BAYESIAN NETWORK APPLICATIONS IN POWER SYSTEMS ENGINEERING. A REVIEW

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Abstract - This paper is areview of last10years research papersrelatedto the Bayesiannetworks (BN)application in power systems engineering (PSE). The various uses of BN in the PSE have been classified according to: forecasting, reliability, stability, defects, steady stateestimation, other. The paper is structured in three parts followed by conclusions. The first part introduces the purpose of the paper, the second part presents the concept of BN, the third part deals with application of BN in the PSE, the paper finalizing with the conclusions.

Keywords: Bayesian networks (BN), power systems engineering(PSE), forecasting, reliability, stability, defects, steady-state estimation.

1. INTRODUCTION

The solution of the various problems that have arisen within the PSE has been achieved over the years through mathematical modelling. Nowadays they are solved with statistics and Artificial Intelligence (AI) techniques. Asstatistical methods, we mention Multiple Linear Regression (MLR), Stochastic Time Series (STS), Spectral Decay (DS), Kalman Filters (FK), Exponential Smoothing (ES). Methods based on Artificial Intelligence techniques areGenetic Algorithms (AG), Swarm Intelligence, Expert Systems (ES), Artificial Neural Networks (ANN), Fuzzy Logic and Hybrid Systems. Each of the above-mentioned methods has advantages anddisadvantages, which has led to various results.

The aim of this paper isto synthesize the tendencies on the last decade of research in the field of BN application in the PSE. The portfolio of scientific papers underlying this research includes a total of 70 articles. Figure 1 shows the distribution of thepapersaccording to the field of interest.

Sources of articles were both journals and conference proceedings (last ten years).

Figure 2 contains research sources classified by type.

Next, the article has a section presenting the BN, followed by a section dealing with the various uses of BN in solving various applications in PSE. The conclusions are what finalize this paper.

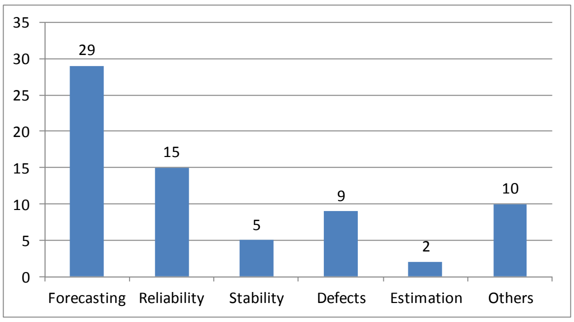

Fig. 1 - Classification of articles in the scientific research portfolio

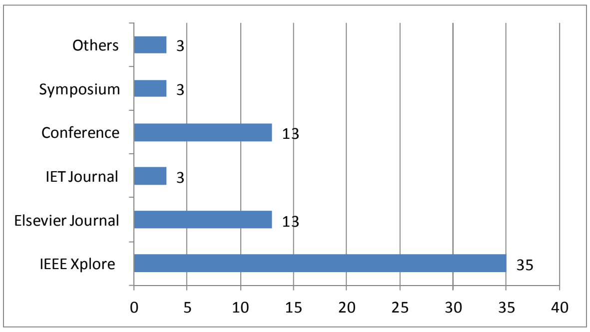

Fig. 2 – Sources type

2. BAYESIAN NETWORKS – BN

Probabilistic models are based on DAGs - direct acyclic graphs with a rich and long tradition based on genetic research. Sewall Wright has been the pioneer of genetic research since the 1920s. In the statistics, such models are known as direct graphic designs and within the AI domain models like this are known as BNs. The name comes from mathematician Thomas Bayes (1702-1761). His foundation of the approach represents the rule for updating probabilities in view of the new evidence.

BN development in the late 1970s was motivated by the need to model the combination of evidence readings from top-down (semantic) and bottom-up (perceptual). The capability of bi-directional inference, combined with rigorous probabilistic substantiation, leads to the rapid emergence of BN as a selection method for uncertain reasoning in AI.

