Integrated Framework for Abnormal Event Management and Process Hazards Analysis

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Process hazards analysis (PHA) and abnormal event management (AEM) are important to plant safety in chemical process industries. PHA deals with the off-line identification, assessment and mitigation of hazards, while AEM addresses process plant malfunctions on-line. Their inherent objectives, however, are similar, such as identifying, avoiding and mitigating hazards, and planning for emergencies. While PHA reasons from causes to consequences, AEM identifies the causes from observed symptoms or faults. The PHA results contain valuable cause and consequence information, safeguards, and other operability issues. AEM can benefit from utilizing this existing knowledge about the plant. However, in current industrial practice, PHA results are not used by operators for AEM purposes. An integrated framework combining both these tasks in a synergistic manner effectively manages and displays information searched from a possibly large number of PHA results, during on-line operation, by using a hierarchical representation of the plant. An automated methodology is developed for this representation based on topology and functional classification of equipment. The application of the integrated framework to an industrial case study is described.

Introduction

As modern chemical plants have become very complex and highly integrated, it has become difficult to analyze and assess in detail the inherent hazards in these systems, thus raising environmental, occupational safety, and health related concerns. They usually process large volumes of hazardous materials and are often operated at extremes of pressures and temperatures to achieve optimal performance, making them even more susceptible to equipment failures. Failure of any component in the process could lead to abnormal events resulting in extended downtimes, flaring of pollutants or, in extreme cases, major accidents. Clearly accidents have significant economic and safety impact. The result of a major industrial accident can be quite devastating as seen in the accident at Bhopal, India (Lees, 1993). Industrial statistics show that even though major catastrophes and disasters from chemical plant failures may be infrequent, minor accidents are very common, occurring on a day to day basis, resulting in many occupational injuries, illnesses, and costing the society billions of dollars every year (McGraw-Hill Economics, 1985; Bureau of Labor Statistics, 1998; National Safety Council, 1999). Hence, there has recently been an increased consciousness in academia and industry alike to come up with methods to prevent the occurrence of, and mitigate the effects of, such events. Process hazards analysis (PHA) and abnormal event management (AEM) are two such methods that are used by industrial practitioners to improve the design and performance of a process, while ensuring safety of people and property involved. These methods are briefly discussed below.

Abnormal event management (AEM)

An abnormal event is any departure of a process from its acceptable range of operation. Abnormal event management (AEM) deals with these situations through timely detection, diagnosis, and countermeasure planning during on-line operation. It is an important part of safe and optimal operation of chemical plants. An estimated $20B is lost annually by the petrochemical industries in the U.S. alone due to

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inadequate AEM (Nimmo, 1995). Nimmo also estimates that there were 240 plant shutdowns during a one-year period that could have been prevented. An effective AEM methodology that properly addresses these issues can, thus, have significant economic and safety impact. The methodology should provide accurate, well organized and timely information, and thereby aid in early diagnosis and correction of abnormal events.

Process fault diagnosis forms the first step in AEM. Fault diagnosis involves interpreting the current status of the plant given sensor readings and process knowledge. Early diagnosis of process faults while the plant is still operating in a controllable region can help avoid event progression and reduce the amount of productivity loss during an abnormal event. However, the problem of fault diagnosis is made considerably difficult by the scale and complexity of modern plants. There are a number of practical challenges in designing diagnostic systems due to factors such as complexity of process dynamics, lack of adequate models, incomplete or uncertain data, diverse sources of knowledge, amount of effort and expertise required to develop and maintain the systems, and so on. A quite comprehensive review of the various model-based (Venkatasubramanian et al., 2002a, 2002c) and history-based (Venkatasubramanian et al., 2002b) diagnostic philosophies has recently been compiled by Venkatasubramanian and coworkers. To address the various challenges in the industrial applications (Dash and Venkatasubramanian, 2000) of fault diagnostic techniques, significant attention has been paid by the research community in the recent years to automate fault diagnosis and considerable progress has been made in all areas of this field.

Process hazards analysis (PHA)

Industrial practitioners view safety as an important design objective in process engineering in order to prevent accidents. Engineers involved in the design and operation of the chemical plants systematically ask questions such as, "What can go wrong?", "How likely is it to happen?", "What range of consequences might there be?", "How could they be averted or mitigated?", "How safe is safe enough?" and so on in order to evaluate and improve the safety of the plant. The answers to these and other related questions are sought in a process hazards analysis (PHA) of a chemical process plant. PHA is the systematic and proactive identification, mitigation, and assessment of potential process hazards which could endanger the health and safety of humans and cause serious economic losses. PHA is an important activity in process safety management (PSM) and is carried out off-line. The importance of this activity was underscored by the Occupational Safety and Health Administration's PSM standard Title 29 CFR 1910.119 (OSHA Regulations on Process Safety Management, 1994) in the U.S. This standard requires that major chemical plants perform PHA on a regular basis when a new process is launched or any change occurs in an existing process. It also requires that at least every five years after the completion of the initial PHA, the safety analysis results be updated and revalidated to ensure that they are consistent with the current process.

A wide range of methods such as Checklist, What-If Analysis, Failure Modes and Effects Analysis (FMEA), Fault Tree Analysis and HAZOP (Hazards and Operability Analysis) are available for performing PHA (Center for Chemical Process Safety, 1985; Khan and Abbasi, 1998). These techniques are aimed at identifying and assessing the hazardous consequences of process deviations. Whatever method is chosen, the PHA, typically performed by a team of experts, is a laborious, time-consuming, and expensive activity which requires specialized knowledge and expertise. For PHAs to be thorough and complete, the team cannot afford to overlook even "routine" causes and consequences which commonly occur in many plants. HAZOP is the most widely used and recognized as a preferred PHA method by the chemical process industries (Venkatasubramanian and Vaidhyanathan, 1994). The basic principle of HAZOP analysis is that hazards arise in a plant due to deviations from the "design intent" or acceptable normal behavior of the plant. In order to cover all the possible malfunctions in the plant, the multidisciplinary team of experts examines all possible process deviations by systematically applying a set of "guide words" such as MORE OF, LESS OF and NONE to the process variables or parameters of the process. Detailed descriptions of the analysis procedure have been reported in the literature (Lawley, 1974, 1976; Center for Chemical Process Safety, 1985; Kletz, 1986; Knowlton, 1989) with examples of industrial accidents that could have been prevented if only a thorough PHA had been performed earlier on the plant.

Given the enormous amounts of time, effort, and money involved in HAZOP reviews, there exists a considerable incentive to develop automated approaches to the HAZOP analysis of process plants. Such a system would reduce the time and effort involved in a HAZOP review, make the review more thorough and detailed, minimize or eliminate human errors, facilitate documentation for regulatory compliance, and make the study results available on-line. In addition it would free the team to concentrate on the more complex aspects of the analysis which are difficult to automate. There have been some efforts to automate HAZOP (Karvonen et al., 1990; Rushton, 1995; Venkatasubramanian and Preston, 1996). Venkatasubramanian and Vaidhyanathan (1994) have proposed a digraph-based approach for automating HAZOP analysis in continuous processes called HAZOP-Expert. It has been reported to have successfully emulated the human experts' reasoning and identified all hazards on several industrial case studies (Vaidhyanathan and Venkatasubramanian, 1995, 1996a,b). The same idea was extended to batch processes and an automated batch HAZOP analysis system called BatchHAZOPExpert (Srinivasan and Venkatasubramanian, 1998a, 1998b) has been developed and tested successfully on industrial case studies. A good review of the existing PHA methodologies, the challenges and automation approaches is presented by Venkatasubramanian et al. (2000).

Integrated view to AEM and PHA: motivation and issues

Figure 1 shows the reasoning involved in AEM and PHA. Broadly speaking, while PHA tries to get to the adverse consequences/hazards from causes, AEM involves diagnosing the causes given the symptoms or faults. The various diagnostic methods used in AEM lay emphasis on the detection and diagnosis of faults. The main aim of PHA, however, is to identify and assess the consequences of an abnormal event.

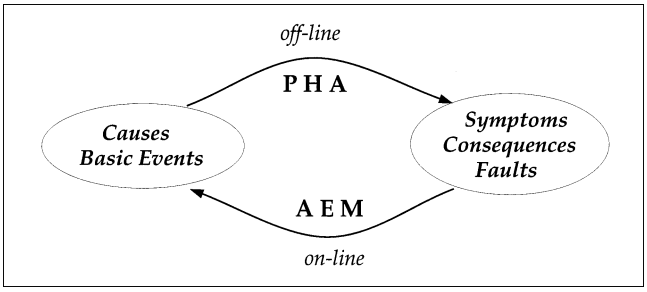

Figure 1. Complementary nature of AEM and PHA.

From the discussion on AEM and PHA above, there is evidence that both techniques have complementary strengths and an integrated framework which combines them in a synergistic fashion would be an approach worth exploring. The results of a PHA, which are determined off-line, can serve as a wealth of information during AEM that is carried out on-line. This is the focus of this article. In this section we discuss the kind of information PHA results contain, their availability, and their relevance to AEM. The motivation to take advantage of the PHA results for real-time operator support and the various issues pertaining to the same are also described.

PHA Results and Relevance to AEM. The PHA results are typically a comprehensive source of what can go wrong in the plant. During PHA, especially using the HAZOP methodology, the process is thoroughly analyzed to find possible causes and consequences for all deviations that can occur. The results are comprised of variable deviations, their causes, consequences, safeguards, and possible corrective actions that need to be taken in the event of an abnormal event. The cause information present in PHA results are the ultimate root causes, that is, they cannot be traced back any further. They include causes due to nature of process materials (process-specific) and due to equipment failures, controller failures (process-generic). For example, the cause of *low flow in the tube-side of a heat exchanger* might be *tube rupture leading to leakage of tube-side process materials to shell side*. This could also be attributed to the *blockage of tubes due to accumulation of solid materials*, where the *nature* of process materials comes into play. The consequence information deals with adverse outcomes from the variable deviations in the process and includes both those resulting from the nature of the process materials (process-specific), as well as process-generic consequences. For example, the consequence of *high pressure in a pipe carrying a flammable material* could be *release of the material into plant due to a leak leading to a fire hazard*. Similarly, the result of *low inlet pressure in a pump* may be *damage to the pump due to loss of NPSH or a cavitation problem*. Since most of the diagnostic systems in AEM reason about the abnormal event based on causal interaction between variables, they invariably end up in identifying the abnormal causes in terms of variables/parameters, and not in terms of these root causes themselves. To illustrate, the result of an investigation by a diagnostic system might be *low flow in tube-side* and not *why* that occurs, which could be due to different basic reasons such as blockage, rupture, and so on. Also, their main focus is to diagnose, that is, find the cause and, hence, they do not usually deal with adverse consequences. As can be imagined then, the information contained in PHA results can be crucial during on-line monitoring of the process to ward off any impending danger by keeping the operator informed and helping him/her act in advance. The recommended safeguards and procedures to be followed in the event of an emergency can also aid in countermeasure planning during AEM.

