Information supported resilience management of bridges

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ABSTRACT: Resilient systems provide sustained functionality and to do so they must be able to generate capacity for adaptation, recovery, and efficient organization after disturbance events. In support of resilience informed management of infrastructure systems, the authors proposed a framework (Turksezer, Limongelli and Faber, 2020) utilizing resilience indicators that inform decision makers on the system characteristics and performances and thereby supports ranking of decision alternatives for the management of the systems.

In this paper, we illustrate the application of the proposed approach through a principal example addressing an existing bridge subject to scour during flash flood events. To this end we model the system using Bayesian Probabilistic Nets, whereby the flow of information between systems states and indicators and not least the hierarchical dependencies between them become explicit. The example includes a number of decision alternatives on how to manage the system characteristics and thereby supports ranking of decision alternatives.

1 INTRODUCTION

Many river crossing bridges are susceptible to flood induced scour events. The possible consequences of scour events include increased risk to safety, interruption of transportation, and expenditures associated with maintenance, repair, or replacement costs. Scour events at bridge sites originates from the combination of diverse phenomena, and are classified as natural, constriction and local scour. Contrary to natural scour, constriction and local scour are related directly to the presence of the bridge (Maroni, Tubaldi, D. Val, *et al.*, 2020).

Flood-induced scour is among the main causes of bridge collapses in US and between 1966 and 2005 more than 20 bridges failed or were closed due to damages of scour (Maroni, Tubaldi, D. V. Val, *et al.*, 2020). Between 1989 and 2000, 53% of recorded bridge failures were due to flooding and scour (Prendergast and Gavin, 2014). In UK, almost 95,000 bridge spans are susceptible to scour processes (Maroni, Tubaldi, D. Val, *et al.*, 2020).

Each bridge must be managed by taking the probability of scour events into account so that the decision alternatives can be assessed, and the optimal action can be identified and implemented for resilience management.

In the literature, the concept of resilience management has been referred as short-term ability of the system to recover from disturbance events. However, the resilient system must be capable of both to sustain functionality and to generate capacity for adaptation, recovery, and efficient organization after disturbance events (Faber *et al.*, 2017; Faber, 2019; Faber, Qin and Nielsen, 2019). To define resilience management of infrastructure systems, the framework (Turksezer, Limongelli and Faber, 2020) has been developed.

In the present paper, we introduce a decision analysis tool based on Bayesian Probabilistic Networks (BPN) for resilience management of systems. With this tool the probabilistic representation of resilience system characteristics and decision alternatives are addressed. This paper is the first attempt of the authors to transform the previously proposed framework into a decision-making tool addressing transport infrastructure systems. Other types of systems such as electricity distribution systems and wind turbine park systems are addressed in e.g.(Qin, Sansavini and Faber, 2017; Qin and Faber, 2019; Qin *et al.*, 2019).

In any decision analysis for the resilience management of systems, the first step is to identify the system. In Section 2, the system representation is given, and the resilience indicators, decision options and making is discussed. In Section 3, the principal example is illustrated by two steps followed to build the tool and the analysis is undertaken. In Section 4 we discuss the results, and finally Section 5 concludes the paper.

2 RESILIENCE MANAGEMENT

Resilience management can be explained as the governance of the system based on ranking decision alternatives through their identification, and organization and communication of actions to be taken on the system constituents during the life cycle of the system.

This section takes basis in the resilience management framework proposed in (Turksezer, Limongelli and Faber, 2020) which represents the management of the system exposed to disturbance events that cause direct and indirect consequences in each subsystem (see also (Faber *et al.*, 2007)). In this framework, the resilience management is supported by information on the system characteristics and on the exposure, provided through resilience indicators.

2.1 *System representation and characteristics*

A complex system, i.e., socio-ecological technological system, consists of a group of interacting, interrelated or interdependent constituents such as assets (e.g., structures, infrastructures), their constituents (e.g., structural, and non-structural components), individuals, environment, technological systems (e.g., telecommunication, IoT), organizations and organizational processes.

