Bayesian Network-Based Decision Support for Pest Management

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INTRODUCTION

Bayesian Network, a key computer technology dealing with probabilities in Artificial Intelligence is one of the most effective and popular methods of modeling uncertain knowledge expression and reasoning such as environmental management (Bi & Chen, 2011; Uusitalo, 2007). BNs emerged from artificial intelligence research wherein originally, they emerged as formal modes to analyze decision approaches under uncertain conditions (Varis, 1997). New computational methods and techniques keep increasing BN's abilities and range of practical applications (Mead, Paxton & Sojda, 2006).

In contrast to the other approaches or techniques used in environment studies, Bayesian networks use probabilistic expressions rather than deterministic to express the relationships among variables of the system. Bayesian network accounts the lack of knowledge in the network by the usage of Bayesian probability theory which allows the subjective estimation of the probability of occurrence of a particular outcome that is to be combined with more objective data quantifying the frequency of occurrence in finding the conditional probabilistic relationships. Bayesian networks are very appropriate technique to deal with systems where uncertainty is inherently accounted in model as this is an important issue in ecological systems, Pollino & Henderson (2010).

BNs can integrate missing data readily by using Bayes' theorem. They can easily be understood without much mathematical background and knowledge. They have been found to possess good accuracy of prediction with small sample size. BNs can also be applied for predicting the probable values of states of a system for different future scenarios. Bayesian networks are also useful for participatory processes. They can assist in evaluating the alternative decisions to optimize a desired outcome. BNs can also help in processes of social learning. BNs express the system as network of reciprocal actions among system variables from main cause to final outcome; subject to all cause-effect assumptions are clearly made (Pollino & Henderson, 2010). Reasoning approaches are very useful in dealing with uncertain information (Heping & Daniel, 1998).

A Bayesian Network is a combination (G; P) (Jensen & Nielsen, 2007; Kjrulff & Madsen, 2008) where

- G = (V; E) is a DAG where set of nodes V = {X1, X2…Xn} represents the variables of the system and E, a set of arcs represents direct conditional dependencies between the variables(nodes);
- P represents the set of conditional probability distributions comparing conditional probability distribution P (Xi/pa (Xi)) for each variable X given the set of parent's pa (Xi) in the graph.

The joint probability distribution over V can be recovered from the set P of conditional probability distributions by the application of following chain rule:

DOI: 10.4018/978-1-7998-9220-5.ch080

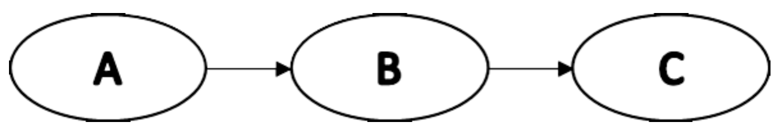
$P(X1, X2 \ldots Xn) = \prod P(Xi/pa(Xi))$ (Singh & Gupta, 2017b)

Conditional probabilities of a BNs can be computed based on the experimental or trial data, results produced by the models and domain expert's knowledge elicitation (Borsuk et al., 2006). Uncertainty is clearly represented by way of presentation of the probabilities (Bromley et al., 2005).

Bayesian Network Theory

BNs are probabilistic graphical model consisting of variables of interest of a system and their conditional relationships (del Águila & del Sagrado, 2012). A BN consists of 'nodes' that represent the set of variables of interest and 'links' represent conditional interdependencies (cause-effect relationship) among nodes via a directed acyclic graph (DAG) (Pearl, 1988). Conditional probability distribution captures the quantum of dependence between system variables and thus explains the relationships between the nodes. For instance, if node A of a system affects another node B, then nodes A and B are linked to each other by an arc having direction from node A to node B. Herein node A is called as parent of node B and node B is referred as child of node A. If node B further affects another node C, then node B be the parent of node C. Figure 1 shows the conditional or causal relationship among nodes A, B and C of a basic Bayesian network.

Figure 1. Conditional or causal relationship among BN nodes
(Source: Landscape logic portal)



A BN can comprise different kinds of nodes i.e., nature nodes, decision nodes, and utility nodes. Nature nodes are the variables which can be controlled by actions of decision maker and represent the empirical or calculated parameters and the probabilities of occurrence of various states. Input nodes are the nodes without parents and can be expressed in as either constant or categorical states with associated marginal probability distributions. The variables or events which can be directly implemented by the decision makers are represented by a decision node. Decision node represents two or more alternative decision options that a manager can choose from. A decision node does not have probabilities associated with it. Decision nodes should always be accompanied by utility nodes (Singh & Gupta, 2017b). A utility node represents the value of an outcome or a decision. Utility node can be directly linked to the decision node (Kragt, 2009). BNs representing and solving decision problems under uncertainty are also known as Bayesian decision networks (Singh & Gupta, 2017a).

Bayesian network uses Bayes' probability theorem to propagate information/evidence among the nodes. Bayes' theorem defines how observed evidence updates the prior information/knowledge about a hypothesis. In Bayes' theorem, prior probability represents the possibility of an input parameter being in a specific state whereas conditional probability estimates the possibility of a parameter state given the states of input parameters affecting it. Estimate of likelihood of a parameter to be in particular state is the posterior probability, given the input parameters, conditional probabilities and the rules controlling how the probabilities combine. The network is solved using Bayes' Rule: