Improve Process Safety with Near-Miss Analysis

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Valuable information about unsafe conditions resides in the large alarm databases of distributed control systems and emergency shutdown systems. This overlooked and underutilized information can be analyzed to identify process near-misses and determine the probability of serious accidents.

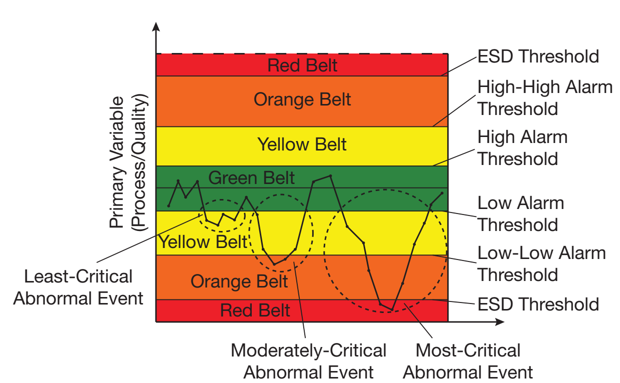
Automated control and safety systems that help a plant return to normal operating conditions when abnormal events occur are prevalent in modern chemical plants. The databases associated with these systems contain a wealth of information about near-miss occurrences that, if subjected to frequent statistical analysis, can provide metrics to predict and ideally prevent accidents. Such analysis is referred to as dynamic risk analysis.

This article introduces the concept of dynamic risk analysis (DRA) based on alarm databases. It provides a general overview of what this is, how it can be used in chemical processing to improve safety, and challenges that must be addressed over the next 5–10 years. It also highlights current research in this area and offers perspective on methodologies most likely to succeed.

Alarms, near-misses, and accidents

Figure 1 is a generic control chart for a process variable. An abnormal event occurs when control systems are unsuccessful in keeping all process (and product-quality) variables within their normal operating ranges, *i.e.*, green-belt zones.

When a variable moves into a yellow-belt zone, a high or low alarm is triggered and the safety systems (operators and/or automated systems) take action to return the variable to its normal range. If the safety systems fail to bring the process variable into normal operation and the variable moves into an orange-belt zone, a high-high or low-low alarm is triggered, causing higher-level safety systems to act. If the variable moves into a red-belt zone, safety systems will attempt emergency shutdown (unplanned shutdown), and if the safety systems are unsuccessful, an accident occurs.



▲ **Figure 1.** A control chart for a process variable indicates an abnormal event when the variable moves outside of its green-belt zone.

These accidents are low-probability, high-consequence events, and are often accompanied by large economic losses, personnel injuries, and even fatalities. (The costs of unplanned shutdowns — which happen more frequently than accidents — are also quite significant.) Of course, the layers of protection in place are usually successful, and therefore the majority of abnormal events are arrested before accidents occur. When an abnormal event is stopped before causing any damage and the variable returns to its green-belt zone, this is considered a process near-miss (which is simply referred to as a near-miss in this article). Near-misses are high-probability, low-consequence events. Accidents are typically preceded by several near-misses.

Many companies record these alarm occurrences in distributed control system (DCS) and emergency shutdown (ESD) databases. Operators, engineers, and managers seek guidance from these databases by recording key indicators and paying special attention when alarm flooding occurs. Most of the time, further analysis is done after process upsets, unanticipated trips, and accidents occur.

Companies are becoming increasingly aware that these databases are rich in information related to near-misses. In recent years, researchers have been developing key performance indicators, or metrics, associated with potential trips (shutdowns with no associated personal injury, equipment damage, or significant environmental problem) and accidents; leading indicators (*i.e.*, events or trends indicating the times these trips and accidents are likely to occur); and probabilities of failure of the individual safety systems and the occurrence of trips and accidents. When conducted at frequent intervals, the analyses that are associated with these performance indicators are often referred to as dynamic risk analyses, or simply near-miss analyses.

Conventional risk analyses

Risk assessment is an important component of the U.S. Occupational Safety and Health Administration's (OSHA) process safety management (PSM) standard, which includes (among other elements) inherently safer design, hazard identification, risk assessment, consequence modeling and evaluation, auditing, and inspection. Over the last decade, PSM has become a popular and effective approach to maintain and improve the safety, operability, and productivity of plant operations. As part of this, several risk assessment methods have been developed.

