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SEVENTH FRAMEWORK PROGRAMME

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Abstract

Bayesian networks are probabilistic models that have been developed extensively since the 1980s. These models allow efficient representation and computation of problems that involve many random variables and provide an efficient framework for probabilistic assessment of component/system performance under multiple hazards.

In this report a brief introduction to Bayesian networks is provided. Then examples of applications of Bayesian network models for the assessment of the performance of CIs against natural hazards are presented together with an application study related to the seismic risk and resilience quantification of a power network. Finally advantages and limitations of this tool are briefly discussed.

Keywords: Bayesian network, critical infrastructures, natural hazards

Acknowledgments

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1 Introduction

A methodology for conducting stress tests on non-nuclear critical civil infrastructures (CIs) is proposed in WP5.1 of this project (Esposito et al. 2016). The 9-step procedure involves conducting a probabilistic hazard and risk analysis for a CI system and a graded evaluation of the performance by a team of experts. The CI under investigation is a complex assembly of components, structures and systems designed to provide a service, in terms of generation and flow of water, electric power, natural gas, oil, or goods in the scope of the built environment of a community. The data on the components, structures and systems of the CI needs to be assembled and held in a framework to facilitate the application of the proposed stress test methodology and the execution of a stress test. The data on the CI includes not only the information about the hazard and the vulnerability of the components and structures, but also the information about the functioning of the system that includes the topology of the system, the links that describe the interactions between the components and structures, and the causal relations between the events in the system.

Representation of complex systems for a probabilistic risk analysis in general, and accident sequence investigation in particular, has been done since the early 1970’s in the nuclear industry. There, the event and fault trees are used to represent the system information necessary to conduct a probabilistic risk analysis.

An event tree is a graphical representation of the various accident sequences that can occur as a result of an initiating event (USNRC 2012). It is an essential tool in analysing whether a complex system satisfies its system-level design targets. It provides a rational framework for enumerating and, subsequently, evaluating the myriad of events and sequences that can affect the operation of the CI system.

A fault tree is an analytical model that graphically depicts the logical combinations of faults (*i.e.*, hardware failures and/or human errors) that can lead to an undesired state (*i.e.*, failure mode) for a particular subsystem or component (Vesely et al. 1981). This undesired state serves as the topmost event in the fault tree, and usually corresponds to a top event in an event tree. Thus, a fault tree provides a rational framework for identifying the combinations of hardware failures and/or human errors that can result in a particular failure mode of a subsystem or component. Once fully developed, a fault tree can be used to quantitatively evaluate the role of a CI subsystem or component in the operation and failure of the CI system.

The top half of **Error! Reference source not found.**.1 shows a simple example of an event tree and will be used to explain its basic structure and logic. All event trees begin with an initiating event, in this example, jumping from an airplane, but in general, an event that perturbs steady-state operation (*e.g.*, an earthquake, fire, flood, etc.) of a CI. After the initiating event, a series of top events follows, each related to a subsystem or component required to prevent the undesired outcome from occurring. In this example, the undesired outcome involves injury or death of the person jumping from the airplane. For a CI system, it is failure to deliver a service, such as failure of a pump in a gas network, or structural damage to cranes in a port.

