Original Research

Assessing the reliability of dynamic systems for safety units recovering flare gas, considering covariates

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Abstract

The Flare Gas Recovery System (GR) is a critical component in preventing the release of pollutants into the atmosphere. However, these systems are expensive to install and maintain, so ensuring their reliability and effectiveness during operation is critical task. Two safety system technologies have been developed for GR, the fast opening and closing valve system (OVS) and the closed drum system (CDS), but the dynamic operating conditions and lack of historical data make reliability estimates as a crucial complicated task. To address this issue, we propose a novel approach to develop a system reliability as a response surface based on multiple operating pressure and temperature using a hybrid fault tree and a fuzzy inference system. The result reveals an average 22.4% improvement in reliability for OVS compared to CDS in various operational scenarios. Our proposed method provides an operative technique to assess the reliability of GR security systems considering various operating conditions. Results also can help decision-makers to choose the security technology that best fits their particular application needs, ultimately reducing maintenance of costs while ensuring optimal performance over the long term.

Keywords- Reliability assessment; Flare gas recovery system; Fault tree analysis; Fuzzy inference system; Expert elicitation

INTRODUCTION

In traditional refineries, due to the lack of sufficient infrastructure, burnt natural gas is released into the air and leads to environmental problems. However, this practice significantly contributes to greenhouse gas emissions, which have a profound impact on global warming. Consistent with Elvidge et al. in 2018, reducing flaring plays a significant role in achieving emission reduction targets and meeting NDCs [1]. As a result, refinery industries are allocating shares of their resources to increase processing plant without flare gas recovery units (GRs) so that they can recover a significant part of released output gas for regeneration usages. To prevent additional emissions into the atmosphere and reap considerable benefits, GRs must operate continuously. Therefore, a safety unit is required to avoid breakdowns initiated by abnormal pressure or temperature. Here engineers face the task of decide on among anticipated strategies for GR safety structures. The nominated alternative should be deployed volatile operating circumstances; consequently, comprehensive system reliability estimates are essential.

The article is the result of a field research to solve the real problem of not polluting the environment due to the exhaust of the burnt refinery gas. The main goal of the research is to nominate the most suitable exhaust gas recovery technology among the two known available alternatives. Hence the complexity is on the methodology to estimate the reliability of two alternatives. Because the correct option should have high stability in operational conditions against the change of many environmental conditions in order to restore the survival of the system.

Due to the strong dependence of the life span and failure time on the operating conditions, as well as the insufficiency of historical data on how failures occur in the two alternatives, it was necessary to apply efficient methods in which the effect of volatile operating parameters in reliability assessment should be considered. Hence operational conditions such as pressure, temperature should be taken into account in the occurrence of malfunctions. Therefore, for the implementation of the present research, the conventional methods for estimating the reliability of systems, which are mentioned in the literature and reference books, could not be applied, and as the novelty a new methodology should be designed and implemented as the contribution of the current research.

In the proposed methodology, a new configuration of multiple tools such as Fault Tree Diagram, Fuzzy Inference System, Response Surface Methodology have been used, which will be briefly reviewed here, and their technical details will be explained in the following sections.

The alternatives chosen have worked for over 20 years, and a wrong choice could lead to further failures leading to significant economic losses and significant environmental pollution. Error data is not available as decisions are made at the pre-installation and purchase stages. Reliability facts and figures should be alert to multiple time points, the output of traditional reliability techniques. Demonstrating changes in confidence for specific factors requires accurate baseline data that can account for such changes, as well as appropriate techniques for processing.

Expert elicitation is a commonly applied method for researchers to compensate for the lack of data when making predictions. Expert judgments revealed that the breakdown likelihood may be assessed under variant circumstances. This information can then be used to calculate changes in safety system reliability, which is essential for prognostic studies. Quantification techniques are used to create likelihoods of verbal term possibilities, allowing for accurate intentions. To nominate the critical components, it is possible to check the failures that cause the failure of the whole system. Fault tree analysis (FTA) as a well-known technique to analyze many types of breakdowns. “AND” and “OR” are two logical gates often used in FTA to analyze the failures based on basic events through using some Boolean algebra rules. However, FTA has its limitations. Its routine calculation methods cannot describe changes in output versus fundamental event values, which can be influenced by factors such as time and stress factors for systems operating under volatile conditions. These limitations must be taken into account when using FTA for safety, risk, and reliability analysis.

Also fuzzy inference system (FIS) could inference rules through experts verbal terms. Therefore, fusing FIS and FTA yields a highly responsive FTA output. Against this background, there are not many reports on the development of FTA. The primary challenges in this research were on changing operating circumstances on the FTA. This will enable accurate predictions of performance, which can aid in making informed decisions between proposed alternatives when historical data is unavailable. The propend their consequences on the FTA approach beside FIS, in special proposed innovative method to estimate system reliability without historical data. FIFTA can also visually represent the reliability as a function of related factors, providing valuable visions for engineers in procuring phase. Section 2 provides a review of similar cases in literature, while in section 3 information on proposed alternatives for safety sub-systems presented. Section 4 discusses some contests involved in calculating excellent reliability for these alternatives, and section 5 outlines the anticipated methodology to address these challenges. The method is realized, and consequences are accessible in section 6 with complementary argument provided for explanation resolutions. Finally, section 7 presented discussion remarks.

STATE OF THE ART

Proper reliability estimation is a crucial task for operating engineers as it allows them to assess the likelihood of systems enduring over time. Evaluating the lifetime of a system under specific conditions for a specified period is a common task in the literature [2]. However, if the operating conditions embeds volatility in circumstances parameters, reliability analysis becomes a complicated duty, which could be categorize as dynamic reliability. Dynamic reliability analysis to handle interactions between components and process variables, resulting in more realistic system modeling for safety analysis [3,4]. It requires more sophisticated tools and requires the application of more complex mathematical approaches [5]. Changes in volatile parameters can be molded deterministically or stochastically, the latter being more complex to model than the former and frequently achieved by simulation. See Damian [6] for the decisive change. On the other hand, for stochastic changes see Radim BRIŠ Pavel Praaks [7]. Ambiguity and vagueness arise due to unknown features of complicated systems or the cases where insufficient historical failure data leading to assess growing error. To reduce the errors, fuzzy logic may be act as an efficient alternative [8].

In recent years, researchers have been studying a new technique called FFTA, which combines FTA and fuzzy logic. This approach replaces expert elicitation with linguistic values that are transformed into stochastic terms for primary events of the fault tree. Rajakarunakaran et al. (2015) used a grouping of expert induction in addressing the vagueness and subjectivity of information. Wang et al. (2013) applied FTA to recognize basic events for crude oil tank fire and explosion (TFE). They applied a hybrid approach of fuzzy logic to analyze the TFE fault tree. Basic events were identified as weak links using importance measuring. Purba (2014) proposed another kind of probabilistic fuzzy approach in a nuclear power plant safety systems. Their results also validated by comparing the theoretical probabilities with the actual failure ones gleaned from operating experience.

