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A Fuzzy Dual Expert System for Managing Situation Awareness in a Safety Supervisory System

Mohsen Naderpour, Jie Lu
Decision Systems and e-Service Intelligence Laboratory
Centre for Quantum Computation and Intelligent Systems (QCIS)
School of Software, Faculty of Engineering and IT, University of Technology, Sydney
P.O. Box 123, Broadway, NSW 2007, Australia
Mohsen.Naderpour@student.uts.edu.au, Jie.Lu@uts.edu.au

Abstract—**Safety supervisory systems continue to increase in degree of automation and complexity as operators are decreasing. As a result, each operator must be able to comprehend and respond to an ever increasing amount of available risky status and alert information. They generally have no difficulty in performing their tasks physically but they are stressed by the task of understanding what is going on in the situation. So in the last two decades, situation awareness has been recognized as a critical foundation for successful decision making across a broad range of complex and dynamic systems. This paper develops a fuzzy dual expert system based approach to enhance situation awareness. The proposed approach has ability to support the operators' understanding and assessing the situations, and to deal with uncertainties, applying fuzzy risk assessment concepts.**

Keywords- Situation Awareness; Fuzzy Logic; Expert System, Safety System, Risk Assessment

I. INTRODUCTION

Situation awareness (SA) involves being aware of what is happening in the vicinity to understand how information, events, and actions will impact the goals and objectives. Lacking or inadequate SA has been identified as one of the primary factors in accidents attributed to human error. Thus, SA is especially important in work domains where the information flow can be quite high, and poor decisions may lead to serious consequences. The idea did not receive much attention in the technical and academic literature until the late 1980s, but has become a hot topic ever since.

The primary research came from the aviation industry, where the pilots and air traffic controllers are under considerable pressure to develop better SA. The importance of SA in maintaining safe control of an aircraft is really obvious. One review of over 200 aircraft accidents found that poor SA was the main causal factor [1]. A similar review in other domains, such as nuclear power showed that this is not a problem limited to aviation, but one faced by many complex systems. Successful system designs must deal with the challenge of combining and presenting vast amounts of data now available from many technological systems in order to provide true SA (whether it is to a pilot, a physician, a business manager, or an automobile driver) [2].

Despite having its roots in aviation, it has been suggested that the concept is equally applicable to human supervisory control for land based industries. It is also argued that problems in human supervisory control may be due to poor situational awareness [3], such as:

1. Failure to detect critical cues regarding the state of the system;
2. Failure to interpret the meaning of information perceived via SCADA (supervisory control and data acquisition) technology;
3. Failure to understand individual task responsibilities and the responsibilities of others;
4. Failure to communicate with other operators in the team; and
5. Failure to communicate with other teams.

Given the potential importance and applicability of the concept to safety, it is important to review the state-of-the-art and consider how the concept might be extended to all manner of application domains, especially as it has been argued that even small faults in SA could have serious repercussions [4].

This paper considers the applicability of SA concepts to safety in the control of complex systems. Safety supervisory systems continue to increase in degree of automation and complexity as operators are decreasing. As a result, each operator must be able to comprehend and respond to an ever increasing amount of available risky status and alert information. In our previous work, we proposed an innovative conceptual model that assesses situations and helps the decision maker to take appropriate action in hazardous situations [5]. In this paper, we will describe implementation of expert system based approach to enhance situational awareness in complex environment.

This paper is organized as follows. In Sections II the concepts of SA, fuzzy logic and expert systems are introduced. Our approach, expert system based situation awareness is presented in Section III. This is followed by a case study, which involves an ethylbenzene process plant in Section IV. Finally, conclusion and future work are presented in Section V.

II. BASIC CONCEPTS

A. Situation Awareness

One of the earliest and most widely used definitions of SA describes it 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" [4]. Based on this definition, SA is comprised of three levels: (1) perception, (2) comprehension, and (3) projection (see Fig. 1).

Level 1 SA, perception, involves the sensory detection of significant environmental cues. For example, operators need to be able to see relevant displays or hear an alarm sound. In the field, the use of other senses to gather information (e.g., the smell of burning wire) may also be pertinent.

