Combining Evidential Clustering and Ontology Reasoning for Failure Prediction in Predictive Maintenance

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Abstract: In smart factories, machinery faults and failures are detrimental to the efficiency and reliability of production systems. To ensure the smooth operation of production systems, predictive maintenance techniques have been widely used in a variety of contexts. In this paper, we tackle the machinery failure prediction task by introducing a novel hybrid ontology-based approach. The proposed approach is based on the combined use of evidential theory tools and semantic technologies. Among evidential theory tools, the Evidential *C*-means (ECM) algorithm is used to assess the criticality of failures according to two main parameters (time constraints and maintenance cost). In addition, domain ontologies with their rule-based extensions are used to formalize the domain knowledge and predict the time and criticality of future failures. Case studies on synthetic data sets and a real-world data set are used to validate the proposed approach.

1 INTRODUCTION

Within manufacturing processes, anomalies such as machinery faults and failures may lead to the break down of production lines. To avoid the outage situation and economic loss may be caused by machinery faults and failures, predictive maintenance is a vital methodology that has been widely used in different manufacturing processes. By collecting real-time data from sensors and other information sources, a predictive maintenance task tries to detect possible anomalies and hazards within different industrial components.

To predict potential machinery failures, heterogeneous data are collected from multidimensional data sources, including the machine historical data and context data. For the analysis and management of these data, data mining and machine learning techniques are widely used for automatically discovering knowledge from data sets. In the predictive maintenance domain, the prediction and assessment of failure criticality is a critical issue for system users. By obtaining criticality levels for different failures, machine operators can prioritize maintenance actions for higher criticality-level failures compared to lower level ones. However, existing predictive maintenance approaches in the manufacturing domain are limited to the deployment of condition monitoring systems for detecting anomalies and predicting the time of future machinery failures, while lacking the solutions for identifying the criticality of machinery failures (Ansari et al., 2019). This brings obstacles to operators to perform appropriate maintenance actions by considering different priorities. As the degradation process of a piece of machinery often involves inherent randomness, techniques that can handle uncertainty are required to avoid the outage situation of the machinery and to ensure the smooth operation of the production system.

In this paper, we propose a hybrid ontology-based approach for the failure prediction tasks in Industry 4.0, which is based on the combined use of evidential clustering and ontology reasoning. Since the prediction of failure criticality suffers from the uncertainty and imprecise knowledge, the ECM algorithm is used to handle such kind of uncertainty and imprecision.

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On the other hand, domain ontologies with their rule-based extensions are used to formalize the classification results and predict the temporal constraints and criticality of future failures.

The remainder of the paper is structured as follows. Section 2 introduces the existing solutions and software that address the similar issues in predictive maintenance. Section 3 gives the foundations and background knowledge, including the introduction to the evidence theory and ECM. Section 4 introduces the proposed hybrid semantic approach for industry 4.0 predictive maintenance, where a domain ontology and ontology reasoning process are presented. Section 5 shows the experimental results we obtained on several synthetic data sets and a real-world data set. Section 6 concludes the paper.

2 STATE OF THE ART

In recent years, several efforts have been proposed to facilitate the predictive maintenance in Industry 4.0. As the manufacturing domain is becoming more dynamic and knowledge-intensive, several domain ontologies and their rule-based extensions were proposed to facilitate knowledge representation and reuse for the predictive maintenance in the industry. In this section, we review the most relevant research works.

In (Zhou et al., 2015), an intelligent fault diagnosis method was proposed based on ontologies and the Failure Mode, Effects and Criticality Analysis (FMECA). The method was proposed to meet the demands of fault diagnosis of wind turbines. In their work, deep knowledge and the shallow knowledge were extracted from FMECA and then modeled in the form of ontologies. To perform failure diagnosis, the knowledge is translated into the facts and rules for ontology reasoning. The knowledge model for fleet predictive maintenance, introduced in (Monnin et al., 2011), was developed to handle contextual knowledge within a fleet scale. In their work, semantic modeling techniques were used to define the context knowledge and the structure of a fleet. The fleet knowledge model has proved its practicability in the context of a marine application.

