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Joining Analytic Network Process and Bayesian Network model for fault spreading problem

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1. Introduction

This chapter deals with fault spreading (fault tree) in infocommunication networks (e.g. computer network, wired or wireless telecommunication network). The probabilistic approach of fault trees is in the focus, where faults can occur in the inner part of the network, spread step by step and can appear at the front end (observable directly by end users) of the network. The probabilities of the different inner faults and conditional probabilities of the steps of spreading are given. At the front end of the network many different errors caused by inner faults can occur; some of them may be serious, others may be not. Serious errors cause large damages in the operation of the network, e.g. material damage (an equipment breaks down), economical cost, human resource loss (expert should prepare it); less significant errors cause only little damages, inconveniences. There is not easy to decide which error is serious and which is not, and how much is significant. The task is to analyse the inner causes of errors at front end, and investigate the relative effects of these causes.

For this problem a method has been developed by joining the Analytic Network Process and the extended Bayesian Network. The generalized Bayesian Network with vector extension has been outlined in a previous work (Szűcs & Sallai, 2008). In this chapter the usefulness, correctness of the new elaborated method will be demonstrated by a numerical example.

The chapter is organized as follows: in section 2 an introduction about Analytic Network Process is given, section 3 summarizes the Bayesian Network and shows its generalization (Vector Bayesian Network, VBN). In section 4 a new concept for solving complex multi-criteria engineering decision problems is presented by combining the Analytic Network Process and VBN. Section 5 describes an example in the area of fault analysis in infocommunication networks. Section 6 summarizes the results and draws the conclusions.

2. Analytic Network Process

2.1. Multi Criteria Decision Analysis Methods

Analytic Hierarchy Process (AHP) is a well-known and one of the most comprehensive procedures in Multi Criteria Decision Analysis (MCDA) area. The AHP – has been introduced by Thomas L. Saaty (Saaty, 1980) – for decision-making is a theory of relative measurement based on paired comparisons used to derive normalized absolute scales of numbers whose elements are then used as priorities.

The Analytic Network Process (ANP) (Saaty, 2001) is the generalization of AHP for decision making with dependence and feedback allowing inclusion of all the factors and criteria. ANP has been proposed as a suitable MCDA tool to evaluate the alternatives during the conceptual planning and design in many areas, e.g. in economical problems, in engineering. The ANP (Saaty, 2005) provides a way to input judgments and measurements to derive ratio scale priorities for the distribution of influence among the factors and groups of factors in the decision. Both the AHP and the ANP derive ratio scale priorities by making paired comparisons of elements on a common property or criterion. Even though the ANP is a new method, there are many validation examples of the Analytic Network Process (Whitaker, 2007).

2.2. Steps of ANP Procedure

An Analytic Network Model of a problem may consist of a single network (or a number of networks), where a network is structured of clusters (i.e. groups of nodes), nodes (any aspect of the problem, e.g. alternative, attribute) and links (connection between nodes). The stages of creating of an ANP model are the following:

  a) Selection of logical groupings of nodes and clusters, which would best describe the problem.
  b) Building a cluster first, and then creating the nodes within it.
  c) Examination of influences.
  d) Creating connections between nodes.
  e) Clusters are linked automatically when nodes are linked.
  f) Pair-wise comparison judgments on nodes and clusters.

After pair-wise comparison judgments the algorithms in ANP take calculations and at the end give the decision: which is the best alternative for the problem. The algorithms solve the problem by supermatrices. There are three supermatrices associated with each network: the *Unweighted Supermatrix*, the *Weighted Supermatrix* and the *Limit Supermatrix*.

The *unweighted supermatrix* contains the local priorities derived from the pair-wise comparisons throughout the network. A component is defined as a block determined by a cluster name/identity at the rows and a cluster name/identity at the columns in a supermatrix. The *weighted supermatrix* is obtained by multiplying all the elements in a component of the unweighted supermatrix by the corresponding cluster weight. Cluster weights come from cluster comparisons. If there are only two clusters, then cluster comparisons cannot be executed, in this case the weighted and unweighted supermatrices are the same. The *limit supermatrix* is obtained by raising the weighted supermatrix to

powers by multiplying it many times itself. When the column of numbers is the same for every column, the limit matrix has been reached and the matrix multiplication process is halted. The priorities, as outputs of ANP for all the nodes can be read from any column, because the columns of the limit supermatrix are all the same.

