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Application of Bayesian Networks in Reliability Evaluation

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***Abstract*—The Bayesian network (BN) is a powerful model for probabilistic knowledge representation and inference and is increasingly used in the field of reliability evaluation. This paper presents a bibliographic review of BNs that have been proposed for reliability evaluation in the last decades. Studies are classified from the perspective of the objects of reliability evaluation, i.e., hardware, structures, software, and humans. For each classification, the construction and validation of a BN-based reliability model are emphasized. The general procedural steps for BN-based reliability evaluation, including BN structure modeling, BN parameter modeling, BN inference, and model verification and validation, are investigated. Current gaps and challenges in reliability evaluation with BNs are explored, and a few upcoming research directions that are of interest to reliability researchers are identified.**

Index Terms—Bayesian network (BN), reliability, hardware, structure, software, human.

I. Introduction

RELIABILITY is an item's probability that it performs its required function under given conditions for a stated time interval. This characteristic is intrinsically uncertain and a stochastic variable of an object, which can be hardware, structures, software, or humans. Evaluating the reliability of these objects is a challenging problem for reliability engineers and researchers.

Reliability can be evaluated using appropriate statistical inference techniques. For example, hardware reliability focuses on the research of systems and hardware and can be researched using fault tree analysis, event tree analysis, reliability block diagrams, Markov and semi-Markov models, and Petri nets. Structures are subsumed under hardware; however, we categorize them separately because they are closely related to structural mechanics principles. Structural reliability has been researched using response surface methods, first-order reliability methods, and second-order fourth-moment methods. Software reliability is defined by IEEE as the probability of failure-free software operation for a specified period of time in a specified environment. It has been researched using relevance vector regression, Gaussian processes, and the Markov-modulated Poisson process. Human reliability is the probability that an individual conducts system-required activities correctly for a specified period of time. It has been researched using ATHEANA, CREAM, and SPAR-H. Each reliability evaluation technique has its advantages and inherent disadvantages. Representing the uncertainties in the dependencies between different components or factors of the evaluated objects with many reliability evaluation methods, such as fault tree and reliability block diagram, is difficult because of the binary variable restriction [1]. Other techniques, such as Markov models and Petri nets, suffer from state space explosion problems [2].

Bayesian networks (BNs) are important probabilistic directed acyclic graphical models that can effectively characterize and analyze uncertainty, which is a problem commonly encountered in real-world domains, and handle state space explosion problems [3]. The applications of BNs has been extended to many fields involving uncertainty [4], from risk analysis [5, 6], safety engineering [7], resilience engineering [8], and fault diagnosis [9-11] to current reliability engineering, which is mainly discussed in the present work. BN-based reliability evaluation is conducted by forward (or predictive) analysis of BNs with various inference algorithms. That is, the probability of occurrence of the node that denotes the state of the evaluated object is calculated on the basis of the prior probabilities of the root nodes that denote the components or factors of the evaluated object and the conditional dependence of each node.

Reliability evaluation with BNs in the hardware, structure, software, and human domains is a particularly active research area that is attracting considerable attention from reliability engineers and researchers. Several review articles have summarized previous related studies. Langseth and Portinale [12] provided a thorough literature survey on BNs applied to reliability engineering, focusing on modeling framework, including BN model construction, causal interpretation, and BN inference. Tosun *et al.* [13] provided a systematic review of BNs applied to software quality prediction, also focusing on BN modeling steps, namely, structure learning, parameter learning, use of tools, data characteristics, and validation. Mkrtchyan *et al.* [14] reviewed the use of BNs in human reliability analysis, analyzed five groups of BN applications, and identified the process of constructing BNs. In another work, Mkrtchyan *et al.* [15] reviewed five approaches to creating conditional probability tables and evaluated the performance of each approach.

This study aims to summarize and review recent studies on BNs used for reliability from the perspective of the objects of reliability evaluation, namely, hardware, structures, software, and humans, because these categories of objects cover nearly the entire BN-based reliability literature. The general BN-based reliability evaluation procedural steps are investigated and compared between evaluation objects. Moreover, the

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potential challenging problems of BNs in reliability evaluation are identified, and upcoming research directions that are of interest to reliability engineers and researchers are presented. The remainder of this paper is structured as follows. Section II presents the BN-based reliability evaluation methodology. Section III summarizes and analyzes the applications of BNs in evaluating the reliability of hardware, structures, software, and humans. Section IV suggests research directions. Section V summarizes the study.

II. BN-based Reliability Evaluation Methodology

A. Overview of BNs

BNs, also known as static BNs, are probabilistic directed acyclic graphical models. They use nodes to represent variables, arcs to signify direct dependencies between the linked nodes, and conditional probabilities to quantify the dependencies. Static BNs are widely used in reliability evaluation, and many monographs have introduced BNs in detail [16-18].

For n random variables $X_1, X_2, \ldots, X_n$ and a directed acyclic graph with n nodes, among which node j ($1 \leq j \leq n$) is associated with X_j variable, the graph is the BN representing the variables $X_1, X_2, \ldots, X_n$ in the following equation:

$$P(X_1, X_2, ..., Xn) = \prod_{j=1}^{n} P(X_j \mid parent(X_j)), \tag{1}$$

where the parents (X_j) denote the set of all variables X_i and an arc connects node i to node j in the graph.

According to conditional independence assumptions and chain rules, the joint probability of variables $U = \{X_1, X_2, \ldots, X_n\}$ can be calculated as follows:

$$P(U) = \prod_{i=1}^{n} P(X_i \mid Pa(X_i)), \tag{2}$$

where $Pa(X_i)$ is the parent node of X_i in the BN.

BNs can perform backward or diagnostic analyses with various inference algorithms based on *Bayes' theorem*, which is expressed as follows:

$$P(U \mid E) = \frac{P(E \mid U)P(U)}{P(E)} = \frac{P(E,U)}{\sum_U P(E,U)}. \tag{3}$$

Several limitations may be observed when BNs are adopted to evaluate the reliability of dynamic or complex systems [16] because BNs are static models and do not involve classes and objects. By contrast, dynamic BNs (DBNs) can represent the dynamic behavior of systems [18], and object-oriented BNs (OOBNs) can model complex systems with identical or similar components [17].

