Overview on Bayesian networks Applications for Dependability, Risk Analysis and Maintenance areas

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Abstract: In this paper, a bibliographical review over the last decade is presented on the application of Bayesian networks to dependability, risk analysis and maintenance. It is shown an increasing trend of the literature related to these domains. This trend is due to the benefits that Bayesian networks provide in contrast with other classical methods of dependability analysis such as Markov Chains, Fault Trees and Petri Nets. Some of these benefits are the capability to model complex systems, to make predictions as well as diagnostics, to compute exactly the occurrence probability of an event, to update the calculations according to evidences, to represent multimodal variables and to help modeling user-friendly by a graphical and compact approach. This review is based on an extraction of 200 specific references in dependability, risk analysis and maintenance applications among a data base with 7000 Bayesian Network references. The most representatives are presented, then discussed and some perspectives of work are provided.

Keywords: Bayesian networks, dependability, risk analysis, maintenance, reliability, safety.

1. INTRODUCTION AND PROBLEM STATEMENT

The management of complex industrial systems contributes to higher competitiveness and higher performances at lower costs. In that way, the relevance of the maintenance and dependability analyses increased due to their role in improving availability, performance efficiency, products quality, on-time delivery, environment and safety requirements, and total plant cost effectiveness at high levels (Alsyouf, 2007 and Kutucuoglu, *et al.* 2001). Nowadays, one of the major problems in the dependability field is addressing the system modeling in relation to the increasing of its complexity. This modeling task underlines issues concerning the quantification of the model parameters and the representation, propagation and quantification of the uncertainty in the system behavior (Zio, 2009).

In previous years, the reliability and risk analysis of systems were studied by making assumptions simplifying the study. One of these assumptions is to focus the study only on the technical part of the system. This assumption is no longer valid, since it has been shown the importance of organizational and human factors contributions (Leveson, 2009). Indeed, if studies were centered on technical aspects of systems until seventies (Villemeur, 1992), several major accidents, such as the Three Miles Island nuclear accident and the Bhopal catastrophe have pointed out cause operator errors and organizational malfunctions. These accidents allowed the scientific community to present and develop, in eighties, first methods centered on the analysis of these human errors. It led to the expansion of the Human Reliability Analysis (HRA). But other accidents (Challenger explosion, Chernobyl nuclear accident …) have emphasized, in nineties, the importance of organizational malfunctions in their occurrences and, have contributed to the emergence of different theories for the study of these organizational issues: normal accident (Perrow, 1990 and Weick, 2001) and high reliability organizations (Robert, 1990 and Leger *et al.* 2008, 2009).

As a consequence, innovative studies aim at covering the whole of these causes (technical, human and organizational). Nevertheless, such analyses are often difficult to achieve because they require a lot of resources. This matter adds complexity to the systems' modeling due to the interaction between different technical, human, organizational and nowadays environmental factors which are necessary to quantify failure scenarios and risky situations. Thus, the challenge is to formalize a model of a complex system integrating all these aspects (Trucco *et al.* 2008 and Kim *et al.* 2006) (Figure 1).

Furthermore, while modeling these factors, it is required to take into account the knowledge integration of diverse natures such as qualitative and quantitative with several abstraction levels. The organization and human analyses are more naturally modeled with a qualitative knowledge (to describe situations, scenarios…) such as knowledge represented in Failure Mode, Effects, and Criticality Analysis (FMECA), HAZard OPerability (HAZOP), Probabilistic Risk Assessment (PRA) analysis, etc.; and in other hand, the technical level is usually known with quantitative information (failure rates, unavailability level, Mean Time To Failure (MTTF), etc.) (Røed *et al.* 2008).

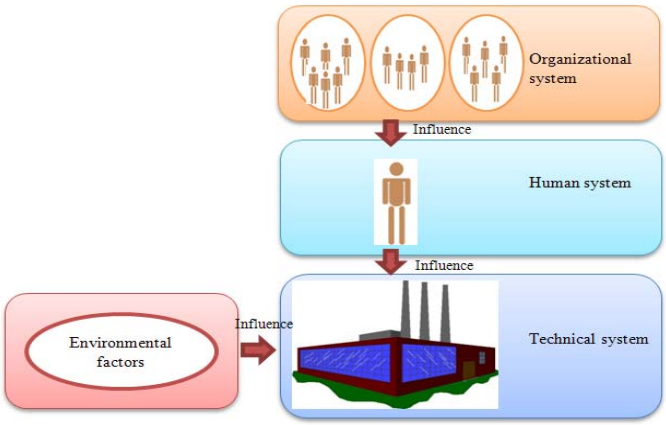

Figure 1. Context of the complex system to be modeled

A complementary point of view to be modeled for the system is the temporal dimension (system dynamics) which consists in describing phenomenon such as: sequences in scenarios, degradations of components, evolution of symptoms corresponding to deterioration mechanisms, impact of preventive maintenance actions on the degradation, influence of environmental conditions and effects of the operation conditions on the evolution of the component states.

Once assessed the failure probability and risk associated to a system situation, the information is provided to support the decision making process. It implies to quantify the uncertainty and imprecision on parameters, for example, the uncertainty of the failure occurrence and its consequences (Zio, 2009).

Therefore, the main characteristics to be modeled in a system for assessing dependability and maintenance aspects are:
- the complexity and size of the system (large-scale systems) (Zio, 2009),
- the temporal aspects (Labeau *et al.* 2000),
- the integration of qualitative information with quantitative knowledge on different abstraction levels (Papazoglou *et al.* 2003) (Delmotte, 2003),
- the nature of multi-state components (Griffith, 1980),
- the dependences between events such as failures (Torres-Toledano and Sucar, 1998),
- uncertainties on the parameter estimation (Zio 2009).

For modeling these requirements, there are some classical dependability methods such as fault trees, Markov chains, dynamic fault trees, Petri nets and Bayesian Networks (BN). In the recent literature, it is observed a growing interest focused on BN. This modeling method is not the solution to all problems, but it seems to be very relevant in the context of complex systems (Langseth, 2008).