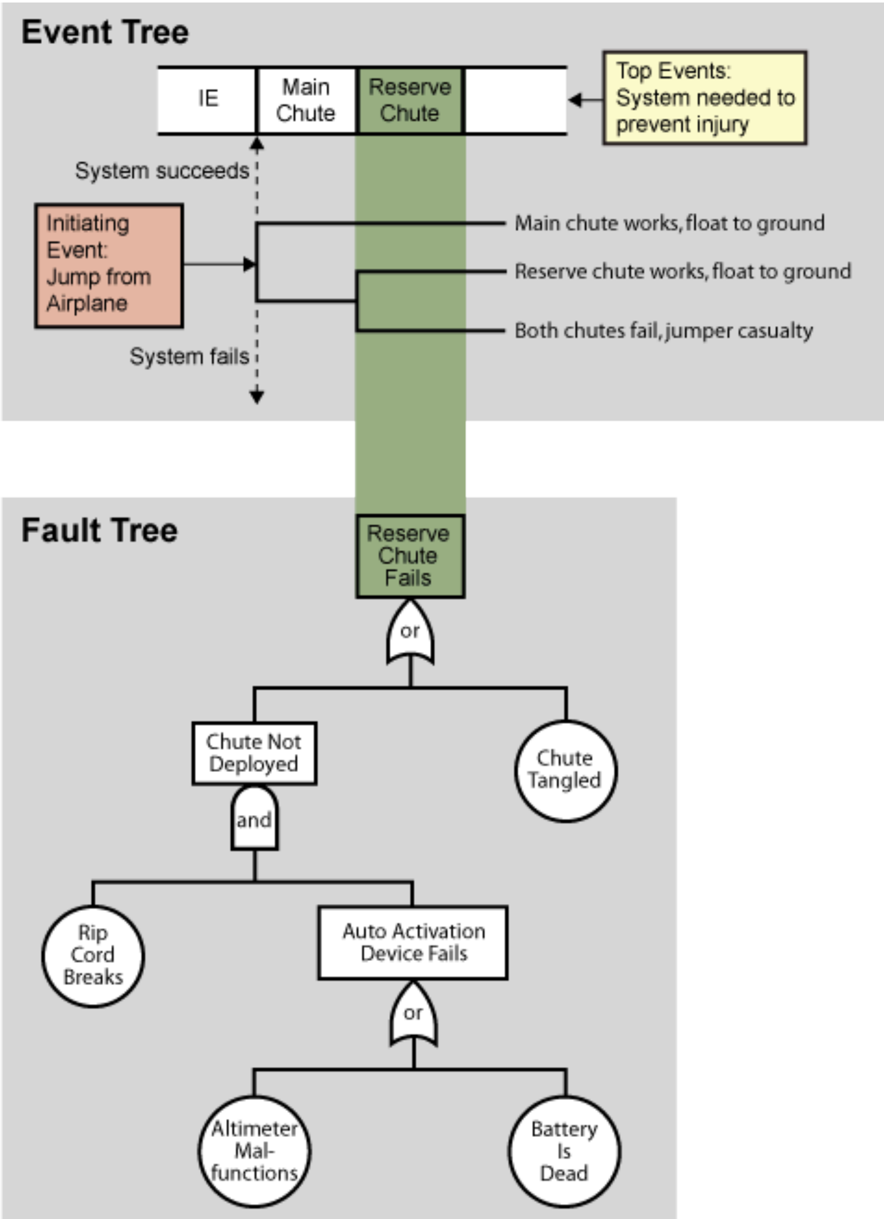


Fig. 1.1 Event and fault tree example (USNRC 2012)

The event tree of **Error! Reference source not found.**.1 contains three accident sequences, with one resulting in the undesired outcome (*i.e.*, injury or death of the jumper). This failure sequence is represented by the Boolean expression: ***Main chute fails ∩ Reserve chute fails***

In order to compute the probability of the undesired outcome, P_f, the probability of the accident sequence in Eq. 1.1 must be computed. If the two events are s- independent, $P_f$is simply:

$$P_f = P_{f,mc}P_{f,rc} \tag{1.1}$$

Where $P_{f,mc}$ is the probability the main parachute fails and $P_{f,rc}$ is the probability the reserve parachute fails. In order to compute these two quantities, an analysis of the operation of both the main and reserve chutes is conducted using a fault tree.

The bottom half of Fig. 1.1 shows the fault tree for the reserve chute subsystems. The top event in this fault tree corresponds to one of the top events in an event tree described above, the failure of the reserve parachute to open. The fault tree describes the events that lead to the top event and their causal relation using "and" and "or" gates. The events at the end of each branch, the roots of the fault tree, are the possible component failure events: A – parachute tangled; B – Ripcord broken; C – Altimeter malfunction; and D – Battery is dead. Assuming that these initiating events are s-independent, the following expression $P_{f,rc}$ the probability of the failure of the reserve parachute to open is obtained:

$$P_{f,rc} = P_A + P_B P_C + P_B P_D - P_B P_C P_D - P_A P_B P_C - P_A P_B P_D + P_A P_B P_C P_D \qquad (1.2)$$

The individual component or subsystem failure probabilities can be estimated from historical data, laboratory testing, and/or analytical modelling, possibly using more detailed event and fault trees.

A particular graphical combination of a fault tree and an event tree, called the bow-tie model Fig. 1.2 (De Dianous and Fiévez 2006), has been used in risk management since the 1980s to visually represent the possible causes and consequences of an accident. Typically, the causes of an accident are shown on the left side using a fault tree, while the consequences of an accident are shown on the right side using an event tree. Some events (initiating, causative) and layers of the fault and the event trees can be viewed as safety barriers, allowing an extension to the Swiss Cheese accident sequence analysis model (Reasons 1990).

