# USE OF MACHINE LEARNING TO DEVELOP AN AUTOMATED RISK CLASSIFIER FOR HAZOP STUDIES

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## ABSTRACT

HAZOP (Hazard and Operability Study) is the most used technique to identify and assess process risk situations in the industry. However, this is a repetitive, time-consuming technique that requires a lot of effort and, since it depends on human factors, it is prone to errors. There are over 30 different approaches to partially automate HAZOP elements, however, few have been used in the chemical process industry due to the considerable effort to obtain a system with sufficient reliability. Thus, this work developed an automatic risk scenario classifier that can be used to facilitate and automate HAZOP studies in a petrochemical plant, using a historical risk scenario database. It was developed through Knowledge Discovery from Data (KDD), defining an order of influence of attributes in risk classifications, developing an easy-to-understand explicit classification tree, and validating the tool with process safety specialists from different operational areas. The acquired knowledge was applied to an interface, where users can obtain an automated suggested risk classification and inform when the classification is done wrongly by the model. Although not a substitute for human labor, this tool can support less experienced engineers, reducing the differences in interpretations, effort, and time of HAZOP studies. In addition, it can support the operational team in risk analysis to release process safety barriers and simpler change management, making it an excellent tool for initial risk analysis.

## 1. INTRODUCTION

Process hazard analysis (PHA) methods are used to identify and evaluate hazardous events that can occur in process plants [1]. Within the chemical process industry, the HAZOP (Hazard and Operability Study) is the most used technique to review the process plant, identify and assess process risk situations in the industry [2]. In HAZOP studies, the process plant is systematically and critically analyzed[1], using a disciplined procedure to identify how a process can deviate from its design intent to find potential risk scenarios and operability malfunctions [2]. It relies on the participation of an experienced and multidisciplinary team from areas such as plant operation, plant engineering, and process control. Process deviations, usually described by guide words such as no, more, and minus, and process variables such as temperature, flow, and pressure, are critically and systematically evaluated in each process step. Thus identifying the possible causes, consequences, and safeguards of deviations, there may be recommendations to minimize the risks found [3].

Usually, HAZOP studies are conducted in the following steps [4]:

1. collect the prerequisite process-safety information;
2. dividing the process plant into nodes based on a piping and instrumentation diagram (P&ID) or process flow diagram (PFD);
3. examine the design intention of each node;
4. apply the process deviations to each node;
5. discussion of potential causes and consequences of the process deviation;
6. definition of safeguards and recommendations;
7. determine the frequency of occurrence and severity of the scenarios.

Most experts agree that the HAZOP methodology is the most viable tool to identify risks in industrial facilities [5]. However, this is a repetitive, time-consuming technique that requires a lot of effort and, since it depends on human factors, it is prone to errors. The quality of the analysis is dependent on the knowledge, personal experience, moderation, communication, discussion culture, and level of training of the participants. In addition, performing repetitive tasks and analyzing large amounts of data can reduce human capacity, compromising HAZOP performance [6]. Furthermore, due to the current COVID-19 situation, HAZOP studies are partly held via web conferencing. This may result in reduced alertness of individual participants because the team is not in the same room and has shared insight into P&IDs and other process-safety information [4].

A computer-aided HAZOP system can support human experts in these studies, as Decision Support Systems [4]. Automated HAZOP is a study aided by computer logic, using systems to remove repetitive tasks and analyze large sets of data in HAZOP studies. For the computer to automatically identify hazards in a process plant, the software must be able to use or create a digital representation of the plant, store generic and specific knowledge, automatically identify plausible risk scenarios, conduct consequence analysis, and select safeguards. Thus, potential hazards can be identified by automatically applying, through reasoning methods, the deviations of process variables. Thus, it is important that the system stores knowledge about processes, process variables, causes, consequences, and safeguards [3].

There are over 30 different approaches to partially automate HAZOP elements, developed in more than 30 years of research. It was developed systems based on: logical trees [7], [8]; rules [9]; integration with CAD software [10]; state graphics [11]; process simulations [12], [13]; qualitative models [14] and models combined with rules [15]. Some of the approaches use artificial intelligence methods, for example, case-based reasoning [16]. Despite the development of several approaches for the partial automation of HAZOP, few have been used in the chemical process industry.

These systems reduce the efforts made by a HAZOP team but do not replace it, as it is necessary to validate the results by the team. These systems must serve as decision support, presenting results that go beyond the experience of the team. They should act as a guideline, automatically identifying hazards to typical plant components and assisting with routine tasks for specialists to direct their efforts on essential or special components [6]. Thus, the tools can support less experienced engineers in HAZOP participation, reduce human effort and time, in addition to increasing the degree of standardization of studies. Also, plant operators can be supported in the early stages of the HAZOP process, in which a safety professional may not necessarily be present [4].

The usability of Automated HAZOP systems depends on the quality of their hazard identification abilities and the completeness and reliability of the results [4]. They can be used for quality control purposes, to improve the degree of standardization, by reusing previous results and therefore supporting human experts during studies. The performance of the analysis of inferred dangerous events, malfunctions, and safeguards depends on the representation of knowledge and the reasoning algorithm, factors also linked to human experts. In contrast, human failures, related to reduced reasoning ability under stressful conditions, repetitive tasks, and large amounts of data, are reduced [3].

According to the current state of research, full automation of HAZOP is not feasible due to the considerable effort to obtain a system with sufficient reliability. However, a semi-automatic methodology can improve the effectiveness and efficiency of the hazard identification and scenario definition process. Also, it can be applied to specific processing units or sections of the plant, serving as specialized decision support systems. Most current research approaches aim to demonstrate an idea, requiring refinement and preparation for industrial use. The results must be transparent and understandable so that professionals, who have considerable authority on the subject, can trust them. Future systems must be extensively tested and evaluated in the process industry to gain acceptance [3].