SA is far more than simply perceiving a bunch of data. Comprehending the meaning or significance of that information in relation to one's goals is also important. This process includes developing a comprehensive picture of the world. Operators with good Level 2 SA are able to understand the immediate impact of an outage on other parts of the system.

Projection, the highest level of SA, consists of extrapolating information forward in time to determine how it will affect future states of the operating environment. This merges what the individual knows about the current situation with their mental models of the system to predict what is likely to happen next – for example, being able to project the impact on the system of removing an element from service. The higher levels of SA allow operators to function in a timely and effective manner, even with very complex and challenging tasks [4].

B. Fuzzy Logic

Fuzzy logic, unlike Boolean or crisp logic, deals with problems that have vagueness, uncertainty, or imprecision, and uses membership functions (MF) with values varying between 0 and 1. Fuzzy logic tends to mimic human thinking that is often fuzzy in nature. In conventional set theory based on Boolean logic, a particular object or variable is either a member (logic 1) of a given set or it is not (logic 0). On the other hand, in fuzzy set theory based on fuzzy logic, a particular object has a degree of membership in a given set that may be anywhere in the range of 0 (completely not in the set) to 1 (completely in the set). This property allows fuzzy logic to deal with uncertain situations in a fairly natural way. It may be mentioned that although fuzzy logic deals with imprecise information, it is based on sound quantitative mathematical theory [6].

Fuzzy theory was first proposed by Zadeh in 1965. The formal definition of fuzzy sets is "A fuzzy set is characterized by a membership function mapping the elements of a domain, space or universe to the unit interval (0, 1)" [7].

There are many types of membership functions that can be applied to fuzzy theory, such as triangular functions, Γ functions, S-functions, trapezoidal functions, Gaussian functions, and so forth. Each function defines different characteristics of fuzzy sets.

C. Expert Systems

Expert systems (ES) are a branch of applied artificial intelligence (AI), and were developed by the AI community in the mid-1960s. The basic idea behind ES is simply that expertise, which is the vast body of task-specific knowledge, is transferred from a human to a computer. This knowledge is then stored in the computer and users call upon the computer for specific advice as needed. The computer can make inferences and arrive at a specific conclusion. Then like a human consultant, it gives advices and explains, if necessary, the logic behind the advice.

ES provide powerful and flexible means for obtaining solutions to a variety of problems that often cannot be dealt with by other, more traditional and orthodox methods. Thus, their use is proliferating to many sectors of our social and technological life, where their applications are proving to be critical in the process of decision support and problem solving [8]. Fig. 2 shows the basic elements of the expert system [6].

A rule-based ES is defined as one, which contains information obtained from a human expert, and represents that information in the form of rules, such as IF–THEN. The rule can then be used to perform operations on data to inference in order to reach appropriate conclusion. These inferences are essentially a computer program that provides a methodology for reasoning about information in the rule base or knowledge base, and for formulating conclusions.

Fuzzy ESs are developed using the method of fuzzy logic, which deals with uncertainty. This technique, which uses the mathematical theory of fuzzy sets, simulates the process of normal human reasoning by allowing the computer to behave less precisely and logically than conventional computers. This approach is used because decision-making is not always a matter of black and white, true or false; it often involves gray areas and the term may be. Some applications implemented by fuzzy ESs are such as: online scheduling, fault diagnosis, ecological planning, control systems, uncertainly reasoning [8].

