Using Artificial Intelligence and Machine Learning Techniques to Analyze Incident Reports

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The consequences of failure for petrochemical separation and refining can be devastating as they deal with hazardous materials, at high temperatures and/or pressures. To prevent such incidents from recurring, we need to understand the causes and controls. Company incident databases contain substantial amounts of incident information that can be analyzed to determine trends, patterns, causal relationships and correlations between incident-causing factors and incidents. The aim of this research is to apply Artificial Intelligence (AI) and Machine Learning (ML) to reduce the human bias involved in providing a risk rating using a risk matrix and better understand the underlying causes of incidents and causal relationships that might be found between different incident types. These correlations could lead to an incident with compounding severity or simply cause other unexpected incidents over time.

Over the course of this study, a total of 31,851 incident reports from an oil and gas company operating in northern Alberta were considered, and 8,199 were selected and analyzed. The selected incident reports provided an adequate description of the incident and included a completed root cause analysis. The research was completed by utilizing machine learning algorithms to classify incidents according to Process Safety Management (PSM) elements developed by the Center for Chemical Process Safety (CCPS). Risk severity was also calculated by utilizing a combination of a standardized risk matrix as a guideline and machine learning methods to assign a final risk score to incident reports. The classified incidents were then used as inputs for a Bayesian Network (BN) which determined causal relationships between incident types, human factors, and the total number of incidents. The three factors having the strongest causal relationship with total incident count were *Asset Integrity and Reliability*, *Management Review & Continuous Improvement*, and *Hazard Identification & Risk Analysis*. Previous research has explored the results of improving *Asset Integrity and Reliability* and *Management Review & Continuous Improvement*. This study will suggest how companies can improve *Hazard Identification & Risk Analysis* and the benefits of doing so.

Key words: Process Safety, Risk Matrix, Incident Data, Bayesian Network, Machine Learning.

Introduction

The oil and gas industry continues to advancement its technology, regulations and standards, and efficiency and safety of operations (Sammeth, 2019). The industry at large has made a concerted effort to control risks and incidents; however, incidents continue to occur demonstrating insufficiencies in safety and risk management systems. Some examples of major disasters within chemical process and oil and gas industries include the Piper Alpha Disaster, Bhopal Disaster, Flixborough Disaster, and Texas City Refinery Explosion. Detailed investigations of these incidents have revealed many causes – including compounding factors – and, increasingly, organizational and management factors (Okoh & Haugen, 2013). Sovacool (2008) states that 179 incidents between 1907 and 2007 have been responsible for 182,156 deaths and approximately $41 billion in property damage globally. Large scale disasters help bring to light externalities often ignored in industry and further emphasize the need for research to reduce the damage and loss caused by incidents.

In seeking to understand the cause of incidents, we use risk principles. Risk is defined by the International Organization for Standardization (ISO) as uncertainty which can affect an organization as it attempts to achieve its goals (ISO, 2018). Managing risk involves tailoring processes specific to each project (PMBOK Guide, 2004). In order to properly manage risk, organizations need to identify, analyze, and evaluate risk before taking appropriate courses of action – planning adequate responses, implementing changes, and conducting regular monitoring and maintenance activities. An effective method for identifying and better understanding risks is to analyze historical data (Patriarca et al., 2018). In the oil and gas industry, particularly in Alberta, it is necessary for companies to maintain incident databases with incident reports that contain information about an incident's location, time, date, name of the employer involved, site contact information, and a general description of the incident (Government of Alberta, 2019). Many companies also include a variety of analyses; for example, Bow Tie (BT) analysis, Root Cause Analysis

(RCA), Fault Tree Analysis (FTA), Hazard and Operability (HAZOP) studies, Failure Mode and Effects Analysis (FMEA), etc. Therefore, by studying incident data, companies to gain knowledge which can be used to train workers to learn appropriate responses and countermeasures in dangerous situations.