The nodes within the BN represent variables of interest(e.g. power system buses voltage, the age of a student, the occurrence of an event), and the links reflects the dependence between the variables. Dependence is quantified by con-ditional probabilities for each node given by its parentswithin BN. The network supports the probability calculation of any subset of variables being given by the evidence of any other subset.

Perhaps the most important aspect of BN is that they aredirect representations of the universe and not representations of reasoning. The arrows in the graphs are real causal connections and not the propagation of information along the reasoning as in the case of rule based systems or neural networks. Rationale can work within BN by spreading information in any direction [1].

We need some basic notions to describe the mathe-matical properties of BN. A *directed graph* (DG) is a pair (V, E), where V is a finite nonempty set, whose elements are called *nodes*, and E is a set of ordered pairs of distinct elements of V. The elements of the set E are called *directed edges* and if $(X,Y)\in E$ we say *there* is an edge from X to Y. Figure 3 represents a directed graph (DG).

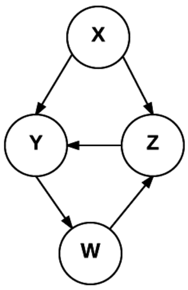

Fig. 3 – Directed graph - DG

The set of nodes $-V=\{X,Y,Z,W\}$.The set of edges $-E=\{(X,Y),(X,Z),(Y,W),(W,Z),(Z,Y)\}$.

A *path* in a directed graph is a sequence of nodes$[X_1,X_2,\cdots,X_k]$ such that $(X_{i-1},X_i)\in E, i=\overline{2,k}$.A *chain* in a directed graph is a sequence of nodes$[X_1,X_2,\cdots,X_k]$such that $(X_{i-1},X_i)\in E \vee (X_i,X_{i-1})\in E, i=\overline{2,k}$.A *cycle*in a directed graph is a path from a node to itself.

A DG is called a *directed acyclic graph (DAG)* if it contains no cycles. In Figure 4 we have a DAG.

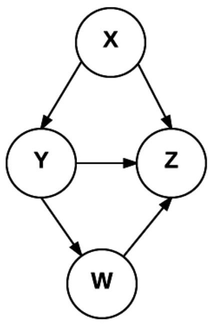

Fig. 4 – Directed acyclic graph - DAG

Given a DAG $G=(V,E)$ and the nodes X and Y in V than:

- Y is called a *parent* of X if there is an edge from Y to X;
- Y is called a *descendent* of X and X is called an *ancestor*of Y if there is a path from X to Y;
- Y is called a *nondescendent* of X if Y is not a descendent of X and Y is not a parent of X.

Suppose we have a joint probability distribution P of the random variables in some set V and a DAG $G=(V,E)$. We say that (G,P) satisfies the *Markov condition* if $\forall X\in V$, X is *conditionally independent* of the set of all its non-descendents given the set of all its parents. If we note with PA the sets of parents of X and with ND sets of non-descendents of X then we obtain: $I_P(X,ND|PA)$.

If (G,P) *satisfies the Markov condition, we call* (G,P)*Bayesian Network (BN)* [2].

Following the BN definition, they can be targeted as graphical models (Figure 5). The nodes removed from the root node "Graphical Models" are specialized versions of their parents. We note that a BN sub-branch is a dynamic BN, from which derives Markov chains.

The BN classification by form [4] is as follows: (a) BN in form of chain; (b) BN in form of tree; (c) BN in form of polytree.

