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An Introduction to Using Bayesian Networks to Model Dredging Decisions

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PURPOSE: This technical note provides a brief introduction to Bayesian networks and discusses how they might be applied to model dredging decisions. This information has been condensed from a more detailed discussion of probabilistic networks in an Engineer Research and Development Center (ERDC) Technical Report (Schultz et al. 2011). That report also includes a detailed example demonstrating how Bayesian networks could be used to model navigation dredging decisions.

BACKGROUND: A decision is an action that leads to an allocation of resources or an outcome that is irrevocable, or nearly so, because it would be very costly to restore the allocation that existed prior to the action (Howard 1966). The term decision analysis was coined by Howard (1966) to describe a logical procedure for the balancing of the factors that influence a decision when the outcomes are uncertain. In practical applications of decision analysis, the objective is to develop a structural model of the decision that includes specific references to sources of uncertainty and to a decision maker's objectives, alternatives, and preferences. Decision models differ from bio-physical and engineering models, such as hydrologic models or fate and transport models, although they may incorporate such models as components. The nominal purpose of a decision model is to identify an alternative course of action that maximizes the decision maker's expected net benefit and to assess the robustness of an alternative in the face of uncertainty and conflicting value systems. However, there are a number of additional benefits to decision modeling. Decision models also help decision makers to identify the most important drivers in a decision, evaluate controversies among stakeholders, evaluate opportunities to obtain better information before making a decision, and implement adaptive management strategies.

INTRODUCTION: There are many sources of uncertainty in dredging decisions. For example, there may be uncertainty about the conditions at the dredging site, the environmental response to dredging operations, and the economic benefits of project investments. These uncertainties can lead to stakeholder conflicts, lengthy and costly project delays, and costly restrictions on dredging activities, including restrictions on the timing of dredging operations and dredging methods (Reine et al. 1998). Decision models can help improve the quality of dredging decisions by analyzing sources of uncertainty that may influence the outcome of a decision to estimate the probability of potential economic and environmental outcomes. This risk-informed decision-making approach is consistent with U.S. Army Corps of Engineers (USACE) planning guidelines.

Bayesian networks provide a practical and broadly applicable means of implementing risk-informed decision making. Examples of dredging decision problems that might be modeled using Bayesian networks include:

- Should a navigation channel be authorized or constructed (or deepened)?
- Which potential location is the best location for the navigation channel?
- Should a more detailed environmental assessment be completed?
- Should the navigation channel be dredged to authorized depth and, if not, how deep should the navigation channel be dredged?
- What type of dredging equipment should be used? Which type is most cost-effective?
- What is the optimal timing of dredging operations (environmental windows)?
- What operating limits should be placed on dredgers (e.g., operating speed, bucket size, etc.)?
- What dredged material disposal alternative maximizes net benefits of a dredging project?
- How frequently should a navigation channel be scheduled for maintenance dredging?
- Which sediment disposal alternative should be selected?

In addition to providing an efficient way to analyze many sources of uncertainty in a decision model, there are a number of other advantages to using Bayesian networks for decision modeling:

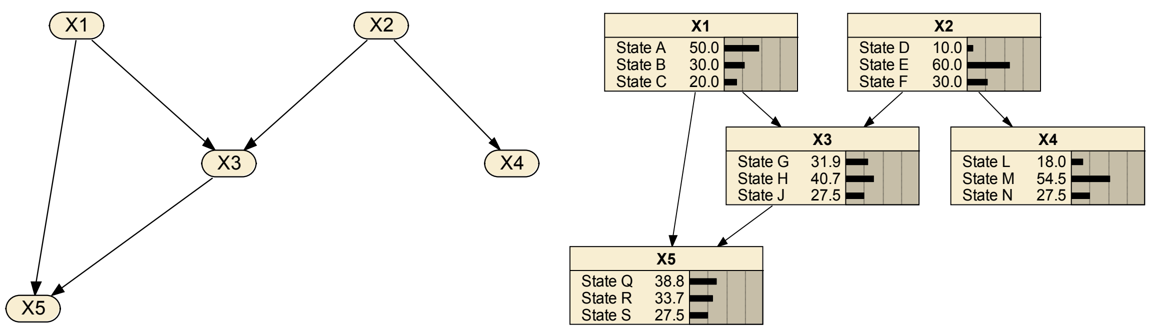
- Bayesian networks enable the developer to integrate the results of multiple bio-physical and engineering models that address different parts of a system to create a comprehensive systems-level model. These models may be considered incompatible because of issues related to, for example, spatial and temporal scale or data transfer.
- Bayesian networks permit information to be expressed in both qualitative and quantitative terms while preserving mathematical rigor in the analysis of uncertainty.
- Bayesian networks permit the integration of objective and subjective (expert) knowledge and the representation of uncertainty in subjective knowledge.
- The graphical structure of Bayesian networks is ideal for communicating information about how uncertain variables may be influencing the decision problem with stakeholders and incorporating information about stakeholder concerns into the decision-making process.
- Bayesian networks provide a platform for adaptive management, a process by which recurring decisions are updated after new information has been collected.
- Bayesian networks provide a platform for value of information analysis to assess the benefits of reducing uncertainty, prioritizing data collection needs, and estimating how much should be invested in collecting additional data.
- Bayesian networks can be used for statistical inference (probabilistic reasoning about the system).