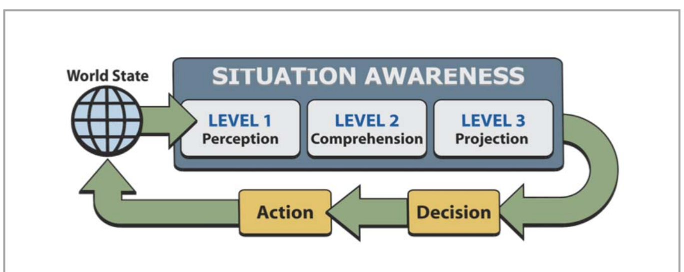

Figure 1. Situation awareness

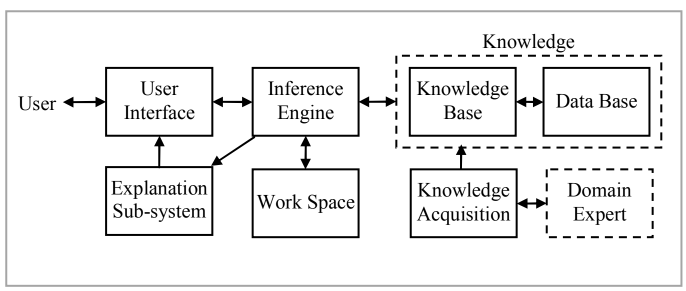

Figure 2. Basic elements in an expert system

III. Expert System Based Situation Awareness

In a complex and dynamic environment, a casualty requires immediate response. There are often multiple actions required in a very short time. One has to determine priorities that we believe the fuzzy risk analysis can do this task.

Otherwise, the trend toward smaller operators' size and increasing automation has resulted larger volumes of more and more complex information in a dynamic environment. Therefore, it is necessary to assist the operators in quickly understanding the available information by providing that data in a format that allows them to act quickly and correctly. Additionally, the large volumes of available information can enable the system to anticipate emerging problems, possibly averting the subsequent casualty.

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 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 [9].

Traditionally, different functions within naval industries have been conducted by separate departments, such as Engineering, Maintenance and HSE. Coordination was accomplished using a chain of command and internal communications systems to relay status to the appropriate decision makers. Thus, engineering and safety control functions were often taking place on the bridge and/or in the control center.

As noted 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].

For determining the aspects that are important for an operator's SA, we use the goal-directed task analysis which introduced in [2]. The results are showed in TABLE I. In this analysis, the major goal and the necessary subgoals are identified. Associated with each subgoal, the major decisions that need to be made are then identified. The SA needed for making these decisions and carrying out each subgoal are identified. These 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 in performing his or her job.

For the safety supervisory system, critical factors in the environment (SA level 1) should be collected from various sensors which are distributed in intended area. The aim is to locate and identify objects. Any variety of relations- physical, organizational, informational, and perceptual- can be considered. Knowledge and experience of the past can be applied to the determination of the potential hazardous circumstances. This includes information such as which safety equipment or system is on- or off-line; in maintenance mode; in auto, manual, or semi-auto mode and other hazards which can threat the system.

SA level 2 relates to the operator's understanding of the system as a whole, and emergent events (such as alarms or casualties), which arise from the hazards. At this level, it is also necessary to understand the causality and consequences of the hazards.

For SA level 3, the system and operator should understand future required actions. Depending on the consequent losses, the hazards may subsequently require risk elimination, mitigation, transfer, control or an appropriate combination thereof. Another useful understanding of what will happen in the near future is the system's (and operator's) ability to recognize deteriorating safety equipment condition, or predictions of required maintenance events.

It should be mentioned, much of approach's success hinges on the effectiveness of the operator. It has long been recognized that increased automation does not necessarily lead to improved capabilities. If the approach is focused solely on the automated features, then the operator can become more disconnected from the tools and resources needed to assess situations and make objective and effective decisions. The functions allocated to automated processes leverage capabilities that humans cannot perform effectively. Still, the proposed approach does not control the course of action and allows the human to act at his discretion for specific contexts [9].

On the other hand while the application of advanced automation can incorporate some disadvantages, it has generally improved the safe operation of complex systems. Intelligent agents, such as the use of expert systems, have the capability to assist the operator in achieving and maintaining increased SA. To provide expert system based situation awareness, there are numerous factors which require careful attention such as alarm management. Fig 3 shows the combined two expert systems for situation awareness.