This work aims to develop an automatic risk scenario classifier that can be used to facilitate and automate HAZOP studies in a petrochemical plant. It is expected:

- Evaluate and define an order of influence of attributes in risk classifications;
- Develop an easy-to-understand explicit classification tree;
- Validate the tool with process safety specialists from different operational areas;
- Establish an interface for users that can support the execution of risk analysis and maintain continuous learning of algorithms.

## 2. METHODOLOGY

The development of this work is divided into three steps, as Figure 1 shows.


*Figure 1 - Steps to develop an automated Risk Classifier for HAZOP studies using Machine Learning*

These steps are related to Knowledge Discovery from Data (KDD), which is a set of data processing steps that lead to knowledge discovery from databases. It is a nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data [17]. The KDD process is interactive and iterative, involving numerous steps with many decisions made by the user. Figure 2 represents the steps of this process and how they are related.

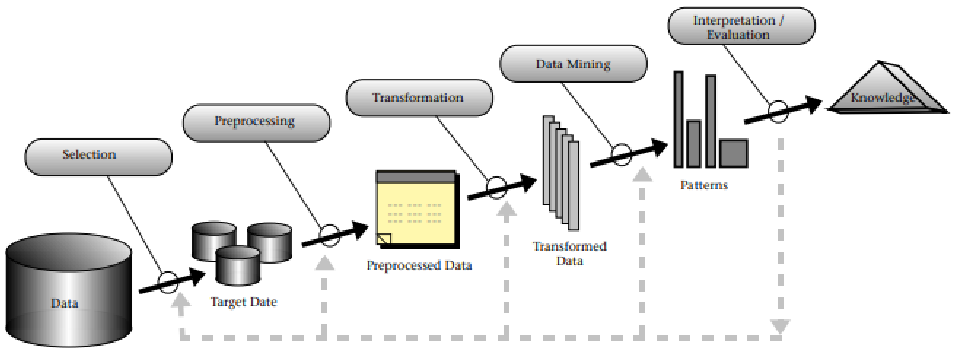


*Figure 2 - An Overview of the Steps That Compose the KDD Process, adapted from* [17]

First, it is necessary to understand the problem to identify and correctly define the goals of the KDD process. Thus, a target data set is created, focused on a subset of variables or data samples, on which discovery is to be performed. This data needs to be treated, such as removing noise and organizing missing data, and, sometimes, reduced, reducing the effective number of variables under evaluation. Thus, the data can proceed to the data mining stage, where machine learning algorithms are applied to find patterns in the database. The applied algorithms must be under the goals defined initially [18].

The patterns found can be represented in different ways, in which their performance is evaluated. After interpretation, the user can return to previous steps, testing other algorithms and/or ways to organize the data. Tile KDD process can involve significant iteration and may contain loops between any two steps. If the results found are satisfactory, the knowledge acquired can be applied in another system for other actions or documented and reported to interested parties [17], [18].

### 2.1 Develop a database

Historical risk analysis data was used to build a database. Attempts were made with historical data from different plants, with unsatisfactory results due to the difficulty of understanding the studies and the lack of risk scenarios with different classifications. It is worth mentioning that the quality of HAZOP and clarity in writing impacted the understanding of information in historical studies, being the main obstacle observed. Thus, data from the operational area of distillation of a polyethylene plant were used, where the problems mentioned above were not found.

The scenarios were organized into a dataset with 21 attributes based on the items evaluated in a HAZOP study. It aims to represent a simplification of reality. The attributes are Plant, System, Node, Equipment, Pressure, Temperature, Product, Class of Product, Deviation, Cause Description, Cause, Fail Mode, Effect Description, Top Event, Effect, Impact, Preventive Barriers, Mitigative Barriers, Frequency, Severity, Risk.

In this representation, there is a Fail Mode that led to Causes to Deviations in the Equipment. These deviations can lead to Top Events, that have an Effect Impact related to different aspects. Preventive and Mitigative Barriers are implemented to mitigate Top Events and Effects and prevent Causes and Fail Modes. The Frequency and Severity of a scenario are analyzed, giving it a Risk classification. Standard classes were created for some of these attributes. Table 1 contains the description of these attributes and some examples of standard classes used in the model.

*Table 1 – Definition and Standard Classes for the Attributes*

| Attribute | Description | Standard Classes |
|---|---|---|
| Equipment | The main equipment where the deviation occurs | Vessel, Pipe, Heat Exchanger, Distillation Column |
| Class of Product | Hazardous substance properties and state of aggregation | Flammable Liquid, Flammable Liquid + Suspension Solid, Flammable Gas, Toxic Liquid, Toxic Gas |
| Deviation | Composed of guide words and process parameters. | Lower Pressure, Greater Pressure, Lower Temperature, Greater Temperature, Higher Level, Lower Level, Contamination, Composition |
| Cause | Causes of the process deviations under consideration. | Block or reducing of outflow, Increase of outflow, Block or reducing of the inlet, Increase of the inlet, Reflux flow reduction, Reflux flow increase, Feed out of specification, Increased thermal exchange, Inefficient thermal Exchange, Equipment Damage |
| Fail Mode | Primary causes of causes, the failure that led to the deviation. | Human error, Corrosion, Block Fail, Control Loop Fail, Operational error, Pipe Breakage, Solid Particle Obstruction, Pump fail, Undue Valve Failure |
| Top Event | Critical problem due to process deviations | Small leakage, Major leakage, Equipment Breakage, Pressurization, Product Contamination |
| Effect | A result of the top event. | Flare relief, Operational disturbance, Pool fire, Pool fire and Vapor cloud fire, Vapor cloud fire, Vapor cloud fire and explosion, Pool fire, Vapor cloud fire, and Explosion |
| Impact | The most important aspect is related to the effect. | People, Environment, Cost |
| Preventive Barriers | Safeguards, operational measures, and alarms to prevent causes and fail mode. | Alarm, Control Loop, Updated Inspection Plan, Instrument, PSV, Interlock |
| Mitigative Barriers | Safeguards, operational measures, and alarms to mitigate the effect of top events | Gas Detector, Manual Shutdown, Emergency response, Manual lock |

| Attribute | Description | Standard Classes |
|---|---|---|
| Frequency | How often does the risk scenario occur | Improbable, Remote, Occasional, Probable, Frequent |
| Severity | How severe are the consequences of a scenario | Catastrophic, Critical, Moderate, Low |
| Risk | Composition of frequency and severity | High, Medium, Low medium, Low |

