A fault tree – Based Bayesian network construction for the failure rate assessment of a complex system

El-Hassene Ait Mokhtar[1], Radouane Laggoune[1], Alaa Chateauneuf[2]
[1]Faculty of Technology, Research Unit LaMOS, University of Bejaia
Campus de Targa Ouzemour
06000, Bejaia, Algeria

[2]Pascal Institute, University of Blaise Pascal
Campus des Cézeaux, BP 206
63174, Aubière cedex, France

Abstract

This paper presents a methodology, for the failure rate assessment of complex systems, based on the Bayesian networks and fault tree analysis. To avoid the problem of the complex system modelling, we have associate the Bayesian network with fault tree method. The expert judgment is also considered for the modelling to complete the lack of data. For the Bayesian inference, we have used the Junction tree method to compute the failure probability of the system, which is transformed into failure rate. This methodology is applied to estimate the failure rate of a turbo-pump, located at a pipeline, of the Algerian company of petroleum "SONATRACH".

Keywords: Failure rate estimation, fault tree, Bayesian network, dependencies, complex system.

1. Introduction

Technological progress have made that modern systems have become more complex, especially regarding their structure. This made it difficult to estimate the reliability characteristics, in particular the failure rate of such systems. The main objective of this paper is to develop a methodology, for the evaluation of the failure rate of a complex system, based on the Bayesian networks and the fault tree techniques.

Some studies have shown that the modeling of complex systems using Bayesian network is very expensive [1]. Therefore, we believe that it is more appropriate to introduce the fault tree method, which is more explicit and less complicate to establish, in order to facilitate the Bayesian network construction. The transformation of the fault tree to Bayesian network is made through a transition algorithm, this algorithm allows a qualitative and quantitative transition [2]. Indeed, the qualitative transition allows the transformation of the components and gates to nodes in the Bayesian network. The quantitative one allows obtaining the probability tables of the nodes. The expert judgments are also used to improve the modeling and to face the lack of data. Then the Bayesian inference permits the computation of the marginal probability, which is transformed to a frequency (the failure rate of the system).

This methodology is applied, for a real complex system, to estimate the failure rate of a turbo-pump of the Algerian company of petroleum "SONATRACH".

2. Background

1.1 Bayesian networks, definitions and properties

Definition 1 (Bayesian networks) *a Bayesian network* $\mathfrak{B} = \{\mathcal{G}, \mathbb{P}\}$ *is defined by:*

- *A directed acyclic graph* $\mathcal{G} = (X, E)$ *where* X *is a set of nodes (or vertices) and* E *is a set of directed links (or edges);*
- *A probability space* $(\Omega, \mathbb{P})$;
- *A set of random variables* $X = \{X_1 \dots X_n\}$ *associated with the graph's nodes* $(\Omega, \mathbb{P})$ *such as* $\mathbb{P}(X_1 \dots X_n) = \prod_{i=1}^{n} \mathbb{P}(X_i / Pa(X_i))$ *where* $Pa(X_i)$ *is the set of the parent's nodes of the node* X_i *in* $\mathcal{G}$.

1.2 Bayesian networks and other methods of dependability assessment

In literature, except the BNs, there are three traditional methods used in dependability of complex systems; the fault tree (FT), Markov chain (MC) and Petri networks (PN) [3]. Several works have demonstrated equivalences between FTs and dynamic Bayesian networks (DBNs) [4, 5]. The FT also gives interesting modeling results; they permit the integration of the dependencies between the events and the exact calculation of the failure probability. But, they don't permit to take into consideration the events with several consequences. The MCs are used to evaluate the reliability and the availability; they allow to represent the multi-state variables and to perform exact calculations. However, the modeling of systems, configured in networks with several causalities, becomes very difficult with a very large number of variables [6]. According to [7] this number is considerably lower using BNs and DBNs. The PNs are used on the maintenance modeling [8] and in the maintenance optimization. It is based on the simulation procedures, so they need an important time of calculation and they don't treat the low frequency events (example: an accident is a law frequency event but it have a big economic and material impact on the system) [3]. Many works have proposed methods allowing the passage form FTs and MCs to BN or DBNs [9, 10].