The use of quantitative risk analysis (QRA), which was pioneered in the nuclear industry in the 1960s, was extended to the chemical industry in the late 1970s and early 1980s after major accidents such as the 1974 Flixborough explosion in the U.K., the 1984 Bhopal incident in India, etc. Chemical process quantitative risk analysis (CPQRA) was first fully described and introduced as a safety assessment tool by AIChE's Center for Chemical Process Safety (CCPS) in the 1990s as a means to evaluate potential risks when qualitative methods are inadequate. CPQRA is used to identify incident scenarios and evaluate their risk by defining the probability of failure, the various consequences, and the potential impacts of those consequences. This method typically relies on historical data, including chemical process and equipment data, and human reliability data to identify hazards and risk-reduction strategies.

> Despite advances in alarm management, existing alarm-data-analysis methods have inadequately utilized the risk information contained in alarm databases.

Other risk assessment methods were subsequently developed to analyze industry-wide incident databases *(1–5)*. These databases include: CCPS's Process Safety Incident Database *(1)*, which tracks, pools, and shares process safety incident information among participating companies; the Risk Management Plan database, RMP*Info *(2)*, developed by the U.S. Environmental Protection Agency (EPA); the National Response Center (NRC) database, an online tool set up by NRC to allow users to submit and share incident reports; and the Major Accident-Reporting System (MARS), which is maintained by the Major Accident Hazards Bureau (MAHB). Recent risk analyses associated with chemical plant safety and operability have used Bayesian statistics to incorporate expert opinion *(6–8)*, and fuzzy logic to account for knowledge uncertainty and data imprecision *(9–10)*. Such methods have significantly improved quantitative risk assessment.

While these methods have been important in quantifying safety performance, a large amount of precursor information pointing to unsafe conditions has been overlooked and unutilized, because it resides in large alarm databases (*e.g.*, DCS and ESD). The alarms help plant operators assess and control plant performance, especially in the face of potential safety and product-quality problems. The alarm databases, therefore, contain information on the progression of disturbances and the performance of regulating and protection systems. However, despite advances in alarm management standards and procedures, existing alarm-data analysis methods reported in the literature have inadequately utilized the risk information contained in alarm databases and have used the data for incident and reliability analyses only.

Several comprehensive algorithms and software packages to evaluate process safety risks with an eye toward developing and implementing appropriate protective measures have been developed over the last two decades *(11–12)*. Most of these systems rely on the accident and failure databases mentioned above, which provide information such as accident frequencies, consequences, and associated economic losses, to perform quantitative risk analyses. (Other tools, discussed later, utilize a quantitative methodology for risk analysis either in real-time or on-demand, but they do not focus on estimating the likelihood of incidents or the failure of safety systems.) The analyses that involve accidents and failures only, and exclude day-to-day alarm information and associated near-miss data, are not highly predictive. They overlook the progression of events leading up to near-misses — information that can only be obtained by analyzing data found in alarm databases.

A study of an ammonia storage facility conducted by the Joint Research Centre and Denmark Risk National Laboratory of the European Commission *(13)* found that risk estimates based on generic databases of reliability and failure data for commonly used equipment and instruments are prone to biases and could provide widely varying results depending on data sources.

For these reasons, the importance of utilizing process-specific databases for risk analyses has been gaining recognition.

