BELIEF NETWORKS UTILIZATION FOR NODAL POWER QUALITY AND AVAILABILITY ASSESSMENT

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The authors present the convenient utilization of a relative new technique, based on Bayesian networks, for nodal power quality and interruption risk evaluation in the case of power networks supplied from renewable energy sources.

Data mining for marginal probabilities calculation in a quantitative adequate analysis of a belief network are the first contribution of the authors focusing on the correlation factor of the two sources: solar and wind. The second contribution means a corresponding Bayesian model structure allowing to asses the nodal quality of supply from the power network including renewable energy sources like wind generators and solar panels as well as the main power network components.

Keywords: Bayesian networks, evidence, renewable energy, power quality

1. Introduction

The last decade proved new developments and applications of the so called Bayesian networks or belief networks, knowledge maps, causal probabilistic networks, influence diagrams, etc. [1]. The main suitable fields of this method are medical and technical diagnosis, language understanding, risk analysis, map learning. Some recent published results are related to reliability [2] and renewable energy sources [3].

In principle, a Bayesian (belief) network consists in a set of random variables, each of them having a finite set of states. Between variables there are a set of directed edges. A direct acyclic graph (DAG) is the formalization of a belief network as shown in fig.1 where A and B are called 'parents" and both are parents of the 'child' C, whereas C is a 'parent' of both D and E. Supplementary C is diverging into D and E. The marginal probabilities to be specified are P(A) and P(B). The *Bayes' theorem based on* conditional probabilities are P(C | A,B), P(E | C), P(D | C), P(F | D) and P(G | D,E,F).

For example, when A receives evidence, then it will directly influence all the subsequent probabilities. Considering the DAG in fig.1, evidence on A can change belief concerning B because of their connection through C. It will not

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affect P(C | A, B), which is constant (and is part of the variable domain specification), but it may lead to a different posterior distribution.

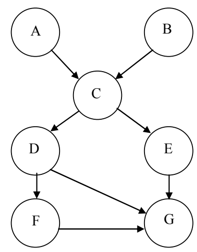

Fig. 1. DAG as formalization of a belief network

To analyze DAG, it is necessary to apply some standard probability rules:
- the fundamental rule for probability calculations: $P(A \mid B)\, P(B) = P(A, B)$;
- Bayes' rule: $P(B \mid A) = P(A \mid B)\, P(B) / P(A)$;
- marginalization: $P(A) = \sum_i P(A, b_i)$;
- conditional independence: A and C are independent given B if $P(A \mid B) = P(A \mid B,C)$.

Of great importance in a causal system is the chain rule. Let *BN* be a Bayesian network defined over $U = \{A1,\dots,Am\}$. Then the joint probability distribution P(U) is the product of all conditional probabilities specified in *BN*: $P(U) = \prod_i P(A_i \mid pa(A))$.

The last concept to be introduced is that of *d*-separation [4]. Two variables A_1 and A_2 in a causal network are *d*-separated if for all paths between A_1 and A_2 there is an intermediate variable B such that either:
- the connection is serial or diverging and the state of B is known, or
- the connection is converging, and neither B nor any of B's descendants have received evidence.

2. Belief network for supply interruption risk analysis

2.1 Real power and belief network structures

Fig 2 present a part of the power network supplied from renewable sources: wind and solar. The power availability is analyzed with respect of load node L considering the up-stream components failures, short-circuits as well as correlated sources reliability: S-solar and W – wind. R denotes an equivalent component from reliability point of view of the circuit-breaker, adjacent isolators and the current transformer. To calculate the marginal probabilities for wind and solar availability as primary electricity resources we need to establish, if any, the correlation degree between the two random variables: wind speed [km/h] and solar radiation [W/m^2].

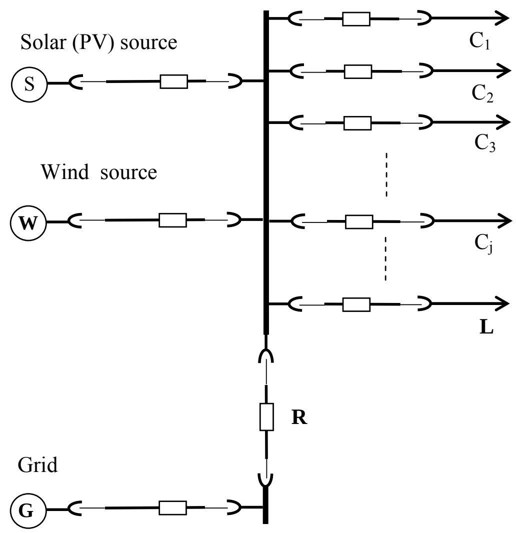

Fig. 2. The circuit considered for interruption risk analysis with respect of load point L: S-solar source; W-wind source; R-circuit-breaker (recloser) reliability equivalent

Fig.3 shows the belief network structure for power interruption risk analysis with respect of load point L in figure 2. The main important problem is to select suitable values for the marginal probabilities of the random variables: *ss, sw, us, rf* and *oa*. While the probabilities for up-stream short-circuit – *ss*, reclosure failures – *rf* and human reliability – *oa* can be estimated from literature data or practical experience the evidence for the two renewable sources, *ss* and *sw* involves a more detailed analysis.