Indeed some papers such as Mahadevan *et al.*, (2001), Boudali and Dugan (2005b), Langseth and Portinale (2007), and Langseth (2008) show the increasing interest on the use of BN to estimate and to improve reliability and safety of systems over the last decade. For example, during the period 1999-2009, RESS journal (Reliability Engineering and System Safety), well known in dependability area, shows an increment of 100% of a ratio consisting on the paper number dedicated to the application of BN to reliability (or risk) divided by the total amount of papers. This type of ratio has strengthened our interest to analyze the evolution of the literature about BN and their applications on dependability, risk analysis and maintenance. For this purpose, we have built a database of references from 1990 to 2008 with different bibliographical research tools (i.e. google scholar, Sciencedirect, Web of Knowledge ...). In this paper, the most relevant articles according to their citation number were referenced until 2008. Nonetheless, some citations on “hot topics” of research until 2009 are also given.

The rest of this paper is organized as follow. Section 2 is introducing the bases of BN and explaining why they are suitable to model complex systems. Section 3 shows a bibliographical review of the relevant research directions for modeling dependability, risk analysis and maintenance problems with BN. Section 4 presents a comparison of the BN modeling capabilities with other modeling methods such as Fault Tree, Markov Chains and Petri Nets. Finally, the conclusions are given by integrating also highlights future research directions.

2. BN IN GENERAL

BN appear to be a solution to model complex systems because they perform the factorization of variables joint distribution based on the conditional dependencies. The main objective of BN is to compute the distribution probabilities in a set of

variables according to the observation of some variables and the prior knowledge of the others. The principles of this modeling tool are explained in (Jensen, 1996; Pearl *et al*. 1988).

Recall of BN characteristics: A BN is a directed acyclic graph (DAG) in which the nodes represent the system variables and the arcs symbolize the dependencies or the cause-effect relationships among the variables. A BN is defined by a set of nodes and a set of directed arcs. A probability is associated to each state of the node. This probability is defined, *a priori* for a root node and computed by inference for the others.

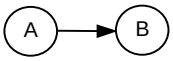

Figure 2. Basic example of a BN

The computation is based on the probabilities of the parents' states and the conditional probability table (CPT). For instance, let's consider two nodes *A* and *B;* with two states (S_{*1} and S_{*2}) each; structuring the BN (Figure 2). The *a priori* probabilities of node *A* are defined as (Table 1):

A	S_{A1}	$P(A=S_{A1})$
	S_{A2}	$P(A=S_{A2})$

Table 1. A Priori probabilities of the node A

A CPT is associated to node *B*. This CPT defines the conditional probabilities $P(B|A)$ attached to node *B* with a parent *A*, to define the probability distributions over the states of *B* given the states of *A*.
This CPT is defined by the probability of each state of *B* given the state of *A* (Table 2).

A		S_{A1}	S_{A2}
B	S_{B1}	$P(B=S_{B1}\|A=S_{A1})$	$P(B=S_{B1}\|A=S_{A2})$
	S_{B2}	$P(B=S_{B2}\|A=S_{A1})$	$P(B=S_{B2}\|A=S_{A2})$

Table 2. CPT of the node B given the node A.

Thus, the BN inference computes the marginal distribution $P(B=S_{B1})$:

$$P(B = S_{B1}) = P(B = S_{B1}|A = S_{A1}).P(A = S_{A1}) + P(B = S_{B1}|A = S_{A2}).P(A = S_{A2}) \quad (1)$$

The added value of a BN is linked to the computation of the probabilities attached to a node state, given the state of one or several variables. BN are a powerful modeling tool for complex systems because providing a lot of modeling advantages.

Indeed for providing global reliability estimation, BN permit to merge knowledge of diverse natures in one model: data from feedback experience, experts' judgment (express through logical rules, equations or subjective probabilities), the behavior of the studied system (functional and dysfunctional analysis) and observations. Moreover to study and to analyze complex systems, it is necessary to model the interaction between organizational, human and technical factors. BN establishes cause-effect relationships between these factors for modeling their interactions. For example, BN can model the effect of maintenance actions and barriers' impact on the global system risk analysis (Leger, 2009). Usually, it is necessary to use several sources of information for developing a model. However, there is few feedback data particularly in the domains of dependability, risk analysis and maintenance. For this reason, the research works use mainly the experts' judgment to build the structure of models (Celeux *et al.*, 2006).

A general inference mechanism (that permits the propagation as well as the diagnostic) is used to collect and to incorporate the new information (evidences) gathered in a study. The Bayes´ theorem is the heart of this mechanism and allows updating a set of events´ probabilities according to the observed facts and the BN structure. It makes the strength of this knowledge management tool.

3. LITERATURE ON BN APPLICATION TO DEPENDABILITY, RISK ANALYSIS AND MAINTENANCE

In the specialized literature about BN, most of the references are related to the learning and inference algorithms. Nonetheless, we found a set of 200 articles about the application of BN to dependability, risk analysis and maintenance. It shows a continuous increment of the number of references and, a scientific and industrial interest for this tool. Most of the selected references are about dependability with 61% of the publications, risk analysis with 26% and maintenance with 13% (Figure 3).

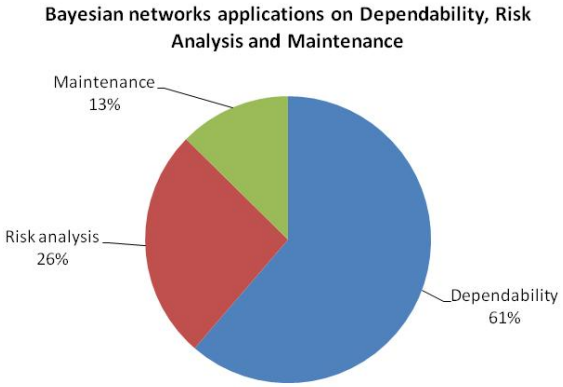

Figure 3. Distribution of references on the topics

3.1 Application to dependability

The dependability aim is to provide a prediction of a parameter (remaining time to fail, MTTF, reliability, etc.) which is an input data for the decision step (for example maintenance optimization, dependable system design …). Thus, it is necessary to take into account some aspects such as multi-state elements (Griffith, 1980), failures' dependencies (Lai and Xie, 2006), system redundancy (Tavakkoli-Moghaddam *et al.*, 2008), dynamic evolution (*e.g.* the degradation process) (Lai and Xie, 2006) and to incorporate the influencing factors of a system dependability such as operations conditions (Bazovsky, 1961).

