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Consequence-based framework for electric power providers using Bayesian belief network

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ABSTRACT

Novel consequence-based framework for electric power providers is proposed. This framework includes six performance objectives, such as reputation, health and safety, environmental, financial, reliability, and system conditions. The six performance objectives are quantified with the consideration of 41 key performance indicators (KPIs). The framework is illustrated with a case study of 10 Canadian power utilities. Furthermore, a sensitivity analysis is undertaken to identify importance of the KPIs on the decision framework.

Introduction

An electrical power transmission system consists of power generating stations, substations, and supervisory control and data acquisition (SCADA) facilities, where all sub-systems (components) are inter-connected through transmission lines. To ensure safe, economical, and reliable delivery of electricity, comprehensive transmission planning is required [1,2]. However, this is not an easy task due to the consistent exposure of today's society to low probability high consequence (LPHC) events, such as earthquakes, floods and terrorist attacks. In response to such events, risk assessment has been used as one of the main decision-making tools in the electrical power industry [3–6].

Risk assessment of power systems, however, requires consideration of technical, organizational, and human factors in order to achieve a complete representation of the system. Different modeling techniques have been developed for managing such complex systems and interaction between several variables. These techniques include fault trees, Petri nets, Markov chains, and Bayesian belief networks (BBNs). One of the major advantages of BBN is the ability to model dependencies between variables, manage non-linear interaction, such us low probability (and high consequence) events, and integrate different kind of information about the system such as expert knowledge, measurement data, feedback experience and information regarding the system behavior. For these reasons, many applications of risk analysis for complex systems using BBN is reported [4–9].

BBN have also been extensively used in different area of electrical power systems such as reliability [10–14], fault diagnosis of the system [15–17], cascading effects [18], and risk assessment [19–23]. Despite the maturity of this field within electrical power systems, these applications are focused on a technical analysis of the system, leaving aside the human and social factors which play an important role in maintenance and operation. In order to address this, the proposed approach presents a novel consequence-based framework, which includes different objectives of a electrical power system, such as people-related, service-related, environmental and economic. The proposed framework encompasses three steps: (1) establish performance matrices and transformation functions, (2) generate relative importance weights and (3) perform consequence-based analysis.

The remaining sections are organized as follows. In section 'Introduction', a literature review introduces previous work on Bayesian belief networks theory and applications. In section 'Bayesian belief networks and applications', a consequence-based framework is developed, consisting of a brief introduction of the methodology (including identification of key performance indicators) and the main steps for building the Bayesian belief network (including performance matrices generation, and the weight and network generation). In section 'Consequence-based framework', a sensitivity analysis of the belief network is used to conduct a consequence-based analysis. In section 'Sensitivity analysis', the framework is applied to a case study of consequence-based

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assessment for Canadian provinces. Finally, conclusions and recommendations are presented.

Bayesian belief networks and applications

BBN also known as Bayesian Net, Causal Probabilistic Network, Bayesian network or simply belief network, is a graphical model that permits a probabilistic relationship among a set of variables [24]. A BBN is a Directed Acyclic Graph, where the nodes represent variables of interest and the links between them indicate informational or causal dependencies among the variables. The uncertainties in a BBN model are described through subjective probability [24]. As depicted in Fig. 1 [25], a BBN is composed of:

(a) a set of variables (e.g. A_1, A_2 and B_3) and a set of directed links between the variables;
(b) a set of mutually exclusive states for each variable (e.g. for A_1, A_2 and B_3 the states are {L, M, H}); and,
(c) an assigned conditional probability for each variable with "parents", which will be defined shortly (e.g. for B_3).

The relations between the variables in a BBN are expressed in terms of family relationships, where a variable A_1 is said to be the parent of B_3 and B_3 the child of A_1 if the link goes from A_1 to B_3 (Fig. 1). The dependencies are quantified by conditional probabilities for each node given its parents in the network. These dependencies are quantified through a set of conditional probability tables (CPTs); each variable is assigned a CPT of the variable given its parents (Fig. 1). In the case of a variable with no parents, the probabilities are reduces to the unconditional probability (UP) (e.g. A_1 and A_2, Fig. 1).