Each subsystem is itself a constituent of the main system and provides specific functionalities that contribute to the functionality of the overall system. There are two functionalities of a physical subsystem: to withstand all actions and service-related functionality, which for example is to ensure spatial connectivity, housing and so on. The information subsystem provides collection, processing, and transmission of information. It is desired that the information subsystem functions both under normal operating conditions as well as under extreme events. The organizational subsystem manages the entire system and as a consequence of its actions the expenditures are generated in this system.

The three subsystems are interrelated and connected through the flow of information provided by the information subsystem, and they are all managed by the organizational subsystem through actions. Moreover, there are demands to be met by each subsystem, implicitly or explicitly defined through the requirements to the functionalities of the overall system.

2.2 *Resilience indicators*

Resilience indicators can be considered as instruments transmitting specific information to the decision makers on the state of the system and its constituents (i.e., subsystems). In the subsystem level, seven indicators (i.e., resistance, ductility, redundancy, diversity, vulnerability, robustness, and functionality), shown in Figure 1, carry information about the state of the subsystem.

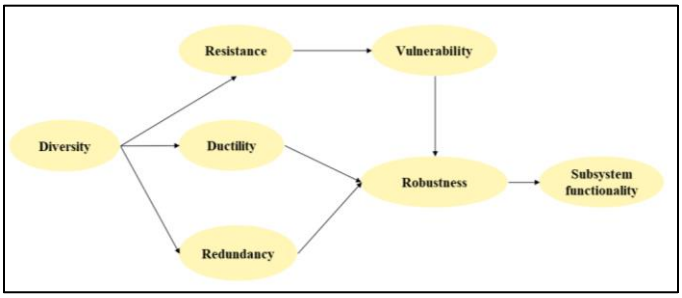

Figure 1 Subsystem level indicators.

At the subsystem level, diversity contributes to resistance, ductility, and redundancy. These indicators are the main indicators that characterize the state and performances of the system and/or its constituents.

Diversity relates to the ability of the system to provide functionality and sustain demands by different means and thereby reduce the likelihood of common cause failures of its constituents. Considering physical/structural subsystems, diversity may be present through the use of constituents made for example of different materials which are not affected by the same deterioration mechanisms.

Resistance relates to the demand the system can meet. When the demand exceeds the ultimate resistance, the system fails. Capacity and strength are sometimes introduced as synonyms for resistance, e.g., for structural systems for which the ultimate resistance can be increased by changing the capacities or strengths of the components.

Ductility is the ability of a system or its constituents to enable service provision through secondary mechanisms in the face of demands increasing beyond the levels for which the design has been based. Figure 2 illustrates the ductility behavior of a system in terms of service provision and demand. In Figure 2, demand and service increase up to a certain level (i.e., a certain characteristic is reached) through Mechanism 1 which is the level underlying the design. When this level is reached, the increasing demand can be fulfilled through the Mechanism 2. The change from one mechanism of service provision to another is represented by a star in the figure.

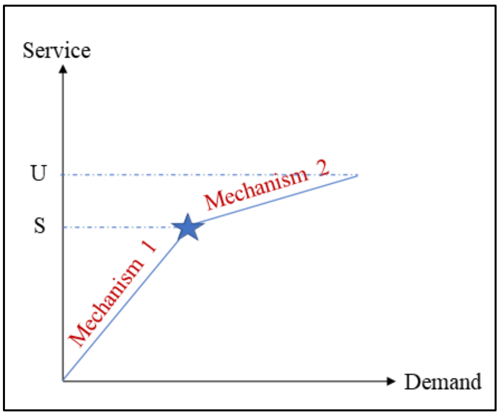

Figure 2 The representation of ductility mechanism-service vs demand graph.

Considering structural systems, the ability to meet the demand by means of Mechanism 2 is related to the deformation capacity. When the ultimate (design) resistance is reached in a linear elastic transfer of energy, and the demand is further increased, additional energy can be absorbed through the deformation capacity of the materials of the structure. A bridge constructed in 50's can be an example. The design purpose of the bridge is to accommodate the traffic in its construction time and in 60 years the demand increases. The bridge may meet demand, but some defects and deformations may occur due to ultimate resistances being exceeded. After reaching the ultimate resistance in elastic deformations, the bridge may start to absorb some energy in plastic deformation modes, may collapse partially or entirely. Ductility can be improved by retrofitting the structure.

