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Semantic framework for predictive maintenance in a cloud environment

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Abstract

Proper maintenance of manufacturing equipment is crucial to ensure productivity and product quality. To improve maintenance decision support, and enable prediction-as-a-service there is a need to provide the context required to differentiate between process and machine degradation. Correlating machine conditions with process and inspection data involves data integration of different types such as condition monitoring, inspection and process data. Moreover, data from a variety of sources can appear in different formats and with different sampling rates. This paper highlights those challenges and presents a semantic framework for data collection, synthesis, and knowledge sharing in a Cloud environment for predictive maintenance.

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Keywords: Predictive maintenance; Knowledge management; Cloud manufacturing;

1. Introduction

Maintenance plays an important and supportive role in the production. Effective maintenance policy improves quality, efficiency, and effectiveness of manufacturing operation and could influence the productivity and profitability of a manufacturing process [1]. Diagnostics and prognostics are two important aspects in a Condition-based Maintenance (CBM) program [2]. In literature several approaches for machining operation and machine tool condition monitoring have been reported [3].

To improve diagnostics and prognostics for better maintenance decision making, there is a need to better correlate process and inspection data with machine condition to differentiate between process and machine degradation [4]. Generally, diagnostics and prognostics models require significant amounts of historical condition monitoring and event data, as the uncertainty of these models decreases when data become more extensive. The means to synthesise smaller available data sets to generate extensive, representative historical condition monitoring and event data sets remains an open research question [5].

To solve those problems more detail information about manufacturing asset across its lifetime need to be gathered, accessed and processed. Targeting cloud-based predictive maintenance, this research aims at developing a semantic framework for the context-aware approach.

The remainder of the paper is organised as follows. Section 2 reviews background. Section 3 highlights available sources of data and benefits of its aggregation. Proposed semantic framework is presented in Section 4. Section 5 provide an example how this framework can be used to retrieve relevant information. Finally, Section 6 conclude the paper.

2. Backgrounds

2.1. Disparate data sources

Development and implementation of Information and Communication Technologies (ICT) in the industry in past decade brings new possibilities and challenges. More data are gathered, however, stored and processed in disparate and heterogeneous systems as Computerised Maintenance Management System (CMMS) for maintenance record-keeping, Condition Monitoring (CM) for asset health state

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monitoring and Supervisory Control and Data Acquisition (SCADA) systems for monitoring process and controlling the asset.

2.2. Industry 4.0

According to the Federal Ministry of Education and Research, Germany (BMBF) after Monostori [6], "Industry is on, the threshold of the fourth industrial revolution frequently noted as Industry 4.0. This revolution is led by development and implementation of Cyber-Physical Systems. A similar concept is also researched under the name of Cloud Manufacturing. Cloud Manufacturing paradigm is a result of a combination of cloud computing, the Internet of Things, service-oriented technologies and high-performance computing [7]. It transforms manufacturing resources and capabilities into manufacturing services. It is not the simple deployment of manufacturing software tools in the computing cloud. The physical resources integrated into the manufacturing cloud are able to offer adaptive, secure and on-demand manufacturing services over the Internet of Things [8].

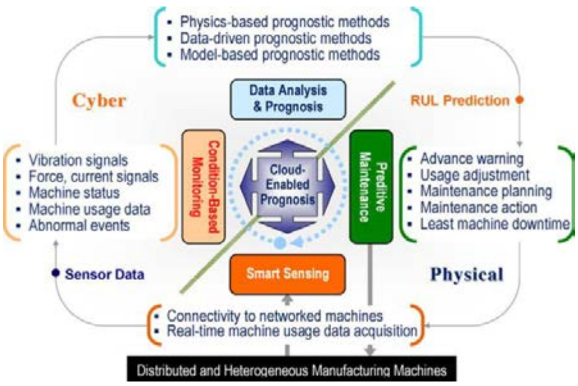

Fig. 1. Cloud-enabled monitoring, prognosis and maintenance [5].

Overview of cloud-enabled prognostics approach within cyber-physical concept has been visualised in Fig.1. Cloud-enabled prognosis benefits from both advanced computing capability and information sharing for intelligent decision-making [5].

2.3. Context

Recently a context awareness is an approach gaining more focus from researchers in the field of CBM and predictive maintenance. This well-known concept in some other fields could be beneficial when employed in CBM and Asset Management [9].