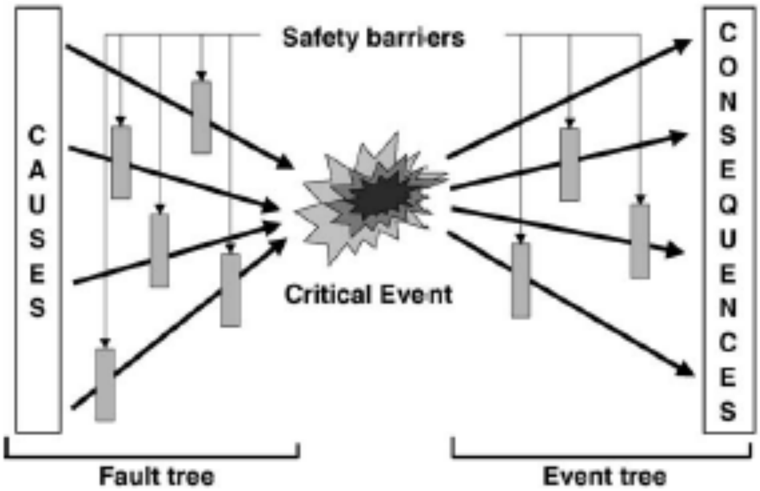


Fig. 1.2 Bow-tie critical event model with safety barriers [ARAMIS project (De Dianous and Fiévez 2006)]

Bayesian networks (BNs) are probabilistic models that have been developed extensively since the 1980s. These models are useful tools in engineering risk analysis because they facilitate the computation, the understanding and the communication of risks in complex systems subject to uncertainty.

BNs provide an efficient framework for probabilistic assessment of component/system performance and can be used to model multiple hazards and their interdependencies. They may also facilitate information updating for near-real time and post-event applications. Evidence on one or more variables can be entered in a BN model to provide an up-to-date probabilistic characterization of the performance of the system. BN is nowadays used for infrastructure risk assessment and decision support, particularly in the aftermath of a natural event (Bensi, 2010).

Similar to event and fault trees, thus also bowties, the topology of a BN is derived from an analysis of the system and remains static. This means that the component, structures and subsystems and the causal links and conditional dependencies among them are pre-determined and do not change during the probabilistic risk analysis process. There are, however, so-called adaptive (Pascale and Nicoli 2011) or reconfigurable (Mirmoeini and Krishnamurthy 2005) BNs whose topology changes (among several pre-determined topologies) to best match an estimate of the varying state of the modeled system. Finally, there are modular BNs (Niel et al. 2000), built out of many BN modules, with each module representing a functionally independent component or subsystem of a system-level BN (Park and Cho, 2012).

More important, the probabilistic nature of the two frameworks is different: the event/fault tree framework is based on the notion of probability as a frequency, while the BN framework represents the state of knowledge or belief. Fundamentally, the BN framework naturally allows for introduction of new knowledge, for example, from observations of the CI system behavior during its normal operation, from inspections, or from previous stress tests. This enables a fundamental aspect of the proposed stress test methodology, that of repeating a stress test in certain intervals depending on the outcome of the previous stress test in order to reduce the risk exposure of the CI through the practice of continuous improvement.

In this report an introduction to Bayesian networks and the probabilistic structure is first provided. Then examples of applications of Bayesian network models for the assessment of the performance of CIs against natural hazards are presented. An application study related to the application of BNs to the seismic resilience quantification of CIs is then presented and advantages and limitations of BNs in the context of CIs are finally discussed.

2 Bayesian Network approaches to engineering risk analysis of CIs

The use of Bayesian networks (BNs) for engineering risk analysis has grown in recent years. The range of topics is varied and the frequency with which BNs are used differs depending on the field of application (Bensi, 2010).

BNs can be used at any stage of a probabilistic analysis especially in the early phase of a risk analysis where potential scenarios and interrelation of events leading to adverse events have to be identified and evaluated.

The following section provides a brief introduction to BNs with the aim of providing knowledge sufficient to understand the possible applications of this tool to CIs and natural hazards. A gentle coverage of BNs is available in Nielsen and Jensen (2007), Straub (2007).

2.1 BRIEF INTRODUCTION TO BAYESIAN NETWORKS

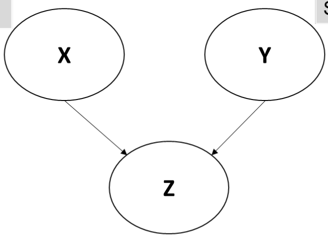
2.1.1 Bayesian Network terminology

A BN is a framework for representing the joint distribution of a number of random variables (Straub, 2007). The relationships between different random variables are expressed using directed acyclic graphs (DAG). A DAG consists of a number of nodes and direct links among the nodes. Such a graph is called acyclic if the directed links do not form a loop.

