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# A generic knowledge management approach towards the development of a decision support system

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## ABSTRACT

The fourth industrial revolution is increasingly implemented in most fields and categories of industry. The use of several highly developed technologies generates huge amounts of heterogeneous data and knowledge, hence the need to manage it in order to facilitate its reuse. This article proposes a global approach of knowledge management, from the analysis and development of the knowledge base structuring models, to the implementation phase using knowledge engineering tools. This research work is part of a global knowledge-based decision support framework that ensures several axes of decision support, this article deals with the diagnosis axis. It provides analysis and comprehension of the failures occurring during production. The approach has been implemented as a first demonstrator tested in a real case study: the aeronautical mechanical machining industry. This article details the issues of this implementation and its interest for the validation of the approach.

## 1. Introduction

Since its appearance, the fourth industrial revolution has not ceased to affect most fields of activity and its implementation presents an interesting research topic in several disciplines. Nowadays, the strong aspect of this revolution is the expansion of the industry with the use of several technologies such as cyber physical systems, Internet of Things, digital twin, etc. (Zuehlke 2010).

Production systems are among the most favourable areas for migration to industry 4.0 because manufacturing industries aim to provide an optimal and efficient product for their customers while maintaining as a main challenge the increase of competitiveness and the improvement of productivity (Brynjolfsson, Hitt, and Kim 2011). Thus, these systems continue to work daily on finding the best tips and tools for continuous production improvement.

Despite the emergence of new technologies and their ability to solve industrial problems, these tools need to remain under the control of the technicians and must be managed by human capacities and skills. The expertise of all industrial actors is crucial to ensure optimal use of available resources. This collaboration is the origin of artificial intelligence, which can be considered as the digitisation of human know-how, skills and experience in order to automate the process of proposing solutions to reduce calculation times and reasoning efforts. Among

the methods of artificial intelligence, decision support systems (thereafter, DSS) are used to analyse a problematic context and to propose a suitable solution to correct or avoid it (Teti 2015). These techniques have been too widespread for years and their usefulness is increasing with the appearance of new information technologies. As long as these systems are based on business rules and industrial knowledge bases, they will generate reliable results.

Given all the resources used in industry, huge amounts of data and knowledge are available but unfortunately not widely exploitable. It is obvious that their reuse is constrained due to the heterogeneity of this knowledge. Several researches deal with the knowledge reuse issues in the field of production and manufacturing (Cochrane et al. 2009; Chungoora et al. 2013; Urwin and Young 2013): they all agree there is a need for a process of knowledge structuring and management in order to facilitate their exploitation.

This research work focuses on a specific field of production: the machining of aeronautical mechanical parts. As these parts are very expensive and complex, the challenge of productivity is to manufacture good parts from the first try. Implicitly, it is necessary to avoid the occurrence of any problems or malicious phenomena that may affect the machining process (Teti 2015). Therefore, it's important to monitor the machining process (Ferretti

et al. 2013) to improve its quality and its efficiency (Psarommatidis et al. 2019).

In addition to the two methods studied in this research, DSS and knowledge modelling and management approaches, the improvement of the performance of the manufacturing process can also be achieved through improving sustainability metrics (Raman et al. 2020). Several standards are working on characterising industry manufacturing processes for sustainability-related decisions. For example, the subcommittee E60.13 of the American Society for Testing and Materials (ASTM) is focused on the issues of sustainable manufacturing.

This article proposes an industrial knowledge management strategy to help the development of a decision support system. The global framework being developed enables several decision-support axes: reporting, diagnosis, prediction and reaction. This work is mainly focused on the second axis.

Therefore, this article begins with a literature review on decision support systems and knowledge management. Next, the first steps of the approach construction are presented; they consist of data and knowledge analysis and modelling. Finally, the scientific proposal ends with the presentation of the usefulness of the knowledge management approach for the development of the second decision support axis: diagnosis.

## 2. State of the art

This literature analysis begins by defining decision support systems, describing their usefulness, and detailing their processes. There are several categories of such systems, among them those based on knowledge management processes. The knowledge, as well as the tools and methods needed for its structuring and management will be described in the second part.

### 2.1. Decision support systems

Research around designing technological solutions capable of supporting decision-making assistance to solve problems began since the 1970s (Gorry and Scott Morton 1971). The DSS consists of developing and implementing systems using information and communication technologies to ensure decision-making (Shim, Warkentin, and Courtney 2002). The DSS are very useful for improving and facilitating management at the different decision levels in the industry: the strategic level, which focuses on long-term planned actions to enhance productivity, the tactical level that manages processes and resources, and the operational level for the control and management of specific operations (Klement, Silva, and Gibaru 2017).

#### 2.1.1. The DSS process

Drucker (1958), Simon (1959) and Archer (1980) define three essential phases of the decision-making process. The first is 'the intelligence phase' which mainly deals with the definition of the problem. The second, intermediary, for structuring and defining the links between problems and proposed solutions 'the design and modelling phase'. Finally, 'the choice phase' allows the decision-making and the proposal of a validated final solution.

Based on these 3 phases, several other works continue to define the steps of the decision support process, and the most frequently cited research remains that of (Shim, Warkentin, and Courtney 2002) which defines seven steps. The first is always the problem identification. For each issue, there is one or more method to eliminate or avoid its occurrence. To analyse these different alternatives, it is important to develop specific models that define the relationships between issues and proposed solutions as well as all the complementary parameters and business rules. These intermediate steps of analysis make it easier to choose the appropriate decision to be able to implement it in the last step.

#### 2.1.2. Different categories of DSS

Along the technological evolutions, and the development of research on DSS, this field greatly evolved and several approaches and subfields emerged over time. Arnott and Pervan (2005) deals with DSS and defines the main subfield and their evolution over time. It is hence possible to describe some types of DSS:

- Personal Decision Support Systems: as the name implies, these are often developed for a single manager or a group of independent managers.
- Group Support Systems: are developed to improve the work and collaboration among a working group. The main objective of this system is to encourage decision-making based on all the suggestions proposed by the various members of the group.
- Negotiation Support Systems: this type of system uses computer technologies to facilitate negotiation. There are two categories of these systems: problem-oriented and process-oriented.
- Intelligent Decision Support Systems: this category of system introduces the use of artificial intelligence in decision support. They are classified into two generations: the first is rule-based systems and the second generation includes genetic algorithms, fuzzy logic and neural networks.
- Knowledge Management-Based DSS: these systems allow the taking based on the capitalisation of knowledge and the development of knowledge repositories.

Also the manipulation, transfer and reuse of knowledge, for the purpose of decision-making and thus the creation of new knowledge.

The Decision Support System developed throughout this research work can be classified as both an Intelligent DSS and a Knowledge Management-Based DSS as it focuses on capitalising knowledge and expertise thanks to artificial intelligence.

## 2.2. Knowledge management (KM)

Before beginning the management process, a literature review was essential, particularly concerning knowledge definitions. Davenport and Prusak (1998) define knowledge as:

A fluid mix of framed experience, values, contextual information, and expert insight that provides a framework for evaluating and incorporating new experiences and information. It originates and is applied in the minds of knowers. In organizations, it often becomes embedded not only in documents or repositories but also in organizational routines, processes, practices, and norms.

Since the 1990s, many researchers have become strongly interested in knowledge management strategies as these methodologies have become crucial to increase productivity and competitiveness in production industries. Knowledge management can affect the organisation in several aspects: its structuring, behaviour, resources, and even organisational and economic strategies. Concerning DSS, several works have focused on the importance of KM to facilitate decision-making and to support knowledge creation processes (Carlsson and Lundberg 2000; Carlsson et al. 2000; Alavi and Leidner 2001; Iaksch and Milton Borsato 2019).

