Understanding Failure Modes, Effects and Criticality Analysis through the Association Rule Mining

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Abstract: The Failure Mode, Effect and Criticality Analysis (FMECA) aims at individuating how a process might fail, estimating the effects of such failures and the related criticalities, in order to improve the reliability of the process. This methodology is surely useful in terms of identification of the actions to implement for avoiding the failures, but it is also important to have a broader knowledge of the environment in which the analysis is performed. Indeed, identifying the occurrence of common factors that may characterize risky situations can represent the key for a further improvement of process' reliability, allowing the operators to anticipate and avoid hazardous events. In this perspective, this paper proposes an approach to deepen the study of the FMECA's results through a data mining technique, the Association Rule Mining. The aim of the proposed approach is defining whether hidden relationships among the outcomes of the FMECA methodology exist and how they can affect the normal functioning of the process, also proposing monitoring or corrective strategies. The research approach is also applied to a case study in order to clarify its deployment.

Keywords: Association Rule Mining, FMECA, data understanding.

1.Introduction

Production companies are nowadays required to comply with a growing number of norms, regulations, and customer expectations for what concerning aspects like safety and environmental protection (Becattini, Cascini, and Nikulin, 2015). In this perspective, plant reliability is the key factor to guarantee the achievement of acceptable levels in these aspects since it is fundamental to ensure the execution of process operations in a safe way (Ciarapica et al., 2009; Viveros et al., 2018). Hence, the adoption of opportune control and monitoring strategies is mandatory, especially in the process industry. Indeed, in this field, a process failure is likely to have a relevant impact not only on the production flow but also on the operators' safety and on the surrounding environment. Several techniques and methodologies exist to ensure compliance with acceptable reliability levels: the well-known Failure modes and Effects Analysis or the Failure Mode, Effect, and Criticality Analysis is a prime example, in this sense.

The current digital transformation enables a higher amount of data available in all the operations field, among whom the asset management one (Crespo Márquez, de la Fuente Carmona and Antomarioni, 2019). Hence, it is possible to gather and modify them in order to extract a growing set of information, from which deriving knowledge (Liew, 2007). The Knowledge Discovery in Databases (KDD) techniques that aim at extracting useful, valid, and unknown relations automatically from large datasets (Pitre et al., 2014) provide a valid support in deploying this process. In the maintenance field, KDD techniques are particularly useful since several variables have to be taken into account and analyzed simultaneously.

The approach proposed in this work takes into consideration the need for extending the knowledge of existing systems and processes, focusing on the need for higher reliability levels in the operations field. Indeed, the aim of the study is to extend one of the well-known techniques for the reliability analysis, i.e., by deepening the analysis of the results through a KDD technique, i.e., the Association Rule Mining (ARM). Data are firstly gathered to complete the Failure Mode, Effect, and Criticality Analysis (FMECA). Then, the output dataset of the FMECA is furtherly analyzed to extract the relations among attributes and values frequently occurring together, supporting the definition of further actions in monitoring the process object of the study.

The remainder of the work is organized as follows: the introduction is followed by a literature review on FMECA applications and KDD in the maintenance field. Then, the methodology is deployed (Section 3), and an example case coming from an offshore platform is presented (Section 4). The conclusions are drawn in Section 5.

