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AVAILABILITY EVALUATION OF NODAL ARCHITECTURES USING BAYESIAN NETWORKS

BY

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Abstract. Bayesian networks proved to be a useful tool in power engineering for: availability and reliability studies, power quality analysis, risk evaluation, components monitoring and fault diagnosis. The paper is dedicated to reliability analysis of power systems and authors present details on how the method based on Bayes’ theorem of conditional probability can be used for reliability evaluation of different architectures of power system nodes and electricity supply chains. The reliability block diagram (RBD), cut-sets or tie-sets methods and event tree or failure tree techniques can be used to construct Bayesian networks based on corresponding real systems.

Key words: Bayesian networks; nodal architectures; conditional probability theorem; availability analyses; power networks.

1. Introduction

Systems reliability and availability are important fields where Bayesian Networks (BNs) proved their efficiency. Starting with Judea Pearl and F.V.

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Jensen (2001) papers, which established the time-series modeling for Dynamic Bayesian Networks (DBN) and finishing with J.B. Dugan *et al*., (1992, 1993) works about dynamic fault tree models, there are many published papers about reliability of power systems, sub-systems and components.

The interest of the scientific community in studying the field of Bayesian networks (BN) has increased significantly in the last two decades, due to the benefits these networks present compared to conventional modelling methods such as Markov Chain, failure trees or Petri networks. The paper (Weber *et al.*, 2012) presents a brief analysis on these issues.

Chun Su and Ye-qun Fu developed the reliability analysis of wind turbines considering the influence of wind speed using Bayesian networks (Chun Su & Ye-qun Fu, 2014). An approximate inference algorithm combined with dynamic discretization of continuous variables is adopted to obtain the reliability index of wind turbine and its elements. L. Gao, Y. Zhou, C. Li and L. Huo authored a paper about the reliability assessment of distribution systems with distributed generation based on BNs (Chun Su & Ye-qun Fu, 2014). They developed a new method allowing not only computing the reliability indices of a distribution system but also evaluating the effect of each component or some components on the system reliability.

Authors of paper Huo Limin *et al*., (2002), developed a method for a simple system's reliability assessment based on fault tree method and minimal path set or minimal cut set. By using the inference theory of Bayesian networks, the system's availability and outage probability can be computed, and the system weak component can be found by means of casual inference, diagnosis inference, and exculpation inference.

Munteanu F. and Nemeş C. presented belief networks utilization for nodal power quality and availability assessment (Munteanu & Nemeş, 2012) starting from a detailed analysis about the correlation factor of the two renewable sources, solar and wind. A corresponding Bayesian model structure allowing assessing the nodal quality of supply from the power network including renewable energy sources as well as the main power network components was developed also. Same authors presented in paper Munteanu *et al*., (2016), details about the manner in which a design structure of power network or a nodal architecture can be modeled by a BN.

A methodology to apply Bayesian networks to structural system reliability reassessment, with the incorporation of two important features of large structures: (1) multiple failure sequences, and (2) correlations between component-level limit states is presented by Mahadevan S. in (Mahadevan S., Zhang R., Smith N., 2001). Finally, an extremely useful book to understand the calculus background, the automatic reasoning in BN and how the probabilities are propagating in BN is that authored by Adrian Darwiche, (2009).

2. The Background of Reliability Calculus for Automated Reasoning with Bayesian Networks

Axioms of probability also known as Kolmogorov's axioms provide the basis for (Bayesian) probability calculus:

1. $P(A) \in \Re \wedge P(A) \geq 0$ for any event $A \subseteq S$
2. $P(S) = 1$ means the probability of a certain event.

For any two mutually exclusive events A and B, the probability that either A or B occur is

$$P(A \,\mathrm{or}\, B) = P(A \cup B) \equiv P(A) + P(B)$$

It can be generalized and, if events A_1, A_2, …, A_n are pairwise mutually exclusive, then

$$P\left(\bigcup_i^n A_i\right) = P(A_i) + \ldots + P(A_n) = \sum_i^n P(A_i)$$

According with these axioms the derived Bayes' theorem can be exposed as

$$p(a \mid b) = p(b \mid a)\, p(b) \,/\, p(a)$$

3. The fundamental multiplication rule of probability calculus is:

$$p(a,b) = p(a \mid b)\, p(b) \tag{1}$$

in which $p(a,b)$ is the probability of the joint event $a \cap b$.