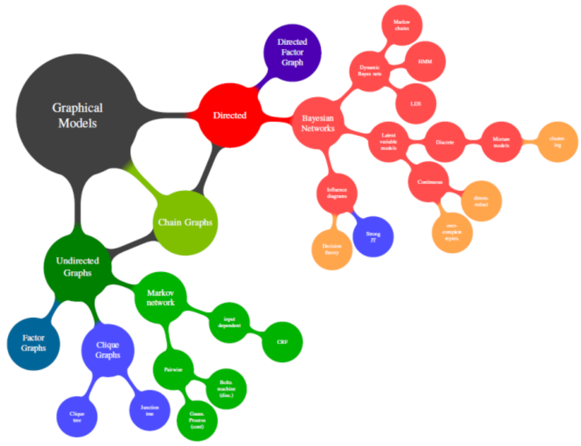

Fig. 5 – Members of the graphical models family and their uses [3]

We continue to present the mathematical properties of BN. A BN (G, P) is by definition a DAG G along with its probability distribution P, which together satisfies the Markov condition. In Figure 6, BN is represented both by topology and by probability distributions[5].

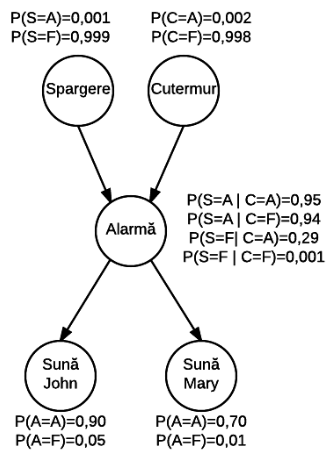

Fig. 6 – Topological representation and probability distributions in a typical BN

This type of BN representation leads us to the next theorem: *(G, P) satisfies the Markov condition (and thus* *isa BN) if and only if P is equal to the product of its conditional distributions of all nodes given their parents in G, whenever these conditional distributions exist.*

The notion of causation within RB was introduced by Judea Pearl. A *causal graph* is a DG containing a set of causally related random variables V such that $\forall X, Y \in V$ there is an edge from X to Y if and only if X is a *direct cause*of Y. If we assume the observed probability distribution P of a set of random variables V satisfies the Markov condition with the causal DAG G containing the variables, we say we are making the *causal Markov assumption*, and we call (G, P) a *causal network*. As a conclusion, the DAG can satisfy the Markov condition with the probability distribu-tion of the variables in the DAG without the edges being causal, so it can be satisfied the Markov condition in the DAG without causality [2].

The notion of Bayesian inference is known both in statistics [6] and BN domain. In the following we will focus on inference in BN. Inference in a two-node BN is a standard application of the Bayes theorem. Larger BNs address the problem of representing the union of the probability distribution of a large number of variables. The inference in this type of BN consists in calculating the conditional probability of some variables (or a set of variables), since the other variables are instantiated at certain values. Sophisticated algorithms are required to achieve this inference [2]. In the following we will present references that describe some of these algorithms. The detailed description of the algorithms below can be found in[7].

J. Pearl has developed the *message-passing algorithm*for inference in BN [8], [9]. Based on a method originating in [10], Jensen and his collaborators have developed an inferential algorithm that involves extracting a non-oriented triangular graph from a DAG into a BN and creating a tree whose nodes are the groups of this triangular graph [11]. Such a tree is called *junction tree*. Conditional probabilities are then calculated using the message-passing algorithm inthe junction tree. Li and D'Ambrosio had a different approach. They have developed an algorithm that approximates optimal path determination to calculate marginal distributions of interest in the probability distribution union. This inference was called *symbolic probabilistic inference* (SPI) [12].

All of these algorithms are worst case non-polynomial (NP)-time. This is not surprising because the problem of inference in BN has been demonstrated by Cooper to be NP-hard [13]. Subsequently, approximation algorithms for inference in BN have been developed. In the 1990s Fung and Shachter developed such an algorithm, namely the *probability (likelihood) of weighting* [14], [15]. In 1993 Dagum and Luby proved that the approximate inference problem in BN is also NP-hard [16]. However, there are restricted classes of BNs which are provably amenable to a polynomial-time solution [17]. In 1996, Pradham and Dagum implement a variance of the *probability (likelihood) weight algorithm*, which is worst case P-time, as long as the network does not contain extreme condition probabi-lities [18].

