Semantic Technologies for the Modeling of Condition Monitoring Knowledge in the Framework of Industry 4.0

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Abstract. Following the trend of Industry 4.0, the demand for high productivity and availability of manufacturing processes has triggered the tendency of automation in various environments. The automation in different manufacturing processes and activities has given opportunities to the use of intelligent condition monitoring systems, which have been applied to many subdomains in manufacturing to improve productivity and availability of production systems. To develop such an intelligent system, semantic interoperability among different system components and system users is a critical issue. For this reason, semantic technologies are of paramount importance. In this paper, we present our proposal for the formal representation of condition monitoring knowledge using semantic technologies. The proposal is based on an ontological framework which consists of a core reference ontology for representing generic condition monitoring concepts and relations, and a domain ontology for formalizing manufacturing domain-specific knowledge. Based on the proposed ontological framework, we will develop an intelligent condition monitoring system which will be capable of detecting faulty conditions in machines, machine tools, and manufacturing processes, and providing appropriate decision support for tasks such as fault prognostics, diagnosis and preventive maintenance.

Keywords: Industry 4.0 · Condition monitoring · Manufacturing process · Availability · Fault prognostics · Semantic technology · Ontology.

1 Introduction

Industry 4.0 is an inter-disciplinary effort to inter-connect all resource of a factory and the factory itself with the Internet to build a smart factory. The tools, machines, workstations, and human operators are all interconnected to facilitate the traceability of processes, the adaptive and flexible control of production machines, and the real-time and decentralized reactions to unexpected events. Following the vision of Industry 4.0, the manufacturing industry today is benefiting from a trend of automation in data exchange. The automatic exchange and analysis of data open up opportunities for manufacturers to further optimize the production processes. Collecting data from various components of a production line and analyzing them in a scalable Cloud infrastructure can significantly improve the productivity, reliability, and availability of production systems in heterogeneous environments [1]. However, the utilization of these advanced technologies not only offer the aforementioned benefits to manufactures but also brings them challenges such as the management of a large amount of data generated by networked machines and sensors.

The management of big data is considered as a challenging task in the context of condition monitoring (CM) [1]. The objective of CM is to determine the correctness of the operating states of physical assets and manufacturing processes. Normally, when a propensity of machinery fault or failure is detected, highly experienced machine operators are capable of performing appropriate actions to prevent the outage situation of the production system. However, as the structure and behavior of production systems are getting more and more complex, the volume of machine operating data grows significantly. Thus it is possible that the domain professionals fail to respond to a machinery fault or failure timely and accurately. For this reason, manufacturing companies are searching for solutions through which they can manage this big data efficiently and perform prognostics tasks intelligently. To this end, the utilization of intelligent condition monitoring systems (ICMSs) is a promising approach [2].

To develop such an ICMS, semantic interoperability among different system components and system users is a critical issue. Since the data collected by the ICMSs come from heterogeneous data sources, the “meaning” of these data varies according to different contexts and domains, thus making it difficult to be harmonized. To deal with this challenge, shared, rigorous and machine understandable vocabularies with robust structures are needed. In this context, semantic technologies, especially ontologies, appear as good candidates to cope with the semantic interoperability problem. An ontology is a formal representation of certain domain knowledge, which computationally captures and structures domain concepts and relationships [3]. The use of ontologies can ensure the consistency of semantics, thus providing a shared understanding of knowledge among different participants within a domain. However, in the CM domain, most of the existing ontologies are only designed to represent a specific portion of domain knowledge of CM and lack the formal representation of manufacturing concepts. Thus, their domain coverage and scope are limited. In this context, there is a need for an ontology which provides a comprehensive representation of knowledge in both CM and manufacturing domains.

This paper introduces in detail a proposal for the development of an ICMS. The development work starts with a formal representation of domain knowledge that is related to CM tasks performed upon manufacturing processes. An ontological framework which consists of a core reference ontology for representing generic CM concepts and relationships and a domain ontology for formalizing manufacturing domain-specific knowledge is presented. Based on the proposed ontological framework, ontology reasoning techniques are adopted for facilitating decision making related to the fault and failure detection in machines, machine tools, and manufacturing processes. The detection of machine fault and failure enables the supervision of optimal preventive maintenance activities, which aims to guarantee high availability of manufacturing processes. This Ph.D. work is under the frame of the HALFBACK Project[1], and it is at the early stage.

