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Multi-attribute Ontology-based Criticality Analysis of manufacturing assets for maintenance strategies planning

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Abstract: Planning maintenance strategies in advance with respect to the installation and running of manufacturing assets positively affects operational expenditure during their usage. However, the early stages of the asset lifecycle are poor of operational data. Thus, domain knowledge of experts, related to the asset, the process and production requirements, is the primary source to determine which maintenance strategy better fits in a specific context. Hence, ontology-based systems represent a relevant help in this direction. In this work, given the importance of the criticality analysis (CA) for maintenance planning, the CA is analyzed from an ontological perspective to automatically associate a maintenance strategy to the asset under analysis. Moreover, to unveil the power of CA, its multi-attribute nature is considered, including not only availability as guiding criterion, but also quality and energy. The developed ontology-based CA allows to (i) semantically align all involved experts, and (ii) potentiate the analysis through reasoning capabilities. Finally, preliminary results from an industrial case in a food company are shown.

Keywords: criticality analysis, maintenance, maintenance strategy, ontology, OWL, SWRL.

1. INTRODUCTION

Planning maintenance strategies in advance with respect to the installation and running of manufacturing assets positively affects operational expenditure during their usage (Roda *et al.*, 2020). However, in the BoL (Beginning of Life) of the asset, operational data are not available, if not from testing phases, benchmarks and data banks, whose conditions are generally far from the reality in which the asset will work. Nonetheless, an a priori maintenance strategy definition provides many advantages (Márquez *et al.*, 2009). Thus, several analyses may be adopted, among which the criticality analysis (CA) is widespread. It combines experts' knowledge to devise a decision on the maintenance strategy that better fits each manufacturing asset (Gopalakrishnan *et al.*, 2020). As such, the CA is useful both in the design phase as well as in the commissioning phase of manufacturing assets.

To promote the use of CA and systemize its steps, a multi-attribute ontology-based criticality analysis (MOCA) is proposed. Two choices are at its root:

1. the multi-attribute nature of CA, defining the criticality of an asset not merely on its availability, but considering other criteria that, properly combined, helps promoting a better maintenance strategy selection (Braglia, 2000);
2. the ontology model forming the backbone of the CA, since (i) it univocally defines the adopted terminology, by semantically aligning involved experts (Matsokis *et al.*, 2010); (ii) it allows for reasoning and inferencing.

After an overview on the application areas of ontologies in maintenance, the ontological model supporting MOCA is presented and applied in an industrial case.

2. ONTOLOGY FOR MAINTENANCE OF PHYSICAL ASSETS: APPLICATION AREAS

In information systems, ontologies (namely, computational ontologies) are artifacts that describe a portion of the world for some purpose (Staab and Studer, 2010). Being the current an information-based (industrial) world (Arp *et al.*, 2015), the application of ontology engineering to maintenance is growing in all sectors due to the potentialities they offer in exploiting domain-related tacit and explicit knowledge (Potes Ruiz *et al.*, 2013). In the scientific literature, ontologies used for maintenance on physical assets could be grouped in two main areas (see 2.1): ontologies for PHA (Process Hazard Analysis), ontologies for PHM (Prognostics and Health Management). Moreover, ontologies for IoT (Internet of Things) and CPS (Cyber Physical Systems) are also relevant in the realm of smart manufacturing (see 2.2), providing the means where to embed advanced maintenance approaches.

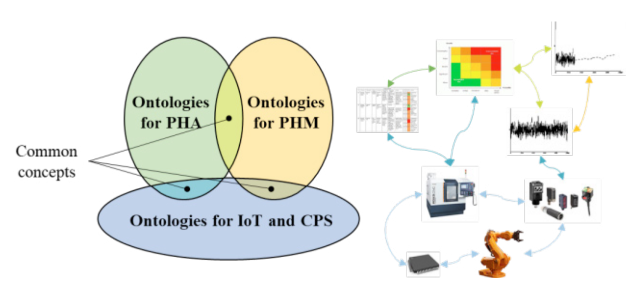

Fig. 1. Application areas for ontologies in maintenance.