Bayesian networks have been used to analyze a broad cross-section of environmental management problems and decisions. The literature on Bayesian network applications includes efforts to diagnose causes of ecological problems and to predict the outcomes of environmental management decisions. Table 1 lists 27 examples of Bayesian networks applied to environmental inference and decision problems. For each entry, the table notes the substantive issue that was addressed in each study.

Table 1. Bayesian network applications from the literature.

Author(s)	Year	Substantive issue addressed in the study
Adriaenssens et al.	2004	Predict the presence and abundance of macro-invertebrate taxa (Gammaridae and Asellidae) in European rivers.
Ames et al.	2005	Evaluate watershed management alternatives by estimating the probability of meeting water quality criteria in the East Canyon watershed of Utah.
Amstrup et al.	2008	Assess the probability of polar bear (*Ursus maritimus*) extinction in out years given projections in habitat conditions under climate change scenarios.
Bacon et al.	2002	Identify factors that might lead to a change in land use from farming to forestry in marginal upland areas of the United Kingdom.
Barton et al.	2008	Evaluate eutrophication mitigation costs relative to benefits in the Morsa river watershed of Southeastern Norway.
Bromley et al.	2005	Select demand-side water management strategies.
Burgman et al.	2010	Assess the probability of locating and successfully eradicating red imported fire ants (*Solenopsis invicta*) in southern Queensland, Australia.
Gibbs	2007	Evaluate the risks posed by aquaculture development to shorebird populations in New Zealand.
Kragt et al.	2009	Evaluate watershed management alternatives in the George watershed on the northeast coast of Tasmania.
Kuikka et al.	1999	Determine the best mesh size for use in the Baltic cod (*Gadus morhua*) fishery.
Lee et al.	1997	Assess the risks of land use decisions to salmonid populations in the Pacific Northwest.
Marcot	2006a	Predict the presence of a species in a plot of land area (Marcot et al. 2006a).
Marcot	2006b	Decide whether to conduct surveys on the ground to determine the presence of a particular sensitive species at a location (Marcot et al. 2006b).
McNay et al.	2006	Classify habitat suitability and evaluate the efficacy of woodland caribou (*Rangifer tarandus*) habitat management alternatives.
Newman et al.	2007	Identify the most likely causes of liver lesions in fish populations of Puget Sound, Washington.
Nyberg et al.	2006	Assess the suitability of forest stands to provide woodland caribou (*Rangifer tarandus*) winter forage employing active adaptive management.
Petersen et al.	2008	Evaluate tradeoffs in the decision to remove barriers to westslope cutthroat trout (*Oncorhynchus clarki lewisi*) migration in mountain streams.
Pike	2004	Assess the probability of drinking water treatment plant violations using information about conditions inside and outside the plant.
Pollino et al.	2007a	Identify the causes leading to dieback of an endangered plant species (*Eucalypt camphora*).
Pollino et al.	2007b	Evaluate the impact of changes in hydraulic and structural habitat on future fish abundance and diversity in the Goulburn River, Victoria, Australia.
Sadoddin et al.	2005	Evaluate the influence of dryland salinity management alternatives in the Goulburn watershed, Australia.
Shepard et al.	1997	Assess the causes behind westslope cutthroat trout population declines in western Montana.
Smith et al.	2007	Assess the suitability of habitat for the Julia Creek dunnart (*Sminthopsis douglasi*), an endangered marsupial.
Stewart-Koster et al.	2010	Identify the best strategies for managing dissolved oxygen in streams.
Stewart-Koster et al.	2010	Identify the best strategies for managing invasive aquatic nuisance macrophytes in streams.
Ticehurst et al.	2007	Assess the sustainability of social, economic, and environmental values in coastal lake catchments in New South Wales, Australia.
Ticehurst et al.	2008	Evaluate management alternatives for Merimbula Lake in New South Wales considering economic, social, and environmental factors.