Baig and Ruzli utilized corrosion simulation software to generate results that were used by experts to improve their elicitation process. They collected data to assess the breakdown density function of CO2 pipelines by applying fault tree. In 2010, Renjith et al. introduced a two-dimensional fuzzy FTA, which incorporated hesitation factors. In this paper, the gathered data requires proper numericalization techniques such as FIS, which has yet to be combined with FTA. However, FIS has been used for approximation and estimation purposes in several cases. Azadeh et al. utilized FIS to approximate human reasoning for timely diagnosis of pump failures while Ratnayake in 2014 combined FIS and risk score for risk assessment of liquid and gas pipeline. In 2009, Elsayed used the FIS to qualitative risk matrices to address the problem of multi-attribute risk from vague data. He found that the FIS is more instinctive, while the Sugeno method effectively guarantees the permanency of the absolute risk [17].

SYSTEM DESCRIPTION

There are two options for safety units of the GR. While they have many similarities. But the key difference lies in the pre-flaring unit. Figure 1 depicts the related illustrations.

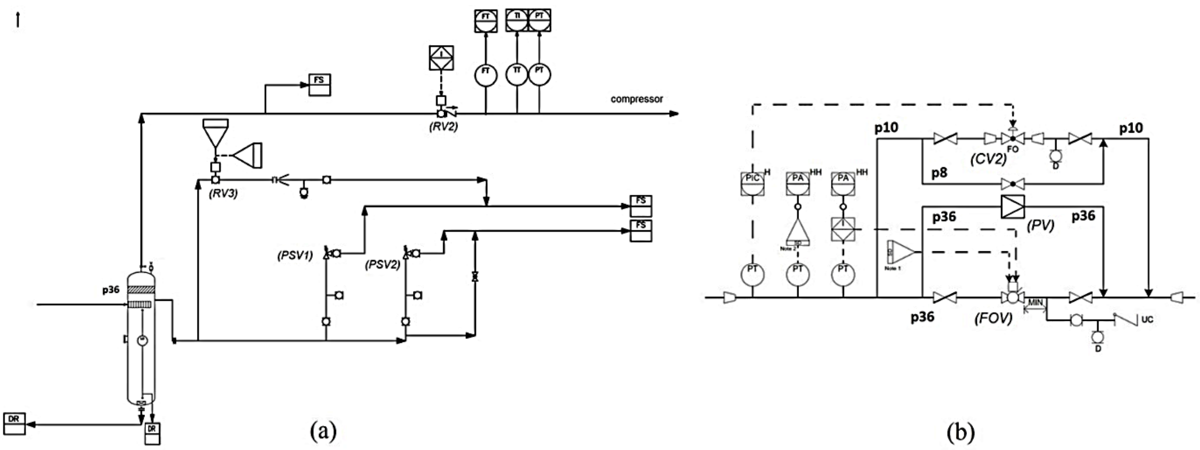
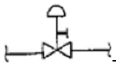
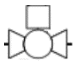
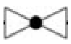


FIG. 1
SCHEMATIC OF SAFETY SUBSYSTEM OVS (A) AND CDS (B)

Many events that can cause failure in GR, with dangerous scenarios arising from abnormal gas pressure or temperature. Section 5.3 discusses three hazardous scenarios in detail. A safety system is used to block paths leading to the GR. Each safety system has pre-defined responses towards each scenario initiated when sensors detect dangerous temperatures or pressures, sending proper messages to valve actuators. These devices receive signals from sensors and open and close valve bodies to direct gases of hazardous nature into the flare tower. If the security subsystem fails to respond to a threat setup, not only will the GR break, but the security subsystem itself can also break. Figure 2 shows a general view of the GR where gas from the flare tip enters the safety system and is sent to the compressor in sufficient quantity for recovery. Table (1) shows the name and symbol for each component involved in this process.

TABLE 1
FAILURE MODES OF DIFFERENT VALVES

Name	symbol	Abb.	Used in	Failure type
Control valve		CV1	Fig. 2	Fail to close
		CV2	Fig. 4	Fail to open
Rotary valve		RV1	Fig. 2	Fail to close
		RV2	Fig. 3	Fail to close
		RV3	Fig. 3	Fail to open
Pin valve		PV	Fig. 4	Fail to rupture
Fast opening valve		FOV	Fig. 4	Fail to open
Pressure safety valve		PSV1	Fig. 3	Fail to open
		PSV2	Fig. 3	Fail to open
Spare Globe valve		SP1		Fail to close
		SP2		Fail to open
		SP3		Fail to open
		SP4		Fail to open

