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An elicitation process to quantify Bayesian networks for dam failure analysis

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Abstract

Bayesian Networks support the probabilistic failure analysis of complex systems, e.g. dams and bridges, needed for a better understanding of the system reliability and for taking mitigation actions. In particular, they are useful in representing graphically the interactions among system components, while the quantitative strength of the interrelationships between the variables is measured using conditional probabilities. However, due to a lack of objective data it often becomes necessary to rely on expert judgment to provide subjective probabilities to quantify the model. This paper proposes an elicitation process that can be used to support the collection of valid and reliable data with the specific aim of quantifying a Bayesian Network, while minimizing the adverse impact of biases to which judgment is commonly subjected. To illustrate how this framework works, it is applied to a real-life case study regarding the safety of the Mountain Chute Dam and Generating Station, which is located on the Madawaska River in Ontario, Canada. This contribution provides a demonstration of the usefulness of eliciting engineering expertise with regard to system reliability analysis.

Keywords

Dam safety, Bayesian network, statistical inference, elicitation, expert knowledge, expert judgment.

1. Introduction

Dams fail due to a combination of more frequent load and reduced resistance to the load exceeding the facility's capacity, design problems, unexpected flood events or inappropriate decisions in managing dams. Such failures, including breaches, may lead to catastrophic events which affect both properties and lives of people. Maintaining dams is challenging, as resources such as labor and capital are limited, facilities are remote and usage profiles are uncertain. Global weather patterns have been changing, causing periods of flooding, which have resulted in an increase in operating the dams. Understanding and anticipating the environment in which the dams will operate is vital for maintaining the availability of the asset. Effectively maintaining the asset requires a mathematical model to explicate the relationship between environment, usage, hazards and management decisions, and to support the optimal long-term productivity of the asset.

While several examples of mathematical and probabilistic approaches used to evaluate the safety of dams can be found in the literature (Yanmaz & Gunindi 2008; Li et al. 2011; Goodarzi et al 2012; Su et al. 2015), in this contribution we decide to use the Bayesian Network (BN) since it has many advantages and it is an increasingly popular method for reasoning under uncertainty and modelling uncertain domains. For instance, in comparison with two most commonly used approaches, i.e. the Event Tree Analysis (ETA) and the Fault Tree Analysis (FTA), BNs can more succinctly represent the dependency relationship between a large number of variables, permit variables to be described in multiple states not just binary, i.e. true or false, describe and represent multiple initiating events, and explicitly integrate different types of data, e.g. technical, environmental and social, in a single unified representation. Comparisons between BN and ETA or FTA in safety analysis can be found in Khakzad et al. (2011), Jong and Leu (2013), Zerrouki and Tamrabet (2015a), Zerrouki and Tamrabet (2015b).

BNs provide a powerful framework for reasoning under uncertainty, and consequently have been recently applied to various engineering problems, e.g. earthquake risk management (Bayraktarli et al. 2005; Bensi et al. 2011; Liu & Nadim 2013), avalanche risk assessment (Gret-Regamey & Straub 2006), landslide hazard mitigation (Medina-Cetina & Nadim 2008), reliability analysis (Langsetha & Portinaleb 2007), climate change assessment (Peter et al. 2009), risk assessment in maritime engineering (Kelangath et al. 2011), environmental modelling and management (Aguilera et al. 2011), risk assessment for fatigue damage (Sankararaman et al. 2011; Ling & Mahadevan 2012), scour management (Maroni et al. 2019). In addition, as regards the topic of this paper, in the literature we can find many papers in which BNs are used to develop dam safety analysis, among the many we recommend Smith (2006), Xu et al. (2011), Zhang et al. (2011), Miroslaw-Swiatek et al. (2012), Peng and Zhang (2013), Ahmadi et al. (2015), Gang et al. (2016), Eldosouky et al. (2017), Liu et al. (2017), Briseno-Ramiro et al. (2019), Dassanavake and Mousa (2020).

Specifically, BNs are probabilistic graphical models that use directed acyclic graph to represent a set of uncertain variables and their conditional dependencies (Charniak 1991; Ben Gal 2007; Jensen & Nielsen 2007). In detail, nodes represent the collection of random variables, while edges represent the interrelationship between these variables. While the topology of the BN provides the causal structuring of the problem under study, the quantitative strength of the interrelationships among variables is measured using conditional probability distributions, which can be updated when new data become available. Typically, the quantification of the probabilities may be obtained from statistical and historical data, existing physical or empirical models and logic inference. However, these quantification sources and methodologies are often not easy to be conducted and not sufficient to quantify the entire BN, due to the lack of sufficient models that interpret the interrelationships among system variables and due to the lack of data and information. Consequently, it becomes necessary to rely on expert judgments to quantify these dependencies: engineering knowledge and experience can be an important data source for estimating these probabilities (Dias et al. 2018).

Eliciting expert judgment in the form of subjective probabilities is a socio-technical activity. As such it requires a structured and facilitated process to extract meaningful judgments because people, even experts, are unable to provide accurate and reliable data simply on request (Ferrell

1994; Vick 2002). An example about discrepancies between experts in risk assessment can be found in Rizak and Hrudey (2005). In addition, since the work of Tversky and Kahneman in the early 1970s (Tversky & Kahneman 1974), there has been awareness of the biases and heuristics people apply in decision-making under uncertainty that can result in poor probability assessments. Elicitation processes are designed to minimize the influence of these biases (Quigley & Walls 2020). In the literature, there are a variety of existing processes for eliciting expert knowledge with engineering applications, see for instance Bubniz et al. (1998), Hodge et al. (2001) and Astfalck et al. (2018). Textbooks such as Cooke (1991), Meyer and Booker (1991) and Dias et al. (2018) are references for general aspects of elicitation. However, very little has been reported about elicitation processes aimed specifically at quantifying BNs using expert judgment (Sigurdsson et al. 2001; Norrington et al. 2008; Christophersen et al. 2018), especially for civil engineering applications, where we require experts to assess a variety of dependent variables, each of which is in one of several possible states. In particular, a methodology to support the collection of valid and reliable data in order to quantify the BN is not available.

In this paper, the aim is to develop a methodology for eliciting expert knowledge in the specific case where the model is described by a BN. We start with an introduction of the fundamentals of BNs in section 2. In section 3, a four-stage structured elicitation process is developed generically so that it can be applied to many civil engineering structures, e.g. dams and bridges. Section 4 presents an implementation of this methodology, with its application to a real-life case study regarding the safety of the Mountain Chute Dam and Generating Station, which is situated on the Madawaska River in Ontario, Canada. Concluding remarks, along with the explanation of the lessons learnt from the application, are presented at the end of the paper.

2. Bayesian Networks

Bayesian Networks (BNs), also known as Bayes networks, belief networks or decision networks, are probabilistic graphical models used to represent knowledge about an uncertain domain using a combination of principles from graph theory, probability theory, computer science, and statistics (Charniak 1991; Ben Gal 2007; Jensen & Nielsen 2007). In the graph, nodes represent the collection of random variables, while edges represent the interrelationship between these variables. In addition, each node is associated with conditional probability values that model the uncertain relationship between the node and its parents; they compose the so-called node probability table (NPT). BNs can model the quantitative strength of the interrelationships among variables, i.e. the nodes, allowing their probabilities to be updated using any new available data and information. They are mathematically rigorous, understandable, and efficient in computing joint probability distribution over a set of random variables, and consequently very useful in supporting risk analysis of complex systems.