The PHA automation tools (Venkatasubramanian et al., 2000) allow fast and accurate analysis leading to well-structured results and, thus, may provide a convenient method for building and maintaining the malfunction knowledge about a plant. Since this knowledge is required by law (OSHA Regulations on Process Safety Management, 1994) for most chemical plants and, hence, is available early in the design stage, an additional effort to manually construct this knowledge for AEM may not be necessary. Also, the results often include operability issues and these can be used to track production and quality. PHA results are also required by the OSHA regulations to be retained throughout the life of the plant and updated periodically whenever any substantial modifications are made to the process that demand a review. The PHA results can, thus, be thought of as representing the "current malfunction model" of the plant. Currently, in the process industry, these results are not used on-line during abnormal event management. They are typically entered into a spreadsheet by the team, printed out for regulatory compliance, and stored with the manuals.

Building a model for a large-scale process, taking into account all variables, the process materials, their properties, and estimating their states in real time, is a very demanding and difficult task. As is true with most processes, this might not be feasible because of the nonlinearity in the process model to solve the system in real time or the unavailability of good models in the first place. The use of PHA results to get at least a qualitative estimate of the situation is an attractive alternative. One could then focus on a few of the identified hazards and perform a detailed simulation to get quantitative estimates. Srinivasan et al. (1998) used this approach in their work, where, in the first stage, HAZOPExpert is used to identify all probable hazards in the worst-case sense and, in the second stage, ambiguous scenarios are evaluated in detail to determine if they are realizable, using a limited quantitative process model. From the above discussion, we find that there is motivation to use the results from an available safety analysis to supplement the existing diagnostic systems (if any). Since they represent information concerning the plant's behavior and safety characteristics that are already available, there may be less need to generate separate process information sources for AEM, allowing their effective utilization to AEM's benefit.

There has been some work to use the results of safety analyses for diagnostic purposes. Heino et al. (1992) describe a joint project called KRM (Knowledge based risk management) of three Scandinavian countries to develop an information system to support process risk management. They made the results of safety analyses available to operating personnel and tried to keep this information up-to-date with safety analysis and disturbance reporting tools that were used as a part of the daily routines at the plant. They describe the difficulties they faced while using the previous HAZOP analysis that had been done 5 years earlier, since the process had

undergone changes and the old results were not well structured. Wennersten et al. (1996) present experiences from a large industrial project, where results from risk identification are used in on-line fault diagnosis in two industrial plants. They describe a MS-Windows database tool for documenting HAZOP analysis sessions which allowed searching mishap reports, a reporting system for disturbances, incidents and accidents, thus making it possible to learn from past near-misses where accidents have been avoided. They point out that the HAZOP analyses must be very carefully performed to make the system maintainable. Ruiz et al. (2001) present an ANN-based supplement of a fuzzy logic system (FLS) for fault diagnosis which utilizes information from a historical database, a HAZOP analysis, and a plant model. Realizing the inherent similarity in the hazard analysis and fault diagnosis tasks, Oh et al. (1998) proposed a unified process modeling methodology suitable for both hazard analysis and fault diagnosis. The approach is applied to the automation and the implementation of safety-related activities by using the same process models instead of different models and methodologies in design, operation, and revision stages. Automated PHA systems such as HAZOPExpert (as discussed earlier) might have possibly saved time and labor, while producing high quality results in terms of thoroughness, accuracy, and structure, thus overcoming some of the problems that these efforts faced.

Issues involved. In this section we outline the primary issues that are involved and that need to be addressed in the AEM-PHA integration task. There are two of them:

(1) Development of a PHA Knowledge Repository: There are typically a large number of results from a hazard analysis, given that they are usually a comprehensive source of what can go wrong in the current state of the plant, their consequences, and related corrective actions. For AEM to potentially benefit from this wealth of information, the results need to be suitably stored in a knowledge repository (database) for on-line use. The issue here is the systematic storage of the results in view of their large number.

(2) Retrieval and Display of information: The other main issue deals with the retrieval and display of information on-line. To maximize the usefulness, their display-format, that is, the way the results are displayed on-line, is important. For example, showing all the consequences that occur from a deviation at once may not be very helpful because of information overload. This second issue deals with the effective and systematic display of relevant results.

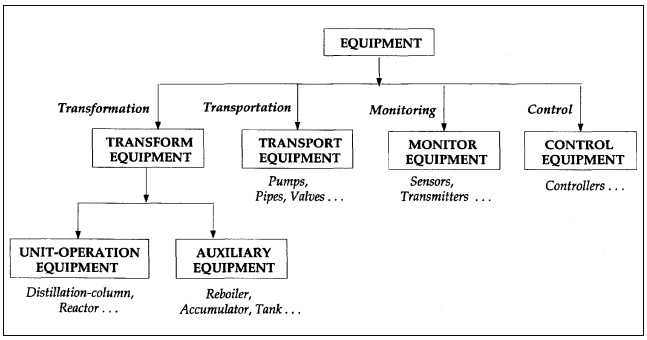

Figure 2. Functional classification of equipment.

A hierarchical representation of the plant can address the above issues by assisting in off-line storage of results, as well as helping the operator systematically navigate the relevant results on-line, by keeping in mind the plant layout. In the next section we describe such a hierarchical representation scheme and develop an automated methodology to generate the same. The aim is to generate a description of the plant at different levels of detail to facilitate results management, that is, organizing, accessing, and displaying results. The integrated framework for AEM and PHA is discussed later. An application of the framework to an industrial case study is described, followed by conclusions.

Management of PHA Results using a Hierarchical Representation

A typical chemical plant has a large number of interconnected process units, pipes, valves, pumps, control-systems, and so on. One could look at the plant as consisting of these numerous individual units or as a single input-output structure. The former would not be very useful because of our limited cognitive capacity, and the latter would miss all the important details. Hence, a hierarchical organization of the process flowsheet is usually required to manage and operate modern plants. For example, during the synthesis of preliminary process flowsheets or plant-wide control configurations, the designer has different viewpoints at various stages of the solution, implying that design decisions are made at distinct levels of process abstraction (Douglas, 1988). Thus, different models are needed to represent the process at the overall input-output level, the process-segment level, the process-unit level, or the process sub-unit level. This is also motivated partly by the way the plants are designed. Every process plant has groups of systems that are collectively responsible for achieving a task that contributes towards the overall objective of the process. For example, a distillation column, overhead-receiver, and bottoms reboiler all are achieving the goal of distillation together and could be grouped into a distillation system. From the point of view of using PHA results for AEM, it would be useful to group the consequences of a deviation in the distillation-system, while also being able to access them for the constituent units. This way one can keep in view the bigger picture while at the same time manage information pertaining to individual units.

The idea of hierarchical representation (HR) is to view the plant at different levels of detail or abstraction. At one end, the plant can be viewed as comprised of all individual units and, at the other extreme, as a single input-output block with varying levels of detail in between. One can look at the process of hierarchy construction as either abstraction, that is, grouping units together (bottom-up) or disaggregation, that is, breaking down systems into its components (top-down). Stephanopoulos et al. (1990a) describe a modeling language called MODEL.LA for the interactive or automatic generation of models of processing systems at various levels of abstraction. MODEL.LA allows representing the same processing system in different ways with the purpose of limiting the complexity in analyzing or synthesizing it, driven by the context of the modeling activity. To allow modeling at different levels of detail, MODEL.LA uses modeling elements and semantic relationships. One of the modeling elements called

Table 1. Logical Units in the Hierarchy

Logical Units	Functionality	Consist of
Equipment	Transport/Transform/Monitor/Control	All Equipment
Pipeline	Transport	Transport-Equipment
Control-System	Monitor, Control	Monitoring and Control Equipment
Input-Output-Unit (IO-Unit)	Transport, Transform, Control	Transform-Equipment, Pipelines/Control-Systems
Subsystem	Transport, Transform, Control	Input-Output-Units/Control-Systems
System	Transport, Transform, Control	Subsystems/Input-Output-Units/Control-Systems
Plant	Transport, Transform, Control	Systems

Generic-Unit has classes such as Plant, Plant-Section, Augmented-Unit, Unit, and Sub-Unit to reflect the different levels of abstraction at which models can be built. Stephanopoulos et al. (1990b) extend the formalism for the multifaceted (multilevel, multiview) modeling of processing systems and the simultaneous maintenance and processing of different context-dependent models for the same process. The hierarchical structure proposed here is similar in spirit, although the emphasis is on being able to effectively manage PHA results for AEM purposes. This means the HR should allow systematic organization through off-line object-oriented storage of results at different levels in the hierarchy. It should also facilitate display of cause-consequence information gleaned from the hazard analysis results, during on-line operation. The ability of the operator to now access results at different levels in the plant hierarchy will make the person more informed of the situation as a whole, as well as make him/her aware of the potential dangers in different sections of the plant. Without such a system, the operator could easily be overloaded with information, potentially causing confusion and, thus, not serving the intended purpose. This will be illustrated in the application of the integrated AEM-PHA framework to an industrial case study later in this article.

Proposed hierarchical representation

Before we describe the structure of the hierarchical representation, and the methodology to construct the same, we present the inputs to the framework. The representation scheme developed here is centered around functionality and topology of the equipment.