From (1) we can write the Bayes' theorem to calculate the posterior probability $p(a|b)$, given prior probability $p(a)$ and the likelihood of $p(b|a)$, available if $p(a)$ is real:

$$p(a,b) = \frac{p(b \mid a)\, p(a)}{p(b)}. \tag{2}$$

The normalizing factor can be calculated with

$$p(b) = p(b|a)\, p(a) + p(b|\bar{a})\, p(\bar{x}) \tag{3}$$

while $p(a|b) + p(\bar{a}|b) = 1$ is the condition used to compute $p(b)$.

The generalized form of Bayes' theorem (Darwiche, 2009) is given by:

$$p(b_i|a) = \frac{p(a \cup b_i)}{p(a)} = \frac{p(a|b_i)\, p(b_i)}{\sum_{j=1}^{n} p(a|b_j)\, p(b_j)}, \tag{4}$$

where $p(a)$ and $p(b) \geq 0$ and $p(b_i)$ are mutually exclusive events.

Another important rule in the domain of probabilistic calculus applied in Bayesian networks field is the rule of total probability (Kjerulff & Madsen, 2013), based on axiom 2. Let $P(A,B)$ be a joint probability distribution for two variables A and B defined on their domains Dom(A) = $\{a_1,\ldots,a_m\}$ and Dom(B) = = $\{b_1,\ldots,b_n\}$ which are sets of mutually exclusive states of A and B. This rule is given by:

$$\forall i: p(a_i) = p(a_i,b_1) + \ldots.. + p(a_i,b_n) = \sum_{j=1}^{n} p(a_i,b_j), \tag{5}$$

Using (5), $p(A)$ can be calculated from $p(A,B)$:

$$p(A)=\left(\sum_{j=1}^{n}p(a_1,b_j),.....,\sum_{j=1}^{n}p(a_m,b_j)\right), \tag{6}$$

Eq. (6) can be reduced to

$$p(A)=\sum_{j=1}^{n}p(A,b_j) \quad \text{or} \quad p(A)=\sum_{j}p(A,B) \tag{7}$$

described in Bayesian theory as marginalization out *B* of *p*(*A*,*B*) or elimination of *B* from *p*(*A*,*B*).

In the followings we supposed the basics of Bayesian theory (Munteanu & Nemeş, 2012) in availability evaluation is known and more examples are given related to this subject, specifically to availability of power systems nodes architectures.

3. Bayesian Networks for Availability Evaluation of Usual Architectures of Power Systems Nodes

In a previous paper Ciobanu *et al.*, (2016) the authors have presented the reliability analyses of two different nodal architectures.

The current paper is dedicated to the analyses of a much more complex nodal architecture, the double busbar architecture and the double busbar with transfer bar architecture (bypass bar), using for modelling Bayesian network technique.

The first nodal architecture, offering a high flexibility, has a double busbar and it is presented in Fig. 1. We considered the busbars also, even practically high reliable, to illustrate their importance on node availability.

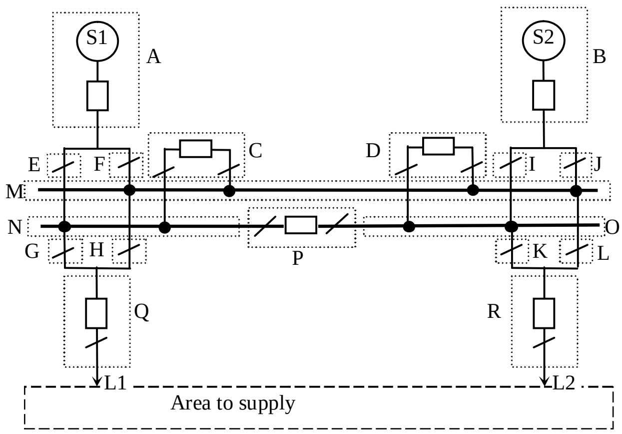

Fig. 1 – Double busbar architecture with components for node availability evaluation using Bayesian network technique.

The authors have established the corresponding tie-sets just for the left half of the diagram of Fig. 1 and they are shown in Fig. 2. The equivalent elements considered for tie-sets are:

a) source A;
b) transversal bus coupler C;
c) busbar isolators E, F, G and H;
d) bus M and bus section N;
e) outgoing lines with switching components Q.