Redundancy relates to the ability of a system to redistribute demands among subsystems and constituents, given damages and partial failures of constituents and subsystems. Redundant physical subsystems such as structural systems, facilitate the transfer and absorption of energy through multiple paths. The simplest example relates to statically indeterminate structural systems, which even if some structural elements are damaged and/or removed will still be able to transfer loads without failure of the structural systems. The redundancy of a structure can be improved by adding new components, or by changing the connection between its components.

2.3 *Decision making*

The management of the resilience of systems may be greatly enhanced by means of monitoring. Based on the observed performances of the system, decisions may be identified which optimally adapt or improve its resilience performances. The information gathered in terms of observations comprise resilience indicators which when conveyed to the decision maker supports the ranking of decision alternatives regarding possible interventions. The optimal decision is associated with the largest expected value of life cycle benefits.

Numerical evaluation of decision alternatives can be performed after formulating the decision problem in terms of a decision/event tree by assigning the appropriate utilities and probability structures to the different branches.

The decision tree shown in Figure 3 starts with the choice among decisions to monitor (or not) the condition of the system. The monitoring decision decreases the uncertainties (by obtaining additional information) and updates the probabilistic model of (condition) state of the system. With additional information (and knowledge through Bayesian updating), the decision maker has an enhanced basis for managing the system.

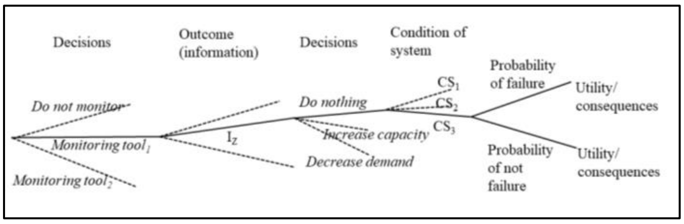

Figure 3 Event tree.

The pre-posterior decision analysis (Raiffa and Schlaifer, 1961) forms the basis for assessing the potential benefits associated with collection of additional information (e.g. through implementation of monitoring), see also (JCSS, 2008).

2.4 *Consequences*

When the system experiences an exposure event, damages to or loss of system constituents may cause direct and indirect consequences. The direct consequences consist of damage and failures of the system constituents and indirect consequences are related to the loss of functionalities of subsystems.

In case of a bridge collapse under an exposure event, the possible direct consequences are environmental effects, loss of cultural and historic values stored in the bridge and loss of lives and injuries. The indirect consequences include loss of reputation of the asset manager or the bridge owner as well as cost associated with the loss of transportation within the transportation network.

3 PRINCIPAL EXAMPLE: BRIDGE UNDER A FLOOD EVENT

The resilience management framework described in the previous sections includes several interacting components that affect the decision-making process.

In this section a principal example is presented to describe how Bayesian Probabilistic Networks (BPN) can be adopted to model the system and to investigate the impact of different decision scenarios on the system resilience. The example addresses the specific case of a bridge exposed to scour and the focus is on demonstrating how a BPN facilitates the inclusion of the possible decision alternatives among which the bridge owner can choose and to rank these decisions in accordance with their expected values of life cycle benefits. The information provided on the state of the system and on the exposure event, through monitoring enhances the knowledge of the decision maker thereby improving the choice of the optimal decision. Herein, the main idea is to use the updated information about the scour event and the system characteristics to inform optimal decision making.

The tool is prepared by using Hugin (Handling Uncertainty in General Inference Network) Expert software (Hugin Expert A/S, 2008) which is utilized to construct BPN that facilitate the modelling of uncertain information, and to solve decision problems. Moreover they are able to manage many dependent random variables (for the terminology and detailed information see (Jensen, 2001; Kjærulff and Madsen, 2013)).