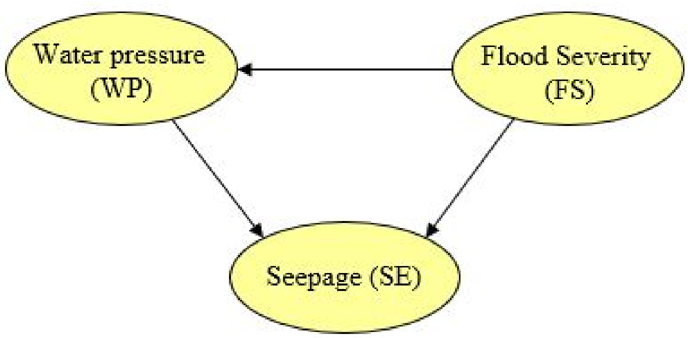
BNs are probabilistic graphical models that use directed acyclic graph (DAG): this means that a set of directed edges are used to connect the set of nodes, where these edges represent direct statistical dependencies among variables, with the constraint of not having any directed cycles. Let $X = (X_1, \ldots, X_i, \ldots, X_n)$ represent the set of nodes, i.e. the uncertain variables. A node X_j is called parent of a child node X_i if there is a directed edge from node X_j to node X_i, meaning that X_i depends on X_j. Each node can have many parents nodes, while nodes with no parent are called root nodes and nodes with no child are called leaf nodes. In addition, each root node is associated with a basic probability table (BPT), while each child node with a conditional probability table (CPT). The joint probability function of random variables in a BN can be expressed as follows:

$$P(X) = \prod_{i=1}^{n} P[X_i \mid Pa(X_i)], \#(1)$$

where $P(X)$ is the joint probability and $Pa(X_i)$ is the parent set of node X_i. If X_i has no parents, i.e. it is a root node, then the function reduces to the unconditional probability of $P(X_i)$. A simple example of BN with three variables as regards dam safety analysis is shown in Figure 1: both the severity of the flood and a high-water pressure can cause the presence of seepage in the dam; in addition, the flood severity has a direct effect on the level of water pressure. The table related to the flood severity, that is a root node, represent an example of BPT, while the tables of the other two child nodes are examples of CPT.

Figure 1. An example of BN with three variables.

	WP	
FS	Low	High
Low	0.9	0.1
High	0.6	0.4



FS	
Low	High
0.9	0.1

		SE	
WP	FS	Yes	No
Low	Low	0.1	0.9
High	Low	0.5	0.5
Low	High	0.3	0.7
High	High	0.7	0.3

Generically, in BNs there are two main types of reasoning: predictive reasoning, i.e. top-down or forward reasoning, in which evidence nodes are connected through parent nodes (cause to effect), and diagnostic reasoning, i.e. bottom-up or backward reasoning, in which evidence nodes are connected through child nodes (effect to cause).

Finally, we can summarize how to build and use a BN with three steps: structuring the problem, defining the conditional probabilities, and making the final inference. The first step aims to define the topology of the BN: first, the relevant variables of the problem are identified and expressed as statistical variables, discrete or continuous; then, the network is created by joining the variables according to their dependency. The second step is about quantifying the interrelationship among connected nodes, i.e. defining the CPTs, as well as the BPTs in the case of root nodes. They may be obtained from statistical and historical data, existing physical or empirical models, logic inference or they may be elicited from experts. Lastly, the inference step concerns entering the evidence in the BN, updating the probabilities, and interpreting the final results.

3. Elicitation Process for Bayesian Networks

In this paper, the aim is to support the collection of valid and reliable data in order to quantify a BN, by developing a methodology for the specific case where the topology of the BN has already been defined, i.e. with the problem already structured. In this case, the elicitation process is then required to extract and quantify the subjective judgments about the uncertain quantities, which are the conditional probabilities that represent the interrelationships among connected nodes.

There are various protocols for probability elicitation (Morgan et al. 1990), for a recent review see Quigley and Walls (2020). The methodology proposed in this contribution is adapted from the Stanford Research Institute (SRI) model (Ferrell 1985; Spetzler & Stael Von Holstein 1985; Merkhofer 1987). Accordingly, the process for eliciting expert judgment is based on seven possible stages: motivating the experts with the aims of the elicitation process, structuring the uncertain quantities in an unambiguous way, conditioning the expert's judgement to avoid cognitive biases, encoding the probability distributions, verifying the consistency of the elicited distributions, aggregating probabilities from different experts and discretizing continuous probability distributions. Moreover, to conduct an elicitation process at least two characters are necessary: a subject, i.e. the expert, and an analyst, i.e. the interviewer. The first one provides expertise, i.e. he/she is "a person with substantive knowledge about the events whose uncertainty is to be assessed" (Ferrell 1985), while the second one has responsibility for designing, developing and executing the process as well as evaluating the procedures. For the rule of analyst, also called facilitator, it is common to have at least one person who is very knowledgeable in elicitation practice and can manage the process, and another one with wide expertise in the area of the design project.

Starting from the SRI protocol and according to the specific requirements of a BN, we develop a four-stage structured methodology to support the elicitation meaningfully. In the next subsection each stage is extensively presented by defining each phase of the process, presenting the roles of the key personnel and highlighting all the potential biases that may influence the process, while proposing appropriate actions in order to minimize the risk of a biased judgment.

3.1 The four-stage structured elicitation process

In the following, each stage of the process is presented in detail; the flowchart in Figure 2 shows the proposed elicitation process.

