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A fuzzy logic and probabilistic hybrid approach to quantify the uncertainty in layer of protection analysis

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A B S T R A C T

Layer of protection analysis (LOPA) is a widely used semi-quantitative risk assessment method. It provides a simplified and less precise method to assess the effectiveness of protection layers and the residual risk of an incident scenario. The outcome failure frequency and consequence of that residual risk are intended to be conservative by prudently selecting input data, given that design specification and component manufacturer's data are often overly optimistic. There are many influencing factors, including design deficiencies, lack of layer independence, availability, human factors, wear by testing and maintenance shortcomings, which are not quantified and are dependent on type of process and location. This makes the risk in LOPA usually overestimated. Therefore, to make decisions for a cost-effective system, different sources and types of uncertainty in the LOPA model need to be identified and quantified. In this study, a fuzzy logic and probabilistic hybrid approach was developed to determine the mean and to quantify the uncertainty of frequency of an initiating event and the probabilities of failure on demand (PFD) of independent protection layers (IPLs). It is based on the available data and expert judgment. The method was applied to a distillation system with a capacity to distill 40 tons of flammable n-hexane. The outcome risk of the new method has been proven to be more precise compared to results from the conventional LOPA approach.

1. Introduction

1.1. Risk assessment and LOPA

Risk is formally defined as the effect of uncertainty on objectives (ISO 31000:2009) (Purdy, 2010). For this study, risk is interpreted as a measure of the severity and probability of occurrence of an event that causes consequences, such as human injury, environmental damage, or economic loss. Besides the inherent uncertainty of risk, there is the possible spread in the derived values of both probability and consequence as a secondary source of uncertainty. This paper focuses on the spread in the frequency values, as these are the main source of the secondary type of uncertainty. For a specific scenario, risk is the function of consequence and probability, and the probability is expressed per unit of time, hence as frequency (Crowl and Louvar, 2011; Pasman, 2015).

LOPA, as described in the IEC61511 standard (ANSI, 2003), is a semi-quantitative technique for analyzing and assessing risk. In LOPA, both frequency and consequence are expressed as an order of magnitude. As defined by the Center for Chemical Process Safety (CCPS) (CCPS, 2001), the primary purpose of LOPA is to determine whether there are sufficient independent protection layers (IPLs) to reduce risk to a tolerable level for a selected incident scenario. An IPL is a protection layer that is independent of the initiating event and other layers of protection associated with the selected scenario. Typical IPLs are illustrated in Fig. 1. LOPA is applied to a single cause-consequence pair at a time. The outcome risk is compared with an acceptable or maximum tolerable risk. If the estimated risk of a selected scenario is too high, additional IPLs will be added to the process. Based on the assumption of independence, the failure frequency of the array of layers can be calculated by multiplying the frequency of the initiating event with the values of the individual

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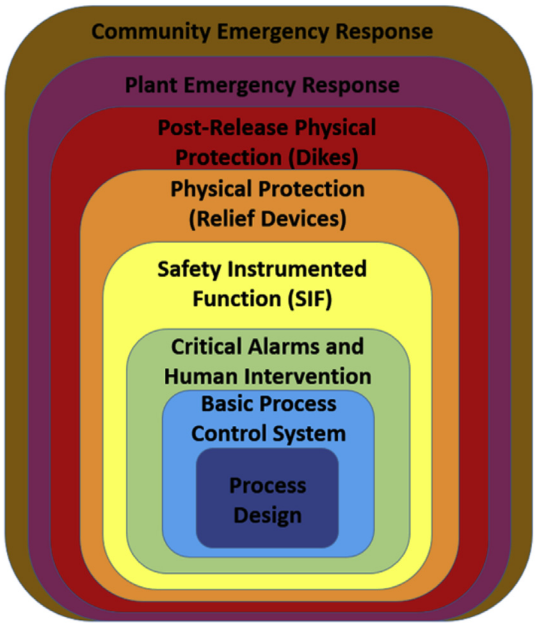

Fig. 1. Layers of protection for a possible incident (CCPS, 2001).

probability of failure on demand,

$$f_i^C = f_i^I \times \prod_{j=1}^{J} PFD_{ij} = f_i^I \times PFD_{i1} \times PFD_{i2} \times \ldots \times PFD_{ij} \quad (1)$$

where, f_i^C is the frequency for consequence C for initiating event i; f_i^I is the initiating event frequency for initiating event i; PFD_{ij} is the probability of failure on demand of the jth IPL for initiating event i.

