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Optimization strategies for improving the interpretability of bayesian networks: an application in power systems

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1. Introduction

The search for new methods, techniques and tools to support the decision-making processes is a subject that has aroused major interest in international research; with intelligent systems emerging as one of the most robust solutions.

Such studies characterize an area called Data Mining (DM), also known as Knowledge Discovery in Database (KDD), which represents a source of mature technologies, largely embedded in organizational processes of modern corporations. DM can be understood as an interactive and iterative process to identify understandable, valid, new and potentially useful patterns from large data sets.

This work presents an analysis to improve the comprehensibility of the patterns discovered in the DM process, which is related to the easiness of interpretation by the human being (Rezende, 2003). Thus, the use of DM techniques that provide mechanisms of presentation and visualization that simplify the analysis of the knowledge obtained can strongly contribute to the users to measure the quality of this knowledge.

Among the many DM techniques found in literature, Bayesian networks (BN) comes as one of the most prominent, when considering easiness for interpreting knowledge obtained from a domain with uncertainty. The reason is that it provides a mechanism for representing the causal model of a given dataset (Pearl, 1988), allowing qualitative and quantitative analyses from the variables of the domain; thus, providing support to the decision making process (Korb & Nicholson, 2003), (Russel & Norvig, 2003).

However, BNs present a restriction to establish the optimal combination of states for given variables (discrete or continuous) that would achieve a certain requirement (state of one or more variables of the domain). In many real applications, the search for situations which would lead to the attainment of certain goals is extremely important.

For example, to achieve a certain level of sales, it is necessary to find which set of factors that can influence in this progression and, thus, determine which are the conditions (states) of these factors that have greater impact on the sales rate obtained. In this work, we present a method to solve such problem, by combining the techniques of genetic algorithms (GAs) with the BNs, built from the domain's data. In light of these indicatives, we point, as contribution of this work, the development of new strategies to extend the power of interpretability of BN, implementing a strategy for the discovery of scenarios.

In summary, the model presented here characterizes the process of discovering scenarios that can lead to achieving a specific goal; for such, we use a novel hybrid model developed using GAs and BNs, that combines the qualities of evolutional algorithms for space search with a Bayesian probability model for inference. It is aimed at identifying the best configuration, among the possible values (states of nodes in a BN) of variables in the domain, corroborating the achievement of a target value for one (or more) variable(s) in the domain in question.

The main objectives are twofold: analysis and use of Bayesian methods for knowledge extraction, basically with respect to the creation of a method capable of extending the power of interpretability of the BN; proposal of a model to measure the causal relationship among the variables of a domain, by discovering the values that compose an optimal combination (configuration) of states for given variables of this domain.

This work is organized as follows: section 2 presents the main motivations for using BN in the data mining process and some related work to this study. In section 3, the method proposed for the search of the optimal configuration is presented, aiming at the improvement of the BN interpretability. As a case study, the method is applied in the power systems domain, as will be presented in section 4. Finally, section 5 presents the final remarks of the paper.

2. Bayesian Networks and related work

A BN represents a probabilistic model of the variables of a given domain, being able to represent the qualitative (dependencies), as well as the quantitative (conditional probabilities distribution) information. Together, these components propitiate an efficient representation of the joint probability distribution of the set of variables $X_i = \{X_1, X_2, \ldots, X_n\}$ of a given domain (Pearl, 1988).

Moreover, three factors have motivated the use of BN in DM processes (Heckerman, 1997): first, the effective manipulation of incomplete datasets; second, the learning of causal relationships among the variables of the domain, which facilitates the analysis of the domain; third, the BN allow the combination of prior knowledge of the domain with the data.

In order to corroborate with the importance and the applicability of BN in the electric sector, used as case study here, some related studies presented in literature are shown next.

BN is known to offer, given its knowledge representation formalism, a natural mechanism for modeling diagnosis. In the power systems domain, there is a massive application on fault diagnosis of equipment and operations.

In (Yongli et al., 2006), an application of BN is presented for the diagnosis of possible transmission faults in power systems. The main motivation presented for the use of this approach is the easiness with which relationships of cause-effect, particularly in domains with a high degree of uncertainty, can be modeled.

