimization and ranking.

In the context of Bayesian pre-posterior analysis, the value of information (VoI) associated with structural health monitoring is defined as the difference in the expected value of life cycle benefits associated with acquisition of new information through SHM and the expected value of life cycle benefits without the new information (see Eq.1). Following the terminology in Raiffa and Schlaifer [19], Eq.(2) and Eq.(3), respectively, provide the expressions of the expected value of the life cycle benefit in prior analysis (no information is observed) and in pre-posterior analysis (with uncertain information, i.e. before observation). In Eq.(2) and (3), a is a vector containing the set of decision alternatives, $\boldsymbol{\theta}$ is a vector describing the uncertain state of the system, $\mathbf{Z}$ is a vector containing information of the system state $\boldsymbol{\theta}$ achieved through SHM and e is a given SHM strategy, the operators E and E'' denote respectively the prior and posterior expected value operators and the maximization operator indicates that $u^*{}_1$ and $u^*{}_2$ correspond to the expect value of utility maximized with respect to $(\mathbf{a}, \boldsymbol{\theta})$ and $u(\mathrm{e}, \mathbf{z}, \mathbf{a}, \boldsymbol{\theta})$ respectively.

$$VoI = u^*{}_2 - u^*{}_1 \tag{1}$$

$$u_1^* = \max_{\boldsymbol{a}} E_{\theta|z} u(\mathbf{a}, \boldsymbol{\theta}) \tag{2}$$

$$u_2^* = \max_{e} E_{z|e} \max_{\boldsymbol{a}} E''{}_{\boldsymbol{\theta}|\boldsymbol{z}} u(\mathrm{e}, \mathbf{z}, \mathbf{a}, \boldsymbol{\theta}) \tag{3}$$

In Figure 1, the classic decision-event tree paradigm of Bayesian pre-posterior decision analysis (adapted from [19]) is depicted. Herein, an influence diagram with integrated Bayesian network is used in our model instead of the decision tree representation.

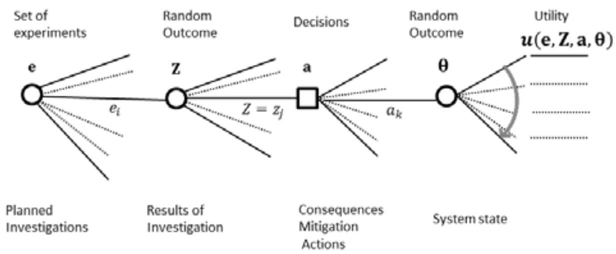

Figure 1: Paradigm of the Bayesian pre-posterior decision analysis (adapted from Raiffa and Schailfer [19])

To evaluate the effectiveness of a monitoring strategy (e), considering the overall system over its lifetime, the utility function may be modelled in terms of the time evolution of net benefits. When evaluating the monitoring strategy at generic level, with the objective to evaluate the VoI associated with a specific variable in the model, to model time evolution of the performance is not necessary and it can be replaced by deterministic scenarios. In our model, the utility function is represented by the net-benefit associated with the service provided by the system and accounts for the consequences associated with disturbance events in terms of direct loss associated with restoring service provisions and additional losses due to lost or reduced service provision. As outlined in Chapter 2.2 additional losses may be assigned to further and delayed effects due to e.g. unmitigated climate change.

2.2 Application of VoI to systems resilience modelling

A Bayesian Network model is used to represent critical infrastructure according to the model presented in Faber et al. ([8], [9]). The interconnection among the components of the system and sub-systems are designed based on an extensive literature review on resilience of socio-economic systems and sustainability of human activities, which to a large part is omitted in the present paper, and partially on simulation data from Faber et al ([8], [9]). A simple representation of the model with time evolution of the functionality according to [8] is illustrated in Figure 2, while the full Bayesian model is depicted in Figure 3.

