Towards a Machine of a Process (MOP) ontology to facilitate e-commerce of industrial machinery

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**ABSTRACT**

Adapting to user’s requirements is a key factor for enterprise success. Despite the existence of several approaches that point in this direction, simplifying integration and interoperability among users, suppliers and the enterprise during product lifecycle, is still an open issue. Ontologies have been used in some manufacturing applications and they promise to be a valid approach to model manufacturing resources of enterprises (e.g. machinery and raw material). Nevertheless, in this domain, most of the ontologies have been developed following methodologies based on development from scratch, thus ontologies previously developed have been discarded. Such ontological methodologies tend to hold the interoperability issues in some level. In this paper, a method that integrates ontology reuse with ontology validation and learning is presented. An upper (top-level) ontology for manufacturing was used as a reference to evaluate and to improve specific domain ontology. The evaluation procedure was based on the systematic methodology for ontology learning (SMOL). As a result of the application of SMOL, an ontology entitled Machine of a Process (MOP) was developed. The terminology included in MOP was validated by means of a text mining procedure called Term Frequency–Inverse Document Frequency (TF-IDF) which was carried out on documents from the domain in this study. Competency questions were performed on preexisting domain ontologies and MOP, proving that this new ontology has a performance better than the domain ontologies used as seed.

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**1. Introduction**

The development of new products1 is a challenging activity that demands highly flexible and adaptable enterprises. Approaches, such as flexible manufacturing systems (FMS) [1], concurrent engineering (CE) [2] and design for manufacturing (DFM) [3] among others, aim to contribute to this challenge. Nevertheless, these approaches are centered in previously existing resources; that means they only consider available resources in a formerly given facility, and they discard the existence of newer resources which could give a better performance for a given production process. Thus, when new products are developed, the decision makers have fewer possibilities to have updated information about the real worldwide available resources for manufacturing. The situation described above becomes error-prone, given that the evaluation of a new product could conclude that an innovative product cannot be manufactured due to the lack of resources. When innovation is a key factor for success in the modern industry [4], this kind of decisions can lead to loss of business opportunities.

The Internet can be used as an information source of digital models of resources for manufacturing: e.g. industrial machinery, spare parts and raw materials. However, these resources require a different treatment from other resources commonly sold on Internet like clothes or other goods for personal use, for which a technical evaluation is unnecessary. Resources for manufacturing are designed for specific tasks and require skilled engineers and planners to decide about their acquisition and use. Thus, selecting such resources implies team work. Additionally, acquiring resources for manufacturing means disbursing considerable amounts of money, if we compare their costs with the cost of other products currently sold on the Web. Moreover, as we will demonstrate in Section 4, resources for manufacturing are becoming abundant on the Internet for sale. So, engineers and planners may require considerable amounts of time to decide among hundreds of similar resources. In fact, without specialized software tools for analyzing such information, taking an efficient decision becomes technically impossible [5]. An immediate consequence of this is the increase of cost to design and to develop new products.

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1 In the definition of products industrial machinery can be included from Business to Business (B2B) approach.
In this vein, ontologies and the Semantic Web are valid approaches to describe resources on the Web [6]. In the domain of manufacturing, ontologies have been used in several use cases [7], [8], but little work has been conducted to make a semantic representation of certain manufacturing resources such as machinery, raw materials, product designs, among others. Such semantic representation would simplify searching them on the Web, and to integrate their model in a virtual environment or factory for reasoning about production processes constrains, in order to determine if any virtual resource should be integrated in a physical factory to get the target product done. We have selected industrial machinery as a resource to model, because this resource was recently refers in research related to ontology development for manufacturing [9].

Because the information about industrial machinery is in a human readable format (html, txt, pdf, among others), links and semantic connections between content and document are missing, thus the adaptation to a machine readable format is necessary. We use ontologies to bridge the gap between the technical document and its content. In this vein, three ontologies and a corpus of technical documents were considered in this study: (i) the Manufacturing’s Semantic Ontology (MASON) [10], defined by its developers as an Upper Level Ontology (ULO) for manufacturing; (ii) the Machine-Tool Model (MTM) [9]; and (iii) the machine ontologies (MO) [11]. A corpus of 633 documents was extracted from the Internet and processed by text mining analysis tools to get significant keywords. The aforementioned ontologies were matched to each other in order to obtain similarities among them. Based on these results, an ontology learning (OL) [12] process was carried out with MTM and MO. In a semi-automatically way, relevant concepts and relations were extracted from MTM and MO to form a new ontology. The result was Machine of a Process (MOP), an ontology that represents industrial machinery as resources on the Web, satisfying the user’s requirements of knowledge for economic evaluation, engineering design and production control for a given production process. In Sub Section 4.2 we will demonstrate how to evaluate the fulfillment of these requirements by means of performing some competency questions to the aforementioned ontologies [6].