As a way to decrease the size of the probability tables used in the mentioned problem, a BN model is proposed with nodes Noisy-Or and Noisy-And. These nodes can be seen as a generalization for the conventional logical connector *or* and *and*, respectively. The idea is to use them in the networks as elements that can simplify the correlations among the variables of the system and their implication with respect to the appearing of transmission faults. Instead of directly establishing the relation of cause and effect between two variables, they imply to a node Noisy-Or or Noisy-And, whose connections are parameterized with the use of probabilities; this way quantifying the impact that each variable has for causing transmission faults.

In (Yonggiang et al., 2005), another application of BN in the context of fault diagnosis is presented, with emphasis in the possible defects that may occur in the functioning of an important class of electric equipment - the transformers. Given the uncertainty of this diagnosis, usually due to the complexity for configuring these equipments, it is necessary to use a method in order to assist the specialist in the analysis of possible defects.

Several other applications of BN in fault diagnosis are investigated in the literature, as presented in (Flores-Loredo et al., 2005).

In (Zhou et al., 2006) BN are used to predict the possibility of faults in the energy distribution, considering some climatic aspects. In this case, a BN is modeled to carry out the fault predictions (in 7 possible states) from the conditions of wind (in 4 states) and the possibility of occurrence of atmospheric discharges (2 states - yes or no).

With respect to the mechanisms for improving the comprehensibility of the patterns discovered by the BN, in most of the available literature, the technique of genetic algorithms is usually employed only for the process of learning the BN structure (Li et al., 2005), (Gamez et al., 2002), (Morales et al., 2004).

Some proposals, however, lean to a hybrid approach of computational intelligence methods to optimize and improve the process of knowledge extraction, in its post-processing stage. For example, in (Yang, 1997) a Bayesian-Fuzzy method is used to manipulate continuous values of evidence in the inference processes.

Although without employing a technique of optimization combined to the inference of BN, an interesting method to accomplish these inferences was proposed in (Andersen et al.,

1989) and is implemented in the Hugin software; allowing to identify the most likely configuration of values for the variables of a BN, given one or more evidences.

This method has two basic differences compared to the method proposed here. First, Hugin seeks to find the composition of states (configuration) of the variables studied, based on the evidence of a given variable. Here, the idea is to attain the states of the studied variables (our particular goal) that would allow to achieve a given state on other variable(s) of the BN. Another difference is related to the capacity of obtaining the continuous values, and not discretized range of values, of the studied variables, to achieve the desired value for the goal variable. In the particular case of power systems, this is primordial, given that a variation of 0.1% in the consumption can represent a considerable financial economy.

3. Optimal State Configuration Search

The objective of this model is to identify the best configuration, among the possible values of the existing variables in the domain, which maximizes a given attribute, identifying initially the other variables that present a dependency from it.

In contrast to the way genetic algorithms are used in the majority of the hybrid systems proposed in the literature, where they are adopted to optimize the process of learning the structure of BN, here, the technique is used for the discovery of the most probable values of the variables of a BN, given the value of a key attribute.

The discovery of scenarios that are conducive to achieving a particular goal is of utmost importance to support the process of decision making. For example, determine which socio-economic scenario corroborate with obtaining a target value of total energy consumption, defined by the user.

The method developed is aimed at subsidizing decision making users with methods to analyze, in advance, the scenarios that can lead to achieving a certain goal; identifying the best configuration, among the possible values of variables in the domain, corroborating the achievement of a target value for one(or more) variable(s) in the domain in question. For this, we used a hybrid method that combines the probabilistic and correlation power of BNs, with the ease of GAs for the incorporation of specific knowledge of the problem, in order carry out optimization tasks.