Evaluating the reliability of objects at the present moment does not involve temporal features; thus, BNs in such an evaluation scenario are appropriate. By contrast, in predicting reliability in the future, temporal features are involved; thus, DBNs are required. DBNs are extended BNs that relate variables to each other between adjacent time steps; that is, DBNs include multiple copies of the same variables, and the different copies represent different states of the variables over time [18]. DBNs are powerful tools in representing dynamic systems and therefore widely used in the reliability prediction of objects.

Establishing a BN-based reliability evaluation model is difficult and tedious when the evaluated object is too complex to be modeled with BNs, especially when the object is composed of collections of identical or similar components. Object-oriented methods are integrated into BNs to form OOBNs. An OOBN is a BN that contains not only the usual nodes but also instance nodes, which represent an instance of another generic BN fragment termed as class. An object, which is the fundamental unit of an OOBN, is produced by instantiating the class. OOBNs allow for simple model reuse, submodel encapsulation, and model construction in a top-down fashion, a bottom-up fashion, or a mixture of the two [17]. OOBNs are suitable tools for evaluating the reliability of objects with large, complex, and hierarchical structures.

Complex dynamic systems can be modeled by dynamic OOBNs (DOOBNs), which are an integration of DBNs and OOBNs [19]. A DOOBN-based model was used in the reliability evaluation of a water heater process in a previous work, from implementation to operation [20].

B. Procedure for Reliability Evaluation with BNs

For each category of evaluated objects (i.e., hardware, structures, software, and humans), BN-based reliability evaluation mainly includes four steps, namely, BN structure modeling, BN parameter modeling, BN inference, and verification and validation. A detailed flowchart of this procedure is given in Figure 1.

The BN structure is the model's qualitative part and corresponds to the directed acyclic graph. BN structure modeling consists of determining nodes and specifying linking arcs. BN structure modeling can be completed using the following methods: knowledge representation (for hardware, structures, software, and humans), mapping (for hardware, software, and humans), and structure learning (for hardware).

BN parameter modeling includes assigning prior probability and specifying conditional probability. Prior probability refers to the probability distribution of variables before any evidence is considered. Conditional probability refers to the posterior probability of variables when evidence is observed. A conditional probability table is used for discrete variables, whereas a conditional probability distribution is used for continuous variables. BN parameter modeling can be completed using the following methods: expert elicitation (for hardware, structures, software, and humans), mapping (for hardware), and parameter learning (for hardware, structures, software, and humans).

In BN-based reliability evaluation, BN inference is used to update the probability evaluation of networks given new observations or information. BN inference can be conducted using exact inference (for hardware and structures) and approximate inference (for hardware and software). Many BN tools, such as Netica and Hugin, are widely used for BN inference (for hardware, structures, software, and humans).

The verification and validation of BN models are of great significance to reliability evaluation because they provide reasonable confidence to the assessment results. Verification is determining whether a model accurately represents the corresponding description and specifications. It can be completed using sensitivity analysis (for hardware, structures,

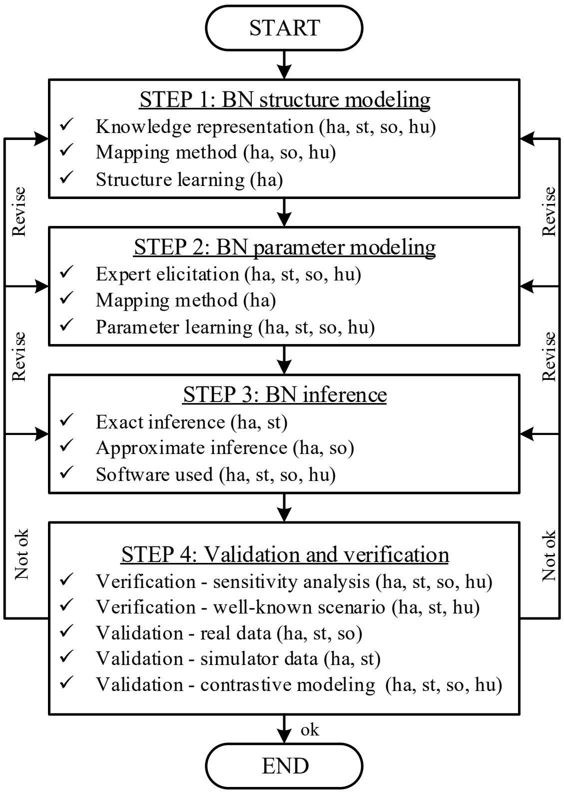

Figure 1. Detailed flowchart of BN-based reliability evaluation (ha: hardware; st: structures, so: software; hu: humans)

software, and humans) and well-known scenarios (for hardware, structures, and humans). Validation is determining whether a model accurately reflects reality and can be accomplished using real data (for hardware, structures, and software), simulated data (for hardware and structures) and contrastive modeling (for hardware, structures, software, and humans).

III. Applications of BNs in Reliability Evaluation

A. Hardware Reliability Evaluation with BNs

Figure 2 shows a typical BN for the reliability evaluation of a series hardware system composed of a series system and a parallel system. Each root node represents the status of each component in the systems, and the final leaf node represents the reliability of the entire system. A review of the procedural steps for hardware reliability evaluation with BNs follows.

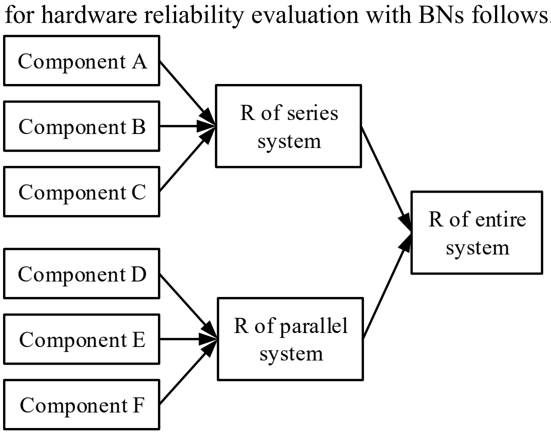

Figure 2. Typical BN for hardware reliability evaluation

1) BN Structure Modeling: In the literature, three main types of methods have been identified for constructing BNs for the reliability evaluation of hardware, namely, knowledge representation, mapping, and structure learning.