Common to all is the goal of enhancing any sort of analysis of data to finally improve the maintenance decision-making performance, by semantically enriching already available

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knowledge (Karray *et al.*, 2012). The remainder of this section reports examples for each of the three areas previously enlisted, i.e. PHA, PHM and IoT and CPS, based on a selection of relevant literature from the review process.

2.1 Ontologies for PHA and PHM

PHA includes all analyses in order to capture the knowledge of the asset and related processes to support maintenance activities, like asset/failure mode prioritization and root cause identification. Among them, FMEA/FMECA, i.e. Failure Modes and Effects (and Criticality) Analysis, covers a primary role and is widely used in industry. For example, (Rehman and Kifor, 2016) proposes an ontology-based system to support experts in completing FMEA with potential causes and associated risk. In (Zhou *et al.*, 2015) an intelligent diagnosis systems of faults for wind turbines based on FMECA, ontologically formalised, is proposed, allowing maintenance personnel be aware of the fault cause and plan a proper solution. Considering another PHA analysis, (Zhao *et al.*, 2009) develops PetroHAZOP, a case-based reasoning expert system fostering HAZOP analyses by comparing already available cases and find the more similar, if any.

On the other hand, elaborating multi-sourced data to take reactive and proactive maintenance actions is the goal of PHM, which is increasingly adopted in the current data-driven approach to the management of assets (Guillén *et al.*, 2016). To semantically enrich data gathered from the shopfloor and reason over available domain knowledge, several ontologies are developed. An example is represented by (Nuñez and Borsato, 2018), where an ontology for PHM, called OntoProg, is proposed, able to guide data collection and support inference over relationships between failure modes and failure causes. Moreover, (Medina-Oliva *et al.*, 2014) developed an ontology for a fleet-wide approach to capitalize dispersed knowledge for advanced diagnosis. Also, a smart condition monitoring systems for triggering maintenance interventions is proposed by (Cao *et al.*, 2019), where the related tasks are formalised though the ontology.

Overall, the common goal of ontologies for PHA and PHM is to promote knowledge sharing between experts to advance and ease the analysis of asset and its failures (and related modes, causes, effects, etc.) to plan at best maintenance strategies and trigger eventual reactive or proactive actions.

2.2 Ontologies for IoT and CPS

IoT and CPS represent the building blocks of smart manufacturing. The former refers to the set of intelligent equipment that gather and share large amount of data (Kharlamov *et al.*, 2019); the latter, instead, relates to the capability of collaboration between smart industrial objects, leveraging on real-time computation in the cyber space to have impact on how real objects act (Garetti *et al.*, 2015).

Regarding IoT-related ontologies, (Gulati and Kaur, 2019) developed an ontological model to represent a reference architecture orchestrating smart objects to completely exploit all services and functionalities made available. Also, in (Mozzaquatro *et al.*, 2018) an ontology-based framework is proposed to connect industrial smart equipment while guaranteeing high standards of cyber-security. On the side of CPS, (Ansari *et al.*, 2018) proposed an ontology that facilitate human-CPS collaboration and thus enhancing problem-solving capabilities. Moreover, (Maleki *et al.*, 2017) supported sensors integration in CPS by allowing engineers select and integrate all those sensors which are really useful for decision-making.

Concluding, ontologies for IoT and CPS are seen as main means to guarantee semantic and technical interoperability between smart objects/systems present in production plants.

2.3 Concluding remarks

The identified areas of application of ontologies outline the directions to address in order to develop an ontology for maintenance decision-making support. Ontologies are in fact usable in order (i) to understand, relate, and infer the asset characteristics in PHA and (ii) to semantically enrich the available data for PHM goals; besides, it is required (iii) to guarantee interoperability between and orchestrate industrial objects and systems based on IoT and CPS. All of them point towards supporting and extending capabilities for modern maintenance in the smart manufacturing context.

Even though the identified areas do not cover the entire set of application of ontologies, they offer some insights for future research. Indeed, most of the ontologies:

1. share some common concepts, mainly related to the physical asset decomposition and manufacturing process description; however, the formalised concepts change from one ontology to another, arising interoperability issue; thus, there is a need to leverage on application-independent ontologies and reuse them to guarantee the very ground compatibility;

2. are confined in the MoL (Middle of Life); indeed, today, maintenance, with the evolution driven by the digitalisation, is majorly analysed and addressed when the asset is already operating and maintained; although, there is a need to concentrate on knowledge exploitation at the very first stage of the asset lifecycle, i.e. BoL; thus, being PLM a most advanced research in ontologies and their practice, a look towards PLM-fitted ontologies should be given to understand how it could help in improving maintenance strategy design and planning.