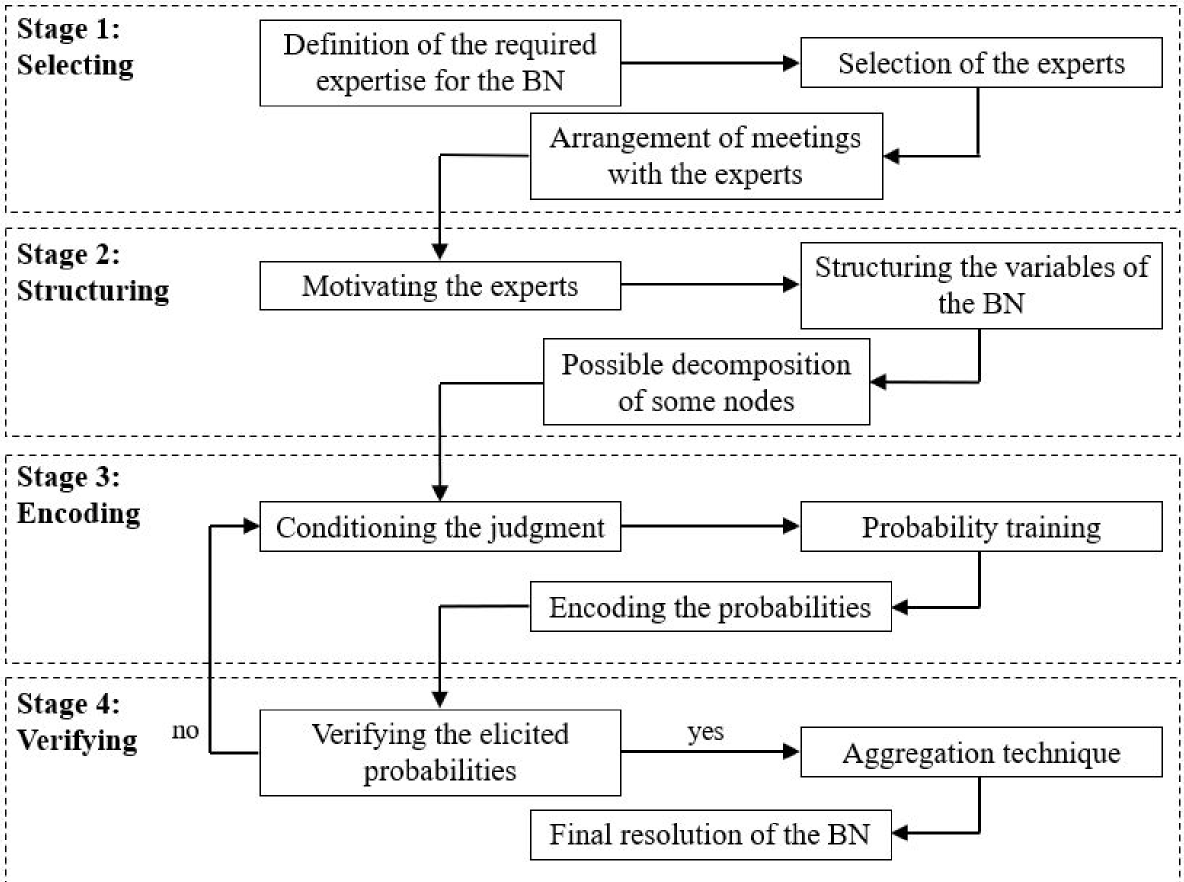
Stage 1: *Selecting*. To start, the analysts have to study carefully the project and the proposed BN, to understand which kind of expertise is required: it is fundamental to ensure coverage of all the different aspects of the problem, so more than one expert is usually necessary. This is even more important in civil engineering applications, because in this field experts are usually very specialized. Therefore, the analysts should identify the essential and desired characteristic of experts and build up profiles of experts who may be able to answer questions concerning the quantities of interest, i.e. the values required to be quantified in the BN. Constructing a profile matrix can be useful (Bolger 2018), which matches the knowledge requirements with the expert roles: it supports the identification of expertise needed as well as justification for the choice of experts. The number of required experts depends then on the variability of expertise per domain. Adding as many experts as possible seems beneficial, however, practically it may be difficult to manage many experts and there will be a diminishing return on adding more experts. In addition, we have to be aware that in real-world it is not so easy to have the availability of many experts. Once the experts have been selected, the analysts have to arrange meetings to conduct interviews. Prior to the meetings, it is recommended to give to the experts an outline about the project and where their knowledge will be useful, so that they have the opportunity to reflect upon the events.

Stage 2: *Structuring*. Individual interviews between the analysts and the selected experts are conducted. The initial part of the interview has two purposes: to introduce the expert to the encoding task as well as identifying and addressing motivational biases (Fischhoff 1989), such as management bias and expert bias. Management bias occurs when experts provide goals rather than judgments, e.g. “the dam will not fail”, while expert bias comes when experts become overly confident because they have been labelled as “experts”. During this initial part of the interview, the BN should be explained, indicating the uncertainty variables that will be elicited and explaining how this process can be useful as regards the resolution of the overall problem. The second part of this stage is concerned with structuring the variables: each quantity of interest that will be quantified needs to be specified so that a measurement scale can be determined. Even if the topology of the BN has already been defined, it is fundamental to review with the experts the definitions of the variables and their states, in order to structure the uncertain quantities in an unambiguous and meaningful way, before starting with the encoding phase. Each variable must have a clear definition that will be understood without any possibility of misunderstanding by the expert. In addition, the states of every variable have to be determined in order to make unambiguous the final estimation of the expert. It is common for a BN to represent the nodes with discrete states: we suggest keeping them binary if possible, to minimize the number of variables to quantify. Depending on the experience and mental models of the experts, it may be appropriate to disaggregate the variable into more elemental variables. This can be very useful in the case of the BN, because each node might depend on several aspects and it can be easier for the experts to evaluate these secondary probabilities. This technique also allows the analysts to combat the motivational biases introduced at the beginning of this stage, i.e. the so-called management bias and expert bias, and also some cognitive biases, e.g. the conjunctive bias, by increasing the level of detail. The conjunctive bias is one of the biases associated to the anchoring heuristic (Tversky & Kahneman 1974), which states that the overall probability is overestimated in conjunctive problems and underestimated in disjunctive problems.

Stage 3: *Encoding*. This stage is concerned with encoding the expert's uncertainty on the quantity of interest as a probability. Prior to eliciting these quantities training experts on probability and providing relevant information for discussion should be conducted to minimize the presence of potential biases (Tversky & Kahneman 1974; Armstrong et al. 1975). In particular, this can address biases such as anchoring (Tversky & Kahneman 1974), i.e. when the evaluation is conditioned by an initial assessment, and availability (Kahneman & Tversky 1973), i.e. when the evaluation is based on the ease with which relevant instances come to mind. Probability training should be provided to calibrate the experts: a brief review of basic probability concepts may be helpful, along with some training questions which can help the experts to become familiar with the elicitation process itself. Experts should be trained on problems relevant to the questions on which they will be providing judgement. When the training is completed, the encoding stage commences. There are many available approaches to elicit probabilities, including direct assessments of probabilities; for a review of methods we refer the Reader to O'Hagan et al. (2006). A popular encoding procedure for distributions is the fractile method (Cooke 1991), where the expert assesses the median value of their subjective probability distribution along with the (25^{th},75^{th}) and the (5^{th}, 95^{th}) percentiles. Once the initial values have been elicited a parametric distribution can be investigated and assessed for fit with the elicited values. The order in which these quantities are elicited should start with the extreme values first and progress towards the central values, in order to avoid the so-called central bias, i.e. the tendency to give an answer that is closer to the center of opinions, and to not give an extreme answer. If the expert is uncomfortable with percentiles, questions can be rephrased using qualitative bands, such as "highly likely" or "highly unlikely", but the percentiles associated with these qualitative terms must be discussed and understood by both expert and analysts. Alternately, graphical techniques (Chaloner et al. 1993) may be useful to improve the quality of the results. We recommend using the technique which makes the expert more comfortable. In the case that there are a lot of probabilities to be elicited for the same node, we suggest that the expert first ranks the factors from the most to the least influential and subsequently quantifying the relationship, for instance following the swing weight method to elicitation used with multi-attribute decision analysis (Belton & Steward 2001). Moreover, sometimes it is not possible to elicit data for all the BN components, especially when it is composed by a huge number of nodes or due to a limited time available. In this case, we recommend identifying the quantities of interest that make the most significant contribution to the assessment of the structure, for example through a sensitivity analysis (Li & Mahadevan 2018). Finally, during the encoding phase, asking the same question in several ways can be a useful way of identifying potential inconsistencies with expert assessments. If this occur the expert should be confronted and encouraged to reflect and respond on the assessments.

