Cognition, Technology & Work (2022) 24:93–111
https://doi.org/10.1007/s10111-021-00667-y

ORIGINAL ARTICLE

Designing human–system cooperation in industry 4.0 with cognitive work analysis: a first evaluation

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Received: 5 May 2020 / Accepted: 7 January 2021 / Published online: 24 January 2021

Abstract

One objective of Industry 4.0 is to reach a better system performance as well as to have a better consideration of humans. This would be done by benefiting from knowledge and experience of humans, and balancing in a reactive way some complex or complicated tasks with intelligent systems. Several studies already dealt with such an objective, but few are done at a methodological level, which forbids, for example, the correct evaluation of design choices in terms of human awareness of the situation or mental workload when designing intelligent manufacturing systems integrating the human. Indeed, increasing the intelligence and autonomy of industrial systems and their composing entities (resources, products, robots…), as fostered by Industry 4.0, increases their overall complexity. This modification reduces the ability to understand the behaviors of these systems, and leads to the difficulty for humans not only to elaborate alternative decisions when required, but also to make effective decisions and understand their consequences. This paper evaluates such a design methodology, the Cognitive Work Analysis (CWA), and its applicability when designing an assistance system to support Human in the control of Intelligent Manufacturing System in Industry 4.0. Among several functions identified through the application of CWA, the assistant system might have to integrate a digital twin of the intelligent manufacturing system. The evaluation of the methodology through the one of the designed assistant systems is done using a micro-world, which is an intelligent manufacturing cell composed of intelligent mobile ground robots, products, and static production robots interacting together and with a human supervisor in charge of the reaching of several time-based and energy-based performances indicators. The assistant system embeds a digital twin of the intelligent manufacturing system. Twenty-three participants took part in experiments to evaluate the designed assistance system. First results show that the assistance system enables participants to have a correct awareness of the situation and a correct evaluation of their alternative decisions, while their mental workload is managed and expected production performances are reached. This paper contains an analysis of these experiments and points out some limits of the CWA method in the context of Industry 4.0, especially the lack of tool enabling to specify clearly the cooperation processes between the supervisor and the intelligent manufacturing system. This paper concludes with potential research avenues, the main one being the potential benefits of coupling CWA with human–machine cooperation principles to fine tune and adapt the cooperation between the human and the intelligent manufacturing system.

Keywords Human–machine systems · Manufacturing system · Cognitive work analysis · Human–machine cooperation · Cyber-physical systems

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1 Introduction

Industry 4.0 objectives aim at proposing an integrated solution for the industry to benefit from the increasing capabilities of machine while being aware of human competencies and adaptabilities. When Intelligent Manufacturing Systems (IMS) start to provide performance but complicated and complex systems, human has to continue to be in control of such systems to have the right decision at the right time to tackle unexpected events or new objectives. The challenge is difficult, since human and IMS have for now competences that have been, respectively, learned and designed in parallel, most of the time without taking care of interactions between both. The objective of this paper is to propose and evaluate a methodological approach, which may help Industry 4.0 designers to analyze humans and systems activities in an existing industry that aims to reach a 4.0 level, or to develop what could be such activities in a new industry, or new part of an industry.

The interrogations around the Operator 4.0 and especially its place in the system are a fertile ground for such development. Studies are oriented on multiple aspects, such as sociotechnical system modeling (Jonese et al. 2018), or interaction through human–machine interface and human–computer interface (Gorecky et al. 2014; Papcun et al. 2018; Wittenberg 2016). In our very case, to avoid out-of-the-loop situation (Endsley and Kiris 1995), we decided to perform an analysis and suggest the improvement of the system design itself to integrate human operators.

For this purpose, we proposed to use the Cognitive Work Analysis (CWA) to conduct an analysis of industry activities and to identify humans and machines roles as well as best organizations to reach industry objectives. Therefore, after the presentation of the specificities of Industry 4.0, with a focus on the Sociotechnical systems, CWA approach is explained and applied in a use case defined within the framework of the French national project called HUMANISM. The experimental platform and the experiments conducted through two experimental conditions, integrating or not supports for human to understand and control IMS, are detailed, as well as first results. The last part discusses the results and suggests an improvement of the different steps of the CWA approach with useful design tools stemming from human–machine cooperation approach.

2 Designing sociotechnical systems in industry 4.0

2.1 The role of operator in the 4th industrial revolution

In a report from the Boston Consulting Group, Rüssman et al. identify nine "technological pillars" supporting the Industry 4.0 (Rüßmann et al. 2015): (1) the Industrial Internet of Things (IIoT), (2) the vertical and horizontal integration of information systems, (3) big data and data mining, (4) the cloud, (5) simulation, (6) cybersecurity, (7) augmented and virtual reality, (8) additive manufacturing, and (9) autonomous robotics.

These new digital technologies provide an opportunity for decentralizing the flow of information, decision-making, and command and control (Hozdić 2015). As explained by Wang et al. (2016), Industry 4.0 can support self-organizing and autonomous cyber-physical manufacturing system, capable of dynamically reconfiguring itself to achieve the goals of the system. This network approach makes it possible to optimize locally or globally the cells of production, to manage very complex industrial processes. Moreover, with the development of digital twins, Industry 4.0 allows the emergence of the virtual enterprise. This combination of "virtual and real worlds" can, for example, bring interesting applications for remote maintenance or operational situations training (Longo et al. 2017).

Nevertheless, the introduction of these Industry 4.0 technologies raises the challenge of defining more precisely the role of human operator in a context where technological revolutions will have an impact on individuals and their activities, as well as on the organization of work:

- At an individual level, Industry 4.0 will employ fewer unskilled personnel than the traditional factory. Routine activities, characterized by a low level of manual dexterity or social interaction requirements, are most likely to be replaced by technologies (Fantini, Pinzone, and Taisch 2018). On the other hand, the need for qualified and well-trained personnel will be increased. Operators will have to demonstrate great adaptation abilities, because they will have to act on complex, interconnected, and autonomous technical systems that they will have to understand and control. Operators will handle more abstract information, and will often be more "distant" from the process to be controlled, with a greater scope of supervision.
- At an organizational level, Hirsch-Kreinsen (2014) identifies two extreme forms of organization concerning the distribution of work between humans: a "polar-

ized" organization with few unskilled tasks and a large group of experts and highly qualified specialists versus a "distributed" organization aiming for the greatest flexibility and based on a high qualification of all the operators which allows them to face unexpected situations.

To better define the role of humans in Industry 4.0, Romero et al. adopted a techno-centered approach proposing typologies of "operator 4.0" (Romero et al. 2016), from the "technological pillars" of industry 4.0 (Rüßmann et al. 2015). This typology of "augmented operators" highlights different types of possible cooperation with intelligent systems (physical, sensory or cognitive) for different types of activities (physical or cognitive):

- The operator 4.0 can be increased physically ("super-strength operator" and "collaborative operator"), using cobots and exoskeletons. This will increase performance for manual operations and reduce musculoskeletal disorders for humans. It will also allow the integration of disabled workers.
- The operator 4.0 may be increased at a sensory level (to better perceive the environment and detect new signs). Biofeedback sensors will provide a sensory increase ("healthy operator") and allow the detection of physical or cognitive workload situations. The new visualization interfaces (virtual and augmented reality) will increase the operator ("augmented operator" and "virtual operator"). The perception of the environment will be enhanced by a subjective vision, a visual warning or index display highlighting the important elements of the environment.
- At a cognitive level (to better process and interpret the information, and for problem-solving), the diagnosis of the situation could be enriched, thanks to the contextualized display of information from the cyber-physical system. Corporate social networks will also contribute to a cognitive increase of the operator (social operator) by improving the diagnosis and the resolution of problems thanks to the knowledge of other experts accessible online, synchronously or asynchronously. Big data analysis and cloud computing will enable to a cognitive increase of the operator ("analytical operator"). By extending the computation, classification, analysis, and synthesis capabilities of information (Longo et al. 2017), the situation analysis of the human operator will therefore be enriched, whether at strategic, tactical, or operational level. Finally, operator 4.0 will benefit from increased interactions with the cyber-physical system ("smarter operator"). These human–computer interactions will be improved by the use of personal assistants and artificial intelligence. Operators will access to high-level information and will be able to modify the system configuration (supervision and control) or carry out maintenance and diagnostic operations. Gorecky et al. (2014) highlight context-sensitive mobile devices (filtering information according to context: place, type of activity, and situation encountered by the operator), and voice or body controlled (through the analysis and recognition of gestures).

In addition to this vision based on assistance to specify augmented operators, Fantini et al. propose a vision based on the concept of social interactions (Fantini et al. 2018). In this perspective, a multi-agent architecture of the social factory is proposed by (Banol et al. 2018; Romero et al. 2017). Starting from the idea that operator 4.0 is at the center of a social network, made up of other social operators, but also of machines and software qualified as "social", this architecture makes it possible to formalize the design and the evaluation of the social interactions of the production system, mediated by interface agents (for supporting the dialogue and the management of interference between cooperative agents) and broker agents (for distributing work among cooperative agents).

Furthermore, the deployment of Industry 4.0 technologies will lead to integrate more "intelligence" into systems. Discussions arise then on how to model this new type of interaction between artificial entities and humans (Jones et al. 2018). Jones et al. (Ibid) state that the traditional human–machine system point of view is not adapted anymore, as, from now, the artificial entities would be able to work more collaboratively with humans to execute cognitive functions. Instead, they support the idea of modeling agents as joint cognitive systems, which remove the separation between artificial entities and humans. Similar to Jones et al. (Ibid), Gely et al. (2020) consider that in the context of Industry 4.0, an autonomous system is a peer, able to trigger cooperation needs with the human to reach its own objectives. These views raise interesting points on the relationship between humans and artificial entities, and may renew questioning on the possible impacts of this relationship such as emotional involvement with artificial entities and relevant risks (Pacaux-Lemoine and Trentesaux 2019).