The main concept of a BBN is rooted in the use of Bayes theorem, in which the relation between two nodes, hypothesis H (parent) and evidence E (child) is represented as:

$$p(H \mid E) = \frac{p(E \mid H) \times p(H)}{p(E)} \tag{1}$$

where $p(H \mid E)$ is one's belief for hypothesis H upon observing evidence E, $p(E \mid H)$ is the likelihood that E is observed if H is true, $p(H)$ is the probability that the hypothesis holds true, and $p(E)$ is the probability that the evidence takes place. $p(H \mid E)$ is known as *posterior* probability and $p(H)$ is called *prior* probability [24].

Fundamentally, a BBN is used to update probabilities as new information is obtained. The network supports the computation of the probabilities of any subset of variables given evidence about any other subset. The efficacy of a BBN is realized in its flexibility to capture top-down inference, observing the cause (or parent) and inferring the possible effect (or child) and bottom-up inference, observing the effect (child) and inferring the possible cause (parent).

Assigning unconditional probabilities

The unconditional probabilities (UPs) of the basic input parameters, often, are not known *a priori*, consequently, equal weights ($1/n$, where n is number of category considered for each basic input) can be assigned using the principle of insufficient reasoning (see for example [26]). For example, if the states for A_1 are categorized as *Low* (L), *Medium* (M), and *High* (H), the UPs will be $P(A_1 = L) = 1/3, P(A_1 = M) = 1/3$, and $P(A_1 = H) = 1/3$. However, from the evaluation, with certainty, if the state of A_1 is determined to be H, the UPs will be $P(A_1 = L) = 0, P(A_1 = M) = 0$, and $P(A_1 = H) = 1$. Indeed, if there is still uncertainty with the state of A_1, the appropriate values should be used. In a case where for example, 25 basic input parameters are involved (parameters without any parents), and, if states of all input parameters are not known, the $1/n$ probability assignment will be useful.

Assigning conditional probabilities

The conditional probabilities shown Fig. 1 that will be used in Eq. (1) can be obtained through expert knowledge elicitation [27,28], or training from data [29]. Where multiple experts are considered, credibility of each decision maker on the decision can be elicited by considering experience and confidence on the assessment [30,31].

The elicitation of knowledge is a process used to determine probabilities of certain events that allow the elicitor to draw conclusions about the system. A group of experts should be establish

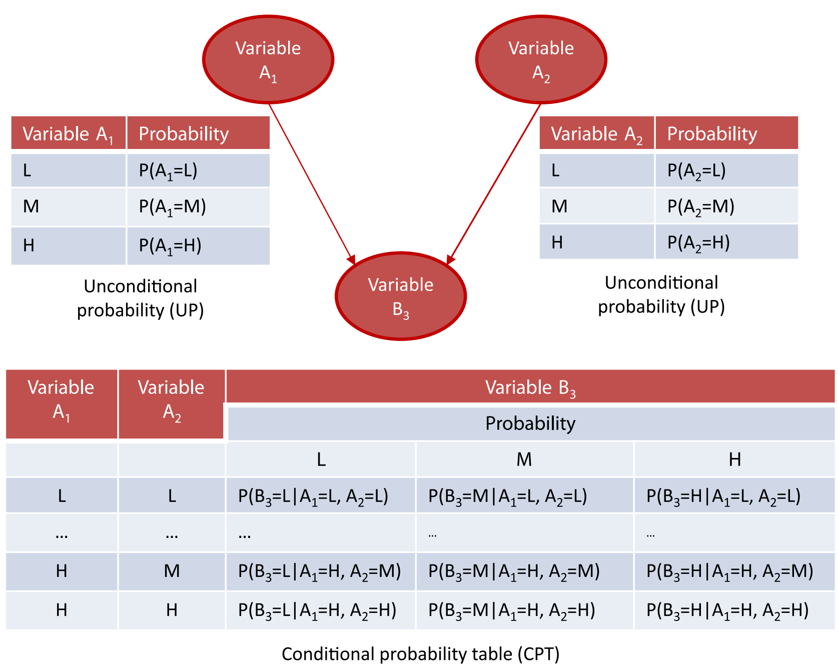

Fig. 1. Schematic of a Bayesian belief network.