In the manufacturing domain, there are also research works considering the predictive maintenance of production lines. In (Emmanouilidis et al., 2010), a domain-specific ontology was developed to define the main elements of a generic condition monitoring system from an abstract level. The aim of the ontology is to facilitate asset self-awareness and to support production-level sustainable machinery operation. As another knowledge-based approach, the prescriptive maintenance model (PriMa) was designed for the prescriptive maintenance of production systems in smart factories (Ansari et al., 2019). Within the framework of PriMa, ontologies and case-based reasoning are used to build semantic learning and reasoning models. Results showed that the PriMa model enhances two functional capabilities of production systems: the efficient processing of heterogeneous big data, and the effective generation of decision support measures and recommendations for improving maintenance plans (Ansari et al., 2019).

After examining the existing research works, we observed that there is a missing link between the temporal information of an anomaly (e.g., the occurrence time of a future machinery failure) and the criticality level of the anomaly. Also, the impact of the estimated economic cost of maintenance on the criticality of the anomaly also remains uninvestigated. To address these issues, we propose a novel hybrid ontology-based approach for failure criticality prediction. The prediction of failures relies on two criticality descriptors: the temporal constraints of failures, and the estimated maintenance cost for avoiding the failures.

3 FOUNDATIONS AND BACKGROUND KNOWLEDGE

This section introduces the foundations and theoretical background that are necessary for describing our approach. It includes the background knowledge of evidence theory and the ECM algorithm.

3.1 The Evidence Theory

The evidence theory (Dempster, 1967; Smets and Kennes, 1994) is based on several fundamentals such as the *Basic Belief Assignment* (BBA). A BBA m is the mapping from elements of the power set 2^Θ on to [0, 1]:

$$m : 2^\Theta \longrightarrow [0,1],$$

where Θ is the *frame of discernment*. It is the set of possible answers for a treated problem and is composed of K exhaustive and exclusive hypotheses $\Theta = \{\omega_1, \omega_2, ..., \omega_K\}$. A BBA m is written as follows:

$$\begin{cases} \sum\limits_{A \subseteq \Theta} m(A) = 1 \\ m(\emptyset) \geq 0. \end{cases} \tag{1}$$

Assuming that a source of information has a reliability rate equal to $(1-\alpha)$ where $(0 \leq \alpha \leq 1)$, such a meta-knowledge can be taken into account using the discounting operation introduced by(Shafer, 1976), and is defined by:

$$\begin{cases} m^{\alpha}(A) = (1-\alpha)\times m(A) & \forall A \subset \Theta \\ m^{\alpha}(\Theta) = (1-\alpha)\times m(\Theta)+\alpha. \end{cases} \quad (2)$$

A discount rate α equal to 1 means that the source is not reliable and the piece of information that is provided cannot be taken into account. On the contrary, a null discount rate indicates that the source is fully reliable and the piece of information that is provided is entirely acceptable.

Within the evidence theory, several combination rules have been introduced among which we find the Dempster rule of combination (Dempster, 1967). Assuming two BBAs m_1 and m_2 modelling two independent reliable sources of information S_1 and S_2, the Dempster rule of combination is defined as follows:

$$m = m_1 \oplus m_2, \quad (3)$$

so that :

$$m(A) = \frac{1}{1-m(\emptyset)} \sum_{B\cap C=A} m_1(B)\times m_2(C) = \frac{1}{1-m(\emptyset)} m_{\cap}(A), \quad \forall A \subseteq \Theta, A \neq \emptyset, \quad (4)$$

where $m(\emptyset)$ is defined by:

$$m(\emptyset) = \sum_{B\cap C=\emptyset} m_1(B)\times m_2(C) = m_{\cap}(\emptyset). \quad (5)$$

$m(\emptyset)$ represents the conflict mass between m_1 and m_2.

The pignistic probability, denoted $BetP$, is proposed by Smets et al. (Smets, 2005) within the Transferable Belief Model (TBM). In the decision phase, the pignistic transformation consists in distributing equiprobably the mass of a proposition A on its included hypotheses. Formally, the pignistic probability is defined by:

$$BetP(\omega_n) = \sum_{A\subseteq\Theta} \frac{|\omega_n \cap A|}{|A|} \times m(A) \qquad \forall \omega_n \in \Theta. \quad (6)$$

where || is the cardinality operator.