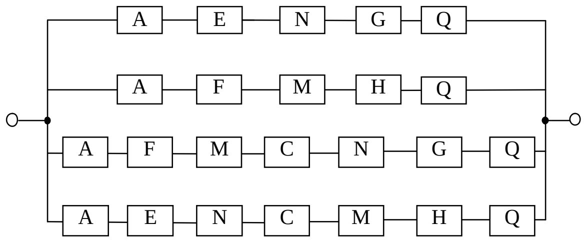

Fig. 2 – Tie-sets for the left half of the double busbar architecture in Fig. 1.

Supposing all components are two states (up and down) from reliability point of view with given probabilities, the corresponding Bayesian network is shown in Fig. 3.

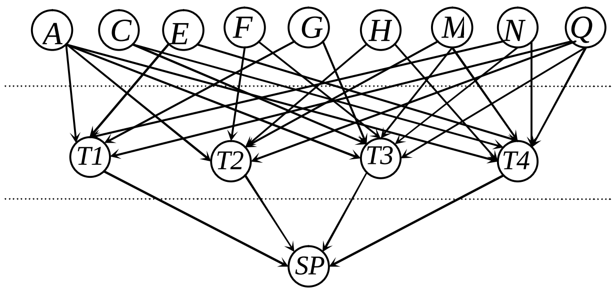

Fig. 3 – Bayesian network for the left side of the double busbar in Fig. 1.

The network structure implies that the joint distribution has the product form, according to the chain rule, given by:

$$\begin{aligned} & p(A,C,E,F,G,H,M,N,Q,T1,T2,T3,T4,SP) = \\ & = p(A)\,p(C)\,p(E)\,p(F)\,p(G)\,p(H)\,p(M)\,p(N)\,p(Q)\times \\ & \times p(SP|T1,T2,T3,T4)\,p(T1|A,E,G,N,Q)\times \\ & \times p(T2|A,F,M,H,Q)\,p(T3|A,C,F,G,N,M,Q)\times \\ & \times p(T4|A,C,E,H,N,M,Q). \end{aligned} \tag{8}$$

Components A and Q, series connected in the supply chain, are of a great importance for the nodal reliability.

The Hugin Expert software (Hugin software package, version 8.2.) was used for some calculations and analysis. It generated the Bayesian network presented in Fig. 4 where the variables are the same as defined in Fig. 3 while edges are showing the causal relationship between variables.

The values for marginal variables were taken according to (NTE 005/06/00, 2006) and introduced as conditional probabilities tables (CPT). For $p_A = 0.98$, $p_C = 0.97$, $p_E = p_F = p_G = p_H = 0.99$, $p_M = p_N = 0.99$ and $p_Q = 0.97$, the results are shown in Fig. 4.

A sensitivity analysis presented in Fig. 5 shows a low influence of the transversal coupler (C) and busbars (M, N) on the node reliability while disconnectors (E, F, G, H), participating in every cut-set, are greatly influencing the node reliability.

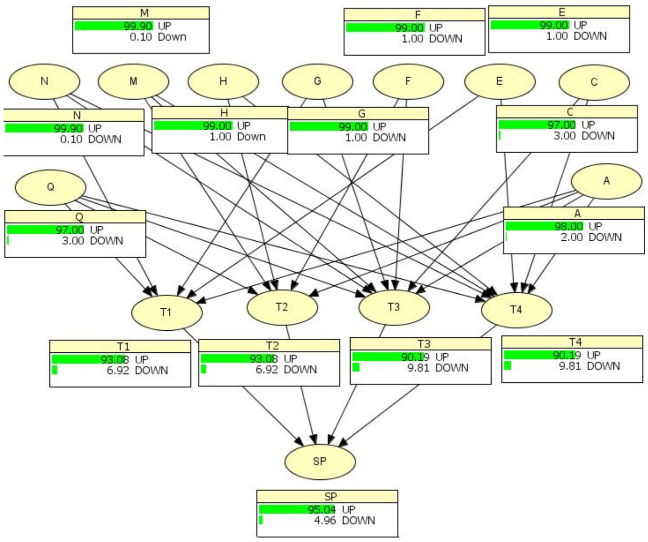

Fig. 4 – Probabilities flow in Bayesian network: input data for marginal nodes, calculated for tie-sets and for probability of supply of load at the end of L1 (left side of nodal diagram in Fig. 1).

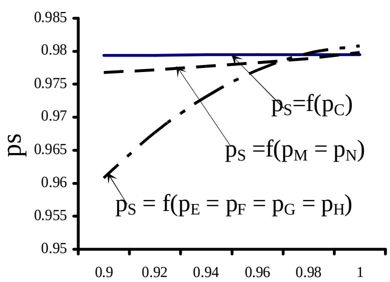

Fig. 5 – Sensitivity analysis from reliability point of view of a double busbar node.

