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Towards a knowledge structuring framework for decision making within industry 4.0 paradigm

O. MESKI*, F. BELKADI**,
B. FURET*, F. LAROCHE**

* *University of Nantes, Laboratory of Digital Sciences of Nantes, UN-LS2N – UMR CNRS 6004, 1 rue de la Noë 44321, Nantes France, (Tel: 0033 2 40 37 69 56; e-mail: firstname.lastname@univ-nantes.fr).*

** *Ecole Centrale de Nantes, Laboratory of Digital Sciences of Nantes, ECN – LS2N – UMR CNRS 6004, 1 rue de la Noë 44321, Nantes France, (e-mail: firstname.lastname@ls2n.fr)*

Abstract: This article discusses the importance of data and knowledge structuring to allow their exploitation in emergent context of industry of the future. The complexity of integrating knowledge into decision support systems is particularly due to the heterogeneity of knowledge sources and the large volume of data to be analyzed. This problematic is challenging in the context of high-speed machining of aeronautical mechanical parts because of the high quality and safety constraints requested in this business area. To answer the above problem, this paper proposes a new semantic modeling framework covering both generic business knowledge and real time data. The application to the proposed semantic models for decision aid perspective within the SmartEmma project is also discussed. Copyright © 2019 IFAC

Keywords: industry 4.0, knowledge reuse, modelling, decision-making.

1. INTRODUCTION

Based on recent developments in enterprise digitalization and information and communication technologies (ICT), the industrial sector is rapidly growing towards "intelligent manufacturing" and "connected factories". The manufacturing processes can be represented with a virtual copy (digital twin) and connected through cyber physical systems (CPS) and Internet of Things (IOT). These new technologies are at the heart of the Industry 4.0 paradigm.

Among the main sectors affected by this revolution, high-speed machining of mechanical parts in aeronautic industry present high challenges of quality and safety constraints. Indeed, the aeronautic parts are characterized by high added value regarding the whole airplane system. Their manufacturing process should be very accurate and produce the good part from the first time, while minimizing working time and costs. To satisfy these constraints, industries start using knowledge-based decision aid systems to support the monitoring and quality control along the production process. Erik Brynjolfsson et al. (2011) argue that companies using this kind of systems can improve their performance and profitability by 5% compared to their competitor.

Decision aid solutions are generally based on the analysis of variety of information flows. In the aeronautic shop floor, the available data are collected from different sources. For example, the detection of the high-risk events is done using machine instrumentation to ensure the acquisition of a large amount of data representing the real behaviour. The processing of this data conducts to big data issues.

The SINTEF, one of Europe's largest independent research organisations estimated that 90% of the world's data were generated between 2010 and 2013. These data flows continue to increase in all fields. This research work focuses on the exploitation of data and knowledge to provide decision aid in the aeronautical mechanical machining industries. The literature survey argues that by 2026, the data generated annually in the aeronautics sector is expected to reach 98 billion gigabytes, or 98 million terabytes, according to an estimate made in 2016 by Oliver Wyman a leading global management consulting firm. Organizations must be able to analyse big data to extract knowledge and to use it at different decision levels: strategic, tactical and operational.

However, the decision process remains complicated due to several problems of industrial digital chain breakdowns. For instance, the lack of communication between businesses services, the interoperability between information systems, the diversity of technological solutions used, etc. In addition, the variety of information sources, and the large size of the databases to be recovered, implies an important step of preparation and structuring of the information flows.

As a support to this critical step, this paper proposes a semantic modelling framework that brings together all industrial information with the aim to handle data management and integration between all decision levels of the factory. This model is part of a decision aiding platform, to cover knowledge finding and interoperability issues.

The remaining of this article is organized as follows. The next section presents a state of the art on the paradigm of industry of the future and the related knowledge management

applications. Section 3 explains the research methodology used to build the knowledge model. Section 4 describes the key parts of the proposed meta-model while the implementation perspectives of the models within the expert system are discussed in Section 5.