Representation Requirements. The framework requires the following: a *functional classification* of equipment, *connectivity information* from P&ID, and *configuration models* from a model library. These are discussed below:

(1) *Functional Classification.* Every chemical plant has certain main equipment that carry out *physical* and *chemical transformation*, such as distillation column, reactor, stripper, and so on. These are classified as UNITOP-EQUIPMENT. In addition, there are numerous other components such as receivers, tanks, and accumulators which do not directly serve in the processing, but help the UNITOP-EQUIPMENT accomplish their goal. These are classified as the AUX-EQUIPMENT. Together UNITOP-EQUIPMENT and AUX-EQUIPMENT are grouped as TRANSFORM-EQUIPMENT since they are involved in some form of *transformation*. Apart from these, there are pipes, valves and pumps whose main purpose is to *transport* material to different sections of the plant. These are classified as TRANSPORT-EQUIPMENT. The sensors and various indicators that measure the variables in the process are grouped as MONITOR-EQUIPMENT. The different controllers fall under CONTROL-EQUIPMENT. This classification of equipment is shown in Figure 2.

(2) *Connectivity Information.* The second input is the way the equipment are interconnected. This *connectivity information* is obtained from the P&ID.

(3) *Configuration Models.* The UNITOP-EQUIPMENT such as distillation column, reactor, absorber, and stripper all achieve their goal with the help of some AUX-EQUIPMENT which are arranged in a particular manner. This configuration, that is, arrangement of the UNITOP-EQUIPMENT with the AUX-EQUIPMENT will be referred to as the *configuration model* of the UNITOP-EQUIPMENT. Such models might be obtained by examining different P&IDs for the arrangement of the UNITOP-EQUIPMENT with the AUX-EQUIPMENT. However, given the complex and variable nature of modern chemical plants, not every such grouping can be pre-conceived. Hence, new models will need to be added to expand the scope of the library, as novel situations are encountered. These models are used here to identify the equipment groupings so as to construct the SYSTEM and SUB-SYSTEM logical units and establish the corresponding relationships (described in the next sub-section). As an example, a distillation column usually has a reboiler at the bottom, a condenser, and a reflux-drum at the top. So, the *configuration model* of the distillation column would include the distillation column, with the reboiler at the bottom, the condenser and the reflux-drum at the top. As a result, the DISTILLATION-SYSTEM would now include as SUBSYSTEMs, the reboiler-subsystem and the condenser-subsystem.

The next section presents the hierarchical representation structure.

Table 2. Relationships in the Hierarchy

First Logical Unit	Second Logical Unit	Relationship	Inverse Relation	Nature of Forward Relation
Input-Output-Unit	System	is-a-io-unit-of-system	the-system-consists-of-io-units	many-to-many
Subsystem	System	is-a-subsystem-of-system	the-system-consists-of-subsystems	many-to-many
System	Plant	is-a-system-of-plant	the-plant-consists-of-systems	many-to-one
Control-System	Input-Output-Unit	is-a-cs-of-io-unit	the-io-unit-consists-of-cs	many-to-many
Control-System	Subsystem/System	is-a-cs-of-system	the-system-consists-of-cs	many-to-many

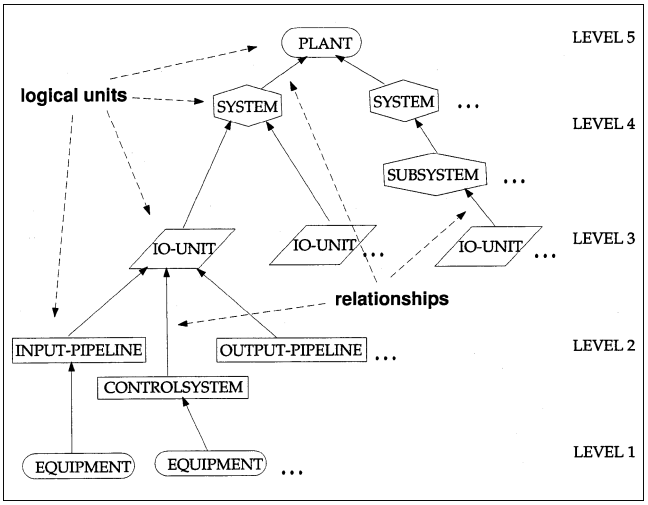

Figure 3. Proposed hierarchical representation.

Representation Structure. The proposed hierarchical representation is shown in Figure 3. The representation consists of data structures called *logical units*, that is, representation of the plant at different levels (Table 1) and *relationships* which relate the logical units across levels (Table 2). Essentially, the logical units are a way to describe the plant at different levels of detail. The logical units in the proposed hierarchy are:

Level-1 Equipment. This level consists of all equipment in the plant. It is the *bottom-most* level.

Level-2 Pipelines/Control-Systems. A PIPELINE is defined as a contiguous train of TRANSPORT-EQUIPMENT. For example, a contiguous connection of a pipe, valve, pipe, and a pump would constitute a PIPELINE. Each PIPELINE starts at a TRANSFORM-EQUIPMENT and ends at another. There are INPUT-PIPELINEs and OUTPUT-PIPELINEs of a TRANSFORM-EQUIPMENT depending on whether they end or start at one. The control-systems are the control-loops.

Level-3 Input-Output-Unit (IO-Unit). The TRANSFORM-EQUIPMENT, their input-pipelines and output-pipelines are grouped together to form a IO-UNIT. The TRANSFORM-EQUIPMENT in an IO-UNIT is called its MAIN-EQUIPMENT. The associated control-systems are related to the IO-UNIT by the relationship *is-a-cs-of-io-unit* (Table 2).

Level-4 System/Sub-systems. The *configuration models* described in the previous section are used to identify the systems and subsystems. This level is related to the above level by the relation *the-system-consists-of-io-units*. The systems are related to the subsystems using *the-system-consists-of-subsystems*. The relationship *is-a-cs-of-system* is used to associate the relevant control-systems to the SYSTEM and SUB-SYSTEM.

Level-5 Plant. This is the *top-most* level and consists of only one logical unit, that is, the plant. The *plant* is related to the above level using the relationship *the-plant-consists-of-systems*.

The composition of all the logical units and their functionalities are given in Table 1. For example, the PIPELINE logical unit consists of TRANSPORT-EQUIPMENT and serves the function of *transportation.* All the *relationships* used to

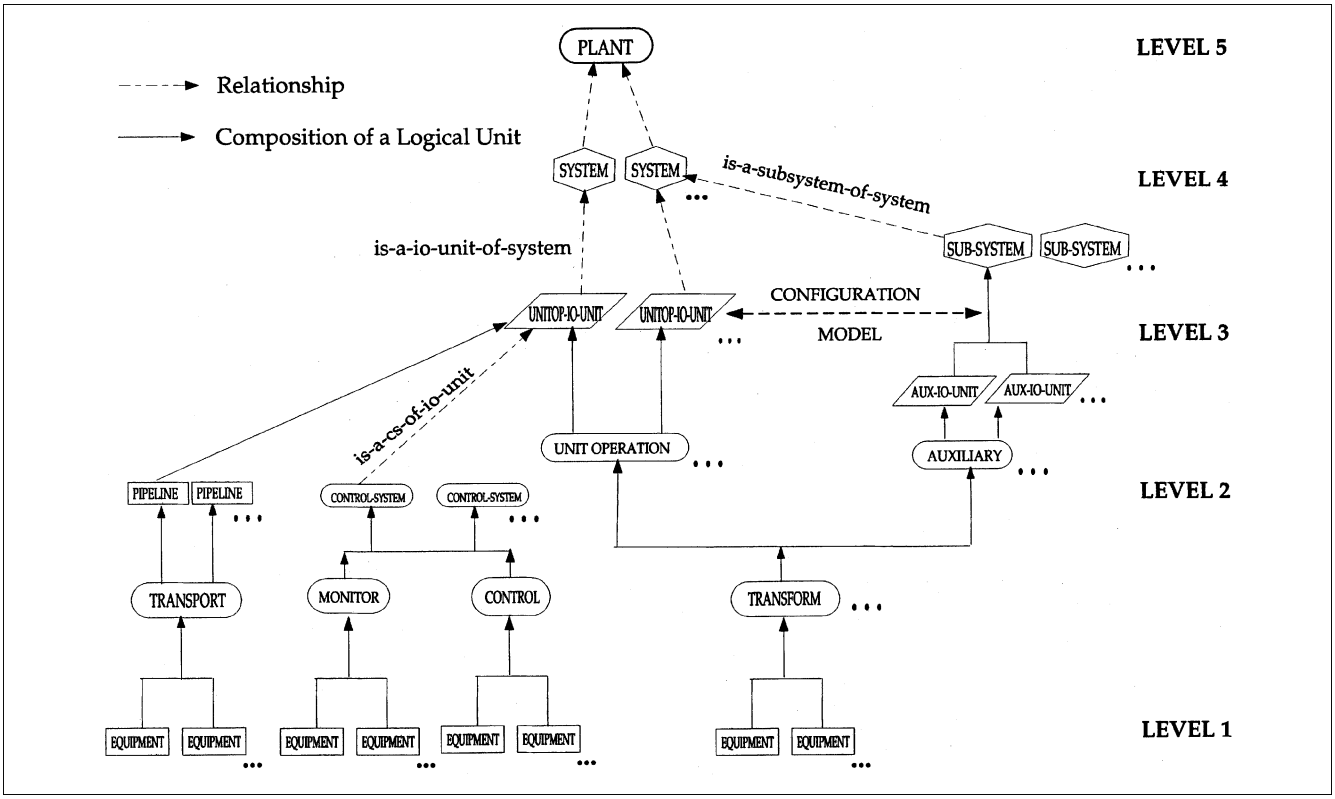

Figure 4. Algorithm for hierarchy construction.

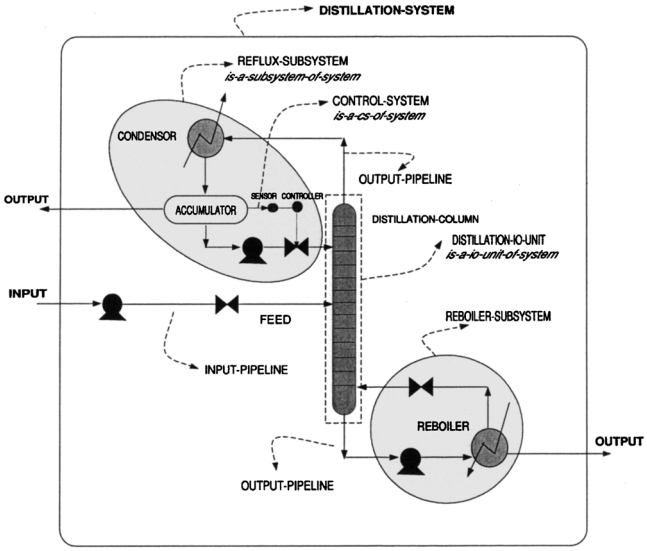

Figure 5. Hierarchy of a distillation system.

relate the different levels are shown in Table 2. For example, the relation *is-a-io-unit-of-system* relates a IO-UNIT to a SYSTEM. The *many-to-many* nature of the relation means that there could be more than one IO-UNIT related to more than one SYSTEM and vice versa to take care of possible overlaps. The relationships used to relate the control-systems are also shown.