In this study, the frequency and severity classes were individually assessed. The risk classification was made with the composition of frequency and severity, according to the risk matrix in Figure 3.

| | | Frequency | | | | |
|---|---|---|---|---|---|---|
| | | Improbable | Remote | Ocasional | Probable | Frequent |
| Consequency | Catastrophic | MEDIUM | MEDIUM | HIGH | HIGH | HIGH |
| | Critical | LOW MEDIUM | LOW MEDIUM | MEDIUM | HIGH | HIGH |
| | Moderate | LOW | LOW | LOW | MEDIUM | HIGH |
| | Low | LOW | LOW | LOW | LOW | MEDIUM |

*Figure 3 – Matrix for Risk Classification*

This matrix was adapted from CEPRAM Resolution no. 4,578 of September 29, 2017 [19], a Brazilian standard that establishes the enforceability criteria and provides subsidies for the preparation of the Process Safety Management Program (PSM) for projects implemented or under implementation in the state of Bahia. It aims to prevent the occurrence of accidents capable of causing damage to human health, the environment, and facilities.

Table 2 contains the criteria used for the frequency classes of risk scenarios.

*Table 2 - Criteria for frequency category*

| Category | Frequency range | Qualitative criteria |
|---|---|---|
| Frequent (FR) | Greater than once per year. ($f \geq 1$/year) | . In existing plants:<br>- History of one or more occurrences per year and no changes made to the system.<br><br>. In projects:<br>- History of one or more occurrences per year in similar ventures.<br><br>. Human error:<br>- Frequent activity with no training and procedure, in the presence of adverse working conditions. |

| Category | Frequency range | Qualitative criteria |
|---|---|---|
| Probable (PR) | Expected in the life of the project. (1<f≤100 years) | . In existing plants:<br>- Occurrence history less than 1 per year or situation that was already close to occurring and no changes made to the system.<br>- Breakage or breakage of equipment admittedly degraded or with inspection deficient.<br><br>. In projects:<br>- Occurrence history less than 1 per year or a situation that was close to occurring in similar ventures.<br><br>. Human error:<br>Human error due to lack of training and procedure, in the presence of conditions of adequate work. |
| Occasional (OC) | (100<f ≤10.000 years) | . In existing plants or projects:<br>- Single failure of equipment in good condition operation and maintenance.<br><br>. Human Error:<br>- Scenarios that depend on a single, human failure in suitable ergonomic conditions, with training and procedure. |
| Remote (RE) | (10.000<f≤1.000.000 years) | . In existing plants or projects:<br>- Double equipment failure.<br>- Breakage of static equipment, lines, and accessories subject to inspection.<br>- Electronic component failure.<br><br>. Human Error:<br>- Double human error on adequate conditions of ergonomics with training and procedure. |
| Improbable (IM) | (f>1.000.000 years) | . In existing plants or projects:<br>- Rupture due to mechanical failure of pressure vessels with periodic inspection and testing of systems protection. No history of pressure overload, temperature or vibration, no history of compromised by cracks or loss of thickness.<br>- Failure of multiple protection systems.<br><br>. Human Error:<br>- Multiple human failures in conditions appropriate, with training and procedure. |

Table 3 contains the criteria used for the severity classes of risk scenarios

Table 3 - Criteria for severity category

| Category | Qualitative criteria |
|---|---|
| Low (LO) | . Accident without leave.<br>. Small magnitude environmental impact with internal reach or external or reversible with immediate actions.<br>. Accident restricted to equipment originating the problem. |
| Moderate (MO) | . Accident with leave or accident without leave with restriction.<br>. Evasion of employees.<br>. Impact of considerable magnitude, but reversible with actions mitigators restricted to the company's area. |
| Critical (CR) | . Victims with permanently disabling injuries or up to 10 victims fatal.<br>. The impact that paralyzes the effluent treatment system.<br>. Impact of considerable magnitude, but reversible with actions mitigators that go beyond the company area.<br>. Outside community evasion. |
| Catastrophic (CA) | . More than 10 fatal victims.<br>. Irreversible impact or difficult to reverse even with actions mitigating or impact of great magnitude and great extension, beyond the company's limits. |

Figure 4 shows the distribution of scenarios by severity and frequency classes present in the database used in this work. It contains few examples of scenarios with moderate severity and frequent or probable frequency, as these classes of scenarios are less observed in practice.

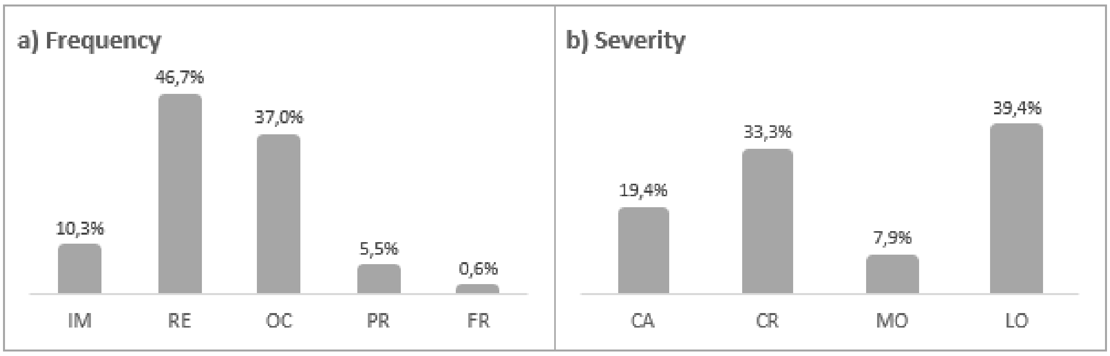


Figure 4 - Database distribution by Frequency (a) and by Severity (b)

## 2.2 Search for patterns

The data mining step was performed using Weka, a workbench developed at the University of Waikato in New Zealand, that provides implementations of learning algorithms. It contains a collection of machine learning algorithms and data preprocessing tools, which provides extensive support for the whole process of experimental data mining, including preparing the input data, evaluating learning schemes statistically, and visualizing the input data and the result of learning. This toolkit is accessed through a common interface, where users can compare different methods and identify those that are most appropriate for the problem. It is written in Java and distributed under the terms of the GNU General Public License [20].