Knowledge representation techniques are also known as cause-and-effect relationship methods. The knowledge about the evaluated hardware is collected by experts and captured into BNs. For example, Sättele *et al.* [21] developed a BN-based reliability evaluation method for alarm systems for natural hazards; the structure of the BNs was constructed on the basis of the influence relationships of the components in the monitoring, data interpretation, and information dissemination units. Honari *et al.* [22] used BNs to evaluate the reliability of an (r, s)-out-of-(m, n): F distributed communication system; the structure of the BNs was constructed on the basis of the logical relationship of the (r, s)-out-of-(m, n): F system. Eliassi *et al.* [23, 24] proposed a BN-based composite power system reliability modeling and evaluation methodology; the structure of the BNs was extracted by a minimal cutset-based approach, and the nodes at the three main levels of the structure were linked together according to the logical relationships of the components, cutsets, and system state. Cai *et al.* [25-27] adopted BNs and DBNs to evaluate the reliability and availability of subsea blowout preventer systems while considering common cause failure, imperfect repair, and preventive maintenance [28, 29]; the structures of the BNs and DBNs were constructed using the logical relationships of the components and knowledge of experts. These knowledge representation methods are largely subjective and may produce inaccurate reliability evaluation models. In addition, BN structures constructed by knowledge representation methods are large and pose substantial computational demand on inference algorithms.

Mapping techniques are also termed translating or transforming methods. The structure of the BNs is transformed from other reliability evaluation models. Fault tree analysis is a popular technique for hardware reliability evaluation and a widely used mapping model. Conversion algorithms from fault tree to BNs have been thoroughly researched. Bobbio *et al.* [1] proposed a mapping algorithm from a fault tree to BNs and evaluated the reliability of a redundant multiprocessor system. Huang *et al.* [30] analyzed the reliability of the electrical system of a CNC machine tool by using BNs; the structure of the BNs was also mapped from fault trees. Mi *et al.* [31] proposed a reliability evaluation methodology for electromechanical systems; the structure of the BNs was translated from dynamic fault trees. Montani *et al.* [32] and Portinale *et al.* [33] developed DBN-based reliability analysis tools; the structure of their DBNs was translated from corresponding dynamic fault trees. Boudali and Dugan [34] proposed a discrete-time BN-based reliability modeling and analysis methodology for critical systems; the structure of the discrete-time BNs was translated from dynamic fault trees. Liang *et al.* [35] proposed a reliability assessment methodology that is based on the integration of DBN and numerical simulation for warships; the structure of the DBNs was transformed from fault trees. Cai *et al.* [36] constructed BNs by transforming fault trees and assessed the reliability and availability of a subsea blowout preventer system by considering imperfect repair. Reliability models aside from

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fault trees can also be mapped into BNs. For example, Liu *et al.* [37] proposed a reliability assessment method for auxiliary feedwater systems by translating GO-FLOW models to BNs. Mapping methods are less subjective, and the accuracy of reliability evaluation by mapping methods is higher than that by knowledge representation methods. The superiority of the former can be ascribed to the use of mapping models, such as fault trees, instead of the knowledge of experts.

Structure learning techniques are machine learning methods. The structure of BNs for reliability evaluation is learned from massive reliability data related to the failure of each component and the entire hardware system. Structure learning methods are completely objective. The advantage of this type of method is the higher accuracy of the reliability evaluation results compared with those obtained by knowledge representation and mapping methods. The apparent disadvantage of structure learning methods is the difficulty or infeasibility of collecting sufficient data for structure learning. An alternative is to use simulation methods to generate sufficient data to fill the gap. For example, Daemi *et al.* [38] proposed a BN-based reliability evaluation methodology for composite power systems by focusing on the importance of components; they used state sampling using Monte Carlo simulation to generate sufficient training data and used common structure learning algorithms to establish the structure of the BNs with the data. Doguc and Ramirez-Marquez [39, 40] developed a generic BN-based evaluation methodology for system reliability; they used the *K*2 algorithm to learn the structure of the BNs from historical data of the system. Only few studies have used structure learning methods in constructing BNs for reliability evaluation mainly because the difficulty in obtaining training data limits the application of these methods.

2) BN Parameter Modeling: This process is similar to BN structure modeling. Three main types of methods for BN parameter modeling for the reliability evaluation of hardware have been identified, namely, expert elicitation, mapping, and parameter learning.

In expert elicitation methods, the prior and conditional probabilities of a BN for reliability evaluation are specified by domain experts on the basis of their knowledge, experience, and statistical reliability data. For example, Daemi *et al.* [38] assigned the parameters of component nodes artificially from forced outage rates to establish a BN-based reliability evaluation model for composite power systems. Yontay and Pan [41] developed a BN-based tool for evaluating the reliability dependencies between components and systems; the prior distributions of the model parameters were obtained by converting knowledge of experts into corresponding statistical expression. Zhang *et al.* [42] proposed a BN-based reliability evaluation method for a power system and evaluated the probabilities of successful cyberattacks on the system; the conditional probabilities of the nodes were determined using simple “AND” and “OR” relationships. Ruijun *et al.* [43] used interval-valued triangular fuzzy BNs to evaluate the reliability of multistate systems; the conditional probability tables of the networks were established by combining the knowledge of experts and practical experience. A major issue that arises when modeling BN parameters is the potentially large size of conditional probability tables. Micromodels such as noisy-or and noisy-max have been proposed to solve this problem. These models present a local conditional probability distribution that depends on fewer parameters than do complete ones. Therefore, these micromodels can be used for local structures. However, they may be inaccurate in real-world scenarios.