A very basic example of a DAG is shown in Fig. 2.1. The nodes X, Y and Z stand for the random variables X, Y and Z, respectively, while the directed edges (connections) represent the dependency relationships between the different variables. In this example, X and Y are a parent of Z, which is, consequently, a child of X and Y. For discrete nodes, each node is associated with a set of mutually exclusive and collectively exhaustive states. Further, a conditional probability table (CPT) is assigned to every node of the BPN, which provides the conditional probability mass function (PMF) of the random variable represented by the node, given each of the mutually exclusive combinations of the states of its parents. For nodes without parents (e.g. X and Y in Fig. 2.1), known as root nodes, a marginal probability table is assigned.

Variable X	Probability
State 1	P_1
State 2	P_2

Variable Y	Probability
State 1	P_3
State 2	P_4



Variable Z		Conditional probability			
	Variable X	State 1		State 2	
	Variable Y	State 1	State 2	State 1	State 2
State 1		P_5	P_7	P_9	P_{11}
State 2		P_6	P_8	P_{10}	P_{12}

Fig. 2.1 A simple example of a DAG.

Often the links represent casual relations among the variables. In this case the DAG is called *Casual network.* If Fig. 2.1 above is interpreted as a casual network, then this means that events X and Y cause event Z.

To represent dependence in BN, it is important to study how information (or evidence) is exchanged between nodes in a network. In casual networks, if no information is passed by two nodes then these are said to be *d-separated*. Then, *d-separation* corresponds to a blockage of the flow of information between two variables (Bayes Nets 2007). Considering two distinct sets of variables X and Y BN. These two variable sets are *d-separated* by a third set of variables Z if X and Y are independent given the variables in Z, i.e. if $p(x,y|z)=p(x|z)p(y|z)$.

In casual networks there are three basic configurations (Fig. 2.2): i) serial connection (head-to-tail), ii) diverging connection (tail to tail) and iii) converging connection (head to head). For each type of connection, the path from X to Y is or is not blocked (d-separated) based on whether or not it is *instantiated, i.e.* its value has been observed (Bensi, 2010). The path between X and Y is blocked for serial and diverging connections when is instantiated. A converging connection is blocked when is not instantiated, i.e. information about X provides information about Y only when Z is observed.

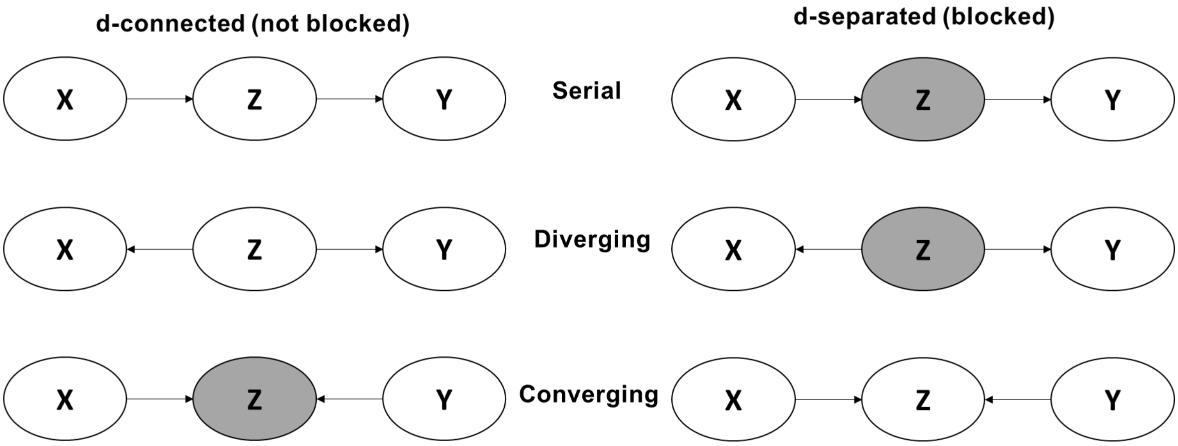


Fig. 2.2 D-separation property for different graphic configurations.

2.1.2 Probabilistic structure of a BN

A BN consists of a DAG and a corresponding probability model. Each variable is described by the conditional probability mass function of the variable conditional on its parents $p\left(x \mid pa\left(X\right)\right)$ If a variable X has no parent, it is simply described by its unconditional (marginal) distribution PMF, *p(x)* (Straub, 2007), see Fig. 2.1.