Nowadays, with all the aspects of development and progress achieved, the challenge is not limited to the use of an efficient information system and developed technological resources: the real issue is to be able to adapt these resources to facilitate the creation of knowledge. (Gunasekaran and Ngai 2007; Chow et al. 2005) define knowledge management as the set of operations and activities that enable the creation and storage of knowledge for its distribution and application in organisations. In the same context, research continues to define the basic functions of the knowledge management process. In 2017, Olson and Wu dealt with the KM processes in the service of the DSS and distinguished the following 4 core functions: the *identification* of the most important information and measures to support the decision-making, the *acquisition* of the data corresponding to these measurements and the *storage*

in specific databases for allowing the *retrieval* (Olson 2018).

Using KM is very important in several fields and especially in production and manufacturing. Berawi and Woodhead (2005) confirm that a good KM strategy helps to improve the overall production management system. Several research works deal with these themes in all the stages of the production process: purchasing (Lau et al. 2005; Zsidisin, Melnyk, and Ragatz 2005), planning (Gernhardt et al. 2016; Miltner, Vogel, and Hemmje 2014; Efthymiou et al. 2015), scheduling (Kant and Sridharan 1998; Chryssolouris et al. 2008), quality control (Muthu et al. 2001), etc.

In the field of manufacturing and production, and more specifically in the mechanical machining domain, the analysis of the available data and knowledge allows the distinguishing of the heterogeneities due to the variability of sources, types, natures, frequency, etc (Grevinitis et al. 2019). Thus, a challenge of adaptability and structuring is key to enable the aggregation, processing and extraction of knowledge from these information flows (Farhoomand and Drury 2002). Research on data and knowledge in the field of production has generally focused on the basic objects that compose the industry, i.e. the product, the resources used, the manufacturing process, the work context, the behaviour, etc. The modelling of industrial data and knowledge revolves around these basic objects. The analysis of the literature helps to distinguish several modelling approaches, for instance: The Product, Process, Resources approach (Cutting-Decelle et al. 2007; Borja Ramis et al. 2016), The Function, Behaviour, Structure – Product Process Resource External Effects approach (Labrousse and Bernard 2008).

Knowledge modelling must ensure a better visibility and understanding of the industrial knowledge flows to the expert (Demoly et al. 2010). It is therefore essential to propose a well-structured and rich representation by adding semantics to relations and objects (Belkadi et al. 2012). Studies in the field of semantic modelling are, generally, connected to the semantic web (Berners-Lee, Hendler, and Lassila 2001). Hence the use of its languages, generally developed by The National Institute of Standards and Technology (NIST) for example: RDF (Resource Description Framework), XML (eXtensible Markup Language) and OWL (Ontology Web Language) (McLean et al. 2005; McGuinness and Harmelen 2004).

Among the most effective methods for ensuring semantic understanding are ontologies (Pavel Vrba et al. 2011). An ontology is a method for representing and organising knowledge of a specific field using reasoning and inference mechanisms (Octaviani, Pranolo, and Othman 2015; Munir and Anjum 2018).

Gruber (1993) which define ontology as an explicit specification of a conceptualisation, he also describes all of its fundamental elements:

1. Concepts or classes: these notions allow the description of a task, a function, an action or a reasoning process.
2. Relationships: represent a type of interaction between two or more concepts. Examples of relations include 'subclass-of' or 'connected-to'.
3. Functions: are a special case of an n-element relationship where the last element of the relationship is unique for the first n-1 elements.
4. Axioms: are used to define the semantics of terms (classes, relations), their properties and any constraints regarding their interpretation.
5. Instances: used to represent elements.

Two types of ontologies can be distinguished: storage ontologies and inference ontologies (Fankam 2009).

The first, as its name suggests, allows to capitalise a maximum of knowledge on a given domain. The second allows, through the execution of a set of business rules, inference rules, restrictions and constraints, the automatic generation of new knowledge (Milicic et al. 2013).

Ontologies are used in several domains to ensure communication, structuring and reuse of knowledge (Gruninger and Lee 2002; Sureephong et al. 2008; Schmidt et al. 2016). And to ensure interoperability (Gunendran and Young 2007) between the different sub-component of an overall system. Thus, they are a good choice for the development of knowledge-based systems (Sanya and Shehab 2015). In each particular field, research work uses reference ontologies (Annamalai et al. 2011; Borsato 2014) which are considered highly generic domain ontologies, often resulting from merging several specific ontologies (Palmer et al. 2018). In the literature there are several examples of these reference ontologies, such as: DOLCE (Masolo et al. 2004; Sanfilippo and Borgo 2015) SUMO (Oberle et al. 2007) BFO (Robert Arp, Smith, and Spear 2015). Some ontologies are more specific to the manufacturing domain such as MASON (Lemaignan et al. 2006), Onto-pdm (Panetto, Dassisti, and Tursi 2012), etc.

Others have used standards for the development of ontologies, for example: OntoSTEP (Krima et al. 2009) based on the Standard for the Exchange of Product model data (STEP). Also, standard languages such as The PSL ontology based on The Process Specification Language (Schlenoff et al. 2000; Gruninger and Koppena 2005). There is also the Standard MTConnect that, according to their website, 'offers a semantic vocabulary for

manufacturing equipment to provide structured, contextualized data with no proprietary format'.

There are several foundations whose objective is to centralise research on ontology development in each specific field. In the area of digital manufacturing, the Industrial Ontologies Foundry (IOF), as stated on their website, tries to create a set of core and open reference ontologies that spans the entire domain (Kulvatunyou et al. 2018).

After the analysis of the ontological solutions proposed in the literature, and considering their interests for ensuring interoperability and communication of knowledge between the services of industry, it is noticeable that most of these works are oriented towards partial communication. It is insured just between the services directly involved in the realisation of the product: basically between the workshop and the design or manufacturing departments. This implies a lack of communication between the different services of the industry, which are closely or remotely related to the realisation of a product as well as the communication between the different information systems of the company. In addition, the proposed solutions do not manage all heterogeneous knowledge from different sources and formats. Another disadvantage is the lack of genericity of the identified solutions. This involves a difficult reuse in other fields compared to our ontological solution, which enables flexibility and adaptability, thanks to its layered structure and the use of norms and standards.

This literature review raises three main issues: how to develop the best knowledge management approach, able to structure the variety of heterogeneous data and knowledge? How to implement such a knowledge repository? How to exploit it, to ensure the reuse of knowledge and to generate new ones in decision-support scenarios?

### 3. The analysis phase

A clear distinction between the different types of heterogeneous data and knowledge circulating in the industry is necessary for optimal capitalisation.

In order to build this classification of knowledge, the first step adopted in the proposed methodology was to develop process models to analyse all information flows in the manufacturing shop floor of mechanical parts. They were built based on literature survey and consolidated with the industrial partners of this research project in order to validate the adequacy of these formalised manufacturing processes (Meski et al. 2019b).

In addition to the output data flows generated from the various phases of product manufacturing, monitoring data are also traced using a specific device composed of hardware components (such as sensors and acquisition

cards) and software components that include monitoring database and processing algorithms.

Several sensors have been installed to monitor machining parameters: acceleration, temperature, vibration frequency, etc. These sensors allow the recording of representative data concerning the health status of the machine and its different components (spindle, cutting tools, platens, etc.). The machine's computer numerical control (CNC) provides additional information related to the operational context of manufacturing process (date and time of operation, working piece reference, program reference, operating mode, etc.). These heterogeneous data are then subjected to several aggregations and data mining operations to generate a new category of data called Smart Data (Ritou et al. 2019). The use of these processing methods adds a new semantic layer representing links between the initial raw data. New indicators are then created and allows for better evaluation, not only of the health status of the manufacturing resources, but also the quality of the manufactured workpiece and especially the potential malicious phenomena that may appear during machining process. Both the use of smart data and key performance indicators (KPIs) require additional knowledge from the expert who therefore acts like an additional knowledge source.