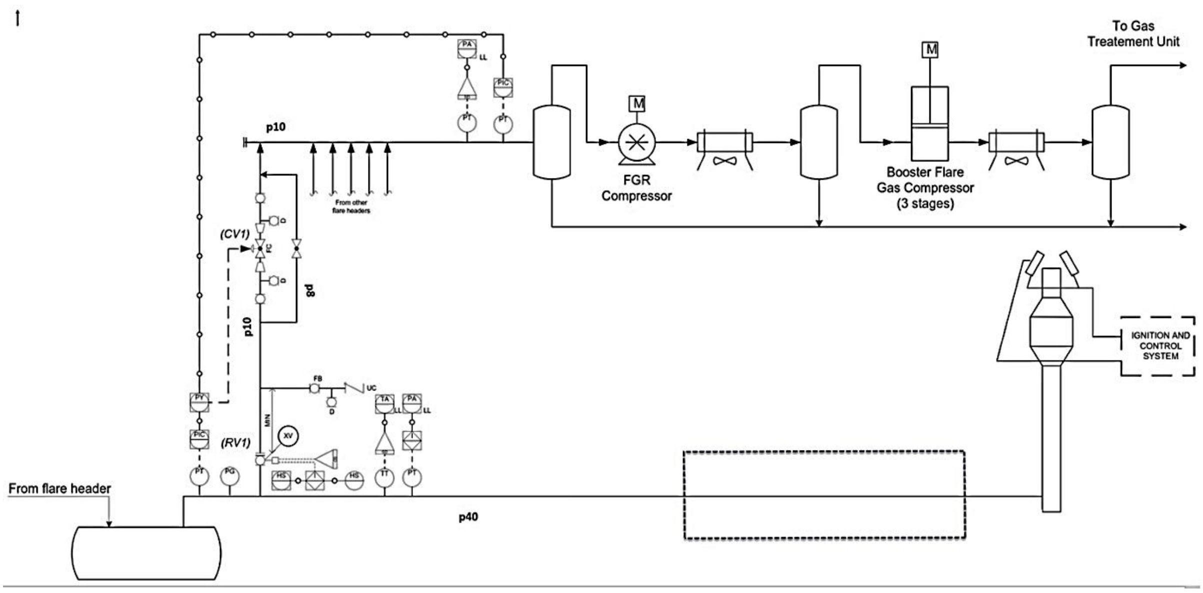


FIGURE 2
A SCHEMATIC DIAGRAM FOR GR

PROBLEM STATEMENT

The high cost of components and repairs for the GR highlights the need for a resilient safety subsystem that can withstand volatile operating conditions and protect against dangerous gas characteristics. In addition to cost considerations, reducing damage to the GR can minimize gas emissions into the atmosphere, helping to meet NDC goals. Two potential safety subsystem options, OVS and CDS, are available, but selecting the one with bigger reliability and lower breakdown is crucial to minimizing GR damage. However, assessing reliability requires considering how each subsystem interacts with other components in the system. Traditional reliability methods only consider time dependency and overlook environmental factors that can lead to unpredictable failures in a volatile environment. To accurately assess reliability values for different operating conditions and scenarios, data is needed that associates failure probability with specific operating conditions such as time, pressure, and temperature. This requires a function with a domain consisting of three axes representing time, pressure, and temperature within their maximum and minimum limits. The codomain refers to a value between 0 and 1 that represents the probability of failure. This means that for each component, there is a specific type of failure data that describes its durability under given circumstances. To accurately describe the simultaneous presence of contributing factors, both data gathering and processing techniques are required. A questionnaire is designed to gather relevant data, which is then processed using FIS to generate a response surface for reliability analysis. More information on these techniques presented later.

PROPOSED METHOD

As it was shown in the literature review, frequently in estimating system reliability, it is assumed that the operating environment of the system has the necessary stability and by using the system configuration and gathering experimental data on the lifetime of the components, as also analyzing independence or correlation between component's life reliability assessment could be followed. In the conditions where the operating environment has instable, estimating the reliability will be a challenging problem because the lifetime of the components will change significantly under the influence of process environment factors such as pressure and temperature. This discussion will be more vital complex task in cases where the experience of objective observation of lifetime is not available. These issues are considered here hereinafter as the proposed methodology. In the proposed method FTA act as central core of the methodology and FIS as a complementary tool for group inference to tackle different operating condition. Due to a lack of historical data, judgments is gathered to determine the likelihood of failure for each component under changing operating circumstances. To quantify this linguistic data, a fuzzy inference method is applied, generating different points in a four-dimensional space to draw the response surface of alternative. Figure 3 provides an overview of the proposed method, known as fuzzy inference FTA.

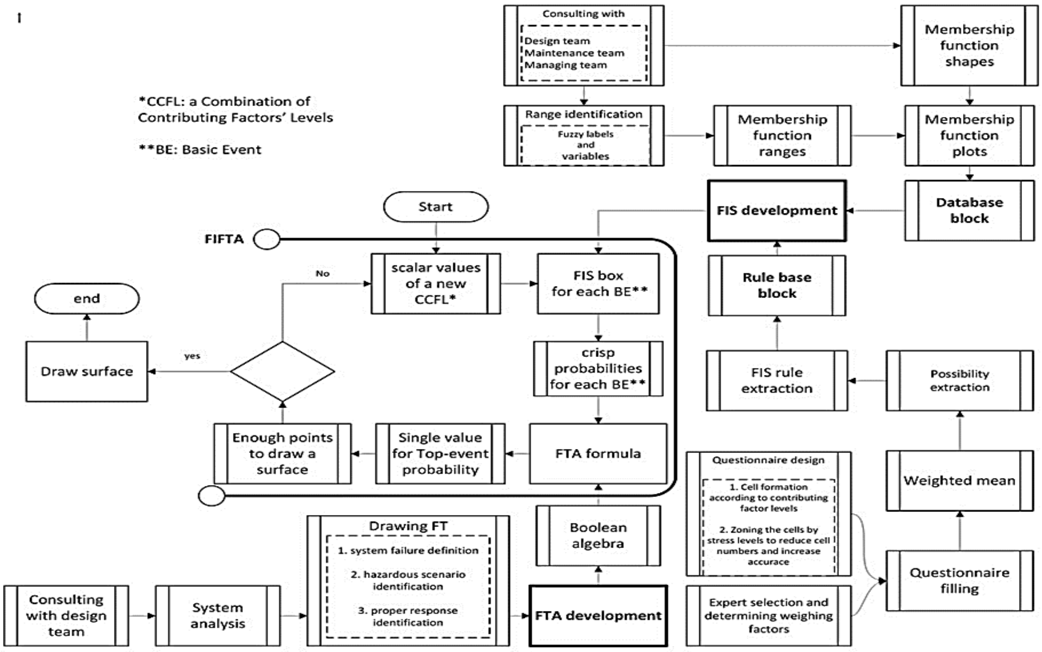


FIG 3
THE ANTICIPATED FIFTA METHODOLOGY

During the purchasing stage, a confirmed questionnaire (Table 2) was prepared breakdown probability based on expert judges. Temperature and pressure were identified as the main contributing factors to component failure. To overcome vagueness, all responses transformed to normalized sets. Here each data exposes the expected lifetime possibility at a given temperature/pressure using a set of triplet showing temperature, pressure and time. The aim is to determine the likelihood of component failure by creating a response surface that associates each breakdown probability with an operating condition. To achieve this, it is necessary to quantify possibility into probability using Fuzzy Inference System (FIS). However, before developing FIS, the first step is to draw a fault tree (FT) that models the failures. Sections 5.1 to 5.3 of Figure 3 provide guidance on drawing FT. To draw FT, it is essential to have a clear definition of failure, which requires studying the structural and functional system failure.