2.Literature Review

Data are produced by all processes of a company, i.e., design, production scheduling, control, and maintenance (Harding et al., 2006): the need for their understanding and interpretation enhances the interest towards Knowledge Discovery in Databases for development of intelligent techniques (Fayyad, 2001). Nowadays, several processes already include the implementation of such techniques in the daily operations: for example, KDD techniques can be applied for anticipating the costs during the design phases of a product (Kusiak, 1999), or in process control to detect the anomalies and ensure the quality of the system (Maki and Teranishi, 2001). Other applications in the maintenance field involve the study of components' failures contextually occurring (Antomarioni et al., 2019) or the definition of the critical components for prioritizing maintenance scheduling (Dehghanian et al., 2012). Realistically, the implementation of KDD techniques should be accompanied by the implementation of traditional techniques, especially in companies where these procedures are already in use. One of the main used tools to study the reliability of a system and consequently to define the opportune maintenance policy is the FMECA (Carpitella et al., 2018). This methodology well-fits the analysis of hierarchical systems and can be applied to a number of different contexts. For example, (Vernez and Vuille, 2009) apply it to study a railway signaling system, while (Bertolini, Bevilacqua, and Massini, 2006) use FMECA for product traceability in the food industry. Often, authors implement the FMECA by combining it with other techniques in order to overcome its weaknesses. For instance, Bevilacqua, Braglia, and Gabbrielli (2000) propose an application in combination with a Monte Carlo simulation, while Zammori and Gabbrielli (2012) integrate the analytic network process. The aforementioned integrations regard the improvement of index calculation, even though none of them is devoted to providing a better explanation of the results obtained in order to define more accurately the maintenance policy. In this perspective, the results of the FMECA could be furtherly analyzed through the Association Rule Mining in order to identify the existence of frequent attribute-value relationships (Buddhakulsomsiri et al., 2006). A similar approach has already been adopted in Crespo Márquez, de la Fuente Carmona, and Antomarioni (2019) since the Association Rule Mining has been applied to deepen the analysis of the power consumption estimated through an artificial neural network. However, in combination with an FMECA, this approach results in being novel.

3.Research Approach

This section details the approach proposed in the current work. In particular, starting from the data collection, the aim of the work is to extend the existing FMECA methodology through a thorough analysis of its results. A schematization of the methodology is provided in Figure 1. The first step of the approach regards the collection of the data useful for the aim of the study. The quality of the data has a direct impact on the goodness of the results since incorrect or unreliable data collection may drive to inconsistent decisions. Multiple sources of data, if available, have to be taken into account and properly integrated. In this regard, when an inconsistency is noticed among the same data coming from different sources, a further search is needed to consider only the right one and possibly correct the error.

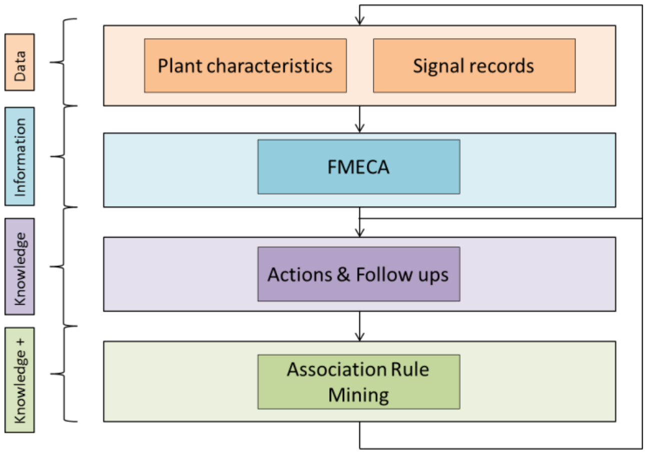

Figure 1 Schematization of the research approach

During the second step, instead, the data collected and the expertise of the operators and engineers involved in the analysis are applied to carry out the FMECA (US Military Standard, 1980, 1983). It is a user-friendly tool aiming at the identification and assessment of the potential failure modes of systems or processes and of the impact of such failures on global performance. A bottom-up approach is followed in developing FMECA since a break-down of a system is carried out in order to identify its elementary components and analyze them separately. In this way, the estimation of the failure modes, effects, and a measure of their criticality is provided more accurately. The output of the FMECA is a list of the components/sub-systems, their related failure modes, their effects, and a Criticality Analysis.

The third step of the research approach regards the study of the information provided by the FMECA in order to define actions and follow-ups to implement for the improvement of the system's reliability. According to the criticality measures, decisions on how to deal with critical failure modes and items are made upon experts' evaluation. During this stage, also company policies have to be considered since the actions and follow-ups have to be implemented coherently with the other operations activities.