2.3.1. Context definition

In predictive analytics, two sets of information can be distinguished namely condition monitoring and context. Condition monitoring data are used to estimate health state of monitored equipment while context information provides support for a better understanding of it. Context information consists of two types of factors: conditions that affect health state estimation, and condition that affects degradation processes. An example of factors that belongs to the first context group is types of used sensor, acquisition parameters, and operational condition at measurement time. Operational conditions and performed maintenance actions are the examples of contextual information belonging to the other group. Overview of different context modelling techniques and its usage in predictive maintenance has been reported in [10].

2.4. Ontology

In computer and information science, ontology determines formal specifications of knowledge in a domain explicit specification of the objects, concepts, and other entities (vocabulary) that exist in some area of interest and the relationships that hold among them [11]. Ontology model O can be described as a set O={C, RS, I}, where C is a collection of concepts in the ontology called also classes, I is set of particulars (instances of classes, individuals), and RS is set of relations between two concepts or particulars. Ontology Web Language (OWL) [12] is one of common ontology formalization languages. Reasoning over ontology specified with OWL is done with the use of Descriptive Logics that makes it more powerful than just reasoning within Resource Description Framework (RDF), as more complicated relations can be represented. Moreover, Semantic Web Rule Language (SWRL) [13] extend the capability of OWL to represent knowledge by means of more complex rules. According to [14], ontology-based context modelling allows:

- Knowledge sharing between computational entities by having a common set of concepts about the concept;
- Logic inference by exploiting various existing logic reasoning mechanisms to deduce high-level, conceptual context from low-level, raw context;
- Knowledge reuse by reusing well-defined Web ontologies of different domains, e.g. a large-scale context ontology can be composed without starting from scratch.

2.4.1. Standards

There are some standardisation initiatives to enable the integration of disparate maintenance IT systems.

MIMOSA (Machinery Information Management Open Systems Alliance) [15] is a not-for-profit trade association dedicated to developing and encouraging the adoption of open information standards for Operations and Maintenance in manufacturing, fleet, and facility environments. MIMOSA's open standards enable collaborative asset lifecycle management in both commercial and military applications. OSA-EAI (System Architecture for Enterprise Application Integration), OSA-CBM (Open Systems Architecture for Condition Based Maintenance), MIMOSA standards are compliant with and form the informative reference to the published ISO 13374-1 standard for machinery diagnostic systems. According to [16] MIMOSA and OSA-CBM are the most evolved standards that cope with CBM technology.

Another standard that provides maintenance taxonomy is ISO 14224: Petroleum and Natural gas industries – Collection and exchange of reliability and maintenance data for equipment. Some typical oil and gas equipment related terms have been categorised as to taxonomy, boundary definition, inventory data and failure modes. These data are specific for each equipment unit. A standardization approach has been applied for classification and subdivision of units. This reduces the total number of different data categories and definitions, while at the same time there are fewer tailor-made definitions and codes for each individual equipment unit.

2.5. Machine Tool condition monitoring

Zhou at al. [17] proposed integrated condition monitoring and fault diagnosis for modern manufacturing system with the use of internal controller signals and sensors. Remote monitoring and maintenance system for thousands of machine tools linked to a central server has been developed in [18]. There exists high potential in knowledge capitalisation in population width approach, as for example existing system reported in [19] connects to over 14 000 machine tools worldwide.

Condition monitoring in [20] dynamically affect the entries in the capability ontology by providing the current status of the machines. If the machine is overloaded or faulty then it will be not shown up in results from a query of the machine that can perform specified task.

3. Valuable data/information

Across industrial ICT systems, there exist a big amount of valuable information from diagnostics and prognostics perspective. To mention some of them:

- Asset related data: information about machine tools across factory – type of machines and their location; hierarchical structure – division into units, subunits, components, spare parts.
- Work orders (WO): machine/unit/component on which maintenance action was performed; type of maintenance action (corrective, preventive); descriptions (symptoms, comments on performed actions); list of acquired spare parts for WO.
- Condition monitoring: vibration, ball-bar measurements; geometry measurements.
- SCADA: number of cycles, type of produced variant.
- Internal Machine Tool Controller data.

The ideal scenario is to have access to all those data and be able to retrieve relevant information, that could be utilised within context-aware approach and provide support for predictive maintenance, see Fig. 2.

Examples provided in following part of the section are based on real data retrieved from ICT systems in one company within the automotive manufacturing industry.

Aggregated information can be presented to the human decision maker in a new way, as depicted in Fig.3. where trend information from condition monitoring are enriched with indications of performed maintenance actions, and replaced spare parts. Automatic query of information related to specified machine/unit/component will improve interpretation of data by including that information as contextual information.