3.1 *STEP 1: Building the BPN*

In the present example, the system includes a bridge, providing transportation of goods and people functionality, and which is exposed to local scour due to a flash flood event. The bridge is managed by its owner who is responsible of decisions aimed to optimally maintain the functionality of the bridge. The optimal decision is intended as the one that maximizes the expected value of benefits associated with the functionality, i.e., the service provided by the bridge, net the costs associated with ensuring this. With reference to the system described in section 2, which is structured into three subsystems; physical, information and organizational, this example only addresses the physical subsystem, i.e., the bridge. However, the approach can be easily adapted to the other two subsystems.

In a BPN, events and their causal relationships are represented graphically in terms of, respectively, nodes and arrows connecting the nodes. Discrete states and relevant conditional probabilities, together with consequences are assigned to each node (event) of the BPN (Faber *et al.*, 2002).

The probability of occurrence of an event is calculated through

$$P(E_1 \cap E_2) = P(E_1|E_2) \times P(E_2) \qquad (1)$$

where $P(E_1|E_2)$ is the conditional probability of event E_1 given that the event E_2 has occurred. When this equation is applied in the following section, the probability of event E_1 is the occurrence of scour event given a flood event has occurred.

Scour is a function of several parameters such as the waterflow (Q), the foundation characteristics (e.g., foundation depth), the nature of the riverbed, etc. A hydrological model can be employed to correlate all these parameters to the scour depth, but this is out of scope of this paper. Herein the causal relationships between events are simply represented assigning values of the conditional probabilities.

For detailed analysis carried out for real case studies the interested reader is addressed to the following references (Johnson and Dock, 1998; National Academies of Sciences Engineering and Medicine (NASEM), 2007; Prendergast, Hester and Gavin, 2016; Department of Transport and Main Roads, 2019; Giordano, Prendergast and Limongelli, 2020; Maroni, Tubaldi, D. V. Val, *et al.*, 2020; Pizarro, Manfreda and Tubaldi, 2020)).

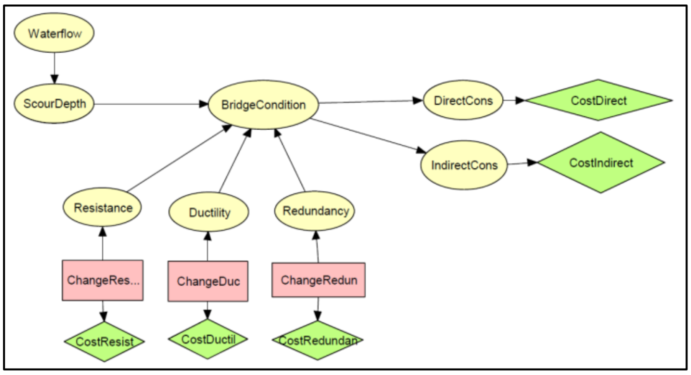

Figure 4 BPN tool for the bridge.

Each node of the BPN is described by a matrix that contains a number of discrete states and the relevant probabilities. Herein for the scour depth node, two states are considered, i.e., high, and low scour depth, that correspond to respectively a scour depth higher or lower than the foundation depth. Low scour is treated as no exposure state.

As shown in Figure 4, scour affects the bridge condition, which depends on the bridge characteristics described through the resilience indicators (i.e., resistance, ductility, redundancy) previously introduced in Section 2.2.

Two states 'bad' and 'good' are assigned to the bridge condition node. The relevant conditional probabilities with respect to the indicator nodes are reported in Figure 7. It is assumed that, when the bridge is under high scour, if it is redundant, ductile and has high resistance, then the probability of being in good condition is 85%. Vice versa, when the bridge is not redundant or ductile and has low resistance under high scour, then it is assumed that the probability of being in bad condition is 100%.

The actions (decision alternatives) that have been considered to change the bridge characteristic are described in Table 1.

