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An integrated safety prognosis model for complex system based on dynamic Bayesian network and ant colony algorithm

Jinqiu Hu [a,*], Laibin Zhang [a], Lin Ma [b], Wei Liang [a]

[a] College of Mechanical and Transportation Engineering, China University of Petroleum, Beijing 102249, China

[b] Cooperative Research Centre for Integrated Engineering Asset Management, Queensland University of Technology, Brisbane, QLD 4001, Australia

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ABSTRACT

In complex industrial system, most of single faults have multiple propagation paths, so any local slight deviation is able to propagate, spread, accumulate and increase through system fault causal chains. It will finally result in unplanned outages and even catastrophic accidents, which lead to huge economic losses, environmental contamination, or human injuries. In order to ensure system intrinsic safety and increase operational performance and reliability in a long period, this study proposes an integrated safety prognosis model (ISPM) considering the randomness, complexity and uncertainty of fault propagation.

ISPM is developed based on dynamic Bayesian networks to model the propagation of faults in a complex system, integrating the priori knowledge of the interactions and dependencies among subsystems, components, and the environment of the system, as well as the relationships between fault causes and effects. So the current safety state and potential risk of system can be assessed by locating potential hazard origins and deducing corresponding possible consequences. Furthermore, ISPM is also developed to predict the future degradation trend in terms of future reliability or performance of system, and provide proper proactive maintenance plans. Ant colony algorithm is introduced in ISPM by comprehensively considering two factors as probability and severity of faults, to perform the quantitative risk estimation of the underlining system. The feasibility and benefits of ISPM are investigated with a field case study of gas turbine compressor system. According to the outputs given by ISPM in the application, proactive maintenance, safety-related actions and contingency plans are further discussed and then made to keep the system in a high reliability and safety level in the long term.

1. Introduction

The assessment and prediction of the safety situation of a complex system is a very critical challenge, due to technical difficulty as well as dynamic environment and because it has a significance on economic, environment and society performance. In complex industrial systems, operating, regulating, maintenance activities and external incidents take place dynamically and multiple entities (e.g., persons, subsystems, components, and environment) in same or different subsystems interact in a complex manner. So any single faults may have multiple propagation paths, which will finally lead to catastrophic accidents.

System safety management nowadays is of vital importance to keep the system safety at an acceptable level, the key issues of which focus on both of how to reduce the probability of fault occurrence and decrease the loss of fault consequence. The implementation of such requirements can be studied in terms of the determination of the fault root causes, possible consequence, estimated risk and timing of various maintenance activities (i.e. repair or replacement of parts), which are considered in a safety prognosis scheme. Safety prognosis is usually carried out based on the historical and current conditions and determines whether and when the underlying system is in need of maintenance or risk control taking into consideration both of fault probability and the level of its severity. With the assistance of prognosis, a pre-warning alarm can be set when the predicted values fall within the warning region (or beyond safety threshold). This provides adequate time for safety engineers to make a proactive maintenance plan, inspect the hardware of a system, conduct a repair on the defect, and even make a contingency plan before the catastrophic failure occurs.

Nevertheless, safety prognosis has been a difficult task and has attracted much attention of researchers in the field (Heng et al., 2008, 2009; Jardine et al., 2006; Kothamasu et al., 2006; Liu et al., 2007; Sutherland et al., 2003). The approaches to prognosis fall into three main categories: statistical approaches, artificial intelligent approaches and model-based approaches (Jardine et al., 2006). Model-based approaches utilise physics specific, explicit mathematical models of the underling entities. Such

* Corresponding author.
E-mail address: hjqcup@hotmail.com (J. Hu).

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approaches can be more effective than other model-free approaches if a correct and accurate model is built. However, explicit mathematical modeling may not be feasible for complex systems since changes in structural dynamics and operating conditions can affect the mathematical model, and it would be very difficult or even impossible to build mathematical models for all real-life conditions.

Statistical prognostic approaches require the component failure history data or event data. They involve collecting statistical information from a large number of component samples to indicate the survival duration of a component before a failure occurs, and use these statistical parameters to predict the remaining useful life (RUL) of individual components (Tran et al., 2009). A few statistical models in survival analysis, such as HSMM (Dong and He, 2007), PHM (Samrout et al., 2009), PIM (Lugtigheid et al., 2008; Vlok et al., 2004), PCM (Sun et al., 2006) and EHRM (Louzada-Neto, 1997) are useful tools for RUL estimation. Iung et al. (2008) and Muller et al. (2004, 2008) also include maintenance policies in the consideration of the machine prognostic process, in order to provide decision support for maintenance actions.

