Chapter 14

A Human Situation Awareness Support System to Avoid Technological Disasters

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In many complex technological systems, accidents have primarily been attributed to human error. In the majority of these accidents the human operators were striving against significant challenges. They have to face data overload, the challenge of working with a complex system and the stressful task of understanding what is going on in the situation. Therefore, to design and implement complex technological systems where the information flow is quite high, and poor decisions may lead to serious consequences, Situation Awareness (SA) should be appropriately considered. A level 1 SA is highly supported in these systems through the various heterogeneous sensors and signal-processing methods but, for levels 2 and 3 there is still a need for concepts and methods. This work develops a system called the Human Situation Awareness Support System (HSASS) that supports the safety operators in an ever increasing amount of available risky status and alert information. The proposed system includes a new dynamic situation assessment method based on risk, which has the ability to support the operators' understanding of the current state of the system, predict the near future, and suggest appropriate actions. The proposed system does not control the course of action and allows the human to act at his/her discretion in specific contexts.

14.1 Introduction

A technological disaster is an event caused by the failure of a technological system and/or human error in controlling or handling the technology. Since the beginning of the industrial revolution many serious large-scale technological systems' accidents that had grave consequences, such as those of Three Mile Island, Bhopal and Chernobyl, have primarily been attributed to "operator error". For instance, the release of methyl isocyanate

B. Vitoriano et al. (eds.), *Decision Aid Models for Disaster Management and Emergencies*, Atlantis Computational Intelligence Systems 7,
DOI: 10.2991/978-94-91216-74-9_14, © Atlantis Press 2013

from the Union Carbide chemical plant in Bhopal, India, in 1984 caused 2000 human casualties, 10,000 permanent disabilities, and over 200,000 injuries, arguably making it the worst industrial disaster in history where the accident was officially blamed on human error [1]. Human error is the biggest challenge within most industries and on the surface, would seem to imply that people are merely careless, poorly trained, or somehow not very reliable. In fact, in the vast majority of these accidents the human operator was striving against significant challenges. Operators have to face both data overload and the challenge of working with a complex system. They are drilled with long lists of procedures and checklists designed to cope with most of these difficulties, but from time to time they are apt to fail. In fact, the person is not the cause of these errors but so much as the final dumping ground for the inherent problems and difficulties in the technologies that engineers have created [2]. Operators generally have no difficulty in physically performing their tasks, and no difficulty in knowing what is the correct thing to do, but they are stressed by the task of understanding what is going on in the situation. Over the last two decades, great deal of research has been undertaken in the area of Situation Awareness (SA).

Today, in technological systems, operators rely on the principles and design of human computer interaction to observe and comprehend the overwhelming amount of process data that varies rapidly. They have often been moved to a control room far away from the physical process, so that their role becomes more of a monitor or supervisor of the automation system, which is able to pass more and more information to the operator. It is widely accepted that more data does not equate to more information. In many cases automation has only worsened the problem [3], and operators are required to handle more data and more responsibility. For instance, in the 1970s, a typical operator manually controlled approximately 45 control valves in one process unit. Today, an operator controls, on average 175 control valves through an automation system interface. More specifically, the number of observable process variables in the power distribution sector grew from 200,000 to 700,000 between the years 1990 and 2000 [4]. Although experienced users tend to filter through the overabundance of data to generate information and acquire good SA, even the most expert operator can become swamped by the excessive amount of data provided by new technologies. In the presence of all this data, operators are finding that they are even less aware than ever before about the situations they are controlling. This has led to a huge gap between the massive amount of data produced and disseminated and the operator's ability to effectively assimilate the required data and to make a timely, accurate decision [5].

SA can be described as knowing and understanding what is going on around you and predicting how things will change [6]. The problem of poor operator SA continues to worsen as technology advances whether the operator is a pilot, a manufacturing operator, or a manager, and it can be seen through automation-facilitated accidents throughout the world. For example, on March 23, 2005, at Texas City, TX BP Amoco Refinery explosion, 15 workers were killed and 170 injured when a column was overfilled, overheated, and over-pressurized on startup. A key problem identified in this catastrophic event was the difficulty experienced by the operator in maintaining an accurate awareness of the situation while monitoring a complex, fast moving environment [7]. Several other studies of accident throughout many industries have found that loss of, or poor operator SA, was related to accidents classified as human error. For instance, loss of SA has been associated with 88% of major air carrier accidents that involved pilot errors and 58.6% of operational error in air traffic control operations [8]. Due to the severity of the accidents that have occurred over the last ten years, SA has become the focus of research that aims to understand operator performance in critical, dynamic environments [9].