2 State of the Art

In recent years, several systems and software have been developed to facilitate the automation of condition monitoring tasks on machines and machine tools. In [4], an automatic condition monitoring system for crack detection of rotating machinery is introduced. The authors process the vibration signals of cracks in a rotating shaft by combining the Wavelet Packets transform energy with Artificial Neural Networks. The proposed system is able to automate the diagnosis process without human interventions. However, the developed system is only capable of detecting crack effects, not other defects such as assembly errors or temperature anomalies. For the condition monitoring of cutting tools, an automatic detector based on vibratory analysis is demonstrated in [6]. In their work, the authors obtained vibratory signatures produced by a turning process, and the mean power of vibratory signatures is identified as the main indicator of the monitored cutting tool. However, the system is developed merely for the evaluation of cutting tool states, and it is not capable of providing prognostic and preventive maintenance decisions, based on the collected vibration signals. An automatic system for detecting wheel defects of rail vehicles is presented in [5]. The system performs analysis of wheel surface defects based on high-quality images of the wheel treads and flanges, and it has been tested for its usability and functionality by being used in an operational railway site. The main limitation of this system is the missing functionality of providing warning signals, such as alert and alarm. This limitation hinders the launching of maintenance activities.

As the manufacturing domain becomes more dynamic and knowledge-intensive, using ontologies to formally represent the knowledge of CM and manufacturing turns out to be a notable research topic [7]. The incorporation of ontologies to support decision making of condition monitoring in many domains has been a promising approach to improve the availability of manufacturing processes. During the last decades, several ontologies and ontological models are developed under different contexts and domains for the goal of facilitating knowledge formalization, sharing and reuse. In this section, we also review the existing ontologies and ontological models that are relevant to our work. The review is carried out according to two aspects: (i) ontologies that model the manufacturing domain; and (ii) ontologies that model the CM domain.

For the first category of ontologies, the Process Specification Language (PSL) ontology [8] is one of the early-stage contributions. This ontology explicitly specifies the terminologies for representing manufacturing activities. These terminologies model the key elements of process scheduling, process modeling, process planning, production planning, and project management. The Manufacturing Service Description Language (MSDL) ontology [7] aims to describe a wide

[1] http://halfback.in.hs-furtwangen.de

range of manufacturing services. This ontology incorporates the formalization of manufacturing processes, machine components, and machine tool capabilities. Based on the formalization of manufacturing-related knowledge, various manufacturing processes such as cutting, milling, and feed motions are expressively described. The MAnufacturings Semantics ONtology (MASON) [9] is another example which drafts the generic and common manufacturing concepts with their interrelationships. MASON is built upon three head concepts: *Entities*, *Operations* and *Resources*. Among them, *Entities* gives an abstract view of manufacturing products, *Operations* describes a wide range of manufacturing processes, and *Resources* covers all the resources that are related to manufacturing.

The second category of ontologies are normally designed for facilitating the tasks of fault or failure prognostics and machine health monitoring (PHM). The OntoProg Ontology [10] is a notable contribution which addresses the PHM issue of machines in smart manufacturing. The ontology is developed based on a set of international standards, from which the formal terminologies for constructing a PHM architecture are extracted. The Sensing System Ontology [11] is proposed to define the embedded sensing systems for industrial Product-Service Systems (PSSs). The ontology provides a comprehensive description of sensors embedded on PSSs, with the goal of monitoring machine health.

After reviewing the ontologies that are designed for either CM or manufacturing, we discover that none of them provides satisfactory knowledge representation of both domains. For example, some ontologies tend to focus on a narrow field, such as the product domain, and they do not formalize condition monitoring-related concepts, e.g. Failure, Fault and Error. Also, none of the existing ontologies provide knowledge representation of the concepts Warning Signal in maintenance tasks, e.g. Alert and Alarm, and also the relationships between them. To perform a CM task on a piece of machinery, the knowledge base of an ICMS should incorporate not only the machine-interpretable knowledge for characterizing the manufacturing entities or processes which are being monitored but also the knowledge about fault or failure detection and prognostics. To this end, in this Ph.D. project, we present our proposal for the formal representation of both manufacturing and CM domain knowledge using semantic technologies. In more detail, we will (i) propose an ontological framework that encompasses expressive knowledge representations for both CM and manufacturing domains; and (ii) develop an ICMS for fault prognostics, diagnosis and preventive maintenance of production lines.