2.2 The correlation factor of wind and solar sources

An important aspect for power networks supplied form renewable sources is related to the nodal power/energy availability. If the load peak is a classical problem in power systems, the same importance is given to the minimum load level when the renewable sources are present. The second case means the generated power exceeds the load and, consequently, the available solar or wind sources cannot be used in a proper manner.

That’s the reason for data mining concerning the correlation between the usual primary power sources: wind and solar. The different correlation factors were calculated using the following relations based on the assumption of a linear dependence of the wind speed and solar radiation.

For the second mentioned model, the major work was done for reliable and systematic input data acquisition and correlation concerning the basic energy sources parameters: wind speed (x) and total solar radiation (y). The purpose was to detect a possible and convenient negative correlation between the two random variables with a view to maintain available power in power system nodes to supply the loads.

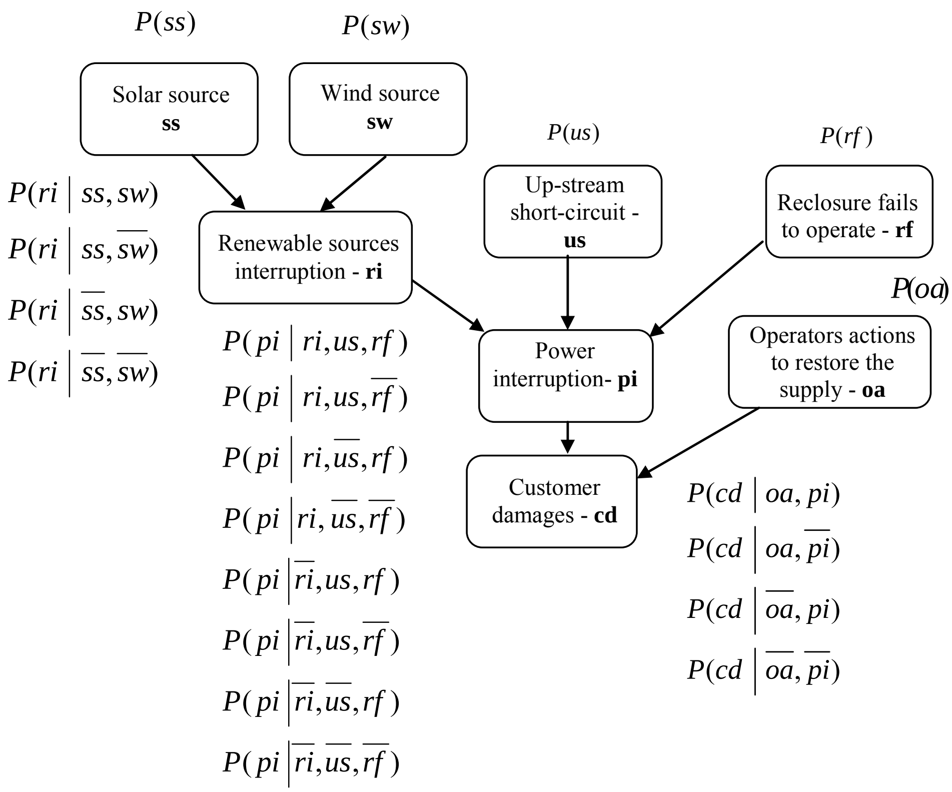

Fig. 3. Belief network structure for power quality (interruption) risk analysis

The selection correlation factor is given by equation (1) where x_i and y_i are measured data (available from meteorological specialized stations) and n is the total number of acquisitions.