AHP – as special case of ANP – can be used for many decision situations; its application area is wide: economy, business, engineering management and other areas, where the problems lead to multi criteria decision making. This can be applied in solving the technological decision problems as well, e.g. in network selection procedure for an integrated cellular/wireless local area network (WLAN) system to guarantee mobile users being always best connected. AHP helps to decide the relative weights of evaluative criteria set according to user preferences, network condition and service applications (Wei et al., 2007). Not only AHP, but ANP can help to take important decisions in network/telecommunication technology (Lee et al., 2009; Büyüközkan, 2007) 0or in media informatics (Chang, 2007). ANP can be applied in managerial practices as well (Chen, 2007; Wu & Lee, 2007). ANP in a little while becomes classical method, many publications deal with improvement, refinement (Saaty, 2007), further development (Yu & Cheng, 2007; Yu & Tzeng, 2006; Levy & Taji, 2007), supplement – e.g. with fuzzy (Dağdeviren et al., 2008; Promentilla et al., 2008) or with integer linear programming (Demirtas & Üstün, 2008) – of this.

3. Vector Bayesian Network

3.1. Bayesian Network Model

A Bayesian Network (BN) is a probabilistic graphical model for representing causal relationship among variables (Judea, 1982; Speigelhalter et al., 1993). This is a very important research topic in artificial intelligence and decision support area (Liu et al., 2009; Cheon et al., 2009; Correa et al., 2009). It consists of a set of nodes and directed arcs. The nodes represent variables and the arcs represent the directed causal influences between linked nodes. The arc starts from the parent node (A) to the child node (B). The child node is dependent on its parent node, but it is conditionally independent of others. The condition probability P(A|B) – showing how a given parent node A can influence the probability distribution over its child node B – is calculated using Bayes' Theorem:

$$p(A \mid B) = \frac{p(A \& B)}{p(B)}$$

(1)

$$p(A \mid B) = \frac{p(B \mid A) * p(A)}{p(B \mid A) * p(A) + p(B \mid \overline{A}) * p(\overline{A})}$$

(2)

BNs can be used for investigation of system in reliability analysis of engineering, there are some works (Wilson & Huzurbazar, 2007; Huang et al., 2006; Kohda & Cui, 2007) deal with it, but these do not handle with other aspects (e.g. financial costs) of the system.

3.2. Extension of Bayesian Network

In a Bayesian Network dependencies are generally complicated, so some preliminary formulas are required to handle the probabilities and variables. In Fig. 1. can be seen two typical types of BN pattern (part of graph), which can be used for building large networks. A such situation can be seen in Fig. 1/a, where more than one parent nodes have the same child node. In this case the conditional probability is:

$$p(_1X \mid Y) = \left\{ p(Y \mid _1X, _2X) \cdot p(_1X) \cdot p(_2X) + p(Y \mid _1X, _2\overline{X}) \cdot p(_1X) \cdot p(_2\overline{X}) \right\} /$$
$$\left\{ p(Y \mid _1X, _2X) \cdot p(_1X) \cdot p(_2X) + p(Y \mid _1X, _2\overline{X}) \cdot p(_1X) \cdot p(_2\overline{X}) + \right.$$
$$\left. p(Y \mid _1\overline{X}, _2X) \cdot p(_1\overline{X}) \cdot p(_2X) + p(Y \mid _1\overline{X}, _2\overline{X}) \cdot p(_1\overline{X}) \cdot p(_2\overline{X}) \right\}$$

(3)

If aggregated conditional probabilities (e.g. $p(Y \mid _1X)$ instead of $p(Y \mid _1X, _2X)$) are given, this can be written more generally: Let us denote $\{S_j\}$ the partition of the event space (S), (i.e. $\cup S_j = S$, $\cap S_j = 0$), the conditional probabilities can be formalized as:

$$p(S_i \mid Y) = \frac{p(Y \mid S_i) \cdot p(S_i)}{\sum_{j=1}^{n} p(Y \mid S_j) \cdot p(S_j)}$$