The capitalisation of this different knowledge allows the implementation of several decision support scenarios (Figure 1). The first axis is the 'Reporting' which

provides several reports that describe malicious phenomena conducted to undesired impact (*i.e.* a degradation of the quality of the working piece due to the appearance of a chatter, a cutting tool breakage, a collision between the tool and the part, or others). These reporting operations are executed within a specific mode (periodic, on-demand, after a phenomenon occurs) and are customised for particular business roles or departments in the company (quality control, maintenance, process planning, programmer, etc.). After reporting and studying the characteristics of detected problems and phenomena, a diagnosis process must be carried out to detect the cause of their appearance. Finally, once the situation has been studied, solutions can be proposed to facilitate the decision-making process to improve the product quality or to prevent any future occurrences.

The separation between data and knowledge types conducts to two repositories. The first one includes raw and smart data (separated in three databases) while the second gathers all the available industry knowledge, the business rules, the set of KPIs and reports generated through the reporting processes. Thus, the four knowledge types distinguished in this work are raw data base, smart data base, traceability data base and knowledge repository (Meski et al. 2019a).

To structure these digital repositories, several categories of models have been created. First, data models were dedicated to clarify all the available industry data

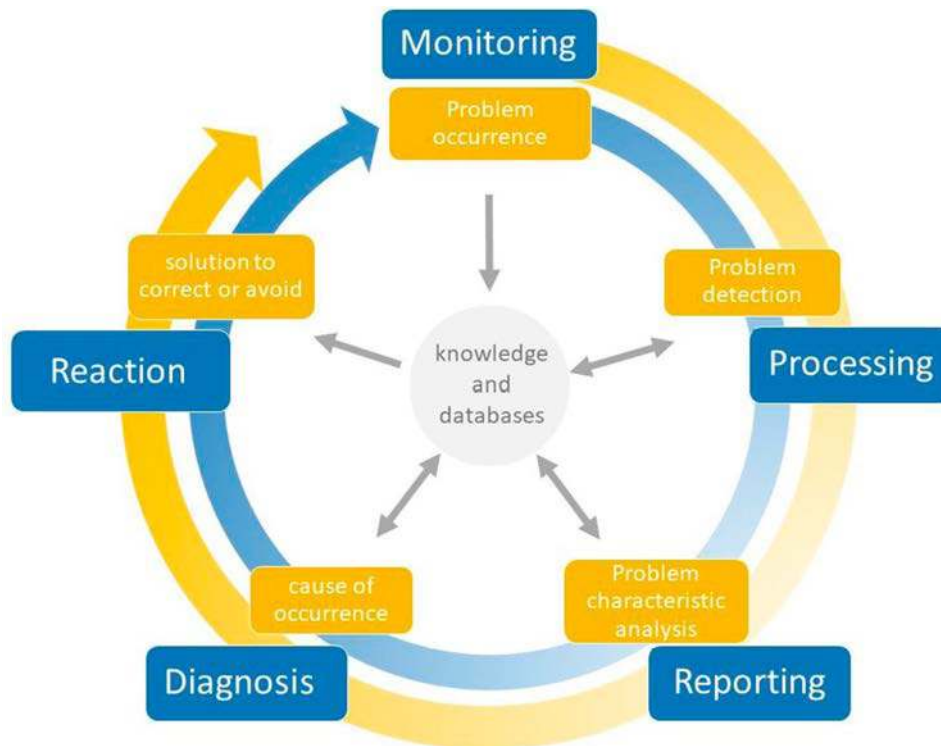


Figure 1. Execution phases analysis.

files, in a standard format, then other models were developed to structure the traceability database.

#### 4. Data-knowledge models construction

Before starting construction of the models, an in-depth study of the state of the art in the field of product and process-oriented modelling was made and coupled with an analysis of real industrial processes. The target was to draw inspiration from the models realised in the field. Following this literature review, several modelling approaches were identified. These models are strongly linked since they are all based on a common list of industrial objects and components. Among these components were identified four that match well with this project: product, process, context, resources, and people. While these objects represent essential elements for each industry and they are considered fundamental to model the global industrial knowledge base, previous modelling approaches do not cover all of these elements simultaneously. This leads to the development of the CR3P (Context, Resources, Product, Process, People) modelling approach. As its name suggests, it initially covers the entire context of the work and the whole set of significant knowledge that can cover information about working conditions, references and identifiers of the different elements used, as well as information about risk assessment or even the constraints imposed by the end customer. This approach also involves knowledge related to the resources used, the product being manufactured or the process followed to manufacture it (Meski et al. 2019b).

The specificity of the approach is also linked to the integration of the 'People' object as a foundation element in the global knowledge model. The CR3P approach emphasises the human by considering it as a main node of the overall industrial structure. An important amount of knowledge is provided by the expert and several decisions must be taken or supported by him and his expertise. This expert knowledge lies in what is called business rules.

Based on the analysis step, the knowledge models have been developed and enriched with high level of granularity and details using ontology modelling paradigm. Indeed, using ontologies is a practical solution given the large amount of heterogeneous knowledge to be considered, the relations and business rules to be integrated, and the reasoning to deduce new knowledge and decision to be created.

The proposed ontology is structured around several layers, gathered into three main groups, which have been formalised according to the specificity, nature and origin of the knowledge acquired (Figure 2).

The first layer contains the dictionaries of resources used in machining process, such as references of the cutting tools used with their specific cutting conditions, characteristics of the resources used for manufacturing, types of raw materials used. There is also the knowledge related to the manufacturing process, the different operations used, etc.

In parallel with this first layer, and in order to ensure the genericity of the knowledge base for future reuse in other fields, norms and standards have been analysed and the most appropriate ones have been considered for structuring the second layer of ontological models. In this research, part of the STEP-NC (14649-10: Data model for computerised numerical controllers – Part 10: General process data) is used. It includes all the parameters, names, concepts and relationships for the majority of manufacturing operations and features. STEP-NC is a data exchange standard for numerical control programming, and for communication between the different parts of the physical industrial chain: design, industrialisation and manufacturing. It is based on the STEP standard (STandard for the Exchange of Product model data) that use the data modelling language EXPRESS to develop several models and schematics. In addition, Step NC uses the graphical standard EXPRESS-G to represent the process model. This standard is widely used in the field of mechanical manufacturing.

The integration of this standard into the global knowledge base consists of transforming EXPRESS-G diagrams into an ontology composed of classes, relationships and attributes. The transformation of this standard into the ontology has resulted in the development of more than a thousand axioms (Figure 3).

The last layer groups all the knowledge necessary to support the decision process. It includes mainly business rules and the structure of a decision support case. In this research work, the business rules are very useful and essential for the implementation of the second development axis in this project: the diagnosis. As shown in the figure above, the three layers constituting the ontology are strongly interlinked. In general, the execution of a decision support scenario should begin by analyzing and identifying the context elements, characterising the situation or case to be treated. They are instantiated based on dictionaries and sometimes-standard layers.