Software packages containing these algorithms have been developed to make inference in BN. Some of these are:NETICA, GeNee, Elvira and other graphical models (GM):

- Hugin: is a comercial GM, provides only junction tree inference and does not support dynamic BN (DBN);
- PNL: is a GM implemented by Intel - Probabilistic Networks Library, it is open source C ++, based on BNT – Bayes Net Toolbox;
- GMTk: is a graphical model tool (Bilmes, Zweig / UW), it is open source C ++, designed for ASR (HTK);
- AutoBayes: is a code generator (Fischer, Buntine / NASA Ames), Prolog generates Matlab / C but is not available to the public;
- VIBES: it offers variational inference (Winn / Bishop, U. Cambridge) and conjugated exponential models;
- BUGS: Gibbs sampling for Bayesian DAGs (Spiegel-halter et al, MRC UK.) [19].

Much of the statistics deal with random variables whose domains are continuous. They have an infinite number of possible values, so it is impossible to explicitlyspecify conditional probabilities for each value. One way totreat continuous variables is to avoid using the *discretization method* to divide the possible values into a fixed set of intervals. Discretization is sometimes an appropriate solution, but often leads to a considerable loss of accuracy and to very high conditional probability tables - CPT. The most common solution is to define the standard families of probability density functions that are specified by a finite number of parameters. Another solution, sometimes called*non-parametric representation*, is to define conditionaldistribution, implicitly, with a collection of instances, each containing specific values of parent and child variables.

If Koch classifies BNs by form, Russel introduces another type of BN depending on discrete or continuous variables. A network with both discrete and continuous variables is called hybrid BN – HBN [5]. To specify an HBN,two new types of distributions, represented in Figure 7, must be specified:

a)The conditional distribution for a continuous variable given by discrete or continuous variable parents;

b)Conditional distribution for a discrete variable given by continuous variable parents.

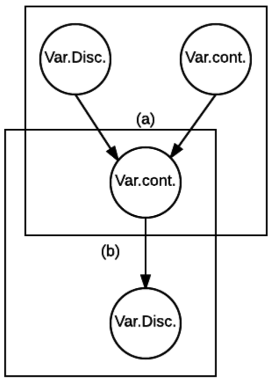

Fig. 7 – HBN Model – hydride Bayesian network

In the case of (a) the most common choice is the *linear Gaussian distribution*, in which the child has a Gaussian distribution whose average μ varies linearly with the valueof the parent and whose standard deviation σ is fixed. Whendistinct variables are added as parent (not as children) of continuous variables, the network defines a *Gaussian conditional distribution*, given by any assignment of discrete variables; the distribution over the continuous variables is a *multivariate Gaussian distribution*.

In the case of (b) the conditional distribution is a "soft threshold" function. One way to do "soft thresholds" is to use the standard normal distribution (Probit distribution). An alternative to Probit is the Logit distribution, which uses the Logit function to produce "soft thresholds". The two distributions look similar, but Logit has longer “tails”.The Probit model is often a better way for real situations, while the Logit model can be managed easier from themathematical point if view. The Logit model is widely used in neural networks. Both models can be generalized tomanage multiples of continuous type parents by considering a linear combination of parental values.

The inference in BN can be: exact, approximate or inference in temporal models. We will briefly present each type of inference from the previous classification.

Under the exact inference in RB when a single cause directly affects a series of effects, all of which being conditionally independent, given the cause, the full union distribution can be written as such:

$$P(Cause, Effect_1, Effect_2, \cdots, Effect_n) = P(Cause) \prod_i P(Effect_i|Cause) \quad (1)$$

Such a probability distribution is called *naive bayesian model (naive Bayes)* because it is often used (as a simple assumption) in cases where the "*Effect*" variables are not actually independent of the "*Cause*" variable. Naive bayesianmodels are also called *Bayesian classifiers*. In practice, Naive Bayesian systems can work surprisingly well, even when the hypothesis of conditional independence is not true.

The main task for any probabilistic inference system is to calculate the posterior probability distribution for aset of variables, given some observed events. They are the assignment of the values of a set of evidence variables.