This research considers the applicability of SA concepts to safety in the control of complex systems. Safety supervision continues to increase in degree of automation and complexity as operators are decreasing. As a result, each safety operator must be able to comprehend and respond to an ever increasing amount of available situations with risky status and alert information. This study introduces a new system for SA enhancement called the Human Situation Awareness Support System (HSASS).

This chapter presents the basic concepts of SA, the proposed HSASS system and how it will be implemented, and looks at related areas of research for the future.

14.2 Basic Concepts and Related Works

14.2.1 *Situation Awareness*

One of the widely applicable SA definitions introduced by Endsley in 1995, describes SA as “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future” [10]. Endsley’s model is arranged into three hierarchical levels of SA, each stage being a necessary precursor to the next higher level (Fig. 14.1). This model follows a chain of information processing, from perception, through interpretation, to prediction. From the lowest to the highest, the levels of SA are [11, 12]:

- *Perception*: Perception involves the sensory detection of significant environmental cues. For example, operators need to be able to see relevant displays or hear an alarm.
- *Comprehension*: Comprehension is understanding the meaning or significance of that information in relation to goals. This process includes developing a comprehensive picture of the world.
- *Prediction*: Projection consists of extrapolating information forward in time to determine how it will affect future states of the operating environment. The higher levels of SA allow operators to function in a timely and effective manner, even with very complex and challenging tasks.

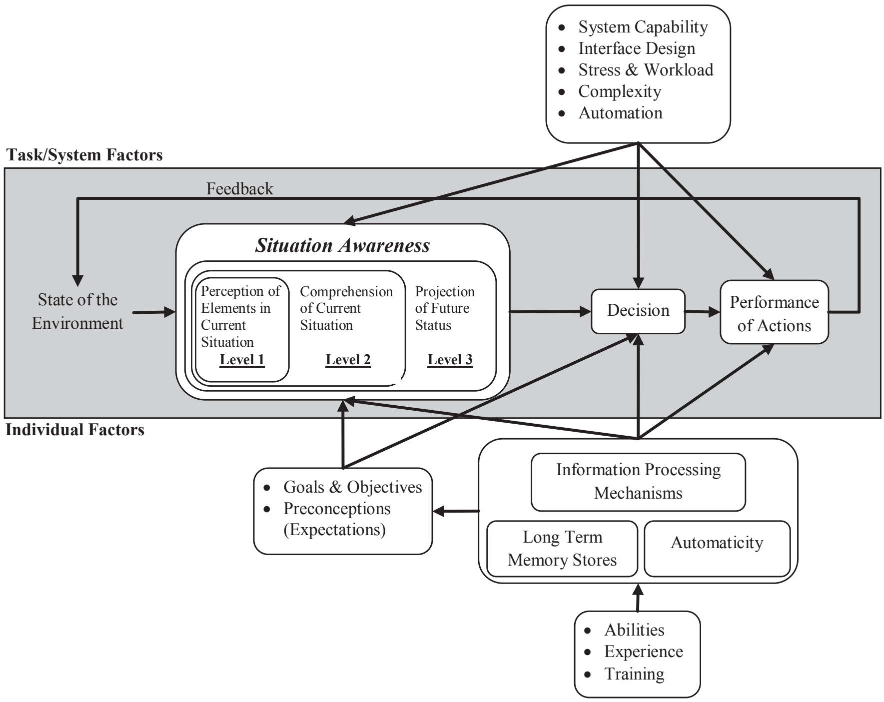

Fig. 14.1 Situations Awareness in Dynamic Decision Making [10].

Endsley's model has been used in a number of studies as a justification for structuring the computer-supported SA process in a variety of complex positions, such as air traffic controllers, nuclear power plant operations, anesthesiologists, military commanders, electronic warfare tacticians, automobile drivers, power plant operators, and so on [2, 5, 11, 13].

14.2.2 *Situation Assessment*

SA is a state of knowledge that has to be distinguished from the processes underlying the achievement of SA, which should be addressed as situation assessment [10]. The situation assessment models describe basic principles and general features about how people process information or interact with the environment to attain their SA. In fact, awareness information for a situation is derived as the results of situation assessment. Since SA is regarded as a dynamic and collaborative process, assessing a situation is often required data integration or called data fusion with support of computer based intelligent techniques. The enhancement of operators' SA in complex systems is a major design goal in developing operator interfaces, automation concepts and training plans in a wide variety of fields [14–16].