The workbench includes methods for the main data mining problems: regression, classification, clustering, association rule mining, and attribute selection. However, this work was focused on classification and attribute selection problems, to apply learning methods to the dataset, analyze their outputs to learn more about the data, and compare their performance to choose one for prediction.

Attribute selection was used to learn more about the data and analyze the influence of attributes in the risk classification. Was used the algorithm *Ranker (weka.attributeSelection.Ranker),* which ranks attributes by their evaluations. It not only ranks attributes but also performs attribute selection by removing the lower-ranking ones. It evaluated the attributes by the evaluator *InfoGainAttributeEval*, which evaluates attributes by measuring their information gain about the class.

Classifiers were used in a learning approach, looking for patterns that lead to frequency and severity classifications. We used a divide-and-conquer approach to this problem, leading to a style of representation called a decision tree. Nodes in a decision tree involve testing a particular attribute. Usually, the test compares an attribute value with a constant. Leaf nodes give a classification that applies to all instances that reach the leaf, or a set of classifications, or a probability distribution over all possible classifications. To classify an unknown instance, it is routed down the tree according to the values of the attributes tested in successive nodes, and when a leaf is reached the instance is classified according to the class assigned to the leaf. The selection of attributes is based on the gain ratio, evaluated by entropy [20].

The divide-and-conquer approach to decision tree induction was developed and refined over many years by J. Ross. Although others have worked on similar methods, Quinlan’s research has always been at the very forefront of decision tree induction and developed a series of improvements that culminated in a practical and influential system for decision tree induction called C4.5 [21].

In this work, was developed a pruned binary decision tree through C4.5, represented on Weka as *J48 (weka.classifiers.trees.J48).* This is the most widely used algorithm in the decision tree, due to its simplicity and suitability for different types of attributes and missing data [22]. For example, it was used to develop a defect classifier on a Wastewater Treatment Plant as a means of achieving early warning and devising a proper response to a critical situation, avoiding the effects of a critical situation in an industrial plant [23].

Classification models were developed using different algorithms, however, J48 was chosen due to its performance. Algorithms were evaluated through their accuracy, that is the percentage of correct answers in the model, and through the kappa, that is the ability to represent reality. Algorithms with kappa values above 0.8 almost perfectly represent the reality of a data set [20].

In the data mining, the dataset was divided into two parts: data training and data test. Algorithms use data training to develop a machine learning model and then, apply it to the data set to evaluate its performance and suitability to the dataset [20]. Was used the cross-validation process, which divides the data set into folds that are evaluated separately. It was used 10 folds, which means that the data set was randomly divided into 100 parts, where 10% of the data were used for testing and the remaining 90% is training data.

### 2.3 Develop interface

An interface was developed to apply previously acquired knowledge using Microsoft Power Apps, which is a large collection of services used to build custom applications for users and businesses. It is Microsoft’s solution to Low-Code development, using an environment that works seamlessly with most of Microsoft Office’s services. Applications developed through PowerApps are runnable on mobile devices, supporting IOS, Android, and windows [24], [25].

Low-Code applications are software services that allow individuals and companies the ability to create services and solutions for their companies that require low programming knowledge, with ease of use in mind. The application was built connecting to the dataset and designing the service through drag and drop options for text buttons, data displays, and pages [24].

Users choose the attributes through checkboxes and the risk classification is given through the algorithms obtained previously, implemented in the tool. If the users do not agree with the risk classifications made by the model, they can inform the correct value. Thus, the new classification is fed back into the database and the model relearns.

## 3. RESULTS AND DISCUSSION

The results obtained in the development of an automatic risk scenario classifier in a petrochemical plant will be presented below.

### 3.1 Influence of Attributes

Select Attributes Algorithms provided a rank, where can be observed the attribute influence on the risk classification, as Table 4 presents.

*Table 4 - Rank of attribute influence on the risk classification*

| **Frequency** | | **Severity** | |
|---|---|---|---|
| **Rank** | **Attribute** | **Rank** | **Attribute** |
| **1º** | Preventive Barriers | **1º** | Effect |
| **2º** | Top Event | **2º** | Top Event |
| **3º** | Effect | **3º** | Preventive Barriers |
| **4º** | Cause | **4º** | Impact |
| **5º** | Deviation | **5º** | Deviation |
| **6º** | Fail Mode | **6º** | Temperature |
| **7º** | Equipment | **7º** | Equipment |
| **8º** | Pressure | **8º** | Cause |
| **9º** | Product Classification | **9º** | Fail Mode |
| **10º** | Temperature | **10º** | Mitigative Barriers |
| **-** | *Mitigative Barriers* | **11º** | Pressure |
| **-** | *Impact* | **12º** | Product Classification |

The effect, Top Event, and Preventive Barriers had a greater influence on both severity and frequency. It was expected since Effect and Top Event are used to classify the Severity and the Preventive Barriers reduce the frequency of occurrence of events with higher consequences. Temperature, Pressure, and Product Classification had little influence on the risk classification since the scenarios used are from the same operational area, where there is no significant variation in operational conditions.

Attributes related to initiating events, such as cause, deviation, failure mode, and equipment, had more influence on frequency than on severity. This shows that the severity of a risk scenario is defined according to the capacity of barriers to reduce and mitigate the occurrence of higher consequences after an initiating event. In addition, acting preventively on the most recurrent causes, deviations, failure mode, and equipment reduces the frequency of initiating events and, consequently, of risk scenarios.

Mitigative Barriers and Impact were removed from the frequency model due to their irrelevant influence on the classification, which reduces the performance of classifiers.

