Intelligent Monitoring Using Hazard Identification Technique and Multi-Sensor Data Fusion for Crude Distillation Column

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Abstract. Hazard assessment techniques and multi-sensor fusion are used for intelligent systematic monitoring. Firstly, a hazard identification technique is considered using failure mode and effect analysis and advantages of using a combined hazard technique is discussed. Data sources are identified considering component failures and some sensors associated with potential failure. Possible consequences in a hazardous situation are identified using failure mode and effect analysis to choose suitable safety measures. Failure mode and effect analysis is systematically considers how sequences of events can lead to accidents by looking at components and faults recorded by sensors and anomalies. Data were presented based on their threat levels using a traffic light color code system. Refineries use sensors to observe the process of crude refining and the monitoring system uses real-time data to access information provided by sensors. Understanding hazard assessments, sensor multi-fusion and sensor pattern recognition in a distillation column could help to identify trends, flag major regions of growing malfunction, model risk threat of a crude distillation column and help to systematically make decisions. The decisions could improve design regulations, eliminate anomalies, improve monitoring and reduce threat levels.

Keywords: Hazard, Sensors, Crude, Distillation, Sensor, Intelligent, Monitoring.

1 Introduction

In gas and oil industries, sensors are used to constantly monitor situations to avoid a likelihood of disasters.

A refinery operates in a closed uniform environment that contains some mixture of varying pressure and temperature conditions. This could result in catastrophic events if not monitored prudently. The monitoring of numerous sensors in a refinery could be time-consuming and labour intensive even with periodic maintenance, faults might not be detected during maintenance [1-3].

Assessing the safety of a complex refinery involves the handling of historic data, fuzzy risk parameters and incomplete models of risk. A quantitative or qualitative approach to safety could be used but to achieve that assessment, it may be possible to categorize risk elements that might cause events leading to systems failure [4].

Analysing risk involves a logical reasoning of cause and effect [5]. Most models for analyzing risk use quantitative approaches, that is a mathematical approach to quantifying risk in terms of consequences and their likelihood of occurring [6]. Risk evaluation is important in studying risk of hazards. Durrant in [7] emphasized a need for machine learning and data mining techniques to extract knowledge / information from gas and oil industry data. Data mining applications have been described in [8-11].

Detecting faults within refinery sensors is important because:

- It helps with making decisions about whether production processes should be halted before situations become critical, even if significant information may be missing.
- It can help operators to decide on maintenance needs.
- Detecting repeated similar faults could provide information about sensor quality and could lead to improved design.

FTA was applied to a section of a crude distillation column and the basic events were identified in Fig. 1. Fig. 1. shows the causes that led to the event as shown.

Fig. 1. Fault Tree Analysis of leak in a pipeline.

2.3 Event Tree Analysis

Event Tree Analysis (ETA) is technique for assessing safety, especially after an abnormal function or accident. ETA is an inductive reasoning process. The process begins with some initiating-event and produces an illustration to analyze the effect of a set of undesirable events [14].

ETA establishes the frequency or probability of an accident. Suitable safeguarding measures can then be put in place to prevent or at least to mitigate escalation following an undesired event [14]. An initiating-event is created depending on some initiating conditions (no / yes, false / true, failure / success) and then the consequences of the event are traced within branches of the ETA [15].

3 Using Combined Hazard Techniques

Bow-tie analysis can be helpful for combining hazard analysis techniques and identifying risk from both techniques.

3.1 Bowtie Analysis

Bowtie analysis is a probabilistic approach based on consequences and causes of undesirable events [16]. It is a logical method that establishes relationships between cause and effect that can be used to mitigate, control and prevent accidents [15].

Bowtie analysis has been used to assess risk, safety and reliability of complicated systems. Bow-tie is a risk approach that graphically displays the relationships between hazardous events; its causes and consequences and the risk control barriers in place to stop the accident sequence (Fig. 2).