Nevertheless, many questions remain to be elucidated to improve human–system integration in Industry 4.0 (Pacaux-Lemoine et al. 2017). Human operator must be kept in the loop, to allow him to maintain a mental representation of situations, and to improve his ability to supervise autonomous agents. The question of optimizing human cooperation with cyber-physical systems (CPS) therefore becomes a major issue. It is about creating a symbiosis (Romero et al. 2016), a "productive" joint cognitive system (Hollnagel and Woods 2005).

2.2 Design methods supporting the optimization of cooperation between operator and IMS

Socio-Technical Systems Engineering (STSE) addresses the question of designing such efficient human–machine systems (Baxter and Sommerville 2010). STSE focuses on the design of complex systems with interconnected human, technical, and organizational components. In particular, this global approach raises the issue of the role of operators faced with increasingly autonomous technical systems in dynamic, risky, and sometimes unforeseen situations. The distribution of activities and the adaptive cooperation between humans and machines is a central process in Socio-Technical System (STS) design and operation (Challenger, et al. 2013). More precisely, dynamic function allocation (DFA) could help a system maintain a satisfying performance in complex situations. This issue must be taken into account as early as the preliminary design phase of a project (Goom 1996; MoD 1989).

Several methods have been proposed to design socio-technical systems: User Centered Design (UCD) approach (Norman and Draper 1986), hierarchical task analysis (Norman and Draper 1986), cognitive task analysis (Chipman, Schraagen, and Shalin 2000), etc. Nevertheless, as stated by Rasmussen (1997), Vicente (1999), or Papantonopoulos (2004), many methods are too normative or too descriptive, unsuitable for designing adaptation, dynamic cooperation, and work distribution. On one hand, normative methods (with ISO standards and ergonomics handbooks) focus too much on the specification of the ideal ways to perform work—and therefore human–system interactions—under certain anticipated conditions, difficult to reproduce in real life within open systems, and with non-expert users that can deviate from the standard procedures. On the other hand, descriptive methods are based on the analysis of the familiar and recurring conditions. As reminded by Romero et al. (2020), the descriptive methods were used to supporting an “Anthropocentric Production Systems” with adjustability to different degrees of user experience or reliability. The resulting design of STS may be more tolerant to the adaptation and the deviation to the rules from the system agents, and it can generate satisfying systems in nominal conditions. Nevertheless, these kinds of methods are again limited to consider unforeseen events and novel conditions that should typically occur in the context of Industry 4.0. Indeed, these two main approaches may forbid the correct evaluation of design choices in terms of human awareness of the situation or mental workload when designing intelligent manufacturing systems integrating the human. Indeed, increasing the intelligence and autonomy of industrial systems and their composing entities (resources, products, robots, etc.), as fostered by Industry 4.0, reduces the ability to understand the behaviors of these systems and increases their overall complexity, leading to the difficulty for human being, supervisors or operators, not only to elaborate alternative decisions when required, but also to make effective decisions and understand their consequences.

By contrast, Cognitive Work Analysis (CWA), proposed by Rasmussen (1986), Rasmussen et al. (1994) and further developed and codified by Vicente (1999), appears as one of the most comprehensive methods to design cooperation within STSE. It combines the contributions of engineering and human factors to provide designers with a powerful framework for Social Technical System design. It is a formative constraint-based approach, consisting of five successive stages: (a) Work Domain Analysis (WDA), (b) Control Task Analysis (ConTA), (c) Strategies Analysis (StrA), (d) Social Organization and Cooperation Analysis (SOCA), and (e) Worker Competencies Analysis (WCA). The issue of function allocation and cooperation is addressed at the SOCA stage. This issue is a crucial one, even if the exploration of the social cooperation and organization phase has received less attention than the application of the WDA or ConTA (Jenkins et al. 2008). Despite this limitation, it appears that the CWA could be envisaged in the context of Industry 4.0 where intelligence is everywhere, enabling various autonomous entities, either digital or humans to interact. From our perspective, it is thus important to evaluate the pros and cons of CWA in the context we addressed and presented here after, which may lead to suggest some improvements to help designers of future IMS to correctly address the integration of the human operator from a methodological point of view.

3 Implementation of CWA to design a system in industry 4.0

3.1 Presentation of the use case

The studied use case relies within the framework of the HUMANISM French ANR project. HUMANISM involves three labs and analyzes three aspects of human–machine interaction with a specific IMS (cf. Fig. 1). It focuses on the strategic, tactical, and operational decisional levels of this IMS, as a subpart of an Industry 4.0 flexible cell, inspired from an existing real pedagogical cell (AIP-PRIMECA/SMART Cell in UPHF, Valenciennes).

The IMS is composed of robots linked by a 1D conveying system on which shuttles transport products from one static production robot to the other. Mobile ground robots, moving freely on the 2D area of the cell, are added to ensure the supply of these production robots and to ensure the download of finished products. In this use case, a manufacturing plan (a given number of different products to realize) has been assigned to human by the industrial managers at the strategic decisional level. Specifications about allocation of tasks

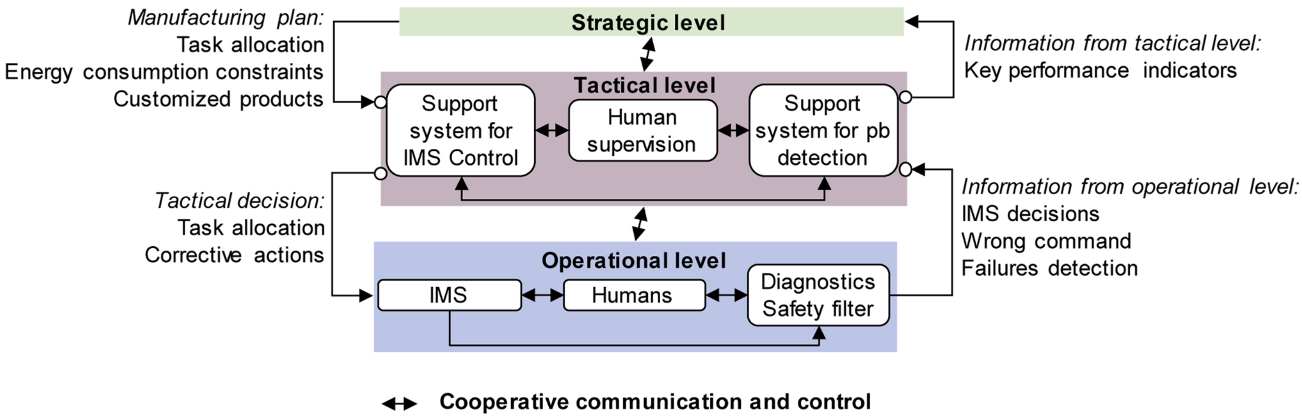


Fig. 1 HUMANISM project: Human–MAchines cooperatioN for flexIble production SysteMs

to humans and machines and performance criteria such as energy consumption and the different types of product that the cell has to make have also been set at this level. Human supervisor at the tactical decisional level has to analyze this plan to send orders to the operational level, especially task allocation, but also corrective actions when unexpected events happened or new objectives (not firstly included in the plan) are requested. At this tactical level, key performances indicators and information from the operational level are gathered to adapt in real time these orders.

In the present paper, the studied interaction lays between the tactical level, handled by both a human supervisor and one support system (cf. Fig. 1: left box on the tactical level), and this IMS at operational level (cf. Fig. 1: left box on the operational level). The decision support system (DSS) provides information about the status of the cell and its components.

In the HUMANISM project, the "intelligence" of the flexible cell holds in the ability for the "smart shuttles" to self-organize themselves according to occurring events and the manufacturing operations to be performed by robots on the product they carry. The behavior of these shuttles is purely reactive. It is based on the principle of the potential fields, where shuttles are attracted by production robots emitting digital fields depending on their distance to the shuttle, their ability to proceed the task required by the transported product, and their real-time load. Prior to the HUMANISM project, several studies have shown that such behavior ease the technical implementation of the flexible cell, providing powerful mechanism to react in real time in front of various unpredicted events (Pach et al. 2014). Meanwhile, it has been illustrated that this approach does not provide sufficient guarantee to reach production objectives even in normal conditions. More, the performance may decrease when perturbations occur and the speed and the complexity of the digital interactions among shuttles and robots make it hard to understand why a specific behavior emerges from numerous local interactions. To handle this, in the HUMANISM project, it is suggested that a human supervisor at the tactical level, given his/her ability to anticipate events, to have a big picture of the whole, and to react and adapt to the unpredicted, becomes the supervisor of this self-organized system. This human supervisor ensures the reaching of production objectives and the consideration of constraints hardly implementable in the self-organized system, such as global energy consumption limits. Meanwhile, the complexity reached by the self-organizing system require that the human is aware of the situation to take effective decisions.

In this context, the CWA has been proposed as a methodology to design and evaluate the integration of the human and the IMS into a "human-aware IMS", paying attention to the capabilities and limits of the human on the one side, and the ones of the studied self-organized IMS on the other side. Obviously, even if realized on a specific Industry 4.0 system where intelligence is purely reactive and embedded exclusively in shuttles, our results and research are aimed to be generalized to help designers of Industry 4.0 systems searching support to design human-aware IMS.