Artificial intelligent (AI) approaches utilise large amounts of historical failure data or condition data to build a prognostic model which learns the system behaviour, instead of building models based on comprehensive system physics and human expertise. Some of the published researches using these approaches can be found in references (Ghorbanian & Gholamrezaei, 2009; Herzog, Marwala, & Heyns, 2009; Huang et al., 2007; Liu et al., 2007; Wang, Golnaraghi, & Ismail, 2004). In the literature, a neural network-based model for prognosis is regularly used because of its flexibility in generating the appropriate model. Tran et al. (2009) proposed a multi-step ahead prediction methodology for forecasting the machines' operating conditions using regression trees and neuron-fuzzy systems. Heng et al. (2009) used a feed-forward neural network to estimate the future survival probability of a monitored item, given the corresponding condition monitoring indices.

The above-mentioned methods have advanced the development of safety prognostics. However several issues need to be further investigated when they are applied to complex industrial systems:

(1) In order to control fault occurrence probability, system reliability or performance prediction is an effective way to track the degradation of system in the future and make a proper proactive maintenance plan to avoid failure or reduce the fault influence range. However the existing literature (Heng et al., 2009; Huang et al., 2007; Lee et al., 1999) largely focuses on the degradation mechanism and remaining useful life from the component or single equipment deterioration point of view; for example, ball bearing, pump, and steam generator. Very few models have taken into account not only the interdependencies among the components and subsystems, but also the impact of degradations and the influence of exogenous variables on the degradation processes. The main reason for this is that, to decrease the model's complexity and avoid combinational explosion, two hypotheses according to which there is no simultaneous occurrence of failure and the statistical independence between events are assumed (Weber and Jouffe, 2006). However, such hypotheses are no longer valid when components have common causes or when components have several failure modes, which make a negative impact on the rationality of the reliability prediction for complex system.

(2) On the other hand, in complex industrial system, most of single faults have multiple propagation paths, and different propagation paths may lead to different consequences, some of which may gradually recover by its self-control system, while others may further cause adjacent components' failure and eventually lead to catastrophic accidents by fault coupling mechanism. So in order to reduce the loss of fault consequence, safety assessment and risk evaluation are the main issues in safety prognosis. Traditional risk estimation model (Gu, 2001) partially depended on subjective factors simply based on the product of fault probability and severity has to make major revision according to the field condition when it applied to specific engineering system. Meanwhile not all of the compatible fault propagation pathways derived from traditional risk analysis would happen in the real world, since a considerable part of them have a very low occurrence probability (Zhang et al., 2008), which usually make safety engineers hard to find the actual fault root cause and miss the best time to repair. So there is an urgent need to develop an effective and systematic quantitative risk evaluation mechanism in the safety prognosis framework.

This work presents an approach for addressing the above challenges. Taking into consideration of the relation among safety assessment, risk evaluation and prediction, an integrated safety prognosis model (ISPM) is proposed based on dynamic Bayesian networks and ant colony algorithm. Utilising both the knowledge of system structure as well as flow process and monitoring data, ISPM is developed to analyse the potential hazards of system (e.g., functional faults, component failures, human mistakes, external destruction), reflecting its hidden degraded states, possible hazard origins (root causes), and consequences with corresponding probabilities. With the knowledge of consequence severity, the risk of hazard and its propagation path are calculated by ant colony algorithm in ISPM, which provides an instruction of decision-making for safety-related actions and contingent plans.

Furthermore, on the basis of safety assessment and risk evaluation, ISPM aims to foresee how a system (or component) will evolve from its current degraded state until its failure and then until the system's breakdown (performance level), analysing the impact of degradation on the component itself and on the other entities of the system to predict system failures and remaining useful life. A field case study for the gas turbine compressor system presents how to apply the ISPM to a real industrial system and to investigate its rationality and validity.

The rest of this paper is organised as follows. In Section 2, the Dynamic Bayesian Network and its inference scheme used in ISPM are described. In Section 3, the integrated safety prognosis model is introduced and then algorithms and work flows are also presented. In Section 4, a real case study is organised explicitly to illustrate the overall flow of this research in detail. Section 5 presents the application results of safety assessment, risk evaluation and prediction given by ISPM, and a further discussion of the proactive maintenance plan. Conclusions are given in Section 6.

2. Dynamic Bayesian networks

A Bayesian network (BN) as a probability-based knowledge representation method is appropriate for the modeling of causal processes with uncertainty. A Bayesian network is a directed acyclic graph (DAG) whose nodes represent random variables and links define probabilistic dependences between variables. These relationships are quantified by associating a conditional probability table with each node, given any possible configuration of values for its parents.

The static Bayesian network can be extended to a dynamic Bayesian network (DBN) model by introducing relevant temporal dependencies that capture the dynamic behaviours of the domain variables between representations of the static network at