One common tool used for risk evaluation is the risk matrix. The PMBOK Guide (2017) defines risk as the product of probability and consequence. Figure 1 displays a standard risk matrix with likelihood (or probability) on one axis and consequence (or severity) on the other. Risk matrices are often color-coordinated and/or zoned based on an organizations' risk tolerability (Kletz, 2005; Markowski & Mannan, 2008). The different zones within a risk matrix demarcate low-level risks as acceptable and high-level risks as intolerable. Medium level risks can be further categorized as tolerable acceptable or tolerable unacceptable. The goal of risk acceptability principles is to understand an organization's risk tolerability, assess all risks, and reduce intolerable risks to an acceptable level by either reducing the likelihood of the risk or mitigating the consequences. Furthermore, continuous risk monitoring must be implemented to identify new risks that might emerge and to ensure that risk prevention and mitigation strategies remain up to date (PMBOK Guide, 2017). Due to its simplicity, ease of use, and presentability, the risk matrix is one of the most widely used tools for risk evaluation and prioritization (Animah & Shafiee, 2019; Gul & Guneri, 2016; Landell, 2016).

		A	B	C	D	E
		Negligible	Minor	Moderate	Significant	Severe
E	Very Likely	Low Med	Medium	Med Hi	High	High
D	Likely	Low	Low Med	Medium	Med Hi	High
C	Possible	Low	Low Med	Medium	Med Hi	Med Hi
B	Unlikely	Low	Low Med	Low Med	Medium	Med Hi
A	Very Unlikely	Low	Low	Low Med	Medium	Medium

Figure 1. A sample risk matrix that can be used for risk evaluation (PMBOK Guide, 2017).

While risk matrices have many benefits, they also have several weaknesses (Bjerga & Aven, 2015). One of the most glaring is the human bias involved in providing a risk rating. Centering bias – the tendency of people to avoid reporting extreme values – is common (Thomas et al., 2013). Yet, incident data is often highly skewed - with a large number of high frequency, low consequence events and a small number of low frequency, high consequence events. With different individuals analyzing incident reports, it is likely that similar incidents can be given different risk ratings by different people. It is even possible that the same person might rate the same risk differently at a different time. Many of the issues pertaining to bias and inconsistencies can be resolved by introducing AI and ML. The rule-based process of using a risk matrix can be bolstered by automating the system using a supervised machine learning algorithm to consistently classify incident reports and assign risk rankings.

In this paper, we use AI to to analyze reports and, ideally, better understand and reduce incidents. The topic of AI is a broad and diverse field that is influencing every aspect of human life. Beyond practical applications, over 20,000 publications in 2019 alone focused on AI research (Brynjolfsson et al., 2019). AI is defined as the ability to process information and generate outcomes that mimic human thought processes and actions. Using AI, a computer can use datasets to 'learn' and then make decisions, allocate resources, and solve problems (Pishgar et al., 2021). As technology advances, AI is being implemented various technologies including sensors, robotics, data management, and software covering a wide range of tasks that include general reasoning, proving mathematical theorems, writing poetry, diagnosing diseases, and playing chess (Wang & Lu, 2019). In the oil and gas industry, AI is being used in initial exploration activities all the way through to the end user. It is being implemented in exploration, design and development, production and operations, inspection and maintenance, transportation, refining, and sales.

Machine learning is a part of AI. Where AI enables computers to imitate human intellect and behavior, machine learning utilizes statistical algorithms to enable AI implementation by using data. Currently, there is great development in the application of ML to inspection and maintenance data. Operations provide a great deal of information, and such data can be used to optimize maintenance schedules and automate the process of inspection. The use of ML algorithms to classify data has several advantages. Automating a process can remove bias and allow for consistent classification. Having a consistent classification system in place will allow a better understanding of data and has the potential to ease follow-up analyses such as trend analysis. The use of AI and ML in risk analysis is becoming more prevalent. For example, Stanojević and Ćirović (2020) modified the traditional FMEA method by integrating fuzzy logic and classification of recognized failures. The application of ML in FMEA reduced methodological inconsistencies and addressed other weaknesses in the traditional use of FMEA. The modified FMEA, aptly named the "intelligent" FMEA or IFMEA has demonstrated an increased precision in failure risk evaluation, better prediction, and reduction in number of failures.

In this research, we use a ML algorithm to provide a risk score to incidents by using a standardized risk matrix to provide a baseline for evaluating risks. Machine learning will also be used to classify incident reports into different PSM elements which will be used as inputs for a Bayesian Network – this process is explained in detail in the next section.

Methodology

This research follows a sequential process: 1) machine learning classification, 2) develop Bayesian Network, and 3) analyze the results of Bayesian Network analysis.