Next, we describe an automated model-based bottom-up development strategy to develop the representation.

Automated hierarchy construction

The algorithm for the construction of the above representation is shown in Figure 4. To better explain the steps, the building process will be illustrated with an example of a distillation system shown in Figure 5.

Step 1. Identify all EQUIPMENT, that is, TRANSFORM-EQUIPMENT, TRANSPORT-EQUIPMENT, MONITOR-EQUIPMENT and CONTROL-EQUIPMENT from the P&ID and place them at *Level 1* as shown in Figure 4. This would identify all the pumps, valves, pipes, the distillation column, reboiler, condenser, and so on, as shown in Figure 5.

Step 2. Identify PIPELINEs and CONTROL-SYSTEMs using connectivity information from P&ID and place them at *Level 2* in Figure 4. CONTROL-SYSTEMs are essentially the control-loops comprising of the sensor, instrument-signal, controller, and the actuator. The train of TRANSPORT-EQUIPMENT are grouped together to form the pipelines (discussed earlier). Figure 5 shows some of the identified pipelines and a control-system.

Step 3. Create IO-UNITs and place them at *Level 3* in Figure 4. As shown, they are just a grouping of the TRANSFORM-EQUIPMENT and the PIPELINES (both INPUT and OUTPUT) connected to them. If the TRANSFORM-EQUIPMENT is a UNITOP-EQUIPMENT, then the IO-UNIT created is called a UNITOP-IO-UNIT; otherwise, it is an AUX-IO-UNIT. In case a CONTROL-SYSTEM can be found that is *associated* with the IO-UNIT, the relation *is-a-cs-of-io-unit* is established between them. Figure 5 shows the distillation-io-unit (UNITOP-IO-UNIT). Similarly, the accumulator-io-unit and reboiler-io-unit (AUX-IO-UNITs) are identified.

Step 4. Create SYSTEM and SUB-SYSTEM and place them at *Level 4* in Figure 4. A SYSTEM is created for every UNITOP-EQUIPMENT and the relation *is-a-io-unit-of-system* established between them. The *configuration-model* of each UNITOP-EQUIPMENT is then invoked to see if any of the AUX-IO-UNITs can be related to it. Those that satisfy a configuration are related to the SYSTEM created for the UNITOP-EQUIPMENT using *the-system-consists-of-io-units*. Similarly, within each SYSTEM, a possibility for the creation of a SUB-SYSTEM centered around the AUX-IO-UNITs is checked. The SYSTEM is related to the SUB-SYSTEM using *the-system-consists-of-subsystems*. Figure 5 shows the distillation-system that is identified. It also shows two AUX-IO-UNITs, namely, the condenser-io-unit and the accumulator-io-unit that are grouped together into the reflux-subsystem which is made *a-subsystem-of-system* distillation-system.

Step 5. Create a PLANT and place it at *Level 5* in Figure 4. This highest level contains only one plant. The plant is now related to the systems using the relation *the-plant-consists-of-systems*.

The methodology has been implemented in the G2 (Gensym, 1996) expert system shell. Later in the article, an illustration of the application of this framework on a case study and its use will be described within the integrated scheme for AEM and PHA that will be proposed in the next section.

Other Uses of Hierarchical Representation. Given the scale of modern chemical plants, the computational complexity for tasks like optimization, simulation, modeling, and so on, can be very high. Hence, solving a large system as a set of smaller interacting subsystems may sometimes be the only feasible approach (Mjaavatten, 1994). The proposed representation, by allowing a hierarchical view of the plant, can help by aiding model building (Stephanopoulos et al., 1990a). Another use could be in the task of PHA itself. When a team of experts perform the conventional HAZOP analysis, it is not possible for them to consider the process variable deviations in each of the pipes, valves, pumps, and other equipment separately. So they group a number of connected pipes, valves, and pumps and other units into *study nodes* for HAZOP. The representation developed here could aid them in deciding what *nodes* they need to review.

An integrated framework for AEM and PHA is described in the next section. The use of the hierarchy developed here is explained in the context of the management of the PHA results for AEM in the framework.

Integrated Framework for AEM and PHA

To exploit the information contained in the PHA results, an integrated framework is proposed in this section. In general such a framework would require:

(1) A monitoring system to monitor the states of important process variables

(2) A structured database of the PHA results, essentially a "safety model" of the plant

(3) A querying system to retrieve and display the results.

A framework incorporating these is shown in Figure 6. The off-line and on-line component modules and their interactions are explained below.

Off-line components

We discuss here the off-line components in Figure 6.

PHA Results Database. The plant is analyzed *off-line* for hazards during the PHA. This component contains the *organized database* of PHA results and the *retrieval methods*. The PHA results could be organized in many different ways. A simple way would be to store them as *causes* and *consequences*. They could be further classified depending on their nature. For example, causes could be grouped as those resulting from the nature of process materials, such as corrosive nature leading to leakage and generic equipment/controller failures. Similarly, consequences could be categorized as those due to the nature of process materials, that is, flammable, corrosive, volatile, toxic, and so on, and generic equipment failures. The *retrieval methods* are search methods which use the organized database and the detected deviations to find the *causes and consequences* that reflect the current plant state. This is shown in Figure 6. To find the causes, the search scans the database for potential candidates that explain all the detected deviations. Similarly, they also find the consequences of the deviations.

Hierarchy Construction Module. The hierarchy construction methodology described earlier is implemented here. As described in that section, the purpose is to organize and display the PHA results for an abnormality in a systematic manner during on-line use.

On-line components

We discuss here the on-line components in Figure 6.

Monitoring and Detection Module. In this module, the plant is monitored on-line for abnormal deviations in the measurements. There are many methods to detect abnormalities such as simple univariate limit-checking schemes or multivariate statistical methods like PCA/PLS (Wise and Gallagher, 1996).

Diagnostic Methods. It is well known that a suite of diagnostic methods is best suited for the complex task of fault diagnosis in AEM (Mylaraswamy, 1996). A combination of diagnostic techniques, ideally model-based and history-based, so as to bring in complementary strengths, would form the knowledge source. The aim is to find the causes for the observed deviations (symptoms/faults) obtained from the Monitoring and Detection module, as shown in Figure 6. However, this module may or may not exist depending on whether diagnostic techniques are currently in place or not. In the event that no diagnostic technique exists, the PHA results' knowledge base will serve as the *only* knowledge source. Since it is required by law that plants have PHA results current, it is conceivable that the off-line PHA database can always be built. Furthermore, diagnostic methods can be added to work in conjunction with the PHA database, as shown in Figure 6.

Results Manager Module. This is the user-interface for the system where the causes and consequences of different deviations are posted. This module uses the hierarchical represen-

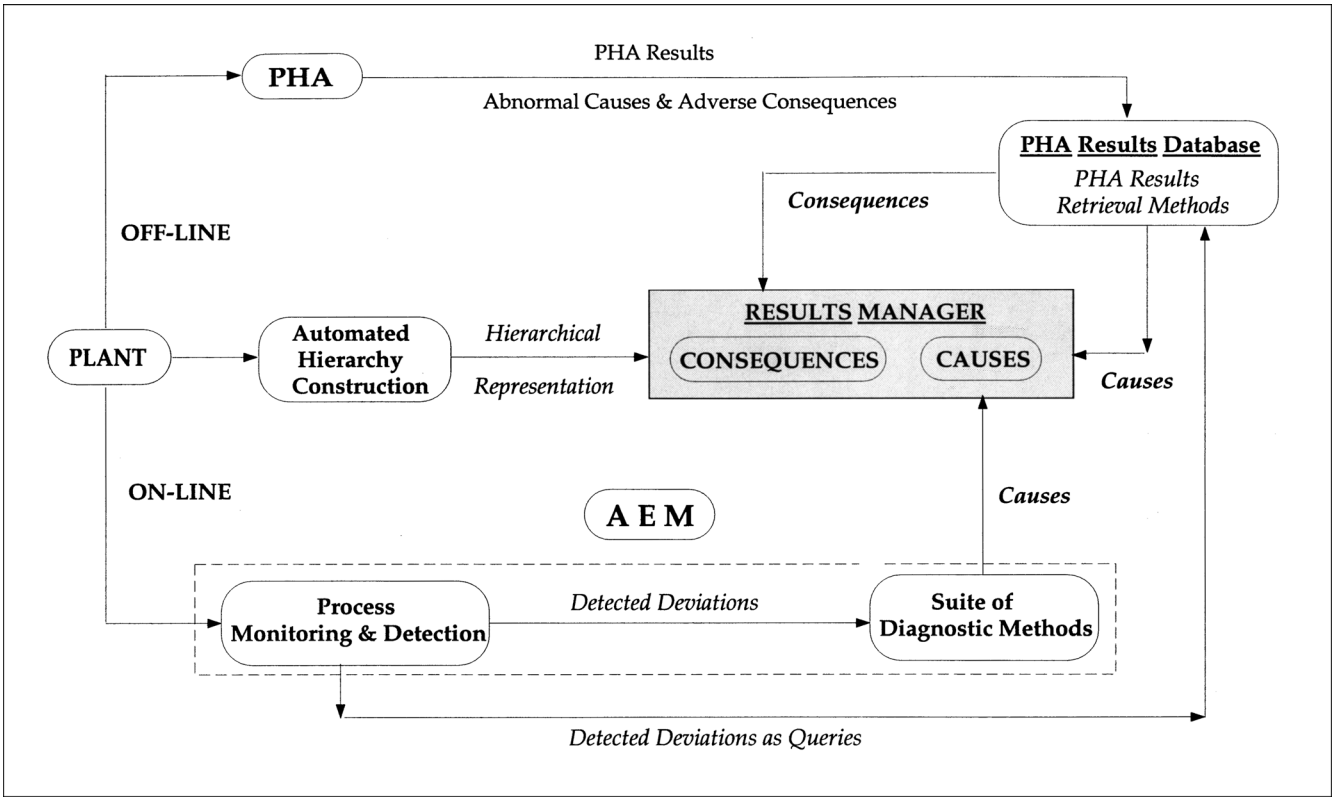

Figure 6. Integrated framework for ASM and PHA.

tation generated from the off-line module. This way, the operator can look at the plant at different levels of detail by narrowing or expanding his view of the process, that is, looking at consequences in individual equipment, IO-units, systems, and finally the whole plant in the hierarchy. The Results manager with the decomposition of the Sour-Water-Stripper plant (discussed in the next section) is shown in Figure 7. The top portion is the hierarchical representation of the plant. The leftmost top box shows the *logical units*: Plant/System/IO-Unit. Selecting one logical unit here updates all the other boxes, which show the main equipment, their input- and output-pipelines, the control-systems, and finally all the individual equipment in the logical unit. One can traverse the hierarchy by selecting a logical unit here and using the *go-up/down* button, that is, to a higher/lower level of abstraction. The bottom portion displays the cause-consequence information retrieved on-line from the PHA database. The causes are displayed in the cause-box, while the *show-consequences* button updates the consequence-box with consequences in the selected *logical unit* of the hierarchy (Figure 3). Such an interface allows for an organized grouping of results for effective on-line use, while also, facilitating easy navigation through the plant. This helps prevent any potential confusion during an abnormal event, and makes all relevant information accessible to the operator, at one place, for decision-making.