3.2 Evidential *c*-means (ECM)

In the following, we present the ECM clustering approach (Masson and Denœux, 2008). The ECM algorithm is based on the concept of credal partition, which extends those of fuzzy and possibilistic ones. To derive such a structure, we minimize the proposed objective function:

$$J_{ECM}(M,V) \triangleq \sum_{i=1}^{d} \sum_{\{j/A_j\neq\emptyset, A_j\subseteq\Theta\}} c_j^{\alpha} m_{ij}^{\beta} dist_{ij}^2 + \sum_{i=1}^{n} \delta^2 m_{i\emptyset}^{\beta}, \quad (7)$$

subject to:

$$\sum_{\{j/A_j\neq\emptyset, A_j\subseteq\Theta\}} m_{ij} + m_{i\emptyset} = 1 \quad \forall i = 1,\ldots,d, \quad (8)$$

where $m_{i\emptyset}$ and m_{ij} respectively denote $m_i(\emptyset)$ and $m_i(A_j)$. M is the credal partition $M = (m_1,\ldots,m_d)$ and V is a cluster centers matrix. c_j^{α} is a weighting coefficient and $dist_{ij}$ is the Euclidean distance. In our case, we use the default values prescribed by the authors in (Masson and Denœux, 2008), i.e. $\alpha = 1$, $\beta = 2$ and $\delta = 10$.

3.3 Ontologies and SWRL Rules

In computer science, an ontology is a specification of a representational vocabulary for a shared domain (Gruber, 2009). Normally, it is designed to support the sharing and reuse of domain knowledge among different AI system components and also among system users. An ontology consists of classes, individuals, relationships, functions, and other objects (Gruber, 2009), which allows ontology reasoning to be performed on individuals, for inferring new knowledge.

Semantic Web Rule Language (SWRL) is based on a combination of its sublanguages OWL DL and OWL Lite with the RuleMarkup Language (Horrocks et al., 2006). A SWRL rule is in the form of an implication between an antecedent (body) and consequent (head), which can be interpreted in a way that whenever the conditions specified in the antecedent hold, then the conditions specified in the consequent must also hold (Horrocks et al., 2006). In SWRL, a rule has the syntax: $Antecedent \rightarrow Consequent$, where both the antecedent (body) and consequent (head) contains zero or more atoms.

4 THE HYBRID EVIDENTIAL ONTOLOGY-BASED APPROACH FOR PREDICTIVE MAINTENANCE

This section introduces our proposed hybrid method for failure time and criticality prediction. Fig. 1 shows the different steps within the approach. The approach starts with the Sequential Pattern Mining (SPM) on machine historical data (Agrawal et al., 1995). The aim of SPM is to extract frequent sequential patterns which contain failure events as well as their temporal information (e.g., the time stamp indicating when the failure happened). Then, the ECM algorithm is applied to cluster the failures according to

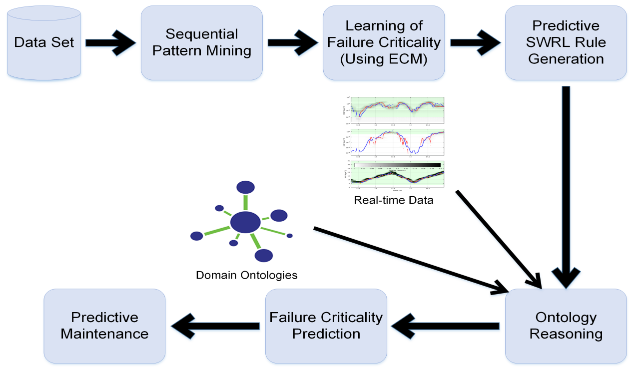

Figure 1: Different steps within the hybrid ontology-based approach for predictive maintenance.

their criticality, based on failure temporal constraints and estimated maintenance cost. After the clustering, we label different clusters with criticality *Low*, *Medium*, and *High*. With obtaining the results from ECM, ontologies with its SWRL rule-based extensions are used to predictive the criticality of a future failure.