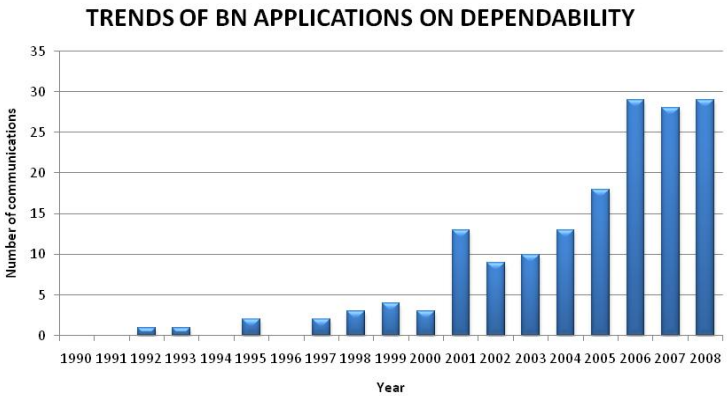

Figure 4. Publication number related to Bayesian Network application on dependability

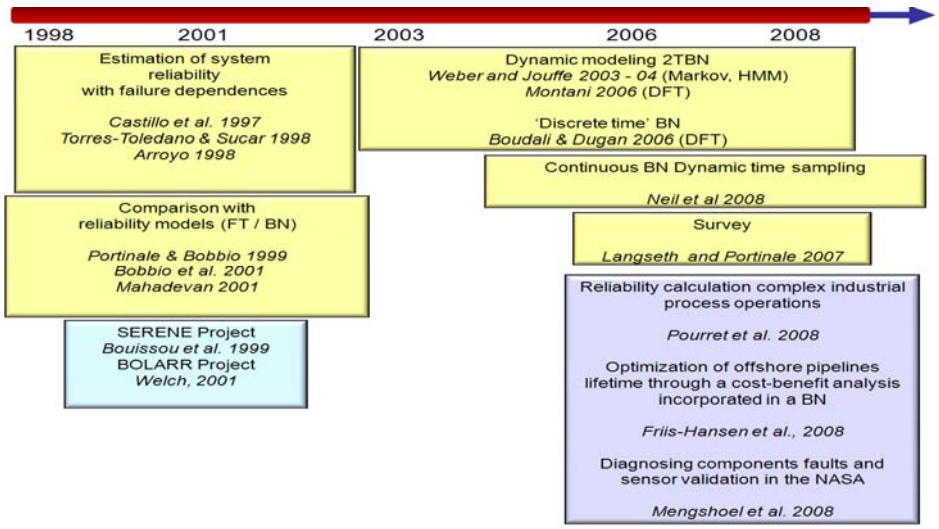

Figure 5. Most relevant papers of BN application on dependability field

BN models are more and more used in dependability analyses to support aspects like reliability, availability and, maintainability. Figure 4 shows the number of references per year related to the BN application to dependability analyses. Since 2000, it is observed a significant rising of 800% on their application due to the modeling benefits that BN can offer. Figure 5 shows the main topics evolution of BN literature and its application on this field with some relevant references.

The first major contributions have been done by (Castillo *et al.*, 1997), (Torres-Toledano and Sucar, 1998), (Arroyo *et al.*, 1998), and (Kang and Golay, 1999). The original work' objectives handled by (Torres-Toledano and Sucar, 1998) and (Arroyo *et al.*, 1998) were: a) to estimate a system reliability including possibilities of failures´ dependencies; b) to model complex systems (2003).

At the same time, BOLARR project emphasizes dynamic modeling for risk analyses (Welch, 2000) through BN. Simultaneously, the SERENE project aims at formalizing the experts´ reasoning in order to evaluate the different aspects of dependability on critical systems (Bouissou *et al.*, 1999). As one of its objective was to provide a model with several abstraction levels, this project is also based on building a hierarchical object oriented BN in order to incorporate the influence factors of the system dependability.

With reference to software reliability area, there are some significant works whose goal is to assess a reliability prediction within software taking into account the operational conditions (Bai, 2005), (Bai *et al.*, 2005). In the context of a software safety standard, Axel & Helminen (2001) present how a BN can be merged with a BN on the reliability estimation of software based on digital systems. Helminen and Pulkkinen (2003) exploit the BN abilities when combining experts' judgments and the feedback experience data to estimate the reliability of a motor protection critical system. Wilson & Huzurbazar (2006) describe different application contexts of BN in the reliability field: known or unknown conditional probabilities, taking into account new data in order to improve the conditional probabilities estimation.

After this first step focused on static BN, the community focused also in dynamic models. Welch & Thelen, (2000) worked on the comparison between Markov Chains and BN application to the reliability evaluation. More recent studies have focused on the reliability estimation including the temporal aspect by the use of Dynamic Bayesian Networks (DBN). Boudali & Dugan, (2005a-b), and Montani *et al.*, (2006) proposed the integration of the dynamic aspect by the transformation of dynamic fault trees (DFT) into DBN. Montani *et al.*, (2006) develop a tool to translate DFT based on two time slices BN (2TBN). Portinale *et al.*, (2009) present the software called RADYBAN (Reliability Analysis with DYnamic BAyesian Networks) which supports an approach to reliability modeling and analysis based on the automatic translation from DFT into a DBN.

In Weber & Jouffe (2006), the model is based on Dynamic Object Oriented BN (DOOBN) and the model structure is deduced from the functional analysis (knowledge represented by SADT method) and malfunctioning (knowledge formalized by FMECA). DBN models are able to represent the impacts of the operational conditions (*e.g.* maintenance actions, production levels, environmental conditions…) on system reliability by means of exogenous variables (Weber *et al.*, 2004).