TABLE 2
THE 12 PERSONS AVERAGE WEIGHTING OF THE PROBABILITY OF FAILURE

	Time																										
	↓									–									↑								
	Pressure									Pressure									Pressure								
	↓			–			↑			↓			–			↑			↓			–			↑		
	temp			temp			temp			temp			temp			temp			temp			temp			temp		
	↓	–	↑	↓	–	↑	↓	–	↑	↓	–	↑	↓	–	↑	↓	–	↑	↓	–	↑	↓	–	↑	↓	–	↑
stress	B	G	G	B	G	G	O	Y	Y	Y	B	B	Y	B	B	R	O	O	O	Y	Y	O	Y	Y	R	R	R
RV1	10	3	3	10	3	3	17	9	9	13	11	11	11	11	9	22	17	17	18	11	11	18	13	11	24	24	23

↑: high —: medium ↓: low

FIS Rules for the basic event, representing RV1 fail to act:

1. If (Time is low) and (Temperature is low) and (Pressure is low) then (possibility is 10) (1)
2. If (Time is low) and (Temperature is medium) and (Pressure is low) then (possibility is 3) (2)
3. If (Time is low) and (Temperature is high) and (Pressure is low) then (possibility is 3) (3)
4. If (Time is low) and (Temperature is low) and (Pressure is medium) then (possibility is 10) (4)
5. If (Time is low) and (Temperature is medium) and (Pressure is medium) then (possibility is 3) (5)
6. If (Time is low) and (Temperature is high) and (Pressure is medium) then (possibility is 3) (6)
7. If (Time is low) and (Temperature is low) and (Pressure is high) then (possibility is 17) (7)
8. If (Time is low) and (Temperature is medium) and (Pressure is high) then (possibility is 9) (8)
9. If (Time is low) and (Temperature is high) and (Pressure is high) then (possibility is 9) (9)
10. If (Time is medium) and (Temperature is low) and (Pressure is low) then (possibility is 13) (10)
11. If (Time is medium) and (Temperature is medium) and (Pressure is low) then (possibility is 11) (11)
12. If (Time is medium) and (Temperature is high) and (Pressure is low) then (possibility is 11) (12)
13. If (Time is medium) and (Temperature is low) and (Pressure is medium) then (possibility is 11) (13)
14. If (Time is medium) and (Temperature is medium) and (Pressure is medium) then (possibility is 11) (14)
15. If (Time is medium) and (Temperature is high) and (Pressure is medium) then (possibility is 9) (15)
16. If (Time is medium) and (Temperature is low) and (Pressure is high) then (possibility is 22) (16)
17. If (Time is medium) and (Temperature is medium) and (Pressure is high) then (possibility is 17) (17)
18. If (Time is medium) and (Temperature is high) and (Pressure is high) then (possibility is 17) (18)
19. If (Time is high) and (Temperature is low) and (Pressure is low) then (possibility is 18) (19)
20. If (Time is high) and (Temperature is medium) and (Pressure is low) then (possibility is 11) (20)
21. If (Time is high) and (Temperature is high) and (Pressure is low) then (possibility is 11) (21)
22. If (Time is high) and (Temperature is low) and (Pressure is medium) then (possibility is 18) (22)
23. If (Time is high) and (Temperature is medium) and (Pressure is medium) then (possibility is 13) (23)
24. If (Time is high) and (Temperature is high) and (Pressure is medium) then (possibility is 11) (24)
25. If (Time is high) and (Temperature is low) and (Pressure is high) then (possibility is 24) (25)
26. If (Time is high) and (Temperature is medium) and (Pressure is high) then (possibility is 24) (26)
27. If (Time is high) and (Temperature is high) and (Pressure is high) then (possibility is 23) (27)

Valves are prone to failure due to changing operating condition accelerate degradation. If a valve fail, pipes and compressors are exposed to risky setups (5.3). Consequently, a failure could be offered as follows:

- ***System failure definition***

To be able to plot the FT, we need to clearly define the error. For this purpose, the structural and functional breakdown deeply investigated. A structural breakdown of the system shows that the key components of the GR are: Pipes, sensors, valves and compressors may be fall in breakdown mode.

System malfunctions are caused by pipes directing gas into the compressor or flare section, and sensors detecting the physical properties of the gas to signal the valves when the gas enters pressures or temperatures outside the acceptable range. It shows that it is transmitting, that the valve is changing the gas path, etc. Discharge capacity to prevent damage to more open compressors and piping. Compressors change the physical properties of the gas so that it can be recovered. A system failure can occur when a valve failure prevents gas from being rerouted when needed, when pipe damage prevents gas from being sent to the compressor, or when gas is sent to the compressor. However, the compressor has been damaged and is not ready to restore the gas. Valves fail under the influence of pressure and temperature fluctuations, which accelerates wear on the valve body. If the valve fails, there is a risk of damage to pipelines and compressors due to hazardous scenarios (5.3). So the error definition can be expressed as:

- Valves gradually deteriorate over time until they become unable to function properly when needed.
- This can lead to a hazardous situation where gas with abnormal temperature or pressure enters the system.
- If the automated system could not respond, the gas may not be directed appropriately due to valve failures,
- It can cause damage to critical pipes and the compressor, ultimately leading to system failure.

These four events occur sequentially, but their order cannot be enforced by FTA logical gates. DFTA gates are not suitable for this study. Therefore, an inhibit gate is used to describe the relationship between these events. The second event is not a failure but an occurrence that is included in the model with its probability presented in section 5.3. Valve failure data is gathered through a questionnaire in Table (2), which will be used as the basis for FIFTA analysis by inserting different numerical levels for pressures, temperatures, and times to study changes in valve and system failure probabilities. Pipe and compressor failure probabilities are obtained where experts specify the likelihood of component failures under one of three hazardous scenarios. The reason for the failure of these systems is due to the occurrence of hazardous scenarios that are not properly addressed. To address this, Rajakarunakaran et al. developed a method in 2015 for defuzzification. The resulting probabilities are not included in the FIFTA process.

- ***Constructing Fault Tree***

The first levels OVS and CDS fault tree diagram is accessible in Figure 4-a and 4-b respectively.

