Prior and Posterior Assessments of Failure Scenario Probabilities and Environmental Risks at Hazardous Industrial Facilities

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Abstract. The paper presents an approach for obtaining prior and posterior assessments of probabilities of various failure scenarios and risks at hazardous industrial facilities. The approach is based on the toolkit of Bayesian nets and allows accounting for new information that is obtained at the stage of the facility operation from monitoring systems and technical inspections. The presented approach can be used for developing risk-based inspection planning and risk-based management programs for hazardous industrial facilities.

1. Introduction
Performance of hazardous industrial facilities (metallurgic plants, oil, and natural gas refineries, petrochemical plants, etc.) is accompanied by storing, processing, and transmission of huge amounts of hazardous substances and energy. The unauthorized release of these substances and energy may cause disastrous consequences and trigger cascading failures in the facility and contamination of adjacent territories.

Hazardous facilities have a complex structure and are characterized by complicated behavior and interaction between their components. Severe uncertainties related to the natural variability of facility parameters, environmental conditions, and external impacts, as well as uncertainties caused by the lack of knowledge about the system and various types of human errors, are inherent in HIFs. Due to this high level of uncertainty, the HIFs performance should be carried out in a probabilistic formulation using branched scenario trees. The list of possible scenarios includes scenarios of normal operation as well as catastrophic ones. In this regard, operation of hazardous industrial facilities becomes impossible without risk assessment, the development of rational criteria for the acceptability of risks, and procedures for reducing risks to levels that society is ready to accept in the view of the benefits provided by these facilities [1, 2].

2. Prior scenario and risk assessment
According to the traditional risk assessment model risk is considered to be a function of threat \( T \), vulnerability \( V \) and consequences \( C \): \( R = f(T, V, C) \). Here threat is defined as the probability of the hazardous initiating event (component failure, extreme external impact) that can occur in HIF: \( T = P(IE) \), vulnerability is estimated as the conditional probability of system’s failure given the
initiating event occurs: \( V = P(F|IE) \), and consequences are defined as losses that occur as a result of the initiating event and subsequent system failure: \( C = E(U|IE, F) \).

\[
R = P(IE) \cdot P(F|IE) \cdot E(U|IE, F) \tag{1}
\]

Hazardous facilities due to their complex nature and behavior are subjected to multiple threats and multiple failure scenarios. Assessment of risk at hazardous industrial facilities implies an assessment of its scenario tree (Figure 1) [3]. The HIF is regarded as a technical system that is designed to fulfill the so-called success scenario \( S_0 \) (i.e. a transition from its initial state (or commissioning) \( IS \) to the designed end state (or decommissioning) \( ES_0 \). Since any accident scenario \( S^* \) presents a deviation from the success scenario \( S_0 \) that corresponds to the successful functioning of the HIF, scenario \( S^* \) must have a disturbance point at which an extreme initiating event (\( IE^* \)), occurs. Each IE gives rise to a branch of the scenario tree that has a corresponding set of scenarios \( S_i \) that ends with an end state (\( ES_i \)).

In this case one can get a similar risk index using a matrix expression:

\[
R = \sum\limits_{\{IE^*_i\}} \{P(IE^*_i); P(IE^*_i); \ldots; P(IE^*_i)\} \times \begin{bmatrix}
P[ES_0 | IE_1] & P[ES_1 | IE_1] & \cdots & P[ES_m | IE_1] \\
P[ES_0 | IE_2] & P[ES_1 | IE_2] & \cdots & P[ES_m | IE_2] \\
\vdots & \vdots & \ddots & \vdots \\
P[ES_0 | IE_n] & P[ES_1 | IE_n] & \cdots & P[ES_m | IE_n]
\end{bmatrix} \times \begin{bmatrix}
U_{ES_0} \\
U_{ES_1} \\
\vdots \\
U_{ES_m}
\end{bmatrix} 
\tag{2}
\]

**Figure 1.** General risk assessment framework.

Equations (1) and (2) give so-called prior estimates of risk. These estimates are based on prior knowledge and statics that were available when the facility was designed and constructed and ignore data obtained in the process of the facility operation. These scenario trees may be assessed using the toolkit of common hybrid graph models combining fault trees describing hazards that may impact the facility and event trees describing the facility’s vulnerabilities.

These models allow one to assess prior probabilities of realization of various scenarios \( P(ES) \) that are based on an initial bank of knowledge about the system and statistics on the performance of similar facilities that are available at the stage of facility design and construction.

In other words, risk assessments that are based on the above models are adequate at the stages of design and construction of HIFs, but they fail to account for new data that is being obtained by the systems of continuous monitoring as well as during technical inspections at the stage of the facility operation. Bayesian networks are an effective tool to overcome these shortcomings.