### 3.2 Classifier Algorithms

Was evaluated the performance of classifiers algorithms through the accuracy, that is the percentage of correct answers in the model, and through the kappa, that is the ability to represent reality. Algorithms with kappa values above 0.8 almost perfectly represent the reality of a data set. Table 5 presents the performance of some classifier algorithms.

*Table 5 - Performance of some classifier algorithms*

| Algorithm | Frequency | | Severity | |
|---|---|---|---|---|
| | Accuracy (%) | Kappa | Accuracy (%) | Kappa |
| Rules - ZeroR | 46,67 | 0 | 39,40 | 0 |
| Rules - JRip | 58,18 | 0,30 | 88,49 | 0,83 |
| Rules - DecisionTable | 61,82 | 0,35 | 80,61 | 0,71 |
| Trees - RandomTree | 67,27 | 0,46 | 84,85 | 0,78 |
| Trees - RandomForest | 70,91 | 0,52 | 93,33 | 0,93 |
| Trees - J48 | 75,15 | 0,60 | 90,91 | 0,87 |

ZeroR and RandomTree are random algorithms, used as a reference to evaluate the performance of other algorithms. RandomForest had the best performance, however, it is computationally complex. Thus, J48 was chosen to build a pruned binary decision tree due to its high accuracy, simplicity, and suitability for different attribute classes.

Figure 5 shows the pruned binary decision tree developed to classify the frequency of risk scenarios.

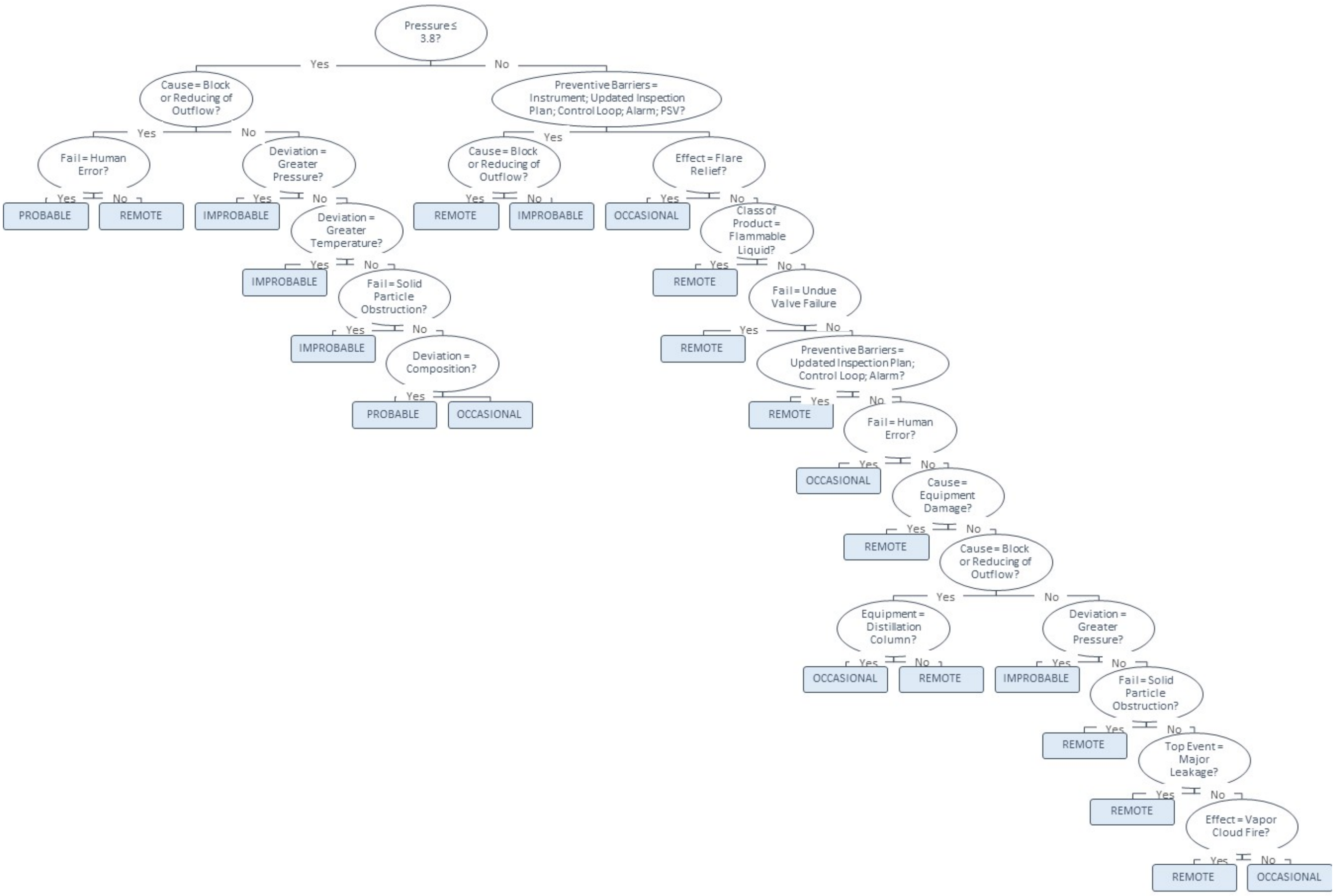


*Figure 5 - Frequency's Pruned Binary Decision Tree*

This decision tree contains a set of rules to simply predict the frequency of a risk scenario. At a node, the algorithm evaluates a condition for an attribute. According to the characteristics of the risk scenario, it evaluates a different condition or attribute in the next node, until it classifies the frequency.

At the first node, the algorithm divides the risk scenarios into two groups: pressure less than or greater than 3.8 kgf/cm². For scenarios with pressure less than 3.8 kgf/cm², it evaluates if the cause is blocking or reducing the outflow. If the reduction in the outflow is due to human error, this scenario is classified as probable and, if not, as remote. Scenarios with pressure less than 3.8 kgf/cm² that are not caused by blocking or reducing the outflow are classified as improbable when the deviation is greater pressure or greater temperature, or when the failure is due to a solid particle obstruction. For compositional deviation, the frequency is probable. Scenarios with pressure less than 3.8 kgf/cm² with classes of cause, failure mode and deviation not mentioned previously have an occasional frequency.