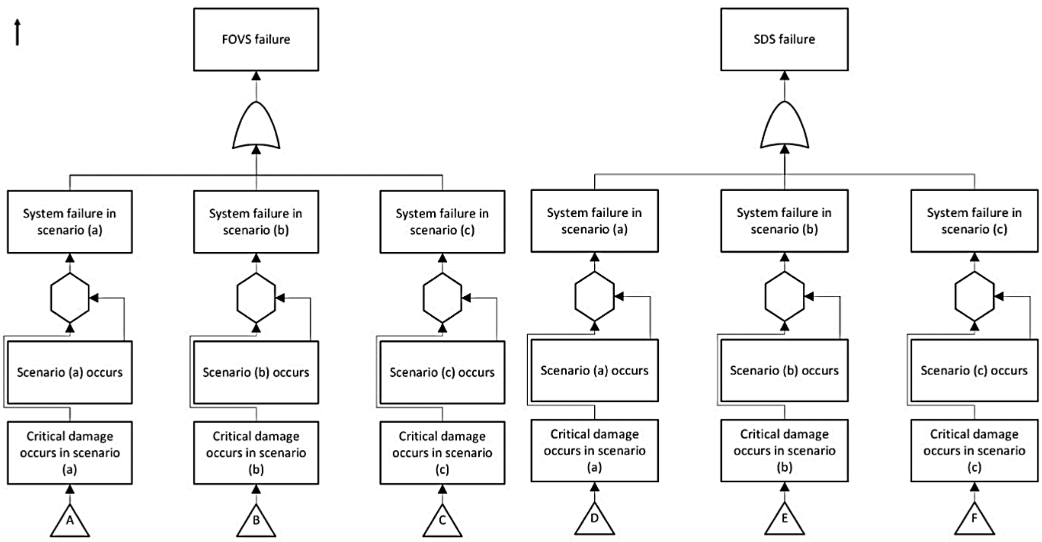


FIGURE 4
BASIC EVENTS OF OVS (A) AND CDS (B) IN FAULT ANALYSIS

- ***Risky Scenarios***

This research aims to analyze dynamic FTA in variant circumstances through examining extreme conditions that hereinafter each one will be referred to as a scenario. to investigate system failure under high-pressure operating conditions with a 33% of historical occurrences (scenario a). Scenario b examines low-pressure conditions with a 29% probability of occurrence, while Scenario c examines low-temperature conditions with a 22% probability of occurrence. To compare the OVS and CDS alternatives in these scenarios, six fault tree diagrams need to be erected. An example of such diagram presented on Figure 5.

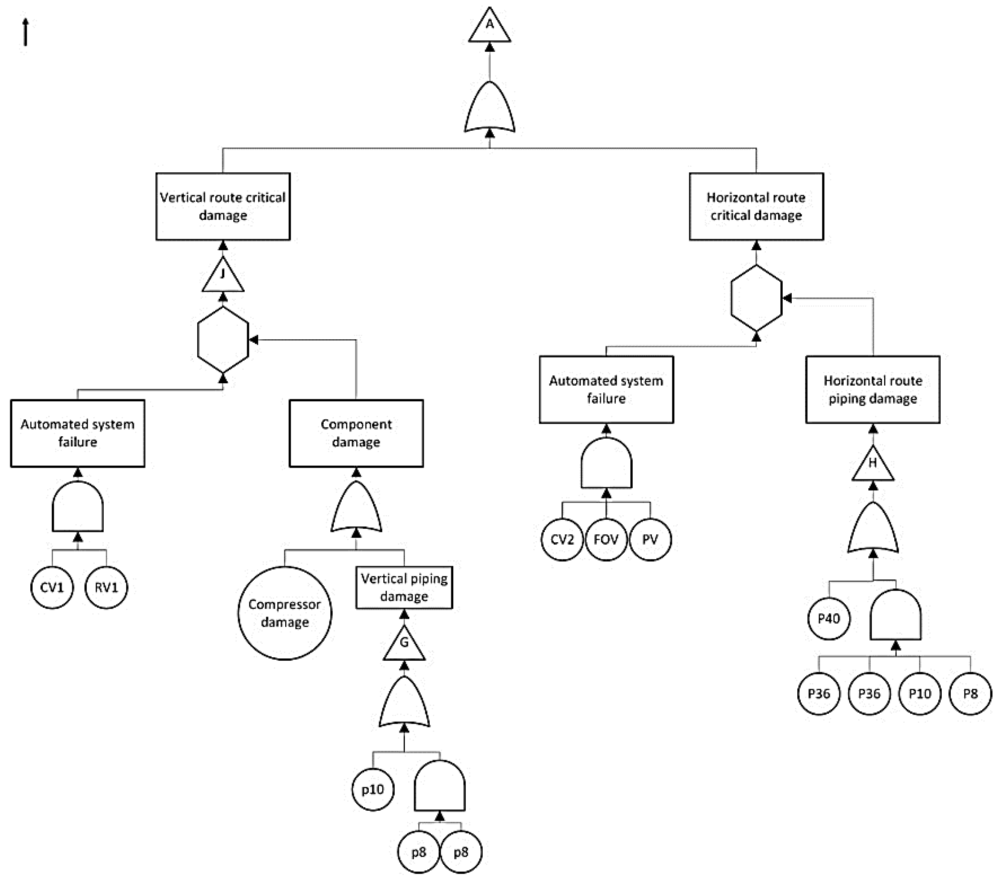


FIG. 5
FTA OF OVS UNDER THE SCENARIO OF HIGH-PRESSURE CIRCUMSTANCES

- ***5.4. To gather Data on Cell Formation***

A well-designed questionnaire must be utilized. This questionnaire asks experts to provide their opinions on the likelihood of component failure under specific operating conditions caused by contributing factors. For instance, the first cell of the questionnaire pertains to condition 1 (component serves at early age and low pressure and temperature exist). In this cell, an expert assigns a fuzzy term such as "low" to describe the likelihood of component failure under these conditions. This linguistic data contains multiple dimensions, including time, pressure, temperature, and failure possibility. Table (2) displays an example of a designed questionnaire. To process this linguistic data effectively, a Mamdani fuzzy inference system can be utilized. This system uses fuzzy logic to convert linguistic variables into numerical values for analysis and decision-making purposes. By using this system, it is possible to make accurate predictions about component failure under different operating conditions based on expert opinions gathered through the questionnaire.

- ***Fuzzy Inference System***

Likelihood of failures are investigated based on information collected by qualified professionals. Their decisions required a variety of operating conditions, using linguistic terms modeled by fuzzy numbers. For example, if one need to know the probability that a trailer that has been in use for 2 years will fail if it withstands at 50 bar pressure and a temperature of 0 centigrade. Here each cell represents this behavioral state with a degree between (0, 1), the membership function. Opinions for each operating condition are aggregated based on each cell's membership function to generate a probability of failure. In the example above, the probability generated by FIS suggests a probability of 0.02 for RV to fail under this condition. There are 9 types of valves in Table (1), and there are different views on the probability of failure for each, so it is necessary to develop an FIS for each. FIS has five functional blocks for measuring data using multiple input and output variables. Of the five blocks shown in (Sivanandam, Sumathi & Deepa, 2007), the database block and rule-based block store the given data, and when these blocks are formed, the other blocks are quantified. Run the composition of these two is as follows. After identifying I-O variables, their range is quantified. Then the range of variation divided by the anticipated fuzzy labels (3, 5, 10, etc.). Here, 3 designations are used for each input variable (the combination of which builds a questionnaire cell): high, medium, and low, and 25 designations are used for the output variables (opinion designations). For each fuzzy set, fuzzy membership functions are defined, consisting of the shape of each function (such as a triangle) and its bounds. This data is stored in database blocks. Its configuration is shown in the upper right of Figure 3. The shape and range of the membership functions for each variable depicted on Figure 6 using experts' judgment.