Stage 4: *Verifying*. This final stage starts by verifying the consistency of the elicited probabilities. First of all, the analysts should verify that each expert has provided a reflection of their true beliefs. Moreover, it is important to check for trends across the elicited probabilities to determine if there are any indicators of anchoring bias or availability bias. If the results are not satisfactory or biased, the previous stage should be repeated. In the case that the same conditional probabilities have been elicited from different experts, the analysts should then develop an aggregation technique to obtain one single final result; see Quigley et al. (2018) for a performance-based approach or, if a consensus amongst experts is desired, see Gosling (2018) for a behavioral based approach. Since the proposed methodology is based on discrete states, the final stage of the SRI model, i.e. discretizing continuous probability distributions, is not needed. Once each elicited probability has been verified and, if necessary, aggregated, the analysts should solve the overall BN to achieve the final results. We suggest discussing with the experts also these final outcomes in order to have a further validation of the developed process. After that, the interview ends and the process can be considered concluded.

Figure 2. Flowchart of the proposed elicitation process.



4. The Mountain Chute Dam and GS case study

The case study motivating our research is the Mountain Chute Dam and Generating Station (GS), which is operated by Ontario Power Generation (OPG). Mountain Chute Dam and GS, presented in Figure 3, is located in Greater Madawaska Township in Renfrew County (Ontario, Canada): it has an electric power generation capacity of 170 megawatts of clean, renewable electricity. It is situated on the Madawaska River, 64 km upstream from its confluence with the Ottawa River, and it is in the upstream of four other hydroelectric facilities on the Madawaska River: Barrett Chute GS, Calabogie GS, Stewartville GS and Arnprior GS. The construction started in 1965 and was completed in December 1967. Three dams are located at the Mountain Chute GS:

one main concrete dam and two earthen block dams, i.e. the north block dam and the whitefish draw dam. The main dam, shown in Figure 3(a), consists of the north and the south concrete gravity walls, the sluiceway and the headworks. It is 436 m long and 55 m above the rock foundations at the deepest section; the elevation of the top of the concrete structure is 249.9 m. The north block dam, which is an embankment structure constructed across a shallow depression about 300 m north east of the north abutment of the main dam north, is about 125 m long and has a maximum height of 12 m. Finally, the whitefish draw dam is a block dam preventing the reservoir from flowing out via a side valley, it is located about 2.5 km north of the main dam, it is 204 m long and it has a maximum height of 18 m. More details about Mountain Chute GS and its case study are provided in El-Awady et al. (2019) and Verzobio et al. (2019).

Figure 3. Mountain Chute Dam and GS: a) the main dam and the sluice gates; b) the downstream of the dam; c) the upstream of the dam with the reservoir.

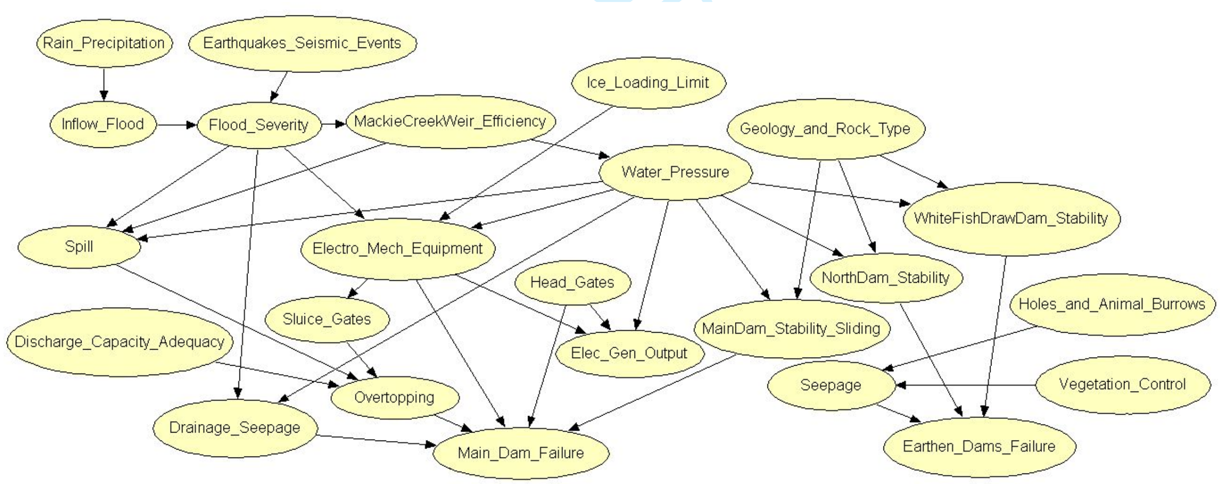
a) b) c)

The main scope of this project is about the general safety of Mountain Chute, with the final aim to estimate the probability of failure of the dams, intended as failure to perform at least one of the required operations, according to the interrelated dam components. In the next subsections, we describe the developed BN and successively the application of the proposed elicitation process, which allows for improving the estimation of the failure probability of the dams, thanks to the acquisition of valid and reliable data from expert knowledge.

4.1 Bayesian Network of Mountain Chute Dam and GS

Mountain Chute station includes different kinds of system components. For the purpose of analyzing the failure of this system, all system components should be defined, explained and analyzed. Specifically, components such as rain precipitation, ice loading, earthquake and seismic actions, water pressure, geology and rock type, flood severity, adequacy of discharge capacity, sluice gate, drainage, vegetation control and other secondary components have to be considered. A BN was constructed based on these components and based on the factors that can lead to the failure of the dams, e.g. overtopping, seepage, sliding, stability issues and any operational failure, such as problems related to the head gates or to the electromechanical equipment. The resultant BN is presented in Figure 4.

Figure 4. Bayesian Network of Mountain Chute Dam and GS showing all the primary variables.



The main purpose of the developed BN, which is represented by 24 different nodes, i.e. the yellow ovals in Figure 4, is predicting the probability of failure of the main dam from overtopping, seepage, sliding or any operational failures. Moreover, it estimates the probability of failure of the earthen block dams resulting from the threats of seepage and sliding. In the following, we analyze in detail the BN.

The basic events are rain precipitation, ice loading limits, earthquakes, geological and rock stability, vegetation control and control of animal burrows. It can be seen from the BN that the amount of rain affects the inflow to Mountain Chute dam; this inflow is considered a flood if it exceeds a certain limit. If a flood takes place, it may be normal or severe. Flood severity is also affected by seismic actions and earthquakes. The inflow rate and the severity level of the flood are controlled by the Mackie Creek weir. Controlling the inflow is about preventing severe floods from reaching the dam reservoir. The weir may be efficient or not, depending on the flood severity. After passing the weir, the water in the reservoir, blocked by two earthen block dams and the main concrete dam, is ready to be controlled by the dam head gates; this means that there is water pressure behind the dams that may affect their stability. The geological and rock stability for the structure of the three dams have been considered as it affects the sliding of the dam; sliding is one of the causes of dam breach failure.

In addition, ice loading, water pressure and flood severity are connected to the electromechanical equipment, including turbines; for instance, ice loading affects the failure of the mechanical equipment and at the time of a severe flood and high-water pressure could result in dam failure from maloperations of gates. As regards the electric power generation, the head gates are opened to let the water flow through the penstock to generate electricity from hydropower turbines. If the head gates fail to open, this is considered a failure of the main dam, especially if the water pressure is high in the upstream side of the dam; this may affect the dam stability and also the amount of power generated by the turbines.