4.1 The Evidential Approach for Failure Criticality Estimation

In our previous work (Cao et al., 2019), one ontology-based condition monitoring method was proposed. However, the method is based on crisp logic, and it fails to classify the criticality of a failure into the correct category when there are uncertain situations. To cope with this issue, an evidential approach which is able to handle such type of uncertainty situations is required. To do so, the times to failures described in rules and the estimated maintenance cost are used as training examples for ECM with 3 fixed clusters/classes which represents three levels of criticality: *(i) high criticality*, which indicates the time from a normal condition to the failure is relatively short and the production line should be stopped for immediate maintenance, or the estimated maintenance cost is relatively high; *(ii) medium criticality*, indicating the failure may happen after a moderate amount of time, or the estimated maintenance cost is moderate; *(iii) low criticality*, indicating the failure may happen in the long future and machine operators will have sufficient time to plan maintenance actions, or the estimated maintenance cost is relatively low.

In this paper, we intend to consider two factors to evaluate the criticality of a failure. Assuming a prediction rule in a form $R : A \xrightarrow[[t_i,t_j]]{} Failure$ that predicts the failure with a time interval with an Estimated Maintenance Cost EMC. The time to failure and the cost of the failure are valuable descriptors to assess the criticality of a failure. Each rule R has a value of support that evaluates its pertinence. We aim to use both predicted maintenance cost and predicted temporal constraints of the failure within a rule to assess the criticality of a predicted failure.

Let us assume a sequence S classified by a rule R as a failure in $[t_i,t_j]$ with an EMC. A BBA is computed from both parameters on the frame of discernment $\{Low, Meduim, High\}$ for each level of criticality. Both $m_{S,Cost}$ and $m_{S,time}$ are discounted using the support[1] of the used rule R as follows:

$$m_S^{1-Sup(R)} = m_{S,Cost}^{1-Sup(R)} \oplus m_{S,time}^{1-Sup(R)}. \tag{9}$$

$m_S^{1-Sup(R)}$ is the BBA obtained from the aggregation of the cost and the time to failure BBAs using the Dempster rule of combination. $1 - Sup(R)$ is seen as the reliability value used to discount the obtained BBAs. The final level of criticality is decided upon the use of the arguments of the maxima as follows:

4.2 The Manufacturing Failure Prediction Ontology

To address the uncertain situations, we extend the the ontology introduced in (Cao et al., 2019), by describing the nominal categories of classes. As a result, we developed the Manufacturing Failure Predictive Ontology (MFPO), within which the classes are associated with pignistic probabilities which range from 0 to 1. For example, in the ontology introduced in (Cao et al., 2019), *hasFailureCriticality* is an object property whose domain is the class *Failure*, and range is the predefined individuals *Low*, *Medium* and *High*. After applying the aforementioned method, this object property is replaced by three data properties: *hasFailureCriticalityLow*, *hasFailureCriticalityMedium*,

[1]The *Support* is measure that evaluate the pertinence of a rule based on its matching frequency within a database and denoted $Sup()$.

and *hasFailureCriticalityHigh*, and the sum of the numeric values of these three data properties is 1.

$$H_n = \underset{\omega_n \in \Theta}{\operatorname{argmin}} BetP(\omega_n). \tag{10}$$

Algorithm 1: Algorithm to transform a chronicle into a predictive SWRL rule, based on evidential c-means.

