A Knowledge-Based Approach for Decision Support System in Additive Manufacturing

Qussay Jarrar, Farouk Belkadi, Alain Bernard

A Knowledge-Based Approach for Decision Support System in Additive Manufacturing

Qussay Jarrar[1], Farouk Belkadi[1], and Alain Bernard[1]

[1] Ecole Centrale de Nantes, Laboratory of digital Sciences of Nantes, LS2N UMR 6004, France
firstname.lastname@ls2n.fr

Abstract. The large amount and different types of data and knowledge generated within the Additive Manufacturing (AM) value chain are highly challenging in terms of management and organization. Understanding the interconnections between all these immaterial corpuses is important for decision making and process optimization issues. Moreover, AM has more parameters than conventional manufacturing processes, and many of these parameters are difficult to assess and monitor. Therefore, it becomes important to develop computer-based solutions that are able to aid the decision maker and to support the management of all information along the AM value chain. In this paper, a knowledge-based decision support framework using ontological models and mechanisms is proposed for the above objective. Cost estimation is conducted as an application of the proposed framework.

Keywords: Knowledge-based approach, Decision support system, Automatic Cost Estimation, Additive manufacturing.

1 Introduction

Even though the history of Additive Manufacturing (AM) technology is relatively short, it has shown expeditiously growing interest in various domains and significant improvement on the quality of the produced parts as well as the efficiency of the related processes [1]. Despite of these benefits and opportunities, many issues and challenges such as traceability, accuracy, and parameters' inconsistency still need to be solved [2]. With the growing complexity of AM process due to multiple interconnections between heterogeneous parameters, changing one parameter could affect multiple criteria of the produced parts [3]. Even for expert users, it is difficult to select the suitable values of process parameters for successful AM building results [4]. Moreover, different types of data generated along the product transformation cycle are creating new opportunities for knowledge discovery [5]. So, understanding these data and knowledge definition and correlation is essential for decision making and optimization from the earliest stages of AM process.

In this topic, it becomes important to develop the right architecture of decision-making system that correctly uses and manages all this corpus of information [6], while paying particular attention to the key performance indicators and process parameters management [7]. Thus, the main objective of this paper is to propose a knowledge-based system (KBS), using an AM dedicated ontology, to support the expert decision along the AM value chain. Section 2 presents a literature review on KBS and decision-aid systems for AM. Section 3 proposes the main foundations of the proposed KBS. Then, an application of this framework to support the decision making in cost estimation is presented in Section 4.

2 Knowledge-Based Decision Support solutions for AM

Decision Support Systems (DSS) have proven an important role to support the experts in various fields related to AM value chain. For instance, process planning support aims to identify and adjust all parameters necessary to optimize the build and post-processing steps [8]. Even though, the decision process is still complicated in terms of data management due to huge amount of data and heterogeneity of knowledge. The use of Artificial Intelligence (AI) leads to improvement of DSS through better exploitation of expert knowledge (rule inferences) as well as smart data mining and machine learning [9]. KBS are kind of computer systems that imitate human reasoning for problem-solving by reusing previous experiences and inferring business rules [10]. These systems are currently coupled with Knowledge Management (KM) practices to capture and formalize tacit knowledge [11]. This kind of system consists of three main components; Inference engine, User Interface, and Knowledge Base (KB) [12]. In this type of approaches, knowledge modeling is a critical issue to satisfy the consistency of the KB. With regard, ontology is one of the most effective tools to formalize the domain knowledge, while supporting the automatic reasoning and information retrieval based on business rules [13,14].

Lately, attempts have been made to develop a knowledge base in a form of ontology as a decision support for AM. Some works have contributed to propose a knowledge base that formalize Design for AM (DfAM) knowledge to be retrieved and reused to support the designers in process planning, [15,16]. For instance, Kim et al. [15] use Ontology Web Language OWL to categorize DFAM knowledge into: Part design, Process planning, and Manufacturing features. SQWRL queries are applied to formalize design rules and retrieve DFAM knowledge to be reused for solving new problems. Using the same mechanisms, Hagedorn et al. [16] aim to support innovative design in AM, by capturing information related to various fabrication capabilities of AM, and their application in past innovation solutions. Samely, Liu et al. [4] propose a KB that uses previous process planning cases and manufacturing rules. Eddy et al. [14] introduce Rules-Based algorithm to select the best process plan as a combination of feasible processes allowing the lowest total cost of the resulted AM part.

