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BAYESIAN NETWORKS AS KNOWLEDGE REPRESENTATION SYSTEM IN DOMAIN OF RELIABILITY ENGINEERING

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Summary. The paper presents Bayesian Networks (BNs) in the context of methodological requirements for building knowledge representation systems in the domain of reliability engineering. BNs, by their nature, are especially useful as a formal and computable language for modeling stochastic and epistemic uncertainty intrinsically present in conceptualization and reasoning about reliability.

Key words: reliability models, probabilistic networks, Bayesian networks, knowledge representation system.

INTRODUCTION

Expressiveness of Bayesian networks (BNs) is sufficient for modeling a wide class of systems that involve uncertainty [1, 2, 3]. Bayesian networks are already accepted as a useful modeling framework that is particularly well suited for reliability applications [4, 5]. The proposal of using BNs as a framework for reliability analysis has initiated a research trend of building BNs corresponding to and comparing with classical reliability formalisms. Features regarding both modeling as well as analysis of reliability block diagrams [6, 7] and fault-trees [8, 9, 10] have been compared to BNs, and it has been showed that BNs have significant advantages over the traditional frameworks [5, 11].

The aim of the paper is the presentation of methodology of building BNs reliability models as a process of translating reliability models represented in classical forms like block diagram, event trees, and fault trees to representation language based on Bayesian network. The reason for BN as reliability knowledge representation language comes from knowledge engineering approach where models are treated as formal and computational symbolic system [12]. Reliability models to be knowledge representation system should have property of being built and adapted with machine learning methods based on empirical data. The second requirement is possibility of functioning as a knowledge base, i.e. answering questions using probabilistic inference algorithms.

Application of BN in modelling both static and dynamic problems in reliability engineering is already well grounded. Authors showed on examples that BN language is at least as expressive as other formal systems used in reliability engineering.

RELIABILITY MODELS AND THEIR BNS REPRESENTATION

Knowledge engineering approach to BN as knowledge representation symbolic system is exemplified as translation of structural reliability models like series, parallel, mixed, bridge and k-out-of-n structures to equivalent Bayesian networks and using them as questions answering system.

Let's assume a system that consists of *n* components each of them is non-renewable after failure and its reliability state is described by two-state random process:

$$X_{e_i}(t)=\begin{cases}1 \text{ if component } e_i \text{ is in operating state at time } t,\\ 0 \text{ in failed state.}\end{cases} \quad t\geq 0, i=1,2,\cdots,n \tag{1}$$

Reliability function of *i-th* component is defined as probability of random event , where is random variable representing time to failure of component , or alternately as expected value of:

$$R_i(t)=P\{\xi_i>t\}=EX_{e_i}(t);\ i=1,2,\cdots,n;\ t\geq 0. \tag{2}$$

State of the system is a binary valued function (structure function) $\varphi(\boldsymbol{X}(t))$ of its components states: $\boldsymbol{X}(t)=(X_{e_1}(t),X_{e_2}(t),\cdots,X_{e_n}(t))$;

$$\varphi(\boldsymbol{X}(t))=\begin{cases}1 \text{ if system is operable at time } t,\\ 0 \text{ in failed state.}\end{cases} \quad t\geq 0, i=1,2,\cdots,n \tag{3}$$

Then system reliability is expressed as:

$$R_s(t)=E\varphi(\boldsymbol{X}_t). \tag{4}$$

All possible reliability structures can be represented as a single Bayesian network with root nodes representing state of components $X_{e_i}(t)$ for required operation time (mission time) $t \geq 0$ and target node representing state of system structure expressed as Boolean function of components states. Example BN representing the following reliability structures: S1 – series, S2 – parallel, S3 – "k-out-of-n", S4 – bridge, S5 – mixed is shown on Fig. 1.