On the other hand, scenarios with pressure greater than 3.8 kgf/cm² have their preventive barriers evaluated. If the scenario has an instrument, updated inspection plan, control loop, alarm, and PSV (Pressure Safety Valve) and the cause is blocking or reducing the outflow, it is classified as remote. Scenarios with other causes are classified as improbable. When the scenario has barriers different from those mentioned above and the effect is flare relief, it is classified as occasional. The scenario is classified as remote if the product is a flammable liquid or the failure is due to an improper valve failure or if the preventive barriers are updated inspection plan, control loop, and alarm. For scenarios with other barriers, the frequency is occasional when the failure is due to a human error. If the cause is equipment damage, the scenario is classified as remote. However, when the cause is blocking or reducing the outflow and the equipment is a distillation column, the scenario is classified as occasional. If the equipment is another one, the frequency of the scenario is remote. If the deviation is greater pressure, the classification of the scenario's frequency is improbable. The scenario is classified as remote when the failure is due to a solid particle obstruction or the top event is a major leakage, or the effect is vapor cloud fire. Scenarios with pressure greater than 3.8 kgf/cm² with classes of preventive barrier, cause, failure mode, deviation and product not mentioned previously have an occasional frequency.

As discussed in the section on evaluating the influence of attributes, attributes related to the initiating event such as cause, deviation, failure mode, and equipment have a strong influence on frequency. Furthermore, preventive barriers reduce the frequency of occurrence of events with greater consequences. It is also possible to see how events with human error have a significant frequency. These rules of classification are considered in most HAZOP studies.

This algorithm correctly classifies 75% of the scenarios, representing 60% from reality. In the confusion matrix, shown in Figure 6, scenarios with remote or occasional frequency are well classified. However, when the frequency is improbable, probable, or frequent, the algorithm does not have good accuracy. It is related to the few examples of scenarios with these classes in the database, making it difficult to create patterns for their classification.

It is worth mentioning that different mistakes may have different relevance. For example, an improbable scenario classified as remote or occasional is less dangerous than a probable or frequent scenario classified as remote or occasional. Therefore, it is important to present more frequent and probable scenarios to the algorithm and with other classes of attributes so that it can learn classification rules for these frequency classes.

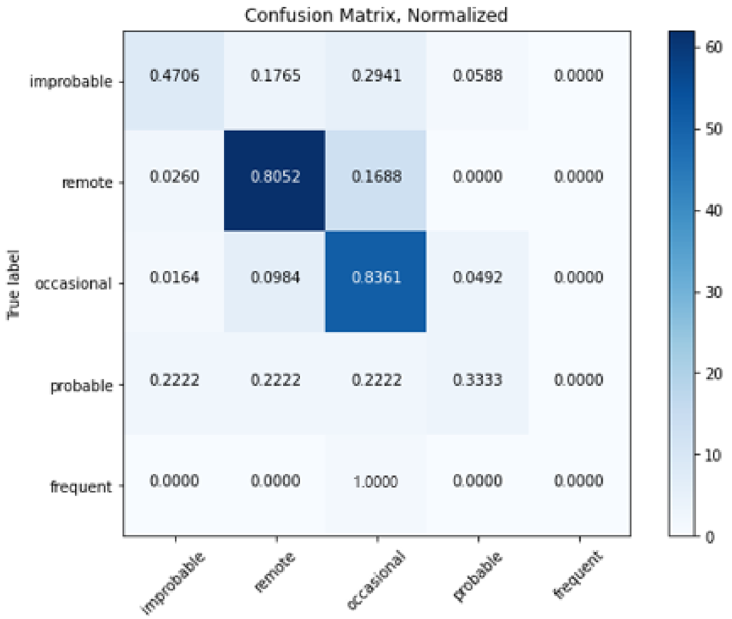


*Figure 6 - Confusion Matrix for Frequency's Model*

Figure 7 shows the pruned binary decision tree developed to classify the severity of risk scenarios.