Table 1 Decision alternatives considered in the BPN

Resistance	Ductility	Redundancy

Repair/maintain the component	Install collar disk on pier	Construct sacrificial components (e.g., dummy piers)
Substitute the damaged component with a new one	Do jacketing on piles	Add underpinning pile
Do nothing	Do nothing	Do nothing

Direct consequences are associated to damages and losses due to the failure of the bridge, whereas indirect consequences are related to its loss of functionality (JCSS, 2008; Turksezer, Limongelli and Faber, 2020). In Figure 4 each decision (pink rectangles) and consequences (yellow nodes) are linked to costs (green diamonds) that herein are defined in terms of monetary values.

When the BPN model is run, the direct and indirect consequences generated by the events and their relevant probabilities, are calculated for each discrete state of the bridge condition. For each decision alternative the total costs are given by the sum of the costs of the relevant actions and of the monetary values of direct and indirect consequences. In this way the BPN evaluates the total costs associated to each decision alternative.

The consequences of the decisions given in Table 1 are computed for specific system states (i.e., bad, or good condition). To illustrate this with an example, when the decision of 'do nothing' is considered, if bridge survives from the exposure event (which means good condition) then the cost of consequences is zero. If the condition is 'bad', the total cost is the sum of direct and indirect consequences (in monetary values).

When the decision maker decides to change one component to increase the resistance, if the bridge state changes into 'good condition', the consequences are the cost of the action (cost of the new component and if the environmental effects due to the use of new material). If the bridge changes into 'bad' after this decision, there will be cost of the action in addition to the direct consequences of the bridge in bad condition (described in Section 2.4).

3.2 *STEP 2: Assigning and calculating the probabilities*

After building the BPN with the necessary nodes, the probability tables are formed. For instance, those relevant to the 'waterflow' and 'scour depth' nodes are shown in Figure 5 and Figure 6. Log-normal probability density function is assigned for the waterflow because the discharge cannot be negative (Maroni, Tubaldi, D. V. Val, *et al.*, 2020). In order to simplify the tables for this principal example, three qualitative values are given to the water flow node, i.e., high, medium, and low, as shown in Figure 5.

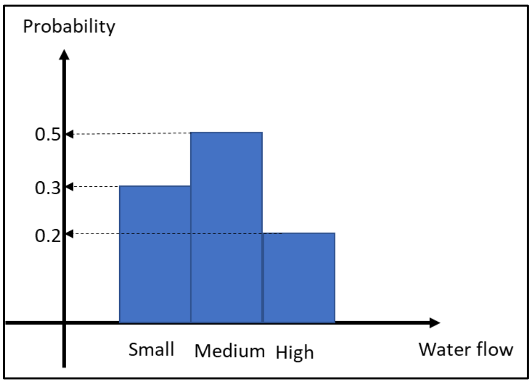

Figure 5 Representation of the probability assignment for waterflow in a simplified example.

Then the conditional probabilities of high or low scour, given the waterflow Q, are assigned as described in Figure 6.

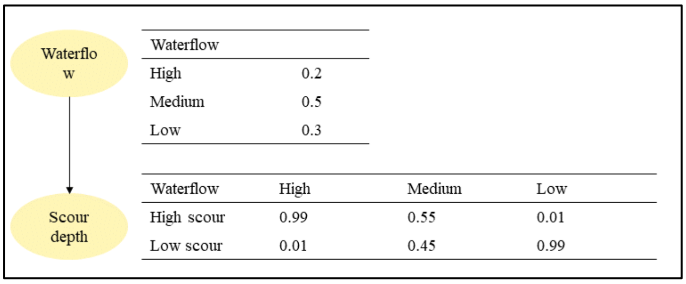

Figure 6 Probabilities assigned to the water flow and the scour nodes.

The values of the conditional probability of scour depth, calculated through Equation 1, are reported in Table 2 for the two considered states (high and low).

Table 2 The calculated conditional probabilities of scour event.

Waterflow	Scour depth	Probability of scour event
High flow	High scour depth	19.8%
	Low scour depth	0.2%
Medium flow	High scour depth	27.5%
	Low scour depth	22.5%
Low flow	High scour depth	0.3%
	Low scour depth	29.7%

The BPN uses this approach to calculate all the probabilities of the internal nodes shown in Figure 4.

