A smart reporting framework as an application of multi-agent system in machining industry

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ABSTRACT
Currently, the evolution of cyber-physical systems within the industry 4.0 paradigm enables the collection of large quantities of heterogeneous data that have not yet been efficiently exploited. One of the reasons is the digital chain disruption and lack of communication between the shop floor and operational management departments. To tackle such issues, this paper proposes a reporting frame-work as a common platform to support communication between the shop floor and operation management teams. The framework is based on a multi-agent system that solves the interoperability issues between tools, software and information systems. Agents are used to represent services such as reporting and are mainly exploited for decision-aiding. A reporting scenario is proposed to address chatter problems in an aeronautic case study. Efficient management of complex data is achieved by providing customized indicators for decision actors.

1. Introduction

Nowadays, industrial companies are faced with uncertain, competitive and rapidly changing markets. They are then pressured to improve their manufacturing systems and to optimize their product cost, quality and lifecycle. These challenges, coinciding with the introduction of advanced information and communication technologies (ICT) (e.g. Internet of Things (IoT) (Wollschlaeger, Sauter, and Jasperneite 2017; Gilchrist 2016), sensing networks (Akyildiz et al. 2002; Gungor and Hancke 2009), cloud computing (Tao et al. 2011; Liu et al. 2019), embedded intelligent systems (Sangiovanni-Vincentelli and Martin 2001; Vahid and Givargis 2001), etc.), have led to the emergence of the so-called 'fourth industrial revolution', commonly referred to as Industry (Henning 2013; Lasi et al. 2014; Brettel et al. 2014). In such a context, one of the most critical issues is the management of Cyber Physical Systems (CPSs) as a combination of physical and digital entities. As a core foundation of industry 4.0 (Lee 2008; Lee, Bagheri, and Kao 2015; Jazdi 2014), CPS is considered as 'an autonomous and reactive entity that interacts with its physical and logical environment and offers a great opportunity to build smart and flexible manufacturing systems' (Wang, Törngren, and Onori 2015; Rossit, Tohmé, and Frutos 2019).

Research on this topic has skyrocketed in the last years and paved the way for new decision-aid applications dedicated to various business actors in the company (Singh et al. 2019). Furthermore, the CPS proliferation has significantly impacted the smart manufacturing systems where a large amount of multi-source, heterogeneous and dynamic data is being generated throughout the production process by highly connected entities (e.g. embedded sensors, information systems, etc.) (Monostori et al. 2016; Maleki et al. 2017).

In this field, more and more sophisticated methods are proposed, including Machine Learning (Qiu et al. 2016; Soto, Tavakolizadeh, and Gyulai 2019), Large-Scale Computing (Schadt et al. 2010), Knowledge Discovery in Database (Maimon and Rokach 2005), Data Mining methods for clustering, classification, regression, and prediction, etc. (Harding, Shahbaz, and Kusiak et al. 2006). The main objective of these techniques is to extract patterns and drive meaningful and understandable knowledge from massive raw databases, initially considered as ambiguous.

Companies are then prompted to adopt knowledge-based strategies to take advantage of big data analytics in improving their processes (Wang and Wang 2016; Waller and Fawcett 2013; Jun, Lee, and Kim 2019). This goal can be achieved by feeding back contextual and useful knowledge to the right actors in order to assist them in their activities. This function, known as Reporting, is considered as a fundamental task of generating metrics and key performance indicators (KPIs). Consequently, vertical information flow can be viewed as a closed-loop stream: descendant flow from the operational management departments (e.g. process planning, quality, etc.), and ascendant flow from machines and operators provide production progress feedback.

However, the growing volume of digital data (several gigabytes of data per day) gathered from the shop floor is a big issue raising the need of efficient technologies which are able to collect (through IoT solutions), store (by means of Cloud Computing) and process (using Artificial Intelligence techniques) (Chen, Mao, and Liu 2014; Lee, Kao, and Yang 2014a; Zikopoulos and Eaton et al. 2011). In addition, the management of this huge quantity of collected data and discovered knowledge has a great impact on the quality of the decision aid process. Hence, the management of the entire digital chain in the company must be carried out through reliable infrastructure (Denkena, Schmidt, and Krüger 2014) ensuring communication between heterogeneous devices, software and information systems (e.g. Computer-Aided Manufacturing (CAM), Computer-Aided Design (CAD), Computer-Aided Engineering (CAE), Product Lifecycle Management (PLM), Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), Supply Chain Management (SCM), etc.). Such a platform should serve also as a common repository that enables knowledge sharing and data consistency checking.

Although the significant efforts that have been made to process big data generated in smart factories, discovered knowledge remains underexploited or disconnected from the decision center. The main contribution of this research work is the development of a digital chain management framework to support the decision-making process through useful knowledge reporting and ICT interoperability. This framework is used for automatic processing of large quantities of complex data. Hierarchical/edge computing of data is proposed to avoid saturating the system. These data are aggregated and transferred to the right person at the right time through a reporting platform. To validate the proposition, an agent-based technique is used as a technical solution. Multi-Agents Systems (MAS) are supposed to have some characteristics such as autonomy, sociability with each other and their environment, reactivity, etc. (Ferber and Weiss 1999). Autonomous agents are also used to manage information flow through the digital chain by connecting the cyber physical entities, management software tools and the company's decisional actors. In this paper, MAS are used for distributed control and decision-aiding. Initial developments of the possible agents are proposed using an application study.

The application context of the proposed framework is related to High-Speed Machining (HSM) of aeronautic parts where many advanced manufacturing technologies are jointly applied. The machining process is managed by a variety of data including production planning and orders, product quality, maintenance scheduling, work instructions, financial constraints, etc. On the other hand, smart sensors collect and monitor internal signals from machine-tools describing several characteristics of the machining process (energy, vibrations, spindle speed, etc.). This data is collected and processed to generate useful KPIs (such as chatter occurrence and sources, failed programs, spindle incidents, etc.). A practical case study using aeronautic company data is implemented to illustrate the feasibility of the proposed architecture.

The aim of this paper is to study the feasibility of the proposed framework architecture from a practical point of view. For this, interoperability and digital chain issues are tackled using agents. Deploying such a module-based system enables the easy integration of future tools, software or information systems that may be implemented in the company. A proposed scenario is implemented in a real case study to validate the framework proposition. The remaining section of this paper is organized as follows: the next section describes in details the problem statement. The third section introduces a literature review about implementing CPSs in an industry 4.0 environment using agent-based technology. The proposed reporting framework is presented in the fourth section where the design and implementation of the multi-agent system are detailed. Section 5 shows the results obtained on an industrial case scenario. In the final section, a selection of future works is listed.