The great advantage of Bayesian network and of its formal representation using direct acyclic graphs (DAG's) is due to the fact that it is easy to emphasis the subsystems and their probability distributions. As an example for the double busbar node architecture, Fig. 6 includes a supplementary node for reliability of the busbars, allowing for changes, viewing, and concluding on. As it can be seen, keeping the same causal relationship between random variables, the node probability of supply is identical to the one in Fig. 4 ($p_S = 0.9504$).

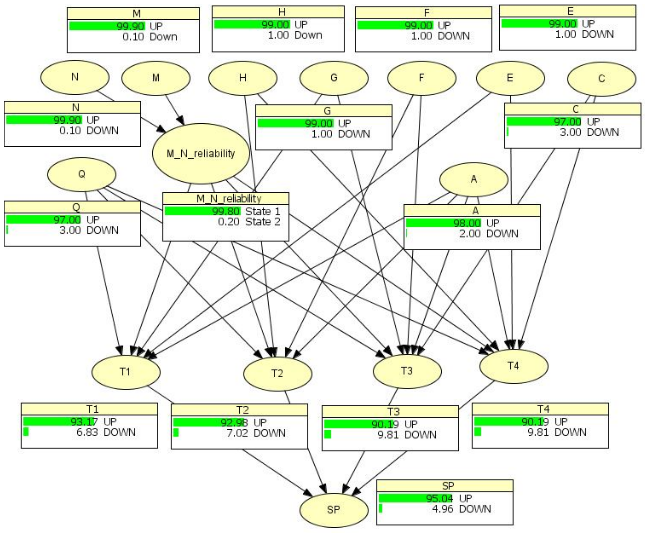

Fig. 6 – Bayesian network and the probability results for the double busbar node (M_N_reliability) revealing its conditional probability.

Developing the cut-sets for the entire diagram in Fig. 1 it is not difficult excepting their total number of elements n = 19 conducting to 2^{19} = 524,288 states as the starting point to establish the cut-sets manually. Utilization of suitable software to generate the cut-sets automatically is a convenient solution for complex reliability block diagrams (RBD)

Back-up supply represented by source B, connected using the longitudinal coupler P is the usual solution used to obtain a more reliable supply.

Another usual solution considered in this paper for reliability analyses of supply is the nodal architecture including a transfer busbar depicted in Fig. 7.

To be able to make a comparison between the first architecture and the current one, authors have established the minimal tie-sets for the same part of the diagram (the left half of the diagram in Fig. 7), and they are shown in Fig. 8.

This time, authors have inserted new equivalent elements besides those already used in Fig. 2, and considered them for tie-sets as:

a) transfer bar W;

b) transfer coupler S;
c) transfer bar isolators C1, C2;
d) transfer isolator U.

Furthermore, it has been established the maximum number of elements considered for tie-sets to be 7, the only difference between the two diagrams remaining the structure of the nodal architecture.

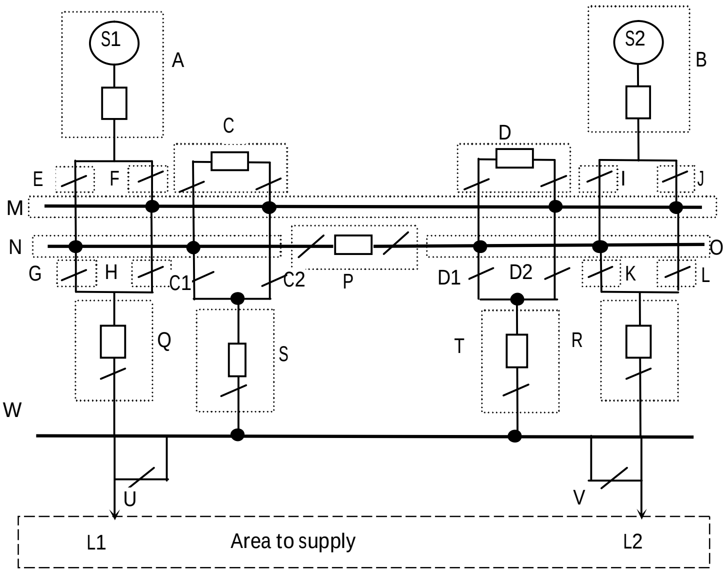

Fig. 7 – Double busbar architecture with transfer bar (bypass bar).