Exact calculation algorithms for posterior probabilitiesare: *inference by enumeration, the variable elimination algorithm, clustering algorithms*, and last but not least *the complexity of exact inference* [5]. The general case being difficult to solve, we will also discuss to approximate inference methods.

The approximate inference in BN refers to the samplingapplied to the posterior probability calculation. Two familiesof algorithms: *direct sampling* and *Markov chain samplingare* defining for approximate inference. As two other approaches can be mentioned: *variational methods* and*loopy propagation*. Within the *direct sampling algorithm*, samples are generated from the primary network distributionspecified by the network. In any sampling algorithm, responses are calculated by counting the actual samples generated. In this algorithm, we have two methods: *rejection sampling in BN* and *likelihood weighting* (the method sets the values for the evidence variables and works only with non-evidence variables). In Markov chain-type inference, *the Markov Chain Monte Carlo (MCMC) algorithm* functionsquite differently from the two previously presented algorithms,namely: rejection sampling and likelihood weighting.Instead of generating each sample from scratch, the MCMCalgorithm generates each sample by making a random change to the previous sample. The *Gibbs samplingis* a particular MCMC algorithm, which is suitable for BN.The algorithmoffers consistent estimates for posterior probabilities. *The sampling process is set in a "dynamic balance," in which the long-term fraction of the time spent in each state is exactly proportional to its posterior probability.* This remarkable property results from the specific *transition probability* with which the process moves from one state to the next, as defined by the con-ditional distribution, given the Markov blanket of the sampling variable. The probability of transition defines the*Markov chain* (Markov's process/chain term was introduced by the Russian statistician Andrei Markov 1856-1922). The process that satisfies the *Markov hypothesis* bears the name Markov process or the Markov chain. The Markov hypothesis means that a current state depends only on a fixed and finite number of previous states) on the state space [5].

Previously we have presented probabilistic reasoning techniques considering the static universe (exact or aprox-imative inference), in which each random variable has a unique fixed value.There are cases where dynamic aspects of the problem are essential. We need to find an answer to the question: "How can such dynamic situations be modeled?" Transient states of the universe are described bya set of random variables to show the state in each moment.They can be established to satisfy *Markov's property*, so that the future is independent of the past through the presenttime. Combined with the hypothesis that the process is stationary – dynamics do not change over time – this greatlysimplifies the representation. A temporal probability model can be thought of as containing a *transition model* (as the universe evolves) describing the state of evolution and a *sensor model* (the way the values are taken over by the evidence variables) that describe the observation process. The basic tasks of inference are as follows: *filtering, predic-tion, smoothing* and computing the *most likely explanation,learning* (as an additional task of inference).

The concrete models are: *hidden Markov model – HMM, Kalman Filter* and *dynamic bayesian networks – DBN.*

A *HMM* is a temporal probabilistic model which uses a single discrete random variable to characterize the state of the process. The small structure of HMM allows theimplementation of simple and elegant matrices of all basic algorithms.

Filtering means estimating status variables in noisy observations over time. If the variables are discrete the system can be modeled with HMM. For *continuous variables*, an algorithm called *Kalman filtering* is used.

A *DBN* is a network that offers a temporal probabilitymodel. For many applications in the real world, flexibility is essential. Real world aspects introduce "nonlinearity" that requires combinations of discrete and continuous variables in order to obtain reasonable models. As in the case of BN, in case of DBN we speak about exact and approximate inference.

Another important aspect in BN is the *learning* of the network. Here we can talk about parameters learning or the network structure learning [20].

The following section presents various applications of BN in the EPE.