The type of classification depends on how the results are used. In this research, BNs are used to better understand causal relationships between different parameters. To input incident reports into a BN, it is necessary for these reports to be classified or labelled. The structure of the resulting BN network will be detailed later. For this research, we analyzed incident reports from 2014 (15,674 incident reports) and 2015 (16,177 incident reports) from an oil and gas company operating in northern Alberta. Classifying such a large number of incident reports might seem to be a gargantuan task, but the process can be simplified by adopting a machine learning approach. Figure 2 displays the sequential process used to classify incident reports using machine learning.

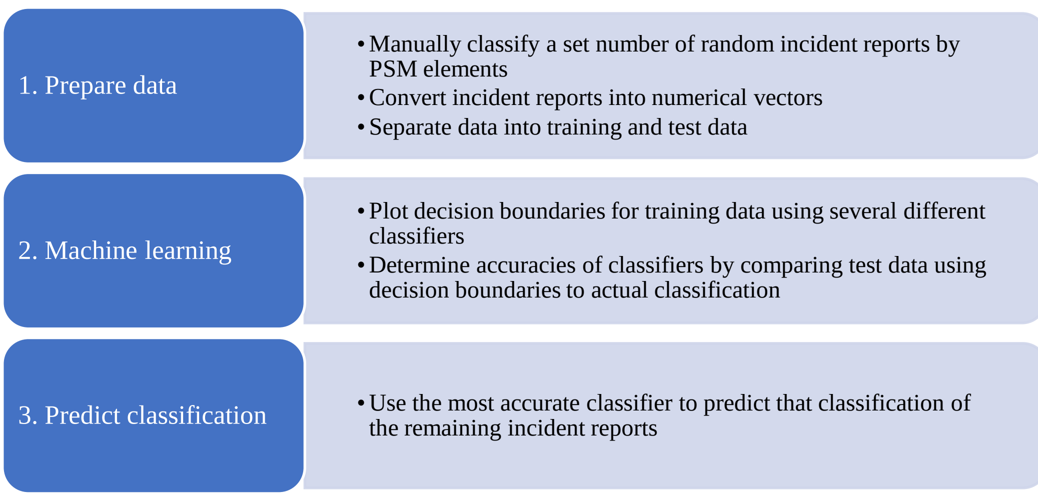

Figure 2. Machine learning process for the classification of incidents according to elements of PSM defined by CCPS

The first step of data preparation was to select which incident reports to use in the analysis. The company that provided the incident database had already completed preliminary investigations for many of their incident reports including root cause analysis. We began by narrowing the scope to incident reports with completed root cause analysis resulting in a total of 8,199 incident reports. By doing this, we were able to reduce the margin of error in classification by avoiding poorly reported incidents.

The oil and gas industry is highly hazardous due to nature of the products, processes, and variety of equipment . These hazards can have severe consequences on people, the environment, a company's financial value and reputation. The Center for Chemical Process Safety (CCPS) has developed a set of guidelines for implementing PSM to manage hazards and risks associated with the use, manufacturing, handling, transportation and storage of hazardous chemicals. The PSM system incorporates a total of twenty elements distributed across four prevention pillars (or foundational blocks) as seen in Figure 3.