Data and knowledge bases are in continuous collaboration: the execution of a scenario starts at the knowledge base level to retrieve the necessary structure then the reasoning system queries the databases to retrieve the corresponding data. The processing is then executed and it instantiates specific elements in the knowledge base. For an event diagnosis scenario, these elements, also known as individuals, are represented by cases and those

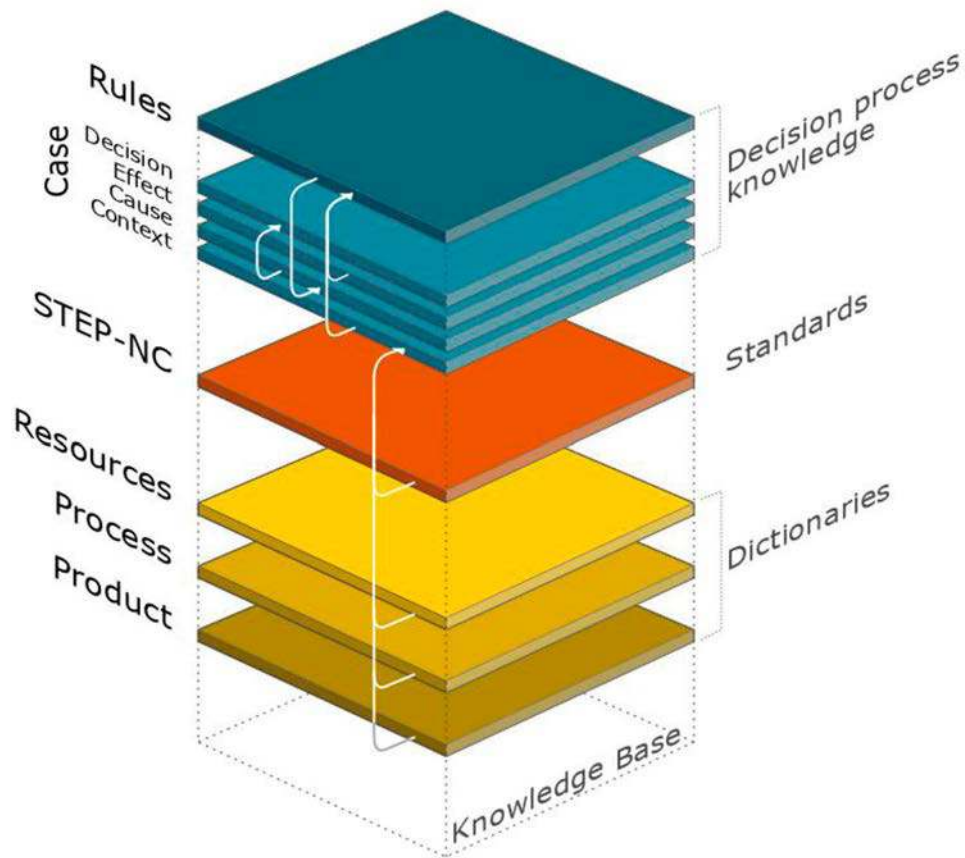


Figure 2. Knowledge base structure and layers interconnection.

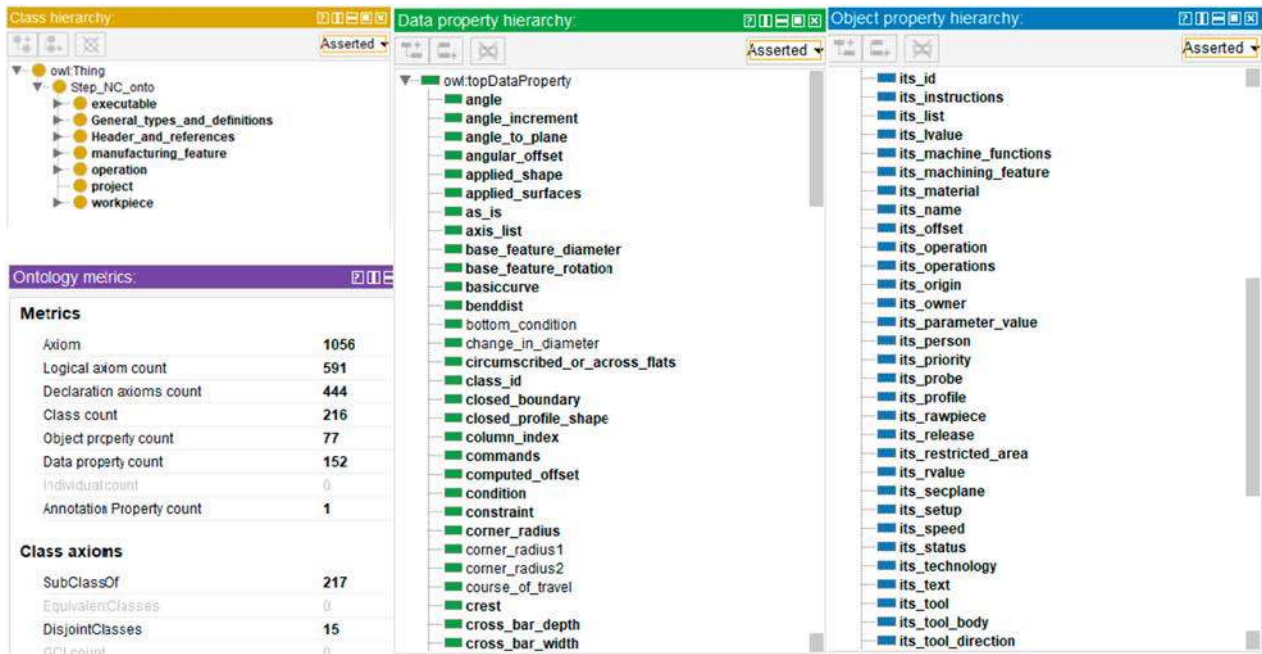


Figure 3. STEP-NC from Express-G to ontology with Protégé software.



are structured with the objects ‘cause, effect, decision, context’, which will be presented in the following section.

## 5. Framework application: the diagnosis process

In order to improve a company’s productivity and competition, a diagnosis process is set up. It allows the analyse of distinguished failures and the detection of the causes of malicious phenomena appearance during machining process. Beyond that, the diagnosis scenario is based on a characterisation of the working context to propose the appropriate solution based on experiences. This will help improving quality and leading time of the entire production process, and especially to lighten the work of the quality department. The proposed solution aims also to support the maintenance department to be preventive and avoid the recurrence of similar undesirable phenomena in the future.

### 5.1. Proposed approach to diagnosis process

At the conceptual level, the proposed approach is based on the well-known FMEA (Failure Modes and Effects Analysis) method in order to set up the main criteria and parameters representing failures, causes and effects. Following this method, new knowledge (rules and procedures) has been integrated into the ontology in order to support the diagnosis process at the decision aid level. This knowledge is structured as a ‘case’ which is composed by the quadric ‘Context-Cause-Effect-Decision’.

- **The CONTEXT** calls, from the other layers of the ontology, all the elements necessary to characterise the manufacturing environment, namely: the name and reference of the tool, the name of the program and subprogram, the date, etc. Additional characteristics of the machining resource can be reached from the resource library. These contextual elements depend strongly on the diagnosis case and can vary according to the related decision needs of the user.
- **The EFFECT** characterises the main failure to be diagnosed. In this project, it represents the malicious phenomenon that has appeared. The instantiation of this element can be either automatic following a direct detection of the problem or indirect following a first phase of in-depth analysis. This object has several features and options, namely: an effect can be the origin of another one, each effect can be generic or detailed, an effect can also be an element of context for another case, etc.
- **The CAUSE** is the key element of the proposed knowledge-based diagnosis approach. It represents

the origin of the malicious events that occurred during the machining of a mechanical workpiece. To be able to propose a cause to an event, the solution was to formalise human intelligence and the best practices in order to propose an artificial intelligence tool ready to be integrated into the machine. More precisely, in this project a set of business rules have been defined to formalise the interpretation of expert about past incidents. So, the reasoning on the current incident can be made based on its connection to similar past situation where the appropriate business rules are applicable. The execution of business rules depends strongly on the contextual elements and the observed effect to generate the most reliable cause, hence the importance of the instantiation stage of the object ‘context’.

