Ontologies in Smart Manufacturing: Approaches and Research Framework

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Abstract—**Successful implementation of smart manufacturing systems requires tight connectivity and intensive information and knowledge exchange. There is still a need for achieving certain level of smartness and beyond (i.e. cognitive manufacturing) by identifying semantic relations between heterogeneous data sources, extract actionable information and subsequently automate the process of knowledge generation and target-oriented recommendation in industrial context. The missing linkage is the quality of knowledge generation and protection process, which requires further investigation along with standard planning and controlling measures. This can be achieved through application of ontologies as a mean to support interoperability, reasoning and decision making. Considering various alternative approaches, this paper describes a research framework for ongoing study on ontology-based planning and controlling in smart manufacturing systems.**

I. Introduction

Smart Manufacturing is a new manufacturing paradigm [1] where machines are fully connected via Internet of Things (IoT) infrastructure including open communication platforms for industrial automation, and equipped with sensors. A successful implementation of smart manufacturing systems requires a tight integration along all the processes what leads to the implementation of cyber-physical system platforms that provide possibilities of integration between the physical equipment and IT services & applications [2]. However, such an integration is usually a challenge since different processes in manufacturing systems have different goals, solve different tasks, and apply different methods that assume application of information models, which fit well to the corresponding tasks, but usually are not interoperable with each other.

Since connectivity is one of the key enablers for this kind of systems, one of the main problems is interoperability between independent heterogeneous manufacturing resources [3]. In Europe, this issue today is receiving a great attention. In the concept of a new European interoperability framework (New EIF [4], [5]), interoperability is defined as the “ability of organizations to interact towards mutually beneficial goals, involving the sharing of information and knowledge between these organizations, through the business processes they support, using the exchange of data between their ICT systems”.

The need for standardization and interoperable systems was recognized almost thirty years ago with the launch of the European Commission’s CADDIA program in 1985, the IDABC program in 1995, the ISA program in 2009 (decision 2009/922/EC) and the creation of current compatibility solutions for European e-government services (ISA^2) in 2016 [6]. However, support for interoperability and integration of information resources into common ecosystems is still an unsolved interdisciplinary problem.

The intelligent connectivity and sensor systems allow data driven intelligence to analyze complex nonlinear relations within smart manufacturing systems and derive recommendations from those with the help of industrial data science methods, in particular machine learning [7]. Yet, smartness is limited to smart connectivity and smart data, i.e. generation and storing of large amount of data by means of various sensors, cloud-based solution and novel data-driven technologies such as augmented reality [7]. Still efforts are required to achieve certain level of smartness and even beyond (i.e. cognitive manufacturing) by identifying semantic relations between heterogeneous data sources, extract actionable information and subsequently automate the process of knowledge generation and target-oriented recommendation in industrial context.

There are four levels of interoperability [5]: technical, semantic, organizational and legislative. Semantic interoperability is understood as semantic interpretation of data presented using meta-models such as the Unified Modeling Language (UML [8]) class diagrams and the Ontology Web Language (OWL [9]). The semantic web (Semantic Web) is one of the ways to solve the problem of semantic interoperability, but today it does not allow working with information as seamlessly as necessary.

To achieve the aforementioned goal, ontology engineering and learning should be integrated into the machine learning pipeline, where new generated data and even knowledge such as diagnosis/prognosis is linked prior (domain or context-specific) knowledge [10].

Ontologies have shown their usability for this type of tasks (e.g., [11], [12]). These are content theories about the sorts of objects, properties of objects and relations between objects that are possible in a specified knowledge domain. Ontologies provide potential terms for describing the knowledge about the domain [13]. An ontological model is used to solve the problem of heterogeneity of descriptions of different enterprise elements. This model makes it possible to enable interoperability between heterogeneous information sources due to provision of their common semantics [14].

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However, ontologies do not only support linking new and prior/background knowledge, but also contribute to improving quality of reasoning, problem-solving and decision-making processes where historical cases are taken into consideration. For instance, Ontology-based Case-based Reasoning (CBR) leverages previous expert knowledge for solving a new given case. This approach can be applied to maintenance, where CBR, in combination with an ontological knowledge base is used to improve the efficiency of maintenance planning. Ontology-enabled CBR as a decision support system can also be applied to optimize the material matching process for manufacturing [15].