The interaction between these two computational intelligence techniques (GA and BN) occurs as follows. As can be seen in Figure 1, the process of scenario discovery starts with supplying the BN, generated from the data, and its parameters; then, a GA is applied using as fitness function for the individuals (scenarios) the actual inference engine of the BN; at the end of its iterations, the optimal scenario to achieve a particular goal is obtained.
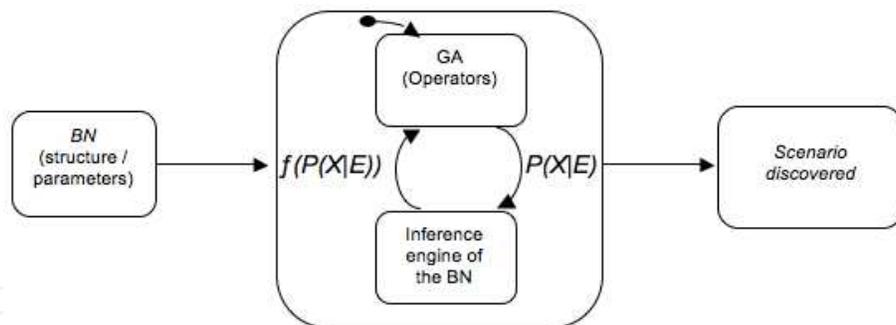
Fig. 1. Representation of the method for discovery of scenarios.

In Figure 1, $P(X|E)$ represents the probability of obtaining a particular state of X (target variable), given the set of remaining variables in the domain E. Thus, the scenarios (configuration of states for variables E) represent the individuals of the GA, which are evaluated (fitness function) by the probability of obtaining the goal X. That is, the probability $P(X|E)$ of occurrence of each scenario is provided as input to the BN method of inference, returning as output the value for this query. As mentioned previously, this value is used as fitness function for the individuals (scenarios) of the genetic algorithm (GA).

```
1.  SCENARIO DISCOVERY (bn)
2.  /* returns the scenario that best contribute to achieving the target
        value for a target variable of the domain */
3.  // bn – Bayesian network that codifies the joint distribution P(X₁, X₂, ...Xₙ)
4.  population ← GENERATE_RANDOM_POPULATION;
5.  repeat
6.      initialize new_population
7.      for i ← 1 to SIZE(population) do
8.          a ← SELECT(population, APTITUDE_FUNCTION(INFERENCE_MODEL_I(bn))
9.          b ← SELECT(population, APTITUDE_FUNCTION(INFERENCE_MODEL_I(bn))
10.         if (CROSSOVER_RATE is met)
11.             child_ab ← CROSSOVER(a,b)
12.         if (MUTATION_RATE is met)
13.             child_ab ← MUTATION(child_ab)
14.         include child_ab in new_population
15.     end for
16.     population ← new_population;
17. until termination criteria is met
18. return the best scenario in the population, according to the
        APTITUDE_FUNCTION
```

Fig. 2. Algorithm for the process of scenario discovery.

BNs and GAs are used in different subsystems that collaborate to reach a solution, i.e., the intelligent paradigms are independent, exchange information and perform separate functions to generate solutions as shown in Figure 1. Therefore, the method presented here can be considered in the category of intercommunicative hybrid methods. Figure 2 shows the algorithm for method presented.

The GA starts with the random generation of an initial population *I* (where each gene corresponds to a node in the BN), consisting of a set of candidate scenarios, which are then evaluated by the method of inference of the BN; in order to obtain the fitness of the scenarios, the probability of obtaining the target value for the queried variable *X* is calculated, given a particular configuration of states (scenario) of the variables of evidence *E*. The process continues with the selection of individuals, through the method of roulette. Next, we apply the operators of crossover, with crossover rate T_c; and mutation, with a mutation rate T_m. The process is completed following one of the following criteria:

- establishment of a predetermined number of generations, i.e. define, a priori, a number *n* of iterations;

- until the algorithm can find an acceptable scenario. The acceptance of the scenario is made based on a subjective quality model for evaluation, considering opinions and definitions of the domains experts.

One can notice that it is possible to employ any inference method (INFERENCE_MODEL_I) for the BN, exact or approximate; the probability is used to evaluate the quality of the individuals in the GA. We point that the parameters used to execute GA are defined by the user and vary according to the application domain.

In order to show the general interaction process of the GA and the BN inference, consider a BN *B*, generated from a dataset *D*. Consider also the general inference process over B, expressed by a set of query variables *X*, a set of E variables for inference, and a set of e observed states from *E*, and a set *Y* representing the remaining variables (not contained in *X* and *E*). A query *P(X|e)* can be expressed by:

$$P(X \mid e) = \alpha P(X,e) = \alpha \sum_y P(X,e,y) \tag{1}$$

Where α is a normalization constant, that ensures that the sum for the probability distribution of *P(X|e)* equals 1; and *y* are possible values for variables in the set *Y*.