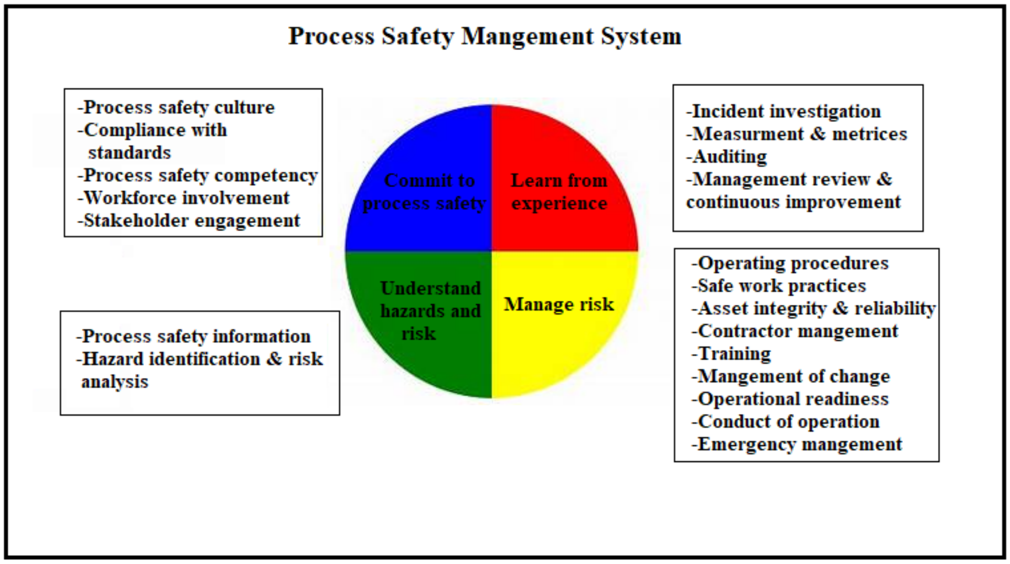

Figure 3. Adapted from risk-based process safety management elements (CCPS, 2011).

Supervised machine learning algorithms use predictor features to predict a class label (Kotsiantis, 2007), given that class labels are known. This is one e of the major differences between supervised and unsupervised machine learning. For this research, the predictor features are the incident reports and features found within incident reports. The class labels are assigned categories – consequences of incidents as defined by the risk matrix and the elements of PSM as defined by CCPS. The likelihood of an incident occurring can be calculated by tallying the actual occurrence of different types of incidents. For this research, we selected elements from PSM that completely classify the incidents in the database provided. These elements are: *Compliance with Standards*, *Process Safety Information*, *Hazard Identification & Risk Analysis*, *Operating Procedures*, *Safe Work Practices*, *Asset Integrity & Reliability*, *Contractor Management*, *Training*, and *Management Review & Continuous Improvement*. It is important to note that some elements were not used as there was insufficient information in the incident reports to be able to justify classifying an incident report under the remaining elements.

In order to train a supervised machine learning algorithm, a large number of incident reports have to be classified manually to set a guideline (Raschka & Mirjalili, 2017). An accepted method for training a machine learning algorithm is to separate data into a training set and a test set, where the entirety of the data must be manually classified. We randomly selected 10% of the total number of incident reports to classify manually. By convention, the 820 incident reports that were manually classified were divided into a training set containing 574 incident reports (70% of the randomly selected data) and a test set containing 246 incident reports (30% of the randomly selected data) using the train/test split method. As the names imply, the training set is used to train the program while the test set is used to determine the accuracy of the different classifiers. Accuracy is determined by comparing the "predicted" values calculated for the test set by the machine learning algorithm to the "true" manually classified data.

Typical classification problems are numerical – a dataset can be displayed graphically, and decision boundaries can be drawn to separate different numerical values. Unlike a typical numerical dataset, however, incident reports are almost entirely textual. Python's scikit-learn library contains a feature called TfidfVectorizer that can be used to convert textual incident reports into numerical vectors. These numerical vectors can then be used for classification (Garreta et al., 2017). Tfidf or Tf-idf is short for term frequency times inverse document frequency. Term frequency refers to the number of occurrences of a term within a document, which can also be scaled for document length. Inverse document frequency refers to a weight that is applied to terms based on their frequency within a document and the final compiled dictionary. A high weight is applied to terms that appear multiple times in the same document but very few times in the dictionary. A low weight is applied to a term that appear frequently throughout the dictionary. Applied to this research, a single word in an incident report is a term, an incident report is a document, and the entire incident database is a dictionary. In summary, a dictionary (incident database) is built using the terms (words) found in the documents (incident reports) and weights are applied based on the occurrence of each term (word). The final result is the transformation of text to a numerical vector. Python has several classifiers built into its scikit-learn library that can be used for supervised machine learning.

For this research, we considered every classifier built into the scikit-learn library that was compatible with the data with the intention of identifying the classifier with the highest accuracy. Compatibility refers to the initial textual nature of the data – the vectors generated using the TfidfVectorizer are considered sparse matrices meaning that the majority of numbers in each vector are 0. This sparseness can result in incompatibility with some classifiers. The classifiers selected include: Adaboost classifier, decision tree classifier, k-nearest neighbors, logistic regression, multi-layer perceptron classifier (MLP), multinomial Naïve Bayes (MNB) classifier, random forest (RF) classifier, and support vector machine classifier (SVC). Once the data from the vectorized incident reports are expressed graphically, these classifiers use different approaches to generate decision boundaries using the training data to categorize the test data.