The probability model of a BN is a model of the joint distribution of its *n* random variables. From the *d-separation* property and through the use of conditional probabilities, the joint distribution may be factored into the product of local conditional PMFs (CPTs), which facilitate more efficient calculations. The joint PMF of all random variables in the BN is constructed as the product of the conditional PMFs, i.e :

$$p\left(x_1,\ldots,x_n\right) = \prod_{i=1}^{n} p\left(x_i \mid pa\left(X_i\right)\right) \tag{2.1}$$

where $pa\left(X_i\right)$ is the set of parents of each node X_i, $p\left(x_i \mid pa\left(X_i\right)\right)$is the CPT of X_i, and *n* is the number of random variables (nodes) in the BN. The joint PMFs in Fig. 2.1 is:

$$p\left(x,y,z\right) = p\left(z \mid x,y\right) p\left(x\right) p\left(y\right) \tag{2.2}$$

This demonstrates that the conditional PMFs of the random variables given their parents, together with the graphical structure of the BN, fully define the joint probability model for the *n* random variables.

The use of conditional distributions in the modelling of a BN is convenient in civil engineering applications, where often only conditional relationships are available. For example, fragility curves specify the probability of damage of a structure *given* a particular demand value.

2.1.3 Inference in BN

An important advantage of Bayesian networks is represented by the possibility to update distributions of a subset of variables given observations on another subset of variables in the model. This process is referred to as *Inference* and basically answers the following question (Straub, 2007): *What is the probability of a set of random variables **Y** being in a specific state **y**, given that another set of random variables **Z** is observed to be in state **z***?

Mathematically, this can be formulated as follows:

$$P\left(\mathbf{Y}=\mathbf{y} \mid \mathbf{Z}=\mathbf{z}\right) = \frac{P\left(\left\{\mathbf{Y}=\mathbf{y}\right\} \cap \left\{\mathbf{Z}=\mathbf{z}\right\}\right)}{P\left(\mathbf{Z}=\mathbf{z}\right)} = \frac{p\left(\mathbf{y},\mathbf{z}\right)}{p\left(\mathbf{z}\right)} \tag{2.3}$$

The quantities of interest to evaluate are therefore the joint PMFs $p\left(\mathbf{y},\mathbf{z}\right)$and $p\left(\mathbf{z}\right)$. A number of algorithms exist, each of which is optimal under specific circumstances (e.g. variable elimination algorithm). These algorithms are implemented in several free & commercial software packages, which can thus perform inference in Bayesian networks.

2.2 APPLICATION OF BNS TO NATURAL HAZARDS AND CIS

The use of BNs for natural hazard assessment has increased in recent years. Straub (2005) presented a generic framework for the assessment of the risks associated with natural hazards using BNs and applied it to rock-fall hazard. BNs have also been applied to the modeling of risks due to typhoon (Nishijima and Faber 2007), geotechnical and hydrological risks posed to a single embankment dam (Smith, 2006), avalanches (Grêt-Regamey and Straub 2006), liquefaction modeling (Bayraktarli et al. 2005, 2006, Tasfamariam and Liu, 2014), tsunami early warning (Blaser et al. 2009) and seismic risk (Bayraktarkli et al. 2005, 2006, 2011; Bensi, 2010; Broglio, 2011).

In particular, regarding seismic risk, Bayraktarkli et al. (2005, 2006) proposed a three components framework (Fig. 2.3) for earthquake risk management using BNs, composed of: i) an exposure model that is an indicator of hazard potential, ii) a vulnerability model which is an indicator of direct/immediate consequences and iii) a robustness model to quantify indirect consequences. However, the framework proposed by the authors does not include many of the main aspects which complicate the applications of BNs to seismic hazard and risk analysis of infrastructure systems such as the modeling of ground motion random fields, directivity effects, or issues associated with the modeling of system performance.

Bensi (2010) proposed a more comprehensive BN methodology for performing infrastructure seismic risk assessment that includes also a decision model for post-event decision making (Fig. 2.4). The methodology developed by Bensi (2010) consists of four major components: i) a seismic demand model where ground motion intensities are modelled as Gaussian random field accounting for multiple seismic sources and including finite fault rupture and directivity effects; ii) a performance model of point-like and distributed components; iii) models of system performance as a function of component states; and iv) the extension of the BN to include decision and utility nodes to aid post-earthquake decision-making.

In addition to demonstrating the value of using Bayesian networks for seismic infrastructure risk assessment and decision support, the study proposed models necessary to construct efficient Bayesian networks with the goal of minimizing computational demands, which represent one of the weak points of BN frameworks.