In order to enlarge the knowledge of the system and its functioning in terms of failure modes, the fourth step is introduced in this work. In particular, the results obtained through the FMECA are furtherly analyzed to extract useful and previously unknown relations among items, considering both the input and the output of the FMECA: the aim of this step is, in fact, enlarging the existing knowledge of the process. Since the traditional statistics techniques can be obsolete when dealing with a large dataset consisting of several records and variables (Hand, 1998), the KDD techniques represent a valid substitute, being able of simultaneously analyzing them. The methodology selected to pursue this aim is the Association Rule Mining (ARM), being an intuitive and easy-to-include in decision making processes (Chen *et al.*, 2005; Ciarapica, Bevilacqua and Antomarioni, 2019).

3.1 Association Rule Mining

The ARM has been firstly applied to the extraction of hidden relationships from large datasets for marketing purposes (Agrawal, Imieliński, and Swami, 1993), but it has then been extended to many different fields. A formal definition is provided in the following: let S = {s_1, s_2,…,s_n} the set of data called items and T = {t_1, t_2, …, t_t} the set of all transactions; a transaction t_i contains a subset of items (hereafter called "item-set") taken from S. An implication L→R is an Association Rule (AR) if L and R are item-sets (L,R ⊆ S) and L∩R=∅. The item-set L is called body or left-hand side of the rule, while R is named head or right-hand side of the rule. The quality of each rule is determined through the calculation of some metrics. The most used are Support (1), Confidence (2).

(1) Support{L ∪ R} = (#{L ∪ R})/(#{T}), where #{T} represents is the cardinality of the transaction set, while #{L ∪ R} the number of transactions containing both L and R. The support indicates the probability of having both L and R within the same transaction set. Hence, it can be considered as a measure of the rule's statistical significance.

(2) Confidence{L → R} = (Support {L ∪ R})/(Support {L→*true*}). The confidence indicates the conditional probability of having the item-set R in a transaction, and given the fact that it already contains L. Hence, it represents the strength of the rule.

The algorithm applied in this paper for mining the ARs is the FP-Growth (Xiao *et al.*, 2016) since it was shown to be more efficient than other ones (e.g., Apriori or Eclat). The ARM is performed in two-step:

(a) the user sets a minimum support threshold: only the item-sets appearing in the dataset more than the specified support are taken into account. The other ones are excluded since they are not considered statistically significant.

(b)) the user sets a minimum confidence threshold: the FP-Growth algorithm is applied to generate the ARs starting from the selected item-sets; only the rules having confidence higher than the minimum confidence threshold are considered.

From the ARs generated, the decision-makers can confirm or modify the policy designed during the third step in order to increase the reliability of the plant through more timely interventions. Moreover, the ARM provides more data useful for further future analysis.

4.Case study

The process analyzed in the case study aims at producing gaseous and condensed hydrocarbons from the offshore reservoir and making them available on land. The reservoir consists of eight wellheads, six of which produce gas. The remaining ones produce both oil and the associated gas, which are initially separated offshore and then pumped and compressed. Then the gas flow is sent together with the oil to a multi-phase marine line (approximately 40 km long) connecting the platform with the onshore plant; there, it is immediately delivered to a Slug Catcher for liquid-gas separation and, then, mixed with the gas coming out of the gas-flash compression unit. After this mixing, a Gas Pre-Heater heats the gas flow through heat exchange with stable condensate flow coming out from the bottom of the Stabilizer Column. If this heat recovery is not sufficient (or if the Gas Pre-Heater is not available for any reason), a Gas Heater allows the total by-pass of the Gas Pre-Heater. The purpose of gas heating is to respect the delivery temperature at the power station inlet: in fact, gas, which is the main process fluid, after passing through the Gas Metering Station, becomes the power supply for an onshore power generation plant located onshore, which will be fed in sufficient quantity to reach its full production, while liquid hydrocarbons will be vaporized through dedicated facilities and delivered to the condensate recovery tank and then to the export terminal. The entire plant, offshore and onshore, therefore consists of:

- one platform and eight wellheads, six for oil production and two for oil and gas;

- a multi-phase marine transport line to the onshore plant;

- an onshore gas processing plant;

- a pipeline for liquid hydrocarbons, which exports them to the oil export terminal.