The integrated framework's application to a case study using the hierarchical representation is discussed in the next section.

Other uses of PHA results. Apart from being useful in AEM, the PHA results could also help in other areas such as:

(1) *Operator training on abnormal events.* Human error is the cause for many accidents; hence, operator training in handling abnormal events is very important. Using a system as described above, the operator can learn the process behavior, the effect of his/her actions on the process, the correct actions that have to be taken to mitigate a particular situation, and also the actions that should be avoided.

(2) *Sharable engineering knowledge bases.* Intelligent systems for various tasks such as process monitoring, fault diagnosis, process design, and so on, all require common functional, structural, and behavioral information about components which constitute the system. PHA results along with a representation framework can help develop, capture, and organize this knowledge at various levels of detail, and, thereby, also in the creation of sharable engineering knowledge bases to be reused across processes and applications (Miller et al., 1997).

(3) *Management of change.* Process changes (equipment, instrumentation, or procedures) are a regular feature in modern chemical plants and need to be managed effectively. It is, therefore, important that all changes be reviewed prior to their implementation to identify potential hazards that may be created by modifications. Now that the law requires a PHA after major process modifications, the results can also help in the integrated approach described in this article.

Application to Sour-Water-Stripper Case Study

In this section the integrated framework is applied to an industrial Sour-Water-Stripper (SWS) case study first reported by Venkatasubramanian and Vaidhyanathan (1994)

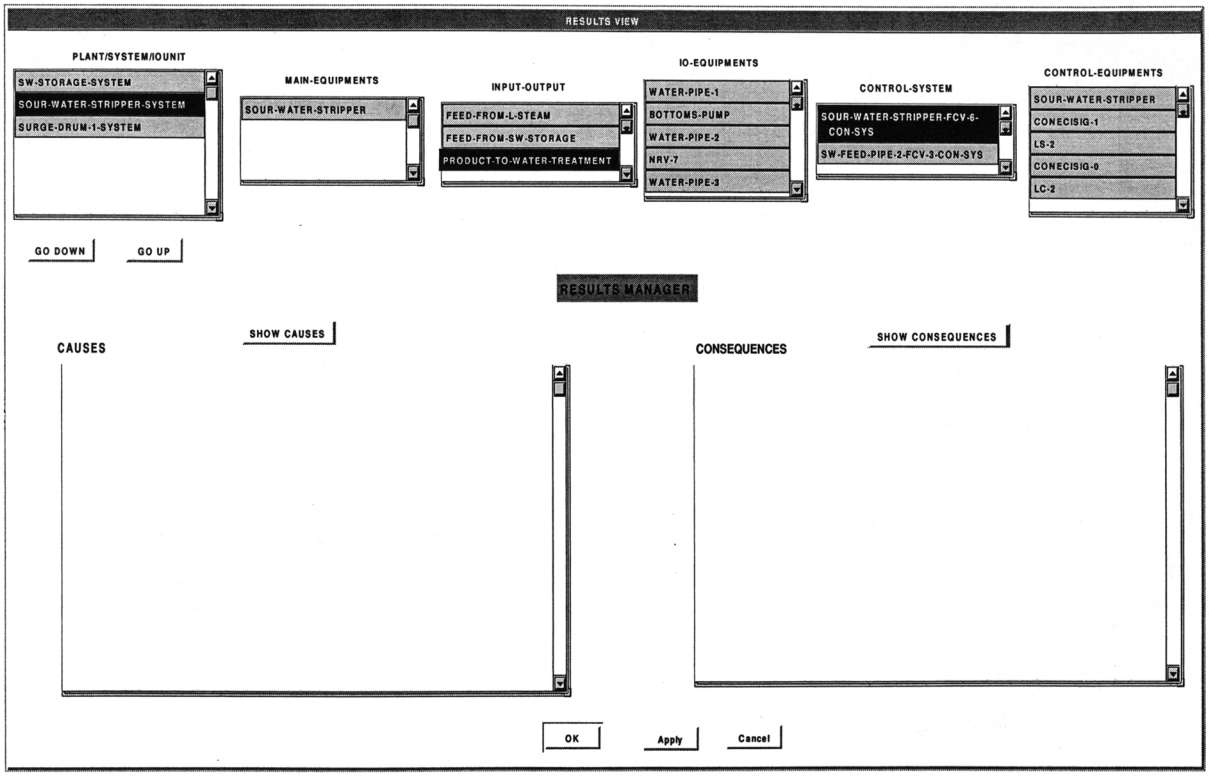

Figure 7. Results manager using the hierarchical representation.

and used later extensively (Vaidhyanathan and Venkatasubramanian, 1995, 1996a; Srinivasan et al., 1998). The P&ID of the Sour-Water-Stripper (SWS) plant is shown in Figure 8. In this process there are 26 pipes, five flow control valves, five nonreturn valves, five pumps, one surge-drum, one storage-tank, one stripper, one condenser, one stripper overhead accumulator, and six controllers. The process treats a refinery sour-water stream, that is separated in a surge drum, to remove slop oil. The sour water is pumped into a storage tank, where the carried over slop oil can be skimmed off. From the storage tank, the sour-water is sent through a heat exchanger to a steam stripper where ammonia and hydrogen sulfide are stripped from the water. Hydrocarbon oil is a flammability hazard, and ammonia and hydrogen-sulfide are toxic hazards. The release of these materials is a safety hazard for the plant. Also, if there is poor separation of hydrocarbon oil from the sour water, the oil will escape into the stripper. This can gum-up the stripper, which can cause operational problems.

Both manually compiled PHA results and results from an automated PHA system, HAZOPExpert, are available for the plant (Vaidhyanathan and Venkatasubramanian, 1995). However, being an automated system, HAZOPExpert, is able to carry out a systematic and quite thorough examination of all the hazards in the plant resulting in a better and more detailed analysis. An example of the comparison of both the results is shown in Table 3. The details of the quality and the kind of results have been extensively discussed in the literature (Venkatasubramanian and Vaidhyanathan, 1994; Vaidhyanathan and Venkatasubramanian, 1995, 1996a).

Integrated system architecture

The integrated framework developed in the last section is applied to this case study. The architecture of the system is shown in Figure 9. The whole system is implemented in G2 (Gensym, 1996) with the simulator for the plant in gPROMS (Barton and Pantelides, 1994) and interfaced using C. There is no other diagnostic method considered here, that is, the HAZOPExpert results are the *only* source of plant knowledge. The individual components are described below.

Off-Line Components. The off-line components described earlier are implemented here. The two parts are:

(1) *PHA Results Database.* PHA results from HAZOPExpert for this case study (Venkatasubramanian and Vaidhyanathan, 1994) are used as the database. The results comprise a total of 734 possible deviations resulting from 279 causes and resulting in 854 consequences. For example, the deviation *low interface level in sw-surge-drum* could be caused