2. KNOWLEDGE-BASED DECISION MAKING WITHIN THE INDUSTRIE 4.0 PARADIGM

The concept of "Industry 4.0" was invented in 2013 by the German government when they introduced their action plan and strategies for the development of the high-tech sector, which promote the digital revolution in industry.

The expression "Smart Industry" also describes the evolution of industrial technologies from microprocessors, and embedded industrial systems to cyber-physical systems. That has allowed connecting cleverly the different services of industry and the industrial chain, by internet (Zuehlke, 2010).

The virtual factory is based on the concept of digital twins. This technology represents a virtual model of an equipment, process, product, or service. It is used to detect problems, or to test and simulate scenarios on a physical model of a production unit. This digital twin also allows real-time analysis of operational data to improve the understanding of equipment functioning and to make timely decisions to optimize their efficiency (Julien et al., 2018).

Decisions take place in every department of a firm (i.e. product design, production policy, marketing focus, etc.). Each of those decision aims at improving the firm performance, either locally or globally. In the context of the Factory of the Future (FoF), a strong correlation exists between data and knowledge management and the performance of workers and industrial processes. Indeed, decision-makers usually need a good understanding of the operational process and resources' capacities.

To help deciders to overcome the psychological aspect of decision making (Bazerman and Moore, 2012), decision support tools have been developed. Previous researches enable to create a large corpus of qualitative or quantitative, determinist and stochastics or fuzzy, decision methods (Triantaphyllou, 2013). They all rely on the integration of data and expert opinions; some of them also integrating simulation tools to estimate the alternatives' expected performances (Daaboul et al., 2014). The actual scientific barrier is to enhance this decision making process by the integration of knowledge.

In particular, the smart factory aims to enhance the control and the optimization of factory processes based on advanced ICT tools for a better use of existing knowledge and data. This can be obtained from simulations as well as the analysis and inference of heterogeneous data (Forestier et al., 2011) (Guibert et al., 2008). To tackle these challenges, engineering systems have moved from being information-intensive towards knowledge-intensive systems (Bernard et al., 2007). Numerous systems and methodologies are developed with the aim to support knowledge modelling, storage and reuse (Liao, 2003). The first generation of knowledge-based

systems was expert systems using a set of facts and rules (Ulengin et al., 1997). This kind of systems is composed of essentially two components: a knowledge base (KB) and an inference engine. Due to the increasing complexity of the knowledge-based systems and variety of application domains, knowledge modelling is a critical issue to guarantee the consistency of the knowledge base. Knowledge models must be based on a rich and structured representation (Belkadi et al., 2012) and should propose an adequate way for using this knowledge by several experts regarding their interest (Demoly et al., 2010). Ontologies are often proposed as knowledge repository for KB systems handling easier classification and finding of knowledge (Sanya et al., 2015). In the area of analysis and modelling processes, structures and information flows in factories, there are several methods available, customized to their individual application area.

Modelling is used in several fields such as cognitive sciences, engineering, management, and computer sciences. A model is generally used to represent and describe a complex system in a formal and simplified way from several points of view corresponding to different business objectives.

The term knowledge modelling is initially a concept of artificial intelligence. It is used to determine the list of knowledge to introduce into a computer system in order to make it "intelligent".

The modelling of data flows and industrial knowledge consists of structuring the most important company objects which are in direct contact with the product and process respectively. Several models have been developed in the literature to represent industrial knowledge. For instance, the following approaches can be cited:

- The Product, Process, Resources approach has been addressed in several works. (Cutting-decelle et al., 2007) (Borja Ramis et al, 2016) (Agyapong-kodua et al., 2014) highlight these three modelling objects and confirm that satisfactory data or knowledge models in this field must revolve around these three axes.
- The Function, Behaviour, Structure - Product Process Resource External Effects approach (Labrousse, 2004) extends the FBS (Function Behaviour Structure) model proposed in the work of (Gero, 1990).
- The People, Process, Product approach that was first used by Motorola in its Six Sigma development. This is a very important one since it highlights the place of the human being in industry. The involvement of the human being remains indisputable.

