Towards Generalized Welding Ontology in line with ISO and Knowledge Graph Construction

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Motivation. Industry 4.0 [1, 2] comes with unprecedented amounts of heterogeneous industrial data [3–5]. This opens new horizons for AI technology in making manufacturing smarter, more optimal [6, 7] and eventually circular and sustainable. A prominent AI approach that has recently attracted a considerable attention in industry is semantic technologies that allow to uniformly integrate manufacturing data via declarative ontologies, transform it into Knowledge Graphs (KG) and then layer Machine Learning [8] and Reasoning over the resulting KGs [9, 10].

An important challenge with the use of semantic technologies in plants and with scaling them from single production lines to the entire factory and beyond to clusters of factories [11] is the development of high quality standardised ontologies that will be accepted by multiple stakeholders ranging from engineers to managers [12–14]. In particular, it is common to develop ontologies that follow expert heuristics and opinions rather than commonly accepted practices and standards.

In order to address this challenge we advocate to ontologies that on the one hand are in line with international industrial standards provided by, e.g., International Organization for Standardization (ISO) or International Society of Automation (ISA) and on the other hand that are tailored towards KGs that allow for a wide range of AI methods over them including Machine Learning via vector space embedding [15].

In particular in our work we focus on ontologies for a particular type of manufacturing – welding – that is crucial in the automotive industry and for Bosch [16], one of the top global suppliers of automated welding solutions for car bodies. Welding is a sophisticated manufacturing technology in which (typically) metal parts are joined together using an energy source to produce a connection between the parts [17, 18]. Besides car building welding is heavily used in shipbuilding, railways, and aerospace. Welding is well established and regulated by ISO and ISA.

Despite to the high number of welding standards, the topic of shared, generalized, and reusable formal welding ontological models is insufficiently discussed in the literature. Most of previous ontologies were rather tailored to one or some welding domains [19], or some specific applications such as solving the interoperability conflict in welding standards [20] or enhancing the machine learning pipeline [21, 22]. In addition, instead of commonly agreed best practice, heuristic knowledge is often followed for ontology engineering and KG construction.

In this poster we give a preliminary report of our ongoing work on welding ontologies with standardised and generic vocabularies. In particular we discuss In particular we aim at a generic *welding core ontology (WCO)* that is in line with ISO standards and existing ontologies, aiming at a common ground for ontology engineering and KG construction for welding. In the following we describe our approach by first giving requirements, then by describing our modelling process, and finally by describing our core ontology and KG.

Requirements to the Welding Ontology. The following requirements help us to ensure that our ontology can be effectively used in the welding domain.

R1. *Capture Domain Knowledge:* The developed ontology needs to capture domain knowledge properly. In particular, this includes to reflect the information provided by the domain documents, domain experts, and to obtain knowledge in which the conflicts are sorted out, terminologies are unified and concepts are disambiguated. This requirement is evaluated with the competency questions.

R2. *Quality Ontology:* A quality ontological model should have good performance in terms of established metrics: e.g., clarity, completeness, and conciseness. This requirement is evaluated with the Ontology Pitfall Scanner (OOPS!).

R3. *Adherence to Industry Standards and Existing Ontologies:* The concepts and relations in the ontology must be possibly in line with ISO welding standards and the existing generic and core vocabularies. For example, ISO 4063, ISA 95, Reference Generalized Ontological Mode (RGOM)[1] , DOLCE[2], Time ontology[3], etc. This requirements is evaluated in generalizability and reusablity section.

Welding Ontology Development Process. To develop the welding ontology, We adopt the ontology development process depicted in Figure 1.

– *Step 1: Domain Analysis and Knowledge Gathering.* During the initial phase of the ontology development process, a series of workshops with Bosch experts were held in order to comprehend the domain Knowledge. Furthermore, welding standards such as ISO 4063 in line with those for production line integration i.e. ISA 95 were identified for gathering extensive knowledge. A comparison study is then conducted with ISO 4063, ISA-95, RGOM, and existing vocabularies are analyzed and compared.
– *Step 2: Formalizing Concepts.* The second step involves the codification of knowledge collected to a formalized structure i.e. classes and the relationship between it, and it's axioms. The classes and relations are semantically

[1] http://industryportal.enit.fr/ontologies/RGOM
[2] http://www.loa.istc.cnr.it/dolce/overview.html
[3] https://www.w3.org/TR/owl-time/