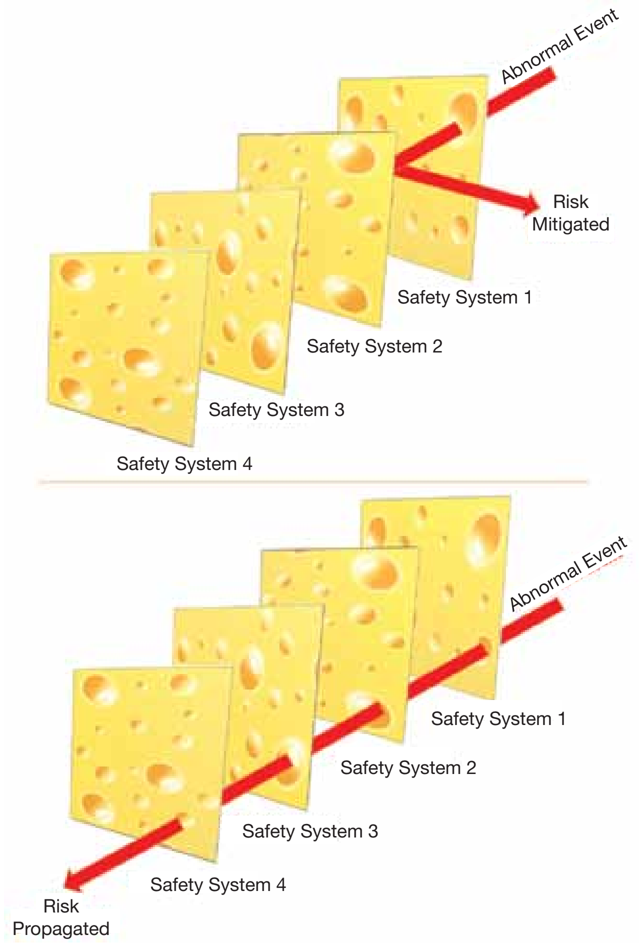
Dynamic risk analysis

Accidents are rare events, often described using the popular Swiss cheese model *(14)*, in which the layers of protection are envisioned as pieces of Swiss cheese lined up in a row, with the holes (which vary in size and placement) corresponding to weaknesses in the individual layers of protection (Figure 2). According to this model, failures occur when the holes in the individual slices line up, creating trajectories of accident opportunities. This view implies that an element of chance is involved in the occurrence of failures.

Most major accident investigations have identified several observable near-misses — *i.e.*, less-severe events, conditions, and consequences that occur before the accident. Unless thorough analyses of process near-misses are performed regularly, plant personnel are likely to overlook the development of risky conditions, and thus, in time, trajectories of accident opportunities develop.

Dynamic risk analysis using alarm data, which was first introduced by Pariyani *et al. (15–16)*, uses alarm data (near-miss information) to identify problems and correct them before they result in sizable product and economic losses, injuries, or fatalities. DRA involves the following steps:

1. Track abnormal events (near-misses) using raw data from alarm databases.
2. Create event trees that show all of the possible paths an abnormal event can take when propagating through the safety systems.

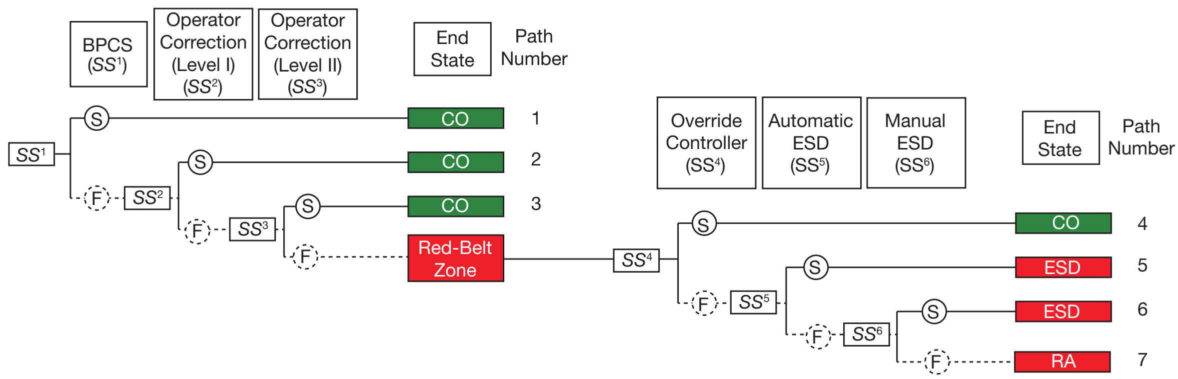


▲ **Figure 2.** The Swiss cheese model depicts the relationship between layers of protection and accidents. Each slice of cheese represents one layer of protection, and the holes in the cheese correspond to weaknesses within each layer. According to this model, failures occur when the holes in the individual slices line up.

3. Use a set-theoretic framework, such as that developed by Pariyani *et al.*, to compact the data into a concise representation of multisets.
4. Perform a Bayesian analysis to estimate the failure probabilities of each safety system, the probability of trips, and the probability of accidents.