This paper has been structured as follows: we present related work classified in three blocks, product description and Semantic Web, ontologies for enterprises, and ontology learning in Section 2; the general methodology, its tools and methods are described in Section 3; while we discuss our results in Section 4; and some conclusions and future work are outlined in Section 5.

2. Previous work

2.1. Product description and the Semantic Web

Semantic description of goods is a key factor for e-commerce. This is so, because nowadays, manufacturing of goods can take place almost anywhere at any time, but with different prices and levels of quality. This means that decision makers require computer-based systems to speed up the analysis of product data and take decisions. In this vein, ontology such as GoodRelations [6] illustrates the usability of product description on the Web to simplify e-commerce. Nevertheless, the scenarios in which GoodRelations is involved correspond to trading goods, and highly technical information related to machinery is not involved. In consequence, as for scenarios like the one drawn by us in Section 1, the requirements are not covered yet.

In addition, the World Wide Web Consortium (W3C) contributed by a Working Group for Product Modeling Using Semantic Web Technologies [13]. This initiative demonstrates the relevance of the topic for the Semantic Web community, but the proposal was limited to describe the role and scope of product data and an initial work on quantities, units and scale specification, together with product structure consideration. We consider necessary to highlight that they mention the requirement of interaction of the given product with other elements of the world, but without showing any course of action to deal with it. Thus, if we consider industrial machinery as a product, and additionally, we recognize that it has the possibility of interaction [14] with other components of the digital factory, then the specification of an ontology for industrial machinery remains as an enterprise requirement and an open issue.

2.2. Ontologies for enterprises

Some researchers propose to model the enterprise as a whole. For instance, Grüninger and Fox [15] proposed the Toronto Virtual Enterprise (TOVE). This model contained a set of related ontologies which represented the entire enterprise. TOVE was specified by means of situation calculus [16]. This formalism enables reasoning about dynamic domains. Given that actions, fluent and situations are the fundamental elements of this formalism, this could be used for modeling and reasoning over activities in the enterprise. Manufacturing resources ontology was mentioned, but machines as concepts were not referred to.

Lemaignan et al. [10] proposed MASON as a manufacturing upper ontology. They aimed to draw a common semantic model in a manufacturing environment. The resulting ontology was used as a part of a system that could estimate manufacturing costs in multiagent systems using the Java Agent Development framework (JADE) [17]. We used the vocabulary of machine given in MASON as a part of our study (see Section 4). Kjellberg et al. [9] proposed a machine-tool ontology model (MTM) to facilitate interoperability between machine-tool specification standards. They considered that an information model of machine-tool was required in process planning, factory planning and machine investment. They claimed that their machine ontology included concepts related to any type of machine. Nevertheless, they did not present a method to obtain such concepts, more than a brief analysis of the standards they mentioned (ASME B5.59 [18], AP239 [19], AP214 [20]) and the concepts referred to such standards, making special emphasis on Kinematics.

2.3. Ontology learning (OL), based on information extraction and evaluation

OL techniques can be divided into two approaches, constructing ontologies from scratch and extending the existing ontologies [19]. For both approaches, several tools and techniques have been proposed, for instance, Luther et al. [20] used text mining to supplement the development of ontologies. They supported their development with a commercial text miner tool, arguing that their contribution consisted on generating the vocabulary without an exhaustive customization effort.

Despite of the benefits of OL, Gil et al. [23] listed several of its shortcomings and proposed a Systemic Methodology for OL (SMOL) to overcome some of them. In our study we will implement and extend SMOL to the manufacturing scenario, but emphasizing the ontology reuse based on OL from another upper ontology, domain ontologies and from a selected corpus. Moreover, we will provide a criterion to determine when an OL process can be carried out with effective results for this particular case.
3. Methodology

We considered the following assumptions before designing our experiments and selecting the corresponding methods, software tools and materials involved in our methodology.

