Natural hazards risk assessment using Bayesian networks

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ABSTRACT: The objective of the present paper is the demonstration of the potential and advantages of Bayesian networks for the application in risk assessments for natural hazards. For this purpose, a general framework for natural hazards risk assessment is presented and a brief introduction to Bayesian networks is provided. The methodology is then applied to rating systems for assessing rock-fall hazard risks on roads, where it is shown how Bayesian networks can improve the consistency and traceability of such models. It is pointed out that Bayesian networks have a large potential for the modeling of natural hazard risks because of their intuitive format, which facilitates the cooperation of specialists from several disciplines, and because they support the modeling of the various inter-dependencies, caused by common influencing parameters, which are typical for natural hazards.

1 INTRODUCTION

It is increasingly recognized by decision makers that the effective and rational management of natural hazards requires a risk-based strategy which explicitly addresses the involved uncertainties together with the consequences of such events. Because in addition the world-wide economical risks from natural hazards are on the rise, as demonstrated by trends on experienced damages observed in MunichRe (2004), there is an increased need for suitable risk assessment and management tools. It is the aim of this paper to demonstrate the capabilities of Bayesian networks (BNs) for this purpose. BNs are a class of probabilistic models originating from the Bayesian statistics and decision theory combined with graph theory; see Pearl (1988) or Jensen (2001). BNs facilitate the consistent modeling of the risks arising from natural hazards and enhance the understanding of the inter-dependencies of the involved processes and decisions. They also assist the planning and the optimization of risk mitigation and protection measures.

Compared to most other risks related to the built environment, the following characteristics are specific for natural hazard risks:

Natural hazards often affect entire portfolios of buildings and structures, both on a local and a global scale. It is thus not sufficient to consider buildings and structures individually, but entire systems and networks must be modeled to assess the effect of natural hazards on the portfolio. This is because in many instances a large part of the uncertainties are related to parameters which are common to the entire portfolio. This causes a strong dependency between the performances of the individual elements in the system, which must be included in the modeling.

Most natural hazard events are rare events, i.e. their occurrence probability is low. Because additionally both frequencies and consequences of natural hazards can vary with time, useful historical data is often not available. This is especially true for regional and local phenomena, where the exposure to natural hazards in many instances is highly site specific. Additionally, most damage mechanisms related to natural hazards are complex and involve various influencing parameters, which are difficult to estimate for specific locations and objects. Under these circumstances, purely empirical models are of limited value; instead models which allow combining empirical information with mechanical and functional models and engineering judgment are required.

An important aspect of the modeling of natural hazards and their interactions with structures is the joint involvement of natural scientists and engineers from several specialist fields. The consequent requirement for a multidisciplinary approach presents an additional difficulty to the modeling, as it is of utmost importance, that a risk assessment follows one single philosophy in regard to the uncertainty modeling to ensure that the obtained results are consistent and comparable with the results from other assessments. It follows that the framework for modeling natural hazard risks, as well as the tool to implement this framework, should be understandable and applicable by all involved specialists, including the decision makers.

In addition, natural hazards comprise of many different phenomena. To ensure an optimal (and therefore sustainable) use of resources, it is of importance that decisions in regard to protection against the hazards are made on a common basis, taking into account the various hazards simultaneously, and in perspective with overall societal goals. In practice, the applied models vary from one hazard type to another and no unique acceptance criterion is used to appraise the risks from all hazard types, although efforts are directed in this way, PLANAT (2004). BNs can serve as a common modeling tool and so enhance a unified approach to the assessment and management of the risks from different hazards.

The paper starts out with the presentation of a general framework for risk assessment and then outlines the advantages of utilizing Bayesian networks for natural hazard risk assessment. This is then illustrated in the second part of the paper on the case of a rock-fall hazard rating system where the usefulness of BNs for decision support is demonstrated.

2 A FRAMEWORK FOR NATURAL HAZARDS RISK ASSESSMENT

A generic framework for the assessment of natural hazard risks is presented in the following; a similar framework is outlined in Bayraktarli et al. (2005). The proposed framework helps to structure the problem and provides an overview on all involved processes and aspects. In doing so it facilitates a rational and consistent approach to the assessment of the risks which can be implemented by means of a BN. This will be illustrated by the example in the second part of the paper.