Same weight, equal to 0.33, is assigned to each decision alternative, as shown in Table 3 where the unit costs assigned to each of the considered action are also reported. This assumption means that the decision maker will select a decision alternative only according to their utility. The action 'do nothing' has a zero cost and the other values are given according to the studies and practices found in the literature (Whitbread, Benn and Hailes, 2000; Salamatian, Zarrati and Banazadeh, 2013; Chandrasekaran and Banerjee, 2016; Liangliang, 2020).

Table 3 Cost and weight of the decision alternatives.

Action	Cost [unit]	Weight
Repair/maintain the component	100	0.33
Substitute the damaged component with a new one	10000	0.33
Install collar disk on pier	1000	0.33
Do jacketing on piles	2000	0.33
Construct sacrificial components (e.g., dummy piers)	60000	0.33
Add underpinning pile	600	0.33
Do nothing	0	0.33

The resilience indicators nodes, in turn, depend on the decisions. The conditional probability values given in Figure 7 are assigned according to how much the decision will increase the state of the bridge. For example, the probability that the bridge condition is resistant after substituting the damaged component with a new one is assigned to be 0.99 whereas it is assumed equal to 0.8 if the ‘repair/maintain component’ alternative is chosen, since there is still uncertainty about the component performance after maintenance activity. The same reasoning is followed for other actions.

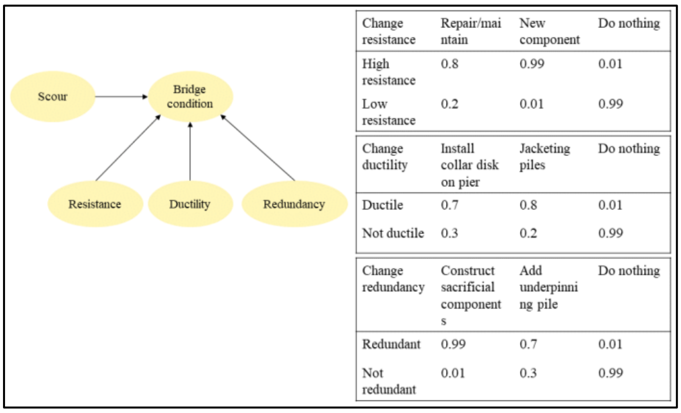

Figure 7 Probabilities assigned to the decision alternatives.

All conditional probabilities are presented in Figure 8.

The direct and indirect consequences are assigned as zero if the bridge condition is good and equal to the values reported in Table 4 if the bridge is in bad condition.

Table 4 Monetary value of direct and indirect consequences related to bridge condition.

	Direct consequences	Indirect consequences
Bad condition	500000	1000000
Good condition	0	0

Scour	High scour								Low scour							
Ductility	Ductile				Not ductile				Ductile				Not ductile			
Redundancy	Redundant		Not redundant		Redundant		Not redundant		Redundant		Not redundant		Redundant		Not redundant	
Resistance	High resist	Low resist	High resist	Low resist	High resist	Low resist	High resist	Low resist	High resist	Low resist	High resist	Low resist	High resist	Low resist	High resist	Low resist
Good condition	0.85	0.6	0.55	0.15	0.3	0.15	0.1	0	1	0.9	0.95	0.8	0.99	0.8	0.85	0.7
Bad condition	0.15	0.4	0.45	0.85	0.7	0.85	0.9	1	0	0.1	0.05	0.2	0.01	0.2	0.15	0.3

Figure 8 The conditional probability table of ‘Bridge Condition’ node.

4 DISCUSSION

In Figure 9 is reported the impact of different decisions in terms of consequences (sum of direct and indirect). This figure shows the bridge condition as a result of given values in the analysis (in previous tables). The green bars shown on the left-hand side are graphical representation of the probability values given next to them (i.e., 64.97, 35.03, 33.33). There are 9 decision alternatives shown in Figure 9. Each decision alternative corresponds to the same importance weight (explained in Section 3.2) and 33.33% of probability is assigned in the figure. Then in the middle of the figure there are bars showing the magnitude of total cost of each action with green color and number on them are the numerical presentation of total costs. For example, the highest costs are associated with the ‘do nothing’ decisions.