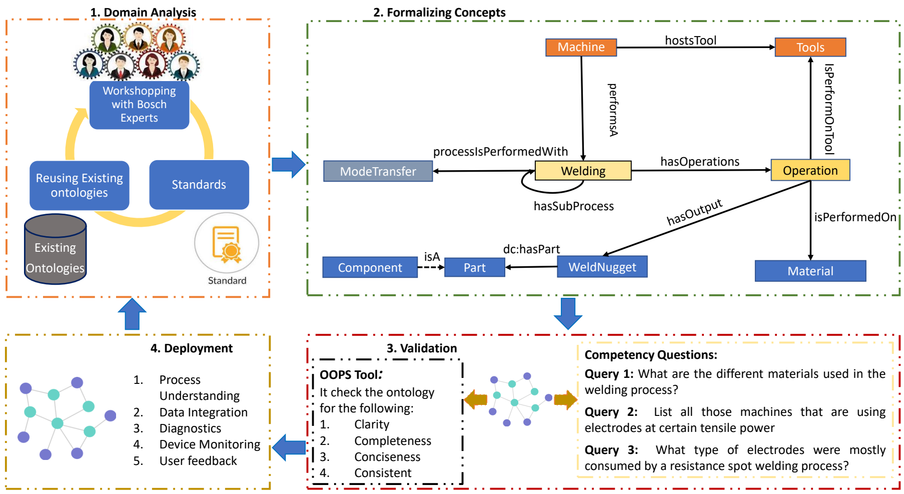

Fig. 1. The workflow for ontology modelling and knowledge construction

modelled in the prospect of welding and manufacturing resources, depicted in Figure 1.2.

- *Step 3: Validation.* The validation step mainly consists of ontology evaluation with respect to the defined requirements, explained in detail in Section 3.
- *Step 4: Deployment.* The WCO is deployed in various activities, e.g., process understanding, data integration [23]. User feedbacks are collected constantly and lead to further domain analysis. The workflow is naturally iterative.

Welding Core Ontology. Our preliminary version of the WCO covers four areas of the welding industry: *Physical Entity*, *Product*, *Process*, *Business*. The initial version of WCO incorporate the domain knowledge from Bosch welding experts, ISO 4063, ISA95, RGOM and other existing ontologies. It consists of 216 classes, 71 object properties, and 32 data properties.

Enterprise Cross-Domain Knowledge Graph. The idea of cross-domain KGs is to construct KGs following the WCO as the upper-level schema, which we create beforehand for a wide range of welding processes. The hierarchy of cross-domain KGs are in this: *Individuals* $\rightarrow$ *Welding Domain Ontologies* $\rightarrow$ *WCO*, in which the *individuals* follow the class definitions in the *welding domain ontologies*, which are all sub-classes of the WCO. Bosch has data from many welding processes, locations, customers and we are working towards enterprise cross-domain KGs [24, 25] to have a seamless collaboration between the manufacturing experts, resources, equipment, etc.

Evaluation. We plan to conduct an evaluation of our ontology in multiple ways. First, we plan to study *Competence Questions* with Bosch experts to analyse the coverage of the domain knowledge (R1) from three aspects in the manufacturing:

- data inspection, e.g., *What are the different materials used in the welding?*

– information summary, e.g., *List the number of welding programs used by the machines?*
– diagnostics, e.g., *Which machine generates the most abnormal welding operations*?

Next, we plan to conduct the *Ontology Pitfall Scanner (OOPS!) evaluation* of the ontology quality (R2) with the metrics such as clarity, completeness, and conciseness. Next we plan to analyse *generalizability and reusablity* of WCO, where the later is achieved by reusing the terminology from ISO standards and existing vocabularies (R3), e.g., 'machine' and 'tool' are from the RGOM, 'sensors' concept from SOSA ontology, 'isPartOf' from Dublin core ontology. The competency questions, OOPS! and generalizability and reusablity metrics were used to assess the R1, R2 and R3, respectively.

Acknowledgements. This work was partially supported by SFI (Grant 16/RC/3918), and the H2020 projects Dome 4.0 (Grant Agreement No. 953163), OntoCommons (Grant Agreement No. 958371), and DataCloud (Grant Agreement No. 101016835) and the SIRIUS Centre, Norwegian Research Council project number 237898. For the purpose of Open Access, the author has applied a CC BY public copyright licence to any Author Accepted Manuscript version arising from this submission.

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