Moreover, the flood severity, the weir efficiency in controlling the inflow to the reservoir and the water pressure are all affecting the probability to have spill in the main dam; the spill is the amount of water that exceeds the reservoir maximum capacity limit after considering various controlled outflows. This amount should be released from the upstream side to the downstream side through the spillway (sluiceway) gates or an overtopping failure could take place. The amount of water spill is also related to the capacity of sluiceway, which may not be adequate for that amount of water to be discharged, and to the condition of the sluice gate, i.e. open or failed to open due to electromechanical failure. If the water spill is not released from behind the main dam because of the inadequate capacity of the sluiceway, or because the sluice gate fails to open, there is an increasing probability, i.e. risk, of overtopping failure.

As concerns the main dam, severe floods with increased water pressure increases the possibility to have seepage in the body of the main dam. If the seepage is not completely controlled and monitored through a drain system which may include drain inspection tunnel, this would result in an increasing risk that reduces the remaining lifetime of the dam. Finally, as regards the earthen dams in Mountain Chute GS, seepage may take place because of uncontrolled vegetation and due to animal burrows and holes in the vicinity of the dams. Seepage in the earthen block dams is then an increasing risk for seepage piping and dam breach failure.

After the development of the topology of the BN with all its variables, the corresponding states have been defined. It was clear that defining more than two states for every component of the BN would have turned the system into a more complex network. On the other hand, more states would have allowed to get more accurate results. Following the proposed methodology of the elicitation process, due to the considerable number of nodes, it has been decided to keep the states of the nodes binary, e.g. fail/no fail, safe/not safe, controlled/not controlled, efficient/not efficient. Table 1 presents the defined states for each node. In addition, each state has been associated with a detailed definition or a numerical value, so as to make them quantifiable. As an example, according to the available data, the threshold according to which the rain precipitation passes from the state *low* to the state *high* is when the rain depth reaches 60 mm.

Table 1. States of the BN variables.

Variable	States	
Rain precipitation	Low	High
Earthquakes seismic events	Normal	Severe
Ice loading limit	Safe	Not safe
Geology & rock type	Stable	Unstable
Discharge capacity adequacy	Adequate	Not adequate
Head gates main dam	Open	Close/Fail to open
Holes and animal burrows	Controlled	Not controlled
Vegetation control	Controlled	Not controlled
Inflow flood	Low	High
Flood severity	Normal	Severe
Mackie Creek weir efficiency	Efficient	Not efficient
Water pressure	Normal	High
Spill	Yes	No
Electromechanical equipment main dam	Efficient	Not efficient
Sluice gates main dam	Open	Close/Fail to open
Electric generation output	Low	High
Overtopping	Yes	No
Drainage main dam seepage	Leakage	No leakage
Main dam stability sliding	Stable	Unstable
Main dam failure	Fail	No fail
North dam stability	Stable	Unstable
White fish drawn dam stability	Stable	Unstable
Seepage	Exist	Not exist
Earthen dams failure	Fail	No fail

Once the BN structure is completely defined, the conditional probability distributions were determined based on logical inference and limited historical data; these probabilities are defined to represent 100 years of operation for the Mountain Chute Dam and GS. Nevertheless, the available data were not enough, and they did not allow to cover all the nodes of the BN. Then, it was necessary to rely on expert judgment to provide subjective probabilities in order to populate completely the model.

4.2 Elicitation Process

By following the methodology proposed in section 3, we implemented each stage of the process as follows.

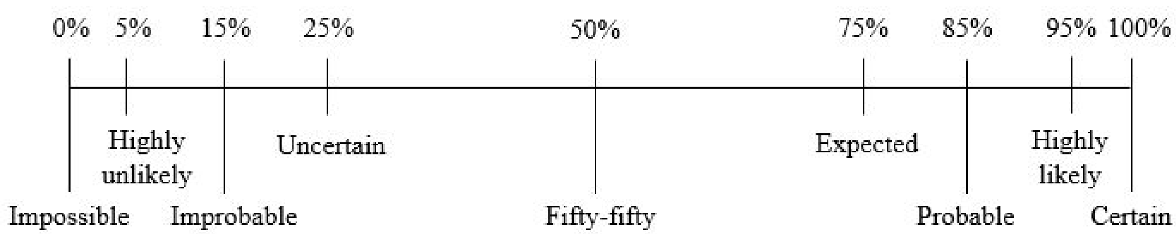
Stage 1: *Selecting*. There were two analysts: one with knowledge in elicitation practice and another with experience in the specific engineering area of failure analysis. After studying the project and the defined model, we identified three areas of expertise from which we sought to elicit expert judgment: structural stability expertise, environmental expertise and system design expertise. While finding one expert per each area was desirable, due to availability constraints we were given access to only one expert, who had a reasonable expertise in all the three areas: he was an engineer of the Ontario Power Generation who was responsible for monitoring the operations of this specific GS. We were aware about the possible difficulty in finding available experts, but managed to satisfy an essential coverage of expertise in all relevant area. A meeting was then arranged at the site of the dam, in order to develop the interview. In preparation, the expert was informed by email about the project and the specific aims of the interview.

Stage 2: *Structuring.* At the beginning of the interview the expert was motivated by explaining the importance of the project, his fundamental rule and how the results will be used. Moreover, the possible presence of motivational biases was investigated, especially the expert bias: it was carefully pointed out to the expert that the goal is not to measure his personal expertise, but to measure his knowledge about the events. Successively, we moved to the second part of this stage: we reviewed the topology of the BN and the states of the variables together with the expert, to ensure that there was no misunderstanding about their definition before moving to the encoding phase. The expert therefore had the opportunity to review the topology of the BN but he decided not to modify it, probably because we arrived at the meeting with a too refined model; he also agreed with the proposed variables, refusing the possibility to disaggregate some nodes too. In addition, we spent more time explaining meticulously to the expert the meaning of each variable and the corresponding states: after this discussion, and based on his opinions, we agreed to change the definition as well as the threshold of some states.

Stage 3: *Encoding*. The encoding phase started by conditioning the expert's judgment in order to avoid the possible presence of some cognitive biases. In particular, we focused mainly on the anchoring, which is of particular concern with BNs given the large number of variables being quantified: after the first assessment of the initial quantity of interest, the expert must avoid linking the subsequent assessment with the previous one, as it would result in a biased adjustment. Following this discussion, a probability training was carried out: we reviewed some probability concepts and trained the expert with some specific questions similar to those that we would be asked in the encoding phase, trying for instance to clarify the difference between a frequent event and a very rare event. In addition, the probability scale illustrated in Figure 5 was introduced, that we had established in order to help the expert during this stage of the process. This led to the encoding phase, which was the most important and the longest, i.e. around 1 hour. It was developed by asking questions in several ways, e.g. direct assessment of probabilities but also rephrasing the questions using qualitative bands, to find potential inconsistencies in the answers and also to reduce the influence of the explained biases. We chose these types of questions because we had noticed that the expert was not completely comfortable using the percentiles. For example, we asked the following questions: "What is the probability of a *high* inflow if the state of the rain precipitation is *low*?"; "How frequently does it occur that the head gates of the main dam fail to open?"; "How many days per year is it highly likely to have an inadequate capacity of sluiceway?" During this phase it is important that the questions are very clear: for instance, we had to pay attention to the reference time of each question in order to avoid misunderstanding with interpreting the expert data, for example caused by the difference between the design time of a dam and the real-life time of the dam.