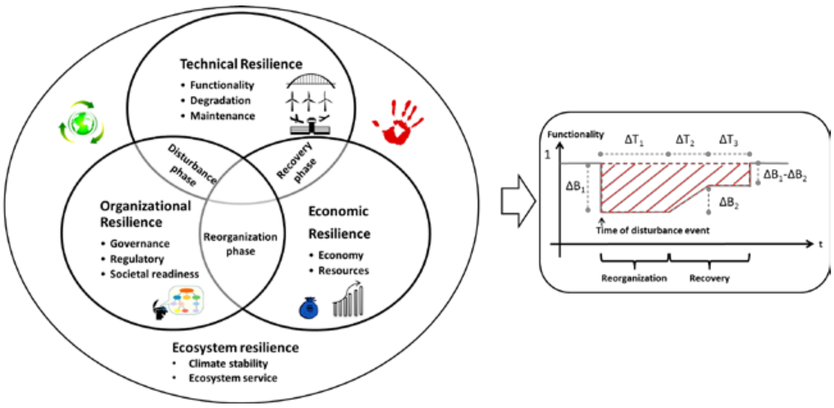

Figure 2: (left) Representation of the multiple dimensions of resilience of the built environment; (right) Functionality of the system after disturbance vs time (Faber et al [8])

The time evolution of the functionality of a generic system according to Faber et al [8] identifies three main phases: 1- disruption phase due to the damage of the system; 2- reorganization phase, whose duration depends on emergency management policy; 3- system rehabilitation phase, which depends on the recovery ability of the system. The quantities $\Delta B1$, $\Delta B2$, $\Delta T1$, $\Delta T2$ and $\Delta T3$ on the functionality curve depend on both initial losses and preparedness of the governance system and the society to respond to the disruption of functionality ([8]).
Technical resilience is represented by the performance of the infrastructure system. The considered infrastructure system is assumed subjected to two different and independent types of disturbance events, namely operational disturbance events (in the act of providing services), which may cause internal demands in exceedance of internal capacities, and geo-hazard disturbance events, which may damage parts of the considered system. Either type of disturbance events may reduce or inhibit provision of services. The performance of the infrastructure system is represented by the probability of different system failure states when subjected to operational and/or geo-hazard disturbance events, conditional on degradation and user demand (see Figure 3). The degradation is modelled qualitatively through a variable with discrete states (low, average and high degradation) and it is assumed that climate change increases the degradation rate, while increased demands on the use of the infrastructure (modelled as a Boolean variable) depends on the societal development level and in turn results in a higher

renewal rate due to obsolescence. The societal development level, intended as an indicator of the general level of wealth, is here used to represent three societal scenarios, namely developing country, developed country and highly-developed country.