Require: $\mathcal{S}_F$: a chronicle within which the last state (event) is a failure, $\mathcal{E}$: a set of the states that are described within a chronicle.
Ensure: R ▷ R: the SWRL rule to be constructed.
$ls \leftarrow LastNonfailureState(\mathcal{S}_F, \mathcal{E})$ ▷ Extract the last non-failure state before the failure within a chronicle.
$f \leftarrow theFailure(\mathcal{E})$ ▷ Extract the failure within a chronicle.
$R \leftarrow \emptyset$, $A \leftarrow \emptyset$, $C \leftarrow \emptyset$, $Atom_a \leftarrow \emptyset$, $Atom_c \leftarrow \emptyset$, $F_{FailureCriticalityLow} = 0$, $F_{FailureCriticalityMedium} = 0$, $F_{FailureCriticalityHigh} = 0$.
for each $e_i \in \mathcal{E}$ **do**
    $pe \leftarrow ProceedingState(e_i, \mathcal{S}_F)$ ▷ Extract the proceeding state
    $se \leftarrow SubsequentState(e_i, \mathcal{S}_F)$ ▷ Extract the subsequent state
    $Atom_a \leftarrow pe \wedge se$
    $A \leftarrow Atom_a \wedge pe \wedge se$
end for
$ftd \leftarrow FailureTimeDuration(ls, f)$ ▷ Extract the time duration between the last non-failure state and the failure.
$mc \leftarrow MaintenanceCost(\mathcal{S}_F)$ ▷ Obtain the estimated maintenance cost for the failure described in this the chronicle.
$F_{FailureCriticalityLow} \leftarrow PignisticProbabilityLow(ftd, mc)$
$F_{FailureCriticalityMedium} \leftarrow PignisticProbabilityMedium(ftd, mc)$
$F_{FailureCriticalityHigh} \leftarrow PignisticProbabilityHigh(ftd, mc)$
$C \leftarrow F_{FailureCriticalityLow} \wedge F_{FailureCriticalityMedium} \wedge F_{FailureCriticalityHigh} \wedge ftd$
$R \leftarrow \{A \rightarrow C\}$

4.3 Ontology Reasoning for Failure Time and Criticality Prediction

To predict time and criticality of future failures, we propose SWRL rules (Horrocks et al., 2006) for ontology reasoning. The proposed SWRL rules reason on the individuals in the MFPO ontology, and infer new knowledge about failure prediction.

In this paper, we use the frequent chronicle mining algorithm introduced in (Sellami et al., 2019) to obtain chronicles, which are a special type of sequential patterns in a rule format. After that, SWRL rules are proposed to formalize the mining results and to predict failures. To enable the generation of SWRL rules, in this work we propose a novel algorithm to transform chronicles into SWRL predictive rules. The pseudo-code of the rule transformation algorithm is shown in Algorithm 1. It runs in four major steps: i). The function *LastNonfailureState* extracts the last non-failure state (event) within a chronicle, and the function *LastNonfailureState* extracts the failure event within a chronicle; ii). For each time interval in a chronicle, the two functions *ProceedingEvent* and *SubsequentEvent* extract the proceeding and subsequent events of it. Then the two events and this time interval forms different atoms in the antecedent of the rule, and they are treated as conjunctions; iii). The ECM algorithm is applied to classify the failures according to their criticality. The failures are classified into three categories, and three object properties in MFPO are used to represent the pignistic probability to different clusters. The pignistic probabilities are treated as a conjunction, to form the consequent of the rule; iv). At last, a rule is constructed as an implication between the antecedent and the consequent.

5 EXPERIMENTAL RESULTS

We validate our approach on several synthetic data sets and a real-world data set [2]. The experimentation starts with the preprocessing of data, followed by the chronicle mining step. The frequent chronicle mining algorithm introduced in (Sellami et al., 2019) is used to extract frequent chronicles.

5.1 Experimentation on Synthetic Data Sets

The experimentation on synthetic data sets begin with the frequent chronicle mining on synthetic data. To do this, the synthetic data was transformed into the form of pairs (event, time stamp), where each data sequence finishes with a failure. With obtaining sequences that contain failures, the frequent chronicle mining algorithm was used to extract the temporal constraints among these sequential patterns. As results, frequent chronicles were obtained. Inside a

[2]The source codes and data sets used in this paper could be found at: https://github.com/caoppg/ICAART-2020-paper-125.git

chronicle, events are ordered and temporal orders of events are quantified with numerical bounds (Sellami et al., 2019).