In summary, most of the developed approaches are specific and dedicated to solve particular aspects of AM process, so they need high labor intensive to operate in general context. In previous work, Sanfilippo et al. [10] propose an ontology as a generic reference model with the ambition to represent all main characteristics of AM value chain. The proposed knowledge-based approach is realized as a part of this research work by extending the scope to the preparation and post-processing steps, and taking into account the link between customer specification and process characteristics, for effective cost estimation at the earliest stage of the AM project.

3 The Proposed KBS framework

The computational ontology proposed by [10] is developed in OWL by means of Protégé tool, and uses the concepts of "template" and "reusable case" as generic containers to structure and reuse useful knowledge for decision-aid perspective. Templates can be seen as a semantic dictionary that organizes the collection of specific types of AM data and knowledge. A "case" is used for the traceability of a given AM project (successful or failed) through the instantiation of a collection of templates.

For instance, the template of machine will be used to create library of existing machine families by defining the main attributes for each category. The first instantiation permits the declaration of a given reference of machine (or process, product, material, etc.) with interval of possible values for the predefined parameters (Ex. Machine XX has heating temperature between 300 and 500 degrees). Then, the creation of reusable case is achieved by combining a set of templates with exact parameters values (ex. Case project ZZ uses the processes PP to transform the material MM in the machine XX with the parameters heating temperature 450°, material density is 4.4 g/cm^3, etc. It results on the product AA with characteristics: surface roughness: 5-18 µm).

Relaying on that conceptual framework, first the ontology has been enriched with high level of granularity and details axioms covering a wider range of control, and post processes, among others. Five types of templates are initially distinguished: Product, machine, feature, material, and process. Then, templates contents have been updated and other types are added to cover project characteristics, customer specifications, and finally, cost model as an example of decision-aid perspective.

By doing so, the proposed KB is structured and formalized around five layers as shown in fig.1. The first layer forms the generic knowledge model representing all AM related concepts (i.e. process, Machine, Material, resource, etc.), and their relationships, following the meta-model proposed in [10] based on the Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE).

The second layer includes the meta-definition of the different types of templates as well as the semantic definition of case as concepts connected through constraints and the relation HasTemplate. Concretely, Project template allows the description of main categories of projects through their classification by customer activity sector, result type (study, prototype, realization, etc.), complexity, etc. Product template classifies the main families of products according to some invariants (i.e. category of size, form of the support, generic shape, etc.). Feature template completes the product template by classifying main elementary geometric shapes, so that a product can be identified as a combination of elementary shapes and other free forms with specific dimensions. Process Template classifies possible standard processes connected to the AM value chain (support optimization, build, control, post-process, etc.), and identify for every type of process the main parameters to be adjusted in and the constraints to be respected (compatible resources and materials, etc.). Material template helps to distinguish all material types based on their physical properties, as well as compatibility and treatment constraints. Finally, Machine template describes the nominal characteristics of existing AM machines and related equipment (manufacture name, max. build dimensions, temperature range, etc.).

Based on these definitions, the real basic templates are defined in the fourth layer as individuals of the types of templates defined in layer 2, with range of values for every parameter. The fifth layer contains the second instantiation where a collection of templates conducts to a specific reusable case. The exact values of these individuals are automatically extracted from the database. This latest contains all the necessary data collected from customer specification, 3D models and other technical documents. By means, the ontology contains only useful information while the real data is still stored in the database to avoid redundancy. Finally, the third layer gathers the needed business rules and similarity constraints to support the decision-making process through linking the current project data with similar cases, on one side, and the generation of new knowledge by inference, on the other side.