TABLE I. 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*

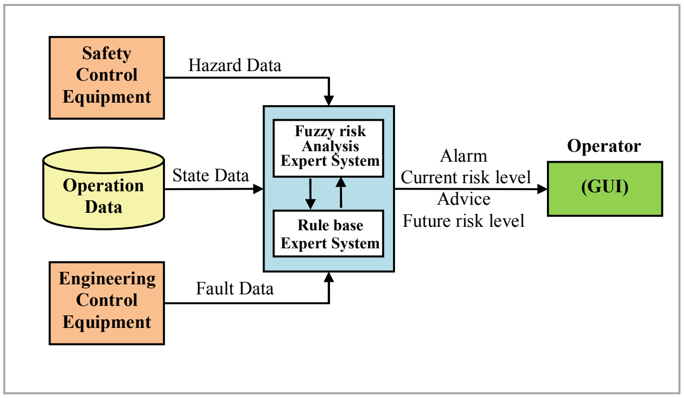

Figure 3. Expert system based situation awareness

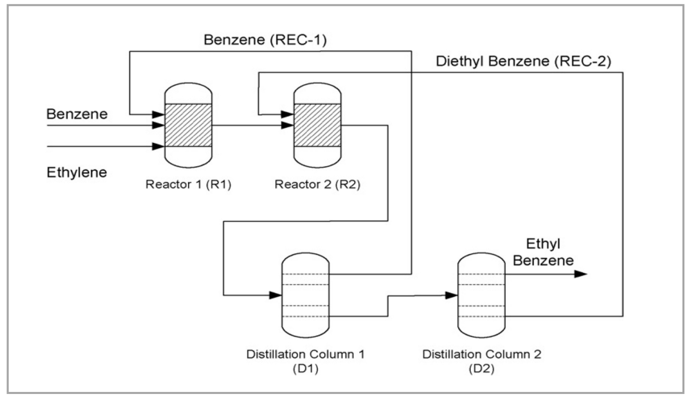

Figure 4. Process flow sheet of ethylbenzene process

Clearly, it is necessary to consider human factors and alarm management for designing system. The authors in [10] proposed nine design principles intended to improve the use of alarms in support of establishing and maintaining SA. These principles will be considered and used as guidelines in the design of the system in future.

IV. FUNCTIONAL DEMONSTRATION

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.

Chemical and petrochemical manufacturing plants are one of the complex environments that the supervision tasks have increased considerably due to the high level of development in process design and control. A decision support system is needed to assist operators in understanding and assessing status and responding quickly to risky situation.

For example, in March 23, 2005, 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 [11].

For functional demonstration, an ethylbenzene process plant, involving two reactors and two distillation columns, as shown in Fig. 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 and DEB in the D1 bottoms product is fed to D2, with EB recovered in the distillate, and DEB recycled to R2 [12].

A. *Implementation of rule base expert system*

Chemical processes are characterized by many variables. However, the experience accumulated through years by domain experts allows for the representation of behavior of chemical processes not only by the mathematical models but also by a set of production rules. These factors allow us to use them appropriately for SA. The format of the rule is as follows:

IF Antecedent; *THEN* Consequent

We use three types of rules in this paper: fact, intermediate and decision rules. In a fact rule, antecedent is a condition which has potential to harm while consequent is a hazard. In an intermediate rule, antecedent is a hazard, while consequent is a description of the hazard causes. A decision rule includes the corresponding suggested action to remove or eliminate the hazard.

To increase the speed of matching, decision and intermediate rules are stored in one rule table, while fact rules are stored in another rule table. This structure increases the speed of matching between facts and fact rules.

The performance of an inference machine is a key factor influencing the quality of the expert system for the real-time response of the system. 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.

1) *Hazards identification*

In the area of hazard identification, there are two main tasks, (i) identification of specific undesirable consequences and (ii) identification of material, system, process, and plant characteristics that can produce those consequences. HAZOP is one of the most powerful hazard identification methods available and has been well described in the literature. The imagination of a selected team is used to perturb a model of the system being studied by using a methodical process to identify hazards. The design intention of each element is defined and then questioned using ‘Guide-words’ to produce deviations from the intention. The causes, consequences and safeguards for each deviation are then discussed and recorded. The HAZOP analysis is useful to build the process deep knowledge base (KB) of the plant [13]. In addition fault trees, analysis of production flow and experts' knowledge are adopted as the knowledge acquisition techniques. For example using experts' knowledge allows us to represent of behavior of chemical processes as a set of rules e.g.

