Risk assessment of worldwide refinery accidents using advanced classification methods: Effects of refinery configuration and geographic location on outcome risk levels

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ABSTRACT: A global dataset of refinery accidents for the years 1990–2016 was analyzed to evaluate the capacity of 16 attributes to differentiate between accidents that cause or not fatalities. For this purpose a Dominance-based Rough Set Approach (DRSA) analysis was carried out. The quality of approximation and accuracy measures confirmed that the established information table is able to distinguish outcome levels in terms of fatalities. Furthermore, the suitability of the extracted rules to describe hidden relationships in the accident dataset was demonstrated. Although, the predictive capacity of the decision rules was not satisfactory, the rules still proved to be useful to identify the attributes that contribute most to assign an accident to the correct outcome class. In summary, this study provided a number of new and substantial insights on worldwide refinery accidents, which complement and extend previous findings for accident frequencies and associated trends as well as different types of consequences.

1 INTRODUCTION

The field of risk assessment and management is a rather young scientific discipline, with most of its fundamental ideas, principles, concepts and applications going back to the 1970s and 1980s (Aven, 2016). One of the first articles addressing risk as a contemporary societal problem was published in Science in 1969 (Starr, 1969). The following publications provide a broad discussion of the concept of risk (Aven, 2012) as well as foundational issues (Aven and Zio, 2014) and important developments in the field (Greenberg et al., 2012, Thompson et al., 2005).

Early developments and applications of probabilistic risk assessment can be traced back to NASA's space program in the 1960s (Cooke, 2009), the aerospace industry (Keller and Modarres, 2005), and the development of nuclear energy in the same

period (Otway and Pahner, 1976). In 1975, the US Reactor Safety Study (WASH-1400) marked a major milestone in probabilistic risk assessment (US NRC, 1975), and subsequently spread to other disciplines and countries (Rasmussen, 1981).

The need for systematic and consistent, comparative risk assessment of energy technologies has been recognized since the 1980s (Fritzsche, 1989, Inhaber, 1979). Since then, it became a central element both in the comprehensive evaluation of the risk performance of energy technologies (Burgherr and Hirschberg, 2014), and in the broader context of sustainability assessment (Cinelli et al., 2014, Hirschberg and Burgherr, 2015, Santoyo-Castelazo and Azapagic, 2014). Recently, an increased interest can be observed to assess the frequencies and consequences of accidents over-time, and to compare them among energy chains, chain stages, activities and

infrastructure types as well as for different configurations and locations. The systematic exploitation of existing datasets to extract such useful information is a very important and promising research avenue (Burgherr et al., 2015, Burgherr et al., 2017, Cinelli et al., 2017, Spada and Burgherr, 2016).

In the industrial realm, risk assessment and management is often carried out according to ISO 31000 (ISO, 2009a, Luko, 2013), and ISO 31010 provides a list of 31 risk assessment techniques (ISO, 2009b, Luko, 2014). Other studies present overviews of risk analysis methodologies for specific facilities such as industrial plants (Tixier et al., 2002) or distinguish between formal and informal risk handling strategies for utility companies (Mascini and Bacharias, 2012). In contrast, Jonkman et al. (2003) and Johansen and Rausand (2014) address risk metrics from a more scientific perspective, but their discussion is also relevant for industry, authorities and other stakeholders. Lastly, loss modeling of industrial and insurance companies is often based on historic incident and accident data and the use of empirical and actuarial models and other approaches (Klugman et al., 2008, Daniell et al., 2018, Mannan, 2012).

In this study, the risk of accidents in refineries is analyzed. Within the oil chain, accidents during transports of crude oil and refined products clearly dominate with a share of about 75%, whereas exploration & production (E&P) and refinery activities follow distantly with roughly 10% each (Burgherr and Hirschberg, 2014). Furthermore, E&P and refinery facilities usually represent multi-billion dollar assets, property damage losses in these two sectors are the dominant contributors in the hydrocarbon industry, and refineries exhibit an increasing trend in frequencies and extent of losses (Marsh, 2016).

Recent publications address a variety of topics, including accidents at specific facilities (e.g., Chettouh et al., 2016, Mishra et al., 2014, Saleh et al., 2014), learning from past accidents (e.g., Moura et al., 2017a, Moura et al., 2017b, Russell Vastveit et al., 2015), occurrence of major accidents (Amyotte et al., 2016), and a sustainability metric for petroleum refinery projects (Hasheminasab et al., 2018).