Furthermore, ontologies support protection of knowledge within the industrial ecosystem and ensures long-term availability of knowledge sources including documentation of various generation of machines, equipment, etc., i.e. a systematic and reliable knowledge protection.

Ontologies have proved themselves as one of the most efficient ways to solve the problem of semantic interoperability support. They are formal conceptualizations of domains of interests sharable by heterogeneous applications [16], [17]. They provide means for machine-readable representation of domain knowledge and enable to share, exchange, and process information and knowledge based on its semantics, not just the syntax. Ontologies include concepts existing in a domain, relationships between these concepts, and axioms.

It is generally accepted that models of specific problem areas (for example, configuration models of complex systems) can be obtained by inheriting or extending a common ontology. However, in systems with a dynamic structure, such as flexible manufacturing systems, this solution does not allow to achieve the required level of flexibility, since the expansion of the general ontology with the appearance of new information objects requires ontology matching.

This would not be a problem if each process had to deal with its own piece of information, however in reality these information pieces overlap and changes made during one process have to be taken into account at the others. As a result, an efficient information exchange between different processes requires solving the problem of interoperability support.

As a result, applying ontologies to digital ecosystems is still a problem due to different terminologies and formalisms that the members of the ecosystems use.

The contribution of the paper is twofold. First, approaches are analysed that can be efficient for the design of ontologies that could take into account heterogeneous nature of components of the smart manufacturing systems. Second, the paper proposes a framework guiding the research on ontology-based planning and controlling in smart manufacturing systems.

The reminder of the paper is structured as follows. Section II introduces smart manufacturing systems and their specifics related to planning and control functions. Section III presents state-of-the-art approaches to ontology engineering that can support heterogeneous nature of the considered systems. It is followed by the description of the designed framework for of ontology-based planning in smart manufacturing systems. Main results are summarized in the conclusion.

II. SMART MANUFACTURING SYSTEMS

Smart manufacturing, in particular cyber-physical production systems (CPPS), have a significant influence on production planning and controlling [18], [19]. Deploying CPPS raises several challenges for industries addressed in [20], [21], in particular with regard to extraction of knowledge from heterogeneous data sources, automation of knowledge generation process, interoperations with production information systems as well as changeability, adaptability and re-configurability in production management. Compared to traditional production planning based on a static knowledge base, smart manufacturing requires a collection of real time information and share from and between products, machines, processes and operations [22]. The application and exchange of data within and between various elements and building blocks of smart manufacturing systems, e.g. production planning and maintenance planning, should lead to an automated and decentralized production, which is an essential characteristic of Industry 4.0 [23], [24].

Following this line of research the key question is “what is required for improving planning and controlling”? In fact, improvement could be interpreted and subsequently measured in terms of industrial KPIs (Key Performance Indicators) such as planning quality (effectiveness, accuracy, etc.), (physical/human) resource efficiency and productivity improvement. The missing linkage is the quality of knowledge generation and protection process, which requires further investigation along with standard planning and controlling measures [25]. In other words, the more smart manufacturing systems become knowledge-driven, the higher is the impact of knowledge on quality of production planning and controlling. This hypothesis has not been extensively investigated yet in the literature of operation management and industrial engineering.

III. USAGE OF ONTOLOGIES IN MANUFACTURING SYSTEMS

Ontologies are a mean to represent knowledge about a problem domain in a machine-readable way. They enable obtaining, exchanging and processing information and knowledge based on their semantics rather than just syntax. Ontologies are a well-proven tool to solve the interoperability problem, but the problem of applying ontologies to manufacturing systems is due to different terminologies used in different manufacturing processes even within one company [26], [27]. E.g., in [28] a model-driven interoperability framework is presented as a technical support of co-evolution strategy of products and manufacturing systems. The authors address connecting possible product modules to all possible production capabilities managed on the Manufacturing Process Management tool through establishing “connector framework” to match different ontologies.