Equation 1 can infer specific queries over *X* from any set of evidence variables *E*, considering for the calculations the state space of variables *Y*, (1). The method for discovery of scenarios can be viewed as a specialization of this equation, which aims to find which values (states) e from the set of variables E maximizes the probability of a given $x \in X$. In this case, *E* is formed by all variables of the domain, i.e. Y = $\varnothing$. Thus, we can write (1), as follows, considering the suitability of a particular individual in the GA that enables achieving the target value x_i,

$$P(x_i \mid e_1, e_2, ..., e_n) = P(x_i) \prod_{k=1}^{n} P(e_k \mid x_i) \qquad (2)$$

Where:

$e_1, e_2, ..., e_n$ are the possible evidences;

and x_i is the event we want to observe.

The chromosomes in the GA are represented by decimal values, characterized by the state space for the variables used for inference, as shown in Figure 3, where e_1 represents any state of E_1, e_2 represents a certain state of E_2 and so forth.
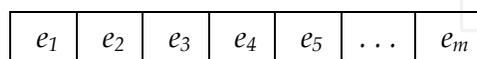
e_1	e_2	e_3	e_4	e_5	. . .	e_m

Fig. 3. Representation of chromosomes of the genetic algorithm.

To calculate of the fitness, the chromosomes are submitted to the inference module of the BN, in order to calculate the probability of the queried variable to attain a given target certain value. The higher the probability, the fittest the considered individual will be. It is worth to mention that, more than a single query variable can be used for the discovery of scenarios.

To illustrate the operation of the method, consider the BN, showed in Figure 4 and its respective variables (nodes) and states (Table 1).
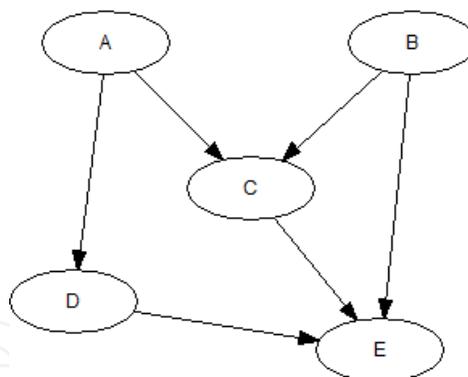

Fig. 4. Bayesian network to illustrate the discovery of scenarios.

Variable	States
A	a_1, a_2
B	b_1, b_2, b_3, b_4
C	c_1, c_2
D	d_1, d_2
E	e_1, e_2, e_3, e_4

Table 1. Nodes and states of the BN.

In the example, d1 is considered the target value, highlighting that it would be possible to choose any variable (or set of variables) of the BN. The GA acts on the inference method of the BN (e.g. the exact method Junction Tree) to find the scenario that maximizes the probability for d_1, to occur.

A possible candidate solution to this simple example could be the set {2,3,1,2}, in which the first position (gene) infers state a_2 of variable A, b_3 of variable B, c_1 of C and e_2 for E. The fitness evaluation, will be given by $P(d_1|a_2,b_3,c_1,e_2)$. Thus, after application of GA operators (selection, crossover and mutation) and at the end of iterations (generations), the best configuration (scenario) for variables A, B, C and E, which maximize the probability of d_1, would be obtained.

4. Case study application

4.1. Motivation and Context of the Proposed Model

The analysis described here was originated from the demands of the research project "PREDICT - Support Decision Tool for Load Prediction of Electrical Systems". This project, a joint venture between the Government of the State of Pará and the Power Supplier of the State of Pará, aims at designing and implementing a decision support system, using mathematical and computational intelligence methods, to foresee the demand for energy purchase in the future market.

With that in mind, studies are usually made to measure the impact that many other variables (temperature, humidity, socio-economic factors etc.) influence over the consumption, so that it is possible to foresee scenarios where the operation of the power systems are economic, safe and reliable.

So, the consumption forecast and the correlation of some exogenous variables to the power system, specifically associated to climatic and socio-economic factors, served as basis for the project. In its first phase the project used methods of regression and artificial neural networks, to apply the forecasts, and BN to model the mentioned correlations.

However, throughout the development of the project, a series of demands for new inferences, necessary for a reliable and safe planning and operation of the power systems, were raised by the specialists (managers and engineers). Amongst these demands we point out the creation of indicators that influence the future performance of the power system, such as mechanisms that would optimize the consumption, given its relation with socio-economic and climatic variables.