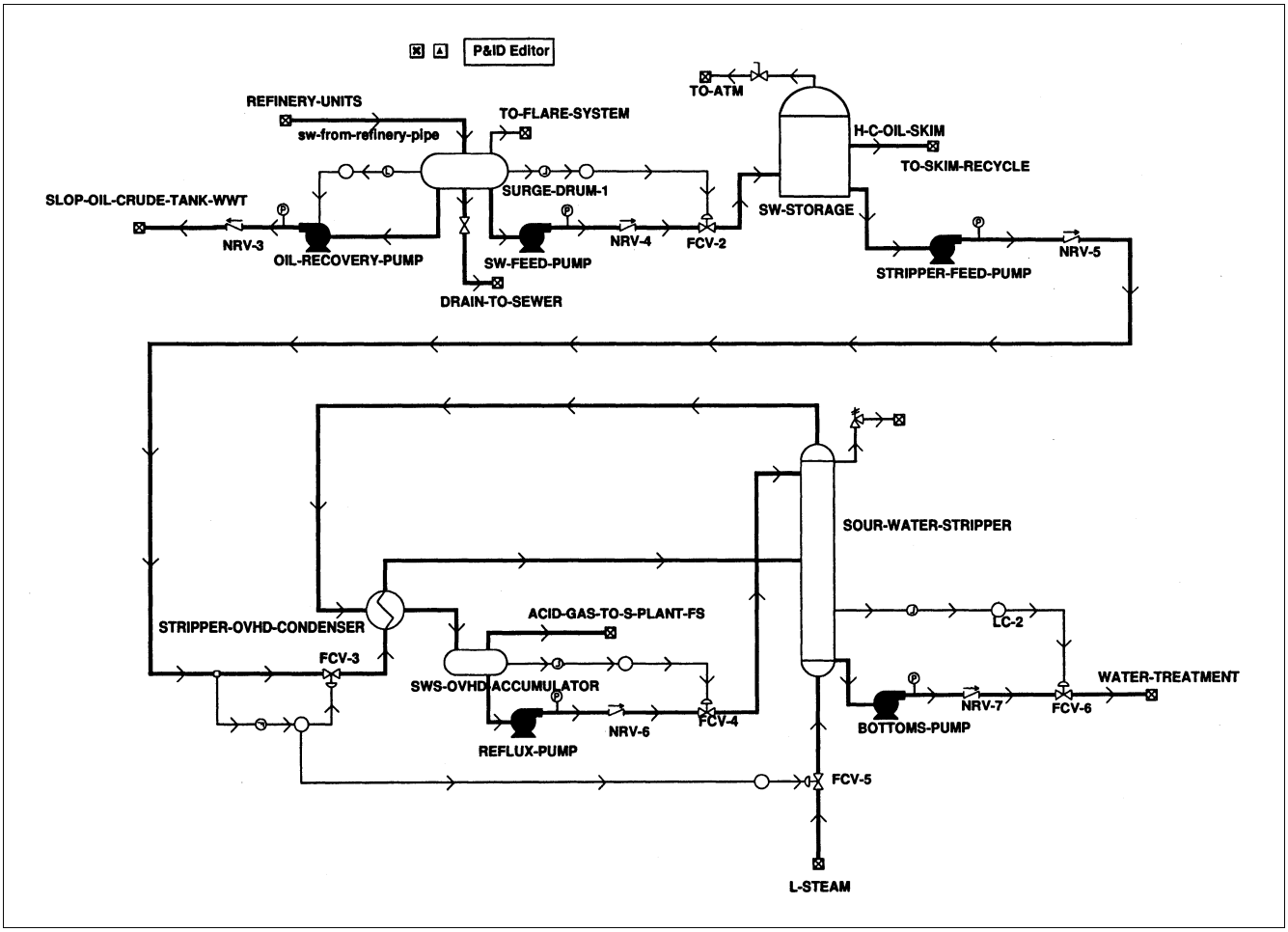

Figure 8. Sour water stripper plant P&ID.

Table 3. Conventional HAZOP Study and HAZOPExpert's Results

Process Variable Deviation: Zero Flow in sw-from-refinery-pipe
Conventional HAZOP study causes:
Valve at battery limits is closed
HAZOPExpert's causes:
Complete blockage of/or major pipe fracture in sw-from--refinery-pipe
Conventional HAZOP study consequences:
Upstream units cannot purge sour water
HAZOPExpert's consequences:
Release of flammable hydrocarbon oil into plant area due to leak, causing fire hazard
Zero interface level in surge-drum-1
Zero level in surge-drum-1
Zero heavy outlet flow in surge-drum-1
Zero lights outlet flow in surge-drum-1

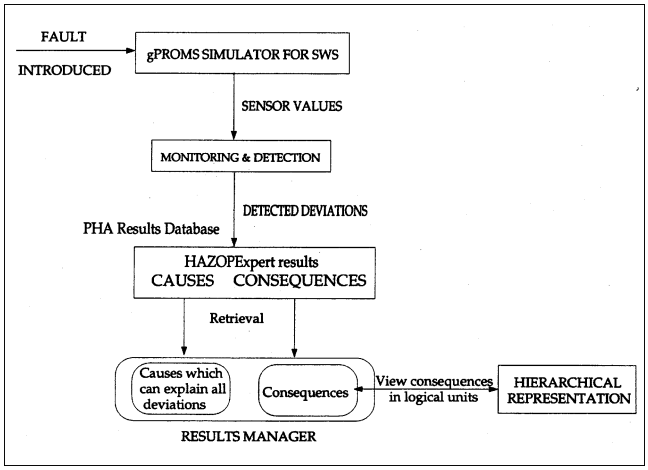

Figure 9. Integrated system architecture.

by *high concentration of hydrocarbon oil from refinery units* and a consequence is *hydrocarbon oil carryover into the stripper: Gumming up of stripper leading to operational problems*. An example of the kind of consequence information present in HAZOPExpert analysis is shown in Table 4. The results are stored according to the *nature* of causes and consequences, as described earlier. To diagnose the deviations, *retrieval methods* search for causes in the database that explain all the observed deviations. Since the HAZOPExpert results are quite thorough and complete, a potential list of causes should be found. Similarly, consequences are also retrieved. This is shown in Figure 9.

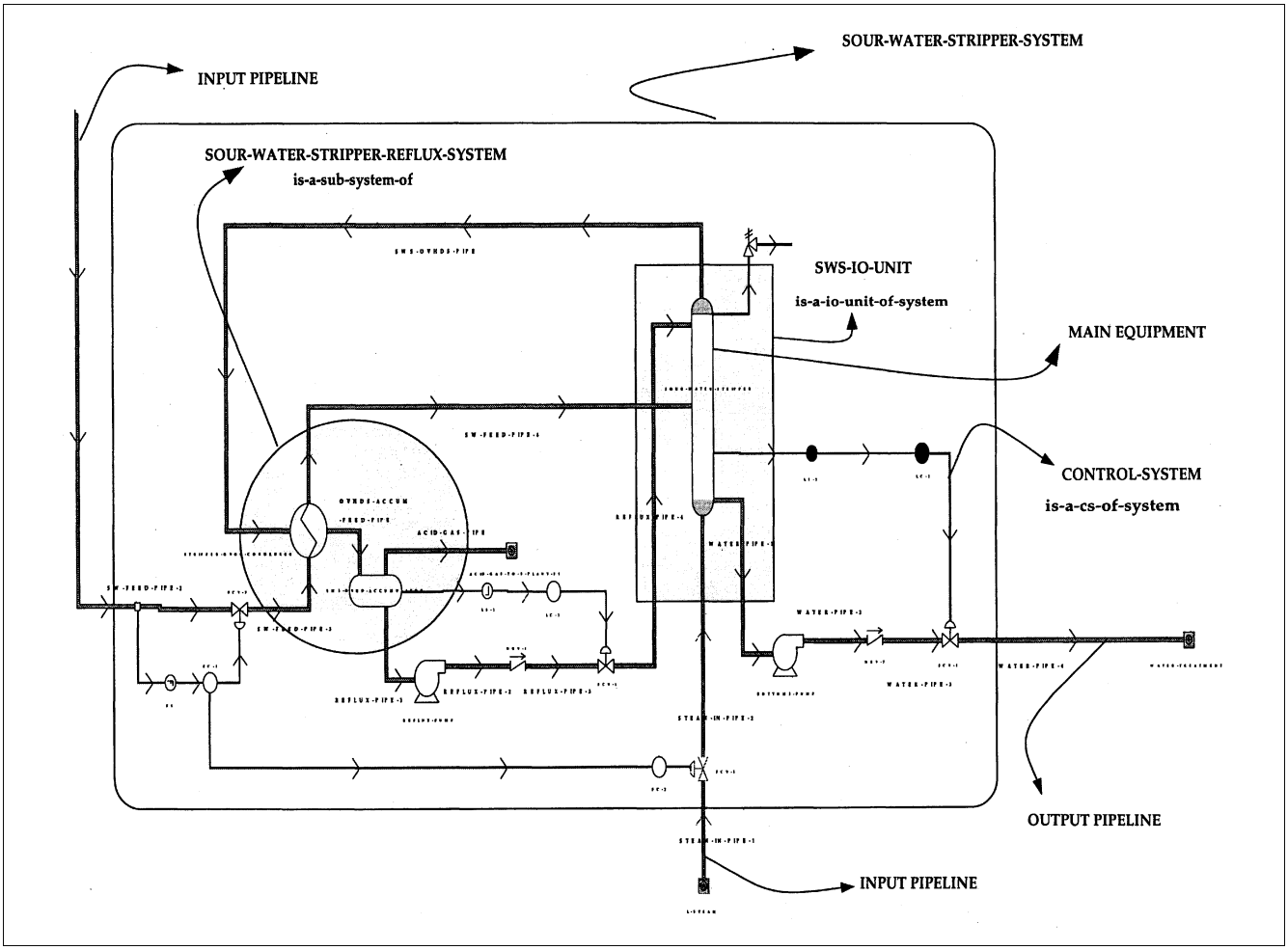

Figure 10. Components of the sour-water-stripper system.

(2) *Hierarchical Representation of SWS.* The hierarchical representation methodology developed earlier and implemented in G2 is applied to the SWS plant. An example of a logical unit thus developed (the SYSTEM level of the hierarchy), namely the sour-water-stripper-system, consisting of the sour-water-stripper-reflux-system (SUB-SYSTEM), its IO-units, pipelines and control-systems, is shown in Figure 10. Some of the constituent logical units and their relationships are labeled in this figure. The complete hierarchy for the full case study with all the different logical units, that is, plant, system/subsystem, IO-unit, pipelines/control systems, and all equipment, is shown in Figure 11. As shown there, three main SYSTEMs and one SUB-SYSTEM were identified:

(a) SWStorage-system
(b) Sour-water-stripper-system
- Subsystem: Sour-water-stripper-reflux-system

(c) Surge-drum-system

On-line components. In the absence of real plant data, a simulator for the plant was built in gPROMS (Barton and Pantelides, 1994). There are five pieces of main equipment: surge drum, sour-water-storage, overhead accumulator, overhead condenser, and the sour-water-stripper in addition to the pipes, flow-control-valves, nonreturn valves, pumps, and controllers. The surge-drum exhibits hybrid behavior depending on the state it is in; hence, a state-transition model is used. The models for the surge-drum and the stripper and the assumptions of fast energy dynamics resulting in algebraic energy balances are given in Srinivasan et al. (1998) are used here. Additional dynamic models for all the other units were created and linked together to simulate the whole plant. The dynamic model resulted in a system of DAEs with 410 algebraic and 20 state variables. There were 19 inputs making a total of 449 variables.

Table 4. HAZOPExpert's Consequences for HIGH Flow in sw-from-Refinery-Pipe

Pipe subjected to surge pressure, flange leak, possible pipe rupture and loss of containment
High interface level in surge drum
High heavy outlets flow rate
High light outlets flow rate
High level in surge drum
Filling up of surge drum, possibility of liquid entering vent
Release of flammable hydrocarbon oil into plant area due to filling up and overflow of surge-drum, causing fire hazard

(1) *Monitoring and detection.* The state of the plant is monitored using five sensors: surge-drum-interface-level, surge-drum-side-level, sour-water-storage-flow-out, overhead-accumulator-level, and the stripper-bottoms-level. The steady-state "normal" values of these variables are shown in Figure 12. A simple univariate scheme for abnormality detection using a high and low threshold for each measurement was employed. The detected deviations are sent to the PHA database as queries (Figure 9).