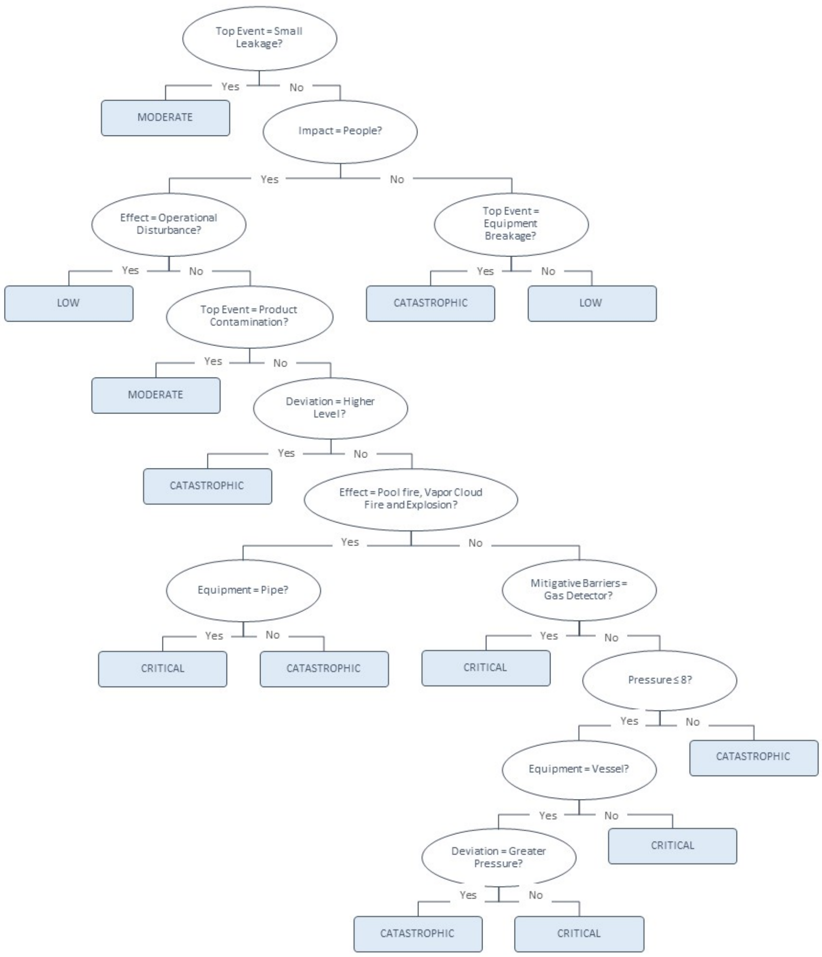


*Figure 7 - Severity's Pruned Binary Decision Tree*

As the decision tree for frequency, this one contains a set of rules to simply predict the severity of a risk scenario. At a node, the algorithm evaluates a condition for an attribute. According to the characteristics of the risk scenario, it evaluates a different condition or attribute in the next node, until to classify the severity.

At the first node, the algorithm evaluates the top event. If the top event is a small leakage, the scenario's severity is classified as moderate. For scenarios with another top event, the algorithm evaluates is there any impact on people. If the scenario does not have a significant impact on people and the top event is equipment breakage, it is classified as catastrophic. Other top events are classified as low. When the scenario significantly impacts people and the effect is an operational disturbance, the severity is low. The scenario is classified as moderate when the top event is product contamination and as major when the deviation is the higher level. When the effect is fire pool, vapor cloud fire, and explosion and the equipment is a pipe, the scenario is classified as critical. For scenarios with other equipment, the severity is catastrophic. When the effect is not fire pool, vapor cloud fire, and explosion and there is a gas detector as a mitigative barrier, the scenario is classified as critical. If there is not a gas detector as a mitigative barrier and the pressure is greater than 8 $kgf/cm^2$, the severity is catastrophic. Scenarios with pressure less than 8 $kgf/cm^2$ have the equipment evaluated. If the equipment is not a vessel, the severity is critical. When the equipment is a vessel and the deviation is greater pressure, the scenario is classified as catastrophic and other deviations are classified as critical.

Through this tree, it can be seen the influence of top event, effect, and mitigative barriers. As was expected, scenarios with higher consequences have catastrophic classes of severity.

This algorithm correctly classifies 91% of the scenarios, representing 87% from reality. In the confusion matrix, shown in Figure 8, it can be seen that all the classes of severity scenarios are well classified. However, it is important to present more scenarios with major severity and with other classes of attributes to the algorithm to improve its classification for this class of severity.

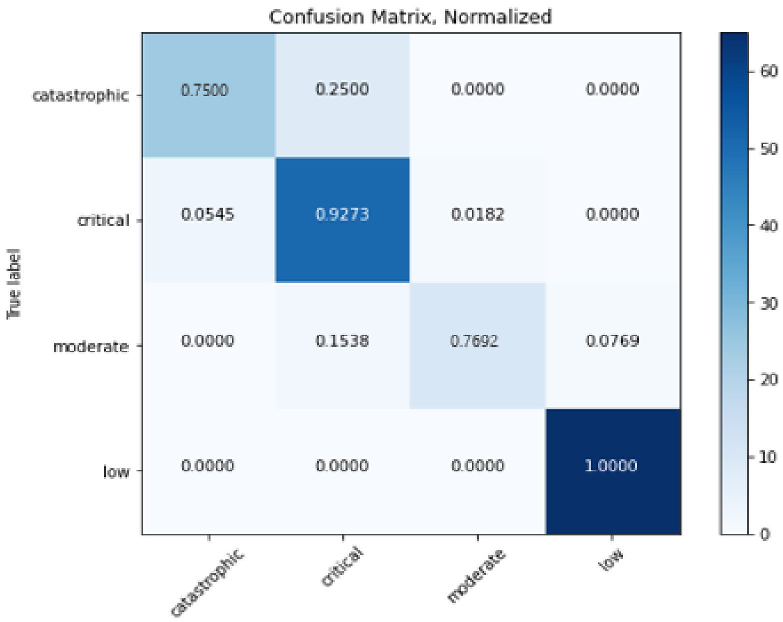


*Figure 8 - Confusion Matrix for Severity's Model*

The risk classification was done with the conjunction of the frequency and severity classes predicted by the algorithms, according to the risk matrix shown in Figure 3. The results were validated with real process data, involving the company's process safety specialists from different operational areas.

### 3.3 Application

The interface developed to apply the knowledge acquired with the classification algorithms is shown in Figure 9. In this app, risk scenarios are classified according to the algorithms described in section 3.2. Users select the attributes to obtain an automated suggested risk classification, frequency, and severity. If the classification is done wrongly by the model, it is possible to inform the correct classification by the user, so the machine keeps learning with the new risk scenario definition. This is a good practice to improve the performance of the algorithm.