3. Application of Bayesian nets for developing posterior assessments of failure probabilities

Bayesian networks are graph models describing probabilistic relationships between random variables. Each node of the graph corresponds to a random variable appearing in the model, and the links reflect
the probabilistic relationships between the variables. Bayesian networks are an effective tool for combining data of different nature: empirical frequencies of occurrence of various states of random variables, data from monitoring systems or technical inspections, subjective estimates made by experts, and theoretical ideas about the probabilities of occurrence of various random events. This property of Bayesian nets is their important practical advantage and distinguishes Bayesian nets from other modeling techniques.

Bayesian nets are widely used to represent data and rationale in the face of uncertainty. Uncertainties associated with interrelationships between random variables are determined by local tables of conditional probabilities, built for each node. The network structure along with the tables of conditional probabilities corresponding to each of the nodes determines the joint probability distributions of all variables in the model. The graphical structure of a Bayesian net provides a representation of probabilistic relationships between variables [4-7].

Bayesian nets are in particular an effective tool for developing posterior assessments of failure probabilities for complex systems when new information on the state of the system components becomes evaluable. This information may come from the systems of continuous monitoring of the state of the facility or technical inspections [8, 9]. By applying Bayesian nets a numerical analysis of the probabilistic relationships between random variables of the model can be carried out.

Figure 2. Bayesian net.

The following Bayesian net was constructed to assess the risk of accident at a HIF. This model not only allows the risk appraiser to conduct the prior scenario assessment it also allows reassessing probabilities of occurrence of various scenarios of accidents as soon as new information about the actual state of the facility components becomes available. In other words when the appraiser gets signals from monitoring systems indicating that one (or several) probabilistic events of the considered failure scenario became certain he can update the probabilities of other events involved in the accident scenario. Thus Bayesian nets allow obtaining updated posterior assessments of the probabilities of the events that constitute accident scenarios and reassess risks.
Figure 2 presents an illustrative example of a Bayesian net describing accident scenarios at a hazardous industrial facility. The GeNie 2.0 software package is used in this study [10]. Root nodes 1 to 3 characterize hazards and indicate initiating events that may trigger accident scenarios. Chance nodes 4 to 19 are referred to as probabilistic intermediate events that constitute accident scenarios and describe the vulnerability of the facility. The states of each of the non-root nodes are set by the table of conditional probabilities under various states of their parents. Node 20 provides the assessments of probabilities of the end states of the facility that correspond to the success ($S_0$) and accident ($S_1$-$S_5$) scenarios. The presented diagram demonstrates the application of the constructed Bayesian net for conducting the prior assessment of probabilities of various accident scenarios.

Figure 3. Prior probability field.

The model also proves the assessment of the economic risk:

$$R' = \sum P'_{S_j} U_{S_j},$$

where $P'_{S_j}$ and $U_{S_j}$ denote the prior probabilities of occurrence of various accident scenarios and consequences attributed to their occurrence. The estimates of losses inflicted in case of occurrence of various scenarios are determined based on expert assessment/judgments and available statistics. Such assessments allow the appraiser to form the following vector of losses whose components are the values of losses corresponding to the identified accident scenarios:
Using the expression (3) the value of prior economic risk is estimated as \( R' = 1.431.23 \) USD.

As soon as some additional information on the state of the facility components becomes available Bayesian nets allow updating the probability field and estimate the posterior probabilities of various accident scenarios. Figure 4 presents the updated probability field that was computed as soon as the signal about the failure of the protection barrier #1 was obtained. One can see that the posterior probabilities of occurrence of accident scenarios \((S_1-S_5)\) increase substantially. Consequently, the posterior economic risk index is also increased up to the value of \( R'' = 9,288.34 \) USD.

The advantages of Bayesian nets include the fact that they allow recalculating the probability field and the magnitude of risk upon additional information is received from monitoring systems about the state of individual model variables, thereby updating the obtained estimates.

4. Conclusions
Traditional risk assessment models based on false and event trees and their combinations in the form of hybrid trees that are commonly used for the so-called prior assessments of risks triggered by hazardous industrial facilities are based on initial knowledge base and statistics about the facility and are not quite adequate for reassessing risk when new information about the facility becomes available.

Bayesian nets are an effective tool for updating risks at the stage of the facility operation when monitoring systems or technical inspections provide additional data about the state of the facility.
components at various stages of its life cycle. Thus Bayesian nets allow providing updated posterior assessments of the probabilities of the events that constitute failure scenarios and reassess risks. This makes Bayesian nets an important element in developing risk-based inspection planning and risk-based management programs for hazardous industrial facilities.

5. References

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