- **The DECISION:** once a new undesirable situation has been detected, its effects observed and its causes identified, the last elements to be computed is a proposed solution and the related decisions needed to solve the problem. The notion of decision (or solution) includes all actions beyond the diagnosis process that aim to remove the observed consequences (reparation) or to anticipate/neutralise the problem causes (preventive). Explicitly, it regroups all the rules, actions and procedures that contribute to reset or maintain the manufacturing system in its normal working conditions. Given the specificity of this research work, the decision is represented by a solution, but it may have different forms in other cases of application, depending on the objective, and the need of the user. Therefore, the loop of the knowledge-based decision-aid framework is closed.

The global objects of the modelling strategy represented by the quadric defined above, are strongly linked and can depend on each other. More precisely, a first phenomenon ‘A’ (represented by an ‘Effect1’ with a ‘Cause1’) can be the cause of appearance of a second phenomenon ‘B’ (an ‘Effect2’ with a ‘Cause2’), as shown in the Figure 4, and this induces a second diagnosis process.

More formally: « Effect1 → Cause1 = Effect2 → Cause2 »

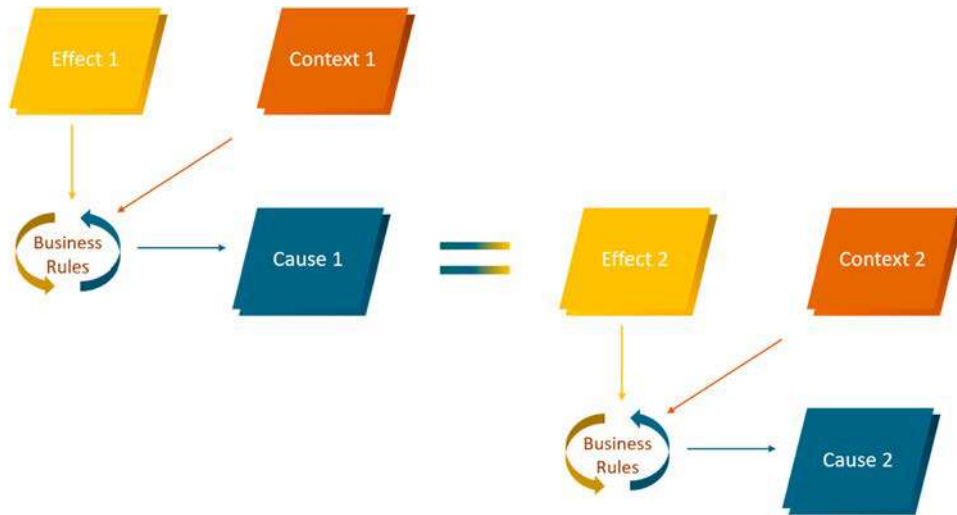
In this case, the context may be the same for both scenarios (referred as ‘ContextGlob’) or may be specific to both (referred as ‘Context1’ and ‘Context2’). More formally:

Either:  $\exists \text{ContextGlob}$  in which « Effect1 → Cause1 = Effect2 → Cause2 »

Knowing that  $\{\text{Cause1}, \text{Effect1}, \text{Cause2}, \text{Effect2}\} \in \text{ContextGlob}$

Either:  $\exists (\text{Context1}; \text{Context2}) \in \text{ContextGlob}$

Such as « Effect1 → Cause1 = Effect2 → Cause2 »



**Figure 4.** Dependencies of diagnosis elements.

Knowing that  $\{Cause1, Effect1\} \in Context1$   
 $\{Cause2, Effect2\} \in Context2$

More technically, in order to structure diagnosis operations at the ontology level, these four objects have been defined as classes. In addition, a list of relationships linking these classes and attributes has been specified. Progressively, as the ontology is implemented and real scenarios are run, these classes will be instantiated by creating the corresponding group of individuals. This instantiation is based on previously structured industrial databases (raw, smart and traceability); this highlights the utility of the knowledge management strategy, promoting the interaction with data to generate new knowledge.

To better illustrate this structuring methodology, a use case scenario is presented in the next section.

## 5.2. The use case

The initial stage was made prior to this research work and concerns the definition of specific data mining algorithms to analyse raw data and extract smart data (Wang et al. 2019). This leads to the generation of traceability data and the management of heterogeneous reports (Ritou et al. 2019). Together, these latter two publications explain the various operations required for the preliminary stage. Many research works define the criteria to be respected and the means to manage large-scale enterprise software systems. A multitude of technologies and standards exist to ensure software interoperability and systems integration in order to facilitate interaction with each other (Andersson and Johnson 2001).

In this research project, given the diversity of tasks, skills, and technologies handled by the different research

teams, the need for a solution to ensure technical interoperability is necessary to develop a common global Framework. The solution chosen in this use case is the use of multi-agent systems. Thus, several agents have been developed over time (Computing Agent, Communication Agents, Databases Agent . . .). In this article, a decision support agent is presented: the Diagnosis Agent.

### 5.2.1. Expertise analysis and scenarios definition

Operations of data mining were able to detect a set of very frequent phenomena: chatter, tool failure, and collision. To ensure this detection, a first phase of machine learning was established to calculate specific thresholds for several detection criteria and parameters. For example, to detect a chatter, it is sufficient to notice an overflow of the threshold for the ' $N_h$ ' parameter which is the sum of the amplitudes of the five dominant non-harmonic contributions of the vibration spectrum (Godreau et al. 2019). A tool failure is also likely due to the exceeding of the threshold defined for the ' $U_b$ ' parameter which is computed as the vibration amplitude of the contribution at the spindle frequency, when the spindle is rotating without cutting (to prevent from false detection due to cutting forces). Several other aspects can be the cause of an abnormal phenomenon, such as significant power variations, which are good indicators of a collision. In addition, the variation of the machine-tool potentiometers is a practical KPI since it allows the detection of any human intervention that could delay productivity. After this first step of phenomenon detection, in order to understand the cause of appearance, a formalisation of all the business rules necessary for an analysis is essential. To realise this second step, the solution is to hold interviews with technicians and industrial experts and discuss possible causes.

**Table 1.** List of possible diagnosis scenarios.

Detection criteria	Effect	Cause	Rules
$U_b > \text{threshold}$	Tool failure	<ul style="list-style-type: none"> <li>– Cutting conditions problem</li> <li>– Tool life badly defined</li> </ul>	<ul style="list-style-type: none"> <li>Compare with reference cutting conditions</li> <li>Tool often broken at the end of its life</li> </ul>
Power variation	Collision	<ul style="list-style-type: none"> <li>– Program error (during machining).</li> <li>– Tool gauge or probing error.</li> <li>– Wrong operator manipulation (manual mode)</li> <li>– Problem returning the tool to the magazine</li> </ul>	<ul style="list-style-type: none"> <li>Checking program and subprogram names (ex: CHANG_OUT.SPF for tool change) + machining time = 0 . . .</li> </ul>
$N_h > \text{threshold}$	Chatter	<ul style="list-style-type: none"> <li>– Either the tool or the workpiece</li> <li>– bad programming</li> <li>– bad workpiece clamping</li> </ul>	<ul style="list-style-type: none"> <li>The recurrence of the phenomenon must be studied to understand the origin of the phenomenon.</li> </ul>

This leads to the definition of an explicit list of business rules. Table 1 shows some of them. On each line, parameters necessary to detect a given effect and the rules applied to determine its cause of appearance are detailed.