With given conditional probabilities the bridge condition is calculated as 64.97% good and 35.03% bad. As it can be expected, the total cost in terms of the consequences for bad condition is almost 8 times more than bad condition.

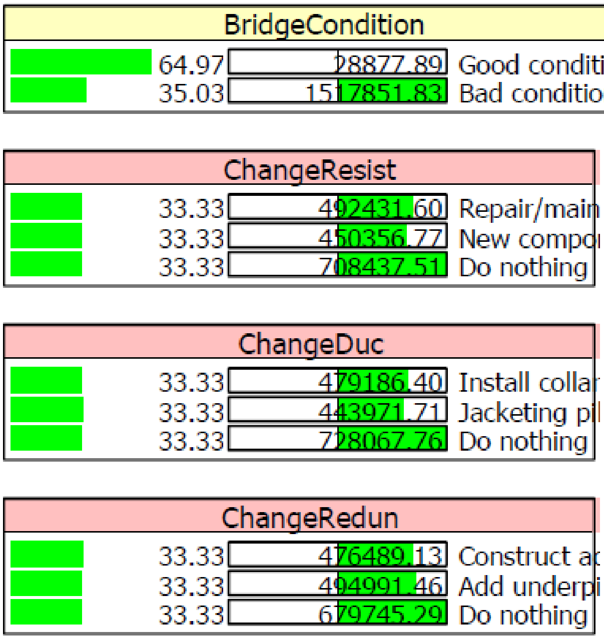

Figure 9 Probabilities and total costs computed by the software.

For the considered values of the conditional probabilities the lowest cost corresponds to one of the 'change ductility decision, i.e., jacketing relevant piles, then the second low-cost decision is to increase resistance by substituting the damaged component with a new one, as shown in Figure 9Figure 9. The Hugin Expert software enables to compute the probability of each of the two considered conditions (good and bad) for different decision alternatives. For instance, if the action leading to the lower cost (jacketing relevant piles) is considered, the probability of the bridge being in good condition improves to 72,15%. If the damaged component is substituted with a new one (decision with the second lowest cost) the probability that the bridge is in good condition becomes 71,10%. Although the probability is almost the same, increasing ductility is the optimal one since it is associated to a lower cost with respect to increasing redundancy.

When the decision of do nothing is made for all the indicators, the probability that the bridge is in bad condition under a flood event becomes higher than 45%. This depends on the high probability of bridge collapse to which the highest consequences are associated.

The results obtained depend on the values of the conditional probabilities associated to the nodes of the BPN and to the weight of the considered decision alternatives.

To see which decision increases the probability of having good bridge condition, each decision can be selected in the tool (setting as the 'condition'). BPN runs the analysis with the selected decision and computes the bridge condition and related costs for this decision. The decision increasing the probability of being in good condition with given conditional probabilities is to add new component instead of the damaged one (18% of improvement) and the second one is to construct sacrificial components (12% improvement).

5 CONCLUSION

In this paper, a decision support tool based on Bayesian Probabilistic Networks (BPN) is built for a bridge under scour hazard. The bridge characteristics are defined in terms of resistance, ductility, and redundancy indicators which affect the resilience of the system. The BPN computes the consequences associated to two conditions of the bridge, defined as 'good' and 'bad', for different management actions. These results enable the decision maker to choose the optimal management actions to provide the highest probability that the bridge is in good condition and to face the lowest consequences.

A principal example is built and scenarios corresponding to different management actions aimed to change the bridge resilience characteristics have been considered. The aim of the study was to build a tool to model the system and to support decisions relevant to its resilience management. For this reason, the details of the model such as the values of the conditional probabilities associated to the events included in the analysis, were assigned taking basis on previous research on the topic and on engineering judgement.

This paper is the first attempt of the authors to propose a decision support tool addressing transport infrastructure systems and including resilience indicators. In the future a detailed example will be developed for a real case study, addressing the probabilistic modelling of the events included in the analysis.

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