Therefore, this work aims at contributing to the use of ontology also in the BoL of the asset, where almost no data are available, and experts' knowledge remain the primary source for decision-making. The next section 3 describes the development of a multi-attribute ontology-based criticality analysis (thus within the *ontologies for PHA* area), called MOCA, which enables maintenance strategies planning of manufacturing assets in BoL.

3. MULTI-ATTRIBUTE ONTOLOGY-BASED CRITICALITY ANALYSIS

The purpose that drives the development of MOCA is to support the selection of the most appropriate maintenance strategy for each asset in a complex production system, which is in its BoL, namely during the commissioning phase. Being this the scope of work, the selection of the maintenance strategy is done at asset as indenture level, looking for a gross design of the strategies, while leaving detailed analyses later.

MOCA is built upon an ongoing research project, in which ORMA (Ontology for Reliability-centred MAintenance) ontology is developed. Thus, when talking about MOCA we refer to the set of concepts, properties and axioms belonging to ORMA and specific for the multi-attribute criticality analysis, as described in subsection 3.1.

3.1 Development of ORMA for criticality analysis

The development of ORMA stems from the need of investigating and enhancing ontology engineering for maintenance-related purposes. In the scope of this work, ORMA is extended in concepts and relationships to foster the adoption of ontology-based knowledge management systems even from the asset BoL.

As a background for ORMA modelling, recent ontology engineering methodologies, such as DOGMA (Spyns *et al.*, 2008) and NeOn (Suárez-Figueroa *et al.*, 2015), are considered, as well as relevant best practice, such as the selection of a reference foundational ontology, the definition of competency questions (CQs), and reuse of ontological and non-ontological knowledge.

As Fig. 2 sketches out, ORMA imports ROMAIN (Karray *et al.*, 2019) and the IOF-maintenance ontology (www.industrialontologies.org/maintenance-wg/), which are domain specific reference ontologies, i.e. a higher level of specialisation of an ontology for specific domains. Indirectly, ORMA reuses also some domain independent reference ontologies, that are CCO (Common Core Ontologies) (CUBRC, 2020), which further includes very basic ontologies like time ontology or unit of measurement ontology, and IAO (Information Artifact Ontology) (Ceusters, 2012). Concerning the reference foundational ontology, ORMA considers BFO (Basic Formal Ontology) (Arp, 2015), as suggested by the draft of the ISO 21838.

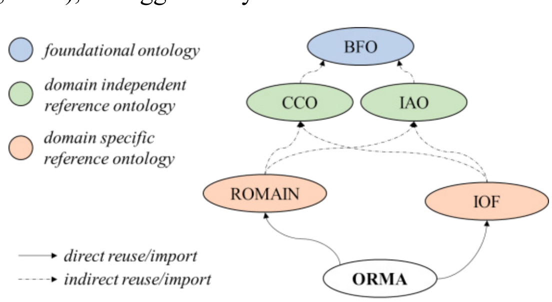

Fig. 2. Positioning of ORMA with respect to other ontologies, all BFO-compliant.

All the reused ontologies are BFO-compliant. Moreover, during the development of ORMA, additional ontological resources are used, like those described in section 2.1, after a re-engineering process. The following subsection 3.2 details the classes of ORMA fitted for MOCA purposes.

3.2 Main classes for MOCA

The very core classes of ORMA, useful for MOCA, are represented by the physical decomposition of the production plant. Both ROMAIN and IOF differ each other in this regard; also, they differ from the international normative, like the ISO 14224. Thus, Fig. 3 reports how ORMA formalises the physical decomposition, complementing and aligning afore-mentioned resources with authors' industrial experience. As for graphical representation, UML (Unified Modeling Language) class diagram is used as formalism.