In a previous study, two of the authors analyzed the frequencies and consequences (i.e., fatalities, injured persons) of refinery accidents among four country clusters (Burgherr et al., 2016). This provided interesting insights and conclusion on how refinery configuration and regional differences reflecting the mode of operation are important factors potentially affecting overall refinery risk.

In the current investigation, this retrospective analysis is extended to determine the combined influence and relevance of selected attributes (e.g., country group, accident type, event chain steps, etc.) of refinery accidents on the outcome level

(e.g., fatalities). Such knowledge on the potential impact of an energy accident can be used as one piece of information for the selection of response mode and resource allocation. According to the class of risk provided by the model, the Decision Makers (DMs) can decide how many resources to allocate to respond. Retrospective analysis for patterns recognition and decision support model development have been recently applied in different studies, e.g., investigation of antimicrobial activity (Pałkowski et al., 2014), selection of sustainable project portfolios (Zaras et al., 2012), and natural gas accidents (Cinelli et al., 2017), among others.

In the current research, a dataset of refinery accidents extracted from PSI's Energy-related Severe Accident Database (ENSAD) was analyzed to address three main objectives:

1. Assess the information structure of accidents from ENSAD to distinguish the events that did cause or did not cause fatalities.
2. Investigate the relationships between a set of descriptors (attributes) for the energy accidents and the outcome level (fatalities or no fatalities).
3. Study the capacity of the attributes to distinguish between accidents that cause or not fatalities.

2 METHODS

2.1 Accident data

The refinery accident data used in this study were extracted from PSI's ENSAD. The ENSAD has first been released in 1998 (Hirschberg et al., 1998), and since then regularly updated and extended (Burgherr et al., 2015, Burgherr and Hirschberg, 2014). Currently, the database is migrated from a standalone MS-Access to an new, interactive, web-based GIS database named ENSAD v2.0 (Burgherr et al., 2017). In ENSAD, complete energy chains are considered because accidents can occur during all stages and activities, and not just the actual power and/or heat generation (Burgherr and Hirschberg, 2008). In general, the focus of ENSAD is on so-called severe accidents because accidents with larger consequences are a major concern for industry and authorities, but also receive most attention by the general public (Burgherr and Hirschberg, 2014). To be classified as severe an accident has to fulfil at least one of seven threshold criteria, for example ≥ 5 fatalities, ≥ 10 injured persons, etc. (Burgherr and Hirschberg, 2008).

For the current study on global refinery accidents all accidents in ENSAD with at least one fatality or one injured person during the years 1990–2016 were taken into account. The lower

fatality and injury thresholds for refinery accidents were possible because a dedicated search for smaller accidents was carried out to ensure a sufficiently complete coverage. This larger dataset allows analyzing a broader set of accident attributes compared to the previous study conducted in 2016 (Burgherr et al., 2016).

In total, the refinery accident dataset comprised 698 accidents, of which 277 resulted in at least one fatality, 597 in at least one injured person, and 176 had both consequences.

2.2 Refinery data

Information on refinery configuration and characteristics was retrieved from the World Wide Refinery Survey (WWRS) of the Oil & Gas Journal (Penn Energy Research, 2010). The coupling between the ENSAD and WWRS databases was based on geo-referenced refinery locations (i.e., geographic coordinates). WWRS data include details on refinery units and processes as well as corresponding capacities expressed in barrels per calendar day (bbl/cd), the Nelson Complexity Index (NCI) and the Equivalent Distillation Capacity (EDC). In some cases, an accident could not be assigned to a specific refinery in the WWRS database: (1) the accident description did not allow identifying the correct refinery if several are located in the same area (10 cases); (2) the refinery can be located, but is not included in the WWRS list, which is mostly the case for small, private refineries (32); or (3) the accident description is so incomplete that the refinery can only be assigned to a country, but no specific location (8).