Metrics can be calculated for how accurately each classifier categorizes the test data using the boundaries drawn by the training data, also using Python's scikit-learn library (Garreta et al., 2017; Pedregosa et al., 2011). Though a number of metrics could be calculated, for the sake of classifying the remaining data, only overall accuracy was considered. The input parameters are the true classification label and the predicted machine learning classification label. Accuracy is defined as the percentage of predicted labels that exactly match the corresponding true labels. The output is a single percentage value where 100% denotes perfect accuracy. Note that this machine learning model was only applied to 820 incident reports. Then most accurate classifier is used to classify the remaining 7,379 incident reports according to their corresponding SMS element. Once the incident reports are classified, then we can better understand, define, and analyze the data.

To develop a more effective safety management strategy, it is important to understand the causal relationships between different safety factors (PSM elements) and the total number of incidents. In our research, we use BN models, which are effective at establishing probabilistic relational networks between causal factors, to analyze causal relationships between organizational factors, human factors, and factors pertaining to asset integrity. These are all factors to consider when analyzing risk and the number of incidents occurring in the oil and gas industry. BNs are statistical models that represent a class of joint probability distributions. They are flexible and powerful tools for graphically modelling and quantitatively expressing the causal interrelationships amongst variables (Jensen & Nielsen, 2009). It is important to note that BNs contain both qualitative and quantitative components. The qualitative component is used to establish the structure of a Directed Acyclic Graph (DAG) which is composed of a set of nodes and directed edges (arrows). A directed acyclic graph is a directed graph with no directed cycles – following the edges within the graph will never result in a closed loop. For two nodes connected by an edge, the first node is called the "parent node" of the subsequent node which is called the "child node." As such, the child node is conditionally dependent upon the parent node (Suk et al., 2011).

The quantitative component of a BN, parameter learning, is used to determine the conditional probability distribution of each node according to the established BN structure. Conditional probability calculations utilize Conditional Probability Theory (also known as Bayes' Theorem, Bayes' Rule or Bayes' Law) which is expressed by the following equation:

$$P(G|D) = \frac{P(D|G)\,P(G)}{P(D)} \qquad \text{Equation 1}$$

In Equation 1, the probability of an event P(G|D) is the likelihood of event G given that event D occurs. Subsequently, P(D|G) is the probability that event D occurs given the occurrence of event G, P(G) is the probability of event G occurring, and P(D) is the probability of event D occurring (Neapolitan, 2004).

Results and Discussion

A standardized risk matrix was created to rate the severity and likelihood of incidents. Risk matrices of several different oil and gas companies were used as a reference, and the scales shown in Tables 1-2 were generated using averages of values from several industry risk matrices. Table 1 demonstrates the likelihood of occurrence for an incident, which was calculated by directly tallying the number of occurrences per incident type.

Table 1. Likelihood (L) scale for standardized risk matrix used for classifying incidents based on likelihood of occurrence.

Likelihood of Occurrence	L5	L4	L3	L2	L1
	Consequence is expected to occur at least three times per year within a facility	Consequence is expected to occur at least once per year within a facility	Consequence is expected to be seen once or twice in a facility's lifetime	Consequence is expected to be seen once or twice in the company's history	Consequence is seen once or twice in the entire industry

Table 2 depicts the consequence scale used to classify incidents' degree of severity. In the oil and gas industry, consequences are typically categorized as affecting health and safety of people, damage to the environment, financial loss, and damage to a company's reputation.

Table 2. Consequence (C) scale for standardized risk matrix used for classifying incidents based on degree of severity.