Figure 3 shows a typical event tree involving six safety systems and the consequences of each of the possible paths, which include continued normal operation (CO), shutdown (ESD) or trip, and accident (*e.g.*, runaway reaction [RA]). The six safety systems, which are typical of those encountered in chemical processing plants, are:

Safety System 1 (SS^1), basic process control system (BPCS). This is an automated basic control system within the DCS that is designed to keep the process and quality variables within their normal operating ranges. When the BPCS is unsuccessful, abnormal events occur, and alarms



▲ **Figure 3.** These event trees for a process with six safety systems depict the actions of each safety system as it responds to an abnormal event. Each safety system (*SS*) is represented by a node with two branches, for the success (S) and failure (F) of that system to return the process or quality variable to its green-belt zone. For example, if the first safety system (SS^1) fails to return the variable of interest to normal operation, the variable will follow the F branch. If SS^2 is then successful in bringing the variable back into normal operation, the variable will follow path 2 with an end state of continued operation (CO). The variables will follow paths 4–7 when they enter their red-belt zones because the first three safety systems were unable to return the variable to its green-belt zone.

notify the operators of the variables' transition into their yellow-, orange-, or red-belt zones.

Safety System 2 (SS^2), operator (machine + human) corrective actions, Level I. This is the human-operator-assisted control system that keeps the variables between their high and low alarm thresholds and returns them to normal operating conditions. When it is unsuccessful, variables enter their orange- and red-belt zones.

Safety System 3 (SS^3), operator (machine + human) corrective actions, Level II. This operator-assisted control system keeps the variables between their high-high and low-low alarm thresholds and returns them to normal operating conditions. These corrective actions are more rigorous than those of Level I. When these actions are unsuccessful, the variables enter their red-belt zones, with the potential to cause an emergency shutdown of the unit.

Safety System 4 (SS^4), override controller. This is an automatic controller that takes radical actions when certain primary variables enter their red-belt zones.

Safety System 5 (SS^5), automatic ESD. This is an automatic, independent system that shuts down the unit after a small time delay.

Safety System 6 (SS^6), manual ESD. This human-operated system shuts down the unit immediately.

Hurricane Sandy

Quantitative risk analysis (QRA) can be combined with dynamic risk analysis. The use of these methods to assess risk is illustrated with an analogy to Hurricane Sandy.

In preparing for large storms such as this one, cities (as well as various government agencies and private organizations) use historical data, the layout of landmasses, and the locations of buildings to estimate expected flood levels and associated damages. Precautions are taken, infrastructure investments are made, and flood insurance policies are written based on these data to minimize, and preferably eliminate, damages and financial losses.

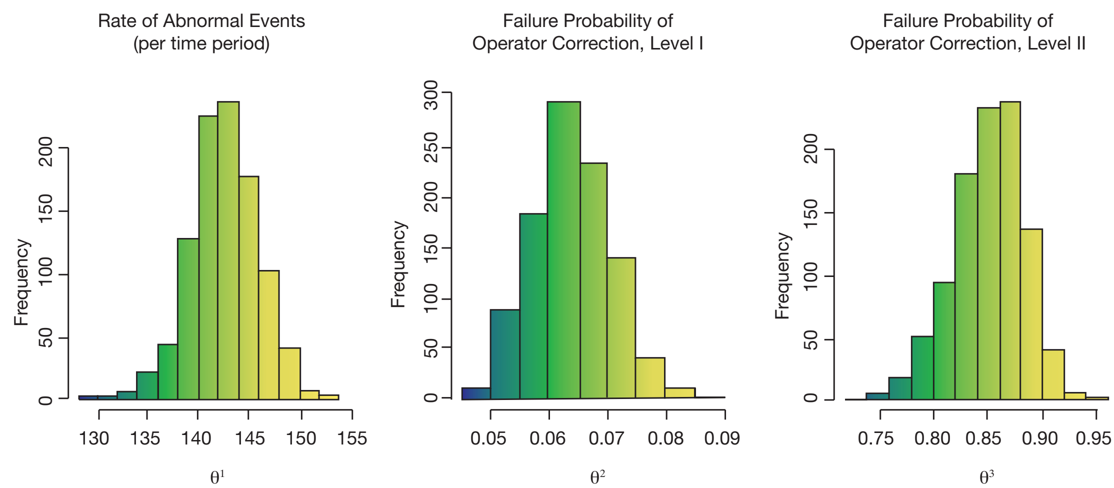
According to available statistical estimates, the probability of flooding in several cities is less than 1%, *i.e.*, there is less than a 1% chance of flooding each year in these areas *(17)*. However, such static probabilistic values do not suggest the times at which flooding is more (or less) likely to occur. Evidently, the probability of the occurrence of flooding in these cities in October 2012 (when Sandy hit the U.S. East Coast) was much higher than the historical estimates. Meteorologists employed dynamic assessments of weather changes and water levels to identify locations with increasing potential for flooding and to warn communities in advance.