1.2. Uncertainty sources in LOPA, and approaches to estimate the uncertainty

LOPA is a simplified model considering only a single cause-consequence pair as a scenario. Failure rate data are conservatively selected due to the fact that data are limited and failure rate data are small in number. These facts make the outcome risk usually overestimated. A high risk indicates the requirement of additional IPLs, which calls for higher installation and maintenance costs.

In classic LOPA, single point values or the upper bounds of intervals of failure rates are derived from historical data or literature, and there is no uncertainty information in a point value. Typical databases are that of the Center for Chemical Process Safety (CCPS) (CCPS, 1989) and the Offshore Reliability Data Handbook (OREDA) (OREDA, 2002). In order to be more accurate, the mean values with the uncertainty information are needed. The ideal situation to eliminate uncertainty is collecting enough plant specific data to get accurate failure rates. However, an extensive data collection system for a plant is much time and money consuming and in practice not realizable. An alternative way is to use generic databases, which provide a much larger pool of data, but are less specific and detailed. Uncertainty is introduced when the sample size of failure rate data is too small, the quality of database is bad, and the environmental conditions and operating conditions of the instrument are different from the databases, *etc.* In these situations, expert knowledge can be used to reduce the uncertainty.

This study focuses on quantifying the uncertainty in failure rate data considering both generic databases, plant specific data, and expert experience. The final frequency is expressed in a distribution. The performance of a specific instrument can depend on operating conditions and the environment of processes, which are not considered in traditional CCPS LOPA model. Expert judgment is applied in the generic database and plant specific data aggregation, especially in situations when there is a lack of data.

There are different approaches to deal with uncertainty in engineering problems including statistics (Guyonnet et al., 1999), fuzzy logic (Siler and Buckley, 2005), sensitivity analysis, and expert method (Paté-Cornell, 1996). In this study, fuzzy logic along with probabilistic approaches will be used for the uncertainty identification in LOPA.

2. Quantifying uncertainty in LOPA

2.1. Literature review on different approaches (fuzzy, Freeman, Bayesian)

For better decision making there is a need for approaches to quantify uncertainty in LOPA. Fuzzy sets and fuzzy logic were introduced by Zadeh in 1965 (Zadeh, 1965). Fuzzy logic was developed to deal with systems that are very complex or not clearly defined. In case of a lack of data, this enables experts to express their estimate of a parameter value in a semi-quantitative way by linguistic terms on an ordinal scale. Fuzzy logic is an effective method to quantify such expressions. Fuzzy logic theory has widespread applications in process safety analysis, including event tree analysis, fault tree analysis, fuzzy risk matrix, bow-tie analysis, *etc.* (Bowles and Peláez, 1995; Cozzani et al., 2006; Gentile et al., 2003a, 2003b; Geymayr and Ebecken, 1995; Karwowski and Mital, 1986; Kenarangui, 1991; Kim et al., 1996; Markowski and Mannan, 2008, 2009; Markowski et al., 2009; Markowski and Siuta, 2014; Misra and Weber, 1990; Najjaran et al., 2006; Quelch and Cameron, 1994; Singer, 1990; Siuta et al., 2013).

Markowski and Mannan (Markowski and Mannan, 2006; Markowski and Mannan, 2009) developed a fuzzy LOPA (fLOPA) approach for risk assessment of transportation of flammable substances in long pipelines. The risk value calculated by fLOPA shows a more accurate result than those given by conventional LOPA. Khalil et al. (Khalil et al., 2012). developed a cascaded-fuzzy LOPA risk assessment model with an application in the natural gas industry. Ouazraoui et al. (Ouazraoui et al., 2013). used fuzzy quantities to represent the data provided from reliability databases and expert judgments in LOPA. Although the result is a parameter value, no uncertainty information is preserved, which is considered a drawback of the method.

Freeman used observed data distributions on component failure where they are available (*e.g.*, a pressure relief valve). However, these are scarce. He also extended an available single data point of a component failure probability to a simple triangular distribution by simply adding a lower and upper limit, which are based on site operator experience (Freeman, 2012, 2013). Given a triangular distribution, the mean value and variance can be calculated. As is known, variance is an indication of uncertainty. The convolution of different failure rate data is through the application of variance contribution analysis (VCA) and a simplified numerical approximation. The final frequency is also a distribution with uncertainty information.

Pasman and Rogers (Pasman and Rogers, 2013) applied Bayesian network in LOPA. The Bayesian network (BN) approach is based on existing data and knowledge including uncertainty. Distributions were developed based on data and expert knowledge to represent the failure rate. The final risk result is a distribution with uncertainty information. By the inference and diagnosis options BN improves understanding of complex systems.