(4)

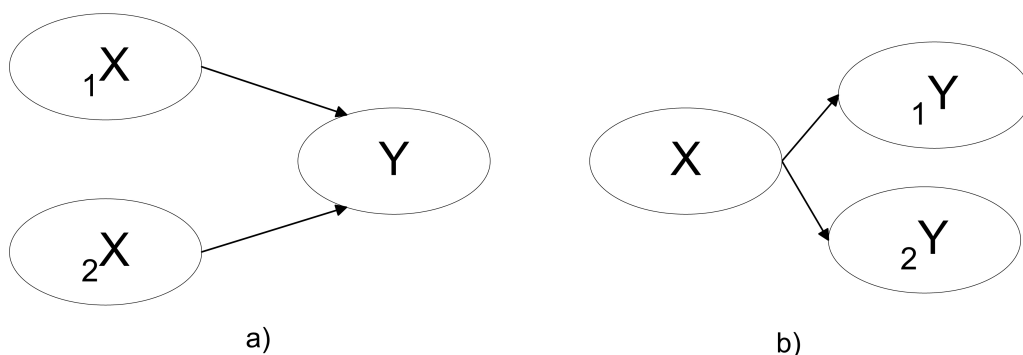a)   b)

Fig. 1. Structure Cases in Bayesian Network

In Fig. 1/b. can be seen such situation, where one parent node has more than one child. In this case the conditional probability is:

$$p(X \mid _1Y) = \frac{p(_1Y \mid X) \cdot p(X)}{p(_1Y \mid X) \cdot p(X) + p(_1Y \mid \overline{X}) \cdot p(\overline{X})}$$

(5)

or generally:

$$p(X|_iY) = \frac{p(_iY \mid X) \cdot p(X)}{p(_iY \mid X) \cdot p(X) + p(_iY \mid \overline{X}) \cdot p(\overline{X})}$$

(6)

Vectors are introduced for each $_iN$ node, $_iW=[_iW_1, _iW_2,…,_iW_m]$ as weight of different effects. By this vector an extension of Bayesian Network is introduced (so called Vector Bayesian Network: VBN), where nodes contain not only probabilities, but these weights (representing any information, e.g. importance, relative effect, cost). The weight vectors at leafs (having no children) in Vector Bayesian Network are given, and the weights at parent nodes should be determined.

In the VBN graph different structures of relationships can occur as well, e.g. parents can have more than one child: *case a* (see Fig. 1/a.), or more parent nodes may be the parents of the same node: *case b* (see Fig. 1/b.). The unknown weights can be calculated in every case.

3.3. Weight Calculations in VBN
The weight vector of $_1X$ node in *case a* is $_1w=[_1w_1, _1w_2,…, _1w_m]$, which depends on the weight vector of Y node $w=[w_1, w_2,…, w_m]$. (The numbers of the dimensions of all vectors are equal.) The ratio of the weight vector of the parent node and the child node is the conditional probability. So each element of the weight vector $_1X$ node can be calculated as follows:

$$_1w_k = p(_1X \mid Y) \cdot w_k =$$
$$= w_k \cdot \left\{ p(Y|_1X, _2X) \cdot p(_1X) \cdot p(_2X) + p(Y|_1X, \overline{_2X}) \cdot p(_1X) \cdot p(\overline{_2X}) \right\} /$$
$$\left\{ p(Y|_1X, _2X) \cdot p(_1X) \cdot p(_2X) + p(Y|_1X, \overline{_2X}) \cdot p(_1X) \cdot p(\overline{_2X}) + \right.$$
$$\left. p(Y \mid \overline{_1X}, _2X) \cdot p(\overline{_1X}) \cdot p(_2X) + p(Y \mid \overline{_1X}, \overline{_2X}) \cdot p(\overline{_1X}) \cdot p(\overline{_2X}) \right\}$$

(7)

for every $1 \leq k \leq m$. The $_2X$ nodes and other $_iX$ nodes – in case of more than two parent nodes – can be calculated by similar way.