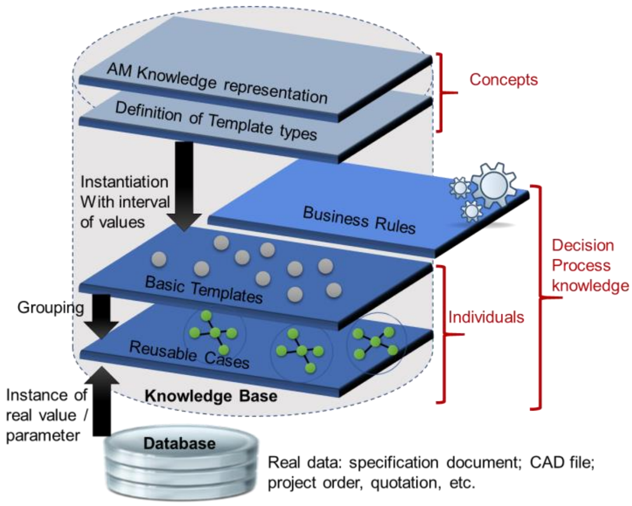

Fig. 1. Knowledge Base structure and layer interconnection

In practice, the execution of decision support starts with the analysis of the customer requirements and additional specifications. New knowledge could be defined and parameters values refined through the application of some business rules. Then, the related templates are identified and business rules are again used to classify the new project in the right category (project complexity, product size, etc.) Based on that, similar cases are searched and the right decision model is identified for application. The results are saved in the database after validation of the expert. However, if similar cases or templates are not found, the enrichment process of the knowledge base is trigged in collaboration with industrial experts to identify new rules and/or cases. The next section illustrates the execution of the decision-aid mechanism for cost assessment, as an important step to help expert for defining cost quotations.

4 Framework Application: (Cost Estimation DSS)

Cost is one of the major performance indicators for the AM manufacturer to be competitive. Its estimation is a challenging task that requires a vast amount of manufacturing knowledge about the whole process in several cases, part of this knowledge is not available in the beginning of the project and the expert should base his quotation on his own expertise with different hypothesizes [17]. Therefore, the proposed solution aims to provide a support for the cost estimation of AM products to help expert when answering specific client demands or to answer call for tenders. For the decision model, the proposed approach is based on Activity-Based Costing (ABC) method for providing appropriate cost structure of the final cost for metal and laser-based Powder Bed Fusion (PBF). The model helps identifying the main cost drivers within AM value chain and their correlations with the available inputs and parameters at early stages when receiving customer specifications. The ABC model is prepared in a form of mathematical equations, coupling the total cost of each activity with the related cost-center resources (machines, labor, tools, etc.).

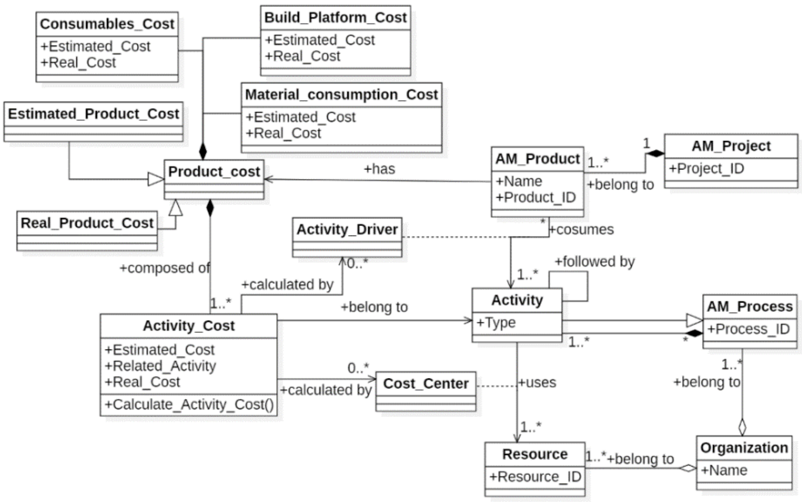

Fig. 2. ABC Meta-Model

Fig.2 illustrates the ABC meta-model for the integration of their useful knowledge as a specific template in the knowledge repository (ontology). For the simplicity of reading, UML graphical language is used. The mathematical equations are integrated as constraints and business rules, while the requested parameters to evaluate these equations are available in different templates to support their automatic evaluation. By means, the global equation of the cost model is given bellow. The detailed parameters are out of the scope of this paper because of the page size restrictions.

$$\boxed{\text{Final Product cost} = \text{Total material cost} + \text{Build Platform cost} + \sum\text{Activity cost} + \text{consumable costs}}$$

For the sake of example, we assume that we want to estimate the cost of fabricating a specific part using Titanium Ti64 material, and manufactured on an EOS290 DMLS (Direct Metal Laser Sintering) machine (example from [18]). In this example only AM process and machine templates are illustrated due to the paper size limitation, and only the costs related to build job, machine setup, and machine output activities are estimated. At first, the required basic templates for the DMLS process are selected from the ontology. Then, the machine type and the resource needed for this process are coupled (machine operator with its cost rate which is equal to 110 euro/hour) as shown in fig.3. Fig.4 shows the characteristics of this machine type including the cost rate for running this machine as a cost center rate for build job activity. However, the estimation of build time obtained from several software packages exist for estimating the build time like (Materialise-Magics, EOSprint, etc.).