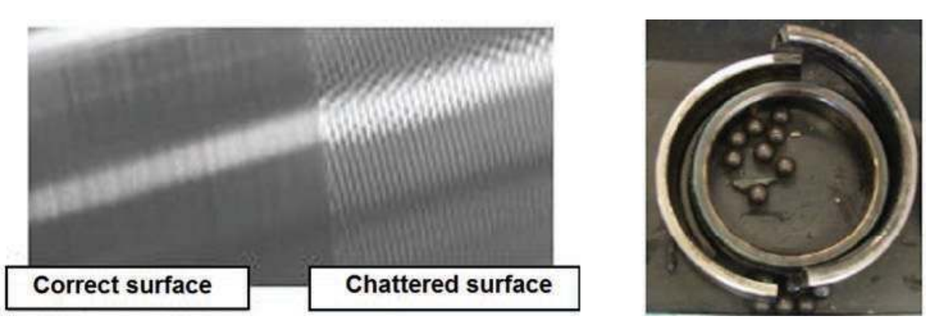
2. Problem statement

This paper deals with High-Speed Machining (HSM) of structural parts in the aeronautic industry. This sector, in contrast to other industries, is characterized by processing a small number of parts but with high added value. Under challenging constraints of quality and safety, the manufacturing process must be accurate and produce compliant parts from the outset. However, due to critical cutting conditions, the machine spindle, the cutting tool and the work-piece are generally subject to unexpected vibrations (Rabréau et al. 2017; Ritou et al. 2018). These issues lead to undesired phenomena hampering the machining process optimization, e.g. chatter, tool breakage, spindle damage, work-piece deterioration.

For instance, chatter generates unacceptable and poor surfaces (figure 1(a)) requiring additional manual operations during the finishing phase (Lamikiz et al. 2005). Besides, these vibrations have negative effects on tools and spindles causing lifetimes reduction (figure 1(b)). All these factors lead to productivity decrease and huge financial losses for industrial companies. For example, chatter cost results from less productivity due to finishing operations and machine unavailability, raw material rebuttal, and unexpected maintenance intervention. Overcoming these problems then becomes strategic. For this reason, process engineering and planning departments seek to carefully design and schedule the machining process. The main objective of the design is to select conservative cutting parameters, including tools and programs settings, to avoid abnormal events. For the quality department, reducing the control and finishing times can be achieved by the early identification of the damaged parts during the machining process (i.e. those affected by particular incidents during their machining). On the other hand, maintenance actors need to schedule condition-based interventions by monitoring the spindle health status and detecting significant deteriorations from undesired behaviour (De Castelbajac et al. 2014). The production department has to define an optimal planning adaptable to demand constraints by tracking the shop floor activity, e.g. breakdown times, production delays, unscheduled downtimes, etc.

Despite their simple statements, these decisions are often hard to make, since the department in charge is disconnected from the real progress of the shop floor. The decision taken becomes unsuitable because it is taken based on non-contextual observations or theoretical recommendations. To make the right decisions, management staff must be able to efficiently exploit all available information. Three levels of decision-making (operational, tactical, and strategic) are identified in the enterprise. Several information systems are available in the company to support information management and exchange at each decision-making level. For instance, ERP (Enterprise Resource Planning) and PLM (Product Lifecycle Management) form the core of the information system. The execution of production orders are managed by a Manufacturing Execution System (MES).

Decision-making often requires the interaction between these three levels. For example, knowledge extracted from real-time data collected at the operational level, when coupled with production orders given by the ERP, could be helpful to understand obvious events which have occurred during the manufacturing operations. Effective decisions can thus be taken regarding process monitoring and quality control. Hence, three key tasks are identified: (1) raw data collected throughout the product lifecycle must be correctly processed to extract meaningful knowledge and generate the adequate reports, (2) efficient data management to enable the creation and the diffusion of useful reports to the right decisional actors in various departments of the company, and (3) interoperability



(a) Chatter problem. (b) Spindle break.

Figure 1. Undesired phenomena during HSM.

between heterogeneous legacy software and information systems at different levels of the company must be tackled to support the data management strategy.

Generally, only descendant decisions are available in the company and no ascendant information is captured. In this work, top down decisions and bottom up feedback are tackled in a closed-loop control system through a decision-aiding reporting mechanism. Data are processed and KPIs are generated and transferred from the bottom (shop floor) to the top management (decision actors). The architecture stops at this point where experts are supposed to use these KPIs in order to take actions on the shop floor. This flow process results in a closed-loop control system between the top management and the physical equipment. From the implementation perspective, a combination of several technologies (i.e. Cyber-Physical, multi-agent and data mining) within a common decision-aid framework is proposed. The problem of chatter is addressed and a reporting scenario is proposed to validate the proposition. This scenario should enable the closed-loop control system. Human-in-this-loop takes place at the top down decision process which is beyond the scope of this work. The reporting mechanism is used above all for decision-aiding and experts are supposed to take decisions based on their knowledge and expertise. The next section introduces the main concepts and applications behind these paradigms before explaining the proposed framework in Section 4.

3. Theoretical foundations

The technical choice of CPS architecture is one of the most important factors affecting the organization of the company services (Herterich, Uebernickel, and Brenner 2015). Monostori et al. (2016) have shown through a statistical survey of CPS related keywords, that agent-based techniques are one of the most commonly used techniques to implement a CPS. Since the aim of this paper is to describe the architecture of the decision-aid system, the literature survey focuses on technical solutions.

3.1. Cyber physical systems

A Cyber Physical System is represented by collaborative computational entities between the physical environment and its on-going processes, providing and using, at the same time, data access/data processing services (Monostori et al. 2016). In the manufacturing field application, an efficient CPS must be based on: (i) a consistent monitoring system ensuring the accuracy and security of the collected data; (ii) a solid control of the large quantities of heterogeneous data by extracting reliable patterns (Rajkumar et al. 2010), and (iii) an efficient decision support system based on smart analytic tools/algorithms (Lee, Kao, and Yang 2014b).

The details of the methodology of deploying a CPS may be ambiguous depending on the usage context. From a general perspective regarding the setting up a CPS, the architecture proposed in (Lee, Bagheri, and Kao 2015) has five layers, known as ‘5-Cs architecture’: Connection, Conversion, Cyber, Cognition and Configuration layer. The particularity of such architecture is the introduction of the cyber layer, which represents the synchronization between the physical world and the cyber virtual space, usually referred to as ‘Cyber twins’ (Lu et al. 2020). This layer highlights the communication between the control commands, the different external applications of a company and the physical connected entities (machines, sensors). This five-layer architecture is used as a guideline for setting up a CPS in industry. However, its implementation depends on the company organization and related information systems. Manufacturing Execution Systems (MES) are usually implemented as an intermediate layer that links the production management layer with the physical layer. The main advantage of such a system is its ability to interconnect with the different physical workshop equipment. However, an MES is usually centralized and often lacks the flexibility to effectively control the workshop. On the other hand, Enterprise Resource Planning (ERP) is implemented in the last layer of a CPS and is used generally to manage the company services. Existing structures of the current ERP though do not take into account the dynamic conditions of the production workshop, such as machine availability. As a result, the connection between ERP and MES is generally limited by the lack of information that goes back to the first physical layer.

To overcome these limitations, different strategies are proposed in the literature, such as the concept of ‘e-manufacturing’ introduced in (Lee, Kao, and Yang 2014a). This concept makes it possible to interconnect via internet-web interfaces, machining operations with the functional objectives of the company. Other management strategies that focus on the maintenance and monitoring of machining machines are proposed, such as 'cloud manufacturing' (Wang 2013), autonomous Multi-Agent Systems (Kumari et al. 2015), etc.

3.2. *Multi-agent systems for interoperability in manufacturing companies*

In manufacturing companies, heterogeneous applications which are implemented in distinct layers using different programming languages, must interoperate with each other efficiently. Moreover, these applications manipulate heterogeneous data collected from several sources with variant representation models. The interoperability becomes then a critical issue in the deployment of manufacturing applications (Leitão 2009). It is defined as the capacity of two systems interacting and ensuring the understanding of the process and data exchanged on both sides (Luck, McBurney, and Preist 2003). To cope with this issue, industrial companies require technological solutions allowing interoperability among software systems in a distributed computing environment (Feng, Stouffer, and Jurrens 2005).