4.1Data collection

The application of the proposed procedure is limited to the oil and gas production wellheads. The data collected before the actual starting of the FMECA are the ones necessary to the expert for the discussion in identifying the failure modes. Hence, a series of records on machinery – and related components - past failures and operating conditions is taken into account for supporting the discussion. With reference to past failures data, two data sources have been scanned: indeed, checking the records reported on the information systems, some missing data were noticed, and, to ensure a reliable dataset, the on-field reports completed by the operators during the inspections are used.

4.2FMECA and Actions & Follow-ups definition

This study allows to quantify how much each failure mode is impacting on the performance of the system. Each equipment is analysed by understanding its functions; for each function, the potential failure modes are considered together with the potential effects possibly resulting from them. The attribution of a scaling to rank the equipment and the related failure modes involves the calculation of the failure probability and the severity of the effects.

The criticality analysis aims at classifying the defined items in accordance with the impact of their failure modes on safety, environmental protection, and plant production separately, also evaluating the related frequency of occurrence. A semi-quantitative screening is performed based on a Risk Matrix, used for defining the critical items versus acceptance criteria. Indeed, the frequency of occurrence is determined quantitatively, while the effects are estimated qualitatively.

In this work, three criticality indexes are calculated as a combination of Severity values assigned during failure modes identification, Failure rates, reduction of system capacity (loss of production). A criticality assessment, for each failure mode, is performed in qualitative terms allowing a priority screening of the failures according to their impact on safety, asset/production/capacity, and environmental protection.

As stated above, the evaluation of the criticality pertaining to an item is based on the calculation of the three criticality indexes detailed below:

- Safety-related criticality index, ICS;
- Asset and production-related criticality index, ICA;
- Environmental-related criticality index, ICE.

The severity of failures' effect is, instead, determined recurring to the severity category table reported in Figure 2. The severity assessment ranges from 0 to 4 and is related to the failure probability, basing on the annual frequency class (i.e., the yearly failure rate of each component), to define the acceptability rate of the failure mode. Specifically, three areas are identified:

- Continuous improvement: the risk of the failure occurrence is tolerable, even though continuous improvements are preferable in order to increase the performance;
- Risk reduction measures: risk reduction measures have to be implemented in order to limit the occurrence of faulty events or, at least, reduce the impact.
- Intolerable risk: the risk of failure occurrence is totally inacceptable, so it is mandatory to identify risk-reduction solutions.

For each failure mode, the Overall Criticality (CFM) is determined as the minimum of the ICS, ICA, and ICE (CFM = min {ICS; ICA; ICE}); for each item, instead, the overall Criticality Index (CI) is determined as the worst CFM associated with items' failure mode (CI_i = min {CFM_i}).

An excerpt of FMECA's output is reported in table 1. Specifically, it refers to the Oil production wellhead analyzed in this study, and the following information is reported:

1. The item to which the failure mode is referred;
2. The failure mode and a textual description;
3. The operating phase during which the effect might verify (e.g., Production/Running - Planned Shut Down - Emergency Shut Down - Start-Up);
4. The effects on the Main Equipment level, i.e., the consequences of the item's failure mode on the operation of the machine to which it belongs, in terms of production, safety and environment (e.g., No oil flow)
5. Loss of production, i.e., the percentage reduction in system capacity caused by the failure mode (without considering the duration of the loss at this stage).
6. ICS.
7. ICA.
8. ICE.
9. Detection method, i.e. description of how effects can be detected.
10. CFM.
11. CI.

Then, upon the experts' evaluation, the more critical failure modes are treated. For instance, referring to table 1, the worst failure mode appears to be the "FTR" (Fail to Regulate), whose effect is uncontrolled oil pressure. In this case, the improvement activities undertaken by the company consisted of the defining specific routes for the valve's pressure inspection.