As SA aims to predict the status of a situation in the near future, which is the third level of the SA model, we need proper and effective situation assessment approaches and tools to conduct the prediction. For example many studies have reported that machine learning techniques could be an effective method for intelligent prediction by extracting rules from previous data to generate new assessment results [14], but their use has been limited, possibly because of the lack of rich training data for this problem [17]. In some research, authors developed a quantitative model based on Bayesian inference and information theory, and described the process of knowledge-driven monitoring and the revision of operators' understanding of the environments [15, 18]. Other studies considered computational methods, but these approaches often do not satisfactorily handle all forms of uncertainty, especially when information conflicts. Therefore, human behavior models have been developed from cognitive architectures. The limitations of these systems are that they do not easily incorporate cognitive factors. Consequently, some approaches used the fuzzy logic system to address the limitations of traditional models in producing the full range of human behaviors [19–21].

14.2.3 *Representing Situation Awareness*

Endsley developed a methodology to determine the aspects of a situation that are important for a particular user's SA requirements. This methodology is known as the Goal-Directed Task Analysis (GDTA) and it is a specific form of cognitive task analysis that focuses on identifying the goals and critical information needs for a task context. The GDTA process has been used in many domains to detail SA requirements. As such, it forms an exemplary template for incorporating human cognition into an actionable model by describing in detail not only a user's information data needs (Level 1) , but also how that information needs to be combined to form the comprehension (Level 2), and projection of future events (Level 3) that are critical to SA, thereby providing a critical link between data input and the decisions to be made in a goal-directed environment [22].

In this analysis, the major goals of a particular job class are identified, along with the major sub-goals necessary for meeting each goal. Associated with each sub-goal, the major decisions that need to be made are then identified. The SA needed for making these decisions and carrying out each sub-goal are identified (Fig. 14.2). These requirements focus not only on what data the operator needs, but also on how that information is integrated, or combined, to address each decision.

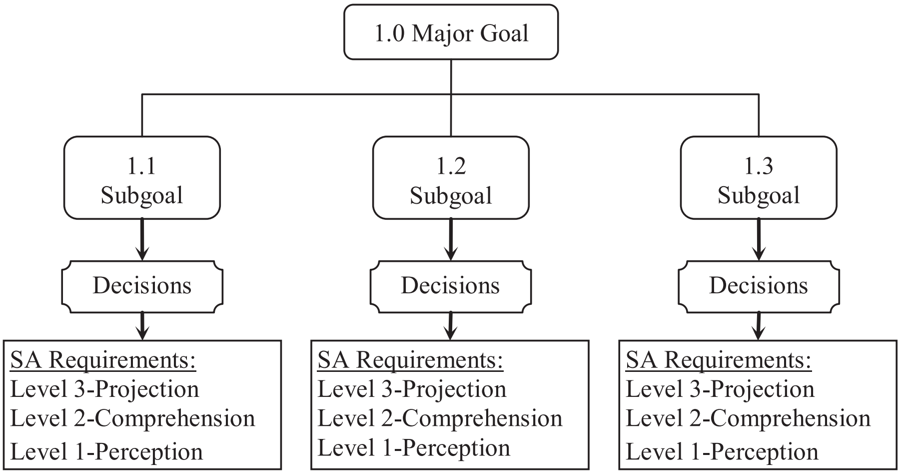

Fig. 14.2 Goal-Directed Task Analysis for Determining SA Requirements [10].

This type of analysis is based on goals or objectives, not tasks. This is because goals form the basis for decision making in many complex environments. Conducting such an analysis is usually carried out using a combination of cognitive engineering procedures such as expert elicitation, observation of operator performance and analysis of documentation [2].

Table 14.1 Safety Goals and Decisions.

- 1.0 Eliminate or reduce the risks to a level that is as low as reasonably practicable
  - 1.1 Determine the risks
    - 1.1.1 Hazards identification
      - *Past hazards*
    - 1.1.2 Likelihood determination
      - *Prior likelihood*
      - *Posterior likelihood*
    - 1.1.3 Severity determination
      - *Past consequences*
      - *Degree of losses*
    - 1.1.4 Level of Risk
      - *Current level*
  - 1.2 Reduce the risks
    - 1.2.1 Establish the practical options
      - *Available reduction and containment options*
    - 1.2.2 Impact of the options
      - *New level of risk*

14.3 A Human Situation Awareness Support System

14.3.1 *A HSASS General Model*

As discussed earlier, SA involves perceiving critical factors in the environment (SA level 1), understanding what those factors mean, particularly when integrated together in relation to the operator's goals (SA level 2), and at the highest level, an understanding of what will happen with the system in the near future (SA level 3) [2]. To determine the features that are important for an operator's SA, we use GDTA. The SA requirements focus not only on what data the operator needs, but also on how that information is integrated or combined to address each decision. In this analysis process, SA requirements are defined as those dynamic information needs associated with the major goals, or subgoals of, the operator to perform his/her job. The results are showed in Table 14.1 [23].