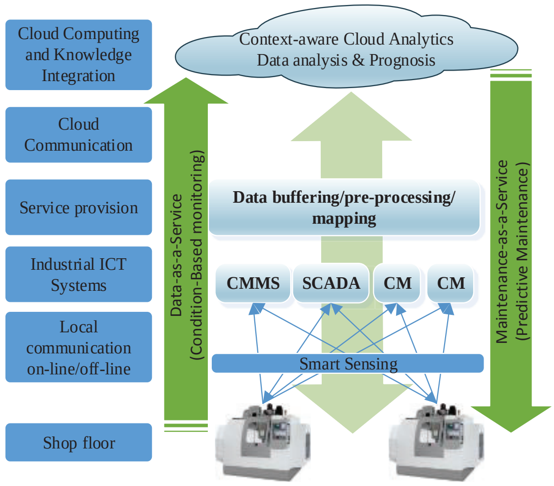

Fig. 2. Information access for context-aware prediction.

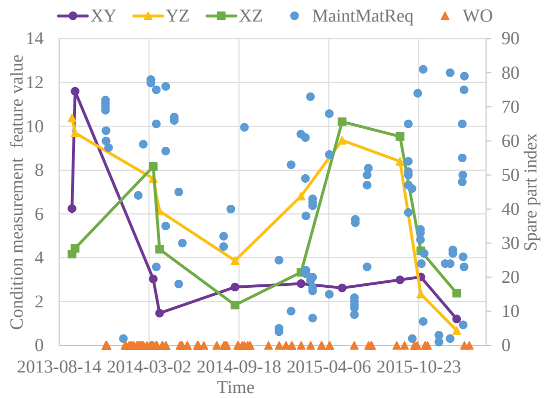

Fig. 3. Aggregation of information from disparate sources in one view: XY, YZ, XZ – trends from ball-bar measurements; MaintMatReq – acquired spare parts; WO – performed work orders.

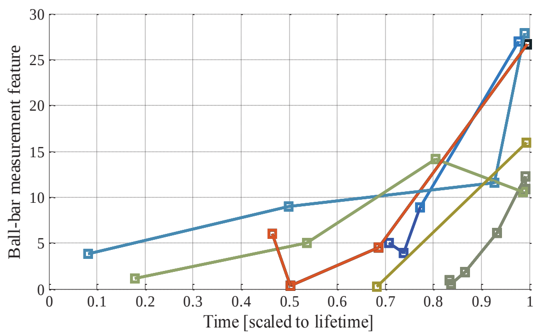

Fig. 4. Condition monitoring data aligned to component instances

Querying for components of the same type and associated condition monitoring data can increase the amount of available datasets that can be used to train the diagnostics and prognostics models. In Fig. 4. an example of ball-bar measurements aligned with instances of replaced ball-screws of the same type across the available population of machines is presented. Taking into consideration the type of performed maintenance work (corrective or preventive) involved in the replacement, obtained trends can be differentiated to ones related to actual lifetime, and to ones related to censored lifetime.

Continuously acquired information from machine tool controllers can provide additional contextual information about machine utilisation. As an example in Fig. 5. calculated mechanical energy delivered to machine tool's linear axes is presented. It is based on on-line acquired information about axes velocities and applied torque. Energy corresponds to the load axes have been exposed to, and could be used as a context information. Despite the same operation is performed, the average energy consumption per cycle varies noticeably.

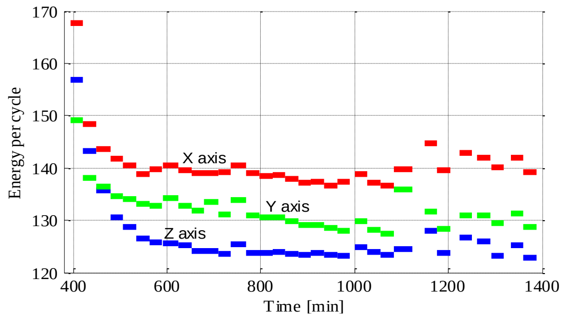

Fig. 5. Variation of machine tool main linear axes energy consumption during one production day

4. Semantic Framework

Overview of the semantic framework for predictive maintenance is presented in Fig. 6. With the use of ontology base mapping and semantic querying, it allows accessing information from disparate sources. Moreover, provision of a service-oriented data access within the cloud concept allows obtaining the relevant information despite its location.

