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Towards BBN based risk modelling of process plants

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ABSTRACT

Recent disasters in high hazard industries such as Oil and Gas Exploration (The Deepwater Horizon) and Petrochemical production (Texas City) have been found to have causes that range from direct technical failures through organizational shortcomings right up to weak regulation and inappropriate company cultures. Risk models have generally concentrated upon technical failures, which are easier to construct and for which there is more concrete data. The primary causes lie firmly rooted in the culture of the organization and determine the way in which individuals go about risky activities. Modelling human activities, especially collectively rather than individual human errors as is done in most human models, is a quite different proposition, in which complex interactions between different individuals and levels change over time as success and failure alter the pattern of payoffs.

This paper examines the development of a dynamic integrated model for risk in a real-time environment for the hydrocarbon industry. It is based originally on the CATS model for commercial aviation safety, which first attempted to address some of these problems in a relatively simple way. Aviation is, however, a relatively simple activity, with large numbers of common components in a constrained environment. The Oil and Gas industry is significantly more diverse, covering the gamut from exploration, drilling, production, transport, refining and chemical production, each with its own potential for large scale disaster, but in the case of an integrated oil company all run by individuals within a common company culture.

1. Introduction

In this paper we describe concepts for the development of a dynamic risk management support tool for the oil industry based on BBNs. This method should enhance the methodologies currently employed by the company and in particular allow the evaluation of the present and future vulnerabilities to catastrophic events. It also should allow the evaluation of the potential effect of actions – by management or by authorities – on these vulnerabilities. The development of such a model employs the latest in the development of the sciences of risk analysis, mathematics and human behaviour. In addition to that, time stepping is added. The approach chosen is innovative in many respects The key steps of the development are reported in this paper.

1.1. Background

The recent blow-out and subsequent environmental disaster in the Gulf of Mexico have highlighted a number of serious problems in scientific thinking about safety. One of these is that our current thinking about how accidents happen and all the management systems based on that approach, while reasonably successful, does not appear to enable us to achieve the goal of zero accidents. These are particularly clear in the case of what can be described as low-probability high-consequence accidents which, while quite rare, do not really appear to be reducing in frequency unlike simpler and higher frequency personal accidents (Christou, 2008; Livonianitou et al., 2006), while their consequences appear to increase. The suggestion is that linear and deterministic models of accident causation are insufficient to catch the residual factors and their interactions (Hudson, 2010). This is further complicated by the fact that the safety culture can either augment or diminish the effects of the best of HSE management systems. The latter appears to be the case for BP's Deepwater Horizon disaster, which was then exacerbated by a poorly managed emergency response, or, at least, the perception of poor response. The challenge, therefore, is prevent that decisions about complex risky operations do not ruin the company as a whole (van Gulijk and Ale, 2012). A deeper and wider-reaching analysis of the risks being taken and run needs to integrate the cultural and regulatory factors into the more accessible technical aspects of risk analysis and assessment.

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Recent proposals have suggested that systems such as the current process industry and the world financial system have become so complex and the interactions so manifold that these systems become intractable, and therefore unmanageable. Accident causation must be regarded as both non-linear and non-deterministic (Hudson, 2010). Simple models, that are linear and deterministic, suffice to approximate to a level that may have been acceptable in previous years, but, as Hollnagel (2011) pointed out, they cannot meet the law of requisite, which means that control systems need to be capable of at least as much variation as the body to control. The Swiss Cheese model, developed as Tripod in the 80s and early 90s, is an example of a more complex model that is no longer necessarily linear, but is still deterministic in its thinking about accident causation and the approaches to safety management it implies. It appears that a more comprehensive description of the accident process now requires a shift from the simpler models based on the principles of hazard – barrier – target concept (Schupp et al., 2004), possibly including failure rates but still deterministic, to inherently probabilistic models.

The current project is primarily aimed at the incorporation and integration of a wide spectrum of factors that play a role in non-linear and non-deterministic in risk-problems. This paper describes the concept for the technique that integrates these new challenges into a single computational entity and addresses them simultaneously. Ultimately, the aim is to develop a user friendly computer program that helps risk analysts in understanding the hazards in a chemical plant.