(2) *Results manager.* The results manager (Figure 7) is the user interface for the results and was discussed earlier. The information generated by the *retrieval methods* using the PHA

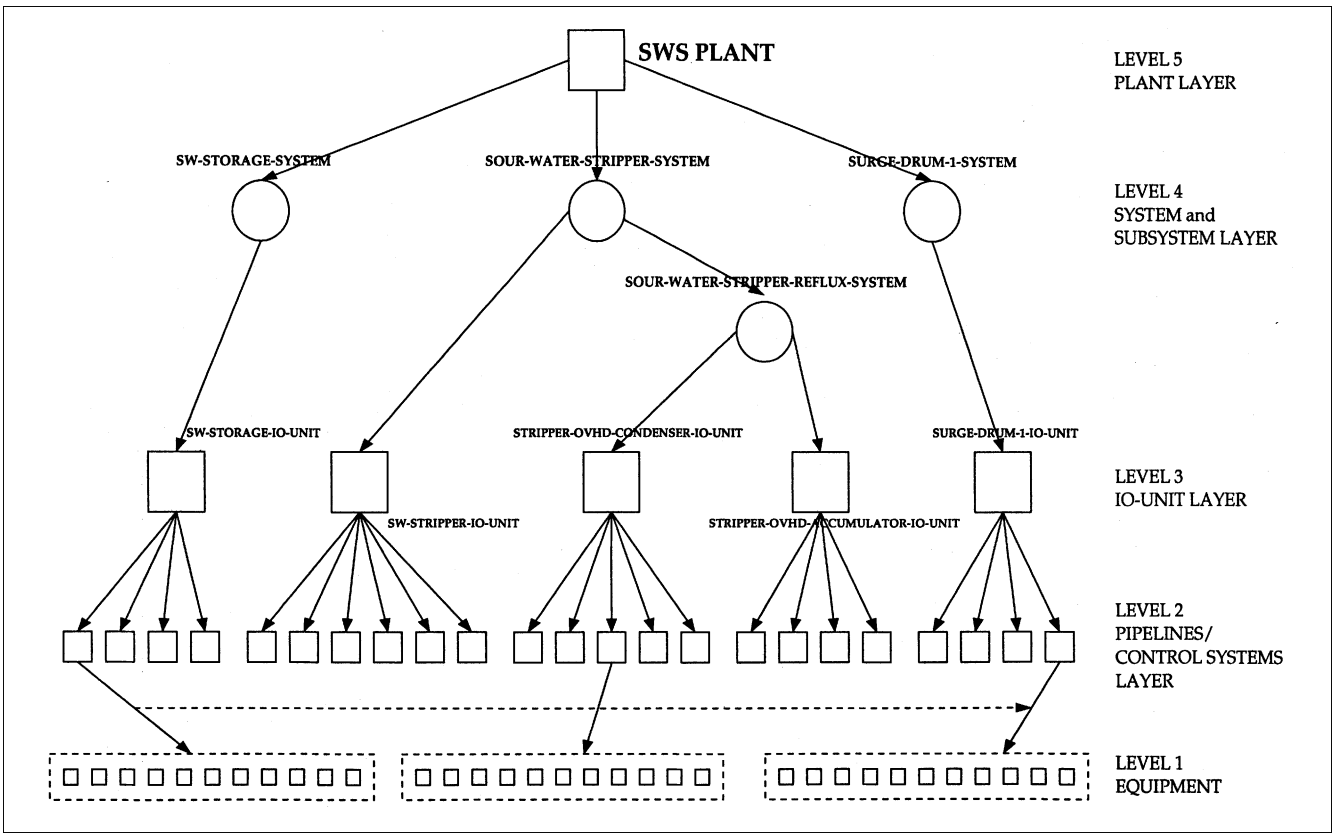

Figure 11. Sour-water-stripper plant hierarchy.

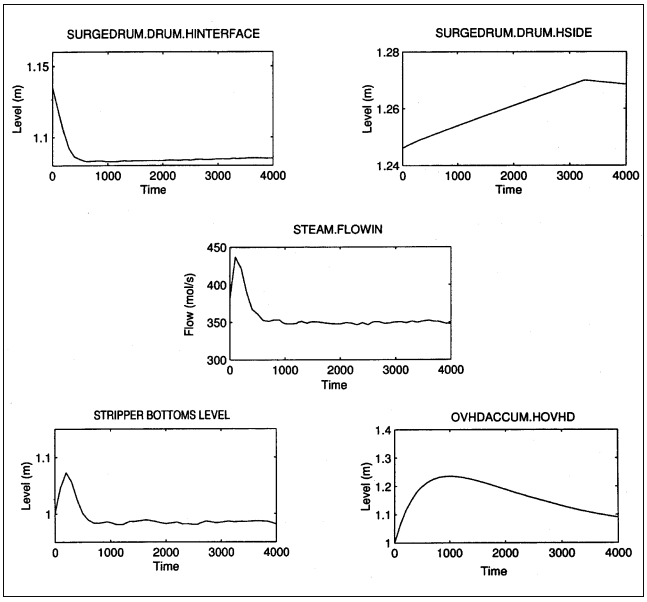

Figure 12. Steady state of monitoring sensors.

Results database and detected deviations are posted to this module. For viewing consequences, use is made of the hierarchical representation for SWS. The top is the hierarchical representation of the SWS plant (Figure 11). The operator can, thus, navigate through the entire plant by traversing up

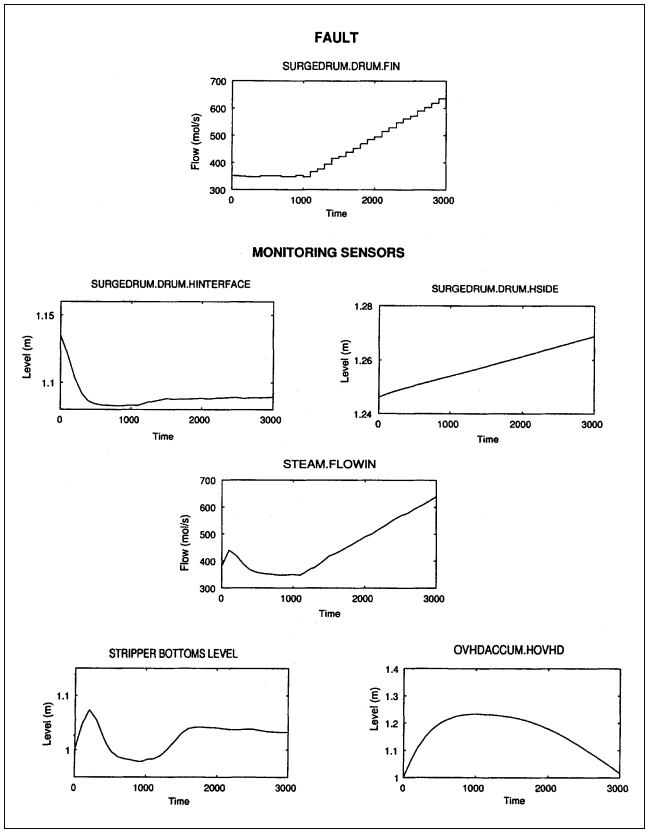

Figure 13. Fault scenario 1: high flow of sour-water.

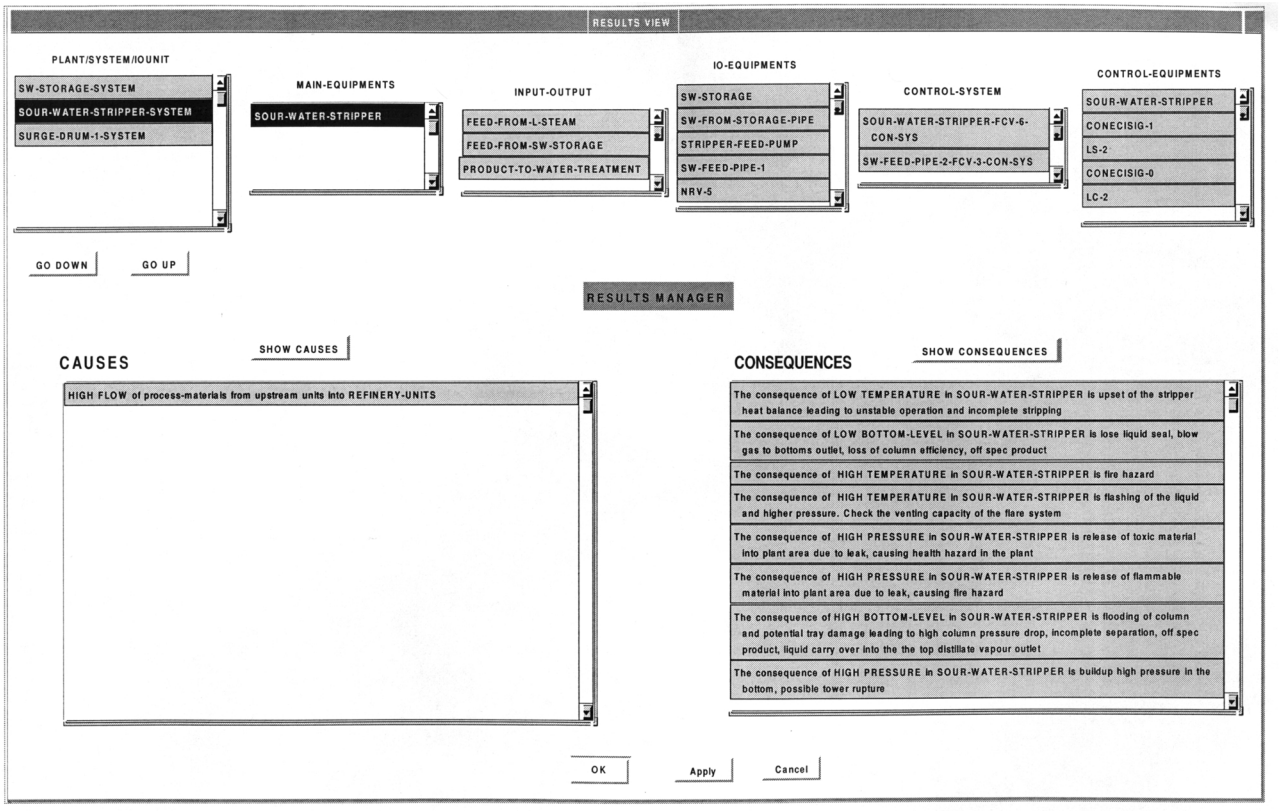

Figure 14. Results manager for fault scenario 1.

and down the hierarchy. The causes and consequences are updated in real-time as the plant's state changes (Figure 9).