5.1.1 Classification of Failure Criticality using ECM

After obtaining the chronicles, we then generate synthetic data for the estimated maintenance cost. To do this, the maintenance cost is generated as uniformly distributed random numbers between [0,100]. In the generated data, each value of maintenance cost is associated with a failure, indicating the estimated maintenance cost caused by the failure. In addition to the temporal constraints of failures, maintenance cost is considered as the second descriptor for the failure criticality. The third step is to apply ECM on the synthetic data set, for determining the criticality of failures based on their temporal constraints and estimated maintenance cost. Following the evidential clustering approach introduced in Section 4.1, we obtained the final level of criticality of the failures described in chronicles. At last, the extracted frequent chronicles are transformed into SWRL predictive rules (using Algorithm 1), and the ECM classification results are also formalized by these rules. The following subsections introduce the different steps in our experimentation in details.

Table 1 shows the 10 failure chronicles (FC) which have the highest chronicle support (CS) among all extracted ones. In this figure, the numeric values of the minimum time duration (Min_{TD}, time unit: second) among the last normal events and the failures, the *EMC* for each chronicle, and the pignistic probability of the final criticality (PPFC) are presented. For the classification results, the final level of a failure's criticality is shown inside the brackets within the last column of the table.

5.1.2 The Generation of SWRL Rules based on Chronicles and ECM Results

To formalize the failure classification results and to predict the criticality of future failures, we generated SWRL rules based on the obtained chronicles and ECM classification results. To do this, Algorithm 1 was used to transform the failure chronicles and ECM classification results into predictive SWRL rules. Fig. 2 presents an example SWRL rule that was generated following our approach.

To evaluate the quality of the SWRL rules, two measures are computed. The first measure is *Accuracy*. It is computed by Equation 11, where n_{rc} is the number of training examples that are covered by a rule R and belonging to the class C. $n_{r\bar{c}}$ is the number of training examples that are covered by a rule R but not belonging to the class C. The second measure is *Coverage*, which is computed by Equation 12. Within it, $n_{\bar{r}c}$ the number of training examples that are not covered by a rule R but belonging to the class C.

$$Accuracy(R) = \frac{n_{rc}}{n_{rc} + n_{r\bar{c}}}. \quad (11)$$

$$Coverage(R) = \frac{n_{rc}}{n_{rc} + n_{\bar{r}c}}. \quad (12)$$

We use the above two equations to obtain the average value of *Accuracy* and *Coverage* for the SWRL rules. Table 2 presents the two measures under different chronicle support. We can observe from the table that as the chronicle support increases, the accuracy of rules also increases. It is reasonable since as the minimum threshold of extracted chronicles increases, we obtain more relevant chronicles. On the other hand, as the number of extracted rules decreases, the sequences that are covered by the rules decreases. This is the reason why the average value of coverage shows a downtrend.

5.2 Experimentation on a Real-world Data Set

To evaluate the performance of the prediction and failure classification, we apply ECM on a real-world data set. The real-world data set is called SECOM (Dua and Graff, 2017), which contains measurements of features of semi-conductor productions within a semi-conductor manufacturing process.

We first compute the hard credal partition on the SECOM data set. In total, at most 2^{Θ} focal sets could be obtained through credal partition, where Θ is the frame of discernment. In our experimentation, Θ represents the three levels of failure criticality. For the SECOM data set, we only use temporal constraints of failures as the descriptor for criticality. The data points on the empty set which have the highest masses are removed as outliers before they are assigned to the clusters.

Fig. 3 shows the hard credal partition computed on the SECOM data set with the following parameters: $\alpha = 1, \beta = 2$, $\delta = 10$, and $\varepsilon = 10^{-3}$. As results, 6 focal elements are obtained, including the universal set $\Theta_{\omega} = \{\omega_l, \omega_{lm}, \omega_m, \omega_{mh}, \omega_h\}$. Each subset of Θ_{ω} is represented by the convex hull. Among them, ω_l is the focal set representing the *low criticality* class, ω_m is the focal set representing the *medium criticality* class, and ω_h is the focal set representing the *high criticality* class. ω_{lm} is the hesitation between the ω_l and ω_m classes, which is $\{\omega_l, \omega_m\}$. ω_{mh} is the hesitation between the ω_m and ω_h classes, which means

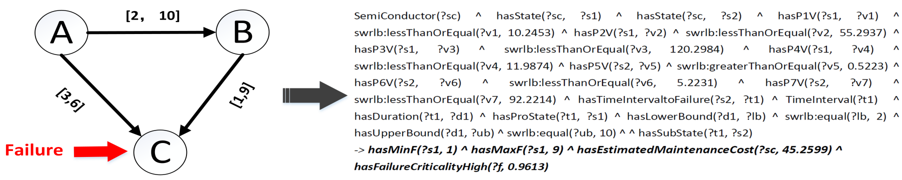

Figure 2: An example SWRL rule generated from a chronicle.