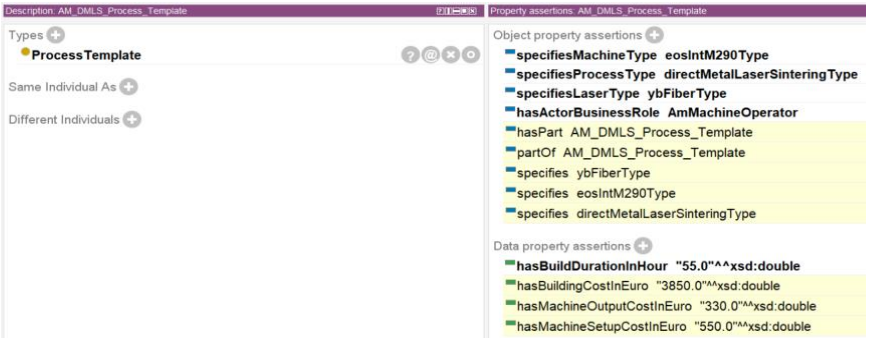

Fig. 3. Individual of AM Process Template (DMLS)

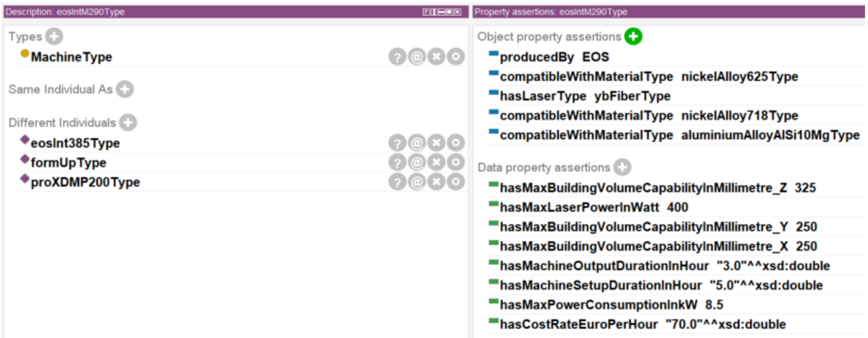

Fig. 4. Individual of Machine Type (EOSM290)

Based on the values stored in the templates, the cost for build job, machine setup, and machine output activities are inferred using the SWRL rules in the ontology and built-in reasoner Pellet that represent the cost estimation equations for these activities, as show in the two rules below R1 and R2. The mapping with the identified templates conducts to the categorization of the project as medium complexity for massive product with medium size. The supporting strategy is standard category.

```
R1: ProcessTemplate(?x) ^ hasBuildDurationInHour(?x, ?y) ^ specifiesMachineType(?x, ?z) ^ hasCostRateEuroPerHour(?z, ?a) ^ swrlb:multiply(?I, ?y, ?a) -> hasBuildingCostInEuro(?x, ?I)

R2: ProcessTemplate(?x) ^ specifiesMachineType(?x, ?y) ^ hasMachineSetupDurationInHour(?y, ?z) ^ hasMachineOutputDurationInHour(?y, ?a) ^ hasActorBusinessRole(?x, ?t) ^ hasCostRateEuroPerHour(?t, ?i) ^ swrlb:multiply(?u, ?z, ?i) ^ swrlb:multiply(?p, ?a, ?i) -> hasMachineSetupCostInEuro(?x, ?u) ^ hasMachineOutputCostInEuro(?x, ?p)
```

5 Conclusion and Future work

The main goal of the proposed knowledge-based framework is to improve the performance of additive manufacturing value chain, by supporting data sharing and tracing along AM value chain, and support the experts' decision making in different cases of AM field. This work details the methodological framework in terms of the conceptual approach, and framework layer's structure. Ontology has been used to constitute the knowledge base with its ability to capture heterogeneous knowledge, along with rule-based approach in a form of SWRL in the ontology to integrate the amount of knowledge provided by experts (know-how, decisions, etc.) in order to deduce new knowledge. One application of this framework is exposed to support the decision making in cost estimation which aims to aid the manufacturing products cost estimation. Using Activity-Based Costing (ABC) method for providing appropriate cost structure of the final cost, identifying the main cost drivers within AM process chain and their correlations to the available inputs and parameters at early stages, considering customer specifications, and product characteristics.