If the structures of BNs are translated from other kinds of reliability evaluation models by mapping methods, then the parameters of the BNs can also be translated from those models. With a fault tree as an example, the prior probabilities of the root nodes in BNs are identical to the corresponding probabilities of the leaf nodes in the fault tree. The conditional probabilities of the nonroot nodes in the BNs are assigned on the basis of the logical relationships of the nodes in the fault tree, such as AND-gate, OR-gate, R/N-gate, PAND-gate, SEQ-gate, and SP-gate [1, 30-37]. The gate logic in a fault tree is usually binary, but mapping the two-state relationship in a fault tree to a multi-state relationship in BNs is difficult. Therefore, inaccurate reliability evaluation models will be established when multistate relationships are considered in reality.

Parameter learning in BNs is known as parameter estimation. It is the task of estimating prior and conditional probabilities corresponding to the network structure. Like structure learning methods, parameter learning methods have the strength of highly accurate reliability models but also the weakness of difficulty in obtaining sufficient training data. Many algorithms have been developed for parameter learning, such as the expectation maximization and the penalized expectation maximization algorithms. Several parameter learning methods have been researched and used in the field of BN-based reliability evaluation. For example, Doguc and Ramirez-Marquez [39, 40] used the unsupervised construction algorithm *K*2 to calculate the conditional probabilities of BNs for system reliability evaluation with the help of Bayes' theorem. Daemi *et al.* [38] specified the parameters of load point nodes using a maximum likelihood method for the BN-based reliability evaluation model for composite power systems. Liu *et al.* [44] established a BN-based reliability evaluation model by considering common cause failures and studied the influence of extreme averse weather on the reliability of composite power systems; the conditional probability distributions of the BNs were obtained using random sampling, a parameter learning algorithm.

3) BN Inference: Exact and approximate inference algorithms are used to update the probability evaluation of networks given new observations or information.

Exact algorithms, such as variable elimination, junction tree, and conditioning algorithms, guarantee correct answers but tend to be computationally demanding. Tien and Der Kiureghian [45] proposed a BN-based reliability evaluation methodology for infrastructure systems, presented a BN parameter compression approach, and developed an exact inference algorithm that is based on variable elimination, which used compressed conditional probability tables without decompressing them, for system reliability assessment. Tong and Tien [46] extended the research from binary systems to multistate systems, which are also based on an exact inference algorithm.

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By contrast, approximate algorithms relax the demand for exact answers to ease the computational demand. These algorithms are usually based on sampling or optimization. This category includes stochastic sampling, importance sampling, Markov chain Monte Carlo, and belief propagation. Marquez *et al.* [47] proposed a novel hybrid BN-based framework containing a mixture of discrete and continuous variables for system reliability analysis and developed an approximate inference algorithm that is based on dynamic discretization for the hybrid BNs by combining an iterative discretization scheme with a junction tree inference algorithm. Zhong *et al.* [48] applied a time-to-failure modeling and reliability evaluation method that is based on a continuous BN for complex mechatronic systems; a revised nonparametric belief propagation inference algorithm, which is an approximation inference algorithm, was developed to perform the reliability analysis.

Notably, research on BN inference algorithms in the field of reliability engineering has received limited attention. Conversely, inference is performed using various commercial or free software, including Netica [26, 27, 36, 37, 49], AgenaRisk [31], MSBNs [25], GeNIe [21, 50], and BayesiaLab [51].

4) Verification and Validation: The verification methods for BN-based hardware reliability evaluation are based on either sensitivity analysis or well-known scenarios. For the first type of method, Cai *et al.* [49] used a three-axiom sensitivity analysis method to verify the DBN-based reliability evaluation methodology for grid-connected photovoltaic systems. For the second type of method, Daemi *et al.* [38] verified the efficiency of a BN-based reliability evaluation model for composite power systems by applying it to the IEEE Reliability Test System. Similarly, Zhang *et al.* [42] and Liu *et al.* [44] verified their BN-based reliability analysis methods for composite power systems by applying them to IEEE Reliability test System 79 and the modified IEEE Reliability Test System, respectively.

The validation methods for BN-based hardware reliability evaluation are based on real data, simulated data, and contrastive modeling. For the first type of method, Doguc and Ramirez-Marquez [39, 40] validated the reliability evaluation results obtained by BNs by comparing them with actual values obtained by other researchers. For the second type of method, Zhong *et al.* [48] validated their reliability evaluation method on the basis of a continuous BN for complex mechatronic systems by using simulated data obtained from an active vehicle suspension simulation that was based on MATLAB's Kernel Density Estimation Toolbox. For the last type of method, Eliassi et al. [23] validated their BN-based reliability evaluation method for composite power systems by comparing it with the state enumeration approach and Monte Carlo simulation. Similarly, Marquez *et al.* [47] and Simon et al. [51] used analytical solutions, exact probability theorem, and Markov chain approach to validate their respective BN-based reliability analysis and inference methods.

B. Structural Reliability Evaluation with BNs

A structure is considered a specific kind of hardware because the reliability of a structure is closely related to the mechanics principles but not to the configurations or relationships of components. The DBN is the main modeling tool for structural reliability evaluation because structural reliability is closely related to the degradation behavior of the structure. Figure 3 depicts a typical DBN for the reliability evaluation of a degraded structure. In general, nodes δ and ρ are the parameters in the structure degradation model, node E represents the observed evidence, and node R represents the reliability of the structure. A detailed review of the procedural steps for structural reliability evaluation with this type of DBN follows.