Following this mapping phase, an algorithm of the diagnosis agent is defined. It starts by an interaction with the user to define the specific context and the diagnosis operation to perform. The scenario category to be executed may depend on the user's profile, or on the importance and seriousness of the phenomena studied. Hence, the importance of defining a criterion or a criticality score for each anomaly. This rating is measured based on the following table (Table 2).

The diagnosis agent is in continuous communication with the knowledge base and databases. Accessing the knowledge base, it retrieves a list of criteria, conditions, thresholds, etc. Afterwards, accessing the databases it recovers data needed to execute the necessary specific reasoning. Finally, it instantiates all the case at the

**Table 2.** The measurement elements of the criticality criterion.

Criteria	Rating
<i>Failure severity rating grid G</i>	
Minor defect without performance degradation	1
Fault can be repaired on site without performance degradation	2
Fault can be repaired on site with impaired performance	3
Non-repairable fault	4
<i>Rating grid for the frequency of appearance F</i>	
Very low	1
Low	2
Frequent	3
Very frequent	4
<i>Non-detection rating grid D</i>	
Effective preventive detection (measurement, optimised threshold, action)	1
Preventive detection (measurement, non-optimised threshold, action)	2
Preventive detection not used	3
Not detected	4

ontology level with the context, effect, cause and decision respectively.

### 5.2.2. General view of the algorithm

To better illustrate these aspects, let's focus on a specific scenario concerning the diagnosis of a tool breakage. Based on the previous list (Table 1), this scenario described in Table 3, will be treated.

The following diagram (Figure 5) represents the detection algorithm. It shows how the analysis of a particular scenario enrich the knowledge base, gradually improving the strength of this decision-support program.

### 5.2.3. Technical aspects and user interface (UI)

The Global Framework is developed using the Java language. The technological issue was to find the most suitable API to communicate with the ontology developed using the Web Ontology Language (OWL). The required solution is to use the Jena API. *Apache Jena*, as stated on the Jena website, is a Java framework to construct Semantic Web Applications. It provides a programmatic environment for:

- *Resource Description Framework (RDF)*, a graph model for describing web resources and their meta-data, so that such descriptions can be processed automatically. Developed by the W3C, RDF is the basic language of the Semantic Web.
- *The Web Ontology Language (OWL)*, a knowledge representation language built on the RDF data model. It provides the means to define structured web ontologies.
- *SPARQL Protocol and RDF Query Language*, a protocol that allows searching, adding, modifying or deleting RDF data available through the Internet.

**Table 3.** The diagnosis scenario selected for the implementation.

Detection criteria	Effect	Cause	Rules
$U_b > \text{threshold}$	Tool breakage	<ul style="list-style-type: none"> <li>– Cutting conditions problem</li> <li>– Tool life badly defined</li> </ul>	<ul style="list-style-type: none"> <li>Compare with reference cutting conditions</li> <li>Tool often broken at the end of its life</li> </ul>

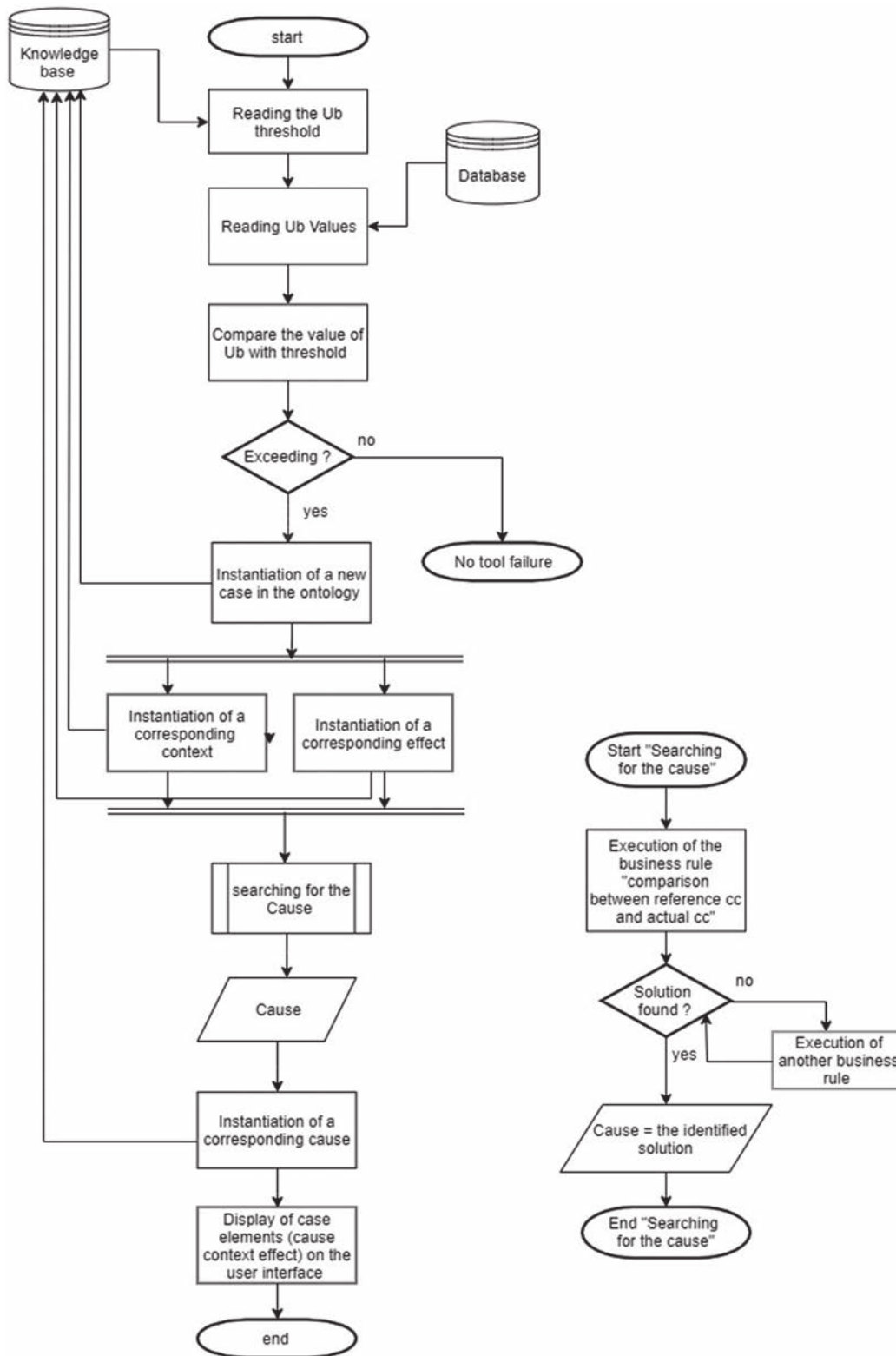


Figure 5. Detection algorithm flow chart.

- The *Jena inference* subsystem, designed to allow a range of inference engines or reasoners to be plugged into Jena. Such engines are used to derive additional

RDF assertions, which are entailed from some base RDF together with any optional ontology information, and the axioms and rules associated with the reasoner.