There is a different situation, when the number of parent node is one and this node has more child nodes, like in *case b*. The weight vector of X node is denoted $w=[w_1, w_2,…,w_m]$. The weight vectors of the child nodes ($_1Y, _2Y$, etc.) are denoted $_1w=[_1w_1, _1w_2,…, _1w_m]$, $_2w=[_2w_1, _2w_2…, _2w_m],…, _nw=[_nw_1, _nw_2,…, _nw_m]$, where *n* is the number of the child nodes. The elements of the weight vector – as representing the effects – at the parent node are cumulated from child node ones. So the weight vector X node can be calculated as follows:

$$w_k = \sum_{i=1}^{n} p(X|_iY) \cdot_i w_k = \sum_{i=1}^{n} \frac{p(_iY \mid X) \cdot p(X)}{p(_iY \mid X) \cdot p(X) + p(_iY \mid \overline{X}) \cdot p(\overline{X})} \cdot_i w_k$$

(8)

for every $1 \leq k \leq m$.

4. Combination of ANP and VBN Methods

The problem described in the introduction can be solved by joining Analytic Network Process and extended Bayesian Network such way, that the weights, the results of ANP will give the input of VBN (as can be seen in Fig. 2.). Bayesian Network (and VBN also) can get inputs in many points, but in our combination VBN adopts the weights, as inputs in leafs of the graph; and these weights are organized in vector format.

Our joint method is able to analyse the reasons and spreading of faults in infocommunication network by the following way. At first step the network (human) expert defines the different types of the front end faults, and the criteria (features) which influence the importance (at the given goal) of the fault type. E.g. if the aim is to minimize the total cost, the criteria should involve the cost of fault repairing, the scope of the fault, the length of the repairing time. The network expert may declare other criteria for another aim. Then the expert compares the fault types with each other (pair-wise comparison with all), and the criteria (pair-wise comparison as well in order to get the criterion relative ratios). After the expert judgements the ANP method calculates the weights of the fault types, at case of economic aim this gives the total costs for each fault type.

At the next step the network expert draws the inner structure of the infocommunication network by nodes and directed edges such way, that the edges should be in the directions of the front end of the network. The expert describes the possible paths of the fault spreading with these directed edges. The arising of faults is modelled in the nodes (included inner nodes and front end nodes), the expert should give the probability of fault arising in every node. The nodes, where the directed edges "only come from", are *fault sources*, the other nodes can be considered as *fault spreading nodes*. The probabilities of fault arising at fault sources are unconditional ones, and probabilities of fault arising at nodes of fault spreading are conditional probabilities. The graph worked out by the above mentioned way will be the structure of the VBN model, furthermore the unconditional and conditional probabilities will be the parameters of VBN.