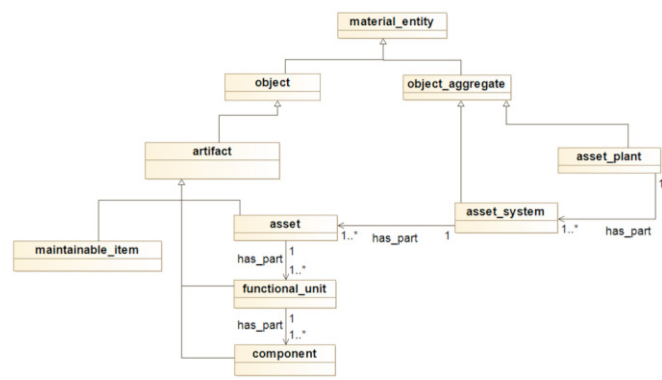

Fig. 3. Physical decomposition in ORMA.

From CCO, the *artifact* is an "*an object that was designed by some agent to realize a certain function*". Then, a*sset*, *functional_unit*, and *component* are inheritance of *artifact*, are disjoint classes, and are related through *has_part* relationships as shown in Fig. 3. Consistently with ROMAIN, *maintainable_item* is also an *artifact*, which is the target of a maintenance strategy. However, *maintainable_item* is not disjoint with any classes "on the other branch" since, according to the specific industrial need, an instance could be a *component* and a *maintainable_item* at the same time according to the interesting indenture level. Also, the three-level physical decomposition is selected according to authors' industrial experience, where decomposing up to the third level of granularity is common. This allows avoiding the use of reflexive relationships (like, *component has_part component*) that may give flexibility to the model, but it is far from the industrial practice and nomenclature.

The classes devoted to the representation of the multi-attribute criticality analysis extends from *maintainable_item*. According to the goal of MOCA, the classes and their relationships must scheme out the three attributes, i.e. Availability, Quality, and Energy, and, for each of them, the three FMECA-related parameters, i.e. Occurrence, Severity, Detectability, must be modelled. All these classes are inheritance of *designative_information_content_entity* since they are symbols denoting entities (Karray, 2019). Fig. 4 reports the class diagram of this part of ORMA.

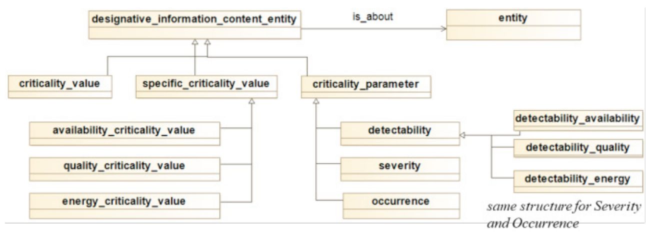

Fig. 4. Criticality analysis: ontological structure.

Also, at certain criticality values, the proper *maintenance_strategy_type* should be inferred, which is a *directive_information_content_entity* since it prescribes the entity. Thus, the last set of main classes needed to complete MOCA refers to the possible maintenance strategy types that could be adopted for each asset, as depicted in Fig. 5, according to ISO 13306.

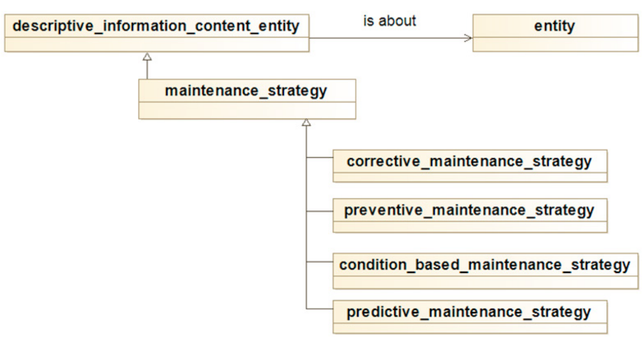

Fig. 5. Maintenance strategy types.

The selection of the maintenance strategy is determined by the criticality value, as described in subsection 3.3.

3.3 Functioning model of MOCA

For MOCA to function correctly, it is fundamental to leverage on the reasoning potentiality of ontologies. In this case, two are the main capabilities required to the ontology: i) compute the criticality values (both the *specific_criticality_value* and the *criticality_value*); ii) infer which is the strategy to allocate to each asset. Fig. 6 depicts how MOCA logically works (functioning model), starting from a *maintainable_item*.