1.3 Bayesian networks in reliability

Many papers have proposed methods in reliability and availability analysis of complex systems using BNs thanks to their interesting properties. In [11], the authors have combined the evidence theory with BNs in order to create an effective tool for the reliability analysis of systems under random uncertainties, using "dempster shafer" theory. In [12], the reliability of a parallel-series system is studied; the obtained result (system reliability) can be updated when a new data becomes available. In [13], the authors have studied a real case which is the maintenance planning of a factory producing carbon black in UK. They have used BN to estimate the system failure rate; the result is then integrated in a maintenance model in order to provide an optimal maintenance plan. is another type of BNs which is also used on dependability analysis of complex systems. In [14], a Dynamic Oriented Object Bayesian Networks (DOOBN) is used to conduct a reliability analysis of complex systems. In [15] the authors have estimated the availability of a system in several cases: known, unknown CPT and integrating additional data. In [2], authors have used the hybrid Bayesian networks (HBN) since the different causes that have influence on the availability assessment are continuous variables (time to repair, programmed preventive maintenance times and delays). We have to know also that BNs are used for the redundant systems and gives improvements on the complex systems modeling by adding a "coverage factor" [16], this factor represents the probability that a simple failure of a redundant component causes the failure of the whole system. The coverage factor can be modeled by FT [7] but according to [16], it is more meaningfully using BNs.

2. Complex system modelling

2.1 Complex systems

Definition 2 (Complex system)
A complex system is a structured set of independent heterogeneous devices that are connected and communicate with each other in order to perform a function.

For the series systems, the failure of any component leads to the whole system failure; in parallel systems, their failure occurs only when all its components fail simultaneously. For the complex systems, it is more difficult to evaluate the impact of the failure of one component because of the different interactions between its components. Therefore, modeling complex systems by BN may be expensive and needs the implication of many experts [1]. For this, we introduced the fault tree method in order to facilitate the modeling of such systems.

2.2 Fault tree method

Fault tree analysis is a basic method used to determine the sequence of events that can lead to an undesired event, which is generally identified thanks to "preliminary risk analysis". This analysis allows exploring the causes one by one until the identification of the origin of the undesirable event. The links between the different components are represented by logical gates (AND, OR, k: n…).

The different steps of this methodology are:

- Define the undesired event (Top event): this event should be defined as clearly as possible. A preliminary risk analysis may help to define the undesired events to be considered. This event will form the head event on the FT (the root event).

- Define the limits of the study (the boundary between the system and its environment);
- Define the level of detail and resolution of the study. For example, it is necessary to determine if the analysis should be stopped at the level of sub-systems or be extended to the components. Note that the choice of this level depends on the study objectives, the technological complexity of the system and the availability of components data;
- Define the links between the events. The FT is developed from the top event by fixing the direct causes that lead for its occurrence. Logical gates (AND, OR, k:n…) are used to describe the different connections between the top event and its causes (intermediate events).

2.3 Mapping fault tree to Bayesian network

The Bayesian networks and fault tree are both considered as powerful techniques of dependability analysis [2], in this paper; we integrated an algorithm that permit the transition from FT to BN. The following assumptions must be verified:

1. The events must be binary (example: working\not working);
2. The events are statistically independent;
3. The relations between the events are represented by logical gates;
4. The root of the FT is the undesired event to be analyzed.

The transition steps from the FT to BN are:

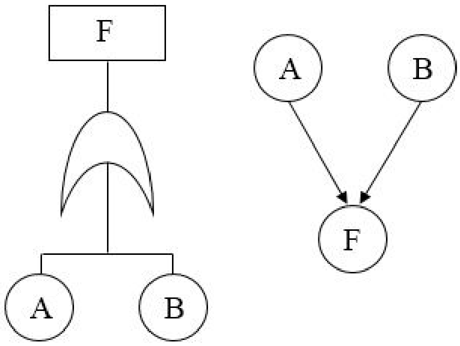
- For each leaf node (primary event or component) in the FT, create a root node in the BN. If more than one leaf on the FT represents the same event, create just one root node in the BN;
- Assign to the root node in the BN the prior probability of the related leaf node in the FT;
- For each logical gate in the FT, create a node in the BN;
- Connect nodes in the BN as the corresponding nodes are connected in the FT;
- For each logical gate in the FT, assign the conditional probability tables to the related nodes in the BN.