To assist in these new demands, the BN were elected as models for representing these correlations. This proposal was elaborated in order to not only cover this domain of application, but also to enable its application in many other areas.

4.2. Description of the Optimization Model

The case study, proposed by the domain specialists of the power system market, and used for the optimization model was to discover under which circumstances the power

consumption would be maximized. For this case, the optimization model was based on a few steps that are described as follows.

Firstly, identify which attributes, among those from the database, influence directly the power consumption by building the BN structure.

The Government of the State of Pará, from its State Executive Bureau of Budget and Finances Planning supplied a database with 15 years of monthly records of the State's socio-economic aspects, consisting 35 attributes.

Only the attributes selected by the specialists were used for the generation of the BN, according to their impact in the variation of power consumption; they are: number of employments in the sectors of the transformation industries and agriculture and cattle breeding, and the values of the total turnover and of the dollar. We point out that their influence reflects directly not only to the total power consumption in the State, but also to the many classes of consumption (residential, industrial, commercial etc).

Given the knowledge that the variables of number of employments in the transformation industries (*emp_ind*), employments in the agriculture and cattle breeding (*emp_agro*), value of the total turnover (*val_turn*) and the value of the dollar (*val_dol*) are the main influences in the variation of the power consumption, they were used in the next step, which consisted in the creation of a BN (Figure 5), using the search and score algorithm K2 (Cooper & Herskovitz, 1992).
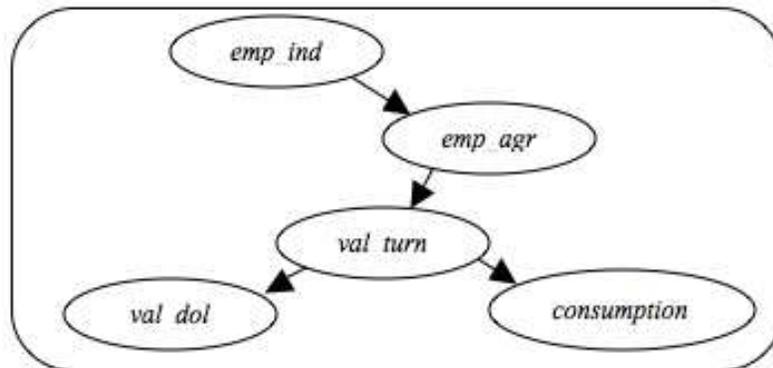

Fig. 5. BN created with the K2.

In the BN, all the attributes were discretized in ten states, according to the frequency of their values, allowing us to verify the probability associated to each one of them, as well as the conditional probabilities existing among the variables.

Once the network is set, the next step is, by making use of the data given by the BN, to search the network attributes for the states that would maximize the power consumption. In this stage we use a modified genetic algorithm.

Here, instead of a cost function to validate the individuals of the population, a Bayesian inference algorithm is implemented (Equation 2); that is, the BN is used as a cost function.

This way, each of the individuals of the genetic algorithm represents an inference configuration of the BN, generated randomly (e.g. evidencing the variables *emp_ind* with state 2, *emp_agro* with state 1, *val_turn* with 7 and *val_dol* with 4 generates the individual 2-1-7-4). Each individual is then, for its classification, submitted to the Bayesian inference module in order to verify the probability in which the power consumption attribute would be maximized, obtaining, at the end of the iterations, the best possible configuration of inferences on the BN for the maximization of the power consumption.

However, we would have at the end of this step (after the genetic algorithm analysis) only the respective states (i.e. band of values) for this maximization, instead of a single value (for each attribute), which is what we seek. Following this phase, we make use, again, of a genetic algorithm; but this time a traditional genetic algorithm, whose aptitude function we obtain from the data.

The function used for the genetic algorithm is obtained from a regression of multiple variables made over the attributes of the BN (Dillon & Goldstein, 1984), (Hair et al., 1998). The multivariate analysis is however made over the consumption data, but considering only the data instances located within the ranges found in the previous step. Thus, we obtain an equation (presented below) with a good representativity (approximately 0.9039) over the domain.

$$Y = 258{,}598{,}510.5 + 3{,}675.6834\,X_1 + 4{,}430.9036\,X_2 +$$
$$+0.4701\,X_3 - 12{,}182{,}208.61\,X_4 \tag{3}$$

where Y represents the power consumption and X_1, X_2, X_3 and X_4 represent the values of the attributes *emp_ind, emp_agro, val_turn* and *val_dol*, respectively.