3.2 Application of the CWA to the use case

As already explained in Introduction, the CWA methodology was used to defining tasks and functions of human and technical agents in the specific case of an IMS. For simplification purpose, the term "agent" is used to describing any decisional entities, being human (here, the human supervisor) or technical (here, the smart shuttles, the production robots and the mobile ground robots). This section steers three of the five phases proposed by the CWA method, the WDA, the CTA, and the SOCA. Indeed, as the study of the IMS is prospective, it was not yet possible to identify strategies to organize agents' tasks (StrA), as well as precise competences of those agents (WCA). The results of the CTA phase help to define the human–machine interface (HMI) and the DSS.

However, even if the CTA provides the main information and functions to be displayed on the HMI and used by the DSS, a great part of the HMI has been innovated by the designers.

3.2.1 Work domain analysis

The work domain analysis is about a “Formalization of constraints linked to system functioning: identification of system goals and links between goals and physical objects”. The objective of WDA is to model the physical, structural, and functional constraints governing the activities of operators. Using an Abstraction Hierarchy (AH) modeling tool, WDA describes a work domain with five levels of abstraction; each level is connected by a structural means-end framework linked to the next upper or lower level:

- the functional purpose (the purpose of the work domain, its "raison d’être"),
- value and priority measures (the criteria ensuring that the system progresses toward the functional purpose),
- purpose-related functions (the general functions that are performed to achieve the functional purpose),
- object-related processes (processes and capabilities characterizing the objects used by the general functions),
- and physical objects.

(1) Functional purposes

The functional purpose of the IMS is the following: to support human to supervise and control the IMS and its mobile ground robots.

(2) Values and priority measures

The values and priority measures consist in the elements that support the evaluation of the system progress. In our use case, as the objective of the research is to design human–IMS integration, the evaluation is based on two types of measures. The first one deals with the performance of the production regarding the Industry 4.0 objectives maximizing:

- safety, if one designs safe environment for human,
- security, if one designs system protected against cyber-attack
- effectiveness, if one succeeds to make products that fulfill customer requirements in due time
- resilience, if one is able to maintain the production while experiencing perturbations or new customer requirements
- efficiency, to keep the gain/loss ratio high,
- sustainability, if one minimizes the environmental impact (energy consumption, waste minimization…).

The second measure is the human experience, which can be analyzed according to three aspects: quality of interaction between human and system, quality of human situation awareness, and human workload. First, a set of questionnaires addresses interaction between human supervisor and IMS, and then, a debriefing and the analysis of task completion will help at analyzing if the suggested organization and tasks are well adapted to human needs and willingness. Second, the analysis of the situation awareness of the human supervisor may help at understanding if all technical agents and their interactions are well understood by the human agent to make decision and act. Third, the analysis of the human supervisor workload may help at knowing if the control of the IMS is too demanding and if allocations of functions to assistance systems and machines allow avoiding human overload or underload.

(3) Purpose-related functions

The purpose-related function step addresses the general functions agents have to complete to achieve the functional purposes. Therefore, human involved in the supervision and control of the process have to understand global objectives, to supervise and control the IMS. Each agent must identify and adapt the control of the IMS according to unexpected events and objectives. The functioning of the IMS can be done autonomously, using a set of predefined algorithms, or remotely overridden or controlled when human defines current target of products to improve efficiency or when an unexpected event occurs. Missions of mobile ground robot involve defining their level of automation, as well as control and update of their trajectory according to objectives and unexpected obstacles.

(4) Object-related functions

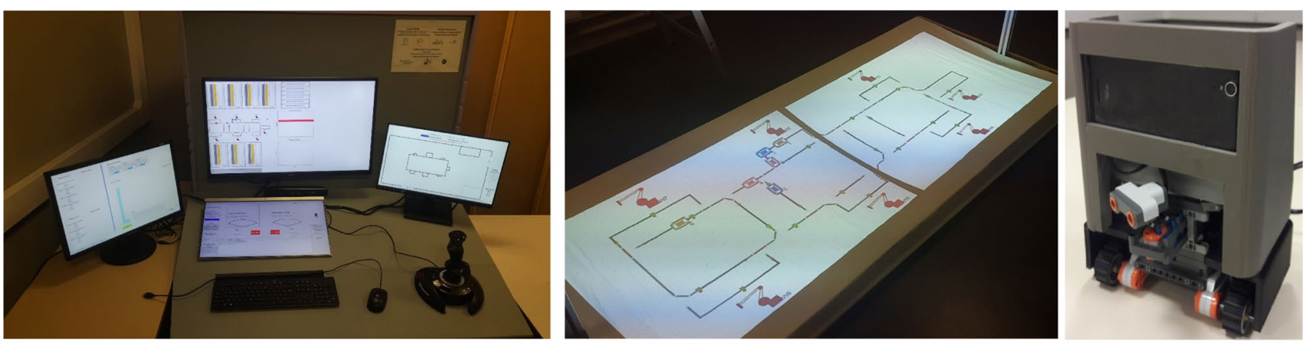
The object-related function step deals with the processes and capabilities characterizing the objects used by the general functions. Human supervisor can request or negotiate objectives with the strategic level, as well as technical resources and raw material supplied to the operational level. Mobile ground robots, static production robots, conveyors, and smart shuttles must provide information about their current state and future state if they can (according to their intention), their current control algorithm, and their achievements. Human supervisor must be able to control over technical agents whenever he/she wants and wherever agents are. Human supervisor can remotely control mobile ground robots, or provide them with the geographic goal they have to reach autonomously. Smart shuttles, conveyors, and static production robots can work autonomously; however, human supervisor may intervene to change one shuttle’s trajectory or modify characteristics of static production robots.

(5) Physical objects

The physical objects consist in three main parts: the human supervisor work position (cf. Fig. 2a), two mobile ground robots (cf. Fig. 2c), and an emulator of the flexible cell with production robots and shuttles (cf. Fig. 2b). The development of this emulator facilitates the test of our developments, which are time-consuming, instead of using the real cell. It is expected to deploy our developments on the real cell when validated. Meanwhile, the ground robots used are real and interact with the emulator of the AIP-PRIMECA cell. As introduced, the smart shuttles and the mobile robots are autonomous or remotely controlled by the human supervisor from the work position. The human supervisor, who is at the tactical level, has only access to production that holds at the operational level through video and sensors feedback, as well as by selected orders that he/she can send. The work position consists of four screens, two dedicated to the flexible cell and two dedicated to the mobile robots (cf. Fig. 2a).Therefore, human supervisor may use the bird's eyes view of the flexible cell emulator and the ground robots, and specific human–machine interface to control each mobile ground robot, each shuttle, and each production robot.

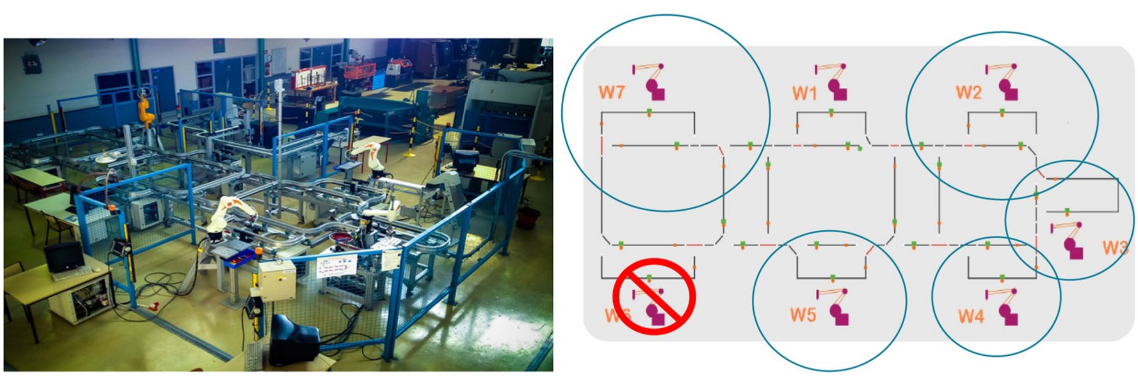
The flexible cell (cf. Fig. 2b) is materialized by the video projection of the emulator of the real flexible cell of the UPHF (cf. Fig. 3a). Fig. 3b depicts the flexible cell, and shows the topology of the cell and its 1D one direction conveying system. The mobile robots are not represented. One production robot (W1) is dedicated to the unloading of finished products and interacts with the mobile ground robots for that purpose. The other production robots can perform one or several operations on products, and have an inventory of raw components loaded by the mobile ground robots, which can reload the inventory on human supervisor request.

As introduced, each production robot emits a potential field (cf. Fig. 3b), and its amplitude increases or decreases according to the products waiting in its queue. The more production robots are overloaded by shuttles waiting in a queue and/or the more they are slow to perform the operations they can handle, the less they are attracting new shuttles, especially if the shuttles are far from the production robots (cf.



(a) (b) (c)

Fig. 2 Work position to control the intelligent manufacturing system (**a**), the flexible cell (**b**), and loaded and unloaded by ground robots (**c**)



(a) (b)

Fig. 3 The real Flexible manufacturing system, UPHF, Valenciennes, France (AIP-PRIMECA FMS) (**a**), and its emulator (**b**): flexible cell (production robots, conveyors) including an example of potential fields emitted by the production robots in blue circle

Fig. 3b). However, the human supervisor can also modify the amplitude and the emitted field to improve or reduce attraction of shuttles by robots according to his/her perception of the current or future IMS performance.