BAYESIAN NETWORKS: Bayesian networks provide an efficient way to address a large number of uncertainties in the decision-making process. A Bayesian network consists of a graphical structure and probability tables (Pearl 1988). A graph is a set of nodes that represent random variables in a system and directed edges (arrows) between nodes that indicate causal influence among random variables in that system (Figure 1(a)). Formally, the graph is a directed acyclic graph (DAG) because influence flows through the network in the direction of the edges, from parent nodes to child nodes, and child nodes exert no causal influence on the parent nodes. For example, in Figure 1(a), node X1 is a parent of nodes X3 and X5. Nodes X3 and X5 are called child nodes in relation to node X1. The directed edge between a parent node and a child node means that knowledge about the state of the parent node will influence the modeler's degree of belief about the state of the child node.



(a) (b)

Figure 1. A graphical model consisting of five nodes and five directed edges (a) and a fully parameterized Bayesian network that corresponds to the graphical model (b).

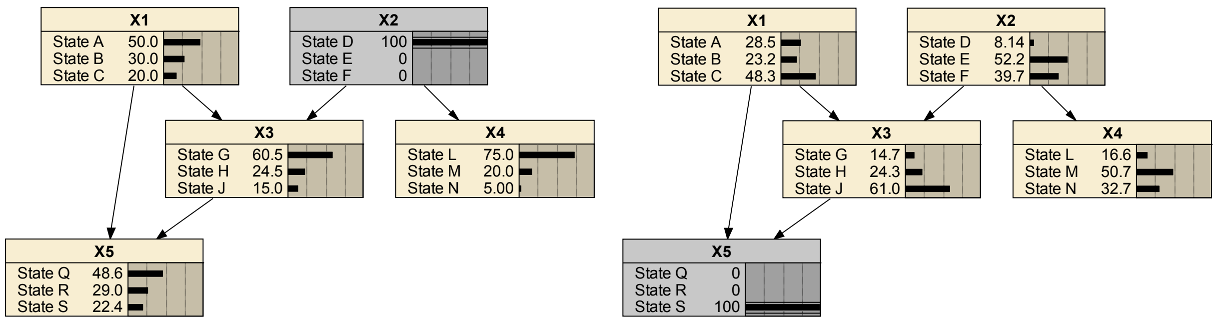
In a fully parameterized network, all of the possible states of each node must be defined. Bayesian networks are generally constructed assuming that all random variables are discrete. Each node in a Bayesian network may take two or more possible states that represent a mutually exclusive and collectively exhaustive set of possible states for that node. Parentless nodes are defined by a marginal probability table that describes the probability of that node being in each possible state. Child nodes are defined by a conditional probability table that describes the probability the child is in each of its possible states given each of the possible states of each parent node. In Figure 1(b), which shows a fully parameterized Bayesian network, each node may take three possible states. Nodes X1 and X2 have no parents, so are parameterized using marginal probability tables. Nodes X3, X4, and X5 are parameterized using conditional probability tables. The probabilities in a network can be based on expert judgment, bio-physical and engineering model simulation outputs, or data from either the system of interest or similar systems. The "belief bars" in Figure 1(b) show the probability that each node is in each possible state. For example, node X1 has a 50-percent chance of being in state A, a 30-percent chance of being in state B, and a 20-percent chance of being in state C. Node X3 has a 31.9-percent chance of being in state G, a 40.7-percent chance of being in state H, and a 27.5-percent chance of being in state J given the probabilities for its parent nodes (X1 and X2).

There are basically two types of dependence relationships in a DAG: *Direct dependence* and *conditional independence*. A node (the child) is directly dependent upon another node (the parent) if there is a directed edge linking the parent directly to the child. The probability distribution of a child node may be determined by knowing only the states of its parent nodes. A node is conditionally independent of another node if, given information about all mediating nodes, it is unaffected by knowledge of the other node. While representation of dependence and independence relationships is a useful feature for communication, the greater value in Bayesian networks is in their ability to perform statistical inference. The computational demands of inference about a joint probability distribution can be extremely high. These demands are directly related to the number of random variables and states in a network as well as the overall structure of the network (in other words, how the nodes are connected to one another) (Koller and Friedman 2009). It is only relatively recently, within the past 25 years, that algorithms have been developed to solve these problems efficiently.