Additionally, five more refinery attributes were based on data from Swiss Re, providing additional information on regional differences in refinery hazards. First, each refinery accident was assigned to one of four regional country clusters, representing different plant operation styles (Pannatier, pers. comm.). Generally, loss burden differs among clusters, which is attributable to operational hazard factors such as mode of operation, attitude towards safety, turnaround period, maintenance, etc. The four clusters were given the following names:

- “USA”: USA, Canada, UK, Australia
- “Europe”: Europe, Singapore, South Korea, Japan, Saudi Arabia, Gulf States, Egypt
- “Russia”: Russia, Former Soviet Union, Eastern Europe
- “Other”: South America, Africa, Maghreb, other Middle East, rest of Asia

Second, all refinery units were allocated to three complexity classes G1, G2 and G3 to reflect increasing fire and explosion hazard (see Table 1), based on a Swiss Re expert categorization (Pannatier, pers. comm.). The class G0 includes all units that do not belong to one of the three other classes. An overview of refinery units considered and their assignment to a complexity class is shown in Table 1.

Three refinery unit attributes were defined, namely (1) the unit in which the accident started; (2) the complexity class of the unit where the accident started; and (3) the complexity class of the most hazardous unit(s) in a refinery.

Third, a Swiss Re Hazard Index (SR HI) was calculated for all refineries, combining the capacity, complexity and toxic hazard of a refinery with weight factors three, two and one, respectively.

2.3 Overview of accident attributes

Table 2 shows an overview of the 16 attributes that were used to analyze the previously defined dataset of refinery accidents. Ten attributes concern specific accident characteristics, whereas the other six provide information about refinery configuration and operational hazard. Out of these, three were directly taken from the WWRS database, and three were established using information from Swiss Re and WWRS.

2.4 Dominance-based Rough Set Approach (DRSA)

The dataset of refinery accidents developed in this study can be seen as an information table, where characteristics of the accidents are condition attributes (independent variables) and the

Table 1. Assignment of refinery units to complexity classes (CC) G0 to G3.

G0	G1	G2	G3
Crude Unit	Vacuum Distillation	Catalytic Cracking	Catalytic Hydro-cracking
Coking	Catalytic Reforming	Isomerization	Alkylation
Thermal Cracking	Catalytic Hydrotreating		Polymerization
Hydrogen Production			Lubes
Hydrogen Recovery			
Coke			
Sulphur			
Asphalt			

Table 2. Overview and description of refinery attributes. O-U: ordered, but direction unknown; O-K: ordered and direction is known; N-O: not ordered.

Attribute name	Description and values	Unit	Ordering
Year	Year in which an accident occurred: 1990–2016.	yr	O-U
Country Cluster	Country clusters represent different plant operation styles (see section 2.2): USA, Europe, Russia, Other.	–	N-O
Start Unit	Name of refinery unit in which the accident started (see Table 1).	–	N-O
Start CC	Complexity class (CC) of refinery unit where accident started: G0, G1, G2, G3.	–	O-K
High CC	Unit(s) with highest complexity class (CC) in a refinery.	–	O-K
No Acc	Number of accidents that occurred in an individual refinery during the period of observation.	–	O-U
Nelson Complexity Index (NCI)	A measure for refinery complexity, replacement costs, and values (Johnston, 1996 and references therein).	–	O-U
HI	Swiss Re Hazard Index (HI) (see section 2.2).	–	O-U
CRUDE	Crude capacity of refinery	bbl/cd	O-U
EDC	Equivalent Distillation Capacity is another measure to compare refineries. is another means of comparing refinery costs, for which a refinery’s atmospheric distillation capacity is multiplied by its overall complexity rating, resulting in complexity barrels (Johnston, 1996).	cbbbl/cd	O-U
Acc Type	Type of accident: Technical Failure (TF), Human Factor (HF), Human-Technical (HT), Natural Hazard (NH), Intentional Attack (IA; not included in current analysis).	–	N-O
EC1 to EC5	Event chain steps 1 to 5; sequence of events as given in available information sources. In total, 27 values are used, e.g., explosion, fire, release, etc.	–	N-O
Fatalities (i.e., outcome of the accident)	Number of fatalities that an accident caused. Two outcome levels are distinguished: no fatalities vs. fatalities.	–	O-K

presence or not of fatalities is the decision attribute or outcome level (dependent variable). To achieve the research objectives, Dominance-based Rough Set Approach (DRSA) analysis (Greco et al., 2001, Słowiński et al., 2015) was applied to the refinery information table using the jRS library and jMAF software package (Błaszczyszki et al., 2013). The method is well suited for this case study as it can handle quantitative and qualitative information without the need of transforming them into numerical or binary values, and it accepts inconsistencies in the dataset.