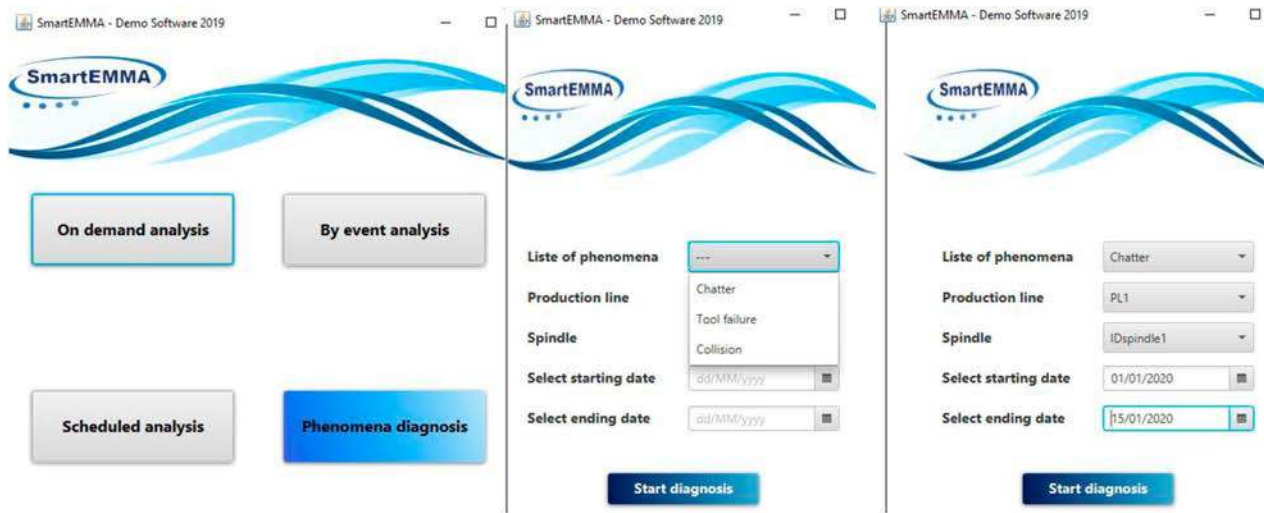


Figure 6. UI diagnosis launch.

These developments are part of a global demonstrator that revolves around two decision-support axes: reporting and diagnosis. On the first part of Figure 6 there are the 3 functionalities enabling to do reporting by event detection, on demand or by planning. Concerning this use case, the user has to choose the fourth, 'Phenomena diagnosis'. Thus, a second interface appears, in which he can choose from a list the context elements (production line, machine tool\_id, period, type of phenomenon to be diagnosed, etc.). In this scenario, the user chooses the 'Tool failure' phenomenon.

#### 5.2.4. Diagnosis process details

In the specific scenario of a tool failure, the first step is the verification of the possible exceedance of the threshold defined for the detection criterion ' $U_b$ '. To do this, a threshold, calculated using machine learning algorithms, has been instantiated beforehand at the knowledge base level. This is the first manifestation of interaction between data and knowledge.

The querying of the ontology for data retrieval is done using the SPARQL query language. The figure below shows an example of a query used in this demonstrator (Figure 7).

Once the threshold value is recovered, the monitoring databases must be analysed by comparing the  $U_b$  variations with this threshold. An exceeding value means the appearance of a tool failure and thus initiates the diagnosis process. Currently, the smart database is in form of a CSV file. Figure 8 shows an excerpt from a smart data file.

The instantiation of the ontology starts with a new individual (Figure 9) called 'Case\_tool\_failure' and also individuals of type 'Cause' 'Context' and 'Effect'.

Subsequently a mapping phase is needed to make the link between these elements using 'Object properties'. And finally, by using 'Data Properties' the attributes of each individual are added.

In order to add the context elements (considered here limited to the instantiation of the tool, the program and the day), it is necessary to position on the line containing

```
queryString1 = "PREFIX ou:<http://www.semanticweb.org/pc/ontologies/2018/9/untitled-ontology-20#> "
+ "SELECT (?x as ?seuil) "
+ "where { ?y ou:Has_thresholdUb ?x."
+ " }";
```

Figure 7. SPARQL query example.

	A	B	C	D	E	F	G	H	I	J	K
1	Jour	ModeCN	progC	ID_Outil	OutilPF	temps_total	temps_arret	temps_arret	temps_Nvar	temps_G1_s	temps_G0_s
2	0	0	0	0	0	1.9	1.9	0	0	0	0
3	0	2	0	0	0	127.2	6.3	19.9	0.1	0	0.9
4	0	2	0	1	1	15.9	8.5	7.4	0	0	0

Figure 8. Smart data file extract

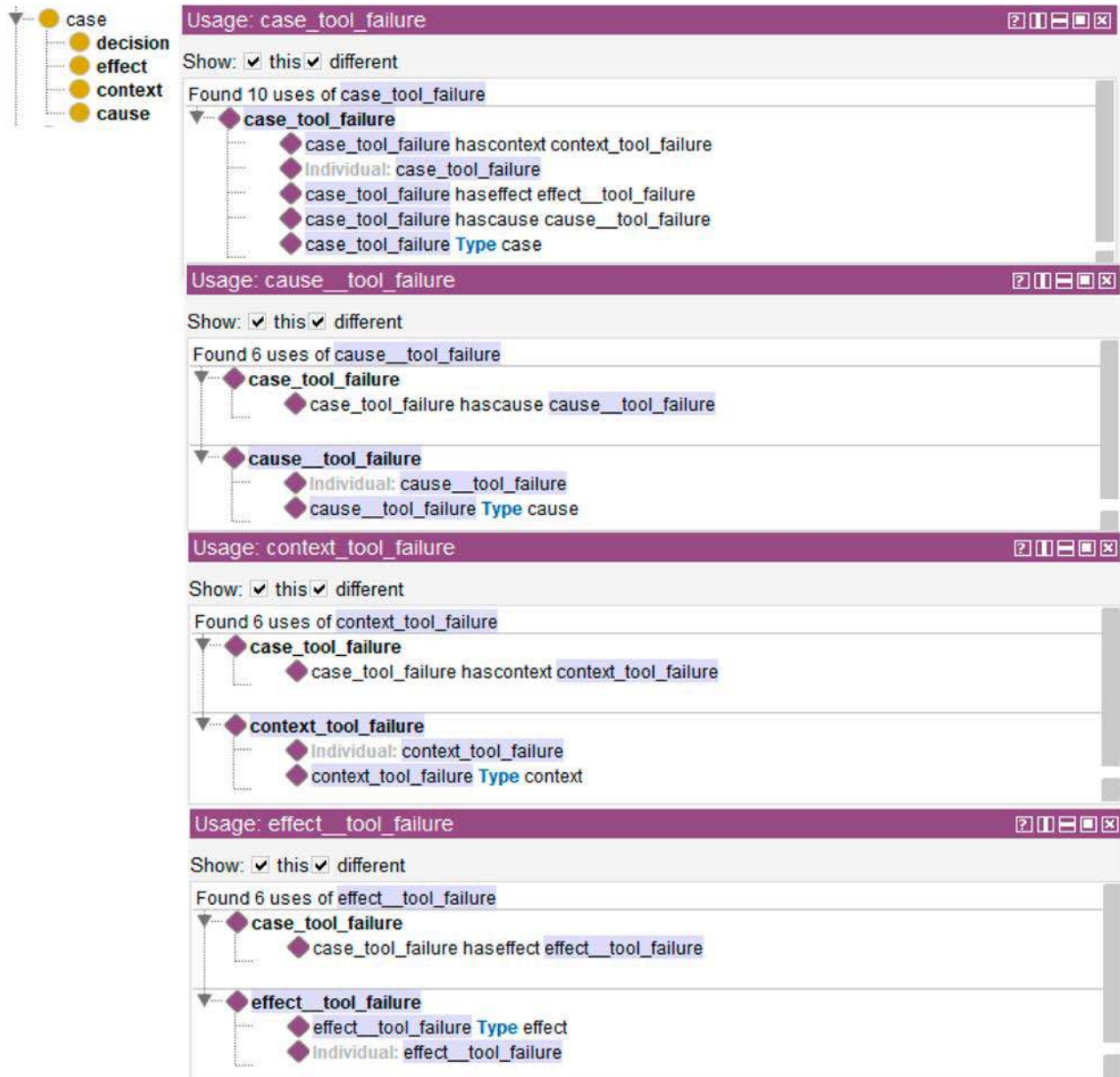


Figure 9. Ontology instantiation.

an exceeding of the threshold of the ‘Ub’ criterion, and to recover all the necessary parameters.