The information provided for situational awareness must be more than just information gathering. This implies collecting the right multi-domain information across a net-centric environment for shared awareness and presenting the results for the human to understand

and make quick decisions. Any new approach must efficiently bring together the human operator, sensor equipment data, and real world events to provide a subset of actionable information [17]. Fig. 14.3 shows the general model of HSASS.

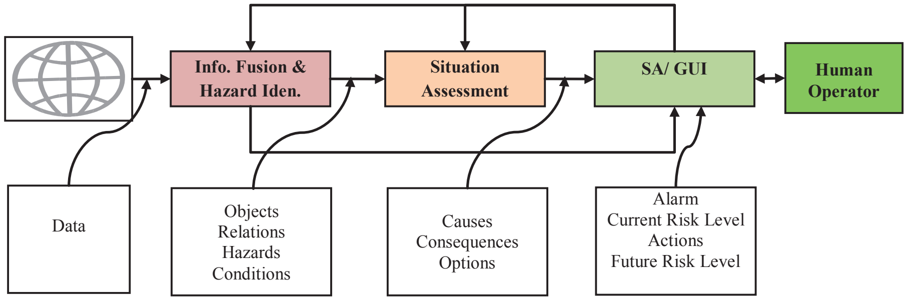

Fig. 14.3 The HSASS General Model.

14.3.2 *Information Fusion and Hazard Identification Component*

Critical factors in the environment (SA level 1) should be collected from various sensors, which are distributed in an intended area. This aims to locate and identify objects, and also provide a global picture of the situation, which is reported by fusing the attributes of an object from multiple sources. Any variety of relations - physical, organizational, informational, and perceptual - can be considered, as appropriate to the given information system's mission. Knowledge and experience of the past can be applied to the determination of the potential hazardous circumstances. The outcome of this step is identification of hazardous entities or relations that have a potential to lead to loss. As can be seen from the Fig. 14.3, this forms what we defined as the information fusion and hazard identification component.

14.3.3 *Situation Assessment Component*

SA level 2 relates to the operator's understanding of the system as a whole, and emergent events (such as alarms or casualties), that arise from hazardous situations. Therefore it is necessary to understand the causality of the current situation. SA level 3 requires that the system and operator should understand the future state so consequences of the current situation should be determined; depending on the consequent losses, the current hazards may subsequently require risk elimination, mitigation, transfer, control or combination thereof, so it is necessary to assist the operators to choose the appropriate actions.

Based on above mentioned points, the situation assessment component involves causal, consequence and option analysis. The causal analysis techniques are predominately applied within reliability engineering and are generally supported by mathematical foundations and a suite of computer based tools. The quantification of causal models entails an objective assessment of the potential frequency or likelihood for the causal factors. These are combined according to the rules of probability calculus and Boolean logic to generate a normalized or absolute measure for the realization of existing hazards. Consequence analysis is concerned with what may potentially follow the occurrence of a hazardous situation. Adverse outcomes associated with the current hazardous situation should be considered, including various degrees of harm to people, commercial detriment to an enterprise, damage to the ecology of the environment, or a combination of these factors. It is useful for all three components to be converted and expressed in a common currency, such as money, for potential comparison and aggregation in order to provide a coherent view of the totality of loss associated with a hazardous situation. Options analysis provides the future necessary actions that should be implemented to eliminate or reduce the risks. On identification and recording, it is essential to estimate the likely effects and potential benefits of each option on the consequent safety, commercial and environmental losses, in order to establish the objective and systematic criteria for selection and implementation. This is a requirement of the statutory legal framework in some countries (e.g. the UK) to ensure that the safety risks are reduced to As Low As Reasonably Practicable (ALARP) levels.

14.4 HSASS Implementation

14.4.1 *Environment Description*

To illustrate how to implement the HSASS into a real world environment, we use the example of a petrochemical plant with expert systems as artificial intelligence tools. An ethylbenzene process plant, involving two reactors and two distillation columns, as shown in Fig. 14.4, is chosen.

An exothermic reaction occurs in Reactor 1 (R1) at 160 °C and 9 bar, in which benzene (B) and ethylene (E) react to produce ethylbenzene (EB). The undesirable reaction of ethylene and ethylbenzene to produce higher-order species, for example, diethylbenzene (DEB) is suppressed by the large excess of benzene in R1. Any DEB produced is separated from ethylbenzene and recycled to R2, which operates adiabatically as DEB reacts with benzene to produce ethylbenzene. Benzene, in the D1 distillate, is recycled to R1. A mixture of EB