Fault scenarios

To illustrate the use of the architecture, two fault scenarios are considered.

Fault scenario 1. At steady-state normal operation, the sour-water flow into the surge-drum is ramped up from 350 mol/s to 650 mol/s in 2,000 s (0.5 h). Thus, the fault - HIGH-FLOW OF PROCESS MATERIALS FROM UPSTREAM UNITS INTO REFINERY UNITS is introduced. The monitoring sensors and the fault during this simulation are shown in Figure 13. The RESULTS MANAGER of the system is shown in Figure 14. The integrated system searches for causes in the HAZOPExpert results that explain the deviations in the monitoring sensors. In this case, only one and the correct cause was displayed. However, in general, the *resolution* will not always be 100%, that is, a potential list of causes is more likely. If the PHA results database contains results from a thorough analysis, we can expect the list to be complete, that is, the actual fault to be a subset of the proposed candidates. Ideally, we would like to have a high resolution while keeping the candidate list short. This is the resolution vs. completeness tradeoff issue, encountered in qualitative analysis such as signed-digraph based diagnosis. The user can also retrieve the consequences in the different logical units of the plant. The consequences in the logical unit SOUR-WATER-STRIPPER (highlighted) are shown in Figure 14. The hierarchy can easily be navigated to see *consequences* in other sections of the plant using the *go-up/down* button.

Fault scenario 2. At steady-state normal operation, the steam flow into the stripper is ramped up from 60 mol/s to 200 mol/s in 2,000 s (0.5 h). The fault and the monitoring sensors during this simulation are shown in Figure 15. The causes and consequences found by the retrieval methods using the detected deviations and the results are posted to the Results Manager shown in Figure 16. Unlike in the above case, this time we get a list of potential causes including the correct cause, HIGH FLOW OF PROCESS MATERIALS FROM UPSTREAM UNITS INTO L-STEAM. The displayed consequences are in SWS-OVHD-ACCUMULATOR-IO-UNIT (highlighted).

For the fault scenarios considered, the system was able to identify the cause/consequences from the HAZOPExpert results using the detected deviations, while allowing easy navigation using the hierarchical representation.

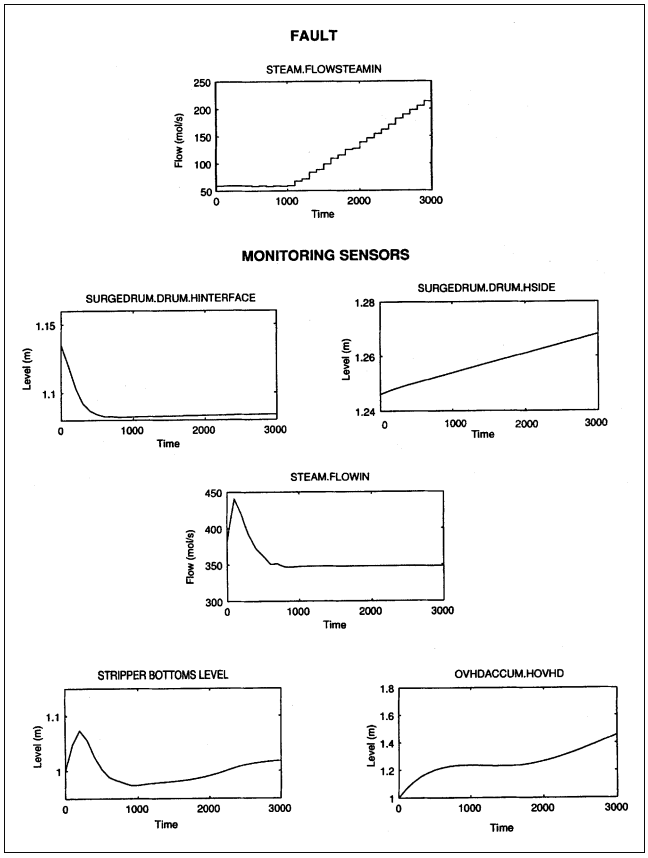

Figure 15. Fault scenario 2: high flow of steam.

Conclusions

PHA and ASM are important tasks in industry due to their economic and safety impact. We briefly described and reviewed some of the main issues involved in PHA and AEM. The similarity of both the tasks in terms of their inherent objectives strengthen the case for an integrated view. PHA results are recognized to be a valuable source of information which could be exploited in AEM. In particular, the use of these results in an assessment of abnormal events and countermeasure planning is seen to be a viable and attractive proposition. This is more so, with their ready availability as a result of regulatory compliance. To manage the results online, a hierarchical representation, developed using an automated bottom-up model-based framework, is proposed. This aids navigation through the results, and their effective display in AEM. The integrated framework for AEM and PHA is then presented and demonstrated on the Sour-Water-Stripper case study in G2. PHA results from the automated HAZOP system, HAZOPExpert, formed the knowledge source for the system. A dynamic simulator for the plant is developed in gPROMS to simulate fault scenarios. Two such fault scenarios are considered, and the integrated system is shown to correctly identify the causes/consequences using the database of PHA results and the generated hierarchical representation.

There are some areas that require more attention for the integration idea to be widely applied. First, the hierarchical representation is developed using configuration models that describe the general arrangement of important equipment in plants. While the construction system will be able to automatically handle situations that can be explained with existing models, it might need the user's help to guide it through novel scenarios. The scope of the library can then be expanded by augmenting it with the new models. In some other cases, the system's recommendations may need to be modified in view of the user's specific needs and preferences. To provide such flexibility, the system would ideally be interactive and this would also enhance the user's confidence through increased awareness of its working. Secondly, PHA results used for the demonstration were obtained from HAZOPExpert, which are well structured and quite thorough because

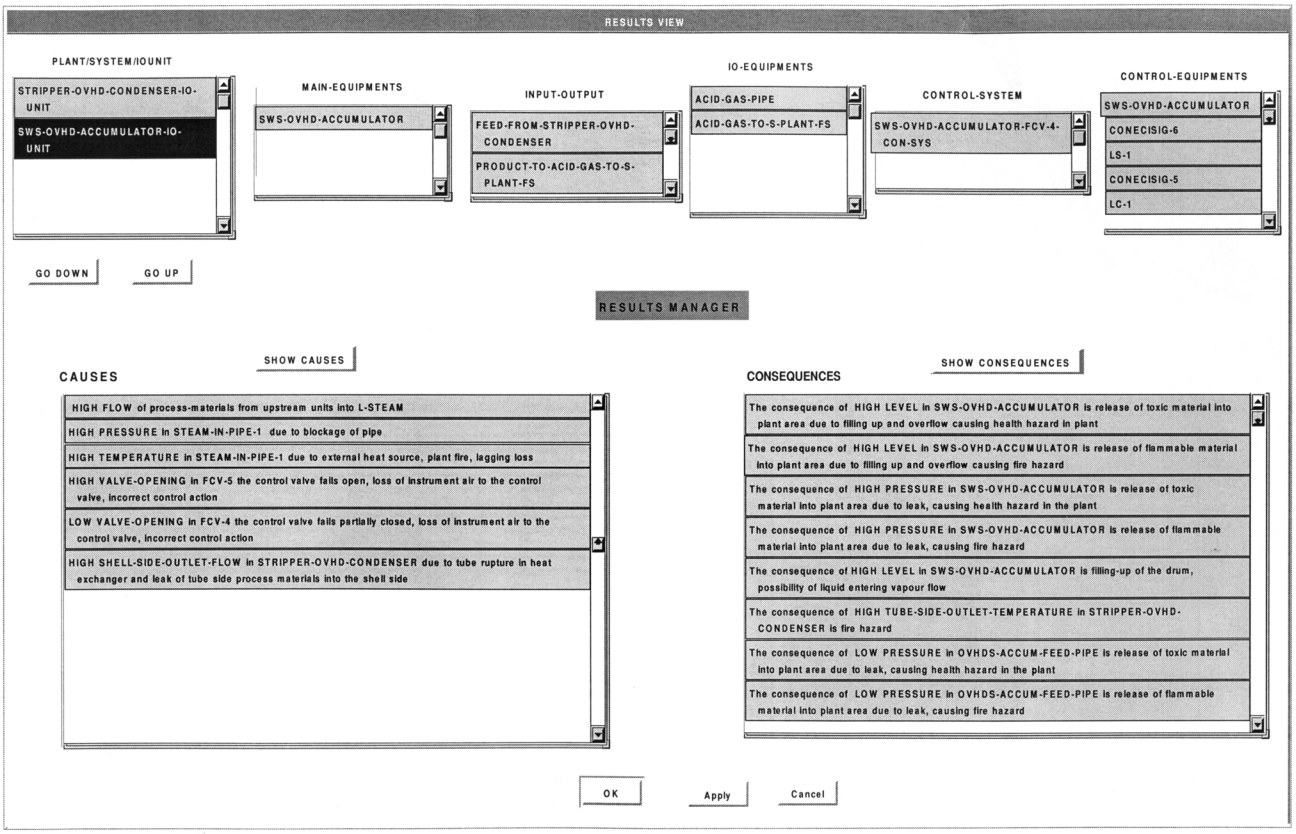

Figure 16. Results manager for fault scenario 2.

of the automated and exhaustive analysis involved. However, the conventional PHA results, which are manually compiled, are not guaranteed to have these properties. Hence, proper translation, representation, and application of such information for AEM is essential. A combination of manually compiled (includes difficult to automate analyses) and automatically generated (usually routine analyses) PHA results would best suit this purpose. Also, since PHA results are qualitative and worst-case in nature, integrating these with other quantitative diagnostic methods would make an effective diagnostic-prognostic tool. This way the existing cause-consequence information can be filtered for ambiguous/spurious scenarios and be used effectively for planning in abnormal situations and emergencies.

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