There are efforts aimed at enriching ontologies with additional information (e.g., extension of DAML+OIL for description of configuration problems [29], introducing semantic annotations [30], etc.), however, they still cannot solve the problem of integrating heterogeneous information and knowledge described in different terminology. For example, it is common understanding that domain specific models (e.g., configuration models) can be derived by inheriting or subclassing the ontologies within the general model. Thus, SWRL is a rule-based language for description of constraints is based on OWL and the resulting ontology is an extension of OWL ontology. Then, actual configuration system can be implemented using Jess what requires mapping of OWL-based configuration knowledge and SWRL-based constraints into Jess facts and Jess, respectively [31].

There are a number of research efforts addressing this problem. For example, in [32] a solution is proposed based on semantically annotated multi-faceted ontology for product family modelling to automatically suggest semantically-related annotations based on the design and manufacturing repository on the example of laptop computers. In [33] an ontology for the musical domain has been developed. The co-authors of this paper have also previously proposed ontology-based solutions for enterprise modelling [34] and self-organizing cyber-physical-social systems [35]. However, these and similar works are aimed at development of a reference ontology that is to be reused, updated or extended in the future. In the considered here problem of smart manufacturing systems support, it is necessary to provide for a mechanism that can be reused for development of ontologies for each particular case (since smart manufacturing systems can differ substantially) with a possible reuse of common fragments.

A possible option is usage of ontology integration supported by ontology matching. However, as it was mentioned before, the smart manufacturing systems are quite dynamic, what would require continuous changes in the resulting ontology. This assumes that the matching process would be used very often, nearly on continuous basis. The problem of this approach is that automatic ontology matching methods are still not sufficiently reliable, and manual ontology matching would significantly reduce the efficiency.

As it can be seen there are many efforts aimed at integration of heterogeneous knowledge into a single complex ontology. After an extensive study of the domain, three main and most promising possibilities, which are discussed below, have been identified.

A. Multilingual ontology

Multilingual ontologies are aimed at solving terminological issues arising from usage of different languages. Among the terminological issues the following can be selected [36]:

1) Existence of an exact equivalent. This is the easiest case when two terms have completely the same meaning. In real life (when talking of regular languages such as English or German) this is a rear situation, however in a company most of terminology would be the case. For example, “product” would mean the same both during the design stage and the production stage, or in the considered company, “feature” during the design stage means the same as “characteristic” during the production stage.

2) Existence of several context-dependent equivalents. This case assumes that one can choose the right translation (the right equivalent) based on the situation. An example could be the term “modular product” that can stand for both product consisting of several modules or product with some variable characteristics.

3) Existence of a conceptualization mismatch. This is an important issue for regular languages, standing for a lack of semantic equivalent for a given term. In the considered case of smart manufacturing systems this is not a common issue since the lack of a certain term in a sub-domain usually would mean that it is not used (not needed) in this domain.

Usually, such ontologies are based on language specific fragments with relationships between terms and it might be a straightforward enough solution for multi-aspect domains. This really helps to overcome the terminological issues, as well as to solve the problem of heterogeneity of information and knowledge between different lifecycle stages.

However, a multilingual ontology is formulated in a single formalism and collecting together for example, configuration knowledge with procurement knowledge would not be possible without losing some semantics. As a result this approach cannot not completely solve the problem formulated.

B. Granular Ontology

Granular ontologies are based on the integration of ontology-based knowledge representation with the concept of granular computing. Granular computing is based around the notion of granule that links together similar regarding to a chosen criteria objects or entities (“drawn together by indistinguishability, similarity, proximity or functionality” [37]). The granules can also be linked together into bigger granules forming multiple levels of granularity.

From the knowledge representation point of view, a granule can be considered as a chunk of knowledge made about a certain object, set of objects or sub-domain [38]. When speaking of smart manufacturing systems, higher-level granules can combine knowledge related to a certain manufacturing system layer, and lower-level granules can be related to processes (Fig. 1). A level is a collection of granules of similar nature. The hierarchy of granules then would form a hierarchy of smart manufacturing system layers.