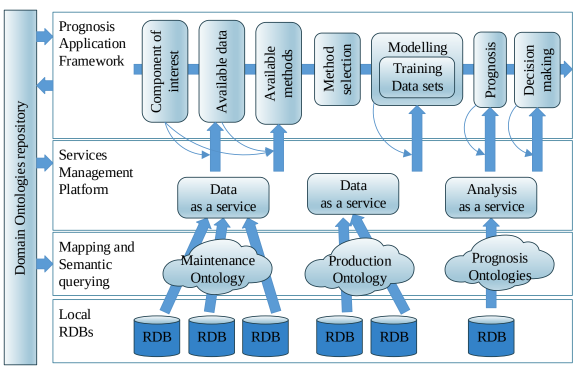

Fig. 6. Semantic framework overview

4.1. Ontology-based data retrieval

To be able to access the local data sources through the domain ontology, there is need to maintain the link between the domain ontology and the data sources. There exist some technology that allows performing this mapping with different autonomy levels.

RDB to RDF mapping language (R2RML) [21], D2RQ Mapping Language [22], RDB2RDF Direct Mapping [23].

After that semantic query language e.g. simple protocol and RDF query language (SPARQL) [24] can be used to retrieve local data represented in RDF (R2RML, D2RQ). Ontology-based information representation and retrieve are similar to the one proposed in the semantic framework presented in [25].

4.1.1. Manual mapping

Manually create a mapping using e.g. R2RML. This is the case when vocabulary and local ontology of RDB differ much from a domain ontology, see Fig. 7.a.

4.1.2. Automatic and semi-automatic mapping

In this case, local ontology is retrieved from RDB by direct mapping. Than ontology, alignment tool has to be applied to automatically generate R2RML file corresponding to this alignment. When two ontologies cannot be fully automatically aligned, there is a need for human intervention to manually modify or add mappings between ontologies, as depicted in Fig. 7.b.

To facilitate the automatic mapping, the standardization of common ontology for data represented in RDBs are needed. Some initiatives in this direction have been mentioned earlier in section 2.4.1.

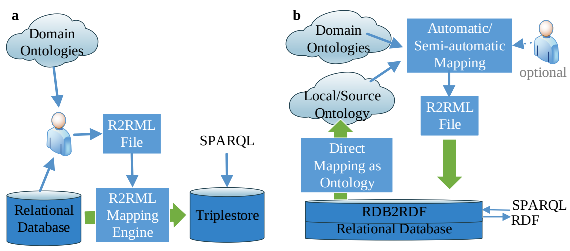

Fig. 7. (a) manual mapping; (b) automatic/semi-automatic mapping

4.2. Domain ontologies

Domain ontology captures knowledge within the domain, specific area, and perspective. Examples of different perspectives that the same asset in a manufacturing environment can be looked from could be: production, maintenance, quality.

Potential domain ontologies that could be distinguished are: Asset ontology – structure of asset, Functional ontology – performed function, Work Order ontology – performed maintenance actions. In most cases, ontologies overlaps and it allows to make bridges between them and this provides an opportunity to use data and knowledge across linked domains.

However, those bridges if not explicit have to be defined by expert across the domains.

5. Demonstration Case

To illustrate the potential usefulness of proposed approach a demonstration case based on part of data that have been explained in section 3 is presented.

In a relational database of CMMS, there are tables that represent the hierarchical structure of the asset. Data model is depicted in Fig. 8. This model corresponds to ontology's classes and dependencies presented in Fig.9. Retrieving data stored in RDB, the ontology can be enriched with instances of individuals that corresponds to existing physical machines, units, components and its hierarchical structure.