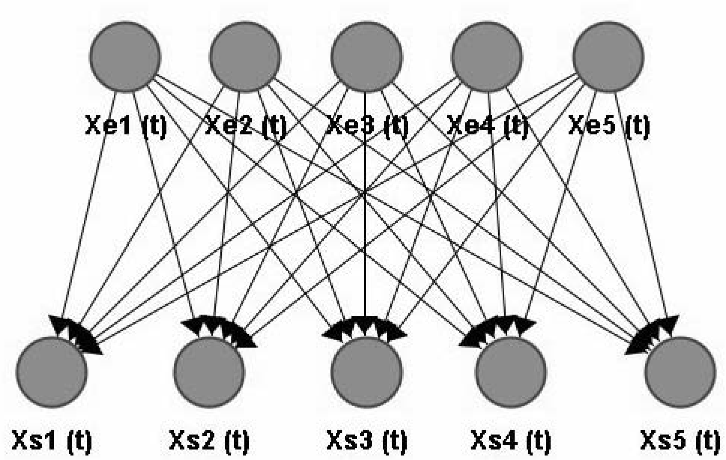


Fig. 1. Bayesian network representing reliability structures (a) and an example of inference (b)

Since BN representing structures contain nodes with conditional probability distribution defined as Boolean structure functions. Figure 1 presents inference to answer a question of how changes the structure reliability when changing components reliability. For example, if we increase all components reliability (for a fixed mission time t) from 0.63 to 0.8 then the structures reliability R_{s1}, R_{s2},…, R_{s5} increases accordingly: 0.099 → 0.328, 0.993 → 0.999, 0.733 → 0.942, 0.747 → 0.914, 0.819 → 0.952.

For presentation system reliability as a function of its components reliability and a mission time we used dynamic BN with two time steps (Fig. 2).

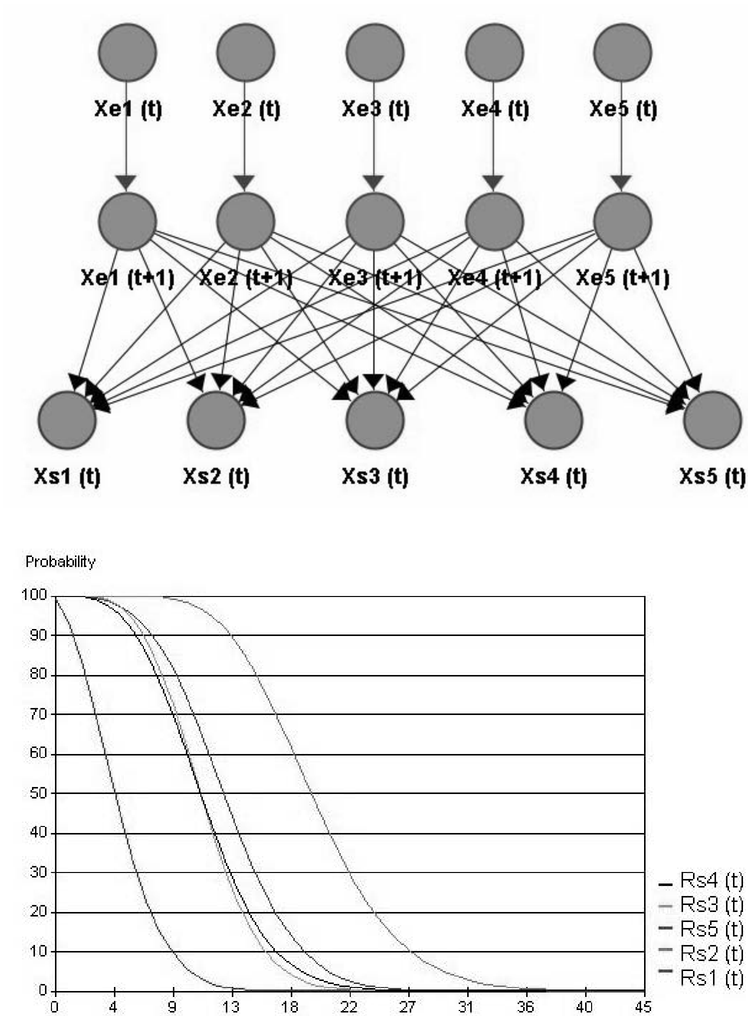


Fig. 2. Dynamic Bayesian network representing system (structure) reliability as a function of components reliability and a function of required operation time

The next figure (Fig. 3) presents a model where reliability is computed for random mission time. Corresponding BN is completed with node representing mission time of each element (not necessarily the same).