The framework is illustrated in Figure 1. It is distinguished between the three main components *system exposure*, *system resistance* and *system robustness*, which lead to *direct consequences* or *indirect consequences*. The components are described by means of models (physical or empirical) and by *indicators* which represent the available information for a specific case. Although not directly part of the risk assessment (but of the risk management), also *actions* are to be considered, i.e. potential measures influencing the risk. The different elements of the framework are treated individually in the following.

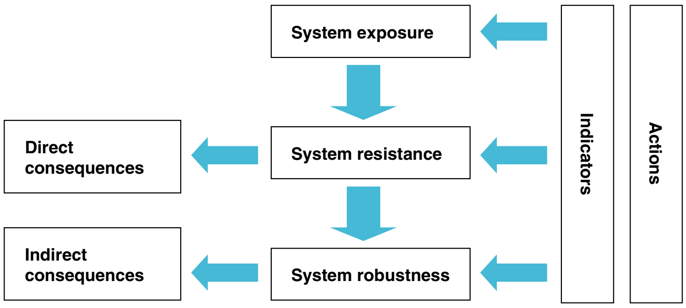

Figure 1. A framework for natural hazards risk assessment.

<u>*System exposure*</u>: The system exposure describes the probability of occurrence of the potential hazards to the considered system. Typically, the exposures are described by the annual exceedance probability $1-\mathrm{F}_E(e)$ or the annual exceedance frequency $\mathrm{H}_E(e)$, where E is generally a physical parameter representative for the damaging potential of the exposure. In principle, E may also be a vector of several parameters. For flood exposure, E is in general the discharge or the water level, for earthquakes this is one of the various applied intensity measures such as the peak ground acceleration, for rock-fall this is the volume of detached rock. The relation between the exceedance probability (which corresponds to an extreme value distribution for the considered time period) and the exceedance frequency is given by

$$1-\mathrm{F}_E(e)=\mathrm{e}^{-\mathrm{H}_E(e)} \tag{1}$$

Depending on the nature of the problem, either $\mathrm{H}_E(e)$ or $1-\mathrm{F}_E(e)$ appropriately represents the exposure, see Schubert et al. (2005). However, frequencies cannot be directly modeled in BN, and it is thus proposed to only work with $1-\mathrm{F}_E(e)$. This may in some instances require that the reference period is shortened; such a case is illustrated in the example presented later.

<u>*System resistance*</u>: The system resistance includes all intermediate processes and elements which may modify (stop, reduce, but also accelerate) the exposures within the system. Generically, the resistance is described as the probability of one or several damaging events F, dependent on the type and magnitude of the exposure E: $\mathrm{P}(F|E)$. Examples of such damaging events are the overtopping of a dam with a specific discharge or the impact of a rock on a road.

<u>*System robustness*</u>: The robustness K describes how the system reacts on the damaging events. In the case of the flood exposure it describes the spatial distribution of the flood after the overtopping event F together with the land-use. In the case of rock-fall K describes the potential for an accident but also the impact on traffic capacities given the event F of a rock falling on the road. For large events also further follow-up consequences have to be con-

sidered, such as the impact on the regional or national economy, Maes et al. (2004).

<u>Consequences</u>: It can be distinguished between direct and indirect consequences C. The former are the physical damage associated with the system resistance, the latter may comprise physical as well as economical, social or ecological damage. Consequences are often expressed in monetary terms, requiring the quantification of the "value of life", see Rackwitz (2000). In principle other value systems may be used, but any optimization of decisions must be based on some sort of trade-off between the different attributes.

<u>Indicators</u>: The indicators I are all variables that influence the risk and on which information may be obtained; they are the input parameters to the model. Indicators are generally available on all levels in the system, as illustrated in the example.

<u>Actions</u>: The aim of risk management is the assessment of cost-optimal mitigation actions. Actions can be applied on all three levels in the system: For rock-fall the risk can be reduced 1) by setting anchors to increase the stability of the rock mass and to thus reduce the exposure occurrence probability, 2) by constructing protection systems such as galleries or flexible nets and therefore increasing the resistance of the system, 3) by increasing the visibility on the endangered road section and to so increase the robustness of the system.