3 Proposed Approach

The ontological framework is developed through a Middle-Out approach, which is a combination of the Top-Down and Bottom-Up approaches [12]. For the Top-Down approach, a set of international standards and textbooks are used to extract concepts from a general point of view, while for the Bottom-Up approach, existing domain ontologies are analyzed exhaustively for providing domain-specific knowledge. The proposed ontological framework consists of a core reference ontology for representing generic CM concepts and relationships, and a domain ontology for formalizing manufacturing domain-specific knowledge. Figure 1 shows the three-layered ontological framework.

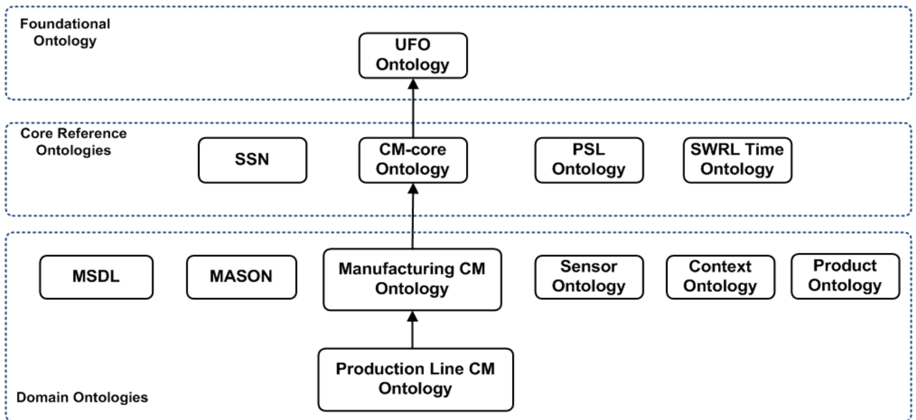

Fig. 1. The proposed ontological framework.

The development of the ontological framework starts with the choice of a foundational ontology which define general and basic notions across a wide range of domains. The reuse of a foundational ontology enables the integration of other ontologies that represents more specific domain concepts and relationships. In our work, we adopted the Unified Foundational Ontology (UFO) [13], as it provides rigorous and expressive representation of general concepts and relationships. The core ontology we developed is aligned to the UFO ontology, to ensure a rigorous conceptualization. The UFO ontology is at the top layer of our ontological framework.

For the middle layer, we develope the core reference ontology for condition monitoring, named CM-core. According to [14], core reference ontologies are built within the scope of a domain. Normally, they catch central concepts and relationships of a domain and are considered as an integration of several domain ontologies. During the development phase, we reuse some existing ontologies such as the Semantic Sensor Network (SSN) Ontology [15], PSL Ontology and SWRL Time Ontology [16].

At the bottom layer, a domain ontology called Manufacturing CM Ontology is developed to formalize domain knowledge that is related to condition monitoring tasks performed upon manufacturing processes. To enhance the reusability and extensibility of the Manufacturing CM Ontology, we followed the ontology partitioning and module extraction approaches introduced in [17], and structured our ontology into three modules: the *Manufacturing Module*, the *Context*

Module, and the *Condition Monitoring Module*. A set of domain ontologies are reused in this step, including the MSDL ontology, MASON ontology, .etc.

To evaluate and validate our domain ontology, which is used as the main ontology for performing ontological reasoning tasks, we use a web-based ontology validation tool named OOPS![2] for detecting potential errors in the ontology. The proposed ontology is evaluated by OOPS! according to three dimensions: (i) Structural dimension, (ii) Functional dimension, and (iii) Usability-Profiling dimension. To examine the robustness, fidelity, and quality of the ontology, we also integrate the evaluation conducted by domain experts, for checking its usability for specific domain tasks.