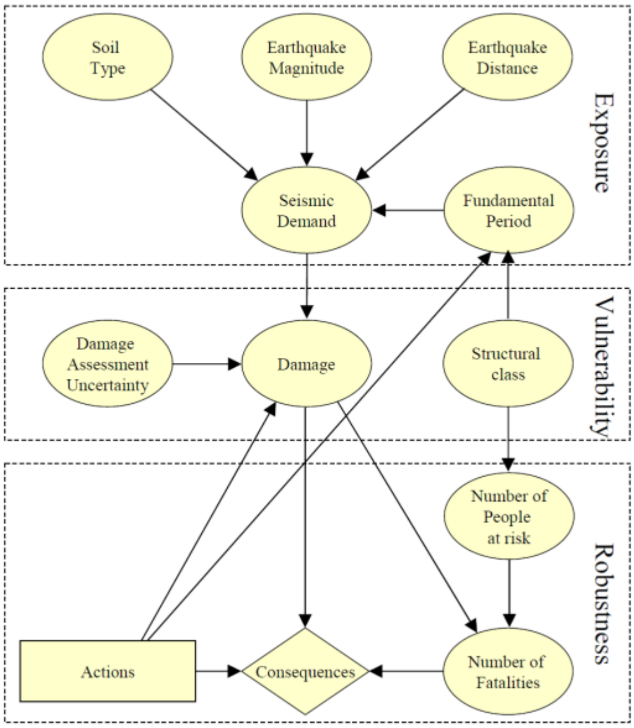


Fig. 2.3 BN framework for seismic risk management (source: Bayraktarli et al., 2005)

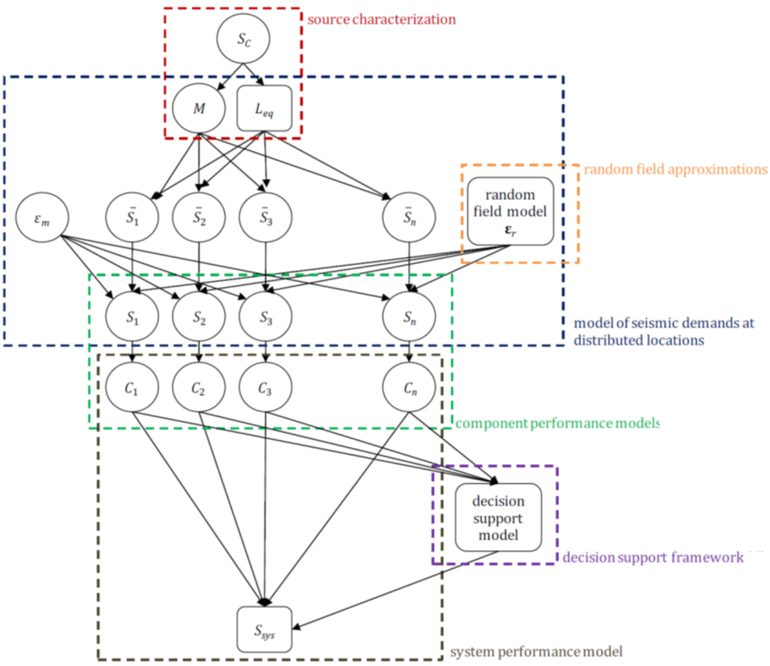


Fig. 2.4 Bayesian network methodology for seismic infrastructure risk assessment and decision support proposed by Bensi (2010).

2.3 APPLICATION OF BNS TO SEISMIC RESILIENCE OF CIS: A CASE STUDY

The material in this Chapter is adapted from the work on the MS Thesis dissertation of Mr. Grauvogl and Mr. Steentoft and on a conference paper of Mr. Max Didier conducted with the assistance of Dr. Marco Broccardo (Grauvogl and Steentoft, 2016 and Didier et al. 2017).

Grauvogl and Steentoft (2016) and Didier et al. (2017) proposed a BN-based model to evaluate the seismic resilience of infrastructure systems. The model is based on the compositional supply/demand resilience quantification framework presented in WP4.5 report (Stojadinovic and Esposito, 2016).

The BN network framework proposed is used to assess the community demand for the services provided by civil infrastructure systems during the absorption phase after a major earthquake. The framework has been then applied to evaluate the resilience of the power distribution network of Nepal after the 2015 Gorkha earthquake. Uncertainties in the hazard model, the fragility functions, and the power demand of the different building types characterizing the community are also considered.

To facilitate a reduction of the computational effort, the problem is divided into five modules: i) the seismic hazard, fragility and damage, ii) the distribution of the number of residential buildings in a specific damage state in each district iii) the distribution of the total number of residential buildings in a specific damage state in Nepal iv) the distribution of the potential electric power demand of each district v) the distribution of the aggregated potential power demand in Nepal.

A schematic overview of the model is given in Fig.2.5.