Clearly the classification of a specific process in the presented categories is not unambiguous. Considering the rock-fall hazard, the exposure can be interpreted as the impact energy on the protection structure or the road, but also as the volume of detached rocks, in which case the process of falling, rolling or jumping down is considered within the resistance of the system. However, the framework is intended as a support to structure the problem and not as a strictly prescribed, unique model of natural hazard risks. The ambiguousness is thus not crucial if the definitions are applied consistently within one project.

The risk is defined as the expected damage (the consequence for the system) per reference time. Although it may be required to describe exposures for different reference times, the risk should always be expressed per year when checking for compliance with given acceptance criteria, Rackwitz (2000). Based on the above definition, the risk R is, in generic format, obtained as

$$\begin{aligned} R &= \mathrm{E}_{E,F,K}\left[C_T\right] \\ &= \int_E \int_F C_T\left(E,F\right) \mathrm{P}\left(F \middle| E\right) \mathrm{P}\left(E\right) \mathrm{d}\,F\,\mathrm{d}\,E \end{aligned} \tag{2}$$

where $\mathrm{E}_{E,F,K}\left[C_T\right]$ denotes the expected value of the total consequences C_T with respect to E,F,K (exposure, resistance, robustness). The total cost as a function of E and F is thereby given as the sum of the direct consequences $C_D\left(E,F\right)$ and the indirect consequences $C_{ID}\left(E,F,K\right)$ as

$$\begin{aligned} &C_T\left(E,F\right) = \\ &C_D\left(E,F\right) + \int_K \left(C_{ID}\left(E,F,K\right) \mathrm{P}\left(K \middle| E,F\right)\right) \mathrm{d}\,K \end{aligned} \tag{3}$$

2.1 *Optimization*

Optimization of risk mitigation strategies is performed by maximizing the expected total benefit of the considered system, which is calculated as the sum of: the benefit from the system (e.g. the impact of a road connection on the economy), the cost of mitigation actions and the risk (the expected damages, see e.g. Faber and Stewart (2003)). If the expected total benefit is always negative for any combination of mitigation actions, then the activity (which could be the construction and operation of a road) should not be implemented at all. When the decision on undertaking an activity has already been made, the benefit of the activity can sometimes be neglected and the mitigation strategies can be optimized by minimizing the expected total cost. However, the benefit of an activity must not be ignored when a mitigation action has an influence on the benefit of the activity. Many mountainous roads are closed when the avalanche risk is beyond a certain level, Margreth et al. (2003), yet this risk mitigation strategy decreases the benefit of the road. This must be taken into account when deciding on this action.

3 BAYESIAN NETWORKS FOR MODELLING NATURAL HAZARD RISKS

3.1 *Bayesian Networks*

A brief and concise overview on Bayesian networks (BNs) is provided in Pearl and Russell (2000), more extensive textbooks on BNs include Pearl (1988) and Jensen (2001). Furthermore, many software packages, both commercial and freeware, are available for the computation of BNs, as discussed in Murphy (2001). In the following only a highly condensed introduction to BNs is given.

Bayesian networks are probabilistic models based on directed acyclic graphs. They represent the joint probability distribution $\mathrm{P}\left(\mathbf{x}\right)$ of a set of variables $\mathbf{X} = X_1, \ldots, X_n$. The size of $\mathrm{P}\left(\mathbf{x}\right)$ increases exponentially with n, the number of variables, but BNs enable an efficient modeling by factoring of the joint probability distribution into conditional (local) distributions for each variable given its parents. A simple BN is illustrated in Figure 2. It consists of three variables X_1 to X_3. X_1 is a *parent* of X_2 and X_3, which are *children* of the former.

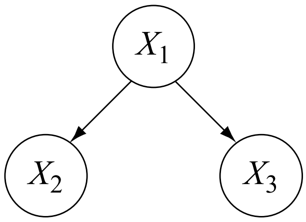

Figure 2. A simple Bayesian network.