Some test concerning the dependence between variables (linear or not) were performed according to the following algorithm:

- the data chain was divided in k classes of variation;
- for every j class having the centre x_j, the mean $\overline{y_{(x_j)}}$ and the variance $s^2{}_{y_{(x_j)}}$

were calculated using equations (2) and (3) where m_j is the number of values (x_{ij}, y_{ij}) of class j;

$$R_{x,y} = \frac{n\sum_{i=1}^{n} x_i y_i - \left(\sum_{i=1}^{n} y_i\right)\left(\sum_{i=1}^{n} x_i\right)}{\sqrt{\left[n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2\right]\left[n\sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2\right]}} \tag{1}$$

$$\overline{y}_{(xj)} = \frac{1}{m_j}\sum_{i=1}^{mj} y_{ij} \tag{2}$$

$$s_{y(xj)}^2 = \frac{1}{m_j - 1}\sum_{i=1}^{mj}\left(y_{ij} - \overline{y}_{(xj)}\right)^2 \tag{3}$$

- for i = 1, 2, ..., n we calculate:

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \quad \text{and} \quad \overline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{4}$$

$$s_x^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2 \quad \text{and} \quad s_y^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2 \tag{5}$$

- calculate $R_{x,y}$;
- calculate

$$F = \frac{\frac{1}{k-2}\sum_{j=1}^{k} m_j\left[\overline{y}\left(x_j\right) - \overline{y} - R_{x,y}\frac{s_y}{s_x}\left(x_j - \overline{x}\right)\right]^2}{\frac{1}{n-1}\sum_{j=1}^{k}\left(x_j - 1\right)s_{y(xj)}^2} \tag{6}$$

where $s_y = \sqrt{s_y^2}$ and $s_x = \sqrt{s_x^2}$;

- compare F with the critical value F_c given in literature according to the given belief levels;

- if $F > F_c$ the linear dependence between variables is rejected;

- calculate

$$H = \left|R_{x,y}\right|\sqrt{n-1} \tag{7}$$

- compare H with the critical value H_c given in literature;
- if $H > H_c$, the variables are correlated, positive or negative.

A set of input data for wind speed, solar radiation and temperature [^{0}C] were collected [4], [5] for airport area of Iasi county, every 1st, 10th and 20th days of every month of the year 2008. Figure 4 shows the wind speed and solar radiation correlation coefficients for every month of the year 2008. The different positive and negative values show a not unique dependence between the two random variables but allows for some conclusions related to its probabilistic evaluation.

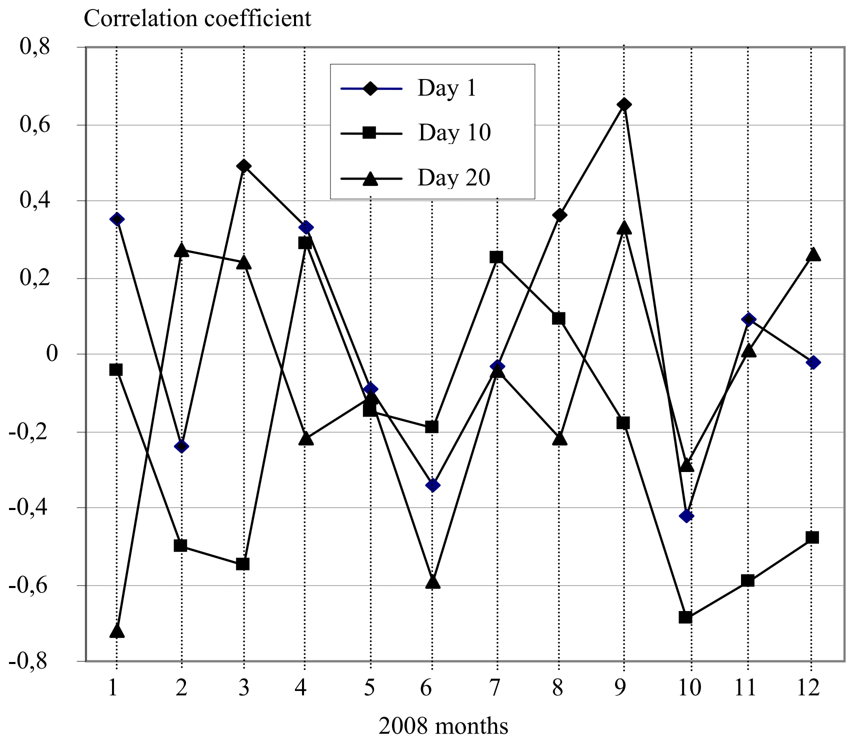

Fig. 4. Monthly correlation coefficients for 2008 between wind speed and solar radiation

The highest dependence, 0.46 was in October while the smallest, 0.11 in May. *From all data, 36.11% indicated a positive correlation and 63.89% a negative one*. This last value is a convenient one because the two sources allow for an alternate load supply, increasing the power node availability. From the positive correlation values, 56.52% were between 0 and 0.25, 21.74% between 0.25 and 0.50 while the same percent, 21.74% were between 0.50 and 0.75. From the negative correlation values, 30.77% were between 0.00 and 0.25, 61.54% between 0.25 and 0.50 and 7.69% between 0.50 and 0.75, [6].