One of these technologies is Multi-Agent Systems (MASs) (Wooldridge and Jennings 1994; Jennings and Wooldridge 1998). Due to their social skills, agents can interact with each other, perceive the environment, provide and ask for services to achieve individual and collective goals through an augmented Agent Communication Language (ACL) (Fipa-ACL 2002). Agent-based approaches provide distributed control where artificial intelligence techniques can be used (Xie and Liu 2017). Agents are supposed to be autonomous, pro-active, reactive with the environmental context, etc.

Agent-based approaches are interesting when it comes to deploying enterprise applications (Bellifemine, Caire, and Greenwood 2007; Bellifemine, Poggi, and Rimassa 1999). Researchers have successfully applied MAS to supply chain management (Fox, Barbuceanu, and Teigen 2000), manufacturing planning and control (Shen 2002; Caridi and Cavalieri 2004; Shen, Wang, and Hao 2006; Zattar et al. 2010; Bussmann, Jennings, and Wooldridge 2004; Mezgebe et al. 2020), enterprise integration (Kishore, Zhang, and Ramesh 2006), and holonic manufacturing systems (Colombo, Schoop, and Neubert 2006). A comprehensive survey of MASs and their potential manufacturing applications are outlined by Monostori, Váncza, and Kumara (2006). Examples of applications are the work of (Alaya et al. 2017), Lee et al. (2013) and Wang et al. (2016). In (Alaya et al. 2017), quality management in a production system is addressed using five agent modules. In Lee et al. (2013), health management of equipment is dealt with using an agent technique called 'Watchdog Agent'. This architecture consists of an intelligent software that performs predictive modelling features based on transparency. Moreover, in Wang et al. (2016), agents are used to model shop floor objects, such as machines, conveyors, products, etc. Then an intelligent negotiation mechanism was designed to enable agents to cooperate with each other so to reconfigure themselves for the flexible production of multiple types of products.

Overall, these solutions show the interest of using the multi-agents techniques in the factory of the future. However, each of the presented solutions lacks genericity and seems more adapted to a specific service (such as quality) rather than to all the company services. In this work, we use agents for modelling services and distributed control. We focus on reporting services where agents are used for two purposes. The first one related to interoperability consists of communicating all entities such as software, tools and information systems of the company. The second one related to decision-aiding and consists of handling complex data, using the right tools/processes and proposing the right information to the right person at the right moment. Such a framework is supposed to be more generic on different scenarios. Moreover, the modularity of multi-agents enables easy adaptation and flexibility for further development.

In the proposed framework, multi-agent techniques are supposed to model the interaction between entities and take intelligent decisions. Agents are used for distributed control and decision-aiding. However, for validation purposes, in the proposed scenario illustrated in Section 5.2, we do not exploit the full characteristics of multi-agents such as intelligent decisions. We first focus on the feasibility aspect and further intelligent agents are under development with other complicated scenarios as explained in the conclusion. The use of such a module-based technique is also a good opportunity for developing flexible solutions that can be adapted to different contexts.

4. Proposed reporting framework

To assist the critical task of decision-making in manufacturing companies, a reporting system is proposed. Its main aim is to connect decisional-making actors to the shop floor and provide them with feedback regarding production progress status and critical events observed during the manufacturing process. The analysis of these reports helps the employees to diagnose and resolve failure problems, thus improving the accuracy of the decision-making process for production optimization and quality control. Therefore, taking into consideration the needs of each department, the developed system creates and transmits synthetic and customized reports, combining several decision-aid indicators as a contextual instantiation of KPIs and smart data. The reports are customized according to the decision-making requirement, working situation, authority and level operator expertise.

At the methodological level, the reporting strategy is based on a multi-level data aggregation approach (Ritou et al. 2019) where the first level contains all measured raw data after cleaning and preparation; the second level regroups new "smart data" obtained after an aggregation of raw data, the third level concerns the evaluation of various key performance indicators (KPIs) obtained through an aggregation of smart data. Processing and aggregation algorithms are configured by means of business rules and formal models as well as based on machine and tools characteristics (Wang et al. 2020). These elements are stored in a knowledge repository, into which additional context descriptors are also added. For instance, based on some mechanical characteristics (such as knowledge), a reliable contextual classification was proposed as a raw data aggregation to detect chatter phenomena among others. It consists of two steps, the first one is to detect chatters based on a calculated threshold, then during the second step, data are aggregated by a day/program/tool. The algorithms behind those aggregations are beyond the scope of this paper. The reader can refer to the work of Godreau et al. (2019) for more details.

At the technical level, the reporting task is handled by an agent-based architecture. This choice is motivated by the successful application of MASs to cope with interoperability issues. The MAS is designed to manage both reporting scenarios and the whole digital chain that feeds the report contents. In the next sections, first, an overview of the proposed framework is given, and then the MAS architecture and agents roles are described.

4.1. Conceptual architecture

The proposed reporting framework is built as an integrated cyber physical system where the different modules are interconnected and linked to the legacy tools. A three-layer architecture is proposed as shown in figure 2 (from bottom to top): (i) Physical layer, (ii) Application layer and (iii) Management layer. Each layer is described as follows:

4.1.1. Physical layer

This includes all sensing systems connected to the physical devices that execute the manufacturing operations on the shop floor. In addition, a Numerical Control (NC) machine is considered as a data source. Machining data are gathered from sensors through a monitoring and data collection system, called EmmaTools (De Castelbajac et al. 2014). It samples sensors from real-time signals, extracts execution data from NC, and stores them into a common raw database (EmmaTools DB) which is propagated to the upper layer.

4.1.2. Application layer

This contains two kinds of smart algorithms. The first one (named raw data aggregation) is related to the contextual classification and the analysis of the big data collected at the physical layer. New monitoring criteria are generated and stored in the Smart DB (e.g. chatter times, tool breakage detection (Boolean), machining operation type, etc.). The second algorithm (named smart data aggregation) is to aggregate the previously processed smart data. The result is a set of exploitable key performance indicators (KPIs) stored in synthetic Traceability data base. This intermediate layer also includes heterogeneous business applications, such as design and simulation tools, ERP/MES, and knowledge repositories containing rules and libraries set up by experts.