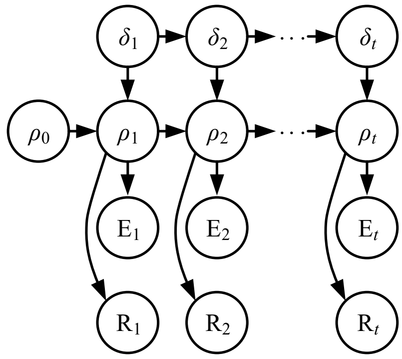

Figure 3. Typical BN for structural reliability evaluation

1) BN Structure Modeling: In the literature, only the first type of method for the BN structure modeling of hardware, which is knowledge representation, is used in structural reliability research. For example, Groden and Collette [52] proposed a BN-based framework for updating the structural performance and reliability of marine structures; fatigue, probabilistic, and permanent set models were integrated into single BNs artificially, and the possible values of various distributions in these models were represented by the nodes of the BNs. Hackl and Kohler [53] proposed a DBN-based evaluation methodology for the structural reliability of reinforced concrete structures, focusing on degradation caused by corrosion; the structure of the BNs was constructed by transforming the parameters in corrosion and structural models into the nodes of the BNs and the causal relationships between the parameters of the models into the edges of the BNs. Mokhtar *et al.* [54] developed an evaluation methodology for the structural reliability of corroded interdependent pipe networks by using BNs, whose structure was constructed using the structural relationships of the pipelines and segments. Lee and Achenbach [55] analyzed the reliability of a jet engine compressor rotor blade with a fatigue crack by using DBNs; the structure of the DBNs was based on a fatigue crack growth model, and the parameters in the model were represented by the nodes. In [56], a similar method was used for the structural reliability analysis of stress corrosion crack growth. Straub [57] established a generic stochastic structural reliability analysis model for deterioration processes by using DBNs; the nodes represented the parameters in structural models, such as the fatigue crack growth model, and the structure of DBNs was constructed artificially. The literature shows that the structure of BNs is mainly constructed from structural performance models or the artificial integration of these models, such as the integration of a corrosion model and a mechanical model. The major feature of BNs is that the nodes represent the parameters in these models.

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Mapping methods have not been used for the BN structure modeling for structural reliability evaluation because of the absence of one-to-one correspondence between the original reliability evaluation models, such as response surface models, and the BNs. In addition, structure learning methods have not been reported because the available structural reliability data are insufficient, especially those on degradation.

2) BN Parameter Modeling: The prior probabilities and conditional probabilities of BNs for structural reliability evaluation are specified using expert elicitation methods or parameter learning methods.

Using an expert elicitation method, Mokhtar et al. [54] established the prior probability table of BNs for a structural reliability evaluation methodology for corroded interdependent pipe networks by using the failure probabilities obtained from a first-order reliability method; the authors specified the conditional probability on the basis of series or parallel relationships. Mahadevan *et al.* [58] proposed a BN-based structural system reliability evaluation methodology and used a branch-and-bound method to construct the conditional probability tables.

Similar to BN structure modeling, parameter learning methods suffer from insufficiency of structural reliability data, especially those on the degradation of structures. Therefore, parameter learning with complete data is impossible. Certain parameter learning algorithms with incomplete data have been developed and used in the field of BN-based reliability engineering. For example, Lee and Achenbach [55] calibrated the parameters of DBNs for the reliability analysis of the rotor blade of a jet engine compressor by using an expectation maximization algorithm for the incomplete available inspection data. A similar method was used in [56] for the structural reliability analysis of stress corrosion crack growth.

3) BN Inference: Given that structural reliability modeling focuses on degradation behavior, the variables in structural reliability models are represented as a continuous space in DBNs. The convergence rate of the approximate inference algorithms for the models involving continuous variables is extremely slow, and in reality, the algorithms may not even converge. In addition, the application of simulation-based approximate inference algorithms in the case of rejection or likelihood sampling is also limited due to the computational inefficiency of such algorithms [57, 59]. A review of the literature shows that only exact inference algorithms have been used in the field of BN-based reliability evaluation. For example, Mokhtar *et al.* [54] used a junction tree algorithm to assess the structural failure probability of corroded interdependent pipe networks. Lee and Achenbach [55] used a forward–backward algorithm to achieve the exact inference of DBNs for the reliability analysis of a jet engine compressor rotor blade. A similar method was used in the structural reliability analysis of stress corrosion crack growth in [56]. In [57] and [60], a forward–backward algorithm was adopted to perform the exact inference of DBNs for a stochastic structural reliability analysis model for deterioration processes, and Straub and Kiureghian [59, 61] applied exact inference algorithms to BNs for their proposed structural reliability framework by minimizing the enhanced BNs into reduced BNs.

Few commercial BN tools have been used in structural reliability evaluation; alternatively, researchers have written their own BN codes for structural reliability evaluation by using MATLAB [54-57, 59, 61-63].

4) Verification and Validation: Verification and validation methods for structural reliability evaluation are identical to those for hardware reliability evaluation. The verification methods are based on sensitivity analysis and well-known scenarios. For example, Mokhtar *et al.* [54] used both types of method as they conducted a sensitivity analysis and behavior tests by simulating known scenarios to verify the proposed BN-based structural reliability evaluation methodology. Using the second type of method, Zwirglmaier and Straub [62] used two application examples to verify the discretization procedures for rare events in discrete BNs for structural reliability assessment.

Three types of validation methods for BN-based structural reliability evaluation are used, namely, validations based on real data, simulated data, and contrastive modeling. Regarding the first type of method, Lee and Achenbach [55] validated a DBN-based model for the reliability analysis of a jet engine compressor rotor blade by using a Bayes factor and filed inspection data. For the second type of method, Lee *et al.* [56] validated a structural reliability analysis methodology for stress corrosion crack growth by using Bayesian hypothesis testing and simulated inspection data. Groden and Collette [52] used synthetic inspection data generated by Monte Carlo simulation to validate a BN-based framework for updating structural performance and reliability of marine structures. Regarding the last type of method, Mahadevan *et al.* [58] validated the proposed BN-based structural system reliability evaluation methodology by comparing its results with those of traditional reliability methods. Zhu and Collette [63] proposed a dynamic discretization method for DBN inference for structural reliability analysis; the robustness and efficiency of the method were validated by comparing it with the existing ones by using crack growth examples. Straub [57] validated a DBN-based stochastic model for structural reliability analysis by comparing its results with those of a second-order reliability method and Monte Carlo simulation. Luque and Straub [60] validated the computational efficiency of a DBN-based reliability analysis method for deteriorating systems by comparing its results with those of a standard Markov chain Monte Carlo method.