- Upper level ontologies facilitate the development of domain ontology [24].
- Reusing existing ontologies can considerably accelerate the development of a new ontology [25].
- Ontologies aim at modeling the fundamental concepts and relations in a specific domain of discourse [26]. That is, ontology pretends to model entities by means of a formal specification that includes their concepts and a logic to define them.
- Modular (small) ontologies improve understandability, maintainability and quality of interoperability of ontology-based systems for the benefit of the end user [21].
- With regards to the users participating in the process, we can distinguish among [22]:
  - Knowledge Engineers/Developers: usually associated with ontology development and (re)structuring tasks.
  - Expert-Users (Domain-Professionals): usually associated with ontology contents procurement and validation tasks. Additionally, they are involved with the user’s requirement specification tasks.
  - End-Users (Domain-Clients): usually associated with the ontology user’s requirements and knowledge needs.

Based on the assumptions listed above, the methodology applied in this case (adapted from the SMOL [23]) is depicted in Fig. 1. This figure includes every activity and decision steps involved in our methodological workflow, moreover it has been clearly specified who performs them and how. To decide about how these actions are performed it is necessary to consider software tool availability and their efficiency. Thus, such actions can be performed complementing manual, semiautomatic and automatic techniques or applying them individually. These activities and decision steps are summarized in four phases and sub-steps, referred below.

3.1. Methodology strategy selection

In this stage, firstable the existence of upper level ontologies (ULO), by means of which the target domain concepts could be contained, is verified. In determining if a given ULO is suitable, a controlled vocabulary and a general model of the domain are obtained from selected documents. Additionally to this, in this stage the availability of ontology documentation, description of use cases in which the ontology could be involved, and its accessibility for manipulation and visualization should be also considered. The last criterion is closely related to the language in which the ontology is implemented and the available software tools. In the case that ontology development from scratch becomes necessary, this ontology can be developed by means of methodologies (e.g. Methontology, OL) using specific tools and techniques.
The selection of any of these methodologies is up to the knowledge engineer duty.

After granting an ULO, the existence of domain ontologies (DO) in which the domain is to be represented is verified and accordingly selected. The criteria are similar to the description in the previous step. Nevertheless, we have to take more into account the presence of concept definitions, axioms, properties, and rules in the target ontology, given that the domain ontology can be more restrictive than a ULO. After finishing the previous stages a corpus of documents is compiled from different general or specialized search engines. We have to select a methodology strategy according to the complexity of the domain and the knowledge sources found. Some learning tools have to be selected in this step to support the (semi)automatic ontology development and OL process.

3.2. Knowledge discovery, query requirements and selection

In this phase, a module in the ULO that could contain concepts presented in the domain ontology is identified and selected. Then the DO has to be evaluated after:

(i) Comparing the ontological structure of DO with corpus.
(ii) Setting up competency questions by domain expert-users (see Section 4.2).
(iii) Performing queries on DO to determine whether current ontologies can answer them.

3.3. Knowledge structure construction and reorganization

Then ontology objects, such as concepts, relations and attributes are identified through text mining on corpus. If the result of the structured evaluation is not satisfactory, then ontology learning (from ontologies and text) is performed on DO to obtain an improved ontology. Then, the expert user should return to the previous step and re-evaluate the ontology. During the re-evaluation, the user’s requirements should be satisfied. The (non-)taxonomic or hierarchical relations of the MOP-ontology should be reviewed and last, but not least, the reorganized concept taxonomy should be validated/compared against the previously identified ontologies and the highlighted terms of the corpus.

3.4. Knowledge base system configuration

If the result of the structured evaluation is satisfactory, then the ontology-based application can be developed or improved, in case it already exists. This last step is out of the scope of this paper and is considered for future work.

In Fig. 1 a simplified workflow of our implemented methodology is presented. There, the user roles are highlighted through the methodological workflow, moreover we put forward how such action should be performed (manual, semi-automatic or automatic) according each role of the users.

4. Results

4.1. Methodology strategy selection

In this section we will describe the results obtained from the application of our methodology mentioned above. We started with an evaluation of the complexity of the domain. This analysis of this domain and an evaluation of software tools are outlined in a detailed technical report [24]. As a consequence of such analysis, a combination of deductive and inductive OL strategy (middle out) was selected. In other words, top-down and bottom-up methodological strategies were considered. In this vein, top-down strategies perform a feedback learning by a matching between ontologies, and bottom-up strategies let us perform a feed-forward learning by matching terms in the corpus against concepts in domain ontologies [25]. Furthermore, some processing tools were selected to support the ontological analysis, validation, and OL processes (Protégé-Prompt [26], Rapid-I [27], and GATE [28]).

In the literature we found that MASON and the Process Specification Language (PSL) [29] have been mostly reported on the development of ontology and applications in the manufacturing domain. Thus, we evaluated them in order to select one.