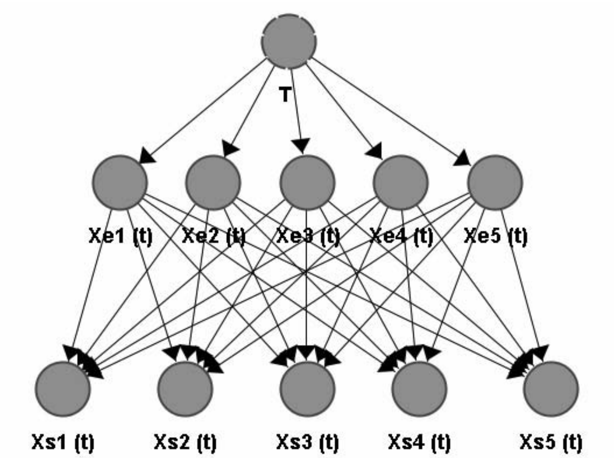
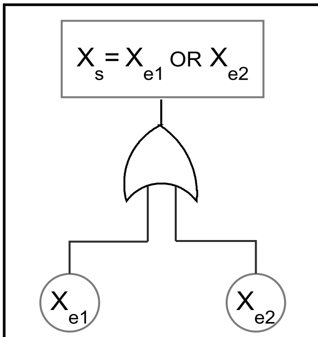
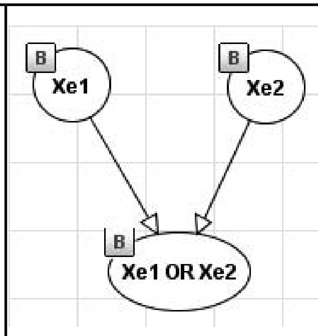
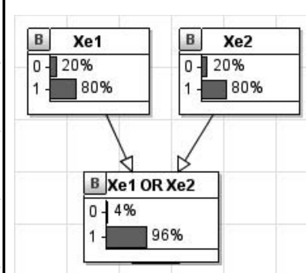
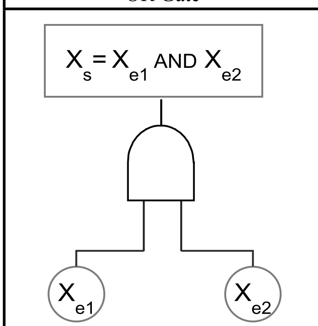
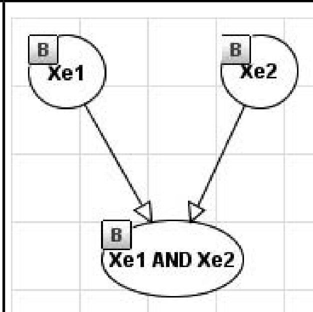
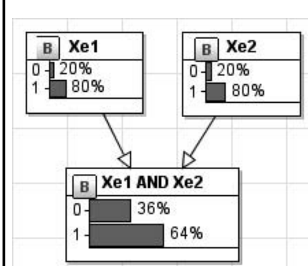


Fig. 3. Bayesian network representing system reliability for random mission time

Similarly simple is translation the event tree or failure tree models to equivalent Bayesian network models. It can be done by implementation in BN the logic gates used in ET or FT models [17], (Fig. 4).

		
Fault - Tree OR Gate	Bayesian Network OR Node	Conditional probability distribution
		
Fault - Tree AND Gate	Bayesian Network AND Node	Conditional probability distribution

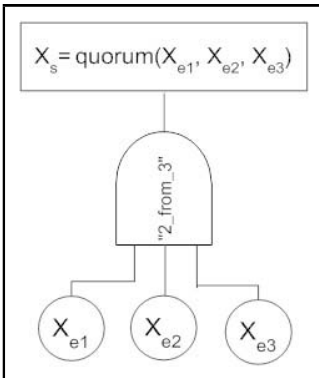
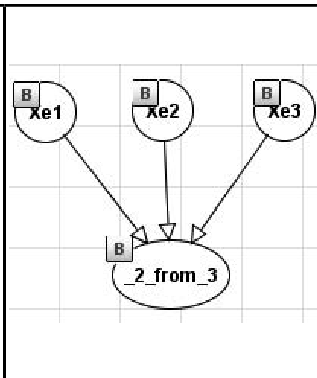
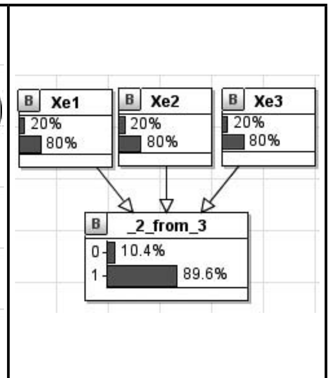
		