Ultimately, from a modelling point of view, these approaches do not cover all the objects of the industrial digital chain, as well as the operational working context, at the same level. Therefore, with the ambition to provide an integrated framework, this research work addresses the problem of:

How to smartly model heterogeneous data and knowledge within decision aid perspective in context of industry 4.0?

3. METHODOLOGY OF MODEL CONSTRUCTION

The ambition of the proposed modelling framework is to be generic and robust enough to support variety of data and knowledge formats, required for the decision aiding system. This section explains the methodology used.

3.1 Data collection

The first step concerns the identification of all data sources and the classification of these varieties of data according to their nature and their contribution to the manufacturing and monitoring processes. The concept of data refers to all measured dimensions related to a given executed manufacturing process and its resulted products. Four categories of data sources are distinguished:

- The data bases connected to the machine and the related digital chain to collect real time and raw data.
- Product data sheets that informs about the result of an executed manufacturing process such dimensions, tolerances, and surface quality.
- Information systems data bases i.e.: MES (Manufacturing Execution System) and ERP (Enterprise Resource Planning) that contain additional data representing the context of the executed manufacturing process (manufacturing order, real time schedules, etc.).
- Other data bases that will store the resulted indicators after data processing.

Concretely, the “Monitoring & collected data” represents the databases collected from the industrial partners. This monitoring data are acquired through a tool for machining optimization and vibration analysis for composite and metal machining operations. It is composed of a hardware part that consists of a set of sensors and a software part that allows through them to collect “Real-time signals”. The other types of data can be collected from a variety of sources.

The smart data are often extracted from the monitoring & collected data, using processing, interpretation, aggregation, etc. Data aggregation, using intelligent algorithms, allows to reduce the size of big data, and to structure them more significantly. This help to make processing and to facilitate data mining and knowledge extraction operations, in order to obtain the “Decision aid indicators”.

3.2 Knowledge extraction

The concept of knowledge refers to all the generic information that allows the definition, the interpretation, and the processing of real time data as well as the evaluation of the resulted products.

The second step is then to identify the knowledge sources based on the analysis of the as-is situation and the decision-making objectives within the monitoring process. For instance, to understand the quality of the product, there is the need to compare the measured dimensions (collected data) with the specified dimensions (described in the Computer-

aided design (CAD) model). Additional business rules can inform about the relation between a manufacturing operation and its impact on the part surface.

Manufacturers still generally curious to know: how other departments contribute in the production process? How they complement each other? How to share information to ensure the continuity of the digital chain? And finally, what opportunities for collaboration they may have?

In addition, manufacturers are also interested in the events that can affect product quality. The company's experts use their expertise to verify the quality of production, the qualification of the parts, and all the decisions to be taken when disqualifying a product. The competence of technicians represents an essential part of the knowledge base.

Other types of information are also important, such as temporal information that indicates business performance (useful time, net time, gross time, time required, etc). For this reason, in the area of industrial and production management, various indicators are often calculated, for example: the Economic Efficiency Rate (EER): indicator of the engagement of production means, or the Synthetic Efficiency Rate (SER): productivity indicator). This type of knowledge is included in the category of Key Performance Indicators (KPIs), which measure the efficiency of processes against a specific objective. KPIs are generally used for a common overall objective: management or continuous improvement.

The knowledge extraction method is based on the observation of operations, the analysis of technical documentation, and the classification of generic information available in information systems (CAD files, Programs, machine tools libraries, etc.). The definition of business rules is obtained from interview with experts and the analysis of reports.

3.3 Models building

In order to maintain the generic nature of the data model, the first two types of data and knowledge were confronted and enriched by other complementary data from the literature and standards. This will extend the scope of the data model to other industries in the future. In addition to the literature, standards and the monitoring database, the development of the data model is also based on the analysis of requirements resulting from the functions developed in the decision-making platform.