The serial of relative weights of fault types calculated by ANP method can be written as a vector, this vector will be the input of VBN at the front end nodes. This vector is a consequence, and the reasons of the consequence are the questions, so the expert users would like to know the origins. The VBN method gives the contribution of the given node to the different types of front end faults for every node in the graph (representing e.g. infocommunication network) as most important result of the joint procedure.
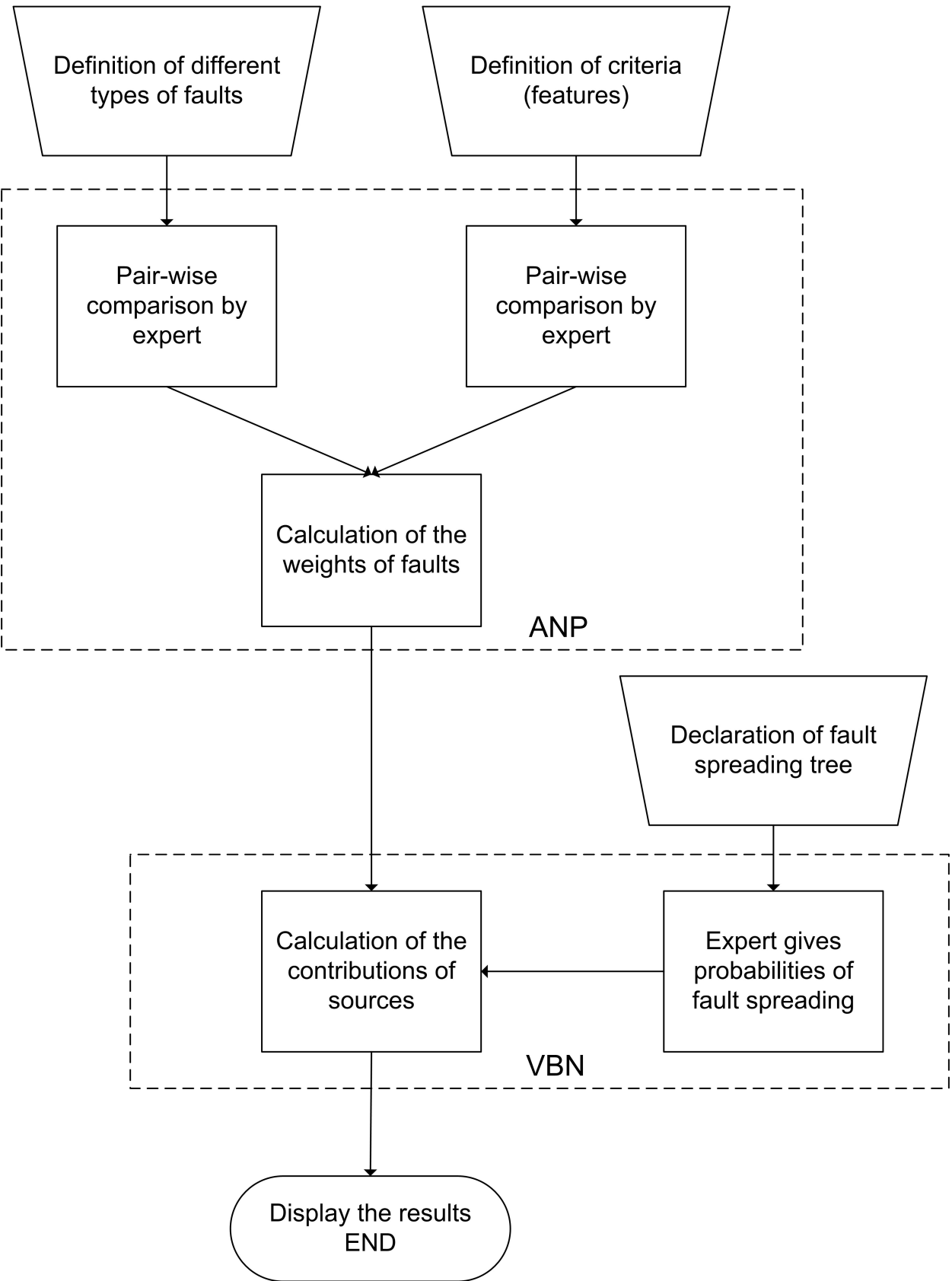
Fig. 2. Block of the Solution Procedure by ANP and VBN Methods

5. Case Study

5.1. Example for Fault Spreading

There are three errors occur at the front end of the network: i) breakdown event at an average user, ii) malfunction at an average user, iii) error at administrator site. These errors are considered as alternatives (A1, A2, A3) in ANP. The relative significance of them depends on many points of views, these criteria are in our example: priority of user, scope of the error, cost of reparation, time of restore (F1,…, F4).
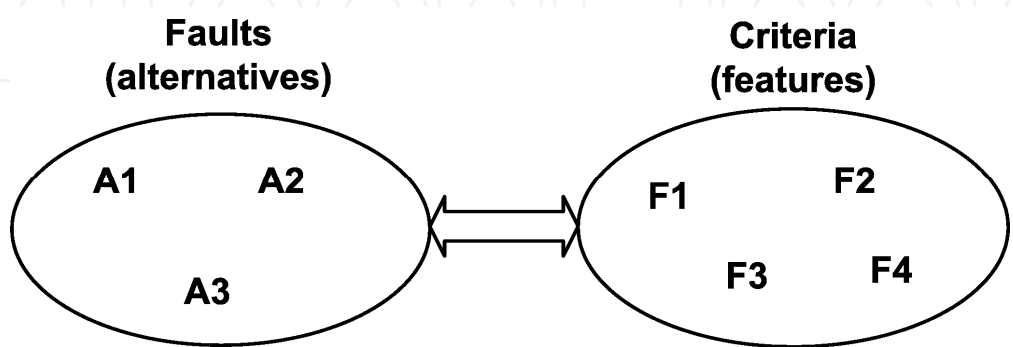