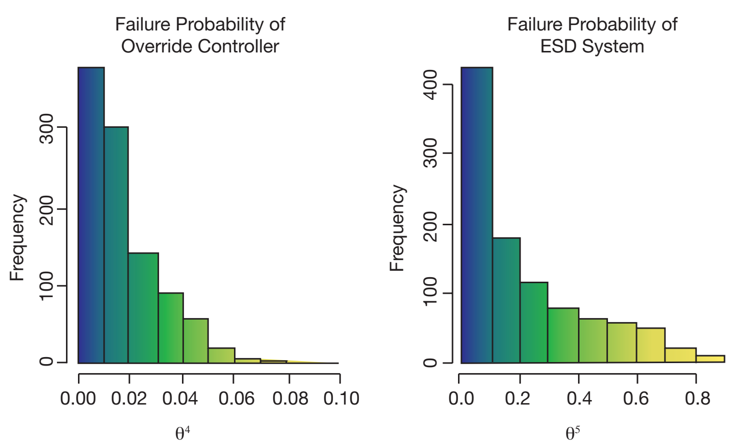
In many aspects, QRA is similar to calculating risks using historical databases, whereas in practice, operating conditions in a process change with time and, consequently, risk levels vary dynamically. Because DRA using alarm data updates risk estimates of the potential for failure periodically (every week in the following example), it complements QRA in measuring the safety performance of a process.

Applying dynamic risk analysis

This example illustrates the application of DRA to an industrial fluidized catalytic cracking unit (FCCU) at a major petroleum refinery. We received data from a period during which as many as 5,000–10,000 alarms occurred daily on this unit. In this analysis, SS^5 and SS^6 (automatic and manual ESD systems) are assumed to be a single safety system.

Figure 4 provides histograms of the failure rate (θ^1)





▲ **Figure 4.** The histograms of the failure rate and probabilities for each of the six safety systems can be used to determine the performance of the system as a whole.

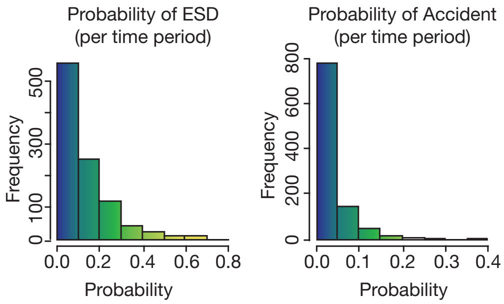
and probabilities (θ^2–θ^5) of the safety systems for a key primary variable over the length of the study, which was divided into 13 equal intervals. These distributions were calculated using multivariate normal copulas, which model the dependencies between the different safety systems. Copulas are multivariate functions used to model the joint probability distribution of random variables (safety system failure in this example) that are modeled as univariate marginal distributions from different distribution families through their correlations *(18)*.

Over 13 periods, an average of 142 abnormal events occurred in each period. The mean failure probability of the operator Level I corrective actions (SS^2) is fairly low (0.074) — indicating their robust performance. However, for operator Level II corrective actions (SS^3), the failure probability is abnormally high (0.851), indicating the difficulties associated with SS^3 keeping the variables within their orange-belt zones. Stated differently, the probability that the key variable moves from its yellow-belt to its orange-belt zone is just 7.4%, while the probability of this variable moving from its orange-belt to its red-belt zone is 85%. Clearly, less-likely, moderately critical abnormal events are very likely to propagate into most-critical abnormal events due to the ineffective Level II control actions (*i.e.*, the weak actions of SS^3). Hence, to prevent the occurrence of most-critical abnormal events on this FCCU, it is important to prevent the occurrence of moderately critical abnormal events.