The mobile ground robots have two levels of automation for motion, autonomous, or remotely controlled. They have four sensors: ultrasound feedback, gyroscope, contact, video (smartphone), and three actuators: motor of the head (ultrasound) and two motors for motion control. They also have communication supports with Wi-Fi (smartphone), ZigBee, and Bluetooth technology.

3.2.2 Control task analysis

Control task analysis concerns the "Formalization of constraints linked to what must be done to reach system goals". The objective of ConTA is to identify goals and activities (physical and cognitive processes) involved for achieving a system's purpose. Using the Rasmussen's Decision Ladder (DL) tool, ConTa models activities that could be carried out by artificial or human resources. Naikar, Moylan and Pearce (2006) suggested characterizing these activities as a set of work functions, which are related to the purpose-related functions level of WDA. Each work functions may be performed in different work situations. The contextual activity was analyzed according to *temporal* and *spatial* dimensions.

The tactical and operational levels were analyzed to define the global organization of the activity. The tactical level tackles the manufacturing plan and the mission plan of the mobile ground robots according to the objectives provided by the strategic level. It aims to control and update the plans previously prepared and launched according to unexpected events, like machine breakdown, human overload, or new objectives, like new type of product. The operational level addresses the trajectories of the shuttles and the mobile ground robots in normal functioning mode and according to unforeseen events such as obstacles for the mobile robots, problem with the human supervisor interaction, or problem with the production robots of the flexible cell. Therefore, critical events and internal/external conditions define and update the contextual activity as proposed by Rauffet, Chauvin, Morel, and Berruet (2015).

The spatial dimension of the contextual activity relates to the complexity of the plan area. The more the IMS is wide and complex, the more the analysis of the spatial representation of the overall system may be difficult for human supervisor, due to his/her attention increasingly split between several areas and screens.

Therefore, the work functions were defined to take into account these contextual activities. The work functions address the control of global process states (long- and mid-term activities), the control of the flexible cell, i.e., the shuttles, the production, and mobile ground robots at the

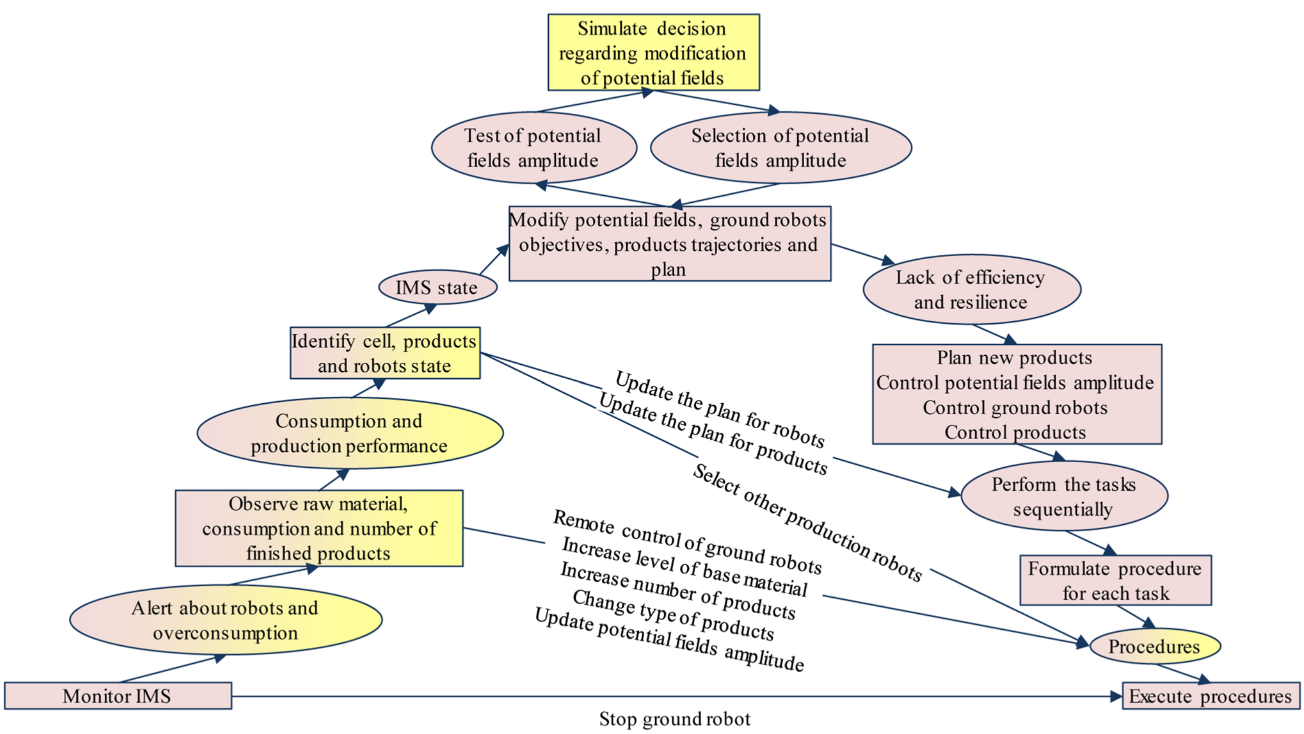


Fig. 4 Decision ladder for functions relevant to the human supervisor only (pink), the human supervisor and technical agents (pink and yellow), and technical agents only (yellow)

short-term activity. The decision ladder presented in Fig. 4 gathers all work functions. Fig. 4 presents the different functions that the human supervisor and/or the assistance systems have to complete to reach the objectives of the IMS. For convenience, colors have been applied on the decision ladder, as it would be done during the SOCA phase.

The interfaces (cf. Fig. 5) have been designed to show short-term activities gathered in the center of the operator's field of view and longer termed activities are on sides, which is planned to be more ergonomic for operators. It is to note that the interface for the IMS and the mobile ground robots are independent due to the legacy design of the ground robots' controls. The only exception being the task planning interface due to the externalization of this functionality. The IMS interface as well as the planning interface are designed following the information extracted from the CWA, such as Abstract Value related to the task, actors involved, required interactions, and such. Ecological interface guidelines (Burns and Hajdukiewicz 2004; Rasmussen and Vicente 1989) have been considered when rendering the extracted information, but further works using human–computer interfaces methods could also be used to improve the interfaces. However, that was not the main objective of our study despite the fact that interfaces play an important role in the operator understanding and trust.

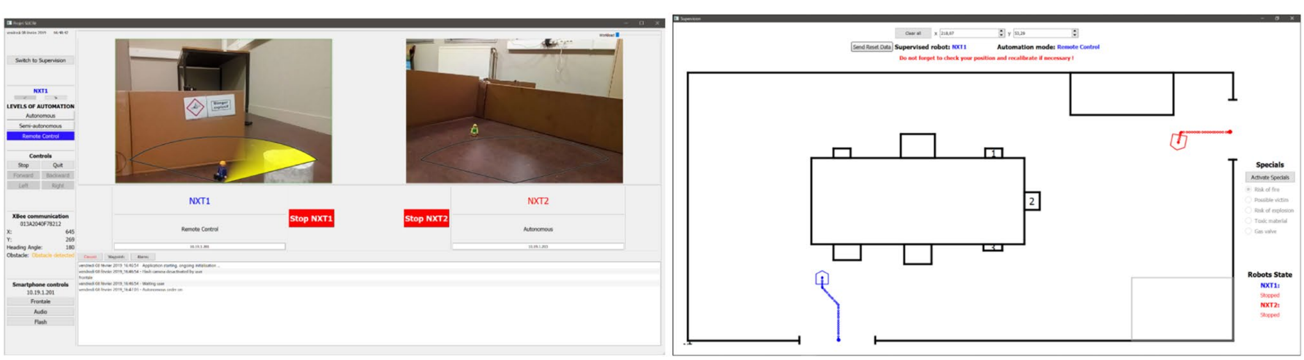
Mobile ground mobile robots alert the human supervisor when they have to stop because of an unexpected obstacle through the interface dedicated to the operational level [cf. Fig. 5(a)]. However, the human supervisor can anticipate such a problem if he/she has the time to perceive it using the video feedback of each robot. He/she can use the interface dedicated to the tactical level to analyze robots' trajectories and decide new targets [cf. Fig. 5b].

A decision support system (DSS) provides information to supervise and control the flexible cell at the two decisional levels. The DSS provides a synthesis about four types of information from the operational level (based on Abstract Values) for the last 2 min through bar graphs situated close to the synoptic of each production robot [cf. Fig. 6a: from left to right]:

- the efficiency of production robot (time spent per product, idle time, and breakdown),
- the quantity of supply (raw material),
- the energy consumption,
- the number of operations that have been done.

Based on this information, at the operational level, the human supervisor can modify the amplitude of the maximum field value emitted by a production robot thank to a slider (on the left of bar graphs), and/or modify the target robot of a shuttle by choosing another production robot using buttons (cf. Fig. 6b). This can be interpreted as either influencing the decisional process of the artificial entities (rule or knowledge-based) or either bypassing this process (skill-based), such as operators have authority over the artificial entities' final decision.