In the near future, we are going to specialize the Manufacturing CM Ontology into a more specific domain ontology, named the Production Line CM Ontology, for representing specific concepts and relationships of manufacturing production lines.

4 Preliminary Results and Future Work

Based on the three-layered ontological framework, rule-based reasoning tasks is performed to propose decision makings about machinery fault and failure prediction. We instantiated the Manufacturing CM Ontology with different examples of machinery in production lines, and then proposed SWRL rules[3] to infer about the correctness of the machinery operating states. Figure 2 shows two example rules, in which the first rule reasons whether a bearing experiences the state "inner race defect" (Dir). The second rule reasons whether a bearing has a minor error. The SWRL rules are extracted from real experiments about machinery defects identification. The results of rule-based reasoning tasks shows that the ontology could be used for the reasoning of machinery operation conditions. The reasoning capabilities of SWRL rules allowed the condition monitoring tasks such as machinery state identification and error detection to be accomplished.

In the near future, we plan to improve the performance of the logical inference tasks by applying a fuzzy semantic approach. The rules we mentioned in the preceding paragraph are based on crisp logic, which may fail to partition numeric values when the values are considerably close to the partition threshold. To deal with this kind of uncertainty situations, a fuzzy approach needs to be implemented. This approach will use fuzzy rules to enhance the representation of imprecise severity level of machinery faults, errors, or failures. For example, an identification of an error will be associated with a fuzzy index, indicating the grade of its membership to a minor or medium-level error. The fuzzy semantic approach will be applied to tackle the symbol anchoring problems [18], thus facilitating the condition monitoring tasks of manufacturing processes.

Another direction of future work aims to involve the joint utilization of machine learning techniques with semantic technologies. To facilitate the prognostic

[2] http://oops.linkeddata.es/response-advanced.jsp
[3] https://www.w3.org/Submission/SWRL/.

Bearing(?b) ^ hasBearingState(?b, ?s) ^ hasBearingParameter(?s, ?p1) ^ hasBearingParameter(?s, ?p2) ^ hasBearingParameter(?s, ?p3) ^ Kurtosis(?p1) ^ CrestFactor(?p2) ^ RMS(?p3) ^ hasParameterValue(?p1, ?v1) ^ hasParameterValue(?p2, ?v2) ^ hasParameterValue(?p3, ?v3) ^ swrlb:greaterThan (?v1, 3.266) ^ swrlb:greaterThan (?v2, 12.446) ^ swrlb:greaterThan(?v3, 20) -> ***hasStateSpecification(?s, "Dir")***

Bearing(?b) ^ hasBearingState(?b, ?s1) ^ hasParameter(?s1, ?p1) ^ Kurtosis(?p1) ^ hasParameterValue(?p1, ?v1) ^ swrlb:greaterThanOrEqual(?v1, 2.544) ^swrlb:lessThan(?v1, 5.158) ^ hasParameter(?s1, ?p2) ^ RMS(?p2) ^ hasParameterValue(?p2, ?v2) ^ swrlb:lessThan(?v2, 6) ^ temporal:hasTime(?s1, ?t1) ^ hasBearingState(?b, ?s2) ^ temporal:hasTime(?s2, ?t2) ^ swrlb:add(?t2, ?t1, 0.23) ^ hasParameter(?s2, ?p3) ^ Kurtosis(?p3) ^ hasParameterValue(?p3, ?v3) ^ swrlb:greaterThanOrEqual(?v3, 3.435) ^ swrlb:lessThan(?v3, 6.974) ^ hasParameterValue(?p4, ?v4) ^ RMS(?p4) ^ hasParameterValue(?p4, ?v4) ^ swrlb:greaterThanOrEqual(?v4, 6) **->** ***hasMinorError(?b, true)***

Fig. 2. Examples of proposed SWRL rules.

results of faults and failures in manufacturing processes, machine learning techniques, especially big data algorithms will be used to mine the collected data in smart factories. Big data algorithms will use the collected data to understand the manufacturing processes and to learn from the experience of the operators, through which a set of predictive rules will be extracted and then used jointly with the ontology for predicting machine damage, quality loss or maintenance demands in the future.

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