One of the current limitations of BN is that they can only deal with discrete variables. Nonetheless, in the reliability field there are some phenomena which should be taken into account with continuous nature (*i.e.* operating and environmental variables). For that reason, one of the important topics of research is the development of inference algorithms for hybrid BN. These models contain discrete and continuous variables. In that sense, Boudali & Dugan, (2006) propose to use continuous nodes with sampling of time to model the failure distribution of the components in a reliability model. In the same way, Neil *et al.* (2008, 2009) built hybrid BN including discrete and continuous nodes to estimate the system reliability. The algorithm combines a dynamic time sampling to the classical propagation algorithms. The time sampling of the continuous variables is updated by taking into account the evidences. The authors present this concept as an alternative method to simulation methods such as Markov Chain Monte Carlo (MCMC).

Langseth *et al.*, (2009) propose a synthesis about the inferences in hybrid BN in the context of reliability analysis. They explore four approaches of inference in hybrid BN: discretization, Mixtures of Truncated Exponentials (MTE), variational methods and Markov Chain Monte Carlo (MCMC). They are interested in obtaining approximations of low probability events in the tails of approximations. For that purpose, the best suited appears to be the MTE framework because it balances the need for good approximations in the tail of the distributions with not-too-high computational complexity.

In addition, Langseth & Portinale (2007) wrote a synthesis about different building steps in a BN and the use of this formalism in reliability. Some applications of BN exist in this area, for example the diagnosis of components faults and sensor validation in the NASA (Mengshoel *et al.*, 2008), the reliability calculation in complex industrial process operations such as the industry of pulp and paper (Pourret *et al.*, 2008) and the optimization of a strategic decision for improving the offshore pipelines lifetime through a cost-benefit analysis (Friis-Hansen *et al.*, 2008).

Complementary contribution is presented by Doguc and Ramirez-Marquez (2009) who introduce a holistic method for estimating system reliability by automatically constructing a BN from historical data on the system. In essence, the method replaces the need of an expert to find associations among the components with the raw data related to the component and system behavior. The proposed method automates the process of BN construction by feeding raw system behavior data to the K2 algorithm (a commonly used association rule mining algorithm).

Finally, an interesting problem is tackled by Simon & Weber (2008) and concerns how BN can handle epistemic and random uncertainties. By extending the usual state of affairs in probability theory and the corresponding belief measure assignment to Dempster-Shafer structures, the authors extended BN to Evidential Networks based on an extended Bayesian inference. Evidential networks can deal with interval valued probabilities (Simon 2008), fuzzy valued probabilities (Simon, 2009a) and multi-states systems for reliability and performance evaluation (Simon2009b).

So far, Table 3 presents a synthesis of the modeling aspects in dependability area that have been covered by research works, those about which researchers are still working on and, those which are still under-developed.

Table 3: overview of the modeling aspects in dependability area

Dependability Items	**Main Contributions**	**Theoretical contribution**	**Methodological contribution**	**Applicative contribution**
Covered aspects				
Considering multi-state elements.	Torres-Toledano and Sucar, (1998) Arroyo *et al.*, (1998) Kang and Golay, (1999) Helminen and Pulkkinen (2003)		× 	 × × ×
Considering dependencies between events.	Boudali and Dugan, (2005b) Bouissou *et al.*, (1999) Wilson and Huzurbazar (2006)		× × ×	
Aspects which researchers are still working on				
Including the temporal aspect in reliability analyses.	Boudali and Dugan, (2005 a-b) Montani *et al.*, (2006) Neil et al. (2008) Welch and Thelen, (2000) Portinale *et al.*, (2009)		× × × × ×	
Considering exogenous variables such as environmental conditions to optimize maintenance decisions.	Weber *et al.*, (2004) Ben Salem *et al.*, (2006) Friis-Hansen *et al.*, (2008) Bai, (2005)		× × ×	 ×
Including continuous variables in the dependability analysis	Boudali and Dugan, (2006) Neil *et al.* (2009) Langseth *et al.*, (2009)	× × ×		
Characterizing, representing and propagating uncertainties (epistemic; random and numeric) in reliability analysis of complex systems.	Simon and Weber, (2008, 2009a, b)		×	
Constructing an automated BN model without human expertise	Doguc and Ramirez-Marquez, (2009)		×	
Managing models with great number of variables	SKOOB Project, (2008)			×
Under-developed aspects (with minor results)				
Integrating, in one model, the technical, organizational, informational, decisional and human aspects and the impacts on the system's functioning.				

3.2 Applications in risk analysis

Risk analysis is a technique for identifying, characterizing, quantifying and evaluating critical event occurrence. The quantification of risk includes the estimation of the likelihood (*e.g.*, frequencies) and the consequences of hazard occurrence. The estimation of the likelihood of hazard occurrence depends greatly on the reliability of the system's components, the interaction of the components taking the system as a whole, and human-system interactions. Risk evaluation needs a systematic research of accidental scenarios, including failure rates for the component (*e.g.* safety barriers) as well as for operator behavior (human factor) within an evolving environment. Additionally, in these kinds of analyses, low probability events and the dependencies between variables must be taken into account. The objective of these analyses is to provide the elements that help decision making in terms of design evolution, operation, preparation and risk management (Modarres *et al.*, 1999).

Since 2001, BN have been used to analyze risky situations. Particularly, BN represent a useful formalism in the risk analyses domain due to their ability to model probabilistic data with dependencies between events. Figure 6 shows the development of BN scientific literature focused on risk analysis. From 2001 to 2008, the number of references per year increased by 4.

Figure 7 shows the main steps of the evolution of BN literature and its application in risk analysis based on the most relevant papers. The first contributions were made by Hudson *et al.*, (2002). The authors use BN as a key element of a decision support system for assessing terrorist threats against military installations. At the same period, Gulvanessian & Holicky (2001) proposed a BN to analyze the efficiency of fire protection systems and to find the most effective arrangements in real situations.