The joint probability distribution of this network is given as

$$\mathrm{P}(x_1, x_2, x_3) = \mathrm{P}(x_1)\,\mathrm{P}(x_2|x_1)\,\mathrm{P}(x_3|x_1) \tag{4}$$

Generally, the joint probability distribution for any BN is

$$\mathrm{P}(\mathbf{x}) = \mathrm{P}(x_1, \ldots, x_n) = \prod_{i=1}^{n} \mathrm{P}(x_i|pa_i) \tag{5}$$

where pa_i is a set of values for the parents of X_i.

For computational reasons, BNs are restricted to variables with discrete states; in some instances, Gaussian variables can be used. For most applications it is therefore required to discretize all random variables.

The BN allows entering evidence: probabilities in the network are updated when new information is available. When the state of X_2 in the network in Figure 2 is observed to be e, this information will propagate through the network and the joint prior probabilities of X_1 and X_3 will change to the joint posterior probabilities as follows:

$$\begin{aligned} \mathrm{P}(x_1, x_3|e) &= \frac{\mathrm{P}(x_1, e, x_3)}{\mathrm{P}(e)} \\ &= \frac{\mathrm{P}(x_1)\,\mathrm{P}(e|x_1)\,\mathrm{P}(x_3|x_1)}{\sum_{X_1} \mathrm{P}(x_1)\,\mathrm{P}(e|x_1)} \end{aligned} \tag{6}$$

Consequently also the marginal posterior probabilities of X_1 and X_3 are updated. BNs facilitate this and various other types of inference from the probabilistic model through the use of efficient calculation algorithms; see e.g. Jensen (2001).

Note that the common influencing variable X_1 introduces a dependency between X_2 and X_3. This is a typical situation in natural hazards modeling: X_1 may e.g. represent the meteorological conditions and X_2 and X_3 are hydrological parameters at two different locations.

Bayesian networks can be extended to decision graphs by including decision nodes and utility nodes in the network. This enables the assessment and the optimization of possible actions in the framework of decision theory: the optimal action (respectively the decision on an action) is the one yielding the maximal expected utility. Such decision graphs are a concise representation of decision trees, commonly applied for the optimization in the framework of Bayesian decision theory, Raiffa and Schlaifer (1961). If no actions are considered, the expected utility simply represents a measure of the total risk.

3.2 *Bayesian networks for natural hazard risk assessment*

In recent years, BNs have received considerable interest for risk assessments and as a decision support tool for technical systems, e.g. Faber et al. (2002) or Friis-Hansen (2001). However, the author is aware of only few reported applications of BNs in the field of natural hazards. Antonucci et al. (2004) describe the application of creedal networks (an extension of BNs to model imprecise probabilities) for the prediction of debris flow. Hincks et al. (2004) use dynamic Bayesian networks to model volcanic hazards. Bayraktarli et al. (2005) describe a framework for the assessment and management of earthquake risks based on BN, where optimal risk mitigation actions are identified based on (simple) indicators.

BNs have a large potential for the application in the modeling of natural hazards and the corresponding risks. Natural hazards risk assessment is, as previously mentioned, a highly interdisciplinary task which requires that models from different specialist fields are assembled into a single model to ensure a consistent treatment of uncertainty and risk. Whereas the modeling of the exposure is typically carried out by natural scientists, the assessment of the system resistance and partly the robustness is generally performed by engineers. Finally, the model must be presented to the decision makers, often politicians or economists. BNs, as demonstrated in the above references or the example presented later, allow representing the entire processes in a concise manner. This highly facilitates the communication between the specialist and thus the integration of the different models. The comprehensibility and traceability of the BNs ensures that the results are accepted by the decision makers. Another large advantage of the BNs is their modular nature which allows different levels of detailing in the model and provides the flexibility to add additional information when it becomes available.