- *IF* TC_{R1} > 170 °C; *THEN* the temperature of R1 is high
- *IF* Mean(PC_{D1},0,1)-Mean(PC_{D1},0,30)>3 bar, *THEN* the pressure of D1 is high

where Mean is a average value function and Mean(PC_{D1},0,1) denotes the average value of pressure in D1 between actual time and 1 min before the actual time.

2) Likelihood analysis

The likelihood function is formed using real time data from the process as it operates. These data are referred to as accident precursor data (ASP) and represent the number of near misses and incident which occur within the process during the period of study. Many approaches exist for selecting likelihood functions, among the most convenient is using the conjugate pair of the prior function. Beta and binomial distributions are conjugate pairs and so binomial distribution is used to represent the likelihood function. This choice is convenient due to the fact that ASP data are specific numbers within a discrete domain which is also best presented by a binomial distribution. Therefore the likelihood function may be defined as:

$$f(Data|x) = \binom{n}{s} x^s (1-x)^f \tag{1}$$

where *f(Data|x)* denotes the likelihood function, *n* is the total number of trials, *s* is the number of successes and *f* is the number of failures which can also be shown as *n–s* [14].

The posterior failure function may be obtained from the prior and likelihood functions using Bayesian inference. Bayesian inference is a tool which uses data to improve an estimation of a parameter in other words; Bayesian inference mathematically describes the learning process. Using Bayesian inference the posterior function can be formulated as shown below:

$$f(x|Data) \propto g(Data|x) f(x) \tag{2}$$

where *f(x|Data)* is the posterior function, *g(Data|x)* is the likelihood function and *f(x)* is the prior [14].

3) Consequence analysis

Consequence analysis is a straightforward approach as the consequence of an abnormal event is considered to remain constant throughout the lifetime of the process.

Generally, consequences of an abnormal event in chemical process industries may be categorized into 4 groups; asset loss, human fatality, environmental loss, and confidence or reputation loss.

The severity matrix used in present study is given in TABLE II. The equivalent dollar value of damage associated with each consequence category based on the severity of damage is also outlined in TABLE II [14].

TABLE II. CONSEQUENCE SEVERITY MATRIX

Severity class	Asset loss	Human loss	Environment loss
Very little	<10k	One minor injury	Around the area, easy recovery
Little	10-100k	One or two minor injury	Within plant, short term remediation effort
Medium	100k-1million	Multiple major injuries	Minor offsite impact, remediation cost will be less than 1 million
High	1-10 million	One fatality or multiple injuries with disabilities	Community advisory issued, remediation cost remain below 5 million
Very high	>10million	Multiple fatalities	Community evacuation for longer period, remediation cost in excess of 5 million

B. Implementation of fuzzy risk analysis expert system

To obtain the risk level of hazards we proposed a fuzzy expert system and for coding our model, MATLAB programming language was used.

1) Linguistic Variables

We present probability of hazards with five linguistic values e.g. very likely, likely, even, unlikely and very unlikely. To explain the severity we present five linguistic values e.g. very little, little, medium, high and very high. The outputs are the risks, which are presented by low, medium, significant and high. Support values and parameters of fuzzy sets are shown in TABLE III.

2) Membership Functions

We use triangular membership function because of its simplicity and high efficiency, but in some bound points we used trapezium membership function to increase the sensitivity of membership function in some bound points, e.g. the upper bound of probability of hazard and upper bound of risk.

We considered triangular membership functions for middle membership functions as it is usual. However, we considered the first value of probability membership functions, very unlikely value, which we used triangular function in order to be more careful about very small probabilities of failure. Fig. 5 shows membership functions for probability, severity and risk variables.

