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Performance evaluation of subsea BOP control systems using dynamic Bayesian networks with imperfect repair and preventive maintenance

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A B S T R A C T

The work presents a dynamic Bayesian networks (DBN) modeling of series, parallel and 2-out-of-3 (2oo3) voting systems, taking account of common-cause failure, imperfect coverage, imperfect repair and preventive maintenance. Seven basic events of one, two or three component failure are proposed to model the common-cause failure of the three-components-systems. The imperfect coverage is modeled in the conditional probability table by defining a coverage factor. A multi-state degraded component is used to model the imperfect repair and preventive maintenance. Using the proposed method, a DBN modeling of a subsea blowout preventer (BOP) control system is built, and the reliability and availability are evaluated. The mutual information is researched in order to assess the important degree of basic events. The effects of degradation probability, failure rate and mean time to repair (MTTR) on the performances are studied. The results show that the repairs and maintenance can improve the system performance significantly, whereas the imperfect repair cannot degrade the system performance significantly in comparison with the perfect repair, and the preventive maintenance can improve the system performance slightly in comparison with the imperfect repair. In order to improve the performance of subsea BOP control system, the single surface components and the components with all-common-cause failure should given more attention. The influence of degradation probability on the performance is in the order of PLC, PC and ES. The influence of failure rate and MTTR on the performance is in the order of PLC, ES, PC, DO, DI and AI.

1. Introduction

A subsea BOP system plays an extremely important role in providing safe working conditions for drilling activities in 10,000 ft ultra-deepwater regions. Subsea BOP failures could cause catastrophic accidents such as the explosion of the deep-sea petroleum drilling rig *Deepwater Horizon* and the oil spill off the coast of Louisiana on April 20, 2010. The subsea BOP on the *Deepwater Horizon* rig was believed to have failed isolating the well before and after the explosions. The subsea BOP might have been faulty before the blowout, or it might have been damaged because of the accident (Harlow et al., 2011; Skogdalen et al., 2011).

In order to improve the system reliability, the N-modular redundant control system configuration is standard for the control of the subsea BOP. Such a system can provide the tolerance against single component failure. For this purpose, a highly reliable fault-tolerant remote control system for subsea BOP was developed on the basis of a PLC-based triple modular redundancy system in a previous work (Cai et al., 2012a, 2012b). In the wake of recent disasters in oil and gas exploration and production, the performance evaluation of fault-tolerant control systems for subsea BOP is becoming recognized.

Performances of the fault-tolerant controllers and safety instrumented systems have been evaluated over the years by using fault tree analysis, Petri nets, and Markov models. Dutuit et al. (2008) presented a methodology to assess the safety integrity levels for safety instrumented systems by means of fault trees analysis. The results were compared with those obtained by means of Monte Carlo simulations based on Petri net models. Kim et al. developed all voting triple modular redundancy system, dual-duplex system and double 2-out-of-2 system, and assessed the reliability with respect to fault coverage by using discrete-time Markov modeling technique (Kim et al., 2005; Wang et al., 2007). Parashar and Taneja (2007) presented a PLC hot standby system based on master–slave concept and two types of repair facilities (ordinary repairman and expert repairman), and evaluated the reliability and profit by using semi-Markov processes.

Recently, driven by the fact that BN and DBN can perform forward or predictive analysis as well as backward or diagnostic analysis, BN and DBN techniques receive considerably increasing

Abbreviations: BOP, blowout preventer; BN, Bayesian network; DBN, dynamic Bayesian network; 2oo3, 2-out-of-3; CPT, conditional probability table; MTTR, mean time to repair; CCU, central control unit; PC, personal computer; PLC, programmable logic controller; ES, Ethernet switch; SEM, subsea electronics module; AI, analog Input; DI, digital Input; DO, digital Output

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attention in the field of reliability analysis, and it is a particularly powerful tool for handling uncertainty information. In predictive analysis, the probability of occurrence of any node is calculated on the basis of the prior probabilities of the root nodes and the conditional dependence of each node. In diagnostic analysis, the posterior probability of any given set of variables is calculated given some observation (the evidence), represented as instantiation of some of the variables to one of their admissible values (Bobbio et al., 2001). Nordgard and Sand (2010) described a methodology for application of BN for risk analysis in electricity distribution system maintenance management. Khakzad et al. (2011) demonstrated the application of BN in safety analysis of process systems, and compared the approaches of fault tree and BN. Jones et al. (2010) applied BN modeling to a maintenance and inspection department, and established and modeled various parameters responsible for the failure rate of a carbon black producing system, in order to apply it to a delay-time analysis study. Honari et al. (2009) showed how one may use Bayesian networks as a statistical technique to develop a new approach to evaluate the reliability of an (r, s)-out-of-(m, n): F system. Wilson and Huzurbazar (2007) extended the applications of Bayesian networks on binary outcomes to multilevel discrete data and discussed how to make joint inference about all of the nodes in the network.