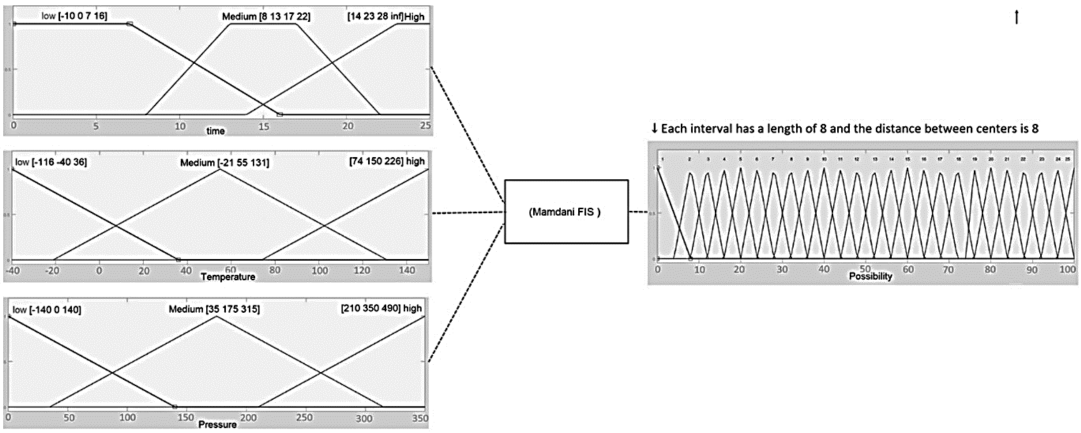


FIGURE 6
ANTICIPATED THE MAMDANI FIS

The opinions provided by 12 experts have fuzzy labels of possibilities and FIS rules kept in the rule base block that configuration is shown in the bottom right of Figure 3. His first two steps of forming a rule-base block are described in section 5.4 and 5.6.

- ***Survey zoning and experts***

FIS structure just will be thinkable when all level of the input variables were present in the questionnaire. Created too many cells, making human comparisons completely inaccurate. To reduce pair comparisons a regional system based on the amount of stress a combination of levels of associated aspects (one of the questionnaire cells) exerts on the component is used. . Components are more likely to fail under conditions of high stress. For comparison, instead of the 27-factor level (i.e., 3*3*3) in Table (2), 5 stress levels were specified to create a stress series consisting of 5 regions. The expert must enter a set of suggested ambiguous labels for each stress area in these areas. However, we were free to choose other values for different combinations within the same stress region if deemed appropriate. Table (3) demonstrates each exogenous level with its corresponding ambiguous label. Table (4) shows the limitations of membership functions for output variables.

TABLE 3
DESIGNATED LABELS

Stress level	C	Levels	Fuzzy labels
Green	G	Very low	(1,5)
Blue	B	Low	(6,10)
Yellow	Y	Medium	(11,15)
Orange	O	High	(16,20)
Red	R	Very high	(21,25)

The data was collected by a team consisted of 12 qualified engineers. Because of the differing opinions, aggregate weighting method applied in Table (5). Table (6) presents the calculated weighting factors for each engineer. Refer to Table (2) as the weighted average result of RV1 as an example. From there the rules are mined and listed in the relevant tables.

TABLE 4
RELEVANT EQUIVALENTS FOR FUZZY NUMBERS

label	Fuzzy range	label	Fuzzy range	label	Fuzzy range	label	Fuzzy range	label	Fuzzy range
1	(0,4,8)	6	(20,24,28)	11	(40,44,48)	16	(60,64,68)	21	(80,84,88)
2	(4,8,12)	7	(24,28,32)	12	(44,48,52)	17	(64,68,72)	22	(84,88,92)
3	(8,12,16)	8	(28,32,36)	13	(48,52,56)	18	(68,72,76)	23	(88,92,96)
4	(12,16,20)	9	(32,36,40)	14	(52,56,60)	19	(74,76,80)	24	(92,96,100)
5	(16,20,24)	10	(36,40,44)	15	(56,60,64)	20	(76,80,84)	25	(96, 100)

TABLE 5
SCORING SYSTEM

Constitution	Classification	Score
professionality	Professor, GM/DGM, chief Engineer, Director	5
	Asst. prof, Manager, Factory inspector	4
	Engineer, supervisor	3
	Foreman, technician, graduate	2
	Apprentice operator	1
Service time	>30 years	5
	20-30	4
	10-20	3
	5-10	2
	<5	1
Education level	Ph.D./M.Tech.	5
	M.Sc./B.Tech.	4
	Diploma/B.Sc.	3
	ITI	2
	technical college	1
Oldness	>50	5
	40-50	4
	30-40	3
	25-30	2
	<25	1

TABLE 6
EXPERTS' SCORES AND CALCULATED WEIGHTING FACTORS

# expe	title	score	service time (years)	score	education level	score	age	score	weighting score	Weighting
1	Engineer, supervisor	3	20-30	4	ITI	2	25-30	2	11	0.09
2	Apprentice operator	1	<5	1	technical college	1	<25	1	4	0.03
3	Foreman, technician, graduate	2	5-10	2	M.Sc./B.Tech.	4	<25	1	9	0.08
4	Foreman, technician, graduate	2	10-20	3	Diploma/B.Sc.	3	<25	1	9	0.08
5	apprentice operator	1	10-20	3	technical college	1	25-30	2	7	0.06
6	Engineer, supervisor	3	<5	1	M.Sc./B.Tech.	4	>50	5	13	0.11
7	Asst. prof, Manager, Factory inspector	4	5-10	2	ITI	2	25-30	2	10	0.08
8	Professor, GM/DGM, chief Engineer, Director	5	<5	1	ITI	2	<25	1	9	0.08
9	Engineer, supervisor	3	10-20	3	M.Sc./B.Tech.	4	<25	1	11	0.09
10	Engineer, supervisor	3	>30	5	technical college	1	25-30	2	11	0.09
11	Apprentice operator	1	5-10	2	M.Sc./B.Tech.	4	25-30	2	9	0.08
12	Professor, GM/DGM, chief Engineer, Director	5	>30	5	ITI	2	>50	5	17	0.14
	Total sum								120	1.00

FIFTA

After constructing the FTA, expert judges are kept to form the rule base block. Therefore, a FIS field is formed for each basic event, leading to points where the FIS should be linked to the drawn FT. An anticipated ranges (e.g. the 7th year at pressure 150 bar and temperature 50 °C) is selected as operating conditions (i.e. combination (i)). This combination is inserted as an input for each FIS, producing a probability value for each significant event. The probability of the causal events are inserted into his FTA to compute the top event probability. New combinations are then selected to generate innovative top event probabilities until enough points are generated to plot the response surface. The result is an n-dimensional surface (n-1) presents here the number of factors, the vertical axis shows the FT output. The horizontal axis displays the contributing factors. This process is shown in the middle of Figure 3. Figure 7 displays how the output points are generated.