2.3. Quantitative belief network analysis

Figure 5 shows the final belief structure based on the circuit in figure 2 and the attached conditional probabilities calculated using Bayes' theorem.

The marginal probabilities for the discrete random variables of the 'parent' nodes are shown in table 1. Table 2 indicates the conditional probabilities for the customer damages (*cd*) and interruption supply from renewable sources (*ri*).

A main feature of the belief networks is direct and back propagation of a new evidence practically based on new information, measurements or experience.

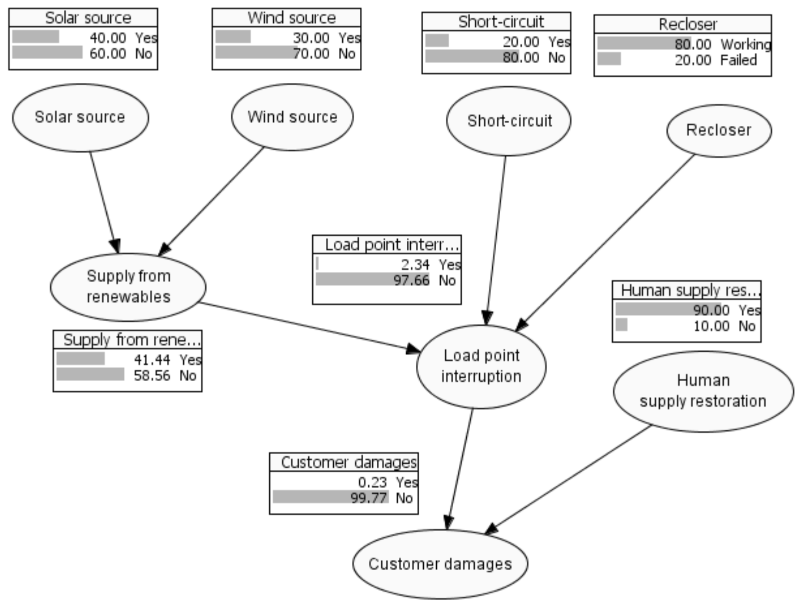

Fig. 5. Belief network with the attached conditional probabilities

For example, compared to the initial probabilities values, if the solar and wind marginal values are changed, the new propagated values for conditional probabilities are shown in figure 5.

Table 1

Wind source *ws*	Yes	0.3	Short-circuit *us*	Yes	0.2
	No	0.7		No	0.8
Solar source *ss*	Yes	0.4	Human restoration *oa*	Yes	0.9
	No	0.6		No	0.1
Recloser *rf*	Working	0.8			
	Failed	0.2			

3. Conclusions

Belief networks have become an increasingly useful paradigm for reasoning under uncertainty, addressing such tasks as diagnosis, prediction, decision making, risk evaluation, classification, and data mining. This paper proved this method like a suitable one for supply interruption in the case when there are renewable power sources. The marginal probabilities have to be carefully calculated even the posteriori evidence can be easily integrated in the network.

Table 2

	Solar *ws*	Yes		No	
	Wind *ss*	Yes	No	Yes	No
Supply from renewable sources *ri*	Yes	1	0.64	0.64	0
	No	0	0.36	0.36	1
	Power interrption *pi*	Yes		No	
	Human restoration *oa*	Yes	No	Yes	No
Customer damages *cd*	Yes	0	0	1	0
	No	1	1	0	1

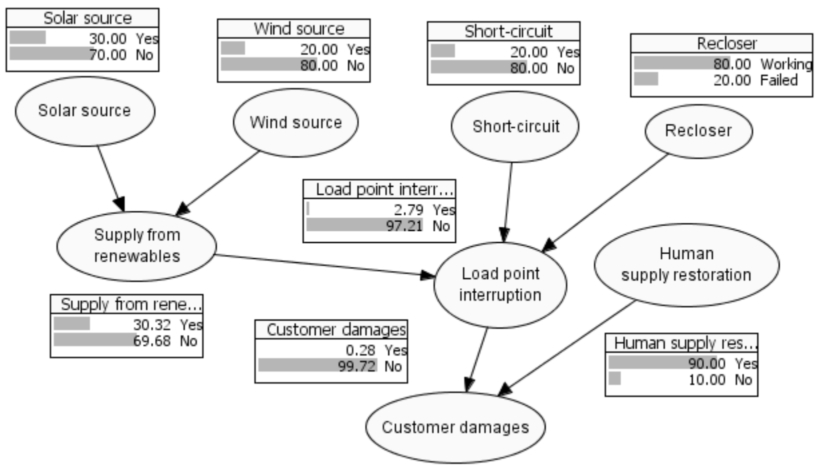

Fig. 6. Belief network with the new propagated conditional probabilities

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R E F E R E N C E S

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