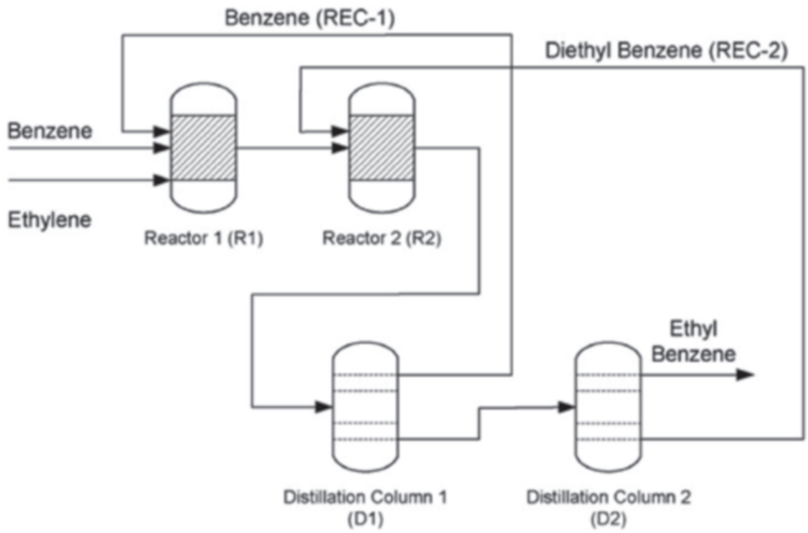

Fig. 14.4 Process Flow Sheet of Ethylbenzene Process.

and DEB in the D1 bottoms product is fed to D2, with EB recovered in the distillate, and DEB recycled to R2 [12].

Chemical processes are characterized by many variables that allow representation of the behaviour, using a set of rules. These factors allow us to use them appropriately for SA. We use three types of rules: fact, intermediate and decision rules. The format of the rule is as follows:

IF *Antecedent*; THEN *Consequent*

Inference direction can be generally divided into three types: (1) backward reasoning: starts with the target, intending to prove the target to be true or false; (2) forward reasoning: starts from the fact, reasoning towards target; (3) mixed reasoning: reasoning in both directions. In our work, the forward reasoning strategy is used.

14.4.2 *Hazard Identification Implementation*

Hazards are often obtained through the design and implementation phase, and various models have been developed to identify them. For example, HAZOP is one of the most powerful hazard identification methods available and has been clearly described in the re-

Table 14.2 Temperature Limits (°C).

Unit	Operating value	Six-sigma quality	High alarm	Automatic shutdown
R1	160	165	170	180
R2	166	170	175	185
D1	186	190	195	200
D2	200	205	210	220

search literature [30]. Fault tree, event tree, bow-tie and experts' knowledge are adopted as the knowledge acquisition techniques.

To show and store the hazardous situations we use fact rules. In a fact rule, 'antecedent' refers to conditions that have potential to harm, while 'consequent' is a name for the current situation. For example:

$$\text{IF } TCR1 > 170^\circ C\text{; THEN } \textit{the temperature of R1 is high}$$

For the ethylbenzene process, hazardous situations include those due to controller failure, loss of cooling, disturbances in the feed temperatures and flow rates, the reboiler heat duty, and flooding in the distillation columns. The safety systems are assigned temperature limits, as shown in Table 14.2, including limits for the six-sigma quality (by definition, when the controller fails to maintain the temperature within the six-sigma quality limit, the controller "Fails"), high alarm and automatic shut-down. For each abnormal event, when these limits are exceeded, time logs for the safety systems are recorded [12]. For example Fig. 14.5 shows a bow-tie diagram for a high-temperature abnormal event associated with reactor R1. The consequences include continued-operation (CO), shut-down (SD), release (REL), and explosion (EXP), based on the performance of six safety systems shown in rectangles across the left. The six safety systems are: S1 (high alarm), S2 (operator observation), S3 (operator correction), S4 (automatic shut-down), S5 (manual shut-down), and S6 (emergency relief system).