Stage 4: *Verifying.* Finally, a verification of the individual elicited probabilities was developed: the results were satisfactory because the numerical outcomes seemed to coincide appropriately with the true beliefs of the expert. Since we had the availability of just one expert, no aggregation technique was necessary. Due to a limited time available the interview ended without the time to solve the overall BN and to discuss the resulting outcomes, which would have been useful also as an additional verification. In the end the interview lasted approximately two hours.

Figure 5. Probability scale used during the elicitation process.



4.3 Case study results

In conclusion, after updating the probability distributions with data inferred from expert engineering judgment as presented in the previous subsection, the overall BN was solved in order to estimate the failure probabilities, which we remember are intended as failure to perform at least one of the required operations. Figure 6 shows the results, achieved using the software Hugin: the Bayesian inference results in a failure probability $p_F = 0.0135$ for the main dam and $p_F = 0.0133$ for the earthen block dams, both evaluated over the lifetime of the dams, i.e. 100 years. It is evident that adding expert engineering judgments helps in reducing the uncertainties in the network, and gives better estimates for the operation of the dam in comparison with those obtained using only the limited available data and logical inference (El-Awady et al. 2019). These final results about the failure probability are satisfactory as they are close to those expected when considering these kind of systems design components: it provides approximately a failure of 1 in 10000 at any year or equivalent to designing a dam for failure due to the so-called ten thousand years flood.

In addition, a BN is useful because explicates the cause-effect relationship, that is essential for a better understanding of the dam safety. For instance, it is possible to understand the main contributors to the failure of the main dam. Figure 7 shows the conditional probabilities of each node given the main dam has failed. The most influential variables and the associated probabilities are: seepage, i.e. 0.4551 leakage, electromechanical equipment, i.e. 0.2469 fail, sliding stability, i.e. 0.2364 unstable, head gates, i.e. 0.2256 failed to open. On the other hand, overtopping has just a probability of the 0.0795.

Figure 6. The quantified BN of Mountain Chute Dam and GS (note that the numerical values are percentage).

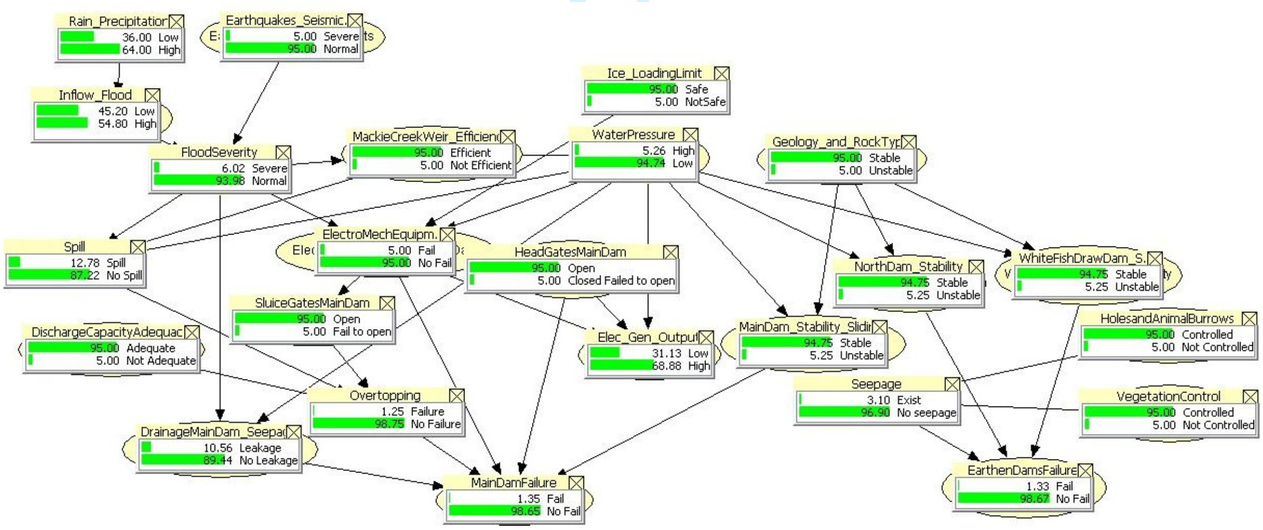
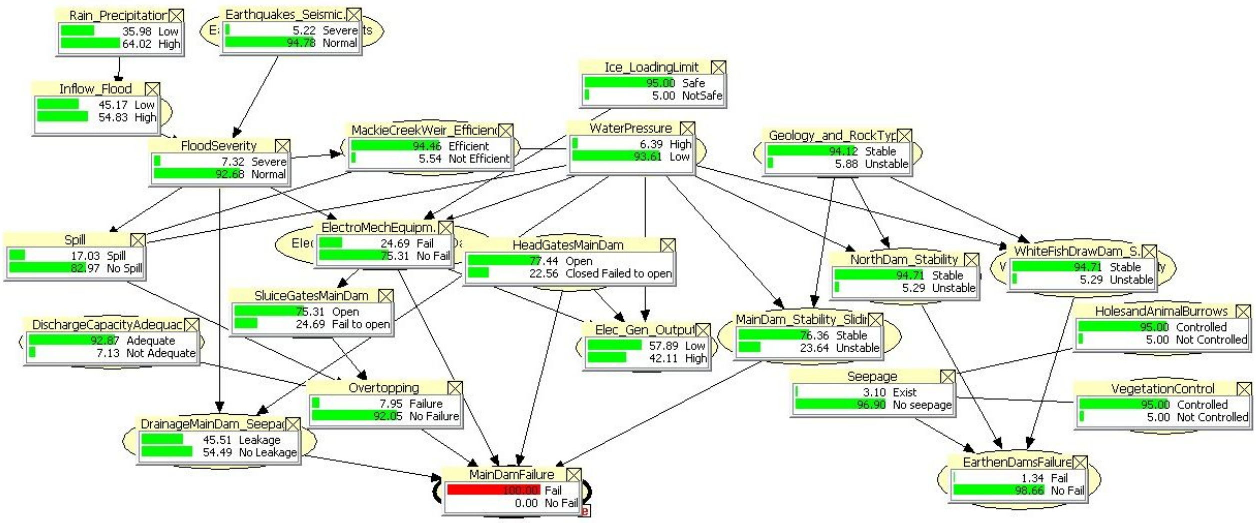


Figure 7. BN of Mountain Chute Dam and GS given the evidence that the main dam fails (note that the numerical values are percentage).



4.4 Evaluation of the process

After discussing the implementation of the planned elicitation process to this specific engineering case study and the consequent results, in this section we propose a critical discussion about the main steps of the process, based on what happened during its application, in order to understand how to improve the process and to give practical guidelines that can be used for similar application in the future.

- The selection of the experts is fundamental and should not be underestimated. In particular, working in a field where experts have narrow areas of expertise rather than generalists requires more experts to be involved in the elicitation to ensure sufficient coverage of the relevant issues. It is worthwhile reflecting on expertise that is desirable for the study or essential. In our case, even if we had the availability of only one expert, we managed to satisfy an essential coverage of expertise in all relevant area. For larger projects, expert profile matrices can be useful at structuring this reflection (European Food Safety Authority 2014; Bolger 2018).