4.1.3. Management layer

This uses MAS to control the execution of smart algorithms and orchestrates the coordination between heterogeneous applications. Communication and information flow between legacy tools and various

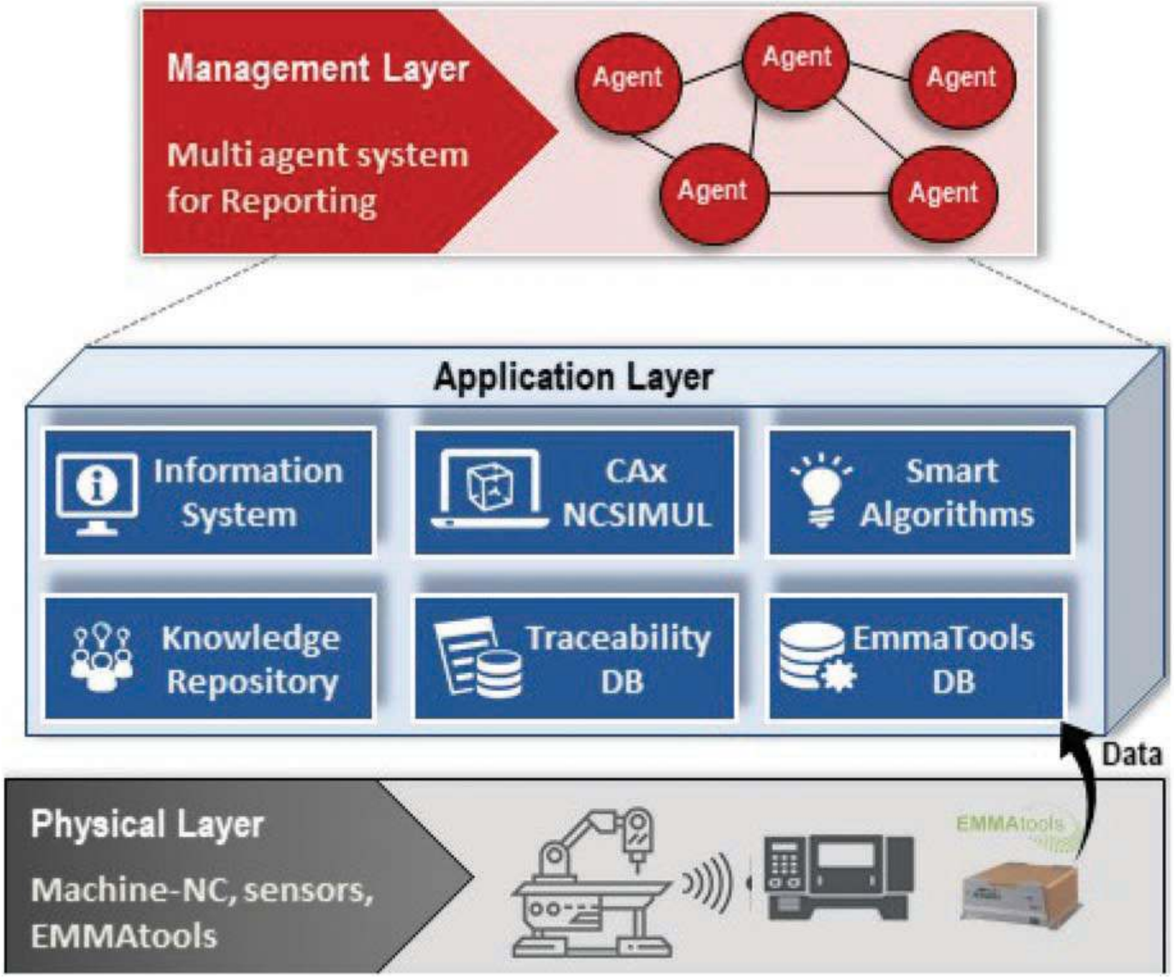


Figure 2. The Conceptual architecture.

digital repositories is also achieved by the MAS. Each agent has the main role of perceiving the environment (equipment or software), understanding the reporting requests received from the user or other agents, and then reacting according to the requested information and context. In this approach, MAS enables the retrieval of the right information from the right source and executes the appropriate algorithm. For instance, it can be the extraction and processing of requested raw/smart data from the suitable DB, retrieving information from the ERP or MES, calculating and storing targeted KPIs in the Traceability DB, and formatting and sending reports via mailing automates.

As shown in the application layer, several repositories are used to store raw, smart and traceability data as well as useful knowledge. They are described in various formats and sampled at variable frequencies. The first step for building data and knowledge bases is to identify, at the semantic level, the right concepts for every type of entity but also to connect these concepts in a logical way, so that the data retrieval for reporting can be easier. The proposed traceability model is described in figure 3.

The traceability database relies on a key concept called a "Traceability node" as a contextual instantiation of various records in the data base according to the traceability objectives and mode as well as the business role of the claimer actor. A traceability node is a smart combination of "trace items" that can be smart data and/or, KPIs. One trace items is referring to one reference attribute linked to a process, program, part and/or hardware resource (machine or cutting tool) so the traceability node could also include a comparative analysis between various elements cited above. Three types of smart algorithms are identified: Raw Aggregation data transform raw to smart data; Smart Aggregation data transform smart

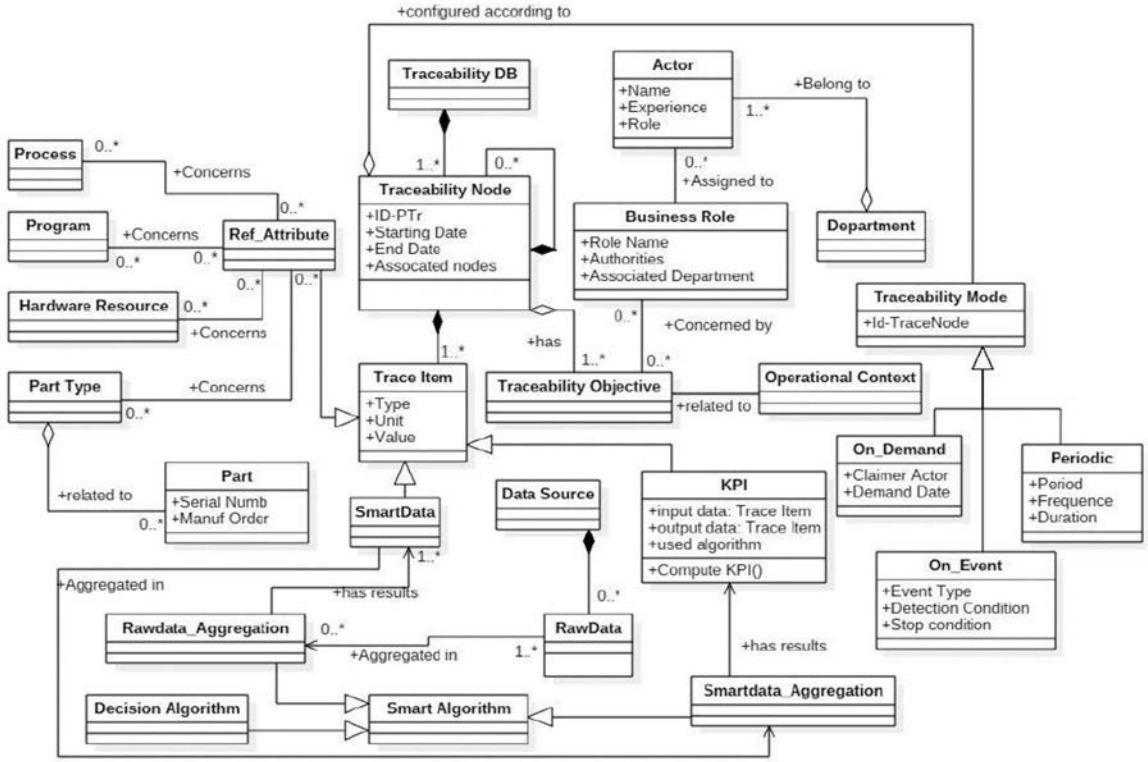


Figure 3. Traceability DB Model.

data to useful KPIs and Decision algorithms will implement additional analysis (for cause-effect detection for example). Concretely, the evaluation of data and KPIs explained above is achieved according to the following process shown in figure 4.