Table 1: Failure chronicles that have the 10 highest chronicle support, and their failure classification results.

C_F	Min_{TD}	EMC	CS	PPFC
C_{F1}	10	33.4163	96.19%	0.6652 (Medium)
C_{F2}	7	50.0472	95.61%	0.5049 (Medium)
C_{F3}	3	14.9865	94.48%	0.6140 (High)
C_{F4}	4	17.3388	94.21%	0.8739 (Medium)
C_{F5}	21	81.8148	92.94%	0.3921 (Low)
C_{F6}	3	65.9605	91.06%	0.8796 (High)
C_{F7}	11	68.1971	90.27%	0.4722 (Medium)
C_{F8}	24	9.6730	90.01%	0.6871 (Low)
C_{F9}	10	64.8991	86.93%	0.4266 (Medium)
C_{F10}	18	66.6338	86.87%	0.4030 (Low)

Table 2: Two rule quality measures under different chronicle support.

Chronicle support	Accuracy	Coverage
0.5	76.52%	74.26%
0.6	74.14 %	75.71%
0.7	76.98 %	74.35%
0.8	79.33%	70.49%
0.9	82.56%	68.10%
1	84.45%	67.71%

$\{\omega_m, \omega_h\}$. The center of each class is marked as a cross.

It can be observed that the ω_h class has the highest number of training examples, and over half of the failures are classified into the ω_h and ω_{mh} classes. As the value of a temporal constraint increases, the criticality level of the failure decreases. We can see that the evidential-based clustering extends the fuzzy and possibilistic methods by not only assigning data points to single clusters but also to all subsets of the universal set Θ_ω. In this way, ECM provides more insights into failures than the classical clustering methods.

To obtain the final level of criticality, the pignostic probability $BetP$ and the maxima of $BetP$ are computed. After comparing the $BetP$ of the three classes, the class with the maximum $BetP$ is selected to represent the final level of criticality. Fig. 4 shows the final criticality for the training examples in the SECOM data set. ω_l, ω_m, ω_h represents the *low criticality* class, *medium criticality* class, and *high criticality* class respectively. It can be seen that there is no hesitation among different classes, which ensures the final criticality to be determined based on a maximum of $BetP$ of the three classes. An example of the ECM clustering results on the training data is shown in Table 3. We select rule #45 and show the obtained BBAs and the pignistic probability of the final criticality (PPFC) of the failure which is described within this rule. Since the *high criticality* class is assigned with the highest PPFC, the final decision on the criticality level of this failure is high.

6 CONCLUSIONS

In this paper, the issue of failure prediction is tackled by introducing a hybrid ontology-based approach. The proposed approach is based on the combined use of evidential clustering and ontology reasoning techniques, where temporal constraints of failures and the estimated maintenance cost are used as training examples to evidential clustering, and domain ontologies with their rule-based extensions are used to formalize the classification results and predict the future failures.

For future work, we will work on experience capi-

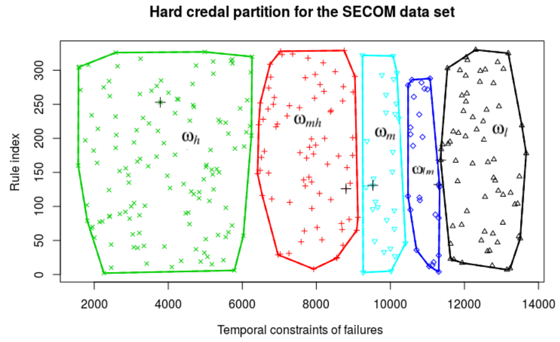

Figure 3: Hard credal partition for the SECOM data set.