4.3Association Rule Mining application

The fourth step of the procedure regards a further analysis of the FMECA's output. The dataset containing the information deriving from the FMECA analysis is processed to extract the ARs with the aim of enlarging the knowledge of the system. As required by the procedure, the minimum support threshold is set to 0, as well as the minimum confidence. Indeed, in this way, none of the relationships is lost during the analysis. For each failure mode, it could be interesting to understand, which is the potential loss of production (Table 2). For example, the rule "Failure Mode = FTR→% Loss of Production = n.a." has a support of 0.12 and a confidence of 0.75. The support value indicates that the failure mode "FTR" (Fail to Regulate) and a "not assessed" loss of production are associated in the 12% of the instances of the FMECA. Moreover, if the failure mode is FTR, there is no production loss in 75% of cases. In 15% of cases, instead, the loss of production corresponding to the FTR is of 16%. In the case of the failure mode "ELP" (External Leakage Process), instead, several consequences can verify. The most likely, both in terms of support and confidence, is a global production loss of the 16% (support = 0.12, confidence = 0.65). In other cases, if the failure mode is ELP, the corresponding percentage of production loss can be of 1.43 for the gas (confidence = 0.17) or 50 for the oil (confidence = 0.11). These events are rarer since their associated support are quite low, 0.03 and 0.02 respectively.

Table 1 Excerpt of FMECA's output table.

Item	Failure Mode	Operating Phase	Effects at Main Equipment level	% Loss of Production	AFC	ICS	ICA	ICE	Detection Method	CFM	CI
Flow Control Valve	ELP	Production	Gas & Oil Leakage	1,43% Gas	C	C1	C0	C0	Fire & Gas detection System	3	
Flow Control Valve	ELP	Production	Gas & Oil Leakage	1,43% Gas	C	C0	C0	C0	Fire & Gas detection System	3	2
Flow Control Valve	FTR	Production	Uncontrolled pressure oil delivery	50% Oil	C	C0	C2	C0	011000-PI-073	2	

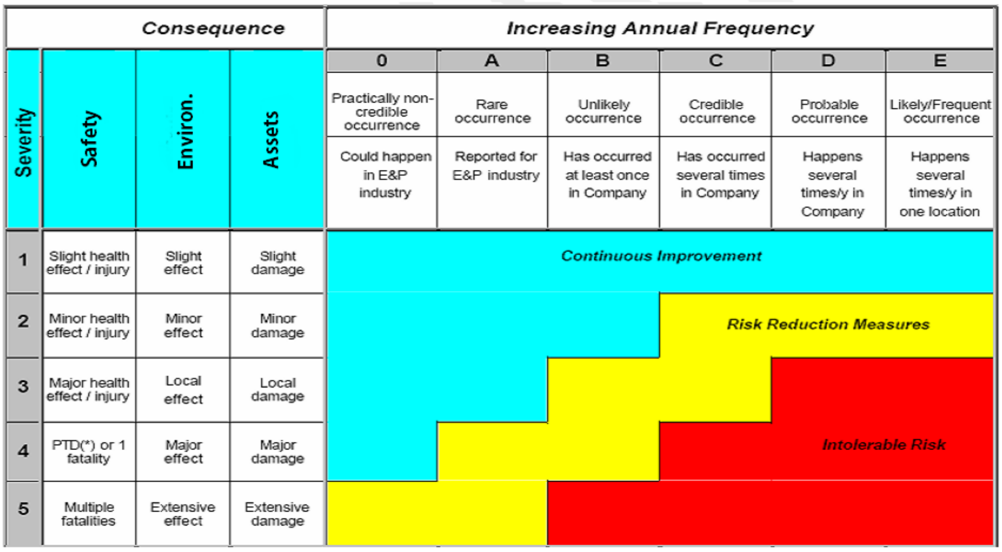

Figure 2 Risk Matrix for failure level identification.

Table 2 Association Rules relating the failure modes and the percentage of production loss.

Left-hand side	Right-hand side	Support	Confidence
Failure Mode = FTR	% Loss of Production = n.a.	0.12	0.75
Failure Mode = FTR	% Loss of Production = 16%	0.02	0.15
Failure Mode = ELP	% Loss of Production = 16%	0.12	0.65
Failure Mode = ELP	% Loss of Production = 1.43% Gas	0.03	0.17
Failure Mode = ELP	% Loss of Production = 50% Oil	0.02	0.11

Table 3 Association Rules relating failure modes and effects.