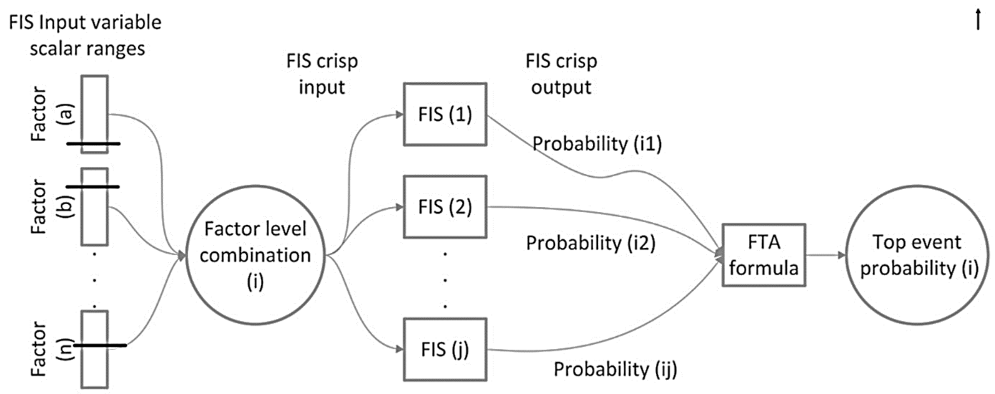


FIGURE7
OUTPUT OF FTA FOR FIFTA

His four-dimensional response surfaces for both systems are drawn and shown in Fig. 8. Time is separated as four dimensions. The ability to simultaneously observe the effects of time and two other factors is a unique feature of this technique.

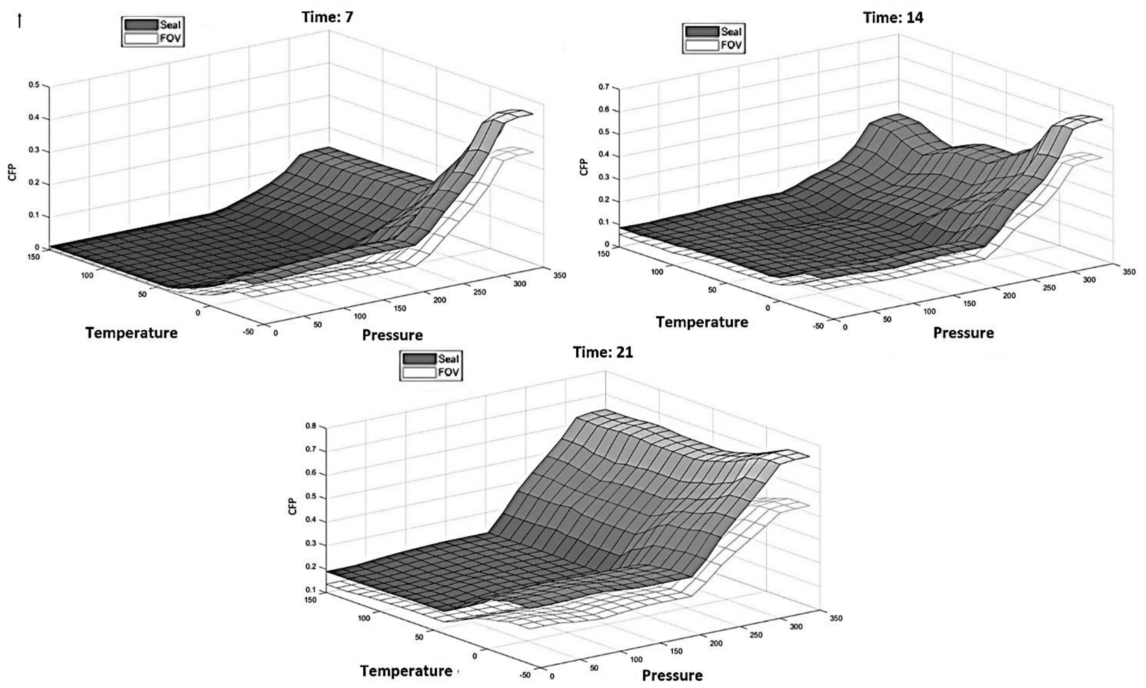


FIGURE 8
CUMULATIVE DENSITY OF FAILURE AT DIFFERENT OPERATIONAL CIRCUMSTANCES AFTER RUNNING LONG PERIODS; 7, 14 AND 21 YEARS

RESULTS AND DISCUSSION

FIFTA will generate enough points to construct the surface for each choice. The cumulative probability of b regions is a function that maps operating conditions to probability values. This demonstrates the resilience of each breakdown under different operating conditions. Note that cumulative failure probabilities are plotted as convex functions instead of reliability for clarity. It is known that R(t) is equal to complementary of cumulative probability. For data generation he uses FIFTA so that the area can be plotted on the plane of pressure and temperature over the age of the system. Each year, 25 surfaces were drawn for the system, and the surfaces embeds the significant changes were selected. The cumulative failure probability are drawn to facilitate selection among the proposed alternatives due to differences in reliability. In the displayed graph, the CFP surface area of OVS is consistently lower than that of CDS, implying that OVS is more reliable than CDS under all operating conditions. So in affected refineries he has better OVS than CDS and could potentially be installed in front of flare towers. In order to simplify the representation, Table 7 displays the pressure-temperature plane which segmented into nine regions.

TABLE 7
OF DIVIDED AREAS ON THE TEMPERATURE, PRESSURE PLAIN

Temp. \ Pressure	[0,200)	[200,300)	[300,350]
[100, 150]	1	4	7
[0, 100)	2	5	8
[-50, 0)	3	6	9

Each domain is a overall operating condition under which the system behaves moderately similar. For each region, some points at the surface are selected and the average of their CFP (ACFP) presented in Tables (8, 9, 10). Percent difference in ACFP for CDS and OVS presented in the last column of the tables.

TABLE 8
ACFPS IN 7th YEAR

Area	score	ACFP (SDS)	ACFP (FOVS)	Difference of ACFP (FOV-SDS)/FOV
1	2	0.012	0.0126	4.76%
2	1	0.014	0.0149	6.04%
3	3	0.112	0.146	23.29%
4	2	0.037	0.048	22.92%
5	1	0.031	0.052	40.38%
6	4	0.227	0.253	10.28%
7	4	0.131	0.144	9.03%
8	3	0.151	0.167	9.58%
9	5	0.257	0.35	26.57%

As expected, the CFP exterior area of CDS is always above than OVS, so there is always a positive difference in the last column. Apart from the results obtained with the alternatives considered in this work, in other cases there may be an ambiguous winner after drawing the surface. In some intervals, one alternative surface may be partially be above or partially below the other one.