The specificity of this research work is the complementarity between the use of data and knowledge. The decision support system allows data processing through the use of a set of knowledge such as the capitalized business rules. Through these rules, the expert system generates new KPI that facilitate decision support and new knowledge “Inferred Knowledge” that can be integrated into the global database and easily reused.

Figure 1 shows the global categories of databases and knowledge represented respectively by the right and left axes. The reuse of data and knowledge allows the enrichment and updating of these databases.

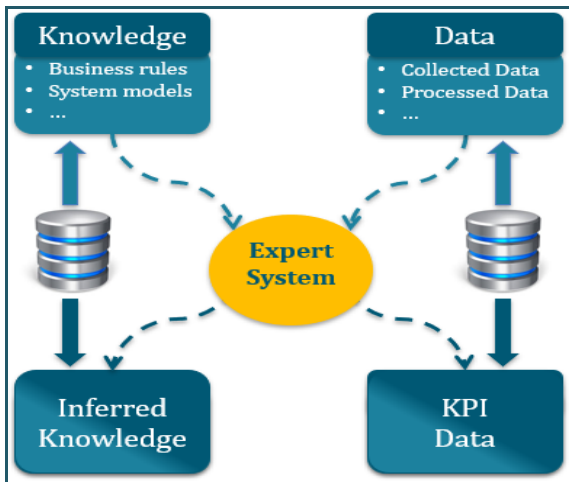


Figure 1. Categories of data and knowledge

The following section of this paper focuses only on the knowledge dimension of the global modelling framework.

4. KNOWLEDGE META-MODELS

The objective of the knowledge models is to support the structuring of data used by the decision aiding platform. Consequently, the construction of these models will have to follow an incremental approach as well as the development of the platform. A first version of the model is defined and will be improved during the project. The generic knowledge model developed is essentially composed by the representative data model that represents a first level of knowledge, to which a second level of knowledge is associated such as KPIs, business rules, resource characteristics and specificities, etc.

Based on this first step of analysis and classification of data sources, the next step was to represent more formally, using modeling standards, the classifications of the identified data.

We therefore choose the UML (Unified Modeling Language). It is a graphical language for object-oriented modeling. There are several advantages that justify the choice of UML language: the simplicity of the use, the modularity of the different kinds of models and especially the adaptability and the possibility of use in several domains. The object-oriented approach provides a unified representation of the different elements of a system, which corresponds to the need of modeling the different entities of the system.

The development methodology adopted is to begin from a generic meta-model and to add more and more granularity as we go along.

Based on product-oriented modelling approaches, the idea was to merge the 3 most important ones:

- Product, Process, Resources Approach
- Product, Process, Resources, Context Approach
- People, Product, Process approach

The merge of these three approaches produce the global package model: CR3P (Context, Resources, Product, Process, People). The Figure 2 represents the first version of the knowledge package model.

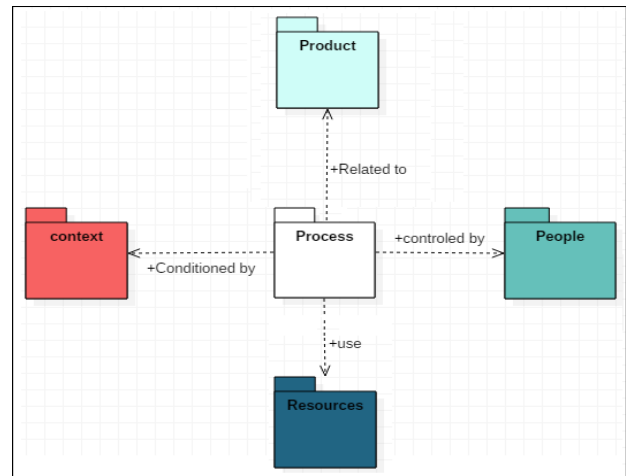


Figure 2. Knowledge package model

The choice of these three approaches was based mainly on the usefulness of the different fundamental concepts or objects in the context of this research work. To highlight the human place in Industry 4.0, the "People" package has been developed. The human has a very important role to play in this project and more generally in the context of the industries of the future. The Figure 3 represents the first version of the "People" package model.