The two just mentioned ontologies are well documented with many use cases referred in the literature. The fundamental differences are: on the one hand, PSL is a process ontology; its core contains basic descriptions about processes, activities and activity occurrences, with the possibility of integrating extensions on it. It is not intended to represent objects or goods or to specify their features. PSL was implemented in knowledge interchange format (KIF) [30]. On the other hand, MASON was built upon three head concepts: entities, operations and resources. MASON was implemented in the Web Ontology Language (OWL) [31], thus it can be visualized and handled in ontology editors such as Protégé [32]. MASON resources include hierarchically: Material-resources, Machine-resources and Machine-tool. Machine-tool is related to the object we want to model in this proposal, the industrial machinery. Therefore, given that MASON contains terms closely related to our domain of interest and that is highly reusable, it was chosen so that we continue with our experimentation.

In Fig. 2, a module of MASON corresponding to machine-tools is presented. This visual representation was obtained by means of OntoGraph (a Protégé Plug-in [38]), thus the solid line arrows shown there correspond to subclass relations, and the dashed line arrows correspond to relations between concepts. Such concepts are represented as circles inside boxes, and certain instantiations are represented as diamonds inside boxes as well. Hereinafter an ontological view is presented, this meaning will be assumed.

The MASON’s module presented there, contains a categorization of four kinds of Machine-tool, with 24 classes of machine-tools (concepts) in total. There is an object property, enablesRealisationOf. Given that there is not more information related to a description of the attributes or concepts, MASON was used as a controlled vocabulary or thesaurus, and as a general manufacturing reference. MTM, as DO referred in [9] and presented in Fig. 3, is proposed to describe machine tools information in a reusable way for process planning, factory planning and machine investment. MTM was tested in a use case for mapping industry standards, in order to facilitate interoperability. This ontology was implemented in OWL; it contains 13 concepts and 9 object properties. No rules or concept definitions were mentioned by [9]. Given the relation with industrial machinery, this ontology was selected as a base to use in our research.

The machine ontology (MO), depicted in Fig. 4, was developed before this research as a germainal version of MOP and is available at [11]. It replicates basic information about concepts commonly found in catalogs and brochures of industrial machinery. For instance, Model (of machine), Description (Operation_Features, Materials_Features and Market_Features), Location and Supplier. This ontology contains eight concepts that are related amongst one another by using ten object properties. Just to mention some concepts of MO and their relations, a Machine is Located_in a given Location. They have a symmetric relation by means of Place_of_Origin.

The relation between the domain in the study and this ontology can be judged as evident, so we selected it to continue our research. However, later the content of MTM and MO will be compared against MASON. The competency questions will be performed and
5. Number of results obtained from specialized search engines.

Additionally, the ontologies will be compared against a corpus of selected documents, in order to demonstrate that such a conclusion should not be taken a priori.

After having our selected ULO, and two DOs, we proceeded to generate a corpus of documents related to the domain. In our case study, MASON presents 24 concepts naming industrial machines. These concepts were used as significant keywords for performing a manual search by means of some specialized search engines on the Internet to get matching documents related to certain machinery which could be available for sale. The result of our search is presented in Fig. 5. In fact, the analysis of Fig. 5 makes evident that selecting industrial machinery can be an overwhelming task for a human being. On average, a decision maker has to evaluate at least 100 machines of any kind, contact the similar quantity of suppliers and perform the same number of technical evaluations. It is necessary to mention that some results were approximately 1000.

A sample of the retrieved documents, resulting from our search, was used to create a corpus. In order to obtain a representative corpus, the concepts distribution of MASON was used as a reference (Fig. 6a). In other words, the proportion of documents regarding specific concepts of MASON was maintained as much as possible in the obtained corpus (Fig. 6b). Moreover, some additional documents were included, such as documents corresponding to industrial standards (ASME [33]) and industrial safety requirements (OSHA [34]). Therefore, the resulting proportions were not equal, but very similar. The final corpus is in Extensible Markup Language (XML) format and was created by 633 documents in pdf, text, html and owl format.

The corpus was analyzed by means of RapidMiner [27]. It let us obtain (applying TF–IDF\(^2\) techniques [35]) the most statistically significant sets of attributes into the corpus. In the following Section, we demonstrate how this set of terms (keywords) was used to determine the incompleteness of MTM and MO.