Fault - Tree Quorum Gate	Bayesian Network Quorum Node	Conditional probability distribution

Fig. 4. Bayesian networks equivalents of Fault-Tree logic gates

Root nodes, in the BN terminology, correspond to the fault tree basic events. The undesired Top Event is represented in the BN model as a leaf node (i.e., a node without descendants)

Normal logic gate represents element failure when all its causes are known. In FTA and MFA, events aren't necessarily concerned with failed elements but can represent other events which only cause or contribute to system components failure. In that case, using BN as a model allows representing epistemic uncertainty being result of incomplete knowledge of all events that can influence resulting failures as their consequence. It can be done by modification the logic gates using Boolean gates with leakage. The effect of using Noisy-OR logic gate [2, 13, 14] is shown on Fig.5.

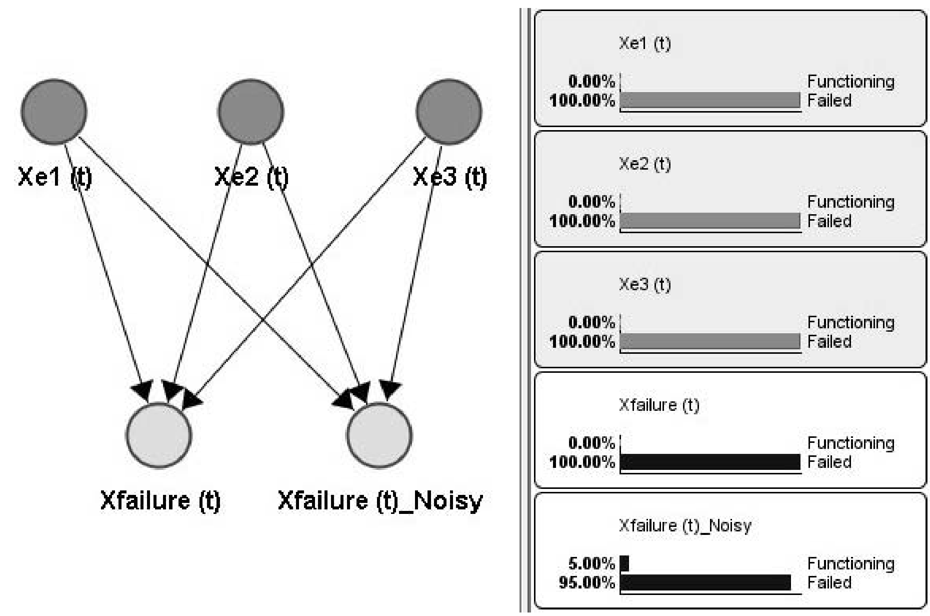


Fig. 5. Bayesian network representing epistemic uncertainty using Noisy-OR gate

Noisy logic function is a very constructive formalism for modelling diagnostic problems and diagnostic reasoning, [14, 15, 16].

CONCLUSIONS

Application of Bayesian networks as reliability knowledge representation language unifies the reliability models building methods. Expressiveness of BN language is higher than probabilistic Boolean logic. Resulting BNs reliability models are automatically adaptable to new data using machine learning methods and efficient inference algorithms enable automate predictive and diagnostic reasoning. It would be very interesting to explore extended conceptualisations of reliability problems expressed in first-order logic Bayesian networks, [18,19,20].

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SIECI BAYESOWSKIE JAKO SYSTEM REPREZENTACJI WIEDZY W DZIEDZINIE INŻYNIERII NIEZAWODNOŚCI

Streszczenie. W artykule przedstawiono sieci bayesowskie (BNs) w kontekście wymogów metodologicznych do budowy systemów reprezentacji wiedzy w dziedzinie inżynierii niezawodności. Ze swej natury, sieci bayesowskie, są szczególnie przydatne jako formalny i obliczalny język do modelowania niepewności stochastycznej i epistemicznej, Takie rodzaje niepewności są istotną cechą konceptualizacji i rozumowania o niezawodność.

Słowa kluczowe: modele niezawodnościowe, sieci probabilistyczne, sieci bayesowskie, system reprezentacji wiedzy.