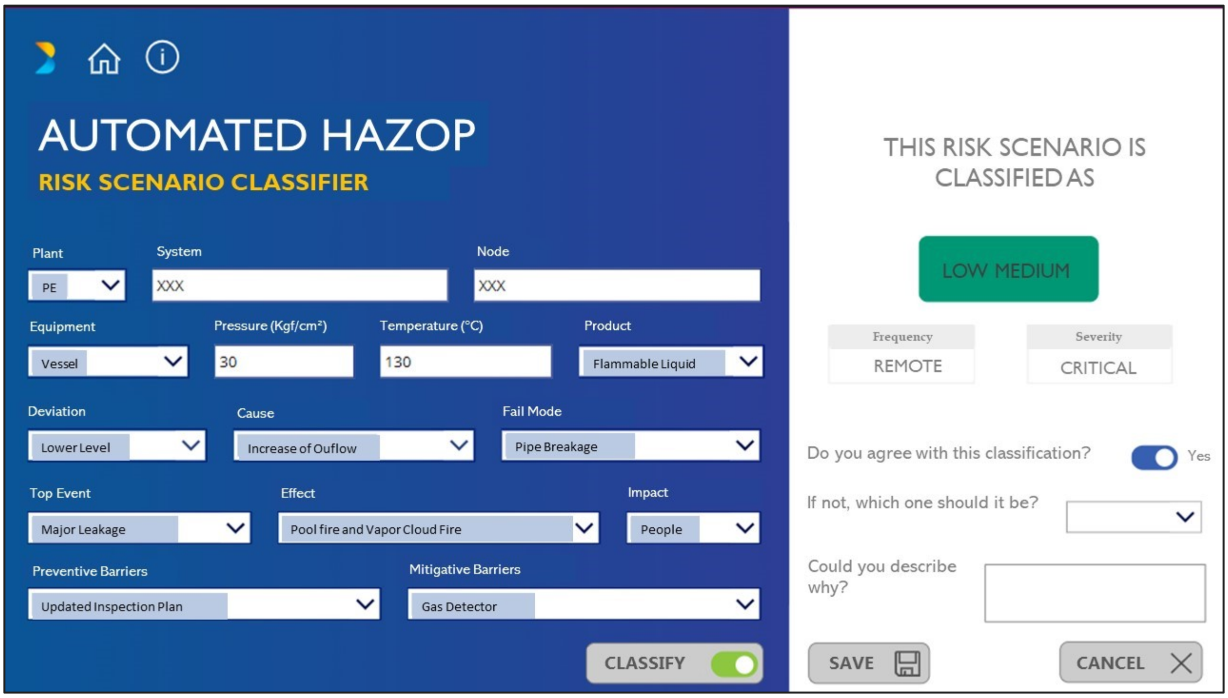


*Figure 9 - Interface to Classify Risk Scenarios*

The example shown in Figure 9 is a classification of a hypothetic scenario from a Polyethylene Plant, with attributes defined as arbitrary. It was considered a Vessel containing a Flammable Liquid under 30 kgf/cm² and 130°C, where occurs Lower Level due to an Increase in Outflow due to a Pipe Breakage. It leads to a Major Leakage with Poor Fire and Vapor Cloud Fire, that impacts more People. It contains an Updated Inspection Plan and a Gas Detector as barriers. According to the model developed, this scenario has a Remote frequency and Critical Severity, which composes a Low Medium Risk.

Following the rules suggested by the Frequency's Tree (Figure 5), the first attribute evaluated is the pressure, which is greater than 3.8 kgf/cm². Since there is no Instrument; Updated Inspection Plan; Control Loop; Alarm and PSV as Preventive Barriers and the Effect is not Flare Relief, the algorithm evaluates the Class of Product. As it is a Flammable Liquid, the scenario is classified as Remote. Thus, the model understands that any effect different from Flare Relief involving Flammable Liquid under Pressure grater than 3.8 kgf/cm² and without Instrument; Updated Inspection Plan; Control Loop; Alarm and PSV is Remote, occurring once in 10000 and 1000000 years.

The first attribute evaluated by the Severity's Tree (Figure 7) is the Top Event, and, since it is not a Small Leakage, the Impact is analyzed. As the Impact is related to People and the Effect is not Operational Disturbance, the Top Event is evaluated again. Since it is not Product Contamination and Deviation is not Higher Level, it evaluates if the Effect is Pool Fire, Vapor Cloud Fire, and Explosion. Since Explosion was not considered in this example and it contains a Gas Detector as Mitigative Barrier, the scenario is classified as Critical, with Impact of considerable magnitude, but reversible with actions mitigators that go beyond the company area; or victims with permanently disabling injuries or up to 10 victims fatal.

According to the Risk Matrix (Figure 3), with a Remote Frequency and Critical Severity, this scenario is classified as Low Medium. Once this classification is coherent, the user agreed with it. It is worth mentioning that these classifications could be different using other databases or criteria for Risk Classification. It can be adapted and applied in another process with different criteria for risk classification.

Although not a substitute for human labor, this tool can support less experienced engineers, reducing the differences in interpretations, effort, and time of HAZOP studies. In addition, it can support the operational team in risk analysis to release process safety barriers and simpler change management, making it an excellent tool for initial risk analysis.

Automated HAZOP systems can be used for quality control purposes, to improve the degree of standardization, by reusing previous results and therefore supporting human experts during studies. The performance of the analysis of inferred dangerous events, malfunctions, and safeguards depends on the representation of knowledge and the reasoning algorithm, factors also linked to human experts. In contrast, human failures, related to reduced reasoning ability under stressful conditions, repetitive tasks, and large amounts of data, are reduced.

## 4. CONCLUSION

Was developed an automatic risk scenario classifier that can be used to facilitate and automate HAZOP studies in a petrochemical plant. Frequency and severity classes were evaluated separately, and the risk classification was provided by the conjunction of frequency and severity according to a risk matrix.

It was defined as an order of influence of attributes in risk classification, where could be seen a greater influence for effect, top event, and preventive barrier on both severity and frequency. Attributes related to initiating events, such as cause, deviation, failure mode, and equipment had more influence on frequency than on severity.

Was also developed an easy-to-understand explicit classification tree, which contains a set of rules to simply predict the frequency and the severity of a risk scenario. Frequency's decision tree correctly classifies 75% of the scenarios, representing 60% from reality. Severity's decision tree correctly classifies 91% of the scenarios, representing 86% from reality. It is important to present more scenarios with other classes of attributes, frequency, and severity to improve even more the performance of these algorithms. The results were validated with real process data, involving the company's process safety specialists from different operational areas.

To the end, was developed an interface to apply the algorithms provided for frequency and severity, where users can obtain an automated suggested risk classification and inform when the classification is done wrongly by the model. Thus, it is possible to maintain continuous learning for the algorithms.

Although not a substitute for human labor, this tool can support less experienced engineers, reducing the differences in interpretations, effort, and time of HAZOP studies. In addition, it can support the operational team in risk analysis to release process safety barriers and simpler change management, making it an excellent tool for initial risk analysis.

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