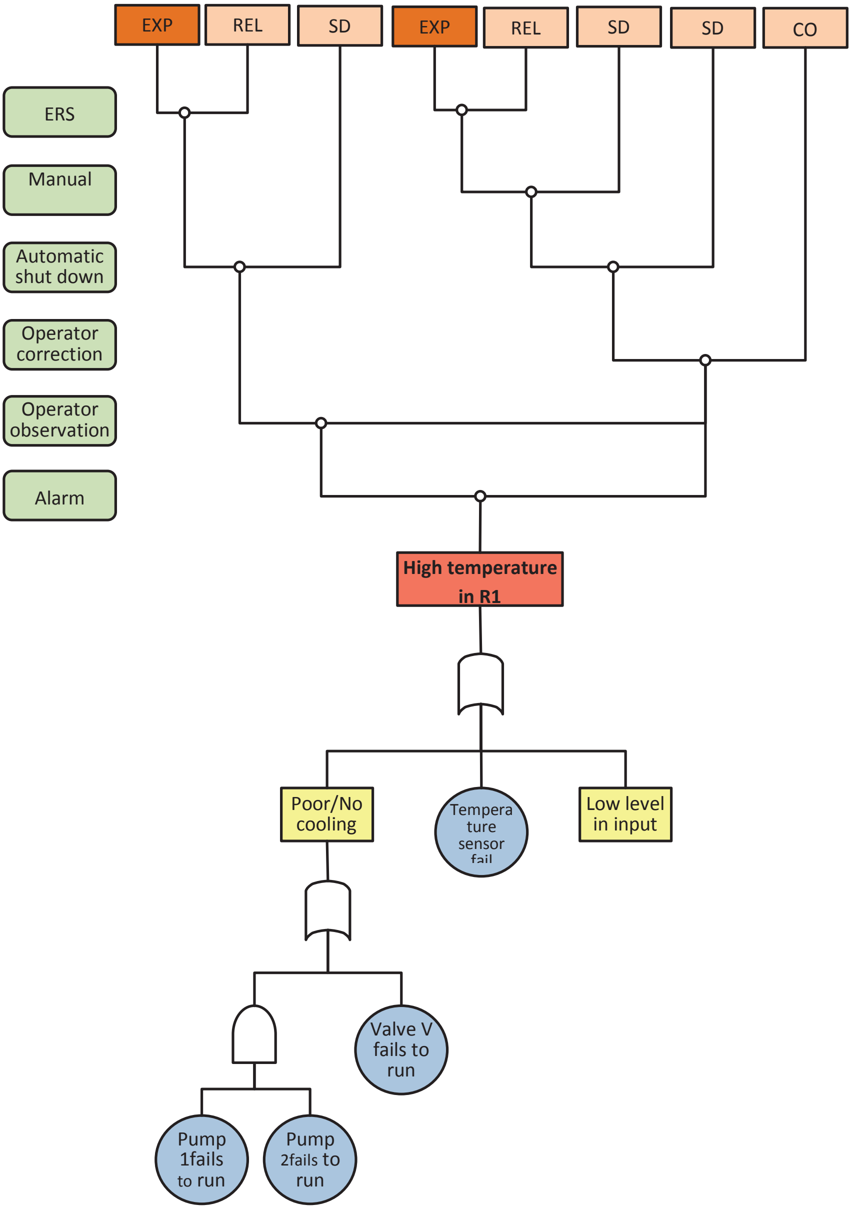

Fig. 14.5 Bow-tie Diagram for High Temperature in R1.

14.4.3 *Situation Assessment Implementation*

The situation assessment component will provide the comprehension and projection levels of the SA. To support these levels, we use intermediate rules. In an intermediate rule, 'antecedent' is a situation, while 'consequent' is a description of causes and consequences.

14.4.3.1 *Likelihood Determination*

To determine the likelihood of a target event, the concept of physical reliability models can be used. Reliability models aim to explain the reliability (or failure) of a component as a multivariate function of operational physical parameters. Among different types of physical reliability models, covariate models and static models can be used to estimate the primary events and consequently the probability of the target event [24].

Operational physical parameters, also called covariates, may be temperature, velocity, pressure, or vibration amplitude. Covariate models explain the failure rate of a component as a function e.g.:

$$F(t) = 1 - \mathrm{Exp}\left(- \left(\frac{t}{\mathrm{Exp}\left(\sum_{i=0}^{n} a_i x_i \right)} \right)^{\beta} \right)$$

where any change in covariate x_i will change the failure probability $F(t)$. Static models do not consider time as an influential parameter and only consider the component's strength and stresses. Both stress and strength can be constant or considered as random variables having probability distribution functions. For example, the failure probability of component Q having a constant strength, k, and being under a random stress, Y, can be defined as the probability of Y being greater than k, e.g.:

$$Pr(Q) = \Pr(Y > k) = \int_k^{\infty} f_y(y)\, dy$$

where $f_Y(y)$ is the probability density function (PDF) of stress, Y. Assuming an exponential distribution for $f_Y(y)$, $\Pr(Q)$ can written as:

$$\Pr(Q) = \int_k^{\infty} \lambda\, e^{-\lambda y} dy = e^{-\lambda k}$$

Therefore the failure probability of component Q can be reassessed when a new value for k is observed.

Table 14.3 Consequence Severity Matrix.