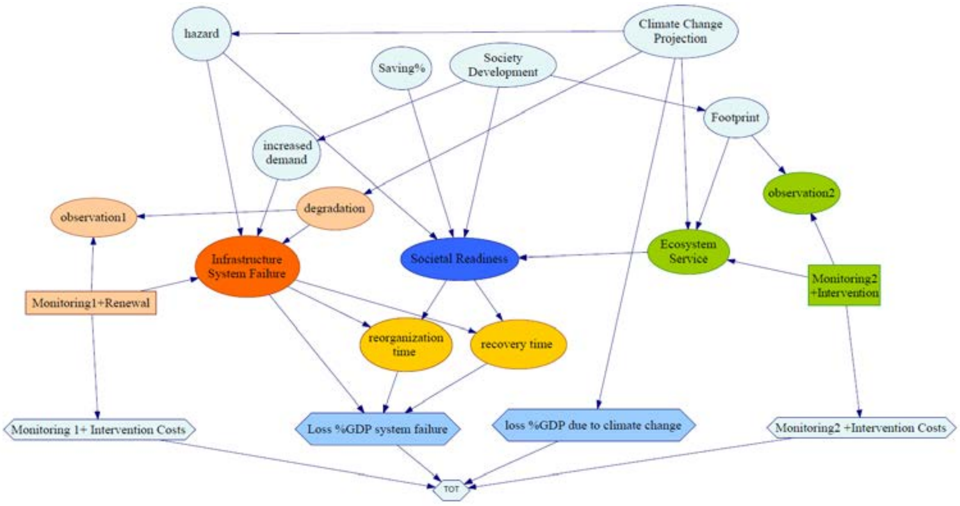

Figure 3: Influence diagram for the representation of the built environment

In order to introduce the effect of decision alternatives regarding the resource availability (i.e. economic resilience dimension), we introduce the variable 'savings' to model the access to financial reserves during reorganization and recovery phase to cope with both contingent needs and reconstruction costs ([5], [12]). We consider three values for the annual savings, 0-5-10% of the annual GDP of the hypothetical society. The GDP (gross domestic product) is used as metric for the performance of the infrastructure system in terms of losses due to failure states, losses due to delay in reorganization and recovery, costs of monitoring and intervention on the system and losses due to unmitigated effects of climate change.

The readiness of the society, intended as the ability to cope with the disturbance events and the ability to restore functionality in the shortest time possible, reflects organizational resilience of the considered society. Here readiness is related to the development level of the society, due to the evidence that a developed and well-educated society recovers faster ([5]). Moreover, readiness depends on the availability of economic resources (savings) from the government to invest, on the management of emergency activities and on the intensity of the event affecting the infrastructure system. We consider the readiness as Boolean variable (Yes/Not) where the model is quantified based on the following hypothesis: 1- readiness is likely to be lower for high intensity of geo-hazard disturbance events; 2- readiness increases with availability of economic, natural resources, and societal development level.

Reorganization and recovery time represent important variables modelling the response of the system and they are related to both failure of the infrastructure system and to the readiness of the society affected by the disturbance event (see [8], [9], [16], [17]).

To represent the ecosystem resilience dimension, the climate change, footprint and ecosystem service variables are introduced. The climate change variable is modelled as a Boolean variable (Yes/Not) representing the exceedance of climatic stability threshold conditions in relation to a selected projection scenario (here RCP2.6 of the IPCC is used, [11],[14]). The reason behind the introduction of a dependency on climatic stability is that the effect of exceeding threshold condition of climatic stability may make more difficult for the societal system to cope with the losses ([12], [17]). In addition, the assumption that exceedance of climate change threshold may cause a 10% increase in the occurrence of geo-hazard disturbance events is made. The carbon footprint ([20]) is then introduced as a normalized indicator representing the resources use made by the system with respect to the available resources. It serves as a proxy of how much of the natural resources is left unused and available for exploitation in case of need. In relation to both climate change and footprint, the ecosystem service variable is introduced, in qualitative terms (low-average-high), to account for environmental damage In fact, quality of ecosystem service depends on both footprint (e.g. high footprint means a large exploitation of natural resources) and on climate change, which can reduce ecosystem service by reducing the availability of redundant species and resources able to support human activities, causing thus a reduced response ability of the societal system and a potential loss of income ([6]).

With respect to readiness and hazard intensity, we can distinguish among four main cases ([8], [17]): case1-High level of readiness and low intensity hazard events; case2- High level of readiness and high intensity events; case3- Low level of readiness and low intensity events; case4- Low level of readiness and high intensity events. According to the described four cases, we can assign expected values to the re-organization and recovery time as a percentage of the considered lifespan of the system (fixed as 100 years). Here we consider both re-organization and recovery time having discrete values, proportional to the service life of the system and with assigned probabilities. Based on the assumption that the use of the infrastructure system allows a generation of benefit equivalent to 40% of annual GDP of the hypothetical society we are looking at, the losses associated to the different system failure states of the infrastructural system are considered equal to 20-50-100% of the GDP. Due to reorganization and recovery time, a fictitious additional loss related to the long recovery time is considered for low readiness and recovery time exceeding 50% of its service life. Additional losses due to unmitigated climate change are equal to 2.4% GDP in 100 years [11].

The VoI analysis is then possible by means of an influence diagram based on the Bayesian model representation of Figure 3. The pre-posterior analysis is performed using the GeNIe software (BayesFusion [2]). The VoI analysis is here used to evaluate if observations on the state of degradation of the infrastructural system and on the state of degradation of ecosystem are beneficial to the resilience of the system, with respect to different initial conditions (scenarios).