C. *Software Reliability Evaluation with BNs*

Software is different from hardware and structure in that it is not subject to degradation. Any operational failure is caused by faults inherent to the software. Software failures are caused by random input data, maintenance activities, or changing environments over time. BNs are used to combine various information sources to evaluate the reliability of software systems. Figure 4 shows a typical BN for the reliability evaluation of software. In general, the root nodes represent the factors affecting reliability, and the final leaf node represents

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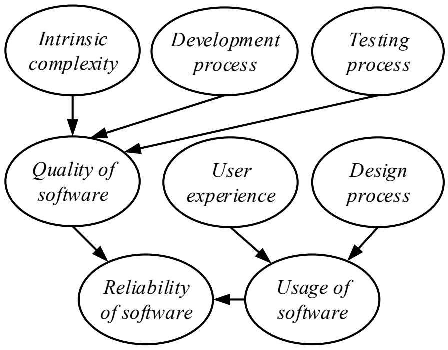

Figure 4. Typical BN for software reliability evaluation

the reliability of the software. A review of the procedural steps of software reliability evaluation with BNs follows.

1) BN Structure Modeling: Knowledge representation and mapping are the two main types of methods of constructing BN structures.

In knowledge representation methods, the information sources related to software reliability and the interdependent relationships are determined mainly by the developers and users of the software. For example, Fenton *et al.* [64-66] proposed a BN-based model for software reliability and defect prediction and constructed the BN structure artificially by considering the factors affecting the reliability of a software product, such as the experience of staff, the use of formal methods, and the complexity of the problem. Neil *et al.* [67] adopted OOBNs to construct large-scale models for predicting software reliability and safety; the structure of the BN fragment was constructed on the basis of the experience of experts. Dahll and Gran [68] proposed a BN-based reliability and safety evaluation approach for the software of programmable safety systems; all available relevant information was integrated into the BNs, and the structure was constructed gradually by integrating the target nodes with observable and intermediate ones. Gran [69] and Dahll [70] used BNs to combine disparate sources of information in the safety and reliability evaluation of software-based systems and adopted a causal direction approach to establish the structure of the BNs on the basis of the experience and judgment of experts. Mohanta *et al.* [71] proposed a BN-based bottom-up method for the early prediction of software reliability from product metrics and established the topology of the BNs by using the faults and corresponding design metrics. Si *et al.* [72] developed a BN-based dependability assessment method for Internet-scale software and established the structure of BNs by analyzing the software architecture on the basis of its characteristics.

In mapping methods, the structures of the BNs are translated from other software reliability evaluation models or from the logic of the software. For example, Zou et al. [73] integrated a flow network model, BNs, and the proposed contribution method to evaluate the reliability of a digital instrumentation and control software system; they analyzed the sensitive edges by mapping the flow network model into the BNs automatically. Roshandel *et al.* [74] applied a DBN-based software reliability prediction approach at the architectural level, constructed the structure of the BNs from the corresponding global behavioral model, and then extended the model to the DBNs; however, they did not perform a strict model transformation. Jiang *et al.* [75] proposed a BN-based reliability analysis model for programmable logic controller systems; the proposed hybrid relation model, which was identified as a BN, was constructed by mapping on the basis of the execution logic of the embedded software.

Software is not subject to aging; thus, the tools used are nearly all BNs but not DBNs. In addition, similar to the structural reliability literature, the software reliability literature has not reported the use of structure learning methods for BN-based software reliability evaluation.

2) BN Parameter Modeling: Establishing a parameter model for BNs by using parameter learning methods is difficult because complete data are required by collecting sufficient software reliability data. In BN parameter modeling for software reliability evaluation, expert elicitation methods and parameter learning methods with incomplete data are mainly used. In the BN-based software defect and reliability evaluation models proposed by Fenton *et al.* [64] and Neil *et al.* [67], the prior probabilities and conditional probabilities of the BNs were determined using expert elicitation and data. Gran and Helminen [69, 76] proposed a method for merging a BN for a software safety assessment with a BN for the reliability evaluation of software-based digital systems; the conditional probability tables of the BNs were elicited through brainstorming exercises with all the project participants, who shared their general knowledge and experience in software development and evaluation. In their BN-based software reliability and safety evaluation models, Dahll and Gran [68, 70] assigned the prior and conditional probabilities of the BNs by using expert judgment. In their BN-based software reliability prediction method, Mohanta *et al.* [71] obtained the conditional probability distributions by using parametric or functional form and conducting multiple linear regression analysis.

For the second type of method, Bai *et al.* [77] proposed a software reliability prediction approach based on Markov BNs and used an expectation maximization algorithm to estimate the unknown parameters in the distribution from incomplete data.

3) BN Inference: No major study has focused on BN inference algorithms for software reliability evaluation. To our knowledge, only one approximate inference algorithm related to dynamic discretization has been reported. Fenton *et al.* [66] proposed a software defect and reliability prediction model based on BNs; an approximate inference method using dynamic discretization algorithm was adopted to perform the prediction, and the method exhibited higher accuracy and required less storage space than did a static one. Alternatively, many researchers have used BN tools, such as Hugin [64, 65, 68-70, 76], Netica [71, 78], and AgenaRisk [66], to conduct BN inference for software reliability evaluation. This situation is similar to that of hardware reliability research and totally different from that of structure reliability research.

4) Verification and Validation: Verification based on sensitivity analysis is the main verification method for BN-based software reliability evaluation models. Roshandel *et al.* [74] used sensitivity analysis to demonstrate that the proposed DBN-based software reliability prediction approach was effective at the architectural level, and its results were helpful

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in making architectural decisions. Liu *et al.* [78] partially used sensitivity analysis to validate that the proposed BN-based software reliability evaluation method for subsea blowout preventers was accurate and rational. Verification based on well-known scenarios is not widely used possibly because no well-known software scenario similar to the IEEE Reliability Test System for hardware has been established for such verification.