Module 1

The goal of the first module is the quantification of the seismic hazard and the subsequent evaluation of the damage distribution for each building type in each of the 75 districts in Nepal. To achieve this, the likelihood of a certain Peak Ground Acceleration (PGA) occurring at the building site needs to be determined first. The PGA node of the BPN is conditioned on its parent nodes, which are magnitude, distance, and a residual. Finally, the marginal distribution of the damage states for the different building types in each district is evaluated. The obtained marginal probability distributions of the damage nodes for the different building types in each district can then be used in a Monte Carlo (MC) simulation to determine the distribution of the number of buildings in the different damage states.

Module 2

The distribution of the number of buildings of each building type in the different damage states in a given district, obtained from Module 1, is used as input for the respective nodes in Module 2. The goal is to calculate, in each of the 75 districts, the distribution of the total number of buildings in different damage states for the different occupancy types and the different building types. In case of the 2015 Gorkha earthquake, the model is used to estimate the aggregate number of residential buildings in DS3 (collapsed or completely damaged) for a given district. For a given district, the BPN of Module 2 is thus composed of one node for each defined residential building type. The structure is used for the 75 districts in Nepal. The needed discrete distributions of the total number of residential buildings in DS3 in each district are then obtained from a MC analysis.

Module 3

The distributions obtained from Module 2 are used to initialize the respective nodes of the BPNs of Module 3. Starting from the distribution for different districts, the distribution of the community-wide number of buildings of an occupancy type in each damage state can be obtained. The output of Module 3 is thus the marginal probability distribution of the total aggregated number of residential buildings in DS3 in Nepal.

Module 4

The seismic performance of the building stock is used in this module as proxy to model the post-disaster evolution of the potential community demand for electric power. The marginal distribution of the electric power demand for each district is evaluated for the 75 districts of Nepal. The module uses the following input from Modules 1-3:

- The distribution of the number of buildings in different damage states for each building type and for each district (from Module 1)
- The distribution of the number of residential buildings in DS3 for each district (from Module 2)
- The distribution of the number of residential buildings in DS3, aggregated for all districts (from Module 3)

The output Module 4 is finally the marginal probability distribution of the total potential power demand of all buildings in the given district in MW.

Module 5

In this last module, Module 5, the distribution of the potential power demand of the Nepalese community after an earthquake is evaluated. The distributions of the power demand of the 75 districts are aggregated into one community-wide distribution for Nepal. It uses as input the power demand distributions obtained for each district from Module 4. The evaluation of the proposed BPN is, however, again computationally too expensive. A Monte Carlo analysis is run to finally obtain the distribution of total potential post-disaster power demand in Nepal.

The proposed BPN was implemented using a combination of MATLAB and HUGIN environment. The possibility of (real-time) updating from given information was also considered. If the new evidence is entered (at one node of the network), it is propagated through the network and affects the (marginal) probabilities of the other variables or nodes in the network. Such evidence can, for example, be obtained through damage survey after the earthquake, classifying the buildings of the different building types in a certain district into the used damage states.

Fig. 2.6 shows the influence of post-disaster evidence on the discrete probability distribution of the power demand of the Nepalese community after the loss phase of the April 25, 2015 Gorkha earthquake. The distribution in Fig. 2.6 (left) was obtained using the presented BPN when no evidence has been considered. Fig. 2.6 (right) shows the updated distribution, when the available data on the seismic source, the epicenter, the magnitude of the earthquake and preliminary damage data from the *Nepal Disaster Recovery and Reconstruction Information Platform* (http://drrportal.gov.np/ndrrip/main.html) covering the most affected districts is entered. A major change, on the order of 100MW, in the distribution of the potential power demand can be observed.

The model can also be (easily) refined by adding further parent nodes, for example to account for other variables affecting the power demand, e.g. to model the probability of certain economic or political decisions (e.g. evacuation of a neighborhood, shutdown of industries).

