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Process accident model considering dependency among contributory factors

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ABSTRACT

With the increasing complexity of the hazardous process operation, potential accident modelling is becoming challenging. In process operation accidents, causation is a function of nonlinear interactions of various factors. Traditional accident models such as the fault tree represent cause and effect relationships without considering the dependency and nonlinear interaction of the causal factors.

This paper presents a new non-sequential barrier-based process accident model. The model uses both fault and event tree analysis to study the cause–consequence relationship. The dependencies and nonlinear interaction among failure causes are modelled using a Bayesian network (BN) with various relaxation strategies. The proposed model considers six prevention barriers in the accident causation process: design error, operational failure, equipment failure, human failure and external factor prevention barriers. Each barrier is modelled using BN and the interactions within the barrier are also modelled using BN. The proposed model estimates the lower and upper bounds of prevention barriers failure probabilities, considering dependencies and non-linear interaction among causal factors. Based on these failure probabilities, the model predicts the lower and upper bounds of the process accident causation probability. The proposed accident model is tested on a real life case study.

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1. Introduction

In recent times, chemical process industries (CPI) are dealing with highly hazardous chemicals at different stages of their process operations. The dynamic technological complexity of process systems which include equipment, management and organisation decisions, operators, operating conditions, external environmental conditions and their various interactions are major causes of accidents in process industries. This complexity has numerous dimensions; interactive complexity is on the increase in systems currently being built. Process systems now contain large amounts of dynamically interacting components. In the current complex system, humans interact with technology and produce an outcome due to their collaboration which cannot be accomplished either by technology or humans operating independently. Therefore, safe operation of the modern complex system demands a thorough understanding of interactions and interrelationships between, human, technical, environmental and organisational phases of the system (Qureshi, 2008; Leveson, 2004).

Recent accident analysis of CPI accidents has shown an increase in the frequency of accidents in most regions of the world, probably due to these complex interactions (Kidam et al., 2014; Khan and Abbasi, 1999). Process accidents are normally due to a chain or sequence of failure of events caused by failure of one or several physical components and abnormalities of process parameters (Tan et al., 2013).

Process accident models give detailed features of accidents and clearly express the relationship between causes and effects. They provide an adequate explanation of why accidents occur and they are a very useful technique for process risk assessment. Process accidents normally follow three steps: initiation, propagation and

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termination (Crowl and Louvar, 2001) and any of these steps could lead to hazardous events.

Accident models systematically relate causes and consequences of the events and play a significant role in accident investigation and analysis. Accident models primarily tend to answer two major broad questions: (i) why accidents occur and (ii) how accidents occur. Classification of accident models can be done in several ways. Accident models are broadly categorised as either traditional or modern accident models. Traditional accident models are further sub-grouped into sequential and epidemiological models. They are primarily descriptive models that lack predictive capacity and emphasise mainly human, organisational and management factors. Modern accident models can be sub-classified into three sub-categories: systematic, formal, and dynamic accident models (Al-shanini et al., 2014a,b; Qureshi, 2008).

One principal limitation of these accident models is that they are usually case-specific, commonly descriptive, qualitative and merely conventional models that cannot utilise accident precursor data to develop prevention strategies. Those that have quantitative units had limitations of data scarcity and uncertainty. However, dynamic accident models have a great benefit of simplicity because of their sequential arrangement or layout and because non-linear interactions can be represented within the main framework. The dynamic accident model is predictive and uses real time precursor data to evaluate the likelihood of all available end-states (Al-shanini et al., 2014a,b).

Kujath et al. (2010) developed a process accident model for offshore oil production to prevent offshore process accidents using the concept of safety barriers. Five major prevention barriers were connected alongside the accident propagation path to prevent and mitigate the consequences of hydrocarbon release. Fault tree analysis was used to analyse the failure of prevention barriers, and consequences were analysed using an event tree. The end state precursor data in the event tree analysis were used to update the failure probabilities of safety barriers via the Bayesian theorem. Despite the application of this model to the Piper Alpha (1988) and BP's Texas city refinery (2005) the model still exhibits some limitations, which are: (1) There is only provision for operational and technical failures; all other accident contributory factors such as human and organisational errors were not part of the model; and (2) Other accident initiating events such as an explosion were not considered (Rathnayaka et al., 2011).