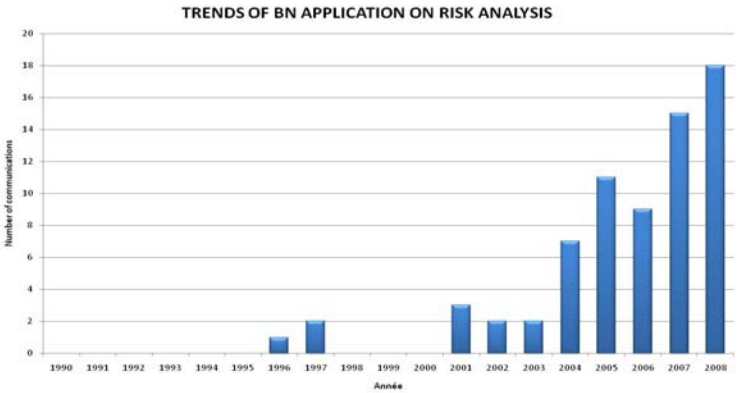

Figure 6. Publication number related to Bayesian Network applications on risk analysis

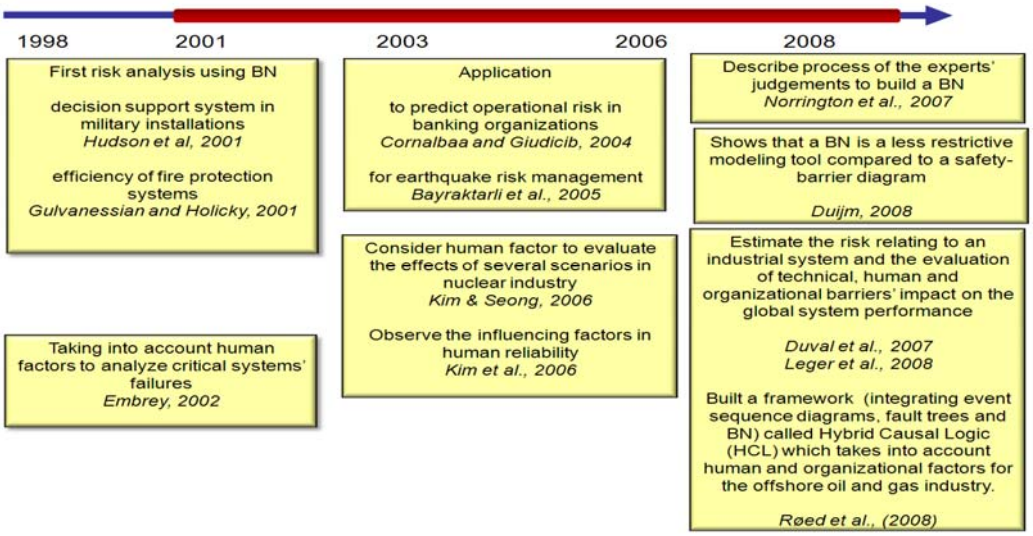

Figure 7. Most relevant papers of BN application on risk analysis.

Øien (2001) proposed a framework to integrate organizational risk indicators for assessing the risk impact. This model could be used to identify qualitatively the root causes of accidents or incidents. The objective is to develop a model for risk control purposes so the organizational risk indicators should be acquired with a certain frequency. For the model quantification, the author used BN due to the possibility of multi-state representation and the intuitive representation of causal relationships linking the organizational factors to the quantitative risk model.

Embrey (2002) takes into account human factors by using influence diagrams to analyze and to anticipate critical systems' failure. Also, Kim & Seong (2006) describe a BN model including human factors to evaluate the effects of several scenarios in the nuclear industry. The same authors use BN to observe the influence factors in human reliability (Kim *et al.*, 2006).

Complementary contributions were made by Cornalba & Giudicib (2004) who develop a work in which a BN approach is used to develop a statistical model to measure and, consequently, to predict the operational risks to which a banking organization is subjected to. Bayraktarli *et al.* (2005) worked with the application of BN to earthquake risk management. The authors propose that the uncertainties associated with all elements in the functional chain of an earthquake (from the source mechanism, site effects, structural response, damage assessments and consequence assessment) can be handled consistently using a BN. Straub (2005) demonstrates the advantages of BN for the application in risk assessments for natural hazards. Lee & Lee (2006) propose a quantitative assessment framework integrating the inference process of BN to the traditional probabilistic risk analysis in order to consider the effects predicted from an evolution of the environmental conditions of waste disposal facilities.

In the maritime field, BN approaches are applied to consider the human and organizational factors in a risk analysis. Norrington *et al.* (2007) describe elicitation process of the experts' judgments to build a BN. A significant BN approach was developed by Trucco *et al.* (2008) to model the Maritime Transportation System by taking into account its different actors (*i.e.*, ship-owner, shipyard, port and regulator) and their mutual influences. The model is used in a case study for the quantification of Human and Organizational Factors in the risk analysis carried out at the preliminary design stage of High Speed Craft.

Røed *et al.*, (2008) built a framework taking into account human and organizational factors within a framework called Hybrid Causal Logic (HCL). This framework let BN be logically and probabilistically integrated into event sequence diagrams and fault trees in order to perform a risk analysis. Then, this framework is applied to the offshore oil and gas industry. A recent comparison between BN and standard modeling methods is made by Duijm, (2009) showing that BN is a less restrictive modeling tool compared to a safety-barrier diagram. For example, a comparison is made between the number of states that can be modeled with a barrier diagram (Boolean model) and a BN (multi-state representation). In risk analyses, the recent publications of Léger *et al.* (2009) propose a BN modeling by structuring the model in different levels: organization/ actions/ technique. The aim of these works is to quantitatively estimate the risk related to an industrial system operation (occurrence probability of scenarios) and the evaluation of technical, human and organizational barriers' impact on the global system performance. The originality of these models is the BN-based unification formalism of functional, dysfunctional, behavioral and organizational knowledge of a system.

The use of BN is developing rapidly mainly due to its capability to represent complex systems with dependencies between variables. Particularly, for risk analyses, BN are well adapted due to its capability to quantify low probability events. In that sense, Hanea & Ale (2009) work on an overall model which takes into account people, fire fighters' action, structure of the building and characteristics of the building and, the environment in order to analyze low-probability-high-consequence scenarios of human fatality risk in building fires. In addition, Cheon *et al.* (2009) worked about the prediction of daily ozone states in Seoul, Korea. They combine real measured data and expert knowledge to overcome the complexity of O_3 reactions.

So far, Table 4 presents a synthesis of the modeling aspects in risk analyses area that have been covered by research works, those about which researchers are still working on and, those which are still under-developed.