The DSS also provides, at the tactical level, information about the instantaneous consumption of all production robots, as well as the total consumption since the start of the production (cf. Fig. 7a). As operators are evaluated depending on the consumption in our scenario, that information is important for the operator to self-evaluate. At this level, a digital twin of the cell (here, of the emulator of the cell) is also proposed. This digital twin enables the fast simulation of the cell activity from its current state, i.e., the production robot activity and the shuttles motion on the conveyors, initiated using the real-time amplitude of the potential fields of each production robot or new amplitudes given by the human supervisor (cf. Fig. 7b). The DSS has the capability to conduct this simulation (highest box on Fig. 4), because it embeds an emulator of the cell (in our experiments, a copy of the introduced emulator of the cell) and the same algorithm as the one used by the shuttles and can accelerate the



(a) (b)

Fig. 5 The Human–Mobile ground robots' interface: (**a**) video feedback, controls, and alerts; (**b**) birds' view of the flexible cell and robots' trajectories

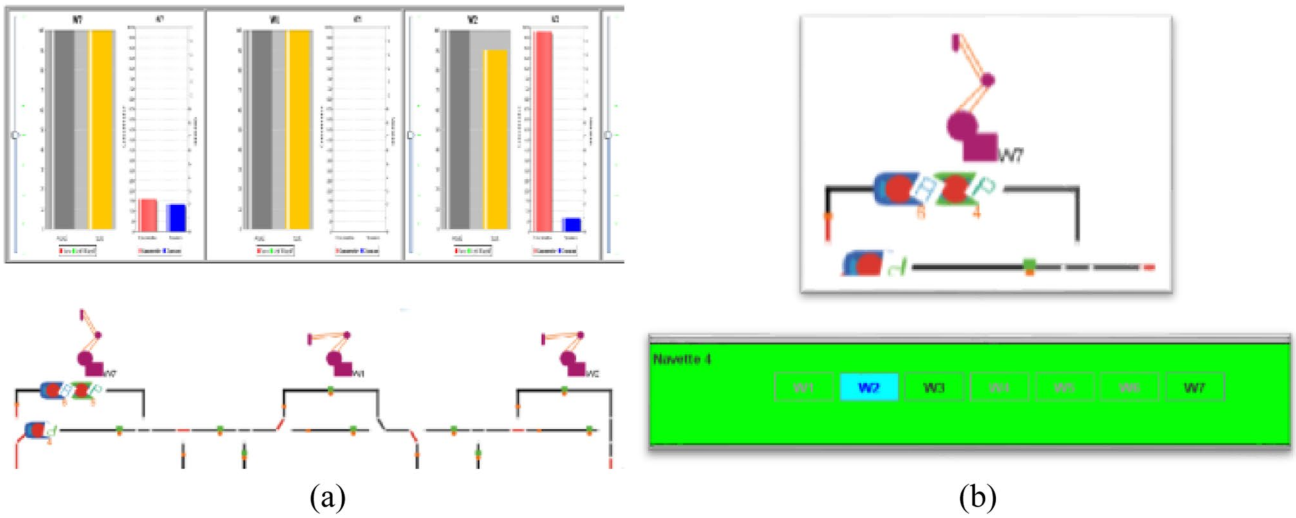


Fig. 6 Information from the operational level in the DSS: (**a**) bar graphs for each production robot; (**b**) remote control of shuttles by selecting the target production robot

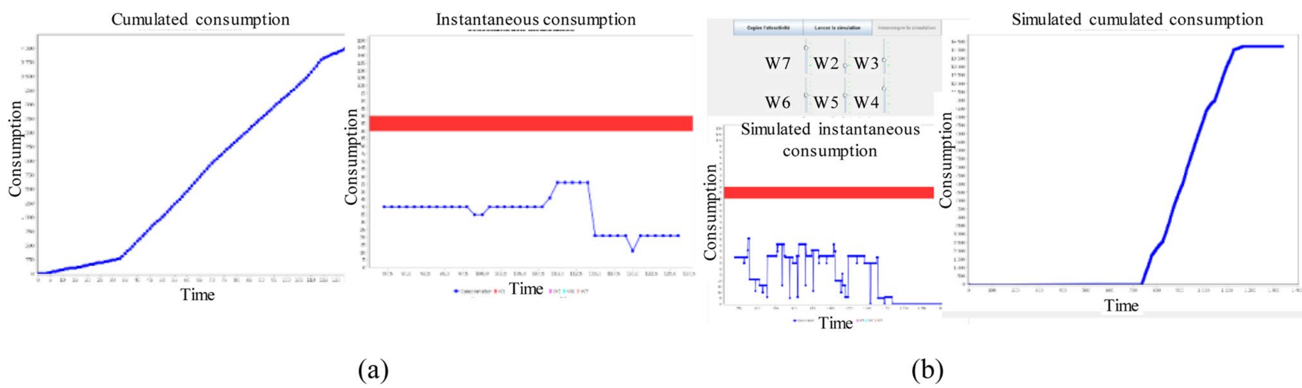


Fig. 7 Element of the DSS relevant to the tactical level: (**a**) cumulative and instantaneous consumptions; (**b**) simulation of consumption according to new amplitudes for each production robot's potential field

simulation process. The consumption graphics produced use the same design as the real-time ones to ease the comparison. The technical description of the digital twin is beyond the scope of this paper, but it enables the human supervisor to test, using the emulator and, from the current state of the cell, different decisional strategies and their impact on the future on a short time window in terms of production and energy indicators. In view of the complexity of the system, this task would be near impossible without technological assistance, whereas being an important function of operators' activities. The technical developments of the emulator and the digital twin of the cell used are described in (Berger et al. 2015) (Fig. 8).

The human supervisor has also to plan the mission of each ground robot and the products sequencing. The human supervisor prepares the mission of each ground robot using of a list of tasks (supply of production robots and download of finished products). A list of the on-going tasks informs about the past states and the current state of the ground robots (cf. Fig. 10a). Fig. 10b depicts the tools to select products according to their operations and the objectives of production (number of products), to add the products in a list (Planned products) that will be launched when the human supervisor makes the decision (green button "Plan"), and to control the on-going products.

To help the human supervisor to manage the products sequencing according to the algorithm used by the IMS, the DSS provides indicators to support the modification of the potential fields' amplitude. Therefore, the HMI presented in Fig. 9 underlines the load according to the possible operations of robots. For each operation, it provides the list of production robots that can complete the operation and if one breaks down. A score for each production robot (one color per robot) has been calculated according to the robot

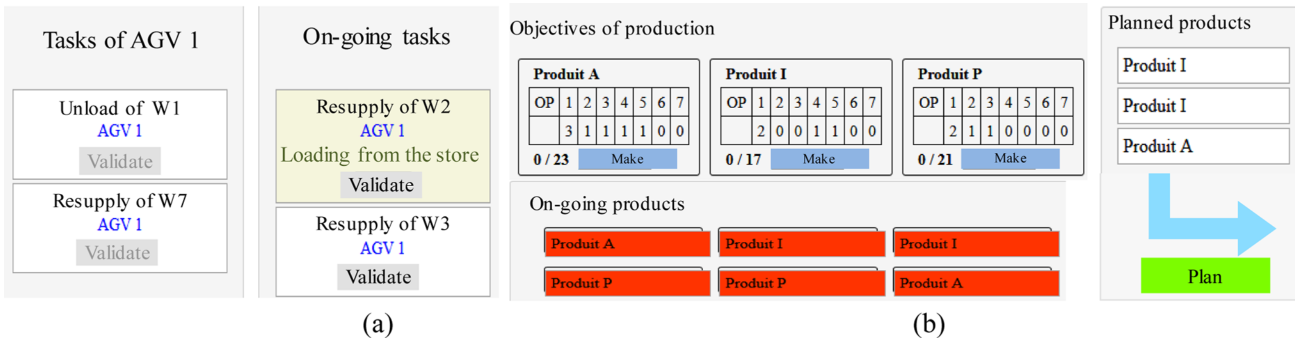
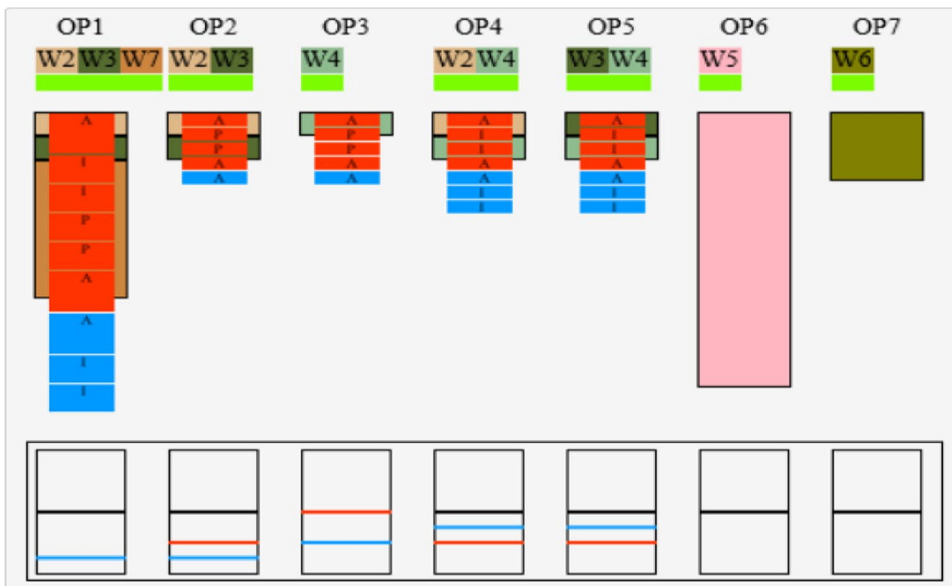


Fig. 8 Planning activities in the DSS: (**a**) the ground robots and (**b**) the products