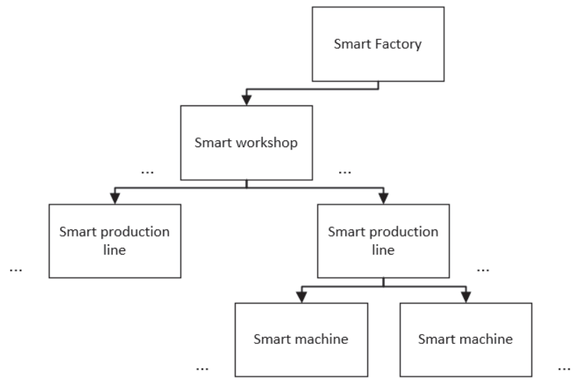

Fig. 1. Example of smart manufacturing system ontology granules from smart factory to smart machine

Granular ontologies seem to be a suitable solution to support various smart manufacturing processes: they enable splitting the domain in smaller areas with consistent terminology and formalisms. The possibility to form a hierarchy (generalization) is also beneficial due to the possibility to define generic concepts and relationships at higher levels.

However, smart manufacturing system processes and layers usually overlap in terms of used information and knowledge. This means that there exist multiple processes that assume collaboration and usage of the same information and knowledge. Pure granular ontologies cannot solve the problem of terms having different meaning at manufacturing processes or different company departments. There are multiple efforts in the area of rough granular computing [39]–[41], however, they are not directly related to ontology design. As a result, additional research in this area is required.

Another possibility is to extend a granular ontology with a concept that would enable certain "roughness" of it, and the following section proposes such a possibility.

C. Temporal Logics-Based Ontology

The authors of [42] propose to address the problem of terms having different meaning at different manufacturing processes Product Lifecycle Management (PLM) stages through usage of temporal logics. The idea of using temporal logics in describing PLM originates from the fact that most of product related information and knowledge is used in the product lifecycle only during some stages. PLM is basically always associated with time. The most often met PLM schemes are "time arrow" (when the PLM stages follow one after another) and "time wheel" (when the time arrow of PLM stages is connected into one or several circles). Time is also considered as one of the key resources in PLM, when, for example one speaks of decreasing lead time or increasing the product usage period.

This can equally be applied to smart manufacturing systems.

The approach presented in [42] is based on the fuzzy extension of temporal logics to enable links and overlapping between different stages of the lifecycle. The metaphor used in the approach is based on the idea of representing processes as time intervals with fuzzy duration.

The ontology (ONT_{LC}) is described by the following formula:

$$ONT_{LC} = <C_{LC}, R_{LC}, O_{LC}, T_{LC}>, \text{ where}$$

C_{LC} is the set of concepts related to the described domain (all the concepts of the ontology used at all manufacturing processes),

R_{LC} is the set of relations between the concepts,

O_{LC} is the set of operations over concepts and/or relations,

T_{LC} is the set of temporal characteristics for processes.

Since the ontology is aimed at separation of concepts between different manufacturing processes, the systemic kernel is represented as the following triple:

$$ONT_S = <S, R_S, O_S>, \text{ where}$$

S is the set of manufacturing processes,

R_S is the set of relations between the processes,

O_S is the set of operations used on the processes.

As it was mentioned the manufacturing processes are considered as time intervals $s = [t^-, t^+]$, with starting and ending time points t^- and t^+ respectively. However, in order to indicate the overlapping of them, the intervals are considered to be fuzzy.

Though the usage of granular ontology with temporal logic for smart manufacturing systems looks complex, it can solve the heterogeneity problem arising from different mental models at manufacturing layers. However, it still doesn't solve the problem of having different formalisms in one big domain.

D. Multi-Viewpoint Ontology

The most promising approach is to preserve the ontologies of services and build some structure on the top of them. An application of top-level ontology called Basic Formal Ontology (BFO) to facilitate interoperability of multiple engineering-related ontologies [43]. The authors present a system of formal linked ontologies by re-engineering legacy ontologies to be conformant with BFO.