Table 4: overview of the modeling aspects in risk analysis area

Items	**Main Contributions**	**Theoretical contribution**	**Methodological contribution**	**Applicative contribution**
Covered aspects				
Modeling the dependencies between events.	Hudson *et al.*, (2001) Gulvanessian and Holicky (2001) Lee and Lee (2006) Straub (2005) Bayraktarli *et al.* (2005)			× × × ×

	Cornalba and Giudicib (2004)			
Quantitatively estimating the risk with barriers' impact on the system.	Leger *et al.* (2008) Leger *et al.* (2009)		× ×	
Aspects which researchers are still working on				
Integrating the technical, human and organizational aspects with different abstraction levels.	Øien (2001) Kim *et al.* (2006) Trucco *et al.* (2008) Røed *et al.* (2008) Norrington *et al.* (2007)		×	 × × × ×
Integrating qualitative information (functional, organizational analysis) with quantitative knowledge (technical and financial levels).	Leger *et al.* (2008) Leger *et al.* (2009) Røed *et al.* (2008)		× ×	 ×
Managing models with great number of variables	SKOOB Project, (2008)			×
Under-developed aspects (with not significant results)				
Taking into account the resilient aspect of human operators and organizations.				
Including the temporal aspect in the risk analysis				
Characterizing, representing and propagating uncertainties (epistemic; random and numeric) in risk analysis				
Constructing an automated BN model without human expertise				

3.3 Application in maintenance

For developing an appropriate maintenance concept, maintenance must be considered holistically. In that way, factors that technically describe each system to be maintained (*e.g*., functional and dysfunctional analyses, causal relationships between degradations, etc.), as well as factors that describe the interrelations between the different systems (*e.g.* maintenance actions) and, factors that describe the general organizational structure, should be addressed. If some aspects are not considered (*e.g.* due to inaccurate analysis or loss of data or knowledge), the maintenance concept will never reach its full potential (Waeyenbergh and Pintelon, 2004). The critical areas for assessing maintenance performances vary from company to company but, generally include areas such as financial or cost-related issues, health and safety and environment related issues, processes-related issues, maintenance task related issues and learning growth and innovation related issues, while at the same time comprising the internal and external aspects of the company (Parida, 2006).

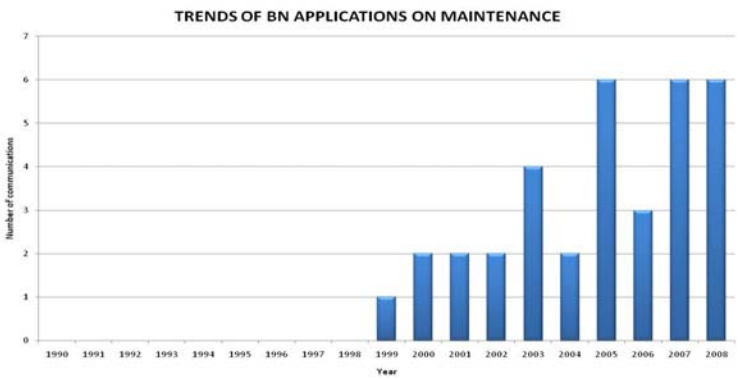

Figure 8. Publication number related to Bayesian Network application on maintenance.

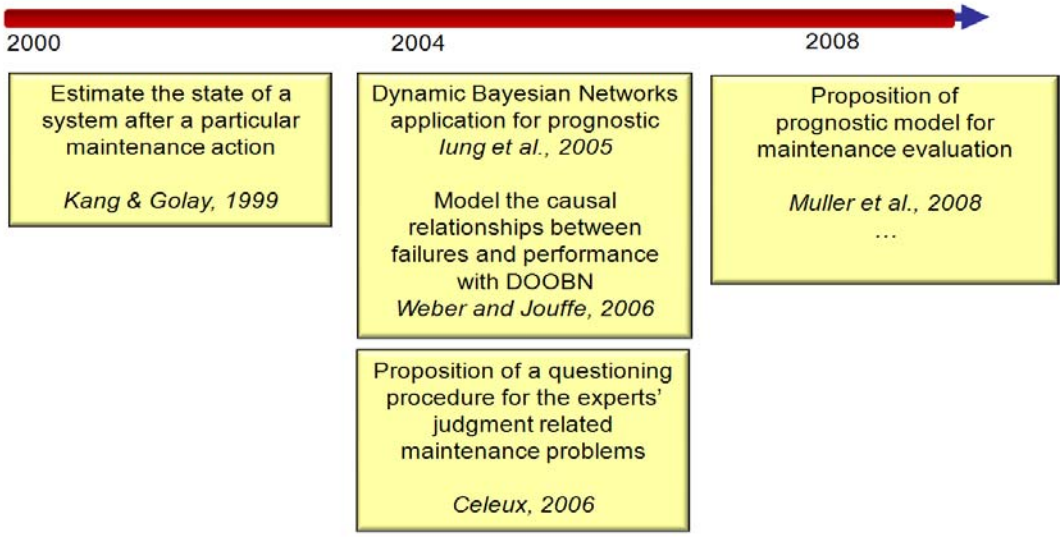

Figure 9. Most relevant papers of BN application on maintenance

BN are used in works concerning maintenance decisions and performance evaluation as illustrated Figure 8. In 1999, a 3-fold increase in the beginning of research activities can be between 2000 and 2008. The activities in this field are recent so, it exists few references. In Figure 9, the most relevant literature on BN for application in maintenance is summarized.

Kang & Golay (1999) proposed a model with influence diagrams which consider evidences. The purpose is to estimate the future state of a system after a particular action. The proposal of an action is made based on the conditional probabilities and the utility values.

The performances' analyses of a system and the establishment of the prognostic process model are the key points for maintenance optimization. The BN model developed by Weber *et al.* (2001) is built including the functional and dysfunctional analysis of the system. It allows its global performance estimation (Muller *et al.*, 2008).

(Weber and Jouffe, 2006), (Iung *et al.*, 2005) and (Borgia *et al.* 2009) investigate the use of DBN for modeling the causal relationships between degradation/ cause/ consequence. Moreover, utility nodes are integrated into the probabilistic model.

For modeling a real maintenance problem, Celeux *et al.* (2006) propose a questioning procedure dedicated to the elicitation of experts' judgment. This procedure is set up by rules to collect information and to build the network structure. The model's parameters are determined by feedback data and later by expertise.