Fig. 9 Product sequencing: the DSS view



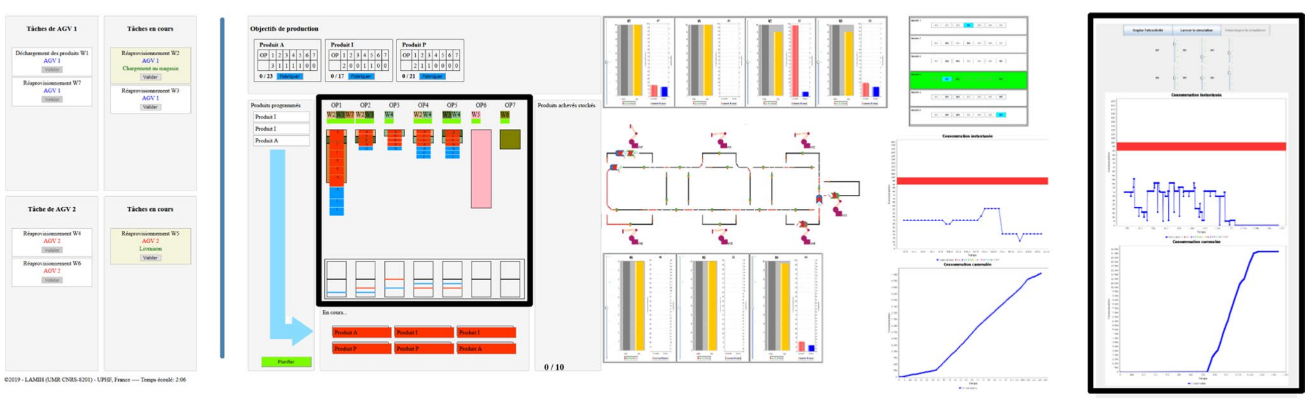


Fig. 10 The production and logistic sequencing screen as seen by the human supervisor, with assistance (with the black square and rectangle) and without assistance (without the black square and rectangle)

speed to complete an operation and the number of operations which it can complete (colored rectangles behind products). The on-going products are in red and the products queued on the production robots are in blue. A score for each product has also been calculated according to the requirements of the product in terms of operations (size of product rectangles).

For example, a product that has a high score and is on a production robot that has a low score would monopolize the robot for a long time. The lower part of the Fig. 9 provides information about the equilibrium between the capacities of production regarding the production demand (black line).

To summarize what is seen by the human supervisor, the Fig. 10 contains the human supervisor's view when the DSS is available (highlighted by the black scare and rectangle), or when the DSS is not used (without the black scare and rectangle).

3.2.3 Social organization and cooperation analysis

This step can be performed according to the abstraction hierarchy, i.e., according to all the previous phases already fulfilled. Therefore, a synthesis is provided through an abstraction hierarchy, as presented in Fig. 11. The identification of the agent who can perform the purpose-related functions and the object-related functions has been made using of color, pink for the human agent and yellow for technical agents. The abstraction hierarchy highlights that only human can perform some purpose-related functions, but only the technical agent can perform associated object-related functions (line between functions). Nevertheless, the authority and the responsibility of these functions allocated to technical agents remains to human.

This abstraction hierarchy, and especially the links between the functions, supports the completeness and the coherence of the analysis.

All these functions and objects have been designed and implemented in the IMS, but only a part of them have been used as independent variables and controlled by the experimenters. The "Supervise and control of the self-organized system" purpose-related function was the function that was supported or not by a DSS. This function plays the role of the independent variable, as detailed in the following part describing the experimental protocol and the first results.

4 Experiment and first results

4.1 Experimental protocol

4.1.1 Participants

The initial set of participants who attended the experiment included 23 students, 2 women and 21 man. After exclusion of burned data, the final dataset was narrowed down to 21 students with 2 women and 19 men. Age of participants lies between 20 and 23 years. Eight students (down to 7) are from robotics and the other 16 students (down to 14) from supervisory control engineering. Participants were split evenly into two groups for the sake of the experiment.

Participants were questioned about their prior experience with remote controlled vehicles, production cells in general, and strategy/management games as three separate questions. After testing of the answer, no significant differences were found between the two groups regarding their experience, as well as their age and gender. However, prior experience of participants within groups show a strong variability, except for experience on production cells.

4.1.2 Scenarios

All subjects are faced with a production plan, including three different product types of orders. In the experiment, three

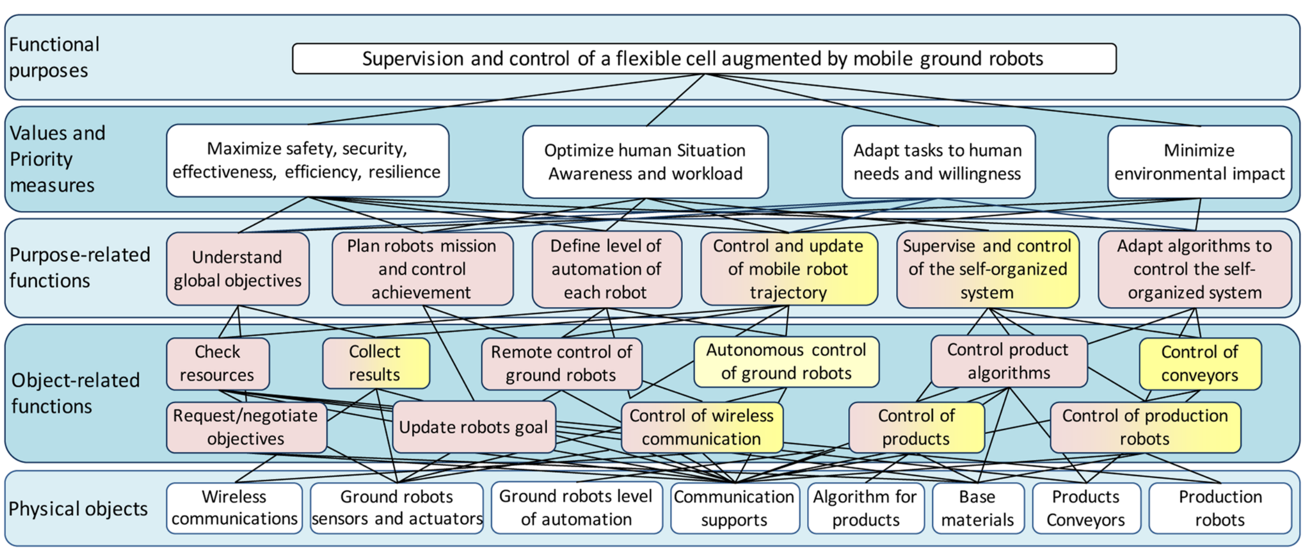


Fig. 11 Social Organization and Cooperation Analysis/Abstraction Hierarchy

product types are labeled '*L*', '*T*', and '*I*'. They require different sets of operation, with some similarities (cf. Table 1). Operations are registered as numbers from 1 to 7 and the same operation can be requested multiple times for a single product type. The products are designed, so 'L' and 'I' are similar, but generate different workload for robots (cf. Table 2). 'T' requires in addition an exclusive operation that requires more time and can be processed by only one specific robot. The requested quantities to produce have been set as follows (production plan): 5 products 'L', 4 products 'T', and 6 products 'I'.

Participants are tasked with the completion of the production plan, and requested to maintain the overall power consumption below a limit. Each production robot is designed to consume one unit of raw material per operation performed (except when W1 loads a new product). However, the stock of raw materials is different between the production robots (cf. Table 2).

The participants faced an automated perturbation scenario (cf. Table 3), whose events were triggered according to a timer. A first perturbation occurs after 3 min of operation, and the energy consumption limit progressively decreases to 65% of its original value over a 45 s timeframe. A second perturbation concerns a production robot breakdown occurring after 5 min of operation, on a moderately important production robot. The robot is brought back available after 3 min of idle time. The third and last perturbation is the increase of the consumption limit to 80% after an additional minute.

4.1.3 Experimental conditions

The two evenly distributed groups have access to a different interface to evaluate the provided help of the DSS. One group has access to the DSS, composed by the digital twin and the production planning helper, while the other does not.

The workload and scenarios remain the same among all the participants. However, a set of procedures adapted to their group and written on paper are made accessible to the participants to help them if they feel lost. These procedures are general in the direction offered not to limit the participants in their decision-making. The situations covered by the procedures are: incident-free supervision, machine breakdown, overconsumption, planned machine interruption, and unexpected behavior.

4.2 Procedures

Participants are welcomed with a 30 min detailed presentation of our system. The presentation is done on a slide show and the participants are free to progress at his/her rhythm and to ask questions to the experiment team to have

Table 1 Products to make during the experiment, and the number and the type of operations they require

Product	Operation 1	Operation 2	Operation 3	Operation 4	Operation 5	Operation 6	Operation 7
L	3	0	0	2	2	0	0
T	2	1	1	0	0	0	0
I	2	0	0	1	1	0	0

Table 2 Available operations per robots and associated processing time with total consumption to perform the operation. Include the amount of storable raw material per machine

Production robot	Operations	Time (s)	Total consumption	Max storage
W1	Loading; unloading	10; 10	100; 100	8
W2	1; 2; 4	20; 20; 20	500; 250; 475	20
W3	2; 5	20; 20	250; 100	25
W4	3; 4; 5	20; 20; 20	450; 300; 100	30
W5	6; 1	5; 20	500; 375	25
W6	7; 4	20; 15	500; 450	25
W7	1	10	500	9999

Table 3 Timeline of events during the experiment

T(s)	0	180 s	195 s	210 s	225 s
Event	Start of experiment	Consumption limit: 90%	Consumption limit: 80%	Consumption limit: 70%	Consumption limit: 65%
T(s)	300 s	420 s	480 s	600 s	780 s
Event	W3 breakdown	W3 repaired & online	Consumption limit: 80%	Production deadline	End of experiment

a thorough understanding of both the system and what we expect from the participants. During the presentation, the participant is introduced to the score system and its main factors: accomplishment of production plan, consumption, overconsumption, and efficiency bonus. Some factors remain hidden from the participants such as the perturbations. The participants are informed that the score will be used by their advisor to grand bonuses on one of their grades as a motivation reward. For the same purpose, participants are asked if they accept to be part of a ranking system, those results are shared among the participants.