4 EXAMPLE: A ROCK-FALL HAZARD RATING SYSTEM USING BAYESIAN NETWORKS

Several rock-fall hazard classification systems are in use for the efficient assessment of the risks from rock-fall on roads, Hoek (2000) or Budetta (2004). These procedures are based on a series of indicators, which are determined for specific sections of the considered road. As a function of these indicators, a rating is obtained, which is the basis for decisions on further actions. These classification systems facilitate a quick overview on the risk from rock-fall on an entire road network. Unfortunately, the basic concepts underlying the applied classification systems are generally inconsistent with risk analysis, because of their over-simplified format, as will be shown. For this reason it should be envisaged to modify these procedures to consistently represent the influence of the indicators on the risk; it is the aim of the following example to demonstrate the potential of BNs for this task.

4.1 *The Rockfall Hazard Rating System (RHRS)*

As an example the classification system proposed in Budetta (2004), which is a modified version of the Rockfall Hazard Rating System (RHRS) developed at the Oregon State Highway Division, is considered. Nine[a] different indicators (in the reference termed as categories) are applied for the classification. These are:

- Slope height
- Ditch effectiveness
- Average vehicle risk (the traffic volume)
- Decision sight distance
- Roadway width
- Slope Mass Ratio (A description of the geological character)
- Block size / Volume of rock-fall per event
- Annual rainfall and freezing periods
- Observed rock-fall frequency

In the original procedure each indicator is divided in four intervals and a score of 3, 9, 27 or 81 points is assigned to each of the indicators depending on its value, see Budetta (2004) for details. The total score, representing the risk from a particular road section, is then obtained by summing up the points of all indicators.

It is not the objective of this paper to investigate the RHRS approach in detail, a task which would require in-depth knowledge on the background of the approach. Here only some general observations are made: At first sight it appears that the procedure assumes equal influence of all indicators on the risk. However, the choice of the four intervals for the different indicators implicitly weights the impact of the indicators, yet it is difficult to assess this effect, due to the major shortcoming of the approach: The additive format does not allow for an accurate representation of the complex interactions between the different indicators and the processes modeled. Simplifying, this can be displayed by recalling that the risk is the product of the probabilities of exposure, resistance and robustness with the consequences, Equations (2) and (3). While some of the indicators are representative for the exposure, others are describing the resistance, the robustness or the consequences. When applying the RHRS approach to some imaginary examples, it can be observed that the multiplicative nature of the problem is not reflected in the results; e.g. for the case where the potential consequences of a rock-fall event are very high, but the probability of this event is close to zero, the RHRS approach may still result in an unacceptable rating.

4.2 *A rating system based on a Bayesian network*

In the following, it is demonstrated how the same indicators as used in the RHRS approach can be implemented in a BN, which reflects the various causal relations between the indicators and the considered processes. It should be noted that the example presented has illustrative character. The aim of this study is not to present a fully functional model, but to demonstrate the capabilities of BN and to compare a BN approach to the existing rating procedure. The modeled relations between the various variables are not exhaustive and the resulting probabilistic model is not completely realistic. However, the example allows comparing the relative changes in the risk as indicated by the existing rating procedure to those indicated by the BN model to study the characteristics of the two models.

The full net is shown in Figure 4. The blue nodes represent the indicators (which correspond to those listed earlier), the white oval nodes are variables introduced to represent the causal relations in the system and the diamond-shaped nodes are the utility functions, characterizing the consequences. The net is arranged in accordance with the generic definitions exposure, resistance and robustness.

Four indicators are directly related to the exposure, which is modeled by the node "rock-fall frequency". This node has five states, corresponding to five different exceedance probability functions, which are modeled by the node "volume of detached rocks". These are illustrated in Figure 3. The probabilities of detachment of a certain rock volume are given per day. This model assumes that the event of more than one rock-fall event in the same day can be neglected, respectively that this event is sufficiently described by the larger rock. If the exceedance probability of rock detachment were given per year, then only the largest event per year would contribute to the risk; in most cases this is an unrealistic assumption, see also Schubert et al. (2005).

To simplify the modeling, an extra node "rock detached" is included, which describes only whether a rock is detached or not (the latter event corresponding to a detached volume equal to zero). This extra node has only two states and thus reduces the size of the probability tables of all nodes which are children of this node (i.e. which are conditional on this node).

[a] In the original approach ten indicators are used. The indicator "Volume of rock-fall per event" is not considered here, respectively is assumed represented by the indicator "Block size".