Degree of Severity	C5	C4	C3	C2	C1
Health/Safety	Minor injuries or illnesses that do not require first aid treatment or may require basic first aid treatment	One or more injuries or illnesses requiring medical treatment or resulting in restricted work	One or more injuries or illnesses resulting in lost time	Single fatality or one or more long term disabilities	Multiple fatalities
Environmental	Inconsequential or no adverse effects, clean up confined to site or close proximity	Minor adverse effects, local emergency response, 0-6 months clean up	Medium adverse effects, local emergency response, short to medium term effects, 7-12 months clean up	Medium to significant adverse effects, intermediate emergency response, 1-4 years clean up	Off property impact requiring remediation taking 5 years or more. Major emergency response with significant adverse effects
Reputation	No media coverage. Single stakeholder involvement with concerns addressed in the normal course of businesses. Temporary side road closure.	Local media coverage. Multiple stakeholders involved with concerns addressed in the normal course of business. Secondary road closure lasting < 24 hours	Extended local media coverage or one-time national media coverage. Key stakeholder involvement. Extended secondary road closure > 24 hours	National media coverage. Involves multiple stakeholders. Operations interrupted. Major road closure < 24 hours.	International media coverage. Multiple key stakeholders involved. Operations shutdown and/or potential of future operations being prevented. Extended closure of major road.
Financial	Cost < $1M	$1M < Cost < $10M	$10M < Cost < $100M	$100M < Cost < $500M	Cost > $500M

By using the methods discussed, we designed a supervised machine learning algorithm that assigned a consequence score to each incident. Table 3 shows the accuracies of different classifiers used in this study when applying a consequence score to an incident report. The classifier with the greatest accuracy was the Linear Support Vector Classifier (Linear SVC). The Linear SVC is a type of SVM that adopts the "one-vs-rest" or "one-vs-all" approach for classification (as opposed to the lowest accuracy classifier, the basic SVC, which uses a "one-against-one" approach) (Kotsiantis, 2007). Each class is compared against every other class when drawing decision boundaries which leads to very accurate classification for data that is linearly separable. The accuracy of the Linear SVC for applying consequence scores was 89.98%. The Linear SVC also had the greatest accuracy for classifying incidents according to PSM elements, as will be seen later. These results are also consistent with the results of Kurian et al. (2020).

Table 3. Classification accuracy of consequence score for different classifiers.

Classification Method	Accuracy
Support Vector Classifier (SVC)	62.86%
Adaboost	65.22%
Multinomial Naïve Bayes	69.43%
k-Nearest Neighbors	70.17%
Decision Tree	73.75%
Random Forest	78.91%
Logistic Regression	85.31%
MLP Classifier (Neural Network)	86.52%
Linear SVC	89.98%

The two scales of probability and consequence were combined to create the risk matrix shown in Figure 4. Again, the different zones of this risk matrix were generated using averages of values found in the risk matrices of several oil and gas companies.

Likelihood						
	L5	4	2	1	1	1
	L4	4	3	2	1	1
	L3	5	4	3	2	1
	L2	5	5	4	3	2
	L1	5	5	4	3	2
		C5	**C4**	**C3**	**C2**	**C1**
		Consequence				

Figure 4. Risk matrix used to assign risk score to incidents.

Incidents were assigned a risk score by combining the likelihood and consequence scores Figure 4 as a guideline. This was done using a simple rule-based approach (e.g., if an incident was assigned a likelihood score of 2 and a consequence score of 3, the incident would be given a risk score of 4). Risk matrices allow companies to understand their own tolerability level, assess existing and potential risks, and to reduce these risks to an acceptable level by lowering the likelihood or minimizing the consequences. By implementing machine learning into the process of using a risk matrix, we are able to simplify reporting, increase accuracy and consistency, and reduce human bias.

Using the supervised machine learning method, incidents were also assigned into categories defined by their corresponding PSM element. The accuracy of the different classifiers when assigning a PSM element to an incident report can be seen in Table 4.

Table 4. Classification accuracy of PSM element for different classifiers.

Classification Method	Accuracy
Support Vector Classifier (SVC)	57.23%
Adaboost	60.64%
Multinomial Naïve Bayes	64.81%
k-Nearest Neighbors	70.17%
Random Forest	76.52%
Decision Tree	76.69%
Logistic Regression	79.55%
MLP Classifier (Neural Network)	83.16%
Linear SVC	85.68%

Again, the Linear SVC was the most accurate classifier for assigning PSM elements to incident reports with an accuracy of 85.58%. The BN methodology can now be applied to the incident reports, classified by PSM elements. Figure 5 depicts a map between different causes and incident rates in this study. The BN that was developed extracted interesting and valuable information about relationships between PSM elements related to incident rates and correlations between different PSM elements. Individually, all nine PSM elements can be considered direct causes of incident rate. However, as an example, *Safe Work Practices* can be considered the parent of *Contractor Management* and *Operating Procedures* can be considered the parent of *Process Safety Information*. We can also infer that lack of proper *Hazard Identification & Risk Analysis* can result in the failure of many other PSM elements.