3) Rule Base

To construct the fuzzy risk analysis expert system of our approach, we considered the risk matrix. TABLE IV shows a common risk matrix which we used in our approach. As can be seen from TABLE IV, the risk matrix has 25 rules e.g.:

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

THEN the risk is high

TABLE III. LINGUISTIC VARIABLE AND THEIR PARAMETERS

Probability		**Severity**		**Risk**	
L.V.	**P.**	**L.V.**	**P.**	**L.V.**	**P.**
Very unlikely	[0 0 0.05 0.25]	**Very little**	[0 0 0.05 0.25]	**Low**	[-0.33 0 0.33]
Unlikely	[0.05 0.25 0.5]	**Little**	[0.05 0.25 0.5]	**Medium**	[0 0.33 0.67]
Even	[0.25 0.5 0.75]	**Medium**	[0.25 0.5 0.75]	**Significant**	[0.33 0.67 0.95]
Likely	[0.5 0.75 0.95]	**High**	[0.5 0.75 0.95]	**High**	[0.67 0.95 1 1]
Very likely	[0.75 0.95 1 1]	**Very high**	[0.75 0.95 1 1]		

C. Example of application

For the ethylbenzene process, hazardous situations include those due to controller failure, loss of cooling, disturbances in the feed temperatures and flow rates, and the reboiler heat duty, and flooding in the distillation columns. Furthermore, the safety systems are assigned temperature limits, as shown in TABLE V, 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].

TABLE IV. Risk Matrix

P. \ S.	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

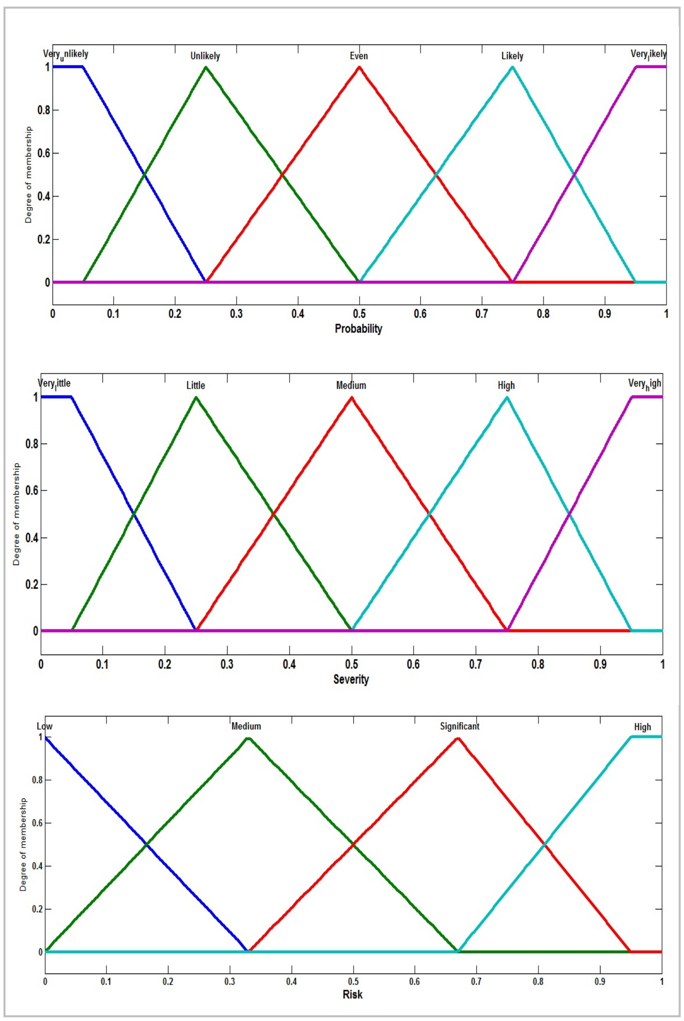

Figure 5. Membership functions

For example Fig. 6 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 safety systems are divided into two categories: (i) equipment-related and (ii) human-related. 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).

Parts of rules for managing the SA are listed in TABLE VI. These rules include the fact, intermediate and decision rules.