In order to overcome the obvious weakness in Kujath's model, Rathnayaka et al. (2011) provided an extension of this model by incorporating other factors (i.e., management and organisational factors) that were completely neglected by Kujath into a new accident model called System Hazard Identification, Prediction and Prevention (SHIPP) methodology. All accident contributory factors were modelled into seven prevention barriers. In this model, accident precursor data were used to update the failure probabilities of every barrier with the Bayesian updating technique. The SHIPP model was validated for two LNG facilities effectively and the results obtained were highly promising (Rathnayaka et al., 2010, 2012).

However, in spite of the promising results obtained with the use of SHIPP methodology, the model still has some weaknesses that may affect the accuracy of the results obtained. These weakness are: (1) External hazards are not considered in the model. (2) The model presumed the causes of failure within safety barriers were independent, although in reality they are interdependent and this could grossly affect the results. (3) Provision was not made for other factors that were not accounted for in the fault tree model of prevention barriers. (4) Nonlinear interaction of various factors were not considered.

This paper proposes a novel non-sequential barrier based accident model, in which interdependency and nonlinear interaction among accident contributory factors within safety barriers are modelled for process accidents. This work also proposes major influencing factors of process accidents. Considering dependencies and non-linear interaction among causal factors, the proposed model is capable of estimating the lower and upper boundary of prevention barrier failure probabilities. The remaining parts of this paper are organised as follows. Section 2 provides a brief description of basic characteristic of BNs. Section 3 presents canonical models based on the assumption of independence of causal influence. Section 4 presents the proposed accident model. Section 5 demonstrates the application of the proposed model using the Richmond refinery accident. Section 6 presents the results and discussion. Finally, Section 7 provides the conclusion.

2. Bayesian network

Bayesian networks (BNs) are direct acyclic graph (DAG) with various nodes representing variables and arcs which represent direct dependencies among the variables. A BN usually consists of both qualitative and quantitative parts. The qualitative part is an acyclic directed graph naturally showing the causal structure of the domain; the other quantitative part denotes the joint probability distribution of its variables. All variables in a BN are adequately represented in a conditional probability table (CPT). A CPT provides complete specification of probabilistic interaction that has the capability to model any type of probabilistic dependence between a discrete node and its parents. The probabilities in the CPT denote the probabilities of each state given the state of the parent variable. However, if a variable in BN does not have parent variables, the CPT denotes the prior probability variable (Kraaijeveld and Druzdzel, 2005).

A Bayesian network represents the joint probability distributions for a set of discrete random variables X, where X is given as

$$X = (X_1, X_2, \ldots, X_n) \tag{1}$$

where n is finite in this case. Eq. (1) can be decomposed into products of conditional probability distributions for each of the variables provided their parent is known. In the case of a root node with no parents, prior probability is used instead. The joint probability distribution for a set of discrete random variables $X = (X_1, X_2, \ldots, X_n)$ can be calculated by taking the product of all the priors and their conditional probability distribution (Kraaijeveld and Druzdzel, 2005). Mathematically this is given by

$$P(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} P(x_i | pa_{(xi)}) \tag{2}$$

3. Canonical probabilistic models

Canonical models are advantageous because they make the construction of a probabilistic model easy and also reduce the computation time. One foremost challenge in using the BN model to model practical problems is the difficulty that arises in obtaining the numerical parameters that are required to fully quantify it. Discrete joint probability distributions are generally represented as CPTs, which are a collection of discrete probability distributions of a variable conditional on its given parents in the BN. The size of CPTs increases exponentially with the number of parents in a BN. Therefore, it is extremely difficult to build CPTs for variables having many parents. This is because these numerical parameters in CPTs are obtained from a database or from human expertise (Oniśko et al., 2001; Diez and Druzdzel, 2007).

One way of overcoming the challenge of obtaining these numerical probabilities is to apply the canonical models. Canonical models permit building of probability distribution from a fewer number of parameters (Bobbio et al., 2001). Noisy-OR and Leaky Noisy-OR are typical examples of a canonical model.

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