Access to the decision indicators above could be possible following three reporting modes: on demand reports (the operator initiates the creation of a desired report with specific settings), periodic reports (e.g. daily, weekly, etc.) or event driven report (triggered after the detection of an malicious event; e.g. chatter, tool break, etc.).

4.2. MAS for reporting

To develop an efficient solution, the number of agent types at management layer was restricted and the involvement of users was limited. Each agent on the platform perceives its environment and executes instructions defined by its behavior in order to reach its goal. The cooperation of all agents is required in order to achieve the global goal, i.e. reporting. Concretely, three types of agents are distinguished as explained below (figure 5):

• *HMI/Configuration Agent (CA)*: this agent supports the human-machine interaction where the user inputs are received and analyzed. Thanks to this agent, the user has only to connect through a GUI (Graphical User Interface) to express his needs and to set up reporting request parameters. The CA is then responsible for handling these query details and routing them to the traceability agent for treatment.

• *Traceability Agent (TA)*: based on the reporting parameters settings sent by the CA, the TA role involves communication with the smart database to extract useful data and with the external application, i.e. Matlab software, to execute the suitable smart algorithms. Predefined KPIs models are selected for each case, and instantiated according to the user needs and, his profile in the enterprise. As a result, the calculated KPIs are then saved in the Traceability DB. Traceability points represent synthetic information that is directly exploitable for decision aiding. The traceability is carried out on demand, periodically, or by the occurrence of an event. The two latest modes are triggered through automatic workflow that executes the on demand traceability at a given time.

• *Reporting Agent (RA)*: Once the synthesized KPIs are successfully calculated and saved in the Traceability DB, RA is notified to manage results as a meaningful combination of KPIs. Different human readable reports formats can be

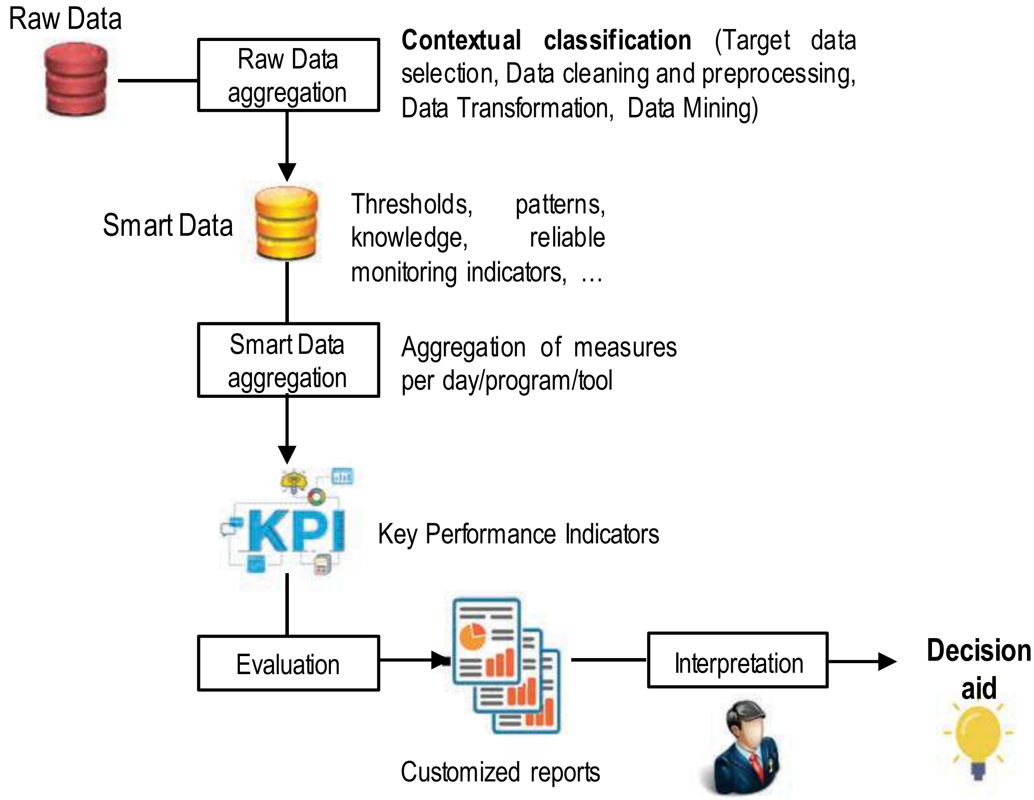


Figure 4. Global process of data management overview.

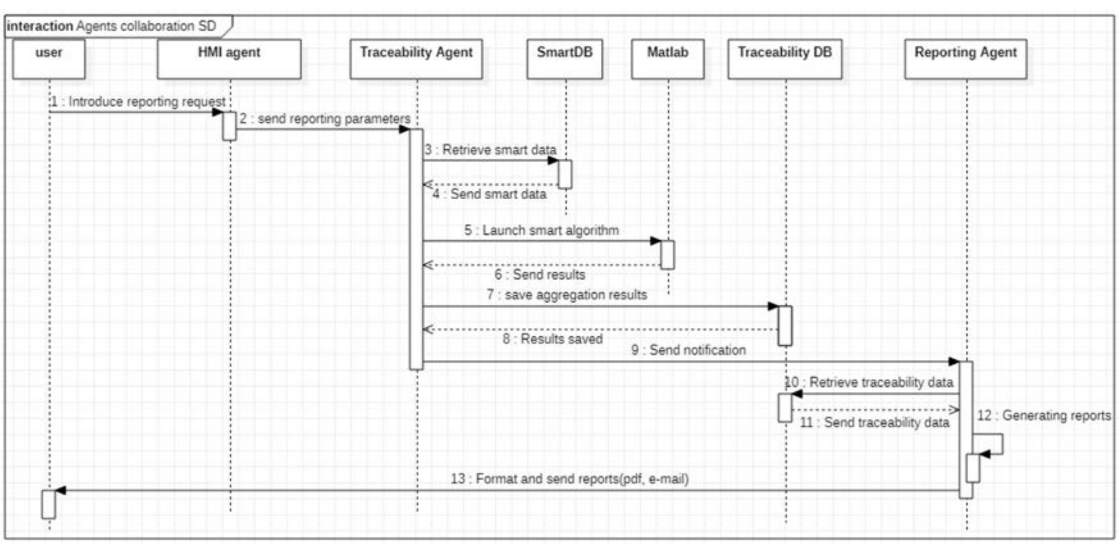


Figure 5. Agents collaboration within the reporting framework.

generated: graphs, tables, text. The user can navigate through an interactive interface or obtain direct access to the report files via e-mails. The CA then takes the role of a presentation module where the system outputs are fed back to the operator who has initiated the reporting demand.

Several agents from the same category can co-exist to achieve different behaviours. Table 1 outlines these behaviours and points out entities interacting with each agent and the communication means used to exchange information.

Table 1. Agents roles specifications.