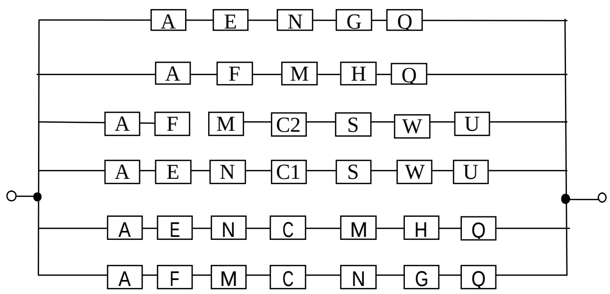

Fig. 8 – Tie-sets for the left half of the double busbar architecture including a transfer bar with maximum 7 equivalent elements.

To be able to develop the corresponding Bayesian network for fig. 8, it has been used the Hugin software, where the values for marginal variables were taken according to (NTE 005/06/00, 2006) and introduced as conditional probabilities tables (CPT) as shown in Fig. 9.

Comparing the results from the two nodal architectures that have been analysed, it can be said that the inclusion of the transfer bar increases the success probability of the network from 0.9504 to 0.9781.

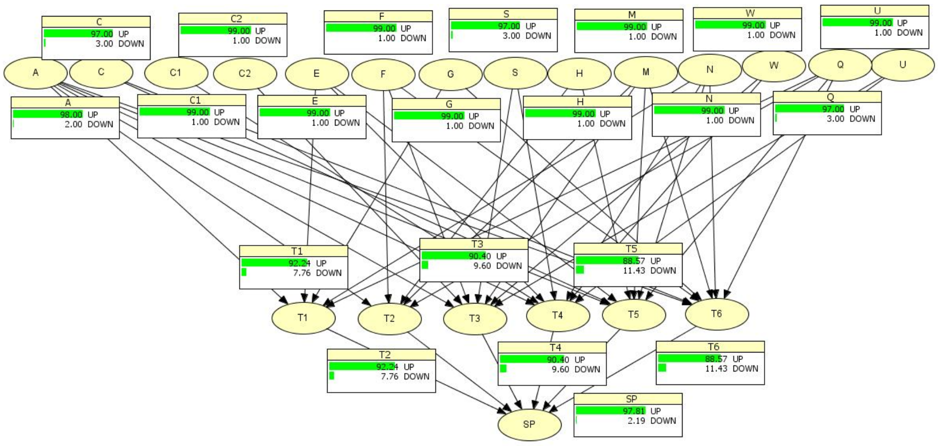

Fig. 9 – Bayesian network for the left side of the double busbar architecture including a transfer bar in Fig. 7.

4. Conclusions

The Bayesian networks are an extreme versatile tool for automated reasoning for systems driven by probabilistic variables. They can be constructed according to the axioms and rules of probabilistic calculus and based on the generalized Bayes' theorem. The power systems nodes availability can be assessed using Bayesian networks based on different techniques like cut-sets, tie-sets, fault trees, event trees or Markov chain method as converting the real technical systems to corresponding Bayesian networks. The authors presented the availability analysis of two usual nodal architectures as well as numerical case studies.

Future work is to be dedicated to more complex systems modeling: multi state circuit-breakers, power transformers monitoring and fault diagnosis, assessment of availability electricity networks with distributed generation and high degree of renewables sources penetration, using Bayesian networks driven by data.

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ANALIZA DISPONIBILITĂȚII ARHITECTURILOR NODALE UTILIZÂND REȚELE BAYESIENE

(Rezumat)

Rețelele Bayesiene s-au dovedit a fi un instrument important în domeniul electroenergetic pentru: analize de disponibilitate şi fiabilitate, analiza calitativă a energiei, evaluări de risc, monitorizarea componentelor şi diagnosticarea defectelor. Lucrarea este dedicată analizelor de fiabilitate ale sistemelor, autorii prezentând detalii în ceea ce priveşte modelarea bazată pe teorema lui Bayes de probabilități condiționate pentru diferite arhitecturi nodale din sistemul electroenergetic.

Diagrama bloc de fiabilitate, metoda căilor minimale, metoda grupurilor de defectare, arbori de evenimente sau arbori de defectare sunt câteva dintre tehnicile care pot fi utilizate pentru construirea rețelelor Bayesiene corespunzătoare sistemelor reale.