Based on Equation (3), the genetic algorithm is then used, thus obtaining the values, for each of the attributes that would maximize the power consumption. It is worth mentioning again that the individuals evaluated by the aptitude function (2) are only those within the range of values that maximize the value of consumption. Thus, in order to achieve the occurrence of the maximum consumption, it is necessary that the values in Table 2 are achieved, for the attributes *emp_ind, emp_agro, val_turn* and *val_dol*.

Attribute	Value
emp_ind	5.380
emp_agro	3.357
val_turn	R$ 100.752.576,00
val_dol	R$ 2,861

Table 2. Values of the attributes for the maximization of the consumption.

The genetic algorithms used were, basically, parameterized according to the values in Table 3. The representation used for the individuals, however, was different. The first genetic algorithm used a representation with size based on the number of possible states that the variables of the BN could assume; and the second one used a binary representation. Other tests specifying different values for the parameters in Table 3 were also made; the results obtained, however, did not present any significant alteration.

Parameters	Values
Initial population	50 individuals
Number of generations	1,000
Selection	Roulette
Crossover	One point
Crossover rate	98%
Mutation rate	0.1%
Elitism	Yes

Table 3. Parameters used in the algorithms.

It is worth mentioning that the optimization model used is restricted not only to the discovery of the maximum values of consumption, but can also be used to identify scenarios that cause a minimum, average or any other value to be achieved by the power supplier, given the variation of the considered economic aspects.

Moreover, it is important to emphasize that although this case study presented a reduced search space, the method can be applied for cases with a sparse number of variables, given the evolutionary heuristics presented.

5. Final Remarks

This paper presented a strategy to extend the potentialities of BN, with respect to their inference process. It also showed, as a motivation for this strategy, assistance to the demands of the electric sector. Among the main contributions of the proposed strategy, we can point out the following.

The extension of the power of interpretability of the BN through the discovery of the optimal combination of values, represents the possibility of quantifying the causal relationships among the socio-economic and electricity consumption variables, and allows to achieve a given goal or a key aspect;

The interest of those involved in this Project, in applying the functionalities of the model in many other scenarios, not only relative to the power consumption, but also for government actions (e.g. discovery of the variables, and their values, that would maximize the generation of employment and income), has encouraged the use of the proposed model. This interest can further seen by the current use of the model in other Brazilian states, whose

energy is also provided by the same group of companies of which the power supplier of Pará belongs to.

We concludes pointing that by applying the hybrid model presented, the following analyses can be implemented:

1. Identify the variables that have the greatest impact in achieving a target value. This feature is particularly useful in situations where a given goal is established, but not all states of the variables are known or manageable. Besides being interesting in intractable high degree networks;

2. Find the singular values (when dealing with continuous variable) within the discretized ranges (states) of each evidence variables, that most contribute to achieving a target value for the queried variable;

3. Extending the method developed to obtain target values for more than one queries variable. This functionality allows to establish a query based on more than one goal, considering the isolated importance and impact of each;

4. Embedding expert knowledge, so that subjective criteria are used to evaluate the scenarios. This provides a stopping criterion guided by the degree of interest, measured from the belief of key aspects related to the target variable, set a priori by the specialist.

Moreover, it is important to point out that the solutions of problems involving the combination of techniques that can establish relations of cause and effect (BN) and of optimization (e.g. genetic algorithms) are not very well defined in the literature, particularly aiming at finding the states of given variables that can establish a desired condition, also influenced by these variables.

6. References

Andersen, S. L. ; Olsen, K. G. ; Jensen, F. V. & Jensen, F. Hugin – A shell for building Bayesian belief universes for expert system. *In Proceeding of the 11th International Joint. Conference on Artificial Intelligence*. Spring-Verlag, (1), (1989) 1080-1085.

Cooper, G. & Herskovitz, E. A Bayesian method for the induction of probabilistic networks from data. *Machine Learning*, (9), (1992) 309–347.