- As regards the number of analysts, the choice of two analysts with different competences seemed appropriate: it is essential to have at least one facilitator with the expertise in the elicitation practice that have to lead all the process, and at least another one with engineering knowledge that have to make his contribution regarding the technical aspects of the specific design project.
- The interview was conducted at the dam site: this choice has proved to be suitable because it allowed us also to understand better some practical aspects of the dam operation. As regards the available time for the interview, we had scheduled a two-hour meeting but in the end we realised that it was not enough to properly complete all the planned elicitation process. During the scheduling phase we had probably underestimated some aspects of the interview that can lead to a delay, so we suggest detailed planning of the interview to identify an appropriate time.
- As concerns the *structuring* phase, we started with a very refined model, which can have some disadvantages, as it was evident that the expert did not propose many changes to the structure and agreed almost completely with our proposal; if the model had been less refined then the expert would have been more empowered to create a different model. Since this phase is fundamental in order to achieve accurate results during the encoding, we recommend involving the experts in the creation of the model and its variables.
- The training phase is fundamental to get accurate and reliable data from the experts. Unfortunately, the time that we spent on training was too little, both because of the limited available time and because the expert did not seem too convinced about the importance of this phase. Consequently, we suggest adding a motivational phase at the beginning of this

stage, i.e. *encoding*, in the same way as in the *structuring* stage, with the aim to explain to the expert why it is necessary its development in order to calibrate him before encoding.

- There is a trade-off between the level of detail in a model and the time required to populate with probabilities. The model structure needs to be flexible and adapt during the *encoding*, as experts may not be comfortable expressing uncertainties on variables and require an elaboration of the node.
- As concerns the *encoding* techniques, the choice to ask the questions with direct assessment of probabilities and rephrasing the question using qualitative bands was made according to the specific features of our expert: it was clear to us for instance that he was not comfortable with the use of the percentiles. A good idea is then to prepare the questions in different ways before the meeting, and to choose which ones to use only during the interview, so as to make the expert as comfortable as possible.
- As regards the *verifying* stage, the limited available time did not let us to carry out it completely. This is a problem that we have already highlighted and should be considered properly during the scheduling phase. In particular, it would have been important to have more time available in order to verify with the expert also the final resolution of the BN, based on the elicited variables.
- Finally, during the implementation of all the stages we have paid close attention to the possible presence of heuristics and biases, by following the appropriate actions suggested in the methodology in order to minimize the risk of biased judgments. The achieved results allow us to confirm the suitability of our four-stage elicitation process.

5. Conclusions

BNs allow for analyzing complex systems like dams in order to develop a safety analysis based on probabilistic estimates of failure. Due to the lack of data, in this paper we proposed a methodology for an elicitation process aimed specifically at quantifying BNs, with the final goal of collecting reliable data from engineering knowledge. The elicitation exercise we carried out for this specific case study regarding the safety of the Mountain Chute Dam and GS, even if developed in a simplified way, demonstrated the potential and the usefulness of the engineering expertise, and allowed us to learn many lessons that are useful for improving the methodology, which we intend to address in future for similar applications. In summary, we can conclude as follows:

- While the elicitation process has been applied in many fields, in civil engineering there is little experience of applying formal elicitation processes to quantify models. This paper demonstrates that engineering knowledge and experience can be very useful to solve appropriately also this type of analysis.
- It is undeniable that the elicitation requires a structured and facilitated process in order to achieve accurate and reliable data, by avoiding the adverse impact of biases. However, there is no perfect elicitation process: it has to be planned according to the particular context and to the specific aims. Consequently, we proposed a detailed methodology for the precise aim to quantify a BN.
- Our four-stage structured elicitation process works properly according to the results achieved in the case study. However, this has been just our first experience in implementing an elicitation process and indeed, during the application, we have noticed some aspects that need to be improved in order to make the process even more successful and reliable.

- As regards to future work, we aim to improve this structured methodology based on what we have learnt from this first application, and to apply it to other civil engineering structures, e.g. bridges.

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The authors would like to thank Ontario Power Generation, especially Tony Bennett and Andy Zielinski, for letting us to work on such an important real-life case study, sharing all the required material and allowing us to develop the interview with one of their engineers, whose availability is greatly acknowledged.

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Tables

Table 1. States of the BN variables.

Variable	States	
Rain precipitation	Low	High
Earthquakes seismic events	Normal	Severe
Ice loading limit	Safe	Not safe
Geology & rock type	Stable	Unstable
Discharge capacity adequacy	Adequate	Not adequate
Head gates main dam	Open	Close/Fail to open
Holes and animal burrows	Controlled	Not controlled
Vegetation control	Controlled	Not controlled
Inflow flood	Low	High
Flood severity	Normal	Severe
Mackie Creek weir efficiency	Efficient	Not efficient
Water pressure	Normal	High
Spill	Yes	No
Electromechanical equipment main dam	Efficient	Not efficient
Sluice gates main dam	Open	Close/Fail to open
Electric generation output	Low	High
Overtopping	Yes	No
Drainage main dam seepage	Leakage	No leakage
Main dam stability sliding	Stable	Unstable
Main dam failure	Fail	No fail
North dam stability	Stable	Unstable
White fish drawn dam stability	Stable	Unstable
Seepage	Exist	Not exist
Earthen dams failure	Fail	No fail

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Figure 2. Flowchart of the proposed elicitation process.

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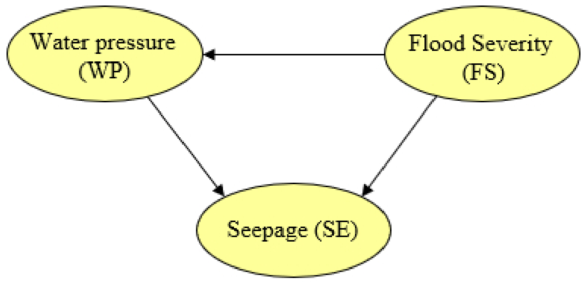
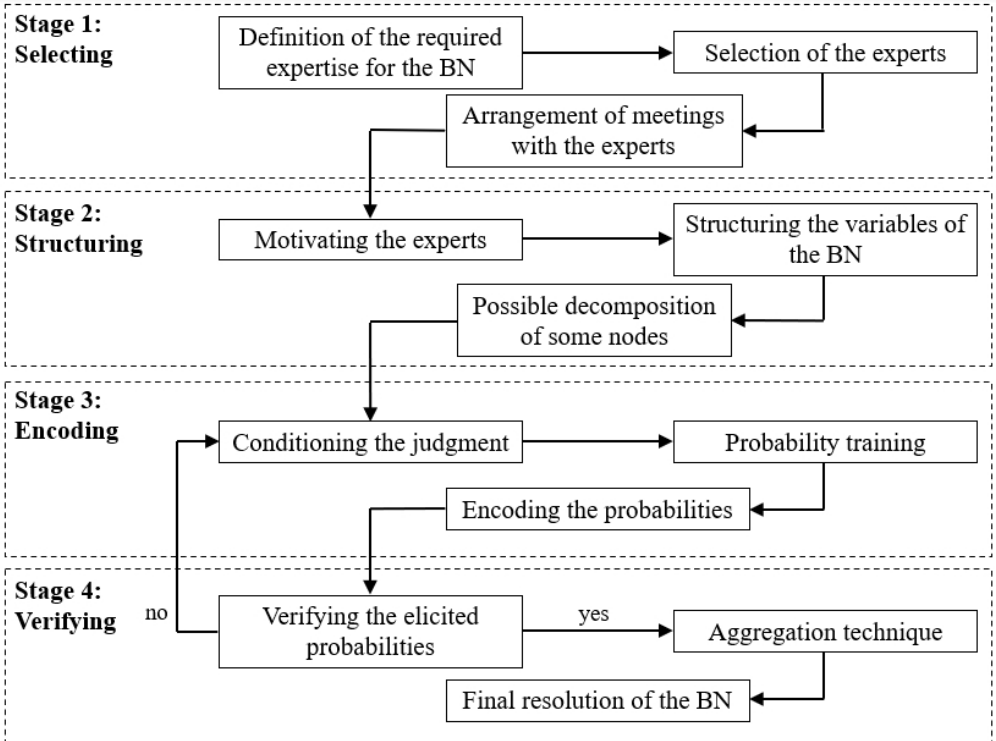
	WP	
FS	Low	High
Low	0.9	0.1
High	0.6	0.4