Severity class	Monetary Value	Human loss	Ass Loss	Environment loss
Very little	<10k	One minor injury	Minorrepairs that can be done immediately by own crew	Around the area, easy recovery
Little	10-100k	One or two minor injury	Repairsthat take several days to carry out	Within plant, short term remediation effort
Medium	100k-1million	Multiple major injuries	Damagethat takes months to repair and cause serious consequences	Minor offsite impact, remediation cost will be less than 1 million
High	1-10 million	One fatality or multiple injuries with disabilities	Very large material damage	Communityadvisory issued, remediation cost remain below 5 million
Very high	>10million	Multiple fatalities	Significant parts of the system destroyed	Communityevacuation for longer period, remediation cost in excess of 5 million

14.4.3.2 *Consequence Determination*

Generally, consequences of an abnormal situation may be categorized into four groups; asset loss, human fatality, environmental loss, and confidence or reputation loss. The severity matrix used in this study is outlined in Table 14.3 including equivalent dollar value of damage associated with each consequence category based on the severity of damage [25].

The failure probability of each safety system can be determined by the probabilistic method and end states are determined by multiplying the related probabilities together.

Previous probabilities are called "Priors", representing our belief about the system before observing the new data. After the initiation of the process, accident precursor data which are the near misses and incidents occurring in the process (defined as events that are not characterized as accidents but indicate the increasing likelihood of an accident occurrence) can be collected from the system. The ASP data can be used to form the likelihood function, which in turn updates the prior knowledge about the occurrence probability of every end state resulting in the formation of the posterior function. Bayesian theory is a probabilistic approach that applies the conditional probability principals to reason with uncertainties. The results obtained by application of this theory in this study will yield the "Posterior" which is the updated knowledge about the end states of the system. Considering

Table 14.4 Risk Matrix.

S. / P.	**Very little**	**Little**	**Medium**	**High**	**Very high**
Very likely	Significant	Significant	High	High	High
Likely	Medium	Significant	Significant	High	High
Even	Low	Medium	Significant	High	High
Unlikely	Low	Low	Medium	Significant	High
Very Unlikely	Low	Low	Medium	Significant	Significant

x as the failure probability of the system and $f(x)$as the probability distribution function (prior distribution), $f(xData)$ will present the posterior distribution that is derived using the following equation:

$$f(x \mid Data) \propto g(Data \mid x) f(x)$$

where $f(x \mid Data)$is the posterior function, $g(Data \mid x)$ is the likelihood function and $f(x)$ is the prior [26].

14.4.3.3 *Current Risk Level*

To obtain the risk level of the target hazard we use a fuzzy risk analysis model. We present probability of hazards with five linguistic values, e.g. very likely, likely, even, unlikely, and very unlikely, and will explain the severity by five linguistic values e.g. very little, little, medium, high and very high. The risks are represented by low, medium, significant and high. Triangular and trapezium membership functions can be used together to increase the sensitivity in some bound points. Fig. 14.6 shows membership functions for probability, severity and risk variables.

To construct the fuzzy risk analysis model, we considered the risk matrix as shown in Table 14.4, which has 25 rules, e.g.:

IF *the probability is likely* AND *the severity is medium*

THEN *the risk is high*

14.4.3.4 *Risk Reduction*

If the estimated risk is unacceptable, it is necessary to identify risk-reducing measures that reduce either the frequency or the consequences of the occurrence of the unwanted event. For each individually considered risk element, a decision must be made whether or not the investment in the risk-reducing measures has the effect of reducing the risk to an acceptable level [33]. A list of available reduction and containment options can be presented as decision rules where 'antecedent' is a situation, while 'consequent' is suggested actions to remove or eliminate the risk. Based on the operator's decision, a new level of risk can be calculated.