Agents	Roles	Interacting entities	Communication
Configuration Agent (CA)	Receives reporting request	User	GUI
	Sends reporting parameters	Traceability Agent	ACL messages
Traceability Agent (TA)	Extracts information	ERP, MES, ...	XML files
	Launches KPIs calculation	Matlab	
Asynchronous TCP/IP communication	Stores calculated KPIs	Traceability DB	JDBC
	Notifies results availability	Reporting Agent	ACL messages
Reporting Agent (RA)	Retrieves report content	Traceability DB	JDBC
	Formats and sends reports	User	SMTP server

ACL (Agent Communication Language) – XML (Extensible Markup Languag) – JDBC (Java DataBase Connectivity) – SMTP (Simple Mail Transfer Protocol)

4.3. Implementation issues

4.3.1. Technical architecture

Several software platforms have been proposed in the literature to support agent-based systems implementation which reduces the development time by providing the decomposition and communication infrastructure. In this paper, the proposed MAS is implemented using the IBM JADE (Java Agent DEvelopment Framework (Bellifemine, Caire, and Greenwood 2007; Bellifemine, Poggi, and Rimassa 1999)), an open source middleware distributed by Telecom Italia 46. Although many other multi-agent frameworks are available, JADE is the most commonly used in several application domains based on extensive available documentation. It provides predefined agent models and tools that enable the realization of different agent architectures with good runtime efficiency, software reuse, and agent mobility (Bellifemine, Poggi, and Rimassa 1999). Communication between agents is promoted by complying with the FIPA specifications for ACL (Agent Communication Language) where information flow among agents is enabled by message exchange (Fipa-ACL 2002). The study of ACLs is one of the most frequent research topics in the field of multi-agent systems (Soon et al. 2019). The two most used standards for defining the encoding and managing of message transfert between agents are FIPA-ACL and KQML (Knowledge Query Meta Language model). They are almost identical in terms of their basic concepts and observed principles. They have also the same syntax and they differ mainly in the details of their semantic frameworks. Although KQML is good for the transfer of messages between agents, its direct exploitation in the construction of a cooperation system is very inefficient (Cost et al. 2000), which better explains the choice of FIPA ACL. Moreover, thanks to predefined libraries of data models and XML parser, the TA is able to interoperate with different information systems and extract contextual information needed for reports (see figure 6).

On the other hand, MAS, specifically TA, has to interoperate with external software to efficiently perform smart data aggregation and calculate required KPIs. This task is achieved by using MathWorks Matlab, a powerful software used to perform complex numerical computations and data analysis (MATLAB 2010). Inputs/outputs are exchanged between agents on the JADE platform and Matlab through an asynchronous TCP/IP communication (see figure 6). Matlab for data aggregation is used to optimize the proposed MAS performance by speeding up the computational time.

To store multi-source data, we use MySQL (DuBois 2008), an open-source relational database management system. Three types of databases are deployed. EmmaTools DB (raw database) includes data collected from machines on the the shop floor: data extracted from machine Numerical Control (e.g. time, program ID, tool ID, power, rotation speed, etc.) and sensors data (vibration, accelerations, temperature, frequencies, etc). Smart DB contains new monitoring criteria and useful knowledge extracted by Data Mining techniques from the raw data structured by tool call, per program per day (e.g. stopped time, machining time, finishing time, chatter time, tool break, excessive vibration time, etc.). Finally, synthesized KPIs calculated by intelligent aggregation of smart data are stored in the Traceability DB (e.g. chatter time by program, total number of tool breaks, ratio of non-machining time, etc.). Traceability points represent synthetic information which is directly exploitable for decision aiding. TA and RA are allowed to access to these databases, i.e. read/write targeted data by means of SQL (Structured Query Language) queries,

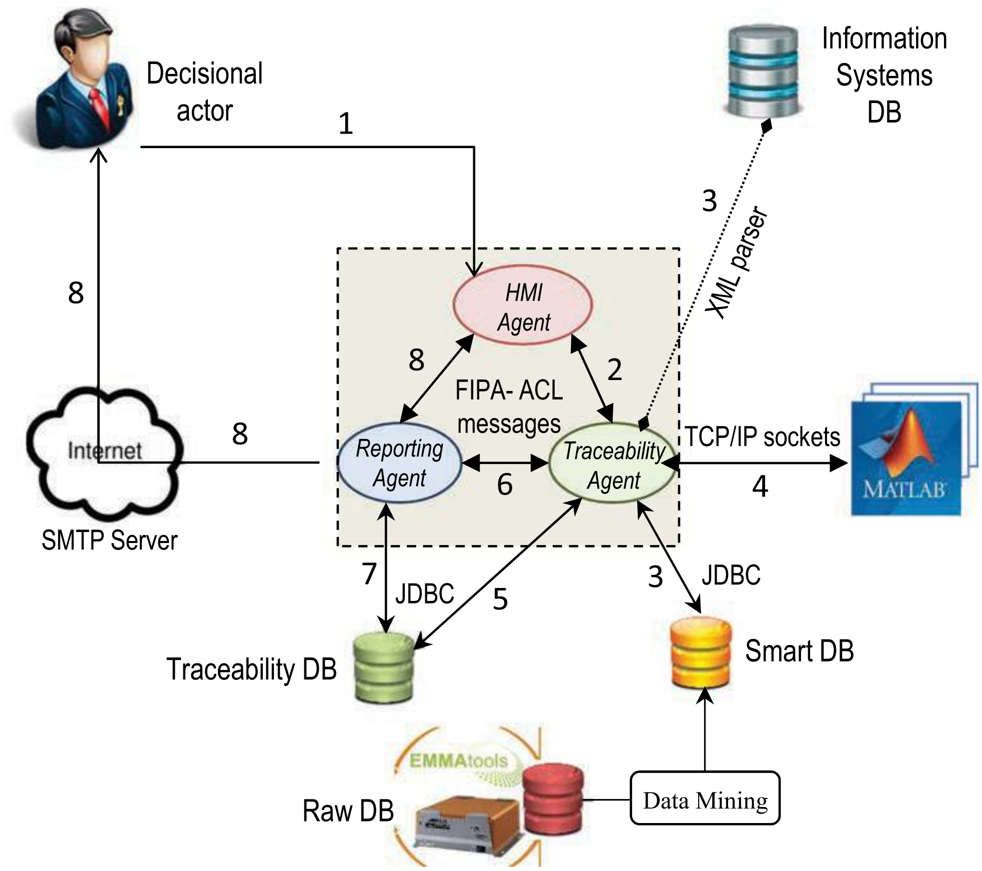


Figure 6. Interoperability in development environment.

through Java DataBase Connectivity (JDBC) set between the agent in the JADE platform and different databases (see figure 6).

4.3.2. Deployment in the industrial network

To reach a satisfactory degree of efficiency, the deployment of the proposed framework remains a crucial issue to be addressed by taking into account the technical constraints of the industrial network (both business departments and shop floor networks).

Hierarchical/edge-based computing is deployed as represented in figure 7. In this solution, data are pre-processed at each Emmatools, then the smart data obtained are generated and centralized at the middle part. The smart multi-agent system in charge of reporting is located at this level as well in order to maintain industrial network performances.

5. Industrial case study

The aim of this section is to show the feasibility of the proposed framework described in Section 4. For validation, the reporting framework has been tested on a real industrial use case from the aeronautic sector. These use cases are related to high-speed machining process with high added-value mechanical parts. These types of parts have thin walls and floors, generally very sensitive to vibration phenomena (which require costly manual finishing operations). Since the aeronautic domain is characterized by highly customized demands, a machine-tool almost never fabricates the same part twice consecutively. Hence, understanding the behaviour of the machine is critical.