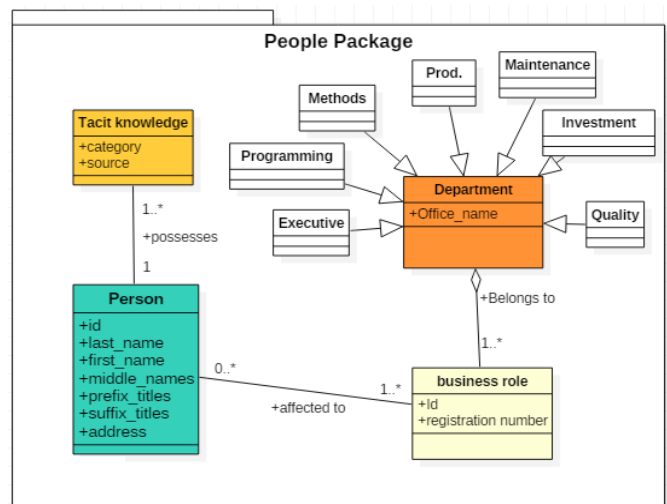


Figure 3. « People » package

The global knowledge model has been developed on the basis of a set of business rules which are originally the expertise of manufacturers. We also remind that the overall objective of developing this model is to capitalize and manage knowledge between the different departments. So, the development of this system allows the integration of knowledge among the company's stakeholders.

Thus, humans have a dual role in producing and exploiting knowledge. Consequently, the "tacit knowledge" class represents an important element of this package which allows the communication with others in order to reintegrate and improve the technicians' knowledge.

Otherwise, concerning the "Context" package, the idea is to develop a package that supports specific and necessary knowledge for the decision-making support system, in which we capitalize the entire context of the use. The Figure 4 represents the first version of the "Context" package model.

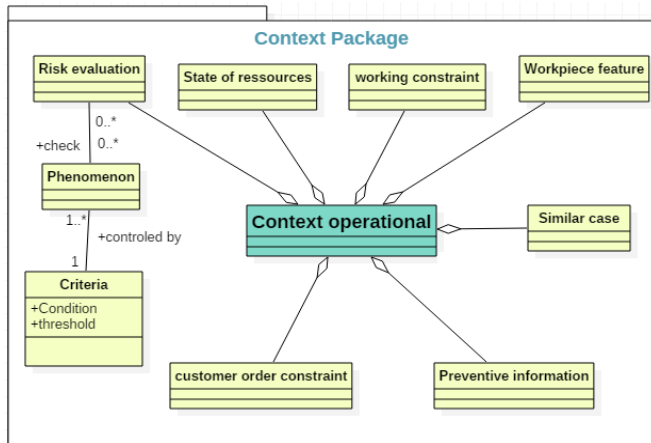


Figure 4. « Context » package

Gradually, by using norms and standards, the meta-model was developed. And, two were very useful: STEP-NC (STEP compliant Numerical Control) and MANDATE (MANufacturing management DATa Exchange).

STEP-NC (ISO 14649) was developed and published by ISO in 2006. It replaced the G-Code (ISO 6893) and improved the STEP (ISO 10303) (STandard for the Exchange of Product model data). It is a data exchange standard for numerical control programming. Above all, it allows communication between the different parts of the digital chain.