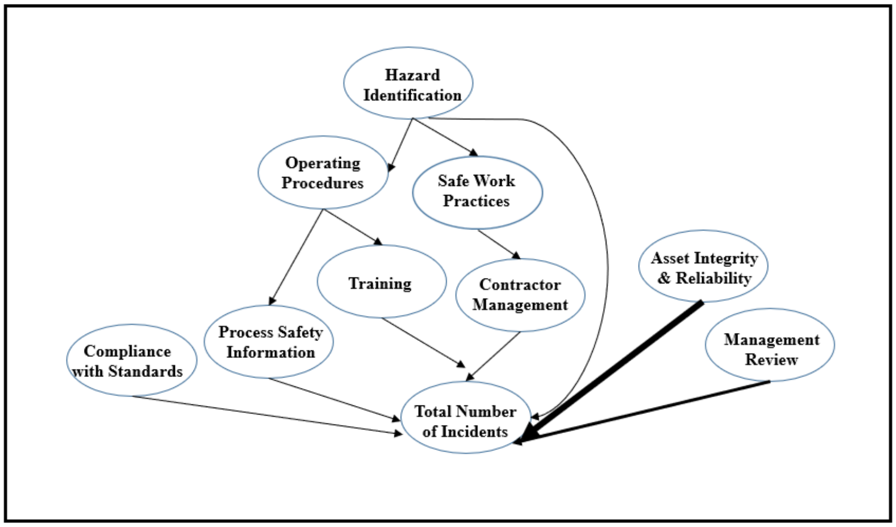

Figure 5. The established BN structure presenting the relationship between PSM elements and total number of incidents (Adapted from Sattari et al., 2021).

Table 5 displays the strength of different arcs between each factor and the total number of incidents. In this case, the maximum dependency belongs to the largest negative number (-315.06). The ramifications of this value are enormous – the total number of incidents have a maximum dependency (50%) on asset integrity and reliability. This means that by focusing on reducing the number of incidents pertaining to asset integrity and reliability, it would be possible to decrease the total number of incidents by half.

Table 5. Arc strength for the reaction network shown in Figure 5.

From Group	To Group	Arc Strength
Asset Integrity & Reliability	Total Number of Incidents	-315.06
Management Review & Continuous Improvement	Total Number of Incidents	-102.35
Hazard Identification	Total Number of Incidents	-78.86
Contractor Management	Total Number of Incidents	-52.13
Operating Procedures	Total Number of Incidents	-50.86
Safe Work Practices	Total Number of Incidents	-30.81
Training	Total Number of Incidents	-9.96
Process Safety Information	Total Number of Incidents	-4.73
Compliance with Standards	Total Number of Incidents	-3.49
Hazard Identification	Operating Procedures	-7.84
Hazard Identification	Safe Work Practices	-4.63
Operating Procedures	Training	-1.67
Safe Work Practices	Contractor Management	-1.07

Previous research completed by Sattari et al. (2020) devised a platform for reducing incidents by enhancing safety, primarily focusing on *Asset Integrity and Reliability* as well as *Management Review & Continuous Improvement*. Consequently, this study seeks to present some approaches that can further improve the next most influential element of PSM that is responsible for incidents in the oil and gas industry: *Hazard Identification & Risk Analysis*.