To resolve these critical problems, several reporting scenarios can be proposed such as productive and stopping time tracking, Overall Equipment Effectiveness (OEE) evolution, spindle signature monitoring, chatter, tool breakage, and collision reports, etc. In this section we focus on a reporting scenario for chatter phenomena. This scenario is conducted step by step to illustrate the functioning of the framework. Chatter is one of the most undesirable phenomena involving unacceptable quality defect on the

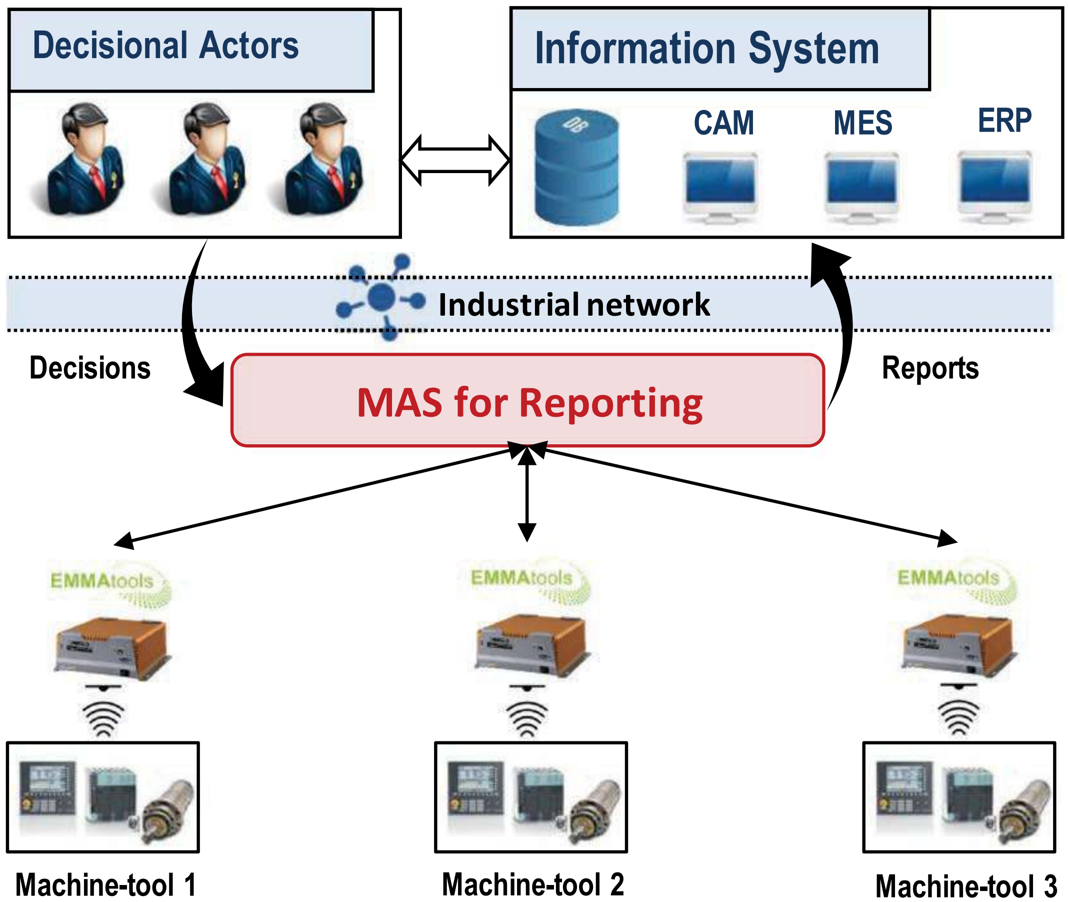


Figure 7. Deployment of the proposed system in the industrial network.

work piece surface. Hence, it must be avoided in order to preserve machine life, improve surface quality, and increase tool life. For this reason, decision-making operators are prompted to restrict the occurrence of such phenomena by inspecting the performance of tools and programs designed to execute manufacturing orders. In this context, the proposed reporting system provides assistance to the methods and programs departments in order to detect unstable programs and tools. It generates summarized feedback including chatter reports which enables detecting programs and tools to include the appearance of recurrent chatter. Based on these sensitive and targeted reports, decision-making regarding harmful programs and tools will be more accurate.

5.1. Machining data acquisition

At present, abundant real-time process data are generated and available in an operating machine-tool, mainly for the motion control in relation to the G-code and the programmed tool path. In the physical layer, the data acquisition device (EMMAtools) is connected to a machine-tool by a field bus to record around one hundred parameters (axes speed, position, power and temperature, the G-code name and line, tool reference, etc.). Data can be retrieved from the NC, the axis drives, the PLC (Programmable Logic Control) (Godreau et al. 2019). Additional sensors are also embedded e.g. accelerometers integrated into a Fischer high speed spindle, on front and rear bearings, for an accurate measure of the vibrations due to the cutting process and the spindle condition.

Signals are measured with a National Instrument 9234 acquisition card at a sampling frequency of 25 kHz. Then, to avoid an excessively big database, online signal processing is carried out every 0.1 s, in frequency domains notably order tracking, and only relevant higher level information is recorded. As a result, about 200 MB is collected daily from each machine-tool. PostgreSQL is used for the management of the HSM process database (EmmaTools DB) which consists of columns and rows. Each column refers to a given parameter and each row corresponds to every 0.1s recording. These data were acquired during the entire spindle life cycle (426 days) where 80 cutting tools and 346 programs have machined 534 workpieces. After processing, smart data are generated and formatted in multiple CSV files.

Data is processed/aggregated using matlab script and then stored as KPI in the traceability database (MySQL). The *Reporting Agent* extracts the results and send it to the user. The aim of this simple scenario is to show the feasibility of the proposed reporting framework.

5.2. Reporting scenario demonstration

The proposed scenario is to report the main tools and programs that caused chatter during the machining process. These reports are very important for decision-making and enable to change the type of tools and programs in similar machining processes in order to avoid chatter. MAS is used as a reporting solution. It communicates between agents and the whole system so to extract the right information about chatter and send it to the right person.

The interaction for such a report starts by the configuration of interfaces using the *HMI Agent* as shown in figure 8. This agent communicates the user request with the *Traceability Agent* and the *Reporting Agent*.

5.3. Results

Two examples of customized reports are generated from this illustrated scenario to investigate chatter causes. In order to highlight the critical tools causing maximum chatter, the first type of reports provides decision makers with statistical results regarding tools performance including a table with the tool reference, chatter time, usage time and a pie chart of the tools contribution to chatter occurrences. For instance, it can be noticed from the report in figure 9(a) that tool number ID 10026 has induced more than half of the total chatter time. Such information is used as a decision aid KPI for improving tools cutting conditions in future machining processes. The second