4.2. Knowledge discovery, query requirements and selection

MTM, MO and MASON content (concepts, properties, attributes and instances) were matched against each other by means of Protégé–Prompt [36]. This plug-in enables the realization of string and substring (concept/relations) matches across pairs of source ontologies. In other words, Prompt aims at finding common content and overlapping terms between ontologies, moreover it supports the creation of a new one or merged ontology based on the source ontologies.

\(^2\) TF–IDF: Term Frequency–Inverse Document Frequency.
Because MASON has a level of abstraction upper than MTM and MO, it can contain them. That is, MTM and MO should be alignable as extending modules of MASON. We tried to find such a relation by means of Protégé – Prompt. Machine-tool was identified as the matching concept between MASON and MTM. Likewise, MTM had other matching of terms with MO. MASON had, though, no matching with (the current syntactical terms of) MO. From this perspective, MTM resulted as preferable to MO.

But, when ontologies were compared against the terms obtained from the corpus, the results were different. At first: all concepts of MO were coincident with some terms in the corpus, second: less than 50% of concepts of MTM were present in the corpus. In this step, MO had a better performance than MTM. That is, all concepts of MO were coincident with some terms collected from the corpus. However, the evaluation indicates that MO can contain less than 50% of the terms in corpus, which is still a low rate. Fig. 7 summarizes the result of this stage of the methodology.

Competency questions were also considered as a standard component of ontology development [37]. In this case study, MO and MTM were queried to try to get answers from. These queries were executed in Protégé for each ontology and the results are presented in Table 1. In this evaluation, MO had a better performance than MTM, given that its content could be used to answer four queries, while MTM answered only two of those.

As shown in Fig. 7, considering that each MO concept was related to some terms in the corpus, as long as MTM had six concepts not related with any term in the corpus, and that MO answered more competency questions than MTM, we decided to use MO as seed for OL, integrating relevant concepts of MTM into MO.

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1. Number with apostrophe indicates result of automatic mapping of ontology with Prompt.

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In the following Subsection, we describe how the OL process was carried out and its results.

4.3. Knowledge structure construction and reorganization

This stage was carried out in two steps. First MO and MTM were merged. Seven classes of MTM were copied into MO, four object properties were also copied. This activity was supported by Protégé-Prompt merging capability. Fig. 8 shows the suggestions given by Prompt at the moment of loading and merging both ontologies in Protégé. The resulting ontology was named as MOP.

The second part of this stage consisted of enriching and populating the ontology with terms from the corpus either as concepts, instances or relations. In this sense, three concepts and two instances were added to this ontology.

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![Fig. 6. Distribution of classes of machines (Concepts) in MASON and documents in corpus.](Image)

![Fig. 7. Term relationships among ontology and corpus.](Image)

![Fig. 8. Merging Process with Protégé-Prompt.](Image)

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<tr>
<th>Table 1 Results of applying competency questions on ontologies.</th>
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<tr>
<td>Competency question</td>
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<tr>
<td>What kind of raw material can be processed with the given machine?</td>
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<tr>
<td>What is the size of the machine?</td>
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<tr>
<td>What kind of power supply does it have?</td>
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<tr>
<td>What kind of operation does this machine perform?</td>
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<td>How many operations can I carry out on it?</td>
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<td>What is the operational space required?</td>
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5. Conclusions

In this work, we have shown how to bind semantic of a manufacturing domain by an upper level ontology and a corpus. By analyzing the corpus, domain ontologies were validated. Our approach differs from other studies in the field of semantic manufacturing in that we aim at re-utilization of ontology, instead of discarding previously existing ontology. Our analysis was carried out by matching ontologies to one another and matching terms in the corpus against concepts in domain ontologies. The result demonstrated that MTM did not contain as many terms as MO in the corpus, but that MTM had a positive mapping with MASON, while MO did not.

Because MO had higher matching with corpus, it was enriched with concepts of MTM and terms of the corpus. So, we obtained a new ontology that we called MOP. This ontology can be used to describe industrial machinery and use this description in Internet. It contains a set of terms, whose likelihood of usability has been validated by means of text mining analysis in corpus.

We have also shown that, despite of having some ontologies closely related to one domain, in our case manufacturing, when they were evaluated several flaws were found. The first flaw was the lack of interoperability among ontologies as a consequence of having few mappings between them. The second flaw was the low level of interrelation between a set of terms automatically extracted from a corpus of documents whose content was related to the domain.

As future work, we consider developing the ontology-based search engine, and applying the methodology followed here to improve ontology of computer aided design (CAD) and ontology of raw materials.

References


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