A rising demand for energy has accelerated exploration around the world. While it is difficult to completely eliminate failures in pipelines, equipment, and industrial construction, preventative and mitigative measures can reduce the probability and the severity of incidents. Thus, there is great value in implementing safety measures and following up with a comprehensive risk assessment to reduce risks to acceptable levels. Risk analysis includes both quantitative and qualitive methods in process industries to develop prevention and mitigation strategies. These strategies can include implementing conventional methods such as HAZOP, Event Tree (ET), Bow-tie (BT) analysis, and hazard and fault trees (FT) as well as researching new methods such as petri networks, BN and Markov chains (Bhandari et al., 2015). The application of BNs in conducting quantitative risk assessment is relatively new, especially in the field of oil and gas. BN analysis is most popular for its probabilistic inference techniques for reasoning under uncertainty. BN analysis can model multistate variables, causes of failure, and conditional dependencies between different factors. Furthermore, BNs can be used to perform probability updating and sequential learning (Khakzad et al., 2013b). One of the primary advantages of BN analysis over other risk assessment techniques is that it is not static. It can also model conditional dependencies between other risk assessment techniques such as fault trees, event trees, and bow-ties. Khakzad et al. (2013a) highlighted the effectiveness of BNs in the case of dynamic safety analysis for process systems by demonstrating how mapping bow-ties into BNs can diminish the limitations of bow-ties (resulting from static components). Furthermore, direct causal arcs among dependent variables are extremely effective at illustrating conditional dependencies.

Cai et al. (2013) proposed a methodology for the application of BNs in conducting quantitative risk analysis of offshore oil and gas operations. Their methods involve using a five-step method: translating a flow chart of the operations into a BN directly, classifying the influencing factors of the network nodes, establishing the BN for each factor, establishing the entire BN model, and finally, analyzing the BN model. Finally, five categories of influencing factors (human, hardware, software, hydraulic, and mechanical) are modeled and added to the primary BN. Using this methodology, Cai et al. (2013) found that mechanical and hydraulic factors have the most significant impact on operational safety. Conversely, software and hardware factors have minimal influence whereas human factors have some impact.

Recognizing that process systems are socio-technical systems is an important step towards improving hazard identification. It is very easy to consider process systems as simply equipment, material streams, and control loops. However, understanding that 40-70% of abnormal conditions in process systems are people-related can change perspectives towards hazard identification (Fiske, 2009). This broadens the scope for hazard identification and better learning how these systems operate, and thus, how they can fail. By doing so, it is possible to generate a more holistic and integrated framework for hazard identification to the reduction of hazards, failures, and incidents in the oil and gas industry.

A novel method for hazard identification was developed by Seligmann et al. (2012) which combined function-driven and component-driven approaches with the purposes of generating outcomes with a large coverage of hazards and describing causal knowledge in a well-structured manner. This method was founded upon principles of Functional Systems Framework (FSF), a conceptual framework which uses an underlying process system model for blended analysis. In this methodology, the framework generates knowledge from the method's outcomes in an effective manner that can be reused in a variety of different applications. The method outcomes would contain detailed information about failure events, causes of failure, and other implications. The amount of detail presented is dependent upon end-use requirement for application of knowledge.

Conclusion

Incidents in the petrochemical sector continues to motivate research in safety and risk management. In this study, we used supervised machine learning to classify incident reports and determine the risk scores of incidents. The Linear SVC was found to be the most effective classifier for the set of incident reports that was used in this study boasting accuracies of 89.98% and 85.68% for assigning risk scores and PSM elements, respectively. Using the results from this machine learning classification, we established a structural BN between different elements of PSM. This process involved developing a causal map between different factors where the probability of each factor was quantified. This equips companies to best allocate resources to reduce the risk of incidents and reduce financial losses, preserving human life and the environment, and maintaining a good public image.

Our previous research analyzes the benefits of preventing and mitigating risks associated with *Asset Integrity and Reliability* as well as *Management Review & Continuous Improvement* (Sattari et al., 2020, 2021) while this study focused on *Hazard Identification & Risk Analysis*. With this focus, two observations became very prominent: 1) there were many incidents pertaining directly and indirectly to *Hazard Identification* and 2) most incidents caused directly by poor *Hazard Identification* had a low risk score. Despite the low risk score, the sheer number of incident reports classified as Hazard Identification provides strong support for improving risk management in this area. Furthermore, the connection between *Hazard Identification* and *Operating Procedures* and *Safe Work Practices* adds further justification for allocating resources to prevent further incidents based on inadequate *Hazard Identification*.

Using BNs, we were able to discover the most effective strategy for reducing the likelihood of incidents. Responsive allocation of resources will most effectively control either single elements or different factors to improve overall safety performance. Cultivating a system that promotes critical thinking towards recognizing hazards is key for high risk industries like petrochemicals. Being able to anticipate and evaluate such hazards is critical to developing a safety culture and maintaining good personal and organizational health.

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