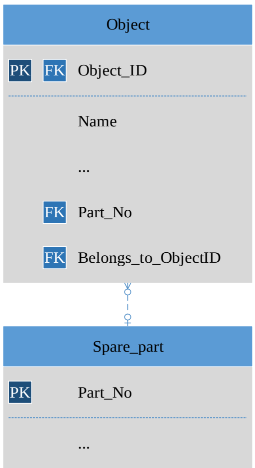

Fig. 8. Data model for the asset hierarchical structure

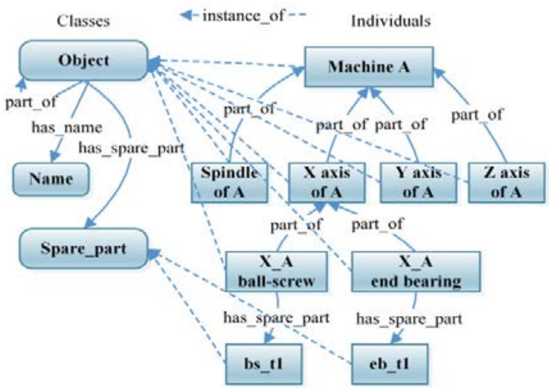

Fig. 9. Part of Asset hierarchy ontology

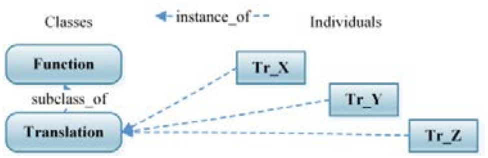

Fig. 10. Part of Functional ontology

Additional ontologies that have been creating are Functional ontology presented in Fig.10. and Measurement ontology depicted in Fig.11. A functional ontology defines functions that can be performed by objects. In presented part, there have been defined three functions related to a linear movement that are translations in 3 main directions (Tr_X, Tr_Y, and Tr_Z). Measurement ontology can describe different types of measurements with an indication of what function performance it corresponds to. In depicted case, the ball-bar measurement is represented that corresponds to a measurement in plain created by motion in two main directions at a time.

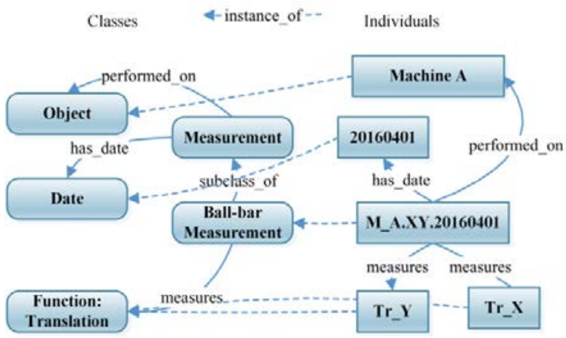

Fig. 11. Part of Measurement ontology

Ball-bar measurements are retrieved form of XML files. It includes a field that consists of machine_id, an identification number of a machine tool on which the measurement has been performed. It is the same number as Object_ID key in the asset database. This leads to straightforward connections between those ontologies as in Table 1.

Table 1. The bridge between Measurement and Asset ontologies.

Measurement:Object	owl:sameAs	Asset:Object

The used sameAs property belongs to OWL vocabulary, and indicates that two terms are synonyms, e.g. identify the same class or individual.

Next step in defining ontologies and connections is to map defined functions with objects that are responsible for it. In presented case of machine tool axes it can be done by following a set of rules from Table 2. represented in human readable form (? denotes a variable).

Table 2. Mapping of functions to asset objects.

Object:has_name(?x, "X Axis")	=>	Object:has_function(?x,Function:Tr_X)
Object:has_name(?x, "Y Axis")	=>	Object:has_function(?x,Function:Tr_Y)
Object:has_name(?x, "Z Axis")	=>	Object:has_function(?x,Function:Tr_Z)

In this case value of one property of an object (has_name) is used to assign the value of another property (has_function). Up to this point following mappings have been performed: measurements to machines, and machines' components to its functions. Table 3. presents rule specified to map measurement instances with relevant objects within the machine tool hierarchical structure (units or components).

Table 3. Mapping of measurements to corresponding asset objects.

Measurement:measures(?measurement,?function) ∧
∧ Measurement:performed_on(?measurement,?objectX) ∧
∧ Object:has_function(?objectY,?function) ∧
∧ Object:part_of(?objectY, ?objectX) =>
=> Object:has_measurement(?objectY, ?measurement)

Now combined ontology can be queried for has_measurement property to retrieve all relevant measurements. For example, for individual corresponding to the X axis of machine A, it will return all ball-bare measurements performed on machine A that has been executed in XY plane and XZ plane, as those measurements involve the motion in X direction.

This approach can be used as a support in selecting suitable diagnostics and prognostics method on its early stages by checking what types of data are available and the amount of available relevant data. Moreover, data from the whole population of identical or similar components could be retrieved. Identical components could be defined as the one that uses the same spare part. However, data from a population of components cannot be simply aggregate, without consideration of contextual information. It needs to be mentioned, that defining similarity in context domain is not a trivial task.

6. Conclusions

This paper presents important data available within ITC systems in the manufacturing industry that have to be integrated to facilitate improvement in diagnostics and prognostics for CBM. A semantic framework with the use of ontology-based approach for data aggregation is proposed to support context-aware cloud–enabled diagnostics and prognostics in application to the maintenance of manufacturing asset. To indicate potential benefits, some examples originated from manufacturing industry have been presented.

Future work will focus on developing and applying more advanced context modelling and prediction method that will be able to utilise the contextual information to improve prediction reliability.

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