The project is currently under progress. At one hand, the approach needs to be complemented with other techniques beside the rule-based approach such as similarity measures, in order to foster the use of this framework in real world setting. On the other hand, the implementation of this framework in software application requests the creation of specific connectors and parsers to automatically extract data from documents and 3D models. Moreover, future work will be important to define other decision-making scenarios focusing on qualitative performance indicators.

Acknowledgement. The presented results were conducted within the French national project "SOFIA" (SOlution pour la Fabrication Industrielle Additive métallique). This project has received the support from the French Public Investment Bank (Bpifrance) and the French National Center for Scientific Research (CNRS). The authors would like to thank all industrial and academic partners for their involvement in this research.

References

1. Negi, S., Dhiman, S., Sharma, R. K.: Basics, applications and future of additive manufacturing technologies: A review. Journal of Manufacturing Technology Research, 5(1/2), 75 (2013).
2. Al-Meslemi, Y., Anwer, N., Mathieu, L.: Modeling key characteristics in the value chain of additive manufacturing. Procedia CIRP, 70, 90-95 (2018).
3. Wang, Y., Zhong, R. Y., Xu, X.: A decision support system for additive manufacturing process selection using a hybrid multiple criteria decision-making method. Rapid Prototyping Journal, 24(9), 1544-1553 (2018).
4. Liu, X., Rosen, D. W.: Ontology based knowledge modeling and reuse approach of supporting process planning in layer-based additive manufacturing. In 2010 International Conference on Manufacturing Automation (pp. 261-266) (2010).
5. Witherell, P.: Emerging Datasets and Analytics Opportunities in Metals Additive Manufacturing. In Direct Digital manufacturing Conference (2018).
6. Kim, D. B., Witherell, P., Lipman, R., Feng, S. C.: Streamlining the additive manufacturing digital spectrum: A systems approach. Additive manufacturing, *5*, 20-30 (2015).
7. Belkadi, F., Vidal, L. M., Bernard, A., Pei, E., Sanfilippo, E. M.: Towards an Unified Additive Manufacturing Product-Process Model for Digital Chain Management Purpose. Procedia CIRP, 70, 428-433 (2018).
8. Gibson, I., Rosen, D., Stucker, B., Khorasani, M.: Additive manufacturing technologies (Vol. 17, p. 195). New York: Springer (2014).
9. Merkert, J., Mueller, M., Hubl, M.: A Survey of the Application of Machine Learning in Decision Support Systems. ECIS Completed Research Papers, Paper 133 (2015).
10. Sanfilippo, E. M., Belkadi, F., Bernard, A.: Ontology-based knowledge representation for additive manufacturing. Computers in Industry, 109, 182-194 (2019).
11. Li, B. M., Xie, S. Q., Xu, X.: Recent development of knowledge-based systems, methods and tools for one-of-a-kind production. Knowledge-Based Systems, 24(7), 1108-1119 (2011).
12. Ghazy, M.M.: Development of an additive manufacturing decision support system (AMDSS). Newcastle University. NE1 7RU, United Kingdom. PhD thesis (2012).
13. Meski, O., Belkadi, F., Laroche, F., Ritou, M., Furet, B.: A generic knowledge management approach towards the development of a decision support system. International Journal of Production Research, 1-18 (2020).
14. Eddy, D., Krishnamurty, S., Grosse, I., Perham, M., Wileden, J., Ameri, F.: Knowledge management with an intelligent tool for additive manufacturing. In proc. ASEM Int. Des. Eng. Tech. Conf. Comput. Inf. Eng. Conf. (Vol. 57045, p. V01AT02A023) (2015).
15. Kim, S., Rosen, D. W., Witherell, P., Ko, H.: A design for additive manufacturing ontology to support manufacturability analysis. Journal of Computing and Information Science in Engineering, 19(4) (2019).
16. Hagedorn, T. J., Krishnamurty, S., Grosse, I. R.: A knowledge-based method for innovative design for additive manufacturing supported by modular ontologies. Journal of Computing and Information Science in Engineering, 18(2) (2018).
17. Kadir, A. Z. A., Yusof, Y., Wahab, M. S.: Additive manufacturing cost estimation models—A classification review. The International Journal of Advanced Manufacturing Technology, 107(9), 4033-4053 (2020).
18. Barclift, M., Joshi, S., Simpson, T., Dickman, C.: Cost modeling and depreciation for reused powder feedstocks in powder bed fusion additive manufacturing. In Solid Free. Fabr. Symp (pp. 2007-2028) (2016).