TABLE 9
ACFPS IN 14th YEAR

Area	**Score**	**ACFP (SDS)**	**ACFP (FOVS)**	**Difference of ACFP (FOV-SDS)/FOV**
1	2	0.0603	0.074	18.51%
2	1	0.0551	0.0667	17.39%
3	3	0.125	0.172	27.33%
4	2	0.15	0.204	26.47%
5	1	0.13	0.181	28.18%
6	4	0.2	0.303	33.99%
7	4	0.253	0.326	22.39%
8	3	0.24	0.3	20.00%
9	5	0.462	0.543	14.92%

To decide between these alternatives, you can assign different ratings to each of the nine areas. Thus, it is meaningless to obtain the same reliability value under different operating conditions.

TABLE 10
ACFPS IN 21th YEAR

Area	**score**	**Average CFP (SDS)**	**Average CFP (FOVS)**	**Difference of ACFP (FOV-SDS)/FOV**
1	2	0.14	0.193	27.46%
2	1	0.157	0.201	21.89%
3	3	0.24	0.33	27.27%
4	2	0.273	0.432	36.81%
5	1	0.261	0.385	32.21%
6	4	0.32	0.402	20.40%
7	4	0.313	0.436	28.21%
8	3	0.307	0.421	27.08%
9	5	0.532	0.715	25.59%

Ratings are listed in column 2 of the table 10. A weighted average can be calculated using the area's score as the weight of the ACFP for that area to get a single number for the entire area over time. A two dimentional graph showing the difference i is depicted in Figure 9.

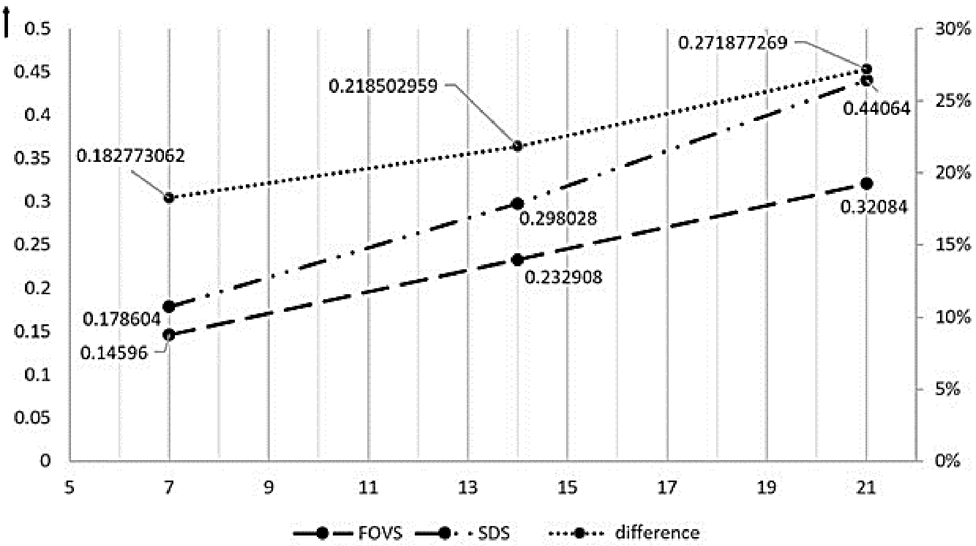


FIG.URE 9
WEIGHTED AVERAGE OF ACFPS OVER RUNNING TIME

Table (11) displays the average weighted of ACFP. Also the Figure 9 presents that OVS has a clear advantage due to the lower lifetime cumulative failure probability (average 22.4% difference). We also see that the performance difference increases over time, and that concludes our comparison.

TABLE 11
WEIGHTED AVERAGE OF ACFPS

Time (year)	SDS	FOVS	Difference%
7	0.15	0.18	18.28%
14	0.23	0.30	21.85%
21	0.32	0.44	27.19%

You can also use the surface to evaluate each option individually. The information below may be of interest to design teams, maintenance teams, and administrators. The most dangerous scenario that can occur in a security system is when high pressure (250, 350) and low temperature (-50, 0) gas flows through the system and failure is most likely. Additionally, Figure 8.c identifies the safest operating conditions and indicates the longevity of the system. The combination of pressure (50, 200) and temperature (50, 150) is the most reliable and safest operating condition for both systems. The minimum pressure level for minimum flow to avoid flashback is '50'. The paragraph above highlights the potential for other uses of the results obtained from FIFTA if the contributing factors can be controlled. Surfaces derived from FIFTA can be used to identify optimal operating regions with higher confidence scores and maintain the level of contributors in the identified regions. These default limits can be implemented in monitoring or control subsystems. In addition, identifying the operating conditions that lead to the lowest reliability can improve the design of the system. Components that are sensitive to that operating condition can then be replaced with more tolerant components (for example, if high temperatures affect reliability, the system can use high temperature tolerant components).

VALIDATION

To determine the validity of the proposed method, the simulation method has been applied and the fault tree analysis calculations have been studied according to the probability of the basic events. For this purpose, failure rates from two different databases have been compared. Valve failure rates are available in the OREDA database, and also pipe failure rates were determined from real refinery maintenance records. We have compared the reliability of each alternative during 5 years of operation and it has been shown that the differences are not significant. The results presented that the reliability of CDS was higher than that of OVS, proving the validity of our method. However, there is a significant difference between the weighted average of ACFP and the unreliability by failure rate. Our conclusion is that the assigned weights used to simplify the four-dimensional plots need to be changed, and the fuzzy region of likelihood is used to make the weighted average of the ACFP closer and closer to the reliability of the failure rate. The proposed method allows designers to inspect each component under different operating conditions. This can lead to errors. In addition, system reliability can be evaluated under various operating conditions.

Conclusion

Although in many practical cases, the choice of decision making on the best option is based on economic and qualitative comparisons, but in cases where the investment costs are high or the occurrence of malfunctions leads to irreparable damages, estimation of reliability a vital task in nominating the appropriate technology. This research focused on a complicated case study in this issue, consequently as the contribution of the paper we proposed a special dynamic reliability assessment methodology using a combinatorial design of FTA and FIS to tackle the challenge arises from vitiate operating condition as well vagueness of data. The two alternatives in the case study compared in terms of reliability surfaces. Results reveals that OVS outperforms than CDS. Since the systems are evaluated under different operating conditions, the comparison is relatively comprehensive and fully justifies the final decision. Considering multiple factors also helps prevent unexpected failures of security subsystems. The surfaces also deliver awareness on design improvements and process control by demonstrating system resilience to different operating conditions. Moreover, given the opportunity to control the contributing factors, the surface may approach the normal limit for that level. Now, based on the results obtained, we can hypothesize that the winner will not be subjected to simultaneous increases in outlet temperature and pressure.

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