Example of logical gate transition

Two simple examples of transition from a FT to BN of two logical gates “AND” and “OR” with their corresponding CPT are given in figures 1 and 2. We can see that for the logical gates, it is very simple to create their corresponding CPT. But for the primary events or components it is not as simple as the gates. In fact, to create prior probabilities we need to transform the failure rate used for FT into a probability in BN. In [13], the authors have proposed a transition method from the failure rate (which is basically a frequency) into a failure probability. The failure rate λ is divided by a factor $\vec{\lambda}$, it represents the maximum frequency rate of failure that causes the failure of the whole system during its operating time. So, the failure probability is given by:

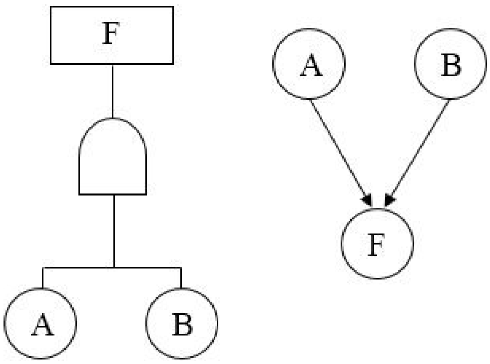
$$P = \lambda \times \vec{\lambda}^{-1} \tag{1}$$

Note that, if the failure rate of node is superior to its corresponding $\vec{\lambda}$, the prior probability of this node is equal to 1. In the transition phase, we can add some nodes representing events which are not modeled in FT (adverse climate conditions, operator skill). These nodes are added after consulting the expert opinion.



A	B	F
0	0	0
0	1	1
1	0	1
1	1	1

Figure 1. Logical gate "OR" with its transition into BN



A	B	F
0	0	0
0	1	0
1	0	0
1	1	1

Figure 2. Logical gate "AND" with its transition into BN

2.4 Inferences in Bayesian networks

When the BN structure is defined, the probabilities are assigned (prior probabilities for the root nodes and conditional probabilities for the rest of the nodes), the Bayesian inference can be conducted, it allows the computation of the marginal probability of a node (component or event) by taking into account the interactions between the nodes of the network. There are two kind of Bayesian inference: the exact inference method and the approximate inference method. In this work, we have used the junction tree method (also called clustering or clique-tree propagation algorithm) introduced by Jensen [17] in 1990. It is an exact inference method and it can be applied for all DAG structures. An algorithm is constructed under MATLAB; it allows computing the occurrence probability of the top event which is the leaf node on the BN.

3. Application

For the validation purpose, this methodology is applied to an industrial system. It consists of a turbo-pump located in a pumping station of the Haoud-El-Hamra-Bejaia pipeline (Algerian company of petroleum SONATRACH). The turbo-pump is a centrifugal type, constituted by the pump and the turbine (fig. 3).

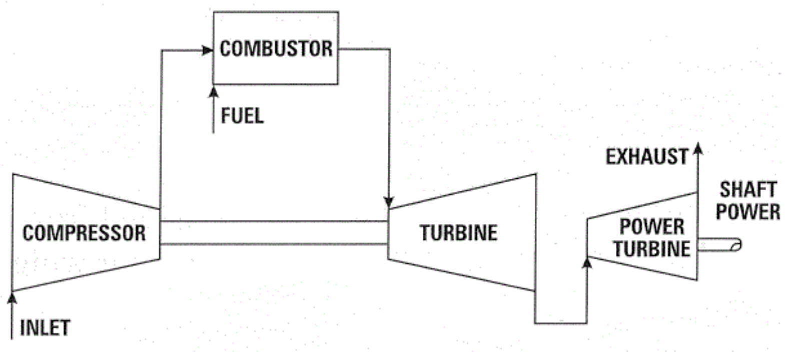


Figure 3. Group turbo-pump

3.1 Fault tree of the turbo-pump

The FT of the turbo-pump is modeled in collaboration with the company experts. The primary event chosen is the breakdown of the whole system. The FT of the system is shown in the figure 4, with:

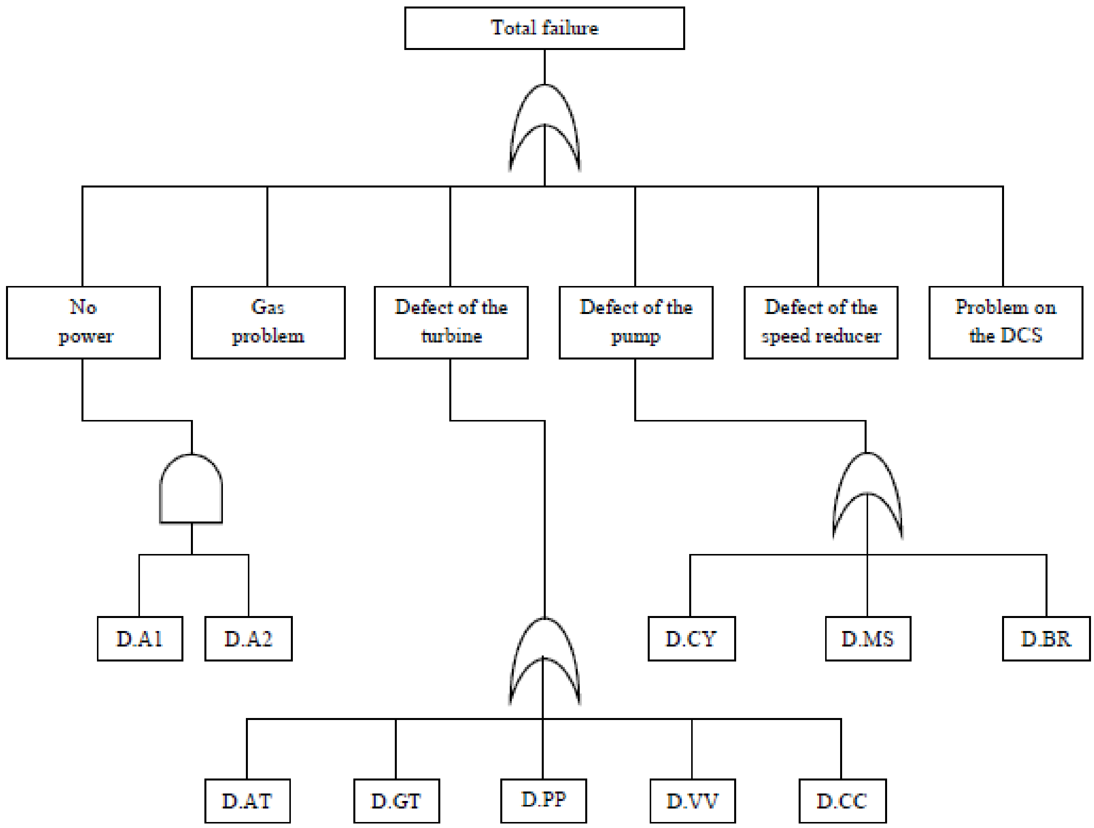


Figure 4. Fault tree of the turbo-pump

DCS: Distributed control system, D.A1: defect of the turbo-alternator 01, D.A2: defect of the turbo-alternator 02, D.AT: defect of the automaton, D.GT: defect of the gate, D.PP: defect on the pressure pipe, D.VV: defect of the valve, D.CC: defect of the combustor, D.CY: defect on the cyclone, D.MS: defect of the mechanical seal, D.BR: defect of the bearings.

3.2 Bayesian network of the turbo-pump

According to the maintenance department of the company, it is to note that the "breakdown state" of the turbo-pump is caused by three (03) main causes: the defect or the failure of one of its components (according to the fault tree of the system), the operator competency and the external environment (climate conditions). The initial BN is given by figure 5.

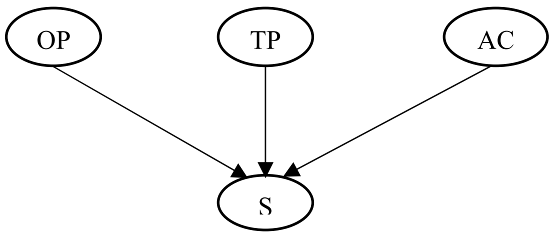


Figure 5. Initial BN of the turbo-pump

With: "OP": operator competency, "AC": adverse conditions ant "TP": total failure of the turbo-pump.