The participant is then presented to the supervision workstation and gets a summary of the major elements in a few minutes. After the presentation, the participant is offered a 15 min trial of the system, assisted by the experiment team to ensure a correct training. The experiment team enables the participant to use all functionalities of the system and presents the major troubles that may happen, while making sure not to give any clues about the scenario. The products used for the training scenario are different of those from the experiment and no perturbations are used. The participants may adopt strategies to organize themselves and be able to face all the functions they have to supervise, allocate, and/or control. Then, they have:

- to supervise the overall IMS to check robots' state, consumption, and production,
- to use the DSS, to simulate new potential fields amplitudes, and improve the self-organization of the products,
- to manage overconsumption by decreasing the potential fields amplitude of high consuming production robots, as well as by postponing the manufacturing of the products requesting such production robots,
- to manage production robot breakdowns by re-planning the production with an adapted selection of the products regarding these robots.

After the training, the experiment team gets the system ready for the scenario and asks the participants to get ready for the experiment. Once the participants state their readiness, the experiment team gives the start signal while simultaneously starting the 10 min experiment. The experiment team stays out of the direct line of sight of the participants not to cause any accidental perturbations (while taking notes, for example). However, the experiment team has a direct view on the participants as well as multiple video feedback to monitor the well execution of the simulation.

In case of troubles, the participant is allowed to ask questions to the experiment team (and is encouraged to if any out-of-scope problem is detected). The experiment team is only allowed to provide basic answers not to influence the participant. These answers include basic system's functionality, to repeat an already presented information and troubleshooting information in the only case of suspected technical issue during the experiment. In case of technical issue, the experimental team can try to remotely solve the problem using exclusives controls, or may access remotely the digital twin to simulate part of the function of the system to ensure the continuity of the experiment.

Once the 10 min are elapsed, the system is let loose during 3 min to check if some products are about to be delivered. This is mainly due to the fact achieved products may take time to reach the unloading workstation and many of them were delivered shortly after the 10 min limit in the pre-experiment testing. During those 3 additional minutes, only the additional products achieved are taken in consideration with a penalty for late delivery. Once the 3 additional minutes elapsed, the experiment is halted and considered done. The participant receives a provisional score based on raw production data and then is requested to answer questions to evaluate the system.

4.2.1 Measures

The first set of questions is focused on knowledge about the system. The participant is requested to provide in decreasing order of the three top production robots corresponding to the different questions that are: what are the most effective production robots, the most efficient production robots, the production robots with highest pressure (time spent processing vs idle time), the production robots with highest operation count, and the production robots with fastest materials consumption. The results are used to assessing the knowledge built by the participants about the system. Then, questions are asked about any prior experience with similar systems and other generic information about the population (age, gender, etc.).

The second set of questions is targeted to the participants' perception of the intelligence of the cell implemented here through smart shuttles. All questions are answered on a scale from 1 (not at all) to 7 (totally). The part one is about the understanding by the participant of smart shuttles' ability, to perceive and analyze the IMS situation, to make decision, and to implement actions. The second part focuses on the participant understanding of the smart shuttles' cooperative ability to obtain information about the smart shuttles, the detection of conflicts with smart shuttles decision-making, the management of those conflicts, and the feeling of control over the smart shuttles.

The third part is how the participant understands the ability of the smart shuttles to perceive the human supervisor activity. Therefore, questions are asked about the evaluation of the smart shuttles' perception of the human supervisor's ability to cooperate on conflict detection and management, and authority management.

The last set of questions collects feedbacks of the participants about the experiment on a scale from 1 (low/poor) to 10 (high/good). Questions are about the complexity of the environment, if they received enough training, and if they used all the information provided on the interface. Finally, the participants are offered the opportunity to express themselves freely during a debriefing and on paper about their feeling, idea, and such related to the system.

In addition, data related to production such as robot consumption and material delivery are recorded to provide the ability to evaluate quality of the production afterward. The participants' interactions are also recorded alongside with multiple miscellaneous logs to be able to reproduce the chain of event and evaluate the use of the interface. In complement, a recording of the experiment team's screen is also saved to provide more insight about the experiment on-going.

4.3 First results

Several measures were done, but only one part of the results is presented in this paper; they are the results that may help to analyze the impact of the method in the design of the human–IMS cooperation. Those results are mainly stemming from qualitative data, i.e., the comments during the debriefing. The objective data, like the energy consumption and the number of finished products, do not provide significant results to distinguish the groups with and without the DSS. However, a deeper analysis of the participants' tasks provides interesting and significant results now presented.

4.3.1 Debriefing

This part presents the results stemming from the analysis of the short report provided by the participants according to their perception of the overall experiment, as well as how they felt the supervision and the control of the IMS, the DSS, the positive and negative aspects, and their recommendations to improve the activities. Such a report might be considered as a debriefing done with the experimenters, but they did not impose any constraints to structure it. The analysis of those reports was organized according to five main parts underlined by the participants: the role of the human supervisor, the smart shuttles, the mobile ground robots, the static production robots, and the DSS.

Regarding the role of the human supervisor, the participants wrote that they were focusing on the tasks at the operational level, so that was difficult to benefit from the DSS of the tactical level. However, they also precise that it is perhaps due to a lack of training on the process and the DSS, especially to organize their activity. For example, after their first experience with the IMS, they would have liked spending more time to prepare the planning of the tasks (for mobile robots and smart shuttles), instead of quickly launching the production.

Regarding the smart shuttles, the participants noted that the shuttles have a bad perception of their environment, especially the production robots that can perform the operations they require. Therefore, they have to remotely control the products and then focus on the operational level. They propose increasing the cooperation between the smart shuttles and the production robots to improve the products self-organization, because it might help the human supervisors to focus their attention on other parts of the IMS. However, the participants request more information about products directly on the flexible cell view, such as the next production robot and the time to reach this robot.

Regarding the mobile ground robots, the participants feel that there are completely dissociated from the flexible cell. They propose implementing cooperation between the mobile ground robots and the static production robots. The production robots may alert the ground robots about their low level of inventory, and for the W1 to alert about the high level of finished products.

Regarding the static production robots, the participants wait for more information, especially the operations they can perform directly on the flexible cell view, and the time to complete an operation or to finish a product.

Regarding the DSS, the participants precise that it was difficult to split their attention between the four screens, and so to benefit from the DSS. They also underline that it is perhaps due to a lack of homogeneity of the information between the several views. The DSS gathering the score of products and production robots per operation may be presented in another way, for example operations and products per production robots. Finally, they would like more coherence and shared activities between the levels of activity, and then more autonomy at the operational level but more advices and alerts at the tactical level.

4.3.2 Objective results

Only few parts of the objective results are presented and they focus on the plan of products performed by the participants. The analysis underlines a difference between the group using the DSS and the other. The different combinations of products type will be referred as pattern and focus on the quantities of each product type within a batch rather than the order. The comparison between the group of participants was made using the pattern among the six first-loaded products (1st batch), corresponding to the initial loading of the six smart shuttles, as well as among the next 6 products (2nd batch) (cf. Table 4). For the 1st batch, the group without DSS opted in majority for two products of each type (54.55%), while the group with DSS is split among multiple patterns. The 2nd batch shows more variable patterns, probably more affected

Table 4 Patterns of product for the 2 first batches of 6 products loaded onto the flexible cell

First	Without DSS, 1st batch		With DSS, 1st batch		Without DSS, 2nd batch		With DSS, 2nd batch	
	2 L; 2 T; 2 I	54.55%	2 L; 2 T; 2 I	16.67%	2 L; 2 T; 2 I	27.27%	1 L; 2 T; 3 I	33.33%
Second	3 L; 2 T; 1 I	9.09%	3 L; 2 T; 1 I	16.67%	1 L; 3 T; 2 I	18.18%	2 L; 3 T; 1 I	16.67%
Third	5 L; 1 T; 0 I	9.09%	1 L; 3 T; 2 I	16.67%	3 L; 1 T; 2 I	18.18%	2 L; 1 T; 3 I	16.67%

The pattern is described by the letter associated with the product type and the associated quantity, while the second column gives the percentage of participant who chose the pattern

by the perceived situation by the participant. However, the group without DSS still shows that a higher number of participants plan 2 products of each type (27.27%) than the group with DSS (8.33%). Therefore, the DSS seems to diversify the participants' strategies.

5 Discussion

From the comments provided by the participants and the objective results, it is worth noting that the participants suggested, from our perspective, to increase the intelligence of the IMS to ease their supervisory tasks. This result militates toward the development of more autonomous, cooperative, and not only purely reactive decisional entities in IMS. In its state, the low intelligence level of the IMS, despite its sufficiency to generate emerging behavior to face unexpected situations, is not adapted to the presence of a human supervisor in the loop. The IMS presented in this paper has been designed with the support of the formative CWA method, but an important part has to be imagined thank to the innovation of designers. Indeed, CWA is used to thinking about the limits within the system will work, not about exactly how the interactions will occur. The method provides the main information and functions that the process has to manage, but the human–machine interface (HMI) must be innovative, especially when the proposed system is a new one, as well as ecological (Burns and Hajdukiewicz 2004; Rasmussen and Vicente 1989). Therefore, the positive and negative results provided by the experiments might be due to incomplete use of the method, lack in the method, or problems in the HMI design or in the experiments. The following paragraphs address the three aspects.