Two validation methods for software reliability evaluation are used, namely, validation based on real data and validation based on contrastive modeling. Real data are easier and more likely to be obtained from experiments on software than from those on hardware and structure. Therefore, many researchers have opted for validation based on real data. Neil *et al.* [67] used real test data and expert opinion that were not used to derive the BNs to validate the proposed OOBN-based software reliability and safety prediction approach. Si *et al.* [72] performed experiments on a real enterprise e-commerce application system to validate the effectiveness of their BN-based dependability assessment method for Internet-scale software. Jiang *et al.* [75] used experimental results to demonstrate the accuracy of the proposed BN-based reliability analysis model for programmable logic controller systems. Performing validation through contrastive modeling, Bai [79] evaluated the performance of a Markov BN-based software reliability prediction model with an operational profile by comparing the results of the proposed model with those of the Kaaniche–Kanoun model. In addition, Mohanta *et al.* [71] validated their BN-based software reliability early prediction method by using real data obtained from a set of experiments and investigated the accuracy of the method by comparing its results with those of the Rome Air Forces Development Centre method proposed by McCall [80].

D. Human Reliability Evaluation with BNs

Human reliability analysis, which is an important research field in reliability engineering, aims to identify and analyze the causes, consequences, and contributions of human failures in various industrial systems [81]. BNs are increasingly used in this field due to their capability to describe the complex influencing relationships of human factors. Figure 5 illustrates an example of a BN used in human reliability evaluation. In general, the root nodes represent the factors affecting reliability, and the final leaf node represents human reliability. A review of the procedural steps for human reliability evaluation with BNs follows.

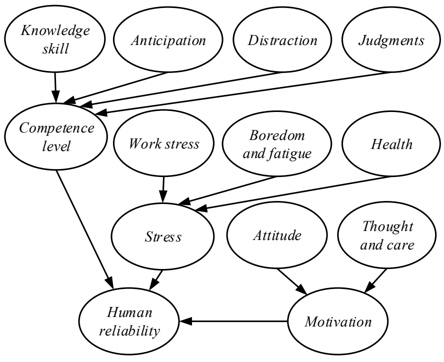

Figure 5. Typical BN for human reliability evaluation

1) BN Structure Modeling: With regard to the structure of BNs for human reliability evaluation, knowledge representation method is still the primary method. The structure can be derived from the judgment and experience of experts, with limited human performance data. For example, Li *et al.* [82] studied organizational influences quantitatively by using a fuzzy BN-based human reliability analysis method and established the structure of the BNs by using the cause-and-effect relationship method on the basis of the experiences of maintenance and human factor experts. Aalipour *et al.* [83] used BNs to research the causes of human errors in the maintenance activities in a production process and constructed the structure of BNs on the basis of the causal dependencies between the variables. Zwirglmaier *et al.* [84] developed a BN-based methodology to capture cognitive causal paths in human reliability analysis and adopted a two-level method (i.e., causal path identification and model reduction) to construct the structure of the BNs.

Numerous human reliability analysis methods have been developed, and some of these methods have been mapped to BNs in the study of human reliability. Groth and Swiler [85] proposed a BN version of SPAR-H for human reliability analysis by directly translating the SPAR-H model to BNs. Sundaramurthi and Smidts [86] proposed a BN-based human reliability modeling methodology for the Next Generation System Code, and the structure of the BNs was transformed from the simplified causal graph.

Cai *et al.* [87] used BNs to study the influence of human factors on offshore blowouts, and the structure of the BNs was mapped from pseudo-fault tree models. Martins and Maturana [88] proposed a BN-based framework for human reliability analysis for collision accidents during oil tanker operation and transformed the collision fault tree into BNs that represented the same domain.

Similar to software, human factors are not subject to degradation and aging; therefore, BNs and not DBNs are mainly used for human reliability analysis.

2) BN Parameter Modeling: The uncertainties in human factors are more numerous and complex than those in hardware, structures, and software. Expert elicitation methods may be the most appropriate method for parameter modeling. Li *et al.* [82] estimated the prior and conditional probabilities of fuzzy BNs for human reliability analysis on the basis of the engineering judgments of domain experts. Aalipour *et al.* [83] assigned the marginal probability tables of BNs for human error analysis in the cable manufacturing industry by using direct elicitation and expert judgment. Zwirglmaier *et al.* [84] quantified a BN for human reliability analysis by combining human performance data and expert elicitation results as information sources. Martins and Maturana [88] obtained the conditional probability tables through an iterative search and linear interpolation approach in the context of the lack of data and expert opinion. Baraldi *et al.* [89] derived the conditional probability tables of BNs for human reliability analysis from the elicitation of a limited number of relationships provided by experts in the form of rules. Musharraf *et al.* [90] developed a collection method for human performance data by virtual experiments and assigned the prior and conditional probabilities of BNs for human reliability analysis in the event of an offshore emergency evacuation. Li *et al.* [91] used

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situational awareness data measured by simulation experiments to determine the conditional probability distribution of a BN-based model for operators' situational awareness reliability.

Collecting sufficient human performance data for general industrial applications is difficult. However, for certain industries, some data have already been collected and sorted, and parameter learning methods can be used to determine the prior and conditional probabilities. For example, Sundaramurthi and Smidts [86] calculated the conditional probabilities and node probabilities by using the parameter learning function of the software GeNIe and data collected from aviation and nuclear accidents.

3) BN Inference: No BN inference algorithms have been studied for human reliability analysis. However, many BN tools have been used directly to perform BN inference, including MSBNx [82, 92, 93], AgenaRisk [83], Hugin [85, 94], GeNIe [86, 90, 95], and Netica [87, 88].

4) Verification and Validation: Validation techniques for human reliability evaluation methodologies were researched and classified by Kirwan [96, 97], but he focused on all evaluation methodologies instead of only BN-based ones. In BN-based human reliability analysis, verification and validation are distinct. For verification, sensitivity analysis is the primary method. Cai *et al.* [87] performed a sensitivity analysis to verify the proposed BN models for human reliability analysis of offshore blowouts. Gregoriades and Sutcliffe [98] used BNs to model the cause-and-effect relationships of performance-shaping factors and assessed the agent's operational reliability; the models were validated using data mining techniques, including relevance analysis, association rules, and classification. Yang *et al.* [94] developed a human reliability quantification method in marine engineering by integrating fuzzy logic, evidential reasoning and BNs and used sensitivity analysis to validate the proposed method. In addition, verification based on well-known scenarios has also been reported. Lee and Seong [93] developed a BN-based computational model to evaluate the situation of nuclear power plant operators and verified the proposed method by comparing the results of expert mental model and less-skilled operator mental model.