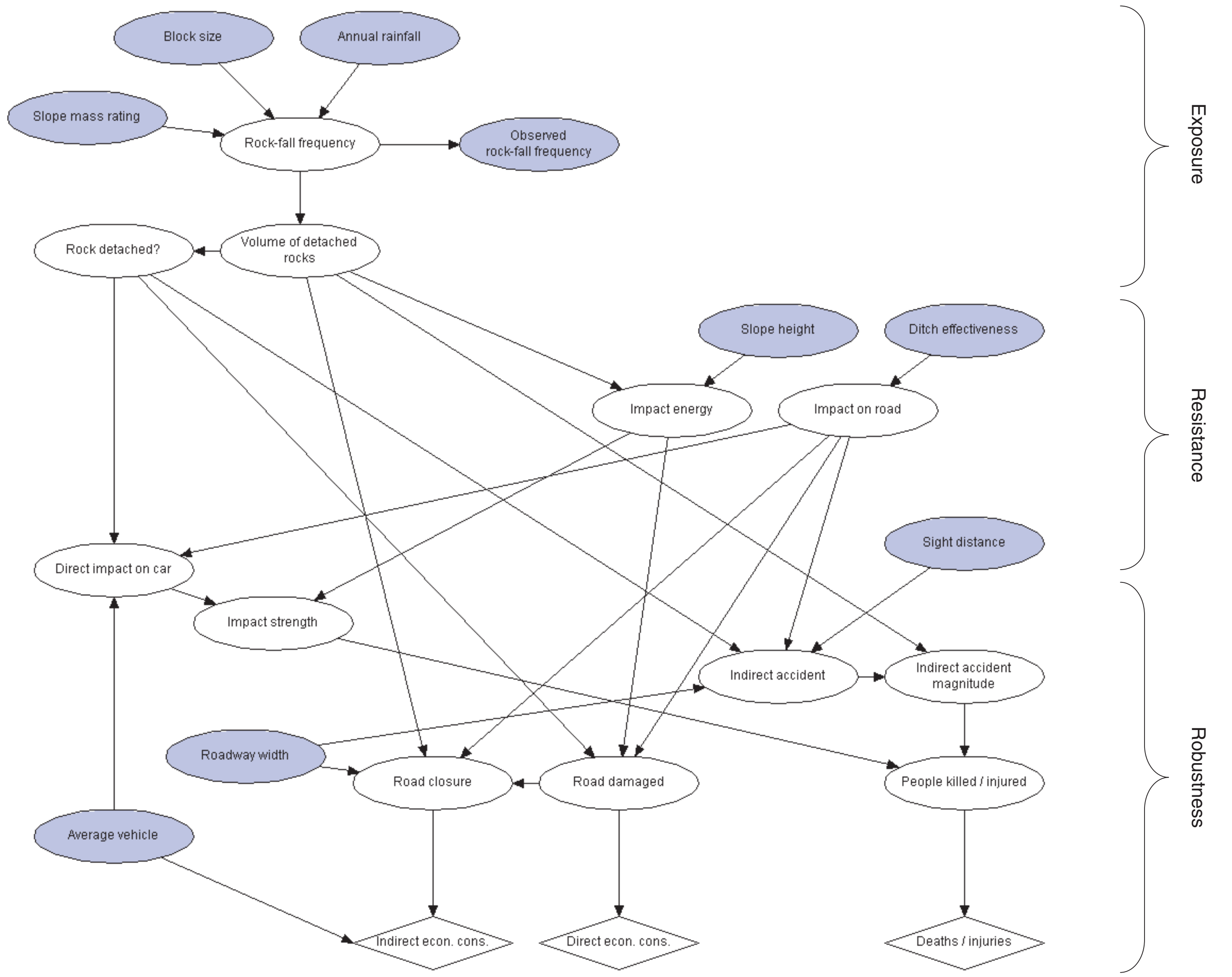

Figure 4. The Bayesian net applied for rock-fall hazard classification.