Fig. 2. Bow-tie analysis explaining the relationship between barriers, threat and consequences

3.2 Fault Tree and Event Tree Analysis

Investigating failure modes using event tree (ETA) and fault tree (FTA) has been an effective way of identifying failure. These might include human error or concurrent component failures. The combination allowed for an analysis of cause and effect that can lead to technical breakdown or accident.

The use of ETA and FTA in the new work described in this paper provided a thorough analysis of potential hazards and their potential causes. That helped improve overall performance. FTA and ETA are complimentary (and they have often been used together) but they focus on opposite sides of an undesired event. Bow-tie analysis can link both methods together and the new combination of FTA and ETA can help to determine a single undesired event that could lead to catastrophe. In reality though, multiple causes can initially lead to different events, with each of them expanding into multiple consequences. FTA focuses on preventive measures and ETA on mitigation measures [15] as shown in Fig. 3.

Fig. 3. Combined hazard techniques using FTA and ETA.

Bow-tie Analysis involved combining both deductive and inductive techniques based on an ETA and FTA.

Table 1, shows a matrix table of 50 years of crude distillation tower failure, with failure modes identified, and effects identified, with possible sensor/fault detection listed. A hazard technique using FMEA was applied to the data using a colour coding system from a scale of 1 -10 to identify the occurrences, detectability and severity to calculate a risk priority number. Red represented a more catastrophic state, amber represented a critical operational margin and green represented an optimal operational condition. A Risk Priority Number (RPN) formula was used.

$$RPN = O \times D \times S \quad (1)$$

The higher the RPN number, the higher the risk value of the system (components). The lower the RPN the lower the likelihood of risk. Data in Table 2 shows that Abnormal operation incidents (Start-up, shutdown, commissioning) represented the highest failure mode in a crude distillation column, while heat integration issues accounted for the lowest number of modes of failure for the system.

Table 2. Crude distillation tower risk matrix.

Function	Failure Mode	Effect Causes	Possible Control /Fault Detection Sensors.	O	D	S	RPN	Action
Tower Column Malfunction	Tower base	High and low base level, Vapour Misdistribution.	Through changes in temperature and pressure.	8	4	6	192	Prevent excessive tower base level, good sump design.
	Re-boiler return	Faulty level measurement or control, Excess re-boiler pressure drop.	Through change in level sensing and change in pressure.	5	3	6	90	Have a frequent assessment checks, have a level sensor in place.
	Damage to internal tower	Insufficient mechanical resistance, water induced pressure, high .	Abnormal operation, change in Temp& Press. Readings.	8	2	7	112	The key prevention is to keep the water out.
	Water induced surge	Undrained stripping steam lines, water in feed/slop.	Change in temperature and pressure.	6	3	8	144	Monitor water in-let, avoid abnormal operation
	Abnormal operation incidents (Start-up, shutdown, commissioning)	Backflow, water removal from refinery fractionators, leads to plugging/coking and internal damage.	Flow transmitter and Level sensing.	8	4	8	364	Implement hazard techniques HAZOP and conduct frequent safety audits.
	Assembly mishaps	Incorrect assembly or packing.	X-ray, acoustics sensors.	7	5	7	196	Introduce / initiate a systematic and thorough tower process inspection programs.

Tower Column Malfunction	Packing liquid distributors	Plugging and overflow, poor irrigation quality, feed entry problems.	Level sensor, Flow transmitter.	6	4	7	168	
	Intermediate draws (includes chimney trays)	Leakage at the draw, restriction or vapour choke of draw line, plugging /coking, level measurement, vapour impingement.	Level sensor, leak detector.	5	3	8	120	Review the design of the intermediate draws, Reduce pushing of towers to maximum capacities.
	Re-boilers	Excess change in pressure in kettle circuit, Forced circulation of re-boilers.	Pressure sensor.	5	4	7	140	Reduction and evaluation of troublesome re-boiler types.
	Chemical explosions	Decompositions of compound, chemical release, violent reactions.	Pressure and temperature sensor.	4	9	8	288	Reduce excessive temperature and catalysis of metal or catalyst by air leaks.
	Leaks	Heat exchangers (re-boiler tube, preheater, pump around exchanger condenser), Column chemicals to atmosphere.	Temp' sensor.	3	7	3	63	
	Simulations	Poor VLE predictions.	Pressure sensor.	3	6	5	90	Understanding and having a good VLE prediction.
	Condensers issues	Inadequate venting, inadequate condensate removal, flooding/ entrainment in partial condenser.	Pressure sensor.	3	2	6	36	Ensure the vent is clean, well vented and draining.
	Heat integration issues	High degree heat integration practiced (multi-feed arrangements), preheaters, inter-reboilers and recycle loops.	Temp' sensor.	1	3	6	18	Bypass tower or preheater.