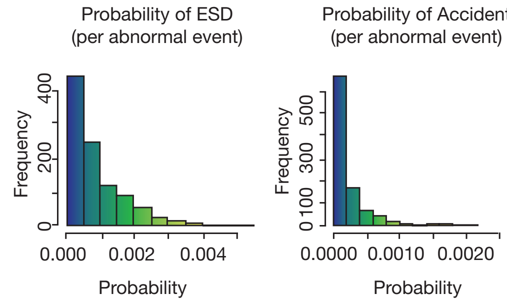
The failure probability of the override controller (SS^4) is also quite low (0.017). The failure probability of the ESD system (SS^5) is relatively uncertain, due to the lack of available data points. Past performance (over several months and years) and/or expert knowledge regarding the failure of these systems can be useful. The latter could be derived from the dynamic risk analysis of near-miss data from related plants.

Given estimates of the failure rates and probabilities of the safety systems, incident probabilities can be estimated, *i.e.*, probabilities of the occurrence of an ESD or accident. Two types of incident probabilities are computed with DRA: incident probabilities per time period (p^{tp}), and incident probabilities per abnormal event (p^{AE}), which are shown as histograms in Figures 5 and 6.

The probability of occurrence of an ESD per period, p^{tp}_{ESD}, is obtained by multiplying the failure rate and the probabilities of $SS^{1–4}$ and the success probability of SS^5. The probability of occurrence of an accident in each time period, $p^{tp}_{Accident}$, is obtained by multiplying the failure rate of SS^1 and the failure probabilities of $SS^{2–5}$.



▲ **Figure 5.** The probability distributions for the occurrence of an ESD and an accident per time period can be estimated from the failure rate and probabilities.



▲ **Figure 6.** The probability distributions for the occurrence of an ESD and an accident per abnormal event can be estimated from the failure rate and probabilities.

Similarly, the probability of the occurrence of an ESD per abnormal event, p^{AE}_{ESD}, is calculated by multiplying the failure probabilities of SS^{2-4}, and the success probability of SS^5. The probability of occurrence of an accident per period, $p^{AE}_{Accident}$, is determined by multiplying the failure probabilities of SS^{2-5}.

Based on the performances of these safety systems over the study period, on average, the probability of the occurrence of an ESD associated with the key primary variable of interest is 0.124 per period and 8.7×10^{-4} per abnormal event. That is, an ESD is likely to occur in approximately one of eight periods, or in one of 1,150 abnormal events. Similarly, an accident is likely to occur in approximately one of 31 periods (1/0.032) or in one of 4,762 abnormal events.

Note that while no accidents occurred during the study

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period and no trips (ESDs) occurred over several periods, the Bayesian analysis estimated finite probabilities of trips and accidents for all periods using abnormal event history data and prior information (expert opinion). Also, because the variance in the failure probability of SS^5 is large, the variances in the probabilities of an ESD and an accident are high. With additional data, this uncertainty can be reduced.

The probabilities of ESDs and accidents can help to assess the compliance of chemical plants with national and international safety standards. For example, the International Society of Automation (ISA) *(19)* defines safety integrity levels (SILs) to measure the level of risk reduction provided by ESD systems. When the probability of failure under demand (PFD) lies between 10^{-2} and 10^{-3}, the SIL is set at 2. For the FCCU, the mean probability of an ESD per abnormal event (which is indicative of the probability of failure of all safety systems except the automatic ESD system when a disturbance occurs) is on the order of 10^{-3}. For the FCCU, the SIL is equal to 2, which indicates that it is sufficient for the unit and is also compliant with safety standards.

More informative charts can be prepared by accounting for other influencing variables, such as the states of interlocks and equipment, that would allow broader areas for risk reduction to be identified.

Current state of technologies

To better understand current practices, one needs to look at alarm-based risk analysis and near-miss management separately. Until recently, in almost all industrial operations, alarms were treated individually as indicators of different risk levels (both for operational and safety risks), but they were not viewed as near-misses of potential accidents, and thus were not analyzed as such. Currently, in advanced operations, alarms are studied periodically based on their frequency of activation, and alarm levels are adjusted to balance the number of alarms against the risk information these alarms convey.

Starting with the pioneering Wharton Risk Management study *(20)* and the subsequent adoption and further development of the concept by CCPS and other organizations, dynamic risk analysis using "observable" near-misses, such as pump and valve failures, gained significant importance. Large, dynamic, near-miss and reliability databases developed by CCPS, DNV, Exida, IEEE, IHS, and others, as well as company-specific near-miss databases maintained internally, are now being used for statistical risk analysis. However, as pointed out earlier, because risk analyses based on these generic databases are prone to bias and subjectivity, caution must be exercised when using these results to predict accidents *(13)*. Note that abnormal-situation detection and condition-based monitor-

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Dynamic risk assessment using alarm data is in its infancy.

ing software that utilizes process data and is designed for the operating team to identify faults and abnormalities (in real-time or on-demand) is currently available. However, this software does not focus on the developments over time associated with the likelihood of potential incidents.