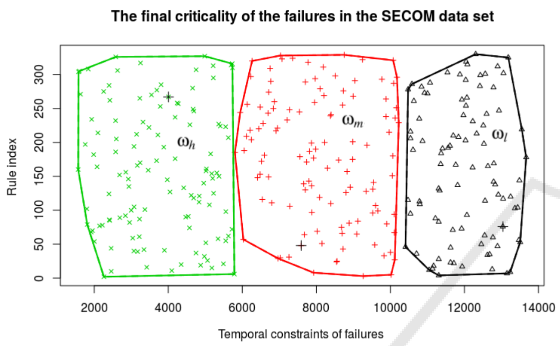

Figure 4: Final criticality levels of failures in the SECOM data set.

talization, which will support the failure classification process in case of failure. To achieve this goal, expert rules will be proposed and launched when the initial rule base fails to predict the machine anomalies correctly. In this way, when the next time a similar situation needs to be addressed, the rule which capitalizes domain experts' experience will also be launched to predict potential failures.

Table 3: Experimental results of a training example in the SECOM data set.

Rule index	BBAs of the failure	PPFC
#45	$m(\{\omega_h\}) = 0.3174$	$BetP(\omega_h) = 0.4683$
	$m(\{\omega_{mh}\}) = 0.2219$	$BetP(\omega_m) = 0.4391$
	$m(\{\omega_m\}) = 0.2929$	$BetP(\omega_l) = 0.0926$
	$m(\{\omega_{lm}\}) = 0.0181$	
	$m(\{\omega_l\}) = 0.0485$	
	$m(\{\Theta_\omega\}) = 0.1012$	

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REFERENCES

Agrawal, R., Srikant, R., et al. (1995). Mining sequential patterns. In *icde*, volume 95, pages 3–14.

Ansari, F., Glawar, R., and Nemeth, T. (2019). Prima: a prescriptive maintenance model for cyber-physical production systems. *International Journal of Computer Integrated Manufacturing*, pages 1–22.

Cao, Q., Giustozzi, F., Zanni-Merk, C., de Bertrand de Beuvron, F., and Reich, C. (2019). Smart condition monitoring for industry 4.0 manufacturing processes: An ontology-based approach. *Cybernetics and Systems*, pages 1–15.

Dempster, A. (1967). *Upper and lower probabilities induced by multivalued mapping*. AMS-38.

Dua, D. and Graff, C. (2017). UCI machine learning repository.

Emmanouilidis, C., Fumagalli, L., Jantunen, E., Pistofidis, P., Macchi, M., Garetti, M., et al. (2010). Condition monitoring based on incremental learning and domain ontology for condition-based maintenance. In *11th International Conference on Advances in Production Management Systems, APMS*.

Gruber, T. (2009). *Ontology*. Springer.

Horrocks, I., Patel-Schneider, P. F., Boley, H., Tabet, S., Grosof, B., Dean, M., et al. (2006). Swrl: a semantic web rule language combining owl and ruleml, 2004. *W3C Submission*.

Masson, M.-H. and Denœux, T. (2008). ECM: An evidential version of the fuzzy c-means algorithm. *Pattern Recognition*, 41(4):1384–1397.

Monnin, M., Abichou, B., Voisin, A., and Mozzati, C. (2011). Fleet historical cases for predictive maintenance. In *The International Conference Surveillance*, volume 6, pages 25–26.

Sellami, C., Miranda, C., Samet, A., Tobji, M. A. B., and de Beuvron, F. (2019). On mining frequent chronicles for machine failure prediction. *Journal of Intelligent Manufacturing*, pages 1–17.

Shafer, G. (1976). *A Mathematical Theory of Evidence*. Princeton University Press.

Smets, P. (2005). Decision making in the TBM : The necessity of the pignistic transformation. *International Journal of Approximate Reasoning*, 38:133–147.

Smets, P. and Kennes, R. (1994). The Transferable Belief Model. *Artificial Intelligence*, 66(2):191–234.

Zhou, A., Yu, D., and Zhang, W. (2015). A research on intelligent fault diagnosis of wind turbines based on ontology and fmeca. *Advanced Engineering Informatics*, 29(1):115–125.