Statistical inference. Statistical inference is probabilistic reasoning about the modeled system. Statistical inference can be classified as either predictive (causal) or diagnostic (evidential) (Kjaerulff and Madsen 2008, Koller and Friedman 2009). In predictive applications, the objective is to reason from cause to effect and so assess the probability of a particular outcome given knowledge about the state of ancestral nodes. The ability to solve predictive inference problems is particularly useful when dealing with complex systems about which understanding of causal effects is limited or direct observations of system states are difficult. In such cases, the state of the system must be inferred from uncertain information about site conditions. Diagnostic inference is reasoning from effects to causes and the objective is to predict the probability that an ancestor node is in a particular state given evidence about the descendent node. When there are multiple possible causes for an effect, this form of reasoning can be used to predict the probabilities of potential causes, a process known as *explaining away*. The ability to explain away the causes of an effect is unique to Bayesian networks and is made possible by the presence of converging connections (Kjaerulff and Madsen 2008).

Inference is accomplished by applying information to the model in the form of *hard evidence* or *soft evidence* and updating probabilities in the network to obtain posterior probabilities using Bayes rule. The posterior probability is simply the probability that one node in the network is in a particular state given evidence about one or more other nodes in the network. Hard evidence is knowledge that a particular variable is in a particular state and that the probability of being in all of the other possible states is zero. Entering hard evidence is called *instantiation*. *Soft evidence* is uncertain knowledge about a variable. If soft evidence is available about a variable, the probabilities that are coded in that variable node can be updated by entering a finding in the form of a probability distribution. Once a finding has been entered in a network, all probabilities in the network are updated using Bayes rule. The ability to perform mathematically exact calculations of the probabilities efficiently is one of the primary advantages of Bayesian networks.

Figure 2(a) demonstrates predictive inference by instantiation of node X2. Node X2 is instantiated with hard evidence to indicate perfect information that this random variable is in state D. Instantiation affects the degree of belief about the state of nodes X3, X4, and X5. For example, the prior probability that node X4 is in state L is 18 percent (see Figure 1(b)). The model uses the information that node X2 is in state D to update the probability that node X4 is in state L from 18 percent to 75 percent. With the exception of probabilities in node X1, all other probabilities in the network have also been updated. Figure 2(b) demonstrates diagnostic inference. Perfect knowledge about the state of node X5 enables users to update beliefs about the state of other nodes in the network. For example, Figure 2(b) shows that if node X5 is in state S, the probability that node X1 is in state C increases from 20 percent to 48.3 percent and the probability that node X3 is in state J increases from 27.5 percent to 61 percent.



(a) (b)

Figure 2. Instantiation of node X2 for predictive inference (a) and instantiation of node X5 for diagnostic inference (b).

CONSTRUCTION OF BAYESIAN NETWORKS: Bayesian networks are constructed by structuring the network and populating marginal or conditional probability tables. There are two approaches to constructing Bayesian networks, although many applications integrate the two (Darwiche 2009). The first, which is largely subjective, is called *knowledge representation*. Using this approach, the modeler uses his knowledge about cause and effect within the system or the knowledge of others to structure the graphical model and assess the probabilities. Alternatively, the modeler can synthesize some other type of formal knowledge, such as blueprints, flow charts, or diagrams. The second approach to constructing Bayesian networks is called *machine learning* or *learning from data*. In this approach, an artificial neural network is derived from data. Both the structure of a network and the probability tables can be learned from data using one of several available algorithms. It is very common for networks to be structured using a knowledge representation approach and then to obtain conditional probability tables from data or model outputs.

Best Practices for Constructing Bayesian Network Models. Network structures should be developed using a causal reasoning approach in which parent nodes represent causes and child nodes represent effects (Koller and Friedman 2009). Like all models, Bayesian networks are simplifications of real systems. The simplest possible network structure should be used (Barton et al. 2008). In an effort to keep network structures as simple as possible, Koller and Friedman (2009) suggest including only those nodes that can be observed or that the modeler may want to query. However, each node should have at least two parents or at least two children. Exceptions to this rule exist, as in the case of a mediating variable designed to transform one node for inference about a downstream node. The number of dependencies represented in the network should be minimized by eliminating edges between nodes if the effect of one node on another is thought to be small (Marcot et al. 2006c). Marcot et al. (2006c) also recommend limiting the number of parent nodes to three to minimize the complexity of conditional probability tables. Large numbers of parents (more than three or four) can cause conditional probability tables to become very complex, particularly if there are a large number of node states. The number of undirected loops in the DAG should be minimized to reduce computational requirements. An undirected loop (not a directed cycle) occurs when there is a pathway leading from a parent through a child and back to the parent via an alternate route (which may go against the direction of the edges).