Dynamic risk assessment based on alarm data is in its infancy. Recently, Near-Miss Management LLC has developed software called the Dynamic Risk Analyzer to utilize alarm data for dynamic risk analysis and identification of process near-misses and anomalies for continuous processes. It seems clear that over the next five years, more tools will be developed to dynamically utilize the rich information encapsulated in alarm databases to obtain objective risk estimates.

Widespread adoption of dynamic risk analysis

Rapid developments in statistical methods and computer capabilities are enabling dynamic risk analysis. Although this concept is in its beginnings, its application should grow rapidly with the ongoing pooling of near-miss data from different sources to create richer databases for more-frequent risk analyses.

In the future, the widespread adoption of alarm-based dynamic risk analysis will require (among other actions) changes in alarm-based risk-management strategies. Some alarms will have fixed thresholds as is current practice, for example, the alarms based on structural limitations of plant vessels. Other alarms, those that help plants operate safely and reliably while producing products within quality specifications, will have dynamic thresholds that vary with plant conditions. These alarms are sometimes grouped together for each interlock or equipment item to provide warning signals related to the physical location of the abnormal events. These would not detract from normal operator actions, but would provide additional valuable risk information. In time, operating personnel will learn to utilize this new information, which will be the key to adopting, and using intelligently, risk-based alerts. The frequency of dynamic risk analyses, the presentation of results in an actionable manner, and the recipient(s) of risk-based information will need to be studied and possibly standardized.

Consider this: Does implementation of alarm-based dynamic risk analysis lead to a different philosophy in setting alarm levels (thresholds)? We will study these and related follow-up questions in our future research.

Finally, it should be recognized that dynamic risk analysis based on alarm data complements quantitative risk analysis, and hence, improves PSM. CEP

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of the future," Zhang says. "Many people believe we will enter the hydrogen economy soon, with a market capacity of at least $1 trillion in the United States alone."

ENVIRONMENTAL

Methane Is No Match for Zeolite Traps

Researchers at the Lawrence Livermore National Laboratory (LLNL) have identified several zeolites that hold great potential for methane capture. One, dubbed SBN, was found to have adsorption sites that are optimally sized for methane uptake.

Methane, the second-most-emitted greenhouse gas (based on concentration) behind CO_2, contributes about 30% of net climate warming. Rising concern over potential methane leaks from unconventional oil and gas extraction, and the growing use of methane as an energy source, have heightened the interest in efficient methane capture. However, unlike CO_2, which can be captured both physically and chemically in a variety of solvents and porous solids, methane is completely nonpolar and interacts weakly with most materials. Attempts to capture methane have thus far been unsuccessful.

Methane is emitted from a wide variety of sources that can be characterized by concentration: high-purity (concentrations >90%), medium-purity (5–75%), and dilute (<5%).

The research team performed systematic computer simulation studies on liquid solvents and nanoporous zeolites to determine their efficacy for methane capture. Two specific application areas were targeted — concentrating methane from a medium-purity source to high purity (*e.g.*, purifying a low-quality natural gas); and concentrating a very dilute stream to medium purity (*e.g.*, enabling energy production from coal-mine ventilation air).

While none of the liquid solvents were effective for methane capture, the screening of over 87,000 zeolite structures uncovered a few nanoporous candidates that appear promising and have good CH_4/CO_2 selectivity, says Amitesh Maiti, a scientist at LLNL. "We used free-energy profiling and geometric analysis in these candidate zeolites to understand how the distribution and connectivity of pore structures and binding sites can lead to enhanced sorption of methane while being competitive with CO_2 sorption at the same time," he explains.

The most successful of these candidates was the zeolite SBN, which has a large number of binding sites arranged in a way that maximizes the CH_4–CH_4 interactions. The amount of methane captured from a medium-concentration source (which could be converted to high-purity methane) was sufficient to make SBN technologically promsing.

Other zeolites, named ZON and FER, were able to concentrate dilute methane streams into moderate concentrations while maintaining high CH_4/CO_2 selectivity. CEP