Fig. 3. Nodes in Two Clusters for ANP Procedure

The Fig. 3. shows the structure of the ANP model with two clusters (Faults and Criteria) and a connection between the clusters. This connection means that there are relationships between every node in cluster *Faults* and every node in cluster *Criteria*, but there is no inner-relationship in a cluster. The clusters contain the following nodes:

A1: breakdown event at an average user,

A2: malfunction at an average user,

A3: error at administrator site,

F1: priority of user

F2: scope of the error,

F3: cost of reparation,

F4: time of restore.

5.2. Numerical Example for ANP

A network expert can compare the features of errors based on these criteria. E.g. the 'scope of the error' feature of A_1 alternative is twice larger important than feature of A_2 alternative (see Table 2). The expert should execute all pair-wise comparisons in each criterion. The following matrices (Table 1-4) contain a possible judgment of expert's opinions.

	A1	A2	A3
A1	1,00000	1,00000	0,25000
A2	1,00000	1,00000	0,25000
A3	4,00000	4,00000	1,00000

Table 1. Comparisons based on Priority of User

	A1	A2	A3
A1	1,00000	2,00000	0,16667
A2	0,50000	1,00000	0,12500
A3	6,00000	8,00000	1,00000

Table 2. Comparisons based on Scope of the Error

	A1	A2	A3
A1	1,00000	6,00000	0,33333
A2	0,16667	1,00000	0,11111
A3	3,00000	9,00000	1,00000

Table 3. Comparisons based on Cost of Reparation

	A1	A2	A3
A1	1,00000	0,33333	0,16667
A2	3,00000	1,00000	0,25000
A3	6,00000	4,00000	1,00000

Table 4. Comparisons based on Time of Restore

	F1	F2	F3	F4
F1	1,00000	2,00000	0,25000	1,00000
F2	0,50000	1,00000	0,16667	0,50000
F3	4,00000	6,00000	1,00000	3,00000
F4	1,00000	2,00000	0,33333	1,00000

Table 5. Comparisons of Faults from the Viewpoint of A1

	F1	F2	F3	F4
F1	1,00000	2,00000	0,33333	1,00000
F2	0,50000	1,00000	0,20000	0,50000
F3	3,00000	5,00000	1,00000	3,00000
F4	1,00000	2,00000	0,33333	1,00000

Table 6. Comparisons of Faults from the Viewpoint of A2

	F1	F2	F3	F4
F1	1,00000	2,00000	0,40000	1,00000
F2	0,50000	1,00000	0,20000	0,50000
F3	2,50000	5,00000	1,00000	2,50000
F4	1,00000	2,00000	0,40000	1,00000

Table 7. Comparisons of Faults from the Viewpoint of A3

Having a comparison matrix the priority vector can be computed, which is the normalized eigenvector of the matrix, e.g. eigenvector of F1 (priority of user) matrix are: 0.166667, 0.166667, 0.666667. The other eigenvectors are also calculated by *SuperDecisions* software (realization of ANP theory helping by Thomas Saaty) and written to the corresponding cells of the supermatrix. This unweighted supermatrix (containing 4 components: Crit.-Crit., Crit.-Faults, Faults-Crit., Faults-Faults) can be seen in Fig. 4., and because of only two clusters this matrix is equivalent to weighted supermatrix.

Cluster Node Labels		Criteria				Faults		
		F1	F2	F3	F4	A1	A2	A3
Criteria	F1	0.000000	0.000000	0.000000	0.000000	0.164653	0.185424	0.200000
	F2	0.000000	0.000000	0.000000	0.000000	0.088255	0.097141	0.100000
	F3	0.000000	0.000000	0.000000	0.000000	0.570584	0.532012	0.500000
	F4	0.000000	0.000000	0.000000	0.000000	0.176509	0.185424	0.200000
Faults	A1	0.166667	0.146760	0.278461	0.091399	0.000000	0.000000	0.000000
	A2	0.166667	0.083999	0.058471	0.217645	0.000000	0.000000	0.000000
	A3	0.666667	0.769241	0.663067	0.690956	0.000000	0.000000	0.000000

Fig. 4. Unweighted and Weighted Supermatrix

The Limit supermatrix is calculated based on ANP theory and the matrix can be seen in Fig.5. In the last 3 rows can be seen the importance values of alternatives in the supermatrix, these can be normalized in its cluster, thus the final results are: A1: 20.81%, A2: 11.24%, A3: 67.95%.