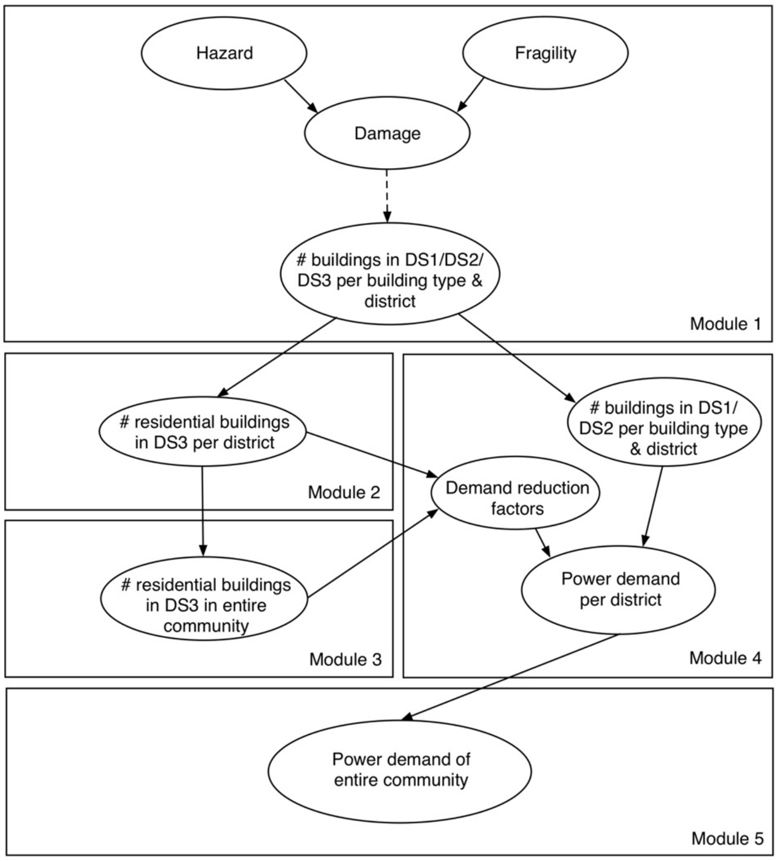


Fig. 2.5 BPN model proposed by Didier et al. (2017).

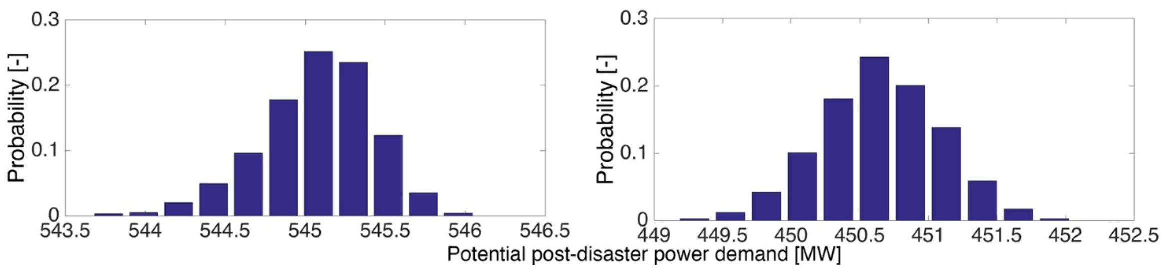


Fig. 2.6 Potential power demand distribution of Nepalese communities at the end of the earthquake damage absorption phase, (left) with no evidence set, (right) with information from April 25, Gorkha earthquake, by Grauvogl and Steentoft (2016).

3 Discussions

Bayesian networks are probabilistic models that have been developed extensively since the 1980s. These models are useful tools in engineering risk analysis because they facilitate the computation, the understanding and the communication of complex problems subject to uncertainty. BNs have been recently used for natural hazard assessment of critical infrastructures as presented in the previous section.

BPNs offer several important advantages. BNs provide an efficient framework for probabilistic assessment of component/system performance and can be used to model multiple hazards and their interdependencies. They are an efficient and intuitive graphical tool that enable representation of the components and subsystems and the causal links and conditional dependencies among them and assessment of systems under uncertainty. They provide a consistent and clear treatment of the joint probability distributions of multiple random variables, and an efficient framework for probabilistic real-time updating in light of new evidence. BN can also be extended to include utility and decision nodes, thus providing a decision tool for ranking different alternatives. Complex BNs can be constructed using verified and validated modules that represent components and subsystems of the CI system.

Fundamentally, the BN framework naturally allows for introduction of new knowledge, for example, from observations of the CI system behavior during its normal operation, from inspections, or from previous stress tests. This enables a crucial aspect of the proposed stress test methodology, that of repeating a stress test in certain intervals depending on the outcome of the previous stress test in order to reduce the risk exposure of the CI through the practice of continuous improvement.

However, Bayesian networks have limitations. Calculations in Bayesian networks can be highly demanding and the application to distributed systems characterized by a complex topology is not always feasible. An accurate modeling via BNs requires thorough understanding of the problem. The need for expert knowledge in generating the preliminary BN structure represents one of the most salient point of this tool. Modeling complex systems via BNs may require trade-offs between accuracy transparency, computational complexity, and detail of modeling (Friis-Hansen 2004).

Further, the availability of statistical data to develop robust models to relate random variables in a BN is often scarce in civil engineering and infrastructure system analysis (Bensi, 2010). Thus, dependence relations between parents and children and the marginal distributions of root nodes should be based on theoretical models and/or expert judgment.

Although BNs represent an appropriate framework to handle uncertainty for pre- and post-event risk assessment and decision support analysis, it is important to acknowledge that challenges remain, particularly with respect to computational demands for application to large civil infrastructure systems.

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