Note that the indicator "observed rock-fall frequency" is a child of the "rock-fall frequency". The direction of this link maintains the causality in the network. It so facilitates the consistent establishment of the probabilities in the nodes and enhances the comprehensibility of the network.

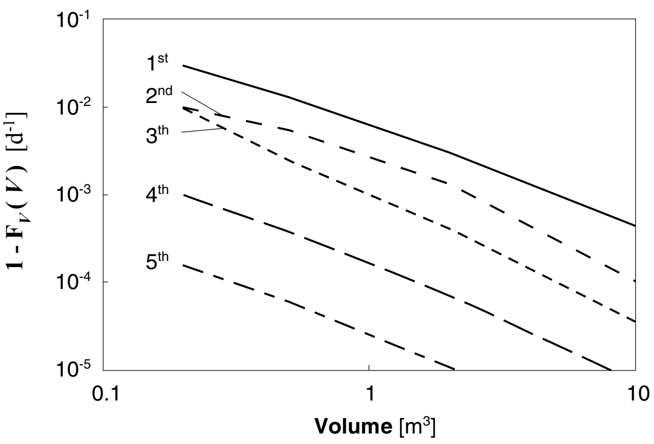

Figure 3. The five exceedance probability curves modeled in the "volume of detached rocks" node.

The system resistance is described by the probability that a detached rock hits the road (the "impact on road" node) and the energy that the rock accumulates (the "impact energy" node). If protection systems are to be evaluated, they can easily be included as separate nodes in this part of the network to assess their effect on the risk. When results of reliability analyses of protection structures are available, such as presented in Schubert et al. (2005), these can directly be translated into nodes of the BN.

Several nodes are introduced to model the relations describing the robustness of the system, i.e. the consequences of a rock impact on the road. The assumed dependencies can be read directly from the network.

The utility nodes define the expect cost as a function of the number of people killed and injured, of the physical damage on the road and of whether and how long the road is closed together with the normal average traffic volume. The utilities are expressed in monetary terms.

For computational reasons, also a dummy decision node must be introduced anywhere in the network; this has been omitted in Figure 4.

The BN model is utilized by entering the state of the indicators as evidence in the respective nodes, in accordance with Equation (6). The resulting score, which corresponds to the expected utility (and consequently to the risk) is then obtained by evaluating the updated probabilities of all nodes in the net.

4.3 *Comparing the two rating systems*

The original rating system is compared with the BN by assessing the rating for eight example cases. These are listed in Table 1, where 1 stands for the most favorable state of the indicator and 4 for the most adverse state. The cases are arranged in the order of increasing risk (as obtained with the BN model).

Table 1. Investigated cases.

Cases:	A	B	C	D	E	F	G	J
Slope height	1	4	2	1	2	3	3	4
Ditch effect.	1	4	2	2	1	3	4	4
Vehicles	1	1	2	1	4	3	3	4
Sight distance	1	1	2	3	3	3	3	4
Roadway width	1	1	2	2	2	3	2	4
SMR	1	1	2	2	4	3	2	4
Block size	1	1	2	1	4	3	1	4
Rain & Freezing	1	1	2	1	4	3	1	4
Observed freq.	1	1	2	2	4	3	4	4

The results are presented for both models in Figure 5. Both scores were transformed linearly, so that case A gives 1 point and case J 100 points.

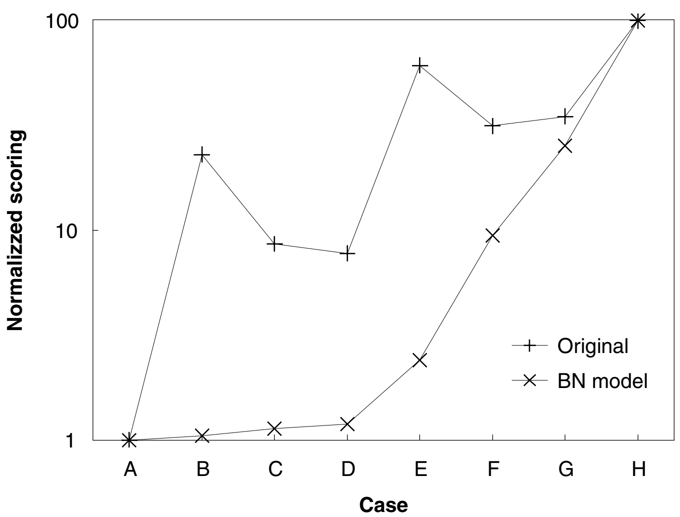

Figure 5. Normalized scores for the example cases.