Cluster Node Labels		Criteria				Faults		
		F1	F2	F3	F4	A1	A2	A3
Criteria	F1	0.095503	0.095503	0.095503	0.095503	0.095503	0.095503	0.095503
	F2	0.048617	0.048617	0.048617	0.048617	0.048617	0.048617	0.048617
	F3	0.259144	0.259144	0.259144	0.259144	0.259144	0.259144	0.259144
	F4	0.096736	0.096736	0.096736	0.096736	0.096736	0.096736	0.096736
Faults	A1	0.104055	0.104055	0.104055	0.104055	0.104055	0.104055	0.104055
	A2	0.056208	0.056208	0.056208	0.056208	0.056208	0.056208	0.056208
	A3	0.339737	0.339737	0.339737	0.339737	0.339737	0.339737	0.339737

Fig. 5. Limit Supermatrix

5.3. Calculations in VBN

The example is continued with the relative weights, which are equal the importance multiplied by the probabilities. The fault spreading and probabilities can be seen in the Fig.6., where A is the link defect, B is the node breakdown, C is the fault in central part, and D_1-D_3 are the front end errors (D_1: breakdown event at an average user, D_2: malfunction at an average user, D_3: error at administrator site). D_i probabilities can be calculated: 0.0639, 0.0213, 0.0229, so the weight vector in D node is $_dw$=[0.013298, 0.002394, 0.015561].

P(A)
0.01

A	B	P(C|A,B)
E	E	0.95
E	N	0.94
N	E	0.3
N	N	0.001

P(B)
0.02

C	P(D1|C)	P(D2|C)	P(D3|C)
E	0.9	0.7	0.8
N	0.05	0.01	0.01
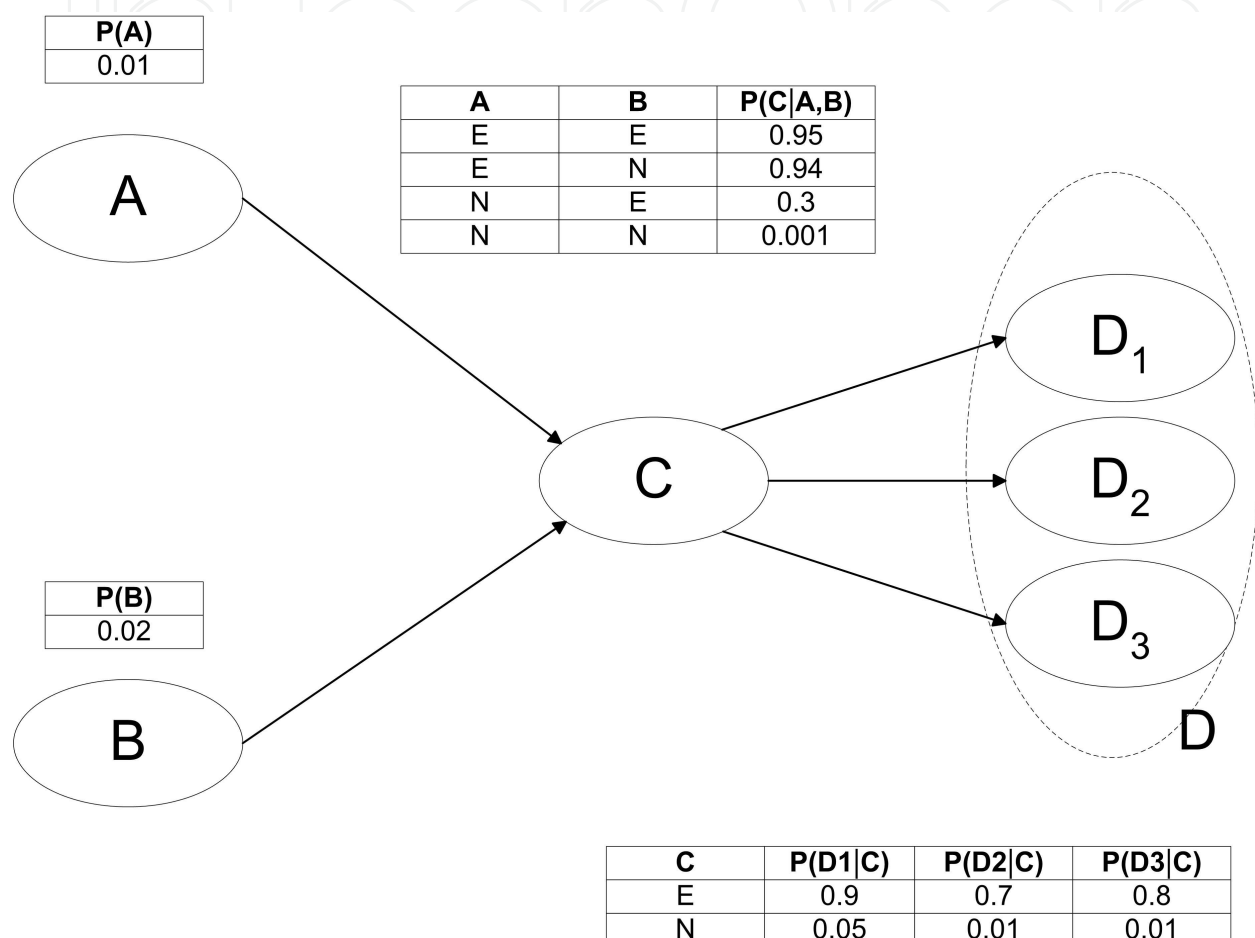
Fig. 6. Fault Spreading Example in an Infocommunication Network