Two different policies over monitoring variables of the model are considered: 1- monitoring the degradation of the infrastructural system; 2- monitoring the environmental footprint of the socio-economic system as a proxy indicator of ecosystem service. In combination with these two policies, upon monitoring, a mitigation action can be taken or not. In the case of SHM strategy, the alternatives are to not repair, perform a small intervention or big renewal. In the case of environmental footprint, the alternative is to do nothing or introduce regulations to decrease the footprint.

To account for all dimension of resilience, the utility functions ${u^*}_1$ and u_2^* in Eq.2-Eq.3, can be rewritten to include the operational and disturbance events (*h*), the vector of system states $\boldsymbol{\theta} = \{\boldsymbol{d}, \boldsymbol{ds}, \boldsymbol{sg}, \boldsymbol{r}, \boldsymbol{c}, \boldsymbol{s}, \boldsymbol{f}\}$, which contains degradation (*d*), demand of service (*ds*), % of savings (*sg*), societal readiness, (*r*), climate change effect (*c*), level of ecosystem service (*s*) and ecological footprint (*f*)the vector of experiments $\mathbf{e} = \{\boldsymbol{e_1}, \boldsymbol{e_2}\}$ corresponding to the two monitoring options with observation on the degradation state (z_1) and environmental footprint (z_2), the decision vector **a** corresponding to the decision of monitoring the degradation condition of the infrastructure and/or the state of environmental footprint and act with an intervention (see Eq.4 and Eq.5).

$$ {u^*}_1 = \max_a E_{\theta|z} u(\mathbf{a}, \boldsymbol{\theta}(\mathbf{a}), h) \tag{4} $$

$$ u_2^* = \max_e E_{z|e} \max_a {E''}_{\theta|z} u(\mathbf{e}(\mathbf{a}), z(\mathbf{a}), \mathbf{a}, \boldsymbol{\theta}(\mathbf{a}), h) \tag{5} $$

2.2.1 Value of information of monitoring infrastructural system degradation

The value of information analysis with respect to the degradation of the infrastructure system is used to show the influence of the system failure over the resilience characteristics represented in the model by the nodes reorganization time and recovery time. Conditional probabilities are assigned as described in Section 2.2. The cost of the monitoring system is considered equal to 1% of GDP (unit used in the example) while the repair cost is considered 2%GDP for small/medium intervention and 10%GDP for large renewals. These costs could seem high, but they are considered as integrated costs over the lifetime of the system (i.e. we assume that an optimization of inspection interval and repairs resulted in this value of the total costs). The value of Information (VoI) associated with collecting information about the degradation state (see node observation 1 in Figure 3) which influences system failure is equal to 0.69 (see utility in Table 1). With respect to the minimization of the losses due to the system failure, the results of the pre-posterior analysis show small differences with higher values of the expected utility for the decision to conduct monitoring. Monitoring degradation when the infrastructure system has such a key role in the overall built environment performance is an advantageous policy, in relation to its efficiency in terms of costs and accuracy. Sensitivity analysis is also performed on the degradation variable by assigning ±5% upper and lower bounds of the conditional probability of degradation and resampling the influence diagram. The resulting variation of utility values is negligible, but a slightly higher sensitivity is found for the probability of degradation being on the upper bound.

Table 1: Expected Utility

Degradation variable, Utility	
Monitoring No	35.82
Monitoring Yes	**36.51**
Small Renewal upon Monitoring	35.81
Big Renewal upon Monitoring	28.5

It is interesting to calculate the VoI for specific scenarios. Three different scenarios are considered: 1- Scenario 1, no economic resources saved for emergency, low level of development, stable demand of service; 2- Scenario 2: 5% GDP economic resources saved for emergency, high level of development, stable demand of service; 3- Scenario 3: 5% GDP economic resources saved for emergency, high level of development, increasing demand of service.