A layered framework is proposed in [44] aimed for integration heterogeneous networked data sources, whose heterogeneity originates from different models (e.g., relational, XML, or RDF), different schemas within the same model, and different terms associated with the same meaning. The authors use metadata representation and global conceptualization with further mapping support in order to provide information translation.

The approach presented in [45] is aimed at description of multi-cloud systems where clouds differ both syntactically and semantically. It is built around an ontology-based abstract model that on the one hand is different from models of the clouds, but on the other hand bridges gaps between them through establishing mappings between own concepts and those of particular clouds.

Viewing a problem domain from different viewpoints has resulted in appearance of Multi-Viewpoints Ontology (MVpOnt) where each viewpoint corresponds to the knowledge representation useful to a particular group of people, which coexists and collaborates with other groups [46]. This approach seems to be the most suitable for the problem set.

The most important progress in this direction was achieved by M. Hemam who in co-authorship with Z. Boufaïda proposed in 2011 a language for description of multi-viewpoint ontologies - MVP-OWL [46], which was extended in 2018 to support probabilistic reasoning [47].

In accordance with this notation, the OWL-DL language was extended in the following way (only some of the extensions are listed here; for the complete reference, please, see [46]). First, the viewpoints were introduced. Classes and properties were split into global (observed from two or several viewpoints) and local (observed only from one viewpoint). Individuals could only be local, however, taking into account the possibility of multi-instantiation, they could be described in several viewpoints and at the global level simultaneously (Fig. 2). Also, four types of bridge rules were introduced that enable links or "communication channels" between viewpoints.

Multi-viewpoint ontologies make it possible to work with knowledge represented in different formalisms, however, the require building additional structure on top of the existing ontologies and there are no best practices to analyze since they are not widely used at the moment.

IV. Research framework for ontology-based planning in smart manufacturing systems

The research framework described below (Fig. 3) is aimed at conducting research to develop models and methods for ontology-based decision-support of dynamic job and function allocation in human-machine world of smart manufacturing systems with the elements of Artificial Intelligence (AI), allowing to effectively select contributors for a particular task, based on job/skill decomposition/reconfiguration methods, taking into consideration human- and machine-specific factors.

The smart manufacturing system ontology is on the top layer of the framework defining the formalism, notations and terminologies used in lower layers. As it was mentioned, it is essential for such an ontology to support multiple (sometimes loosely coupled) domains and at the same time to provide for interoperability between these. The aim of this layer of the research framework is not to develop a particular ontology, but to provide for methodology and models that would enable quick building of such an ontology for particular cases.