5.4. Numerical Results

Fig. 6. shows the unconditional (at node A and B) and conditional (at node C and D) probabilities of faults. In VBN the parent vector weights can be determined by the formulas shown above. The weight vectors, as final results at A, B, C node are $_aw$=[0.001769, 0.000742, 0.005118], $_bw$=[0.001293, 0.000499, 0.003428], $_cw$=[0.003057, 0.001213, 0.008320] respectively. These values represent the aggregated information about the average effect of faults at the front end. For example $_aw_1$ shows that inner link defect causes average 0.1769% damage in 'breakdown event at an average user' provided the damage of once occurrence of this front end error is 20.81% of total damage of the system.

6. Conclusion

The ANP has been applied to a large variety of decisions: marketing, medical, political, military, social, prediction and many others. ANP is able to take analysis of benefits, opportunities, costs, and risks (BOCR) (Wijnmalen, 2007).

Bayesian Networks are applied in query languages in scientific area of information retrieval (Cheng & Yang, 1999)0, in environmental modelling (Uusitalo, 2007). There are some improvements or combined versions of BN, e.g. combination with fuzzy (Li & Kao, 2005), and many authors deal with further development.

There are some complex (decisional and engineering) problems, where neither ANP nor BN could help to solve alone. Some of these problems are usually such sophisticated, which involve human opinions with uncertainty, causal relationships, and uncertainties in the occurrence of events. These tasks can be solved by the proposed method constructed by combination of ANP and extended version of Bayesian Networks, i.e. by joining these two methods in cascade. Vector Bayesian Networks (VBN) is a generalized BN, which able to handle not only the probabilities, but any numerical value attached to nodes. This extension is able to calculate spreading of effects in any network. The combined method is particularly useful to investigate fault spreading problem in infocommunication networks.

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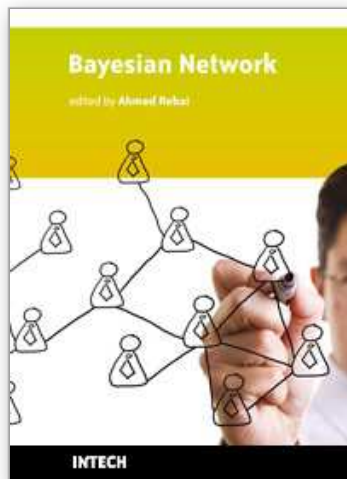
Bayesian Network

Edited by Ahmed Rebai

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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