TABLE V. 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

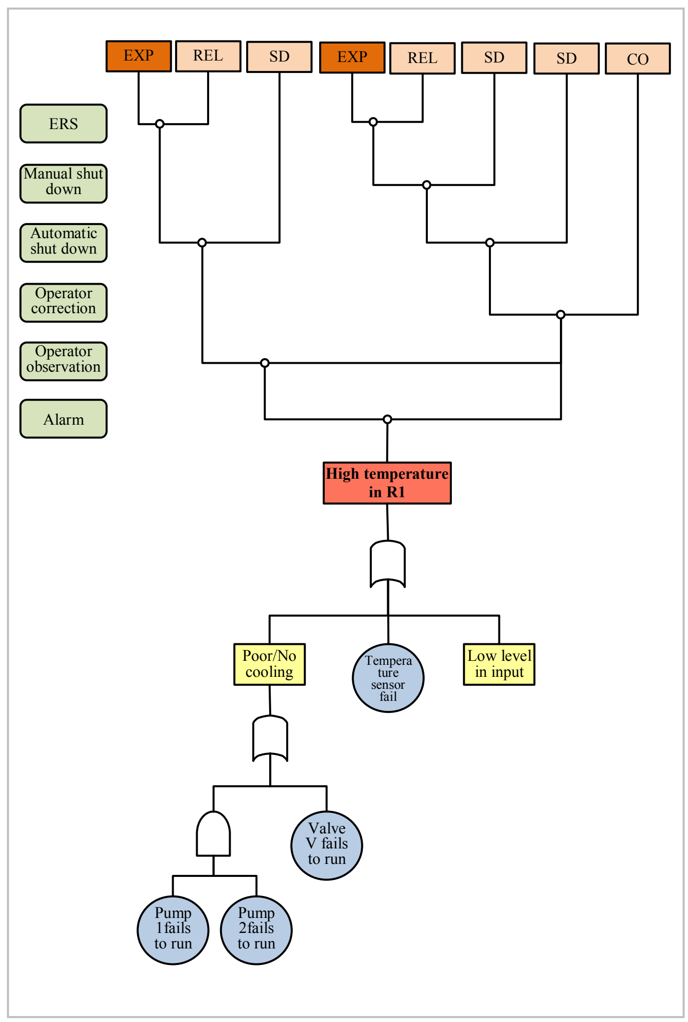

Figure 6. Bow-tie diagram for high temperature in R1

TABLE VI. EXAMPLES OF KNOWLEDGE RULES

Rule 1	IF	T_{R1}>170°C	Fact
	THEN	Hazard (H1R1) : high temperature in R1	
Rule 2	IF	T_{R2}>175°C	Fact
	THEN	Hazard (H1R2) : high temperature in R2	
Rule 3	IF	T_{D1}>195°C	Fact
	THEN	Hazard (H1D1): high temperature in D1	
Rule 4	IF	T_{D2}>210°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. When the system is initialized the abnormal situation, 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 recall from database.

The posterior probability is calculated by using Bayesian inference. The possible number of occurrence of an abnormal situation in each interval can be formulated using Poisson distribution:

$$y \sim p(y = yt) = \left\{\frac{\lambda^{yt} e^{-\lambda}}{yt!}\right\} \tag{3}$$

where $yt => 0$ is the number of abnormal events in time interval l, and $\lambda > 0$ is the average number of abnormal events in the time intervals. For this example the abnormal event occurred at interval 20 and the posterior probability is 0.0132.

According to the fuzzy risk analysis expert system the current risk level is 0.65 and the system presents "significant" risk level on the GUI. The causes of hazard are searched by the inference machine and Rule 21 is written to the cause's area of GUI. And Rule 40 is chosen as its suggestions. The operating suggestions are displayed on the monitoring windows of system. Usually in a process plant, hazards are many and often during a short time period multiple alarms occur, and it is not possible to remove them all. One has to attribute priorities that in our approach the fuzzy risk analysis expert system does this task.

V. CONCLUSION AND FUTURE WORK

As safety supervisory systems continue to increase in degree of automation and complexity, the task of providing actionable information for situation awareness becomes more difficult and costly to achieve. The proposed approach employs expert system and risk assessment concepts to support two important aspect of safety supervisory system. First it conducts the complicated task of understanding what is going on in the situation and second it assess the current situation by risk analysis concept.

In the near future, our safety supervisory system would include an expert system that learns and stores behavior information to use them for predicting the near future. The expert system would also customize the displays to personal preferences, previous experience/behavior and even physical characteristics. This requires a form of machine learning either implemented completely within the expert system, or as a hybrid system incorporating multiple smart technologies.

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