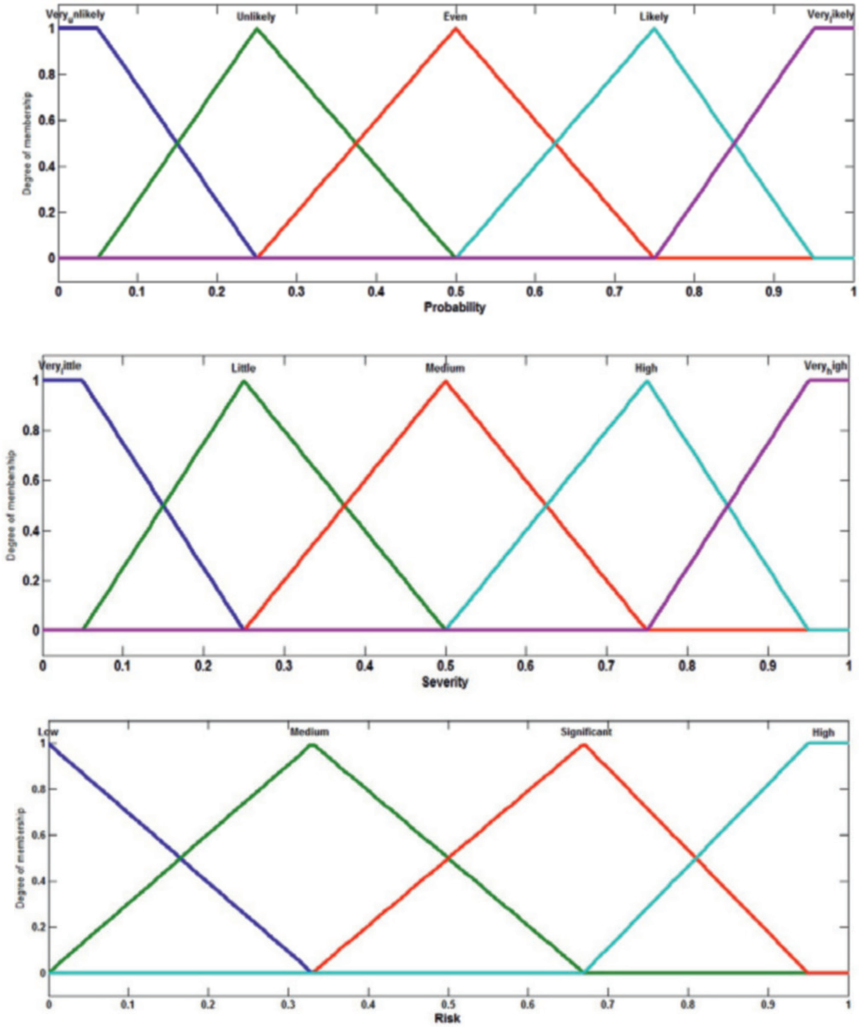

Fig. 14.6 Membership Functions.

Table 14.5 Examples of Knowledge Rules.

Rule 1	IF	$T_{R1} > 170\,^{\circ}C$	Fact
	THEN	Hazard (H1R1) : high temperature in R1	
Rule 2	IF	$T_{R2} > 175\,^{\circ}C$	Fact
	THEN	Hazard (H1R2) : high temperature in R2	
Rule 3	IF	$T_{D1} > 195\,^{\circ}C$	Fact
	THEN	Hazard (H1D1): high temperature in D1	
Rule 4	IF	$T_{D2} > 210\,^{\circ}C$	Fact
	THEN	Hazard (H1D2): high temperature in D2	
...			
Rule 21	IF	(H1R1)	Intermediate
	THEN	Poor cooling or TC_{R1} fail or input low level	
Rule 22	IF	(H1R2)	
	THEN	. . .	
...			
Rule 40	IF	(H1R1)	Decision
	THEN	switch to redundancy pump in cooling system and administrative checks	
...			

Assume the temperature in Reactor1 is increased to 170 °C. The system is initialized an abnormal situation occurred; the results are sent to the inference machine and stored in the integrated database. Rule 1 is selected and returned according to the knowledge rules. The system reports that the hazard (H1R1) occurred and an alarm will be shown on the operator's interface. At the same time, H1R1 characteristics are recalled from the database.

The posterior probability is calculated using Bayesian inference. For this example the abnormal event occurred at interval 20 and the posterior probability is 0.0132. According to the fuzzy risk analysis model the current risk level is 0.65 and the system presents "significant" risk level on the GUI. The causes of hazardous situation are searched by the inference machine and Rule 21 is written to the cause's area of GUI, and Rule 40 is selected. The operating suggestions are displayed in the monitoring windows of the system. Usually, during a short time period when multiple alarms occur, it is not possible to remove all of them. One has to attribute priorities, and our approach has this ability.

14.5 Conclusion and Future Study

During the operation of complex systems that include human decision making, acquiring and interpreting information from the environment forms the basis for the state of knowledge of a decision maker. This state is often referred to as situation awareness (SA). Lacking or inadequate SA has been identified as one of the primary factors in accidents attributed to human error and it is especially important in work domains where the information flow can be quite high, and poor decisions may lead to serious consequences. As technological systems continue to increase in degree of automation and complexity, the task of providing actionable information for SA becomes more difficult and costly to achieve. In this study we proposed a new system to support SA for the safety operators. Initially, our system conducts the complicated task of understanding what is going on in the situation, and it then assesses the current situation by the risk analysis concept through a case study.

The enhancement of SA is a major design goal for developers of operator interfaces, automation concepts, and training programs in a verity of fields. To evaluate the degree to which new technologies or design concepts actually improve operator SA, it is necessary to systematically evaluate them based on a measure of SA, which can determine those ideas that have merit and those that have unforeseen negative consequences [8]. Therefore, developing a SA measuring method and a system prototype evaluation based on the proposed SA measurement will form the basis for future study in this work.

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