FS	
Low	High
0.9	0.1

		SE	
WP	FS	Yes	No
Low	Low	0.1	0.9
High	Low	0.5	0.5
Low	High	0.3	0.7
High	High	0.7	0.3

Figure 1. An example of BN with three variables.



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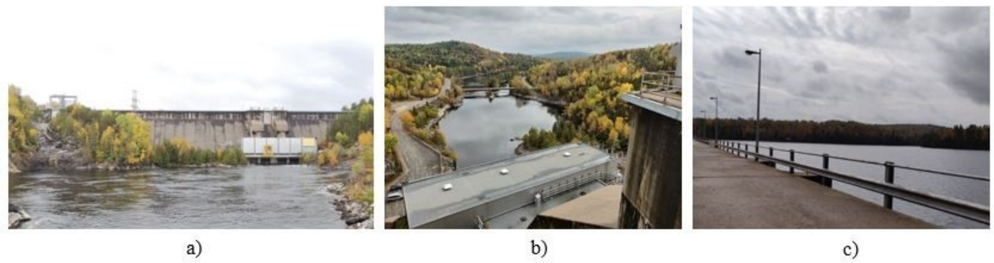

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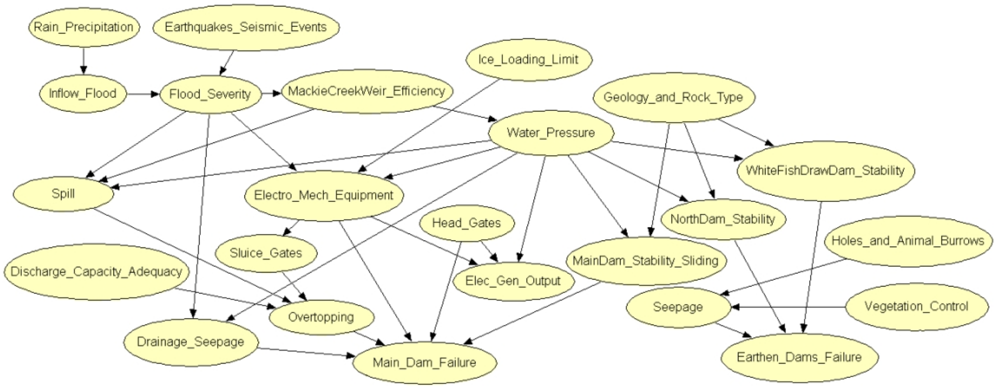

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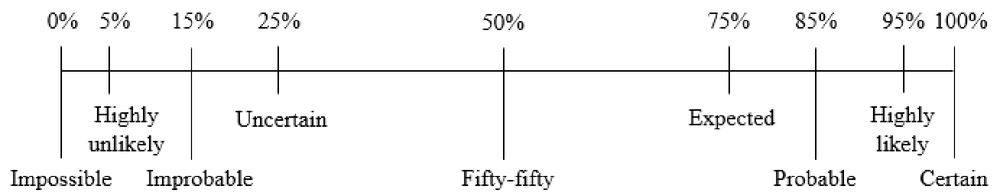

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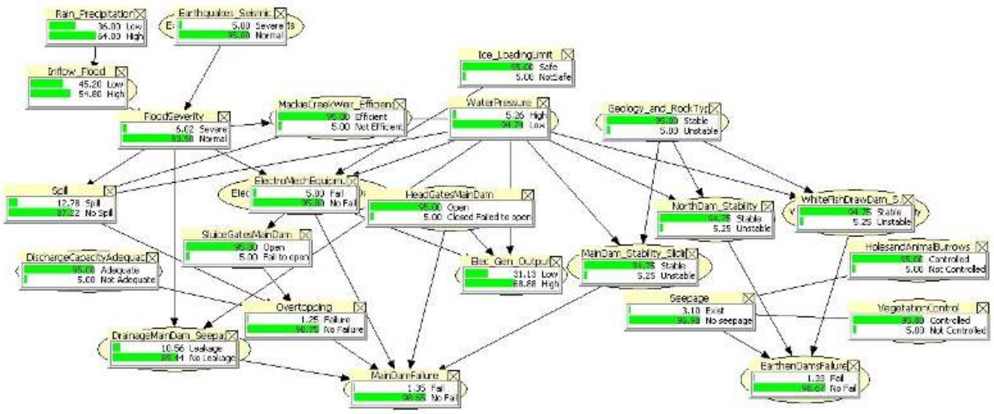

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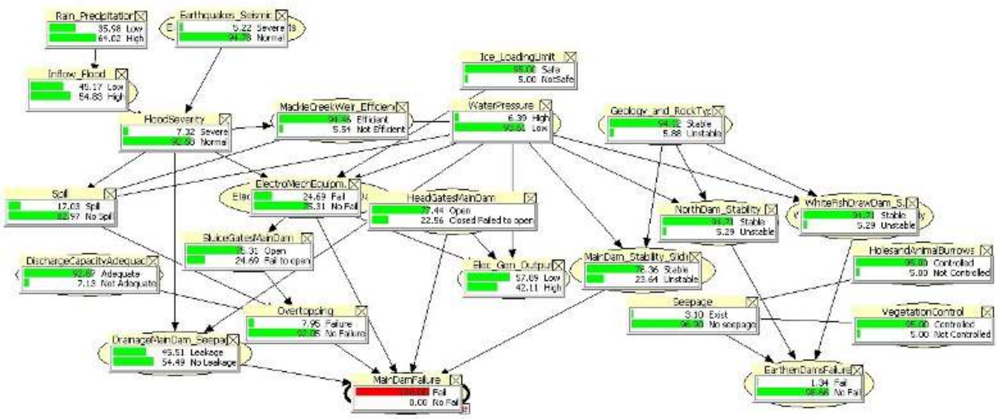
103x43mm (300 x 300 DPI)



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103x43mm (300 x 300 DPI)