A key issue in this thematic field is the integration of two important features of redundant control systems including common cause failure and imperfect coverage into a BN and DBN model. They have significant effects on the system reliability, which have been studied by the traditional reliability methods (Hoepfer et al., 2009; Li et al., 2010; Amari et al., 1999; Doyle et al., 1995). Few researches about Bayesian networks for reliability evaluation with respect to common cause failure and imperfect coverage were reported. Liu and Singh (2010) proposed a BN based method to investigate the overall effects of hurricanes on the reliability evaluation of composite power systems. This method used the Noisy-OR gate model to consider both common cause failures and independent failures of transmission lines and generating units. Langseth and Portinale (2007) introduced a coverage factor, which is defined as the probability that a single failure entails a complete system failure, to Bayesian networks in order to model the inaccurate recovery mechanism of redundant system.

Another key issue is the integration of repair actions into a BN and DBN model. Flammini et al. (2009) presented both a failure model for voting architectures based on BN and a maintenance model based on continuous time Markov chains, and proposed to combine them according to a compositional multiformalism modeling approach in order to analyze the impact of imperfect maintenance on the system safety. Neil and Marquez (2012) presented a hybrid BN framework to model the availability of renewable systems. They used an approximate inference algorithm for hybrid BN that involves dynamically discretizing the domain of all continuous variables and used this to obtain accurate approximations for the renewal or repair time distributions for a system. Portinale et al. presented an approach to reliability modeling and analysis based on the automatic conversion of dynamic fault tree or series and parallel modules into BN taking repair into consideration (Portinale et al., 2010; Codetta-Raiteri et al., 2012). However, few researches about BN with imperfect repairs and preventive maintenance are reported.

The work focuses on the DBN modeling of series, parallel and 2oo3 voting systems, taking account of common-cause failure, imperfect coverage, imperfect repair and preventive maintenance. The paper is structured as follows: Section 2 presents the DBN modeling of series, parallel and 2oo3 voting systems. Section 3 analyzes a case of subsea BOP control systems to demonstrate the application of the proposed DBN modeling. Section 4 summarizes the paper.

2. DBN modeling of series, parallel and voting systems

2.1. Overview of DBN

BN are widely used in quantitative risk assessment because the model can perform both of predictive and diagnostic analysis. A BN consists of qualitative and quantitative parts. The qualitative part is a directed acyclic graph in which the nodes represent the system variables and the arcs symbolize the dependencies or the cause–effect relationships among the variables. The quantitative part is the conditional probabilistic table, which gives the relations between each node and its parents.

BN models relationships between variables at a particular point in time or during a specific time interval. Although a causal relationship represented by an arc implies a temporal relationship, BN does not explicitly model temporal relationships between variables. The only way to model the relationship between the current value of a variable, and its past or future value, is by adding another variable with a different name.

DBN are a long-established extension to ordinary BN that allow explicit modeling of changes over time. Each time step is called a time-slice. The relationships between variables in a time-slice are represented by intra-slice arcs. And the relationships between variables at successive time steps are represented by inter-slice arcs. The number of time-slice is determined by (a) the purpose of research and (b) the time the Netica runs. The bigger the number of the time-slices, the more the time the Netica runs.

The important degree of basic event to the system failure can be assessed by using Shannon's mutual information (entropy reduction), which is one of the most widely used measurement for ranking information sources (Pearl, 1988). It is assumed that uncertainty of system can be represented by entropy function as given

$$H(T) = -\sum_{t} P(t)\log\ P(t) \tag{1}$$

where $P(t)$ is the probability distribution of random variable T.

The mutual information is the total uncertainty-reducing potential of X, given the original uncertainty in T prior to consulting X. Intuitively, mutual information measures the information that T and X share: it measures how much knowing one of these variables reduces our uncertainty about the other (Wang et al., 2011). The mutual information of T and X is given by

$$I(T,X) = -\sum_{x}\sum_{t} P(t,x)\log\ \frac{P(t,x)}{P(t)P(x)} \tag{2}$$

where $P(t,\ x)$ is the joint probability distribution function of T and X, and $P(t)$ and $P(x)$ are the marginal probability distribution functions of T and X, respectively.

2.2. DBN modeling with common-cause failure

A common cause failure is defined as the failure of more than one device due to the same cause for redundant systems. Experience has shown that common cause failures have a dominant impact on accidents. Common cause failures are usually modeled in fault tree by adding an OR gate, directly connected to the top event, in which one input is the system failure, the other input the common cause failure leaf to which the probability of failure due to common causes is assigned.

In DBN, seven basic events are proposed to model the common-cause failure of series, parallel and voting systems with three components, as shown in Fig. 1. The basic events S1, S2 and S3 refer to the individual states of Components C1, C2 and C3, respectively. The basic events S12, S23 and S13 refer to the common states of