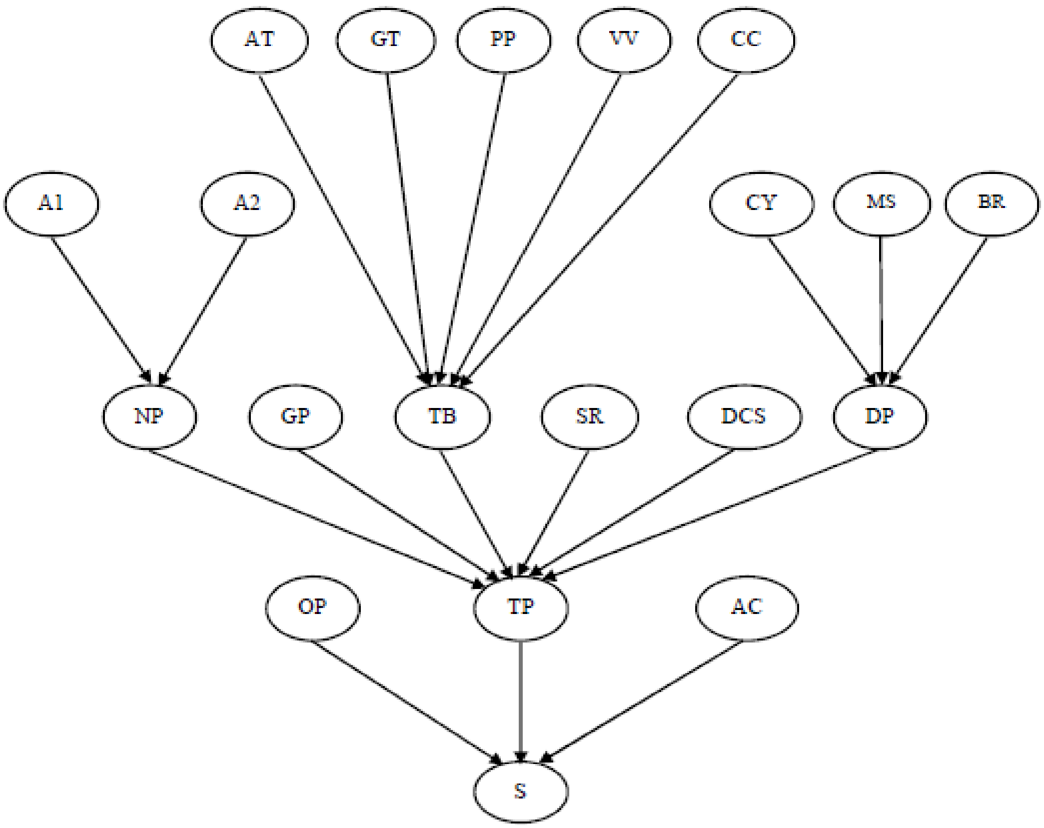


Figure 6. Bayesian networks of the turbo-pump

By transforming the last node ("TP") from the FT of the fig.4 to a BN using the algorithm of transition developed previously, the structure of the overall BN modeling the studied system is shown in fig.6, with:

A1: defect of the turbo-alternator 01, A2: defect of the turbo-alternator 02, AT: defect of the automaton, GT: defect of the gate, PP: defect on the pressure pipe, VV: defect of the valve, CC: defect of the combustion chamber, CY: defect on the cyclone, MS: defect of the mechanical seal, BR: defect of the bearing, NP: No power, GP: gas problem, TB: defect on the turbine, SR: defect of the speed reducer, DP: defect on the pump.

3.3 Probability of the Bayesian network

The prior probability tables of the root nodes are created from the failure rate of the corresponding component (we suppose that the system follow the exponential distribution). Except the nodes "OP" and "AC", the failure rate is given by:

$$\lambda = \frac{1}{MUT} \tag{2}$$

With: MUT is the Mean Up time, it is computed from the historical data.

For the transformation of the failure rate into a failure probability we have taken (with the collaboration of the experts of the maintenance department) $\vec{\lambda}$ equal to one (01) failure per two (02) days (0.5 failures per day). The failure rate and the failure probability of nodes are summarized in the following table.

Table I: Failure rate and failure probability of nodes

Node	**Failure rate**	**Failure probability**	**Non failure probability**
A1	0,00093	0,186%	99,814%
A2	0,00043	0,086%	99,914%
AT	0,00093	0,186%	99,814%
GT	0,00093	0,186%	99,814%
PP	0,00187	0,374%	99,626%
VV	0,0014	0,28%	99,72%
CC	0,00093	0,186%	99,814%
CY	0,00187	0,374%	99,626%
MS	0,00187	0,374%	99,626%
BR	0,00043	0,086%	99,914%
GP	0,00054	0,108%	99,892%
SR	0,00027	0,054%	99,946%
DCS	0,00093	0,186%	99,814%

The prior probability tables of the nodes "OP" and "AC" are estimated by the experts and the historical data (table II).

Table II: Estimated prior probability table

Node	Failure probability	Non failure probability
OP	0.5%	99.5%
CD	0.8%	99.2%

The CPTs of the nodes “NP”, “TB” and “DP” are obtained from the transition of the logical gates “AND” and “OR”. For the node “S” which represents the system, its CPT is estimated with concordance of the maintenance department.