Acquiring real and even simulated data is difficult; consequently, only validation based on contrastive modeling has been used. For instance, Groth and Swiler [85] validated the proposed BN version of SPAR-H for human reliability analysis by comparing it with the SPAR-H method. Musharraf *et al.* [90] validated their BN-based human reliability analysis method for offshore emergency evacuation by comparing its results with those of the Bradbury-Squires method [99] by using the same data. Musharraf *et al.* [95] used a success likelihood index methodology to validate another BN-based human reliability assessment model for offshore emergency conditions. Kim and Seong [92] proposed a BN-based analytic model to evaluate the situation of nuclear power plant operators and validated this method by comparing it with the situation evaluation model proposed by Miao *et al.* [100]. This comparison of methods validates existing human reliability evaluation methodologies partially but not completely. A complete validation should be performed further in real industrial applications with real data.

E. Discussion

The applications of BNs in reliability evaluation are reviewed in the previous section. The important issues mentioned can be summarized as follows.

(1) Most of the studies on BN-based reliability evaluation focus on hardware, whereas only few studies explore the BN-based reliability evaluation of structures, software, and humans. In the reliability evaluation of hardware, structures, software, and humans, most studies focus on BN structure modeling and BN parameter modeling, whereas only few studies include BN inference, verification, and validation.

(2) Knowledge representation and expert elicitation methods are the predominantly used techniques for structure and parameter modeling because they offer the simplest solution to determining the uncertainty between the nodes of BNs, that is, by using the knowledge of experts. However, these methods are highly subjective and may produce inaccurate reliability evaluation models.

(3) Mapping methods are less subjective, and the accuracy of reliability evaluation by this type of method is higher than that by knowledge representation methods. Therefore, if the structure modeling is using mapping method, the parameter modeling is not always using mapping method, just like software and human.

(4) Structure and parameter learning are the most accurate methods for constructing BNs; however, in practice, obtaining sufficient and valuable data for training structure and parameter models is nearly impossible.

(5) BN inference algorithms, including exact and approximate inference, have been seldom investigated in studies on BN-based reliability evaluation methodologies. Instead, inference is mainly performed using various commercial or free software programs because they can help solve computational complexity and reduce memory usage considerably.

(6) Verification and validation are important to BN-based reliability evaluation methodologies; however, many proposed methodologies have not been verified and validated using suitable methods. Real data have only seldom been applied to the verification and validation of BN-based reliability methodologies. Instead, contrastive modeling and simulated data are widely used.

(7) DBNs are extensively used to study the reliability of hardware and structures. However, their application in software and human reliability evaluation is limited mainly because only hardware and structures are subject to degradation and aging, which can be well described by DBNs.

IV. RESEARCH DIRECTIONS

In view of the literature review of BN-based reliability evaluation methodologies, a few upcoming research directions in this field that are of interest to reliability researchers and practitioners are presented in this section.

A. BN Modeling Methods Considering Cascading Failures

Failure dependency remarkably affects the reliability of systems, particularly hardware and structures. Common cause failure and cascading failure are two typical examples of failure dependency. BN modeling methods considering

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common cause failure have been extensively researched [25, 101]. A cascading failure is a failure in an interconnected system, in which the failure of a part can trigger the failure of successive parts. Few studies on the BN-based reliability evaluation methodology have considered cascading failures [102]. For hardware and structure reliability evaluation, constructing the structure and parameter models of BNs for reliability evaluation by considering the cascading failure of components, especially when temporal and dynamic features are involved, is a challenging problem.

B. DBN-Based Reliability Prediction for Software and Humans

Software and humans are not subject to degradation and aging when they are modeled for reliability evaluation. Software behavior changes with time because maintenance activities occur or the environment changes over time. Human errors are more complex than software errors because human reliability is influenced by intrinsic factors (e.g., skill) and external factors (e.g., weather). Reliability can be predicted well if the dynamic changes in the environmental factors related to software and human reliability can be modeled using DBNs.

C. Integration of Big Data and BN Reliability Evaluation Methodology

Big data is a popular research topic and has three attributes: volume, variety, and velocity. Massive amounts of data on hardware, structures, software, and humans are collected or recorded by sensors or humans. Numerous pieces of useful information, especially those about system or component failures, are contained by these data. The structure learning and parameter learning of BNs need these useful data for reliability modeling. The integration of big data and BN reliability evaluation presents a definite orientation for interdisciplinary research. However, extracting useful information from big data and constructing reliability evaluation, analysis, and prediction models by using BNs are challenging problems.

D. Rapid Approximate Inference Algorithms for DBNs for Reliability Evaluation

For reliability prediction, DBN inference is mainly accomplished using various commercial or free software programs. In reality, a complex reliability model leads to high computational cost of the inference with software. A time slice with a long period of time should be set, thereby leading to inaccurate prediction results. By contrast, rapid approximate inference algorithms may achieve good prediction results. Therefore, research on rapid approximate inference algorithms for DBNs is a worthwhile future direction.

V. Conclusion

Since the introduction of BNs by Pearl in the early 1980s, their application in reliability engineering has been widely researched and obtained favorable achievements. This work provides a literature review of BN-based reliability evaluation methodologies from the perspective of the objects of evaluation, focusing on the general procedure of reliability modeling with BNs. For each evaluated object (i.e., hardware, structures, software, and humans), the various methods for each procedural step (i.e., BN structure modeling, BN parameter modeling, BN inference, and model verification and validation) are reviewed and analyzed in detail. The potential problems and current gaps in applying BNs to reliability evaluation are discussed, and upcoming research directions that are of interest to reliability researchers are presented. We hope that the current paper can provide researchers and practitioners a helpful guide for BN-based reliability evaluation methodology with BNs.

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