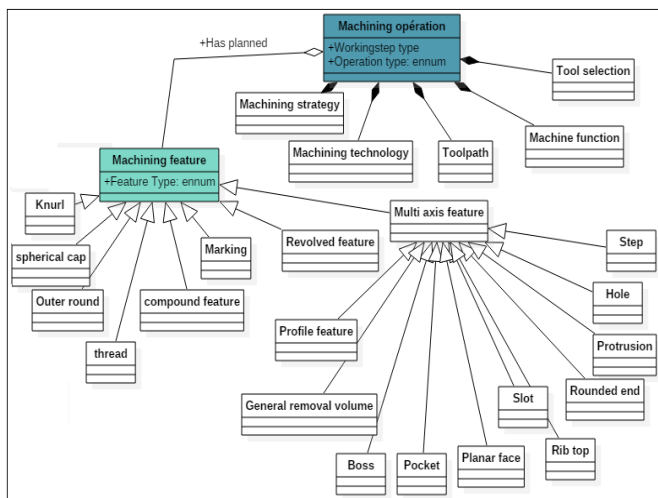


Figure 5. Integration of Step-NC into KM

The figure 5 shows a small overview about the use of these standards for the development of our knowledge model by defining generic classes, inspired from the detailed definitions presented in the norms.

The objective is to develop a model capable of gathering as much as possible of the useful knowledge for the development of our decision support system.

5. IMPLEMENTATION PERSPECTIVE

After the first phase of development of models for data and knowledge structuring, an implementation phase is required.

The implementation makes it possible to evaluate the efficiency of the models for the global organization of knowledge. It also provides an initial test phase to validate or to update the models during the development of the expert system.

In this project, the technology of multi-agent systems was chosen to ensure information piloting. This system is mainly composed by several agents and each one is specific to a precise role. We have traceability agents, configuration agents, reporting agents, decision support agents, etc.

The functioning of this system is based mainly on the global knowledge base. By using the knowledge models we will develop a complete ontology that combines all the data, knowledge, and business rules in a static way.

In order to develop the multi-agent system, several scenarios have been defined specifying the needs in terms of input and output data, also the departments concerned by these data and the mode and frequency of collection and restitution. A first scenario has been implemented.

This initial scenario is integrated into the implementation of our first management axis in the project: "the reporting". The first multi-agent system prototype allows the traceability of several specific input data, to produce after a treatment, a set of output data. The system can also send treatment reports, by email, on demand.

The storage of this data is done in a traceability database in the form of a traceability point. It is also structured through a generic traceability database model. The storage on this database is dynamic.

The figure 6 illustrates our methods of knowledge management and capitalization of data.

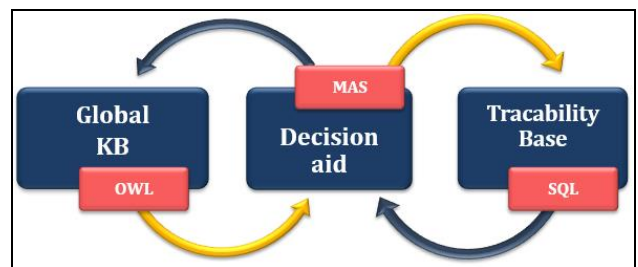


Figure 6. Implementation strategy

The figure illustrates the decision aid framework system's ability to recuperate data from the global knowledge base structured using the Web Ontology Language (OWL) and store them in the traceability database developed with the Structured Query Language (SQL) in a dynamic way. This technique avoids duplication of the database. But above all, it allows us to validate and upgrade our structuring models so that they can support the consistency of our global base on one hand and the heterogeneity of knowledge on the other hand.

6. CONCLUSION AND OUTLOOK

The structuring of knowledge is the key to ensuring the generation and the reuse of new ones. This article details a methodology based on a meta-model for model construction. They are used to structure all the information and knowledge flows available mainly in the mechanical machining industries and especially the aeronautical ones.

The development of ontologies makes it possible to capitalize on the maximum of heterogeneous knowledge. The project is currently in the development phase of a knowledge repository, using ontologies and standards, the methods of questioning and interacting with this knowledge base remain our current research issues

7. ACKNOWLEDGEMENT

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