The next step, ‘searching for the cause’, is the most important step, and is presented in the flowchart (see Figure 5) as a separate process.

Concerning this scenario, a first business rule was formalised following the interviews with the industrial partners of the project:

The tool is the cause of the breakage when the measured cutting conditions are different from the reference cutting conditions.

Here, measured cutting conditions are those recovered using the monitoring tools and the reference cutting

conditions are the ideal ones predefined by the methods office.

To implement this rule at the ontology level, a transformation step is needed to convert this rule from the natural human language to the formalised rule language specific to the JENA API, which is shown below:

```
@prefix ns: < SpecificPrefix > .
[rule1: (?a ns:hascontext?b)(?a ns:hascause?c)(?b ns:hasTool?x)(?x
ns:hasVf?d)(?x ns:hasVfReal?w) notEqual(?d,w)
→ (?c ns:hascausedirect 'tool problem: non-compliant cutting condition')]
```

The execution of this business rule implies the verification and the comparison between the two categories

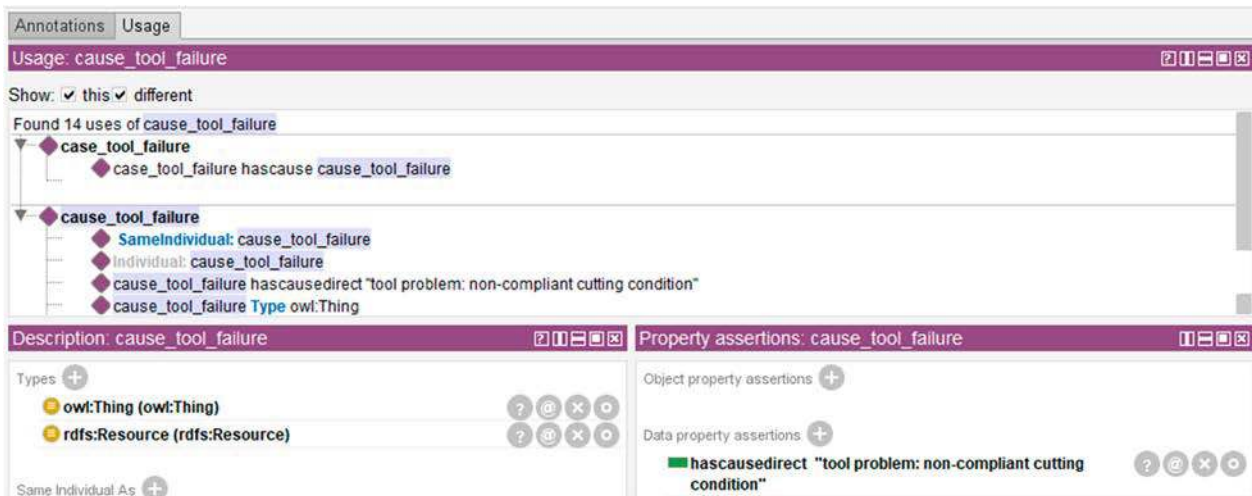


Figure 10. The Automatic instantiation of ontology.

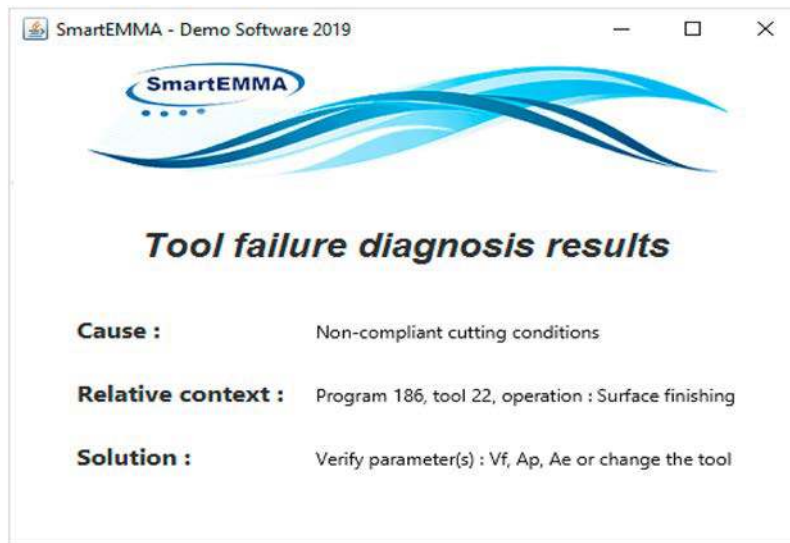


Figure 11. The final interface representing the result of the diagnosis.

of cutting conditions. In case of an inequality the individual ‘Case\_tool\_failure’ is instantiated and the cause is determined, as shown in the figure below where the cause was found to be ‘Tool problem: non-compliant cutting condition’ (Figure 10).

After the automatic instantiation of the ontology, the user receives the result of the entire diagnosis operation in the interface shown in Figure 11 and is presented with solutions.

This scenario represents a simple execution of a single business rule; other scenarios require multiple rules and iterations to find the origin of a single problem. Therefore, a typical scenario would not necessarily end at this stage since the determination of a first direct cause can lead to a new diagnosis process for the determination of indirect ones.

## 6. Conclusion

The implementation of the industrial knowledge management methodology proposed in this article, and the testing of several decision-support scenarios have shown the feasibility and the interest of the approach. However, there are some limitations to this approach, most notably the availability and accessibility of industrial knowledge. Such a tool must be implemented in a favorable industrial context that offers the necessary resources and means, and encourages collaboration between the digital system and the experts. The complexity of the development is hence mainly focused on the formalisation of the business rules base, through the transformation of the expertise and all the implicit and tacit knowledge into explicit formal rules. This aspect favors and highlights the

importance of the human place in the context of digitisation and the fourth industrial revolution. The need for a first phase of direct interviews with the business experts highlights this crucial role. In a nutshell, the challenge is to promote the importance of collaboration between the system and users who remain masters and controllers of the operations: the initial objective of a decision support system.

Our approach is specific in its layered structure and especially the separation between the domain ontology layers that regroup the generic knowledge sets and libraries, and the decision support layer. This in turn guarantees adaptability and modularity in various other research domains by changing the first layer with another reference ontology of another field. In addition, the structuring of knowledge as a quadruplet 'Context-Cause-Effect-Decision' would allow several perspectives for the development of the system. For example, the capitalisation of diagnosed cases and all the elements describing the work context would enable the elaboration of reasoning based on similarity indices. This would in turn facilitate future diagnosis operations, solution proposals, but also the prediction of the appearance of a phenomenon and the proposal of preventive actions.

Multiple perspectives could be envisaged for the continuation of this work. In the short term, the objective is to improve and enrich the business rules base, to be able to implement other diagnosis scenarios. Interviews with industrial experts continue to be held enabling the capitalisation of their expertise into an artificial intelligence embedded in the production machines. In this article, the use of the knowledge management methodology to implement a diagnosis process is demonstrated. Among the possible perspectives envisaged is the use of this strategy to implement other axes of decision support, especially, to provide reaction and prediction. Another perspective of this work consists in validating the adaptability and genericity of the methodology developed in other fields such as architecture and archaeology for example. This could demonstrate how the Context-Cause-Effect-Decision methodology is suitable on a comprehensive panel of knowledge-based diagnosis.

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