4 Sensors and Sensor Fusion

Sensors are devices designed to receive prompt and respond with an electrical signal and they can be modified and amplified by electronic devices.

Sensors are energy converters and some quantities that could be sensed include: motion, displacement, force, strain, pressure, flow, sound, moisture, light intensity, radiation, temperature, chemical presence velocity and acceleration.

White [21] defined multi-sensor fusion as a multifaceted and multi-level process to automatically detect, associate, correlate, estimate, and combine data (or possibly information) from numerous sources. Klein [18] generalized the definition, saying data could be from multiple sources or a single source.

4.1 Sensor Pattern Recognition

Research described in this paper investigated using Artificial Intelligence (AI) techniques for sensor fusion, especially pattern recognition. Pattern recognition depended mainly on trend data and data acquired from sensor's information. Combinations of data from multiple-sensors were considered. Pattern recognition and AI techniques can convert large amounts of real time data into smaller pieces of information. That can allow complete system analysis and clustering methods and to be used.

The new proposed strategy is shown in Fig. 4. It aims to combine both the potential failure mode of a system with various sensor faults, and a scoring technique to analyze and identify systemic risk. The goal was to improve accuracy and reliability.

Fig. 4. Sensor pattern recognition and failure mode identified.

5 Machine Learning Using Data Fusion

Sensor fusion was used within machine learning to build a prototype intelligent monitoring system. The combination of multiple sensors could establish a pattern that could help create machine learning to find patterns in existing data. It used a model that recognized patterns in new data (Fig. 5).

Fig. 5. Machine-learning Patterns through sensor fusion.

6 Discussion and Conclusion

A methodology for intelligent monitoring using multi-sensor fusion for a crude distillation column was presented. The method explained the technique using simple input and output information and observing information. The idea was to provide a control solution using a binary matrix to predict trends in order to create an accurate monitoring system.

Focusing on risk assessment methods applied to a distillation column helped with the identification of trends and some regions where the likelihood of malfunctions may be growing. The history of malfunctions was studied and future work may simulate column malfunctions to assist operators and engineers. Using combined hazard-modelling techniques to model risk threat to a crude oil distillation column during operational disturbances could help to systematically make suitable decisions. That could help to improve design regulations and identify potential hazards, eventually leading to safe operation.

Table 1 identified the failure mode and effect analysis technique used. It was integrated into a practical example using 50 years of historical data (Table 2). FTA was introduced. Bow-tie analysis (Fig. 2) demonstrated how two-hazard analysis techniques could be combined to create a more robust risk identification technique to improve fault detection and data reliability, and eliminate any previous improper datasets.

Multi-sensor fusion improved observability by broadening the baseline of physical observable and this could result in significant improvements. The use of a single sensor might not be effective in creating an intelligent monitoring system. With the complexity of combining sensors to create a learning algorithm, it is easy for a data set to be mismatched. Multiple sensor fusion could help to establish a pattern from independent sensors though to form a systemic way of thinking. This method helped in improving pattern recognition which could be implemented into machine learning. That could be used to detect or predict anomalies, predict faults and possibly predict catastrophes.

A limitation was a concern with the accuracy and reliability improvements. Future work will investigate phase changes and material balance on sensor fusion performance and the data will be fed into some intelligent control systems that have recently been used to control powered wheelchairs [24-28]. It will also be used with decision-making systems [29-31] and decision-making algorithms that are currently being investigated [32-40].

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