Table III: CPT of the node “S”

AC	TP	OP	Node "S" 0	Node "S" 1
0	0	0	1	0
0	0	1	1	0
0	1	0	0,07	0,93
0	1	1	0,05	0,95
1	0	0	1	0
1	0	1	1	0
1	1	0	0,02	0,98
1	1	1	0,001	0,999

3.4 Bayesian inference and results

The Bayesian inference is then used to compute the marginal probability of the node “S” corresponding to the whole system. By using the toolbox BNT of MATLAB and the junction tree algorithm, we have found the failure probability P_S of the node “S”.

$P_S = 3.44\%$ With $P = \lambda \times \vec{\lambda}^{-1}$, the failure rate of the system is:

$\lambda = 0.0172\, days^{-1} = 0.000716\ h^{-1}$

We have to note that the execution time of this algorithm is substantially minimal. So, it is recommended to use this method even for the complex systems with a great number of components and complex linking or interactions.

4. Conclusion

The main objective of this paper is the failure rate assessment of a complex system. We have used a methodology based on the fault tree method for mapping a complex system into Bayesian network. The fault tree method is introduced to allow defining the interaction between the system components and events.

It is shown that it is possible to associate the experts’ judgment to the statistical (historical) data in order to improve the modeling. The reduced CPU time makes that we can use this approach even for systems with great number of components and complex linking.

References

[1] Corset F. Aide à l'optimisation de maintenance à partir de réseaux bayésiens et fiabilité dans un contexte doublement censuré. Thèse de Doctorat. Université Joseph Fourier 2003.
[2] Bobbio A, Portinale L, Minichino M, Ciancamerla E. Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. Reliability Engineering and System Safety 71 (2001) 249–260.
[3] Weber P, Medina-Oliva G, Simon C, Iung B. Overview on Bayesian networks applications for dependability, risk analysis and maintenance areas. Engineering Applications of Artificial Intelligence 25 (2012) 671–682.
[4] Boudali H, Dugan J.B. A new Bayesian network approach to solve dynamic fault trees. In: Proceedings of the IEEE Reliability and Maintainability Symposium (January 24–27). (2005) 451–456.
[5] Montani S, Portinale L, Bobbio A, Varesio M, Codetta-Raiteri D. A tool for automatically translating Dynamic Fault Trees into Dynamic Bayesian Networks. In: Reliability and Maintainability Symposium (RAMS'06) (2006) 434–441.
[6] De Souza E, Ochoa P.M. State space exploration in Markov models. Performance Evaluation Review 20 (1992) 152–166.
[7] Amari S, Dugan JB, Misra R. A separable method for incorporating imperfect fault-coverage into combinatorial models. IEEE Transactions on Reliability 48 (1999) 267–74.
[8] Nourelfath M, Dutuit Y. A combined approach to solve the redundancy optimization problem for multi-state systems under repair policies, Reliability Engineering & Systems Safety 86 (2004) 205–213.
[9] Bobbio A, Montani S, Portinale L. Parametric dependability analysis through probabilistic horn abduction. UAI, (2003), 65–72.
[10] Padhraic S. Belief networks, hidden Markov models, and Markov random fields: a unifying view. Pattern Recognition Letters 18 (1997) 1261–1268.
[11] Simona. C, Weber. P, Evsukoff. A. Bayesian networks inference algorithm to implement Dempster Shafer theory in reliability analysis. Reliability Engineering and System Safety 93 (2008) 950–963.
[12] Marquez D, Neil M, Fenton N. Improved reliability modeling using Bayesian networks and dynamic discretization. Reliability Engineering and System Safety 95 (2010) 412–425.
[13] Jones. B, Jenkinson. I,Yang. Z, Wang. J. The use of Bayesian network modelling for maintenance planning in a manufacturing industry. Reliability Engineering and System Safety 95 (2010) 267–277.
[14] Weber P, Jouffe L. Complex system reliability modelling with Dynamic Object Oriented Bayesian Networks (DOOBN). Reliability Engineering and System Safety 91 (2006) 149–162.
[15] Alyson G. Wilson, Aparna V. Huzurbazar. Bayesian networks for multilevel system reliability. Reliability Engineering and System Safety 92 (2007) 1413–1420.
[16] Langseth H, Portinale L. Bayesian networks in reliability. Reliability Engineering and System Safety 92 (2007) 92–108.
[17] Jensen F, Lauritzen S, Olesen K. Bayesian updating in recursive graphical models by local computations. Computational Statistical Quaterly 4 (1990) 269–282.