The SOCA phase of the CWA method enables to determine the possibilities for work allocation, distribution, and social organization in a system (Stanton et al. 2017; Walker et al. 2014), in our study of an IMS. We applied this phase to the Work Domain Analysis, to determine which system functions are allocated to human and technical agents (SOCA-WDA Fig. 11). We also applied this phase to the Control Task Analysis to specify the allocation of functions that the human supervisor and/or the assistance systems have to complete to reach the objectives of the IMS (SOCA-DL Fig. 4). Our application of the CWA method remains limited to a "static" approach. Cooperation in dynamic and uncertain environments requires a dynamic adaptation of the distribution of functions and coordination between cooperative agents. It is necessary to allocate these functions temporally and spatially, and to define different strategies and conditions for implementing these situated functions. The lack of precise strategies certainly leads to the various patterns adopted by the participants with the DSS. The SOCA phase could be applied in a more dynamic perspective by the deployment of representation tools associated with the CWA method such as the Contextual Activity Template (SOCA-CAT) or the Information Flow Map (SOCA-IFM). This extension of the CWA could enable to define the modes or strategies of cooperation adapted to the situations (Rauffet et al. 2015).

Furthermore, in our application, CWA seems to be a little too evasive to analyze all the possible interactions between the potential agents. Indeed, the participants put forward the relevance of increasing the autonomy of the technical agents, and especially the cooperation between all the technical agents, to prevent the human supervisor to have to spend time to manage tasks at the operational level at the expense of the tactical level. The tasks of the operational level, like giving a new direction to a shuttle, or to control a ground robot remotely, capture the participants' attention on the short-term loop without leaving time to manage planning tasks. More cooperation between the smart shuttles and the production robots, i.e., a cooperation not only based on the potential fields while taking into account other indicators, might improve the efficiency and the human supervisor awareness. The shuttles could have other strategies to select production robot, strategies displayed to the human supervisor. In the IMS, there was no interaction designed between the production robots and the mobile ground robots. The human supervisor had to give order to the mobile robots to reach a production robot that requires to be supplied and the W1 robot to be unloaded of finished products. Such orders can be easily automated if the production robots send a precise request to the mobile robots that can design a common plan according to their current task and position, and priority assigned to each production robots. The mobile robots' decision-making could be displayed to support the human supervisor awareness. Therefore, the increase of cooperation between the technical agents may improve the efficiency and prevent the human supervisors to waste time at the operational level. However, their situation awareness must be supported by more coherence between the several screens through the technical agents' cooperative activities, and their decision-making supported by a DSS able to propose solutions and not only indicators. The digital twin of the cell presented in this IMS could be extended to take into account mobile robots and new cooperative activities. With such a digital twin, solutions, suggested by experts or learned from human supervisors, might be implemented to train and support new human supervisors, or to help less-qualified human supervisors. The adaptability of a DSS to human competence and needs tackles the IMS flexibility at the organization level.

The Human–Machine Cooperation (HMC) approach may help to support the design and the evaluation of Human–IMS Cooperation and might answer to the demands of the participants for more cooperation between all the agents. Indeed, in the HMC principles, a model of cooperative agent, human or technical, has been specified to support the design of cooperative interaction. A cooperative agent has two competences, the "Know-How", the "Know-How-to-Cooperate" (Hoc and Lemoine 1998). The Know-How (KH) of an agent focuses on the control of a process or an environment, and not the interaction with other agents. The KH relates agents' problem-solving processing, i.e., their competences and capacity to control a process. The more complex a process is, the more an agent needs competence (or procedure) to control it. The more complicated a process is, the more agents require training and practice to control it, while managing their capacity (e.g. workload). The KH also relates the ability to access the process information and the ability to act on this process. The identification of the KH of each agent in the control of a process helps the designer to identify type of data, functions, and sub-functions that can be shared or traded between those agents. The Know-How-to-Cooperate (KHC) allows one agent to take advantage of the complementary KH of other agents. The KHC allows agent to build up a model of other agents to facilitate the cooperation with them. This model allows them to be aware of the other actors' concerns, expectations, and intentions (Schmidt 2002). Working, training, and interact with others enable the development of such a model. Agents progressively identified, memorized, and used KH and KHC of other agents to achieve cooperative activities. A Common Work Space, materialized by HMI, is a combination of a representation of a process and a representation of each agent's KH and KHC, and it supports those cooperative activities (Pacaux-Lemoine and Debernard 2007). Therefore, when the CWA method proposes to analyze the functions to be achieved and at the end of the method the identification of workers' competences, the HMC approach uses the opposite direction by identifying at first the current or future competences of agents, i.e., their KH and KHC. When designers reach to have a detailed description of those competences, they can combine them to extract the shared or traded functions that answer to the process objectives. In the use case previously presented, designers would have studied the KH and KHC of all the agents involved in the control of the IMS, i.e., the human supervisor and the three types of technical agents, the shuttles, the production robots, and the mobile ground robots. The HMC approach proposes using grids to conduct the analysis (Pacaux-Lemoine, Simon, and Popieul 2015). In this use case, six grids would have been used to analyzing cooperation: human supervisor vs. shuttles, production and mobiles robots; shuttles vs. production and mobile robots; production robots vs. mobile robots. The shared or traded functions, as well as individual functions, are identified and displayed on the Common Work Space to support the communication and negotiation.

However, the HMC approach focuses on functions that can be shared between human and technical agents, and usually deals with sub-parts of the process and specific categories of workers. Moreover, there is no way to cross various points of view about the process to check and improve models and system design, except with experiments. Therefore, CWA method and HMC approach are complementary. CWA and HMC could be conducted in parallel and/or bridges could be built to connect some aspects of both methods. For example, from CHM to CWA, the Work Domain Analysis would be enriched by criteria about the quality of cooperation between agents, cooperative functions, and supports for cooperation with dedicated HMI-based, i.e., Common Work Space. The strategies analysis would be enriched by strategies for task allocation as proposed by Rauffet et al. (2015). The SOCA and the Workers Competences Analysis would be detailed through the grids previously mentioned and enriched by the human supervisor's KHC and the technical agents' HK and KHC. From CWA to HMC, all functions stemming from the CWA method would be crossed with functions identified with HMC to check the coherence and completeness.

The last part of the discussion concerns the participants' answers to questionnaires and comments regarding the shortcomings in the training. It is due to the complexity of the process and/or the DSS, but it was not perceived in the same way by all the participants. The participants who were not used to working on production cells agreed the shuttles' actions, though they were enough trained and found the HMI useful. In the experiment protocol, it would have been interesting to test the training level of the participants to improve the training or to adapt the IMS. Flexibility and adaptability are ones of main objectives of Industry 4.0 with a continuous adaptation of the work according to the physical, sensory, and cognitive abilities of the workers. Human factors' characteristics and models were already studied [e.g., (Grosse et al. 2017; Oborski 2004)] to conduct such an adaptation. Therefore, more training can be provided and an evaluation can be done to control if a requested level is reached. However, another way to proceed would be to use the evaluation, or knowledge an industry has about its employees, to adapt the IMS functioning to human competences. A graduated adaptation could be performed and controlled by defining the levels of automation of the IMS (Dencker et al. 2009; Frohm et al. 2008; Lindström and Winroth 2010; Säfsten, Winroth, and Stahre 2007). However, how to manage the balance between a high level of automation of an IMS and human competences? Industry 4.0 deals with an increase in human competences, but what happens if enough trained and competent workers are not available? Is it possible to compensate lack of human competence with robust and efficient IMS? Nevertheless, in this case, workers might be less competent than the IMS, and so the IMS might have more authority? Is it an ethical possibility, especially if workers are still responsible? The right balance between, ability, authority, and responsibility must be found (Flemisch et al. 2012). Studies carried out on Human–Machine Cooperation, on Shared, Traded, and supervisory control may give some answers to those questions (Flemisch et al. 2019). Moreover, regarding the organizational level, some answers may be given by the study of cooperation between the decisional levels (Pacaux-Lemoine and Flemisch 2018).

6 Conclusion and perspective

This paper evaluated the Cognitive Work Analysis methodology, and its applicability when designing an assistance system to support Human in the control of Intelligent Manufacturing System in Industry 4.0. The evaluation of the methodology through the one of the Designed Support System was done using a micro-world, an intelligent manufacturing system composed of intelligent mobile ground robots, products, and static production robots interacting together and with a human supervisor in charge of the reaching of several time-based and energy-based performances indicators. Twenty-three participants took part in experiments to evaluate the DSS and the interactions between the human supervisor and the technical agents. In the current state of the analysis, the scope of the evaluation of the DSS usefulness is reduced and other analyses will be deepened soon. However, several interesting comments and results from answers to questionnaires put forward the need to increase the autonomy of the technical agents of the operational level. The participants require more cooperation between those agents.

This result points the methodological aspects out. Indeed, even if the Cognitive Work Analysis would have deepened the analysis of the strategies for task allocation, this method could benefit from the method initiated by the Human–Machine Cooperation approach. The continuation of our work will include studies of the possible combination of both methods, as well as further experiment to strengthen our results and refine the system used as demonstrator.

Acknowledgements The research presented in this paper is carried out in the context of the HUMANISM N° ANR-17-CE10-0009 research program, funded by the ANR ''Agence Nationale de la Recherche''. The authors gratefully acknowledge these institutions.

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