Left-hand side	Right-hand side	Support	Confidence
Failure Mode = ELP	Effects at Main Equipment level = Gas leakage	0.12	0.65
Failure Mode = ELP	Effects at Main Equipment level = Gas & Oil Leakage	0.04	0.22
Failure Mode = ERO	Effects at Main Equipment level = Wrong value indication	0.06	1.00
Failure Mode = FTC	Effects at Main Equipment level = n.a.	0.13	0.84
Failure Mode = FTC	Effects at Main Equipment level = Uncontrolled gas pressure delivery	0.02	0.16
Failure Mode = FTO	Effects at Main Equipment level = No gas flow	0.10	0.63
Failure Mode = FTO	Effects at Main Equipment level = n.a.	0.03	0.21
Failure Mode = FTO	Effects at Main Equipment level = No oil flow	0.02	0.16
Failure Mode = FTR	Effects at Main Equipment level = n.a.	0.12	0.75
Failure Mode = FTR	Effects at Main Equipment level = Uncontrolled gas pressure delivery	0.02	0.15

For each failure mode, it could also be interesting to understand, which is the potential loss of production (Table 2). For example, the rule "Failure Mode= FTR →% Loss of Production = n.a." has a support of 0.12 and a confidence of 0.75. The support value indicates that the failure mode "FTR" (Fail to Regulate) and a "not assessed" loss of production are associated in the 12% of the instances of the FMECA. Moreover, if the failure mode is FTR, there is no production loss in 75% of cases. In 15% of cases, instead, the loss of production corresponding to the FTR is 16%. In the case of the failure mode "ELP" (External Leakage Process), instead, several consequences can verify. The most likely, both in terms of support and confidence, is a global production loss of 16% (support = 0.12, confidence = 0.65). In other cases, if the failure mode is ELP, the corresponding percentage of production loss can be of 1.43 for the gas (confidence = 0.17) or 50 for the oil (confidence = 0.11). These events are rarer since their associated supports are quite low, 0.03, and 0.02, respectively.

Another interesting investigation involves the rules associating the failure modes to the effects. Some examples are reported in Table 3. Depending on the failure mode, the effects are different, even though for some of them there are common effects: for example, if the failure mode is FTC (Fail to Close on demand), then the effects can be "not assessed" (confidence = 0.84) or "Uncontrolled gas pressure delivery", with a confidence of 0.15. Similarly, when the failure mode is FTR (fail to regulate), the same effects are foreseen, respectively, with a confidence of 0.75 and 0.15. In this case, a unique inspective policy can be planned for both the failure modes since the effects are the same and with similar conditional probabilities.

5. Conclusions

In this work, a research approach for deepening the results' analysis of the FMECA is proposed, by defining a procedure based on the application of the Association Rule Mining. This technique, indeed, represents a simple but powerful method to deal with large datasets and extract useful attribute-value relationships from them. Being conscious of the common effects verifying when different failure modes occur or of the entity of the production losses can provide a support in defining a more accurate maintenance policy and, possibly, avoiding the occurrence of more dangerous events.

Since we are living in the digital transformation era, it is also important to include in the standard procedures even techniques like those belonging to the Knowledge Discovery in Databases field. In this way, there is contamination among different environments, namely the pure information system area and the operations-related one. Together with the benefits brought for the operations field, some major opportunities are also offered in a managerial perspective: firstly, the understanding of the importance of conscious data collection since data quality is vital to extract meaningful results from the data analysis. Secondly, a deeper knowledge of the system related not only to the plant itself but also considering the hidden relationships highlighted by the data.

However, the proposed approach represents a preliminary technique for enlarging the analysis carried out through an FMECA. Applying it to different case studies may highlight other benefits as well as limitations of the approach. Further development of the study can involve the use of multi-criteria decision making approaches and network analysis for representing the inter-relations identified and provide the visual user support.

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