Another important characteristic of the present dataset is that it is not always known a priori whether the condition attributes are of the gain—or cost—type in relation to the fatalities. Gain-type means that the greater the value of an attribute, the less likely the accident causes fatalities; conversely, cost-type means that the lower the value of the attribute, the less likely the accident causes fatalities. DRSA is capable of discovering this type of information, named global monotonicity (Błaszczyszki et al., 2012). Furthermore, local monotonicity can also be discovered, meaning the interval of attribute values in which an attribute shows a gain—or cost-type behavior in the discovered pattern (see Table 3). The applied transformation is non-invasive, i.e., it does not bias the matter

of discovered relationships. With reference to the set of refinery attributes, those without an indication of their preference order for which global and local monotonicity were studied are “Year”, “No Acc”, “NCI”, “HI”, “CRUDE”, and “EDC” (O-U type in column Ordering, Table 2).

The relationships between the values of the attributes of the energy accidents and the cause or not of fatalities were discovered by means of decision rules, which are objective cause-effect patterns hidden in the refinery dataset. A decision rule is in the form of EàH, namely “if E, then H”. E is the condition part (also called premise or evidence) and H is the conclusion part (also called decision part). Sets of decision rules, which are essential for this analysis, were induced using the Variable Consistency Dominance-based Learning from Examples (VC-DomLEM) algorithm (Błaszczyszki et al., 2011b). Accidents that consistently cause either fatalities or not are assigned to what are called lower approximations. VC-DomLEM uses accidents that belong to such lower approximations as training examples to induce sets of certain decision rules, which may be later used to classify new accidents.

Sets of rules, induced by VC-DomLEM, may be used to construct more accurate ensemble classifiers in variable consistency bagging (Błaszczyszki et al., 2009, Błaszczyszki et al., 2010). Another

Table 3. Selected examples of decision rules obtained from the DRSA of the refinery accident dataset for accidents causing fatalities or not. Mbbl: million barrels; Supp.: Support; Conf.: Confidence. Other abbreviations see Table 2.

Year	Country cluster	Start Unit	Start CC	No Acc	NCI	HI	CRUDE Mbbl/cd	EDC	Acc Type	Supp.	Conf.
Rules for accidents that did not cause fatalities											
> 2002 ↑	Europe				≤ 5.4 ↓					11	0.92
> 2010 ↑	Other				≤ 6.3 ↓		≤ 110 ↓			13	0.93
	USA			≤ 4 ↓			≤ 96 ↓		HT	11	0.92
	USA		≤ 0			≤ 18.57 ↓	≤ 149.5 ↓		TF	15	0.82
> 2011 ↑	Russia				≤ 7.4 ↓					13	0.93
Rules for accidents that caused fatalities											
[2002;2004]		Alkylation							HF	10	0.91
[1996;2004]		Crude						≥ 1521 ↓	HF	11	0.85
≤ 2007 ↑						≥ 18.42 ↓	[126.9;189]		HF	11	0.79
≤ 2011 ↑			≥ 2			≥ 21.28 ↓			TF	12	0.80
	USA		≥ 2		≥ 10.65 ↓	≥ 20.0 ↓			TF	15	0.75

extension of the bagging approach is applied when the analyzed dataset suffers from class imbalance. In our case, Neighbourhood balanced bagging (NBBag) was used to increase the predictive capabilities of constructed rule classifiers (Błaszczynski and Stefanowski, 2015). Moreover, the strategies, which were used to evaluate our proposition, consisted in learning the decision rules from a subset of the original accident dataset and testing them on the remaining accidents to evaluate whether they assign the correct fatality class or not.

The capacity of the attributes to distinguish between accidents causing or not causing fatalities was assessed through a relevance measure called confirmation (Błaszczynski et al., 2011a, Greco et al., 2001). It assesses the degree to which presence of an attribute in the condition part of a rule confirms correct prediction (i.e., fatalities or no fatalities) on a subset of accidents the rules were not extracted from. The higher the value of the relevance measure (i.e., confirmation measure) the more important for correct prediction the attribute is.

3 RESULTS

3.1 Quality of classification and accuracy

The ENSAD-based refinery accident dataset is close to unitary classification quality (0.99 on a 0–1 scale), which means that there are very few inconsistent accidents that have the same values for the attributes and either caused fatalities or did not. In other words, the 16 attributes selected to develop the information table are relevant to differentiate between accidents causing or not causing fatalities. This is confirmed by the accuracy for not causing or causing fatalities with values of 0.98 and 0.97 (also on a 0–1 scale), respectively.