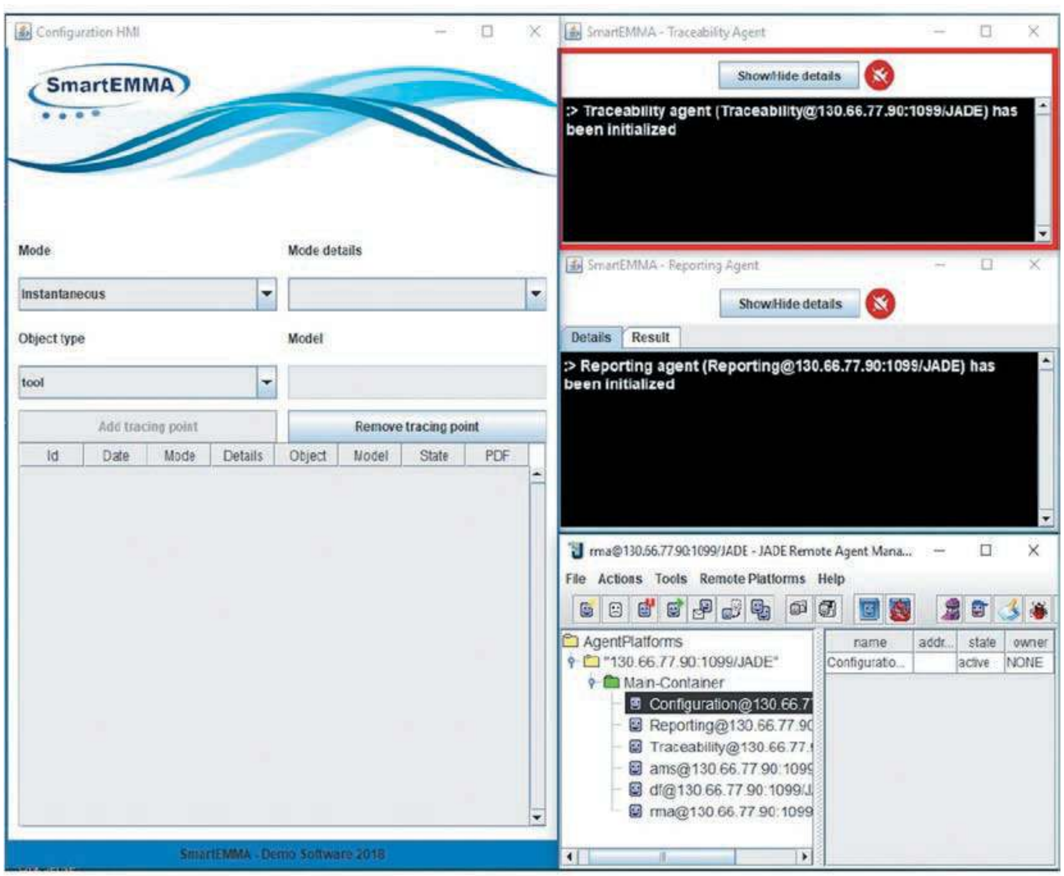
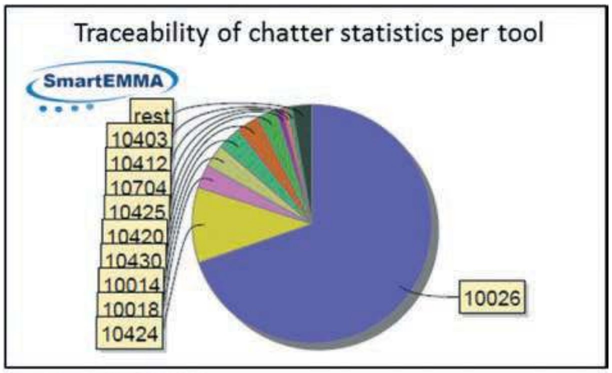
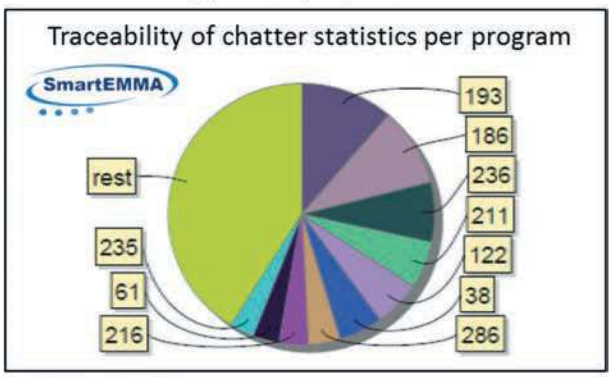


Figure 8. Main GUIs of the Reporting system with JADE framework.



Time Usage Statitstics		
tool name	chatter time (h)	time usage (h)
10026	7,72	317,11
10424	1,13	41,48
10018	0,35	259,44
10014	0,35	33,48
10430	0,35	151,22
10420	0,34	6,54
10425	0,29	2,39
10704	0,1	54,88
10412	0,07	31,58

(a) Chatter report per tool.



Time Usage Statitstics		
program name	chatter time (h)	time usage (h)
193	1,15	83,09
186	0,98	72,47
236	0,76	21,29
211	0,59	43,13
122	0,58	25,17
38	0,54	20,92
286	0,4	12,31
216	0,35	81,88
61	0,33	34,9
235	0,3	7,18
rest	4,16	2764,74

(b) Chatter report per program.

Figure 9. Chatter reports.

reports presents the same results regarding programs (9(b)). To produce these results, chatter times are aggregated by each program and the most important ones are selected and presented in a pie chart. The results of this chart show that almost half of the chatter time (excessive vibrations) was caused by program ID 193. The decision that can be made from these results is to update or code this program again to reduce chatter time.

6. Conclusion and future works

This paper proposes a reporting system devoted to assist operational management actors in manufacturing companies in making effective decisions to improve the quality of their products. One idea behind this framework is to adapt the paradigm of MAS as a solution for interoperability issues between heterogeneous cyber physical components. Agents cooperate with each other and interact with external applications to handle user requests and generate customized reports to be shared regarding the work context of the user.

Designed as a key function for "industry 4.0" future applications, a reporting scenario has been proposed and tested in a real industrial use case where useful and synthesized decision-aid indicators are extracted from big data collected throughout the machining process. Disruption of the digital chain caused by less feedback from the manufacturing shop floor to the operational management is then reduced. Furthermore, the reporting system relies on an integrated data and knowledge management strategy that aims to optimize the size and usefulness of data generated from large databases. One of the complex problems within the paradigm of big data is their under exploitation in concrete industrial situations because indicators are difficult to interpret according to business needs. The Big Data issue is then solved by aggregating and generating smart and meaningful data.

The positive feedback from the industrial partners of the project provided a first validation of the results and the utility of such initiatives in the enterprise of the future. In this context, multi-agent technology is relevant in the deployment of flexible solutions where it is possible to dynamically integrate new behaviors to cover additional reporting scenarios. An example of future scenarios under development consists of generating periodic or automatic reports for health monitoring of spindles, tools, machines, parts, etc. This mechanism can be triggered by agents without any requests from users. Internal decisions that can be taken by agents in this situation consist of deciding when to start the reporting mechanism and what to do based on the results. An interesting situation is to warn the decision maker when an unplanned event occurs.

However, some concerns still exist with these scenarios: firstly, decision needs are important and sometimes hard to obtain from the experts. In the same company, several points of view are possible on a given set of data that will make it hard to create all combinations of indicators for highly customized reports. Furthermore, the critical step is the configuration of the efficient data mining process in order to validate the useful types of information. Manual analysis of data is often requested before launching the automatic reporting system. Further studies integrating knowledge based approaches with MAS are under development.

Finally, those who are expert in this field focus primarily on the reporting mechanism. With the development of other complicated scenarios, other complementary agents can be proposed for other services and problems such as fault diagnosis, failure prediction and rescheduling. An example of ideas that are being studied is to monitor spindle health using multi-agent. In this situation, machining tasks can be reallocated to the available spindles based on task complexity (cutting conditions) so as to avoid risks such as spindle breakage.

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No potential conflict of interest was reported by the authors.

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