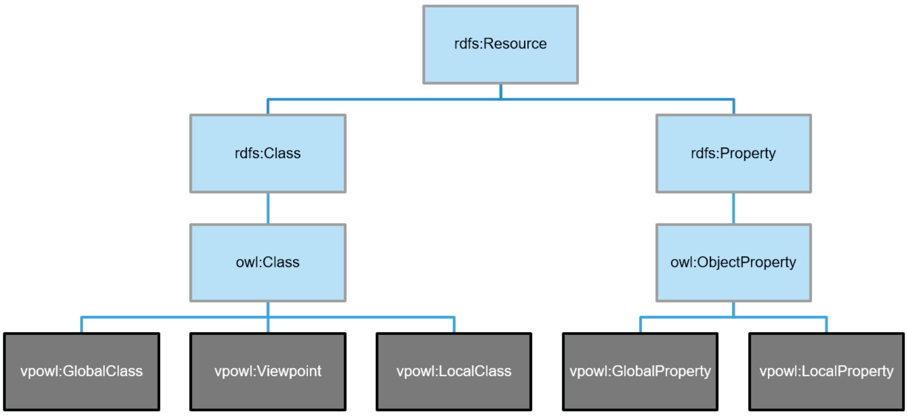

Fig. 2. Global and local classes and properties in the RDF_MVP notation

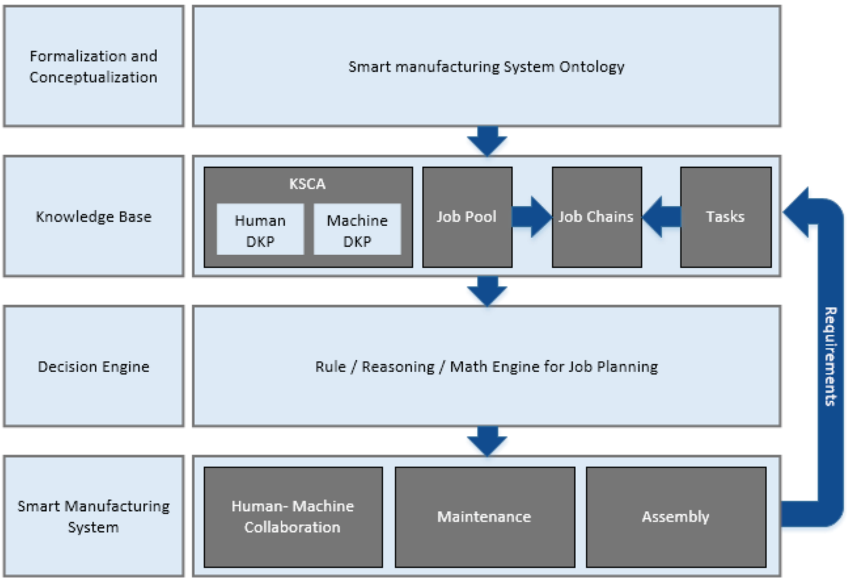

Fig. 3. Research framework of ontology-based planning in smart manufacturing systems

The knowledge base layer contains different pieces of knowledge required for smart manufacturing system planning and job scheduling. The first block represents Knowledge, Skills, Competences and Abilities (KSCA) of the smart manufacturing system parties, which are represented via Digital Knowledge Profiles (DKP) for both humans and machines. They are described in terms of the common ontology and identify how these are to be described in order to be accessible and understandable by the next layer.

Tasks and jobs identified from existing documents through application of text mining approaches (topic modeling and vocabulary detection/enrichment) constitute a job pool and task storage together with their descriptions. Usage of the common ontological representation makes it possible to integrate this knowledge. Further joint analysis of jobs and tasks and identification of their inputs and outputs make it possible to build job chains that are to be executed by the smart manufacturing system.

The question to be answered at this layer is how this information should be described and what information is important and enough for planning in smart manufacturing systems.

At the next layer, the decision making process takes place. Given the requirements, goals and constraints from the upper layer, a model can be built such that it could be processed by a certain engine (depending on the formalism used it could be a rule or reasoning engine or a mathematical solver) to produce feasible job execution plans. The research question at this layer is what kind of engine could efficiently solve the task set. This has to be aligned with the formalization layer since the common ontology has to support the appropriate for the engine knowledge representation (constraints, rules, etc.) along with representations for other components.

The lowest layer represents the smart manufacturing systems itself (a typical use case that can be implemented in the available to the authors research facilities) where such processes as human-machine collaboration, equipment maintenance and assembly processes take place. It is also aimed at testing the developed solutions in a close to real life environment.

In case of any changes occurred, updated requirements a passed to the knowledge base layer so that the decision support process could be repeated to update the current job execution plan.

V. Conclusion

The paper aims at developing a research framework for approaching the problem of ontology-based support of smart manufacturing systems. State-of-the-art approaches to ontology engineering that can support heterogeneous nature of the considered systems are presented. Unlike works aimed at development of a reference ontologies for heterogeneous domains, the present research tries to provide for a mechanism for development of ontologies for each particular case (since smart manufacturing systems can differ substantially) with a possible reuse of common fragments. Four approaches that were found most promising (multilingual ontologies, granular ontologies, temporal logics-based ontologies and multi-viewpoint ontologies) are analysed in details taking into account the specifics of the considered systems. A four-layered ontology-based research framework for planning and control in smart manufacturing systems is proposed that is based on interoperable knowledge representation about different components of the considered systems and application of existing optimization or reasoning techniques for decision making.

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