3.2 Decision rules

Decision rules represent unique patterns hidden within the dataset and they unveil the cause-effect relationships between the values of the attributes and the outcome level, i.e., the fatalities class in this case. Decision rules do not only include important condition attributes, but they also contain a minimal number of elementary conditions that are necessary for representation of the cause–effect relationships existing in the information table, from which all inessential and redundant information is removed.

Decision rules are induced by DRSA using the VC-DomLEM algorithm. Table 3 shows ten representative rules, five for the description of accidents causing fatalities and five for not causing fatalities. These decision rules can be viewed as interesting patterns among all patterns that can be found to describe features of the refinery accident dataset. The rules are characterized by useful parameters, including the support (i.e., the number of accidents that support the rule) and the confidence level. The selected rules have all a strong confidence level, close or above 0.75. This indicates that at least 75% of the accidents in the dataset with the stated values for the condition attributes lead to fatalities or not.

In the following, some rather simple explanatory examples for the interpretation of the rules given in Table 3 are briefly discussed. Accidents after 2002 in the cluster Europe with a NCI smaller 5.4 caused no fatalities. For Russia the same was only true after 2011 and for a higher threshold of NCI, indicating a general better performance of Europe. The same combination of attributes for the cluster Other ranks between Europe and Russia, but additionally crude capacity has to be lower than 110,000 bbl/cd. In contrast, accidents with fatalities tend to have higher values for NCI, HI, crude capacity and EDC. Additionally, fatal

Figure 1. Confirmation measure for attributes most relevant to distinguish between accident outcomes in terms of fatalities.

accidents for combinations of these attributes generally appeared to occur more likely in the earlier years of the observation period. Finally, accidents starting in higher hazardous units (i.e., higher complexity class) cause more often fatalities, and even still in more recent years.

3.3 Relevance of attributes

The predictive capacity of the rules was tested by means of 10-fold cross-validation, but unfortunately the predictive accuracy of DRSA decision rules was not satisfactory. In fact, only 48% of the accidents causing fatalities and 53% of those not causing fatalities were assigned the correct class. Nonetheless, these rules can be used to extract the attribute relevance, which indicates to what extent attributes are relevant (useful) to distinguish between accidents causing fatalities or not.

The confirmation measure used for the computation of the attributes relevance quantifies the extent to which the presence of an attribute in the rule suggests a correct class (Figure 1). Attributes CRUDE, Start Unit and the Country cluster are the most relevant for discerning between the accidents in terms of the outcome. Other attributes which are still relevant, though at a lower extent, for correct prediction are the first and second event chain (EC1, EC2), the highest complexity class (High CC) of the unit(s) present in a refinery, the year when the accident took place, and the type of accident.

4 CONCLUSIONS

For the current analysis refinery accident data from ENSAD for the period 1990–2016 were com-

bined with selected refinery characteristics using data from the WWRS database and from Swiss Re. The results demonstrated that the application of the Dominance-based Rough Set Approach (DRSA) analysis to such a complex dataset is feasible and useful to gain detailed insights about the structure and to reveal hidden relationships between accident attributes and their outcome in terms of fatalities.

The quality of approximation and accuracy measures confirmed that the information table based on 16 attributes is useful to differentiate between accidents causing or not fatalities. Furthermore, the extracted decision rules helped to evaluate hidden relationships in the accident dataset that go beyond traditional measures such as aggregated risk indicators or frequency-consequence curves. In particular, aspects of the monotonicity of attributes could be addressed as well as how higher (gain-type) or lower (cost-type) attribute values contribute to a reduced likelihood that an accident results in fatalities.

Finally, the decision rules were tested with regard to their predictive capacity to use the set of rules to assign potential future accidents to the correct outcome level. Although, the predictive accuracy was not satisfactory, the rules still proved to be useful to identify the attributes that contribute most to assign an accident to the correct outcome class.

In summary, the current study provided a number of new and substantial insights on global refinery accidents; thus extending and complementing a previous study by Burgherr et al. (2016).

Potential avenues of future research include options to enhance the predictive capacity of the

rules, which could be achieved either by adjusting the present attributes or by considering additional attributes. This is an essential aspect for decision makers and other stakeholders. They are, for example, concerned with the development of low-probability high-impact scenarios, pre- and post-event strategies to mitigate potential consequences of future accidents or the improvement of general safety culture.

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