Best practices should also be considered with respect to the discretization of variable nodes. It is a requirement of the method that the set of possible states for each node are mutually exclusive and collectively exhaustive. Mutual exclusivity means that if the state of a random variable is known precisely, there would be no ambiguity in assigning it to one of the possible states defined for that variable. This should not be a problem if nodes are "well-specified," meaning that the quantities represented by a node pass a clarity test: "Could a clairvoyant say unambiguously whether the event will or had occurred, or could he give the exact numerical value of the quantity?" (Morgan and Henrion 1990, Howard and Matheson 1984). A collectively exhaustive set of possible states simply means that, for any state of the random variable that might be observed in nature, there is a node state that corresponds to that state in the model. The level of resolution in each node is important because too few states can lead to errors in inference and too many states can lead to high levels of computational effort and complex conditional probability tables. It is best to choose variable states that are meaningful in terms of the problem under consideration. For example, Marcot et al. (2006c) suggest that, when modeling ecological systems, the modeler include only ecologically significant states.

INFLUENCE DIAGRAMS: Bayesian networks have been adapted for decision modeling. While a Bayesian network is designed for reasoning under uncertainty, an influence diagram is designed for reasoning about decision making under uncertainty (Kjaerulff and Madsen 2008). In addition to the customary chance nodes of a Bayesian network, an influence diagram includes a decision node that identifies the decision alternatives under consideration and a utility or value node that describes the outcomes, which are expressed as some mathematical function of value node parents. Figure 3 is an influence diagram consisting of five chance nodes, one decision node, and one utility node. Decision nodes and utility nodes in influence diagrams are fundamentally different from chance nodes that represent random variables. Chance nodes are defined by marginal or conditional probability tables, while decision nodes are defined by a list of alternatives, and value nodes are defined by a table of outcome values conditional on the state of its parents. It is possible to include multiple decision nodes and multiple utility nodes in an influence diagram. Influence diagrams differ from Bayesian networks in one other respect. When constructing influence diagrams, the links among nodes *must* represent both causality and probabilistic dependence (Kjaerulff and Madsen 2008, p. 24).

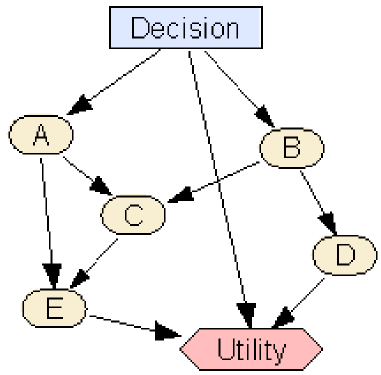


Figure 3. An influence diagram consisting of five chance nodes, one decision node, and one utility node.

CONCLUSION: There are many advantages to using Bayesian networks. Project conditions that might motivate the use of Bayesian networks as a decision modeling approach include the need for a coherent and mathematically sound handling of uncertainty, an intuitive and compact representation of cause-and-effect relationships, a representation of dependence and conditional independence relationships, and diagnostic statistical inference (Kjaerulff and Madsen 2008). Other project conditions that might motivate the use of Bayesian networks include:

- The decision problem transcends multiple disciplines and information or models originating from multiple disciplines must be integrated into one common representation of a system.
- The system being represented is complex, and multiple models that are functionally incompatible must be integrated to represent the system.
- Objective and subjective knowledge must be integrated, or expert knowledge is being incorporated into the decision-making process.
- One has data about conditions within a system, but the level of understanding is insufficient to explain the relationships among the observable quantities in the system.
- A recurring decision will be updated as new information emerges (adaptive management).

It is also important to recognize when Bayesian networks might not be the best approach to solving a problem. Bayesian networks should not be used when processes can be fully explained mechanistically using first order principles or as a substitute for mechanistic models, the variables and events of the problem domain cannot be well-defined, or when there is no uncertainty. None of these conditions seem to apply to most navigation dredging decision problems.

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