VoI analysis is applied to the three scenarios in the case of operational and geo-hazard disturbance events and for exceedance of climate change threshold or not. For all scenarios, the VoI for degradation monitoring is small for the operational hazard for both cases of climate change thresholds exceedance (see Table 2, Table 3, Table 4). For geo-hazard disturbance events the VoI of monitoring degradation becomes significantly higher, since climate change and related ecosystem variables of the model have more influence on the utility function together with the system failure due to extreme events. The same behaviour is observed for all scenarios where scenario 3(Table 4) shows a higher VoI for operational load due to the fact that an increased demand of use of the infrastructures will affect operational conditions.

Table 2. Value of information for monitoring degradation for Scenario 1 for different combination of hazard and climate change (in %GDP).

Scenario 1	Climate Change Not Exceeded		Climate Change Exceeded	
	Operational	Geo-hazard	Operational	Geo-hazard
VoI	0.25	6.82	0.61	6.66

Table 3. Value of information for monitoring degradation for Scenario 2 for different combination of hazard and climate change (in %GDP).

Scenario 2	Climate Change Not Exceeded		Climate Change Exceeded	
	Operational	Geo-hazard	Operational	Geo-hazard
VoI	0.25	6.84	0.61	6.59

Table 4. Value of information for monitoring degradation for Scenario 3 for different combination of hazard and climate change (in %GDP).

Scenario 3	Climate Change Not Exceeded		Climate Change Exceeded	
	Operational	Geo-hazard	Operational	Geo-hazard
VoI	1.15	4.25	1.3	4.27

2.2.2 Value of information for monitoring ecological footprint

For the generic case, the VoI with respect to monitoring of the carbon footprint (see node observation 2 in Figure 3) is calculated. It is assumed that the carbon footprint contributes to resilience as a proxy for quality of environment and resources availability. Monitoring costs are set as twice the costs considered for monitoring degradation. Monitoring the carbon footprint as indicator for the ecosystem service is inefficient as can be seen from the results of the pre-posterior analysis (Table 5). Sensitivity analysis is also performed on the footprint variable by assigning a ±5% upper and lower bounds of the conditional probability of exceeding threshold value of the footprint and resampling the influence diagram. The resulting variation of utility values is negligible.

When considering scenarios 1&2 defined in the previous section, the VoI becomes significantly higher (see Table 6 and Table 7). The value increases by passing from operational to geo-hazard event and with the exceedance of the climate change carbon emission threshold.

Table 5. Expected Utility

Footprint	Utility
Monitoring No	**35.82**
Monitoring Yes	33.83
Intervention after Monitoring	25.83

Table 6. Value of information for monitoring footprint for Scenario 1 for different combinations of hazard and climate change

Scenario 1	Climate Change Not Exceeded		Climate Change Exceeded	
	Operational	Geo-hazard	Operational	Geo-hazard
VoI	1.42	7.10	7.10	0

Table 7. Value of information for monitoring footprint for Scenario 2 for different combinations of hazard and climate change

Scenario 2	Climate Change Not Exceeded		Climate Change Exceeded	
	Operational	Geo-hazard	Operational	Geo-hazard
VoI	0	7.10	2.13	7.10

Conclusions

The value of information analysis is utilized for quantifying the Value of Information of two different monitoring strategies applied as a means for improving the resilience of an interconnected system comprised by infrastructure, economy and environment. Both operational and geo-hazard disturbances are considered and the assessed strategies comprise monitoring of degradation of the infrastructure system and the carbon footprint on the ecological system. The introduction of monitoring of the deterioration of the infrastructure as well as of the carbon footprint has a positive effect on the performance of the interconnected system since observations from monitoring facilitate that future risk reducing measures may be invoked and optimized in accordance with the collected observations. By addressing two scenarios, the analysis of the sensitivity of the model with respect to the monitored variables in terms of their utility gain is facilitated. The expected value of utility gain from monitoring of the carbon footprint is higher when looking at geo-hazard disturbance events and when the system is highly vulnerable to climate change; being characterized by a high degradation and a low level of resources available in support of reconstruction. . Moreover, the VoI is higher when monitoring degradation state than for the case of monitoring the carbon footprint, implying that the model is more sensitive to infrastructure system failure.
The model presented has the limitation of being quantified on the basis of judgment and data from literature and in limited part from simulations. Further work is necessary to better quantify the dependency among the variables of the model.

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