5 DISCUSSION

5.1 *Discussion of the example*

It is observed from Figure 5 that the resulting scores of the BN model vary considerably from the original RHRS procedure. Whereas the former gives a score proportional to the risk (the expected consequences), the latter is intended for risk ranking; the score of the RHRS approach is thus not necessarily proportional to the risk and the absolute differences between the results from the two models cannot be directly interpreted. However, insights can be gained by looking at some specific cases in detail.

For case B, the BN model results in a low risk, in contrast to the original model. Case B has very unfavorable indicators for the system resistance, but very favorable indicators for both the exposure and the robustness of the system. The results in Figure 5 show that the RHRS approach does not capture the multiplicative nature of the risk, Equations (2) and (3), for this extreme case. A similar observation can be made for case E, where the very favorable indicators for the system resistance reduce the risk, as demonstrated by the BN model.

An important advantage of the BN model is that is can consistently cope with contradicting information. The observed rock-fall frequency is modeled as a child of (i.e. conditional on) the actual rock-fall frequency. Consider case G where all indicators on the rock-fall exposure are favorable with the exception of the observed rock-fall frequency. In the BN model, this observation has a large impact, because it contradicts the other three indicators. If the observed frequency indicator is set to 1, the resulting risk is reduced by a factor of 100! Applying the original model, the score is only reduced by less than 1/3.

The presented BN can be easily extended to include potential mitigation actions such as the construction of protection structures. Also the model can be modified when a detailed geological assessment of the area is available. Because such an assessment will not influence the modeling of the consequences, i.e. the system robustness, these parts of the net can be directly adopted and only the exposure nodes would be modified.

Finally, note that indicator nodes that have no children can be neglected if no information on this indicator is available. Such a case is the observed rock-fall frequency in the presented model. If no observations are available then no evidence must be entered here. In the original rating system, it is unclear how to consistently deal with unavailable indicators.

5.2 *General*

Many important aspects of an integral risk management strategy, as presented e.g. in Faber and Stewart (2003), are not covered in this paper, which focuses solely on the modeling parts. Such aspects include the hazard identification and the identification of mitigation actions, the determination of risk acceptance criteria, the implementation of measures as well as the process of reviewing and validating the models and other quality control measures. Yet it is believed that the presented framework for risk assessment supports a structured approach to all tasks involved in the management of natural hazards.

The presented example can easily be extended to include other hazards. Many road sections that are exposed to rock-fall are also subject to snow avalanches. These two processes should be considered simultaneously, because they have many common parameters; e.g. all parameters describing the robustness of the system, such as the average traffic, are identical for the two hazards. Furthermore, many risk reducing measures influence the risk from both hazards; optimization of these must thus consider the effect on the risk from all processes.

The BN format also allows establishing a common model for the entire road link, considering all road sections and all exposures integrally. An example is the decision on a temporarily road closure, where the risk from all sections must be taken into account. Again, many parameters of the model are identical along one road. This introduces a dependency in the behavior of the individual road sections, which must be considered in the modeling. In the BN this can be easily accounted for by having nodes which are common for all individual road sections.

6 CONCLUSIONS

The general characteristics of natural hazards risk assessment are discussed and it is found that Bayesian networks have a large potential for this task because of their flexibility, traceability and intuitive format. This is demonstrated in the paper by the presented example on the assessment of the risk from rock-fall hazards based on indicators, where an exemplary Bayesian network model is compared to a traditional rating system. It is found that the Bayesian network model allows a detailed evaluation of the joint influence of the different indicators on the risk; it thus gives results which, in contrast to the traditional methodology, are consistent with the mathematical concept of risk and can thus be directly used for optimization purposes. The Bayesian network model also ensures that the model can be further extended when additional investigations are performed or that the unavailability of indicators can be handled.

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