The first SWRL-based rule (Rule#1) represents the set of rules that allows to evaluate the RPN (Risk Priority Number) for each attribute, by multiplying occurrence, severity, and detectability. For the availability, the rule is expressed as:

maintainable_item(?a) ^ has_avail_sev_param(?a, ?AS) ^ has_value(?AS, ?ASv) ^ has_avail_det_param(?a, ?AD) ^ has_value(?AD, ?ADv) ^ has_avail_occ_param(?a, ?AO) ^ has_value(?AO, ?AOv) ^ swrlb:multiply(?ACv, ?ASv, ?ADv, ?AOv) ^ has_avail_criticality(?a, ?AC) -> has_value(?AC, ?ACv)

The rules for quality and energy are defined analogously. Also, Rule#2 (weighted RPN per attribute) and Rule#3 (RPN of the asset) are expressed similarly. Then, to associate to each maintainable item a certain maintenance strategy, an axiomatic expression should be used, after the Rule#4 linked the *maintainable_item* with the criticality value. Here an example for the *predictive_maintenance_strategy* (when inferred, it will collect all maintainable items eligible for that strategy):

maintainable_item and (has_criticality_value some xsd:decimal[>=45])

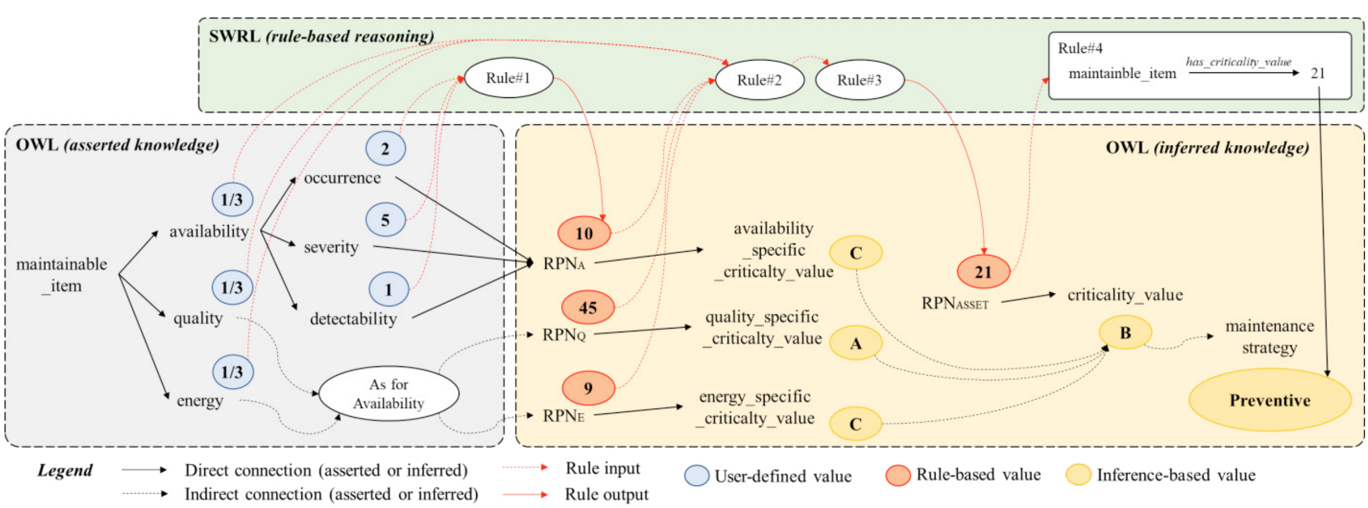

Fig. 6. Functioning of MOCA: asserted and inferred knowledge complemented by rule-based reasoning.

4. INDUSTRIAL CASE IN A FOOD COMPANY: PRELIMINARY RESULTS

The industrial case is the one of a world leader food company, whose goal is to plan the maintenance strategies for production plants in their commissioning/ramp-up phase, so no operational data are available. As a Proof of Concept (PoC), one plant is selected, which includes around 380 assets. For each of them, thus considering the *asset* as *maintainable_item*, a maintenance strategy should be selected amongst corrective, preventive, condition-based and predictive. Thus, firstly, ORMA (with MOCA-related classes) needs to be validated; then, it is applied to allocate maintenance strategy and results are briefly shown.