3. APPLICATION OF BN IN PSE

1) Power consumption (energy) and load curves forecast [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35]:
   - short-term power consumption forecasting, having random behaviour (normal distribution), in order to assess the generating units' loading;
   - short-term peak power forecasting (few days) based on bayesian hierarchical model;
   - probability density functions' hourly bayesian forecast model for renewable sources generated power and smart grid consumption;
   - wind sources generated power forecasting studies based on sparse bayesian classification;
   - bayesian mediation model combining the results provided by 5 different forecasting methods
   - artificial neural networks based forecasting using bayesian inference background (several types ANN, having bayesian learning algorithm, including the "bayesian back propagation" concept);
   - bayesian networks based approach integrated into the "support vector machine" techniques;
   - the use of a "bayesian working environment" in order to assess the best parameter values of ANN;
   - medium and long term forecast based on bayesian betworks.
2) BN based power system reliability studies [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46]:
   - risk evaluation for coal fuel based generating units;
   - protection devices faults consideration for power system risk assessment;
   - electrical networks safety operation assessment including SCADA systems cyber-attacks;
   - distribution network reliability analysis;
   - statistical electrical networks faults analysis;
   - electrical substations monitoring software systems reliability;
   - bayesian based approach for human operator errors effects over the reliability;
   - assessment the faults caused by animals in distribution networks (bayesian model with Monte Carlo simulation).
3) Power system stability analysis [47], [48], [49], [50], [51]:
   - transient stability analyses and contingency studies;
   - bayesian approach of power system voltage collapse assessment;
   - bayesian learning algorithm based dynamic power system frequency evolution;
   - power systems stability quick estimation;
   - low frequency oscillations' identification based on power systems recordings;
4) Electrical networks faults diagnosis [52], [53], [54], [55], [56], [57], [58]:
   - comprehensive faults diagnosis bayesian modelfor small scale power system;
   - component oriented bayesian model, based on concordance analysis between protection devices and circuit breakers;
   - bayesian networks based intelligent system for power transmission lines faults diagnosis and forecast;
   - bayesian model development for transformer faults diagnosis;
   - probabilistic bayesian model for electrical transformer life cycle assessment;
   - bayesian model based faults location within the rural distribution networks.
5) Power system state estimation [59], [60], [61], [62], [63]:
   - smart grids cyber-attacks or erroneous data detection;
   - different bayesian state estimators for distribution networks
   - (auto)transformers tap position estimation;
   - network elements parameters values estimation;
   - bayesian dynamic estimator for electrical networks configuration changes detection.
6) Other BN applications [64], [65], [66], [67], [68], [69]:
   - electrical transformers parameters estimation though indirect measurement;
   - load profile distribution assessment using variational bayesian inference;
   - power quality disturbances diagnosis (voltage sag etc.).

4. CONCLUSION

As a conclusion to BN we point out the following aspects:

- BN is a DAG whose nodes correspond to random variables; each node has a conditional distribution for the node given by its parents.
- BN specifies a total union distribution; each input in theunion is defined as the product corresponding to inputs in the local conditional distribution (RB is often expo-nentially less than an explicitly listed union distribution.
- Many conditional distributions can be represented by compact canonical distribution families.
- HBN, containing continuous and discrete variables, uses a variety of canonical distributions.
- The inference in BN is equivalent to computing the probability distribution of a set of query variables given by a set of evidence variables.
- In poly-trees (individually connected networks), exact inference requires linear time in network size (this problem is didfficult to solve).
- Stochastic approximation techniques, such as the likelihood weighting and the Markov Monte Carlo chain, can give reasonable estimates of true basic task
- ior probabilitiesin the network and can handle much larger networks that can extract algorithms.
- The main tasks in the temporal model inference are: filtering, prediction, smoothing and computing the most likely explanation.
- Families of temporal models include Markov Hidden Models, Kalman filter and DBN.

As a conclusion to BN application in PSE we point out the following aspects:

- In last 10 years there are many researches using BN to solve various PSE applications.
- Power consumption (energy) and load curves forecast.
- BN based power system reliability studies.
- Power system stability analysis using BN;

- Electrical networks faults diagnosis using a BN model.
- BN based Power system state estimation.
- Transformers parameters estimation with using BN.
- BN based power quality disturbances diagnosis.

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