1.2. Continuation of prior developments

The current development builds on the earlier developments in the IRISK (Bellamy et al., 1999; Papazoglou et al., 2002, 2003), ORM (Ale, 2006; Papazoglou and Ale, 2007; Ale et al., 2008) and CATS (Ale et al., 2009a, Ale et al., 2009) projects to connect the descriptions of management, human behaviour and technology into a single framework that allows a more in-depth analysis of the interdependencies (refs). Important contributions from IRISK and ORM were the construction of an abstract framework that encompasses risk problems on an industry wide scale. In CATS, the integration is virtually complete since management; human and technology are combined into a single non-parametric BBN. Also, in the CATS project probability *distributions*, rather than simple bifurcations are used. The use of distributions is beneficial since uncertainties about risk are engraved into the model; a subsequent separate sensitivity analysis is no longer necessary. The CATS model is used as the blueprint for the current risk model in the process industries. However, two major problems need to be addressed. Firstly, the model has to cope with large numbers of process equipment that can be present in a single process plant. Secondly, interactions between various pieces of a process plant are not always clear.

2. Bayesian Belief Nets in risk analysis

By definition, a BBN is a directed acyclic graph which gives a concise representation of the joint probability distribution of a set of variables (Pearl, 1988; Jensen, 1996, 2001). Basically, a BBN is defined by a qualitative part and a quantitative part. The qualitative part consists of a set of nodes which represent the system variables, and a set of directed arcs between variables, representing the dependencies or the case-effect relations between variables. The quantitative part consists of conditional probability distributions for each node, given the states of the influencing nodes, called also parent nodes. Together, the quantitative and qualitative parts encode all the relevant information about the system variables and their interrelations, which, mathematically, means the joint distribution of these variables. The conditional independencies which are represented in the network by a missing arc between variables allow the decomposition of the joint distribution in a product of conditional probability distributions. In this way, instead of working with a large joint probability distribution, one can work with smaller pieces of it, but preserving the overall component interaction within the system. The mathematical methods are described elsewhere (Kurowicka and Cooke, 2004).

A distinct advantage of using BBNs is that they provide a useful tool to deal with uncertainty and with information from different sources, such as expert judgment, observable information or experience. BBNs also solve some of the problems occurring with the classical risk analysis methods, especially the one related to common causes and human influence, which are not logically deterministic, but rather probabilistic influences. Human error probabilities in risk analysis can be quantified by BBNs (Hanea et al., 2012). Within a BBN framework it is also possible to model the organizational and management factors that affect human error probabilities (Lin et al., 2012, 2013). Currently, the existing studies (e.g. Embrey, 1992; Mosleh et al., 1997; Murphy and Paté-Cornell, 1996; Øien, 2001; Trucco et al., 2008) have suggested using discrete BBNs or influence diagrams to quantify human and management influences on risk. The nodes in the discrete BBNs represent variables with a finite number of discrete states, e.g. yes/no, or true/false, or bad/medium/good".

Large effort has been spent to deal with the limitations of discrete and Gaussian BBNs when complex real systems are modelled. Among the most serious problems are the large input for the conditional probability table in a discrete BBN, the discretization of a continuous variable and the strong assumption of joint normal distribution for a Gaussian BBN. For detailed description of these BBN methods and discussions on their limitations, one can refer to (Pearl, 1988; Shachter and Kenly, 1989; Marcot et al., 2006; Kuhnert and Hayes, 2009).

The newest version of BBNs, called non-parametric BBNs (NPBBNs) have significantly less assumptions than the Gaussian BBNs and, moreover, are less expensive in terms of input, comparing with the discrete BBNs (Kurowicka and Cooke, 2004). In NPBBNs, nodes are associated with discrete or continuous, parametric or empirical distribution functions. Moreover, nodes which are defined as functions of probabilistic nodes are allowed. The influences between variables are expressed in terms of (conditional) rank correlations, which show the strength of monotone association between ordered values of two variables. Rank correlations are independent numbers between -1 and 1. High positive rank correlation (close to 1) between two variables means that high values of one variable are associated with high values of the other variable, while low negative rank correlation (close to -1) means that high values of one variable are associated with low values of the other variable.

Quantification of a NPBBN means assigning a marginal probability distribution for each node in the network and a (conditional) rank correlation for each arc. The marginal distribution and the rank correlations can together specify all the relations between the random variables and determine in a unique way the joint probability distribution. In case that a functional node is included, formula of the functional relation has to be specified; neither marginal distribution for functional node, nor rank correlations for the incoming arcs to that node are needed anymore. When data is available in the form of a join distribution, both marginal distributions and (conditional) rank correlations can be computed. When data is not available, structured ways to use expert judgment both for the marginal distributions and the (conditional) rank correlations are available (Cooke and Goossens, 2000).