4.1 Implementation and verification of MOCA

The ontological model ORMA, and its classes related to MOCA, is implemented in OWL. The ontology editor is Protégé, which allows to interrogate the asserted and inferred knowledge through several plug-ins. The verification of MOCA is carried out by answering to competency questions (CQs), like *Which are the assets, their categorises and the corresponding asset systems to which they belong? Which are the assets that has manufacturing as main function?*. These CQs are answered through SPARQL queries and can reflect the current system knowledge.

4.2 Results

The selection of the most suitable maintenance strategy is based on the reasoning and inferencing capabilities of ORMA. The evaluation of the RPNs is obtained through the application of SWRL-based rules (see subsection 3.3), while the allocation of proper maintenance strategy to each asset is up to the reasoner (Pellet is selected). The mapping of the criticality value of the *maintainable_item*, i.e., the *asset* in this PoC, with the maintenance strategy is driven by the expertise of the company manager and defined in Table 1.

Table 1. Criticality value – maintenance strategy map.

Criticality value (CV)	*Maintenance strategy*
$CV \geq 45$	Predictive or Condition-based
$15 \leq CV < 45$	Preventive
$0 \leq CV < 15$	Corrective

The CV thresholds are defined qualitatively with the asset manager. It is worth noting that for CV $\in [45; +\infty)$ the maintenance strategy may be predictive either condition-based (currently, also, the ontology does not discern between the two); this will be assessed later in the project. Leveraging on the company expertise the user-defined values (i.e., the values of occurrence, severity, and detectability) are inserted. Then, ORMA can infer which is the best maintenance strategy for each asset type, as shown in Fig. 7 (?asset is a proxy for *maintainable_item*, and ?mStrat is a proxy for *maintenance_strategy_type*), where Snap SPARQL query is used since it allows querying over inferred knowledge.

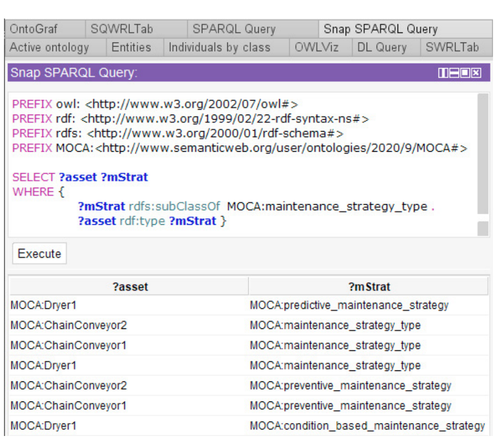

Fig. 7. Allocation of assets to suitable maintenance strategy.

5. CONCLUSIONS AND FUTURE RESEARCH

This research work focuses on the development of MOCA to enable knowledge exploitation in the BoL of the asset. As support to this activity, an ontological model (ORMA) is realised. MOCA is formalised and demonstrated for the commissioning phase of the asset, whilst advantages may be also envisioned for the design phase, where experts' knowledge may be even more impactful. The industrial investigations demonstrate the MOCA capability to infer the maintenance strategy according to criticality value provided by company experts. In the long run, the developed ontology will help the company in aligning how CA is performed in the several facilities the company owns.

Ongoing and future research are on the side of the ontological model extension:

1. Integrate knowledge from similar assets operating in other facilities and used as benchmarks to improve maintenance strategy allocation, also with additional information (such as preventive maintenance frequency defined based on the benchmarks).

2. Integrate knowledge from the operating assets to dynamically update the criticality values, leveraging on specific algorithms, like in PHM, for asset healthiness definition and eventual maintenance strategy adaptation.

Instead, on the side of technological deployment the effort is on: adopt Apache Jena–Fuseki semantic framework (https://jena.apache.org) for industrial usage of the knowledge base; introduce multi-stakeholders support, mitigating opinions through traditional and fuzzy techniques; develop a web application to ease knowledge introduction by experts, especially in the global context.

Furthermore, the retrieval of the plant layout and asset structure from company EIS represents a step forward. This will remove the manual inputting so that the activity will be less error prone, and it will guarantee always up-to-date data in ORMA/MOCA for shopfloor-synchronized decisions.

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