Recently, De Melo & Sanchez (2008) have worked on the prediction of delays for software maintenance projects. In this approach, they considered the factors that could induce uncertainty during the maintenance process such as the maintenance complexity, the expertise of professionals, the system documentation, the opportunity of using new resources, etc. This study helps to compute the probability distribution of a maintenance project delay based on project features.

So far, Table 5 presents a synthesis of the modeling aspects in maintenance area that have been covered by research works, those about which researchers are still working on and, those which are still under-developed.

Table 5: overview of the modeling aspects in maintenance area

Items	**Main Contributions**	**Theoretical contribution**	**Methodological contribution**	**Applicative contribution**
Covered aspects				
As previously mentioned, there are few covered aspects since it is a recent research field.				
Aspects which researchers are still working on				
Modeling the functional and dysfunctional analysis with impacts on global system performances	Muller *et al.* (2008) Weber and Jouffe (2006) Kang and Golay (1999)		× ×	 ×

Including the temporal aspect in maintenance analyses.	Borgia *et al.* (2009)			×
Modeling the causal relationships between degradation/ cause/ consequence	Iung *et al.* (2005) De Melo and Sanchez (2008)		× ×	
Managing models with great number of variables	SKOOB Project, (2008)			×
Under-developed aspects (with not transcendental results)				
Integrating qualitative analysis (functional, dysfunctional and organizational analysis) with quantitative knowledge (technical and financial level)				
Modeling the degradation mechanisms and to represent: the influence factors (service time, age, number of requests, environmental conditions, etc), the degradation symptoms, the relation between the degradation observation and the appearance of other failure modes, the effects of preventive and corrective maintenance activities, and the planning and execution of maintenance actions				
Modeling the effects of preventive and corrective maintenance activities, and the effect of the planning and the execution of maintenance actions.				
Characterizing, representing and propagating uncertainties (epistemic; random and numeric) in maintenance studies				
Constructing an automated BN model without human expertise				

4. BAYESIAN NETWORKS MODELING CAPABILITIES

This section corresponds to the bibliography related to the comparison of the modeling capabilities between BN and three classical methods of dependability evaluation: Fault Trees (FT), Markov Chains (MC) and Petri Nets (PN). Some publications are also mentioned with regards to the transformation (translation) of the previous methods into a BN.

4.1 Fault trees (FT)

Fault Trees are based on the hypothesis of Boolean representation of elementary events. The computing of probability in fault trees is efficiently solved by binary decision diagrams (BDD) which enable an exact computation, considering dependencies between the branches due to redundancy of elementary events unfactorized. However, it is necessary to respect the hypothesis of elementary events independence (IEC61025, 2006).

In relation to the problem statement developed in this paper, FT is a very interesting modeling solution since it allows to consider dependencies between events and to integrate different kinds of knowledge (technical, organizational, decisional and human aspects) for obtaining a complete risk, reliability or maintenance analysis. It allows also to calculate exactly the probability of failure of a safety barrier for risk analysis or the probability of failure of an equipment for reliability and maintenance optimization.

Nevertheless, when multiple failures can potentially affect the components with several different consequences on the system (which is usually the case for risk and dependability analyses), the model needs a representation of multiple state variables. In this context, FT are not suitable. Another constraint is that the FT model is limited to assess just one top event. In contrast BN allow similar capabilities to the FT with the advantages of a multi-state variable modeling and the ability to assess several output variables in the same model. Castillo *et al.* (1997), Portinale & Bobbio (1999) Bobbio *et al.* (2001), Bobbio et al., (2003) and Mahadevan *et al*., (2001) present a relevant contribution in which they explain how FT can be translated to BN, maintaining its Boolean behavior.

So, it is possible to represent FT as BN, but the reciprocity is not true. BN enable the use of multi-modal logic with an unlimited number of modalities and, they make possible and easier the treatment of dependencies based on a DAG (Bouissou and Pourret, 2003). BN can also represent reliability block diagrams. The initial work on this area is presented by Torres-Toledano and Sucar (1998) who explain the translation from one representation to the other. As a consequence, reliability analysis by BN can be based on success paths or by equivalence with minimal cuts or every representation based on Boolean equation.

Recently, some papers have dealt with the link between the new modeling techniques such as dynamic fault trees and BN (Boudali & Dugan (2005a, 2006)). In these papers, the equivalence between dynamic fault trees and BN has been proven. They propose to include the temporal notion on the variables. This technique requires the BN modeling with continuous variables. The dynamic process can be modeled as DBN; also there are several techniques called dynamic fault trees. For instance, the publication by Montani *et al.* (2006) presents the transformation of a dynamic fault tree into a BN, with a representation of a discrete DBN with 2 time slices (2TBN).

4.2 Markov Chains (MC)

A stochastic process can be represented through a group states' description and their transition rate among states. According to the hypotheses assumed for the state transition specifications, the process is markovian, semi markovian or non-markovian. The representation of the state space is identified on the dependability specialized literature (Aven and Jensen, 1999), (Ansell and Phillips, 1994), as well as industrial standards IEC61511, (IEC61511, 2004).

This method is suitable for reliability and availability studies of systems. It allows analysis of the exact failure probability even when there are dependencies among components. The MC also allows the integration of diverse kinds of knowledge and to represent multi-state variables. So, they are a relevant tool for the analyses in the fields studied in this paper.

However, in order to explain behaviors and causalities, the systems' modeling becomes complex with a large number of variables. This requirement constitutes the main drawback of MC method since there is a combinatory explosion of the states' number that leads to an unreadable model when studying real industrial systems (De Souza and Ochoa, 1992). With BN there is no longer such a constraint since the number of parameters within the conditional probabilities table is considerably lower compared to a MC.

DBN can represent MC in a compact form. The first contributors on DBN application to the reliability and availability analyses of systems are Welch and Thelen (2000). Then, Weber & Jouffe (2003) have shown the factorization possibility of a markovian model by DBN. The factorization permits to reduce the model complexity and to open the possibility to model more complex systems.