Dillon, W. R. & Goldstein, M. *Multivariate analysis - methods and applications*. John Wiley & Sons, 1984.

Flores-Loredo, Z. ; Ibarguengoytia, P. H. & Morales, E. F. On line diagnosis of gas turbines using probabilistic and qualitative reasoning. *Intelligent Systems Application to Power Systems.* Proceedings of the 13th International Conference on, (1), (2005) 297-301.

Gamez, J. A. ; Campos, L. M. & Moral, S. Partial abductive inference in Bayesian belief networks - an evolutionary computation approach by using problem-specific genetic operators. *Evolutionary Computation. IEEE Transactions*, 6 (2), (2002) 105–131.

Hair, J. F. ; Anderson, R. E. ; Tatham, R. L. & Black, W. C. *Multivariate data analysis.* Prentice-Hall. 1998.

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Heckerman, D. Bayesian networks for Data Mining. *Data Mining and Knowledge Discovery*, Kluwer Academic Publishers, (1), (1997) 79-119.

Korb, K. B. & Nicholson, A. E. *Bayesian Artificial Intelligence*. Chapman & Hall/CRC, 2003.

Li, X. ; He, X. & Yuan, S. Learning Bayesian networks structures from incomplete data based on extending evolutionary programming. *Machine Learning and Cybernetics*, Proceedings of 2005 International Conference on, (4), (2005) 2039–2043.

Morales, M. M. ; Dominguez, R. G. ; Ramirez, N. C. ; Hernandez, A. G. & Andrade, J. L. A method based on genetic algorithms and fuzzy logic to induce Bayesian networks. *IEEE Proceedings of the Fifth Mexican International Conference in Computer Science*, (1), (2004) 176-180.

Pearl, J. *Probabilistic reasoning in Intelligent System*, Morgan Kaufmann Publishers, 1988.

Rezende, S. O. *Intelligent systems: concepts and application*, Manole, 2003.

Russel, S. & Norvig, P. *Artificial Intelligence – a modern approach*. Prentice Hall, 2003.

Yang, C. C. Fuzzy Bayesian inference. *Proceedings of IEEE International Conference on Systems, Man, and Cybernetics*, (1997) 2707-2712.

Yonggiang, W. ; Fangcheng, L. & Heming, L. The fault diagnosis method for electrical equipment based on Bayesian network. *Electrical Machines and Systems*, (ICEMS). Proceedings of the Eighth International Conference on Publication, (3), (2005) 2259-2261.

Yongli, Z. ; Limin, H. & Jinling, L. Bayesian networks-based approach for power systems fault diagnosis. *IEEE Transactions on Power Delivery*, (21) 2, (2006) 634-639.

Zhou, Y. ; Pahwa, A. & Yang, S. S. Modeling weather-related failures of overhead distribution lines. *Power Systems, IEEE Transactions*, 21 (4), (2006) 1683–1690.
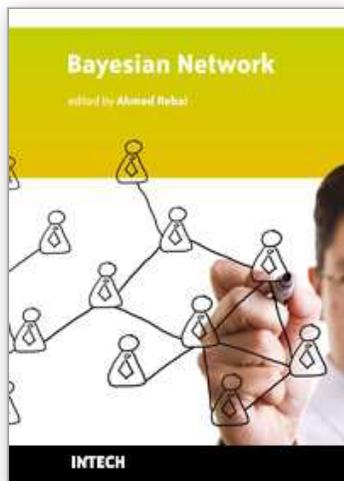
Bayesian Network

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Bayesian networks are a very general and powerful tool that can be used for a large number of problems involving uncertainty: reasoning, learning, planning and perception. They provide a language that supports efficient algorithms for the automatic construction of expert systems in several different contexts. The range of applications of Bayesian networks currently extends over almost all fields including engineering, biology and medicine, information and communication technologies and finance. This book is a collection of original contributions to the methodology and applications of Bayesian networks. It contains recent developments in the field and illustrates, on a sample of applications, the power of Bayesian networks in dealing the modeling of complex systems. Readers that are not familiar with this tool, but have some technical background, will find in this book all necessary theoretical and practical information on how to use and implement Bayesian networks in their own work. There is no doubt that this book constitutes a valuable resource for engineers, researchers, students and all those who are interested in discovering and experiencing the potential of this major tool of the century.

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