One main contribution is a DBN representation of non homogeneous markovian processes when using changeable parameters through time (Ben Salem *et al.*, 2006). Additionally, Weber *et al.* (2004) have formalized the inclusion of exogenous variables representing events (maintenance actions, production level, environmental conditions) in a degradation process by using a process called MSM (Markov Switching Model), or IO-HMM (Input-Output Hidden Markov Model). The originality of the proposed approach is to formalize a component's degradation process and its interaction with the environment by an IO-HMM. The models of these processes, interacting with the environment, can be integrated in a system's global model formalized by an object oriented dynamic bayesian network (OODBN) (Weber *et al.*, 2006).

4.3 Stochastic Petri Networks (SPN)

Stochastic Petri Networks (SPN) (Dutuit *et al.*, 1997), (Nourelfath and Dutuit, 2004) are now considered as a traditional method to model reliability, availability, etc. SPN are used in the domain of dynamic reliability (Volovoi, 2004) and the maintenance policy optimization (Zouakia *et al.*, 1999). This method is a powerful modeling formalism but unfortunately the reliability analysis is based on a simulation procedure. The dynamic behavior of SPN is analyzed by Monte Carlo simulation or by other variants of this simulation method since the numerical and analytical methods do not enable to deal with non markovian processes and the interdependence process resulting from the SPN. Unfortunately, the use of SPN with simulation methods has two disadvantages: inefficient consideration of low-frequency events and the simulation time. The consideration of low-frequency events is an important issue especially in risk analysis since an accident remains a rare event with high consequences. Moreover, SPN don't allow easily integrating evidences. These events could be taken into account with the BN.

BN do not have the same modeling objective as SPN since they are based on a probabilistic inference. In contrast, the SPN are based on the principle of modeling the behavior of processes coupled with a simulation tool and, the extraction of the probabilistic characteristics by statistical analysis.

Even when the final goal of both methods is similar, the way to deal with the issue is very different. Thus, there are few bibliographical references in which can be found a valid comparison or a transformation from SPN to BN. Bobbio *et al.* (2003) compare BN, FT and SPN in their application to a safety system on a gas turbine. However, this article does not propose a transformation from one representation to another.

One of the possibilities that could be developed is the transformation of a SPN into a DBN. On one side it is possible to obtain the marked graph from a SPN which could be coded as a Markov Chain. On the other side, the DBN could be transformed into a Markov Chain (as explained in the previous section). This is a clue for the transformation from one method to the other.

5. CONCLUSION

The research works and applications of Bayesian Networks in risk analysis, dependability, and maintenance have shown a significant upward trend since 2000, especially in dependability. Recently, there have been about 30 articles per year and, an increase of 800% of publications between 2000 and 2008. BN in reliability, risk and maintenance areas are chosen since they are easy to use with domain experts. BN are particularly suitable for collecting and representing knowledge on uncertain domains but also enable to perform probabilistic calculus and statistical analyses in an efficient manner.

The difference of BN, in comparison with other classical methods, is their polyvalence. They allow dealing with issues such as prediction or diagnosis, optimization, data analysis of feedback experience, deviation detection and model updating. The graphical representation is interesting since the model complexity is understandable in a single view. In the case of large size model, object oriented representation OOBN or probabilistic relational descriptions (PRM) provide manageable models.

One of the weak points of BN is that there is no specific semantic to guide the model development and to guarantee the model coherence. Therefore, a relevant issue is the use of tools for the formalization of BN models in order to integrate various dimensions (technical, organization, information, decision, finance) correlated with system's behavior in reliability, risk analysis and maintenance fields (Øien 2001, Kim *et al.,* 2006, Trucco *et al.*, 2008). For solving this issue, the research can follow two directions: The first one concerns the translation of the classical dependability model into a BN model. The second one is to define new methodologies of model development. The first solution leads to a coherent model but is limited by the conditions and hypotheses related to the classical dependability model translated in BN. In opposition, the second approach is more innovative because it leads to a model exploiting all the flexibility of BN formalism but it is difficult to prove the result consistence by comparison with other methods classically based on restrictive hypotheses.

In addition, since there is no specific semantic to build a BN, it is necessary to verify the models and to validate them in accordance with the system reality. One aspect to be developed is formalizing some methods for the sensibility analysis of a model in order to investigate its robustness according to the problem studied (Pollino, 2007).

When exploiting a DBN model, there are several inference algorithms that are appropriated to different situations. For example, with the exact inference algorithm proposed by Jensen (1996), the 2TBN model is similar to a markovian model with dynamic independent variables. It means that when calculating variables at step (i+1), the past before step (i) is forgotten thanks to the Markov property. Thus, the inference using junction tree computes the exact distribution if the variable of the dynamic processes respect the Markov property and no dependency exists between the processes. In this particular case, the results are only exactly the same as the computation in the unroll-up BN model. In that sense, one of the research directions is to guide the use of BN taking into account the limitations of the current inference algorithms in order to warn the community on the possible erroneous use in the models with the temporal aspect. For these representations, several inference algorithms exist and are still in development. Their efficiency depends on the model complexity (Murphy, 2002).

In the dependability analysis there are different phenomena of diverse natures that should be considered *i.e.* discrete and continuous variables. For this reason a lot of work has been developed in this area in order to integrate continuous variables in BN models. As a result, a significant part of the community is directing its efforts on the development of inference algorithms for hybrid BN (Boudali and Dugan, 2006, Neil et al. 2009 and Langseth et al., 2009).

An interesting issue would be to deal with large systems (several hundred variables) in order to formalize complex models For example, the SKOOB project is developing a generic model based on PRM (Getoor *et al.,* 2007) which enables a better understanding of complexity and the reutilization of generic parts of a model to represent systems. The network is not defined by a graph but in a language. The inference is performed through partial views of the global model which is actually never built entirely as it is approached in SKOOB project (SKOOB 2008).

Another interesting issue is the manipulation of the imprecision within the parameters and the knowledge of the model (uncertainty). The theory of Dempster Shafer proposes a relevant formalism, and the definition of evidential networks developed by Simon and Weber (2009a, b) are suitable for decision making, considering the imprecision on the utility computation.

As a final point, BN are limited by the modeling aspects that they can deal with. Thus, it is necessary to make BN interoperable with other dependability/risk tools in order to complement the capabilities of BN to better represent the characteristics of a system.

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