Toward production operator 4.0: modelling Human-Machine Cooperation in Industry 4.0 with Cognitive Work Analysis

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Abstract: The integration of Industry 4.0 technologies must consider the place of the operator in the production. In this paper, we adopt a human-machine cooperation perspective for modelling operator 4.0 in industrial systems. Our approach is supported by Cognitive Work Analysis (CWA) method. We used three phases of the CWA: Work Domain Analysis (WDA), Control Task Analysis (ConTA), and Social Organization and Cooperation Analysis (SOCA), to model the functional and cognitive constraints as well as the function allocation. The paper especially uses two modeling tools – Abstraction Hierarchy and Decision Ladder – that could support the positioning and the design of Technology 4.0-based assistance systems. This model is applied to the specific activity of orders picking. This activity integrates both function of planning and organization of the different production lots and these functions can be shared between order picker 4.0 and specific Industry 4.0 technologies.

Keywords: Human-Machine cooperation, Cognitive Work Analysis, Decision Ladder, Picking.

1 INTRODUCTION

Industry 4.0 is characterized by technological revolutions that offers increased capabilities for cyber-physical systems of production (Rüssman et al., 2015). With the implementation of these digital revolutions in Industry, new questions are raised on the place of human operators in these systems. Fantini et al. (2018) address some challenges for the design and evaluation of future work:

- to better understand cooperation between human operators and these new technologies;
- to gain insight about the contribution of human activity in the analysis and problem solving for usual and new situations, considering human skills and knowledge.

For Fantini et al. (2018), the human integration within cyber-physical production systems need to characterise activities from four perspectives (abstraction, decision-making, innovativeness and social interaction). Based on digital revolutions of Industry 4.0, some authors emphasize on the idea that these technologies are means for improving human capabilities. For example, Romero et al. (2016) built on a typology of operator 4.0 considering these augmentations from physical and cognitive interactions between human and technologies (e.g. super-strength operator, analytical operator, etc.). From this work, the technologies for industry 4.0 can be grouped into four categories (Tech 1 to Tech 4, respectively coloured in blue, orange, green and purple in table 1 as well in the following figures), according to their impact on information processing or implementation of the action (Rauffet et al., 2018). Processes of information gathering, analysis, planning and decision-making or task executing can be supported by these four categories of technologies. Sensor technologies (Tech 1) can dynamically collect raw information related to various resources of the industrial system (e.g. IoT for temperature of a machine, biofeedback for heart rate variation of a human operator). With calculation capabilities of Tech 2, diagnosis can be managed as much as prognosis (e.g. predicting breakdown). Through a learning process (e.g. history of incidental situations), Tech 2 can infer new rules to improve models and generate adaptations of the industrial system (e.g. re-allocations of functions between operating agents). Tech 3 facilitate perception, understanding or projection of future states of the situation, including the context of the task in which situated information can be transmitted. With Tech 3, Human-machine interactions can be improved by the use of personal assistants (e.g. queries and commands can then be transmitted in natural language). Finally, the human can be assisted by Tech 4 in performing physical tasks (Tech 4) in a parallel or a sequential process activity shared between the agents.

Technologies 4.0		Impact for industry 4.0	
Internet of Things & biofeedback sensors *« conncected & healthy operator »*	*Tech1*	Information processing	Raw information collected by new sensors
Bigdata, Cloud computing, Machine Learning *« analytical operator »* Enterprise social network *« social operator »*	*Tech2*		Information enriched by models enabling simulation and prediction
Augmented reality *« augmented operator »* Virtual reality *« virtual operator »* Personal Digital Assistant *« smart operator »*	*Tech3*		Situated information, adapted to context
Cobot *« super-strength operator »*	*Tech4*	Implementation of action	Assistance for repeated actions (Norm NF EN 1005)
Exoskeleton *« collaborative operator »*			Assitance for constraining action (lift, carry, push-pull / Norm NFX35-109)

Table 1. Industry 4.0 technologies (from Romero et al. 2016)

Adopting a human-machine cooperation (or symbiosis) perspective, the different issues pointed out by these authors are related to:

- the dialogue management rules between humans and machines. Here, information transparency levels (Chen et al., 2014; Lyons, 2013) appears as a central concept. The interfaces must present information that has been pre-treated and aggregated, so that the production process is easily understandable by all actors without affecting efficiency (Kumar & Kumar, 2019);

- the distribution rules of functions allocation between the two components, considering levels of automation (LOA, Sheridan and Verplank, 1978) or Schmidt (1991) modes of cooperation.

In their multi-agent architecture of the social factory, Romero et al. (2017) propose two types of agents that could support a dynamic human-machine cooperation:

- The *interface agent* rules to support information interactions with transparency (information supply and request) and thus contributes to keeping the social operator or the social machine in the loop when they encounter difficulties.
- The *broker agent* rules of function allocation to adapt the level of automation, to determine the sharing or delegation of authority;

Using the Cognitive Work Analysis (CWA) approach, the paper aims to discuss how the technologies 4.0 can be assistance for supporting the cognitive processes and representation of smart factories' operators.

2 METHOD

2.1 Using CWA for thinking interface/broker agents

CWA is a framework developed for the design of complex socio-technical systems (Rasmussen, 1994). In the literature, many applications of CWA are the design of information display systems (e.g. Jenkins et al., 2010) in relation with EID (Ecological Interface Design) researches (Vicente, 1999). The idea of this work is to represent relevant information to the right people at the right time for the activities to be carried out. In the socio-technical context of industrial systems where humans and cyber-physical systems can cooperate by exchanging information, the presentation of data is still a key aspect. The questions of information transparency could guide the dialogue, by promoting the sharing of information, and enabling understanding of decision-making. The Situational Awareness-Based Transparency model of Chen et al. (2014) define three levels of machine-to-human transparency ranging from disclosure of basic information (reporting of actions and goals), sharing of explanations on the reasoning used (constraints considered, methods chosen), until the transmission of elements on the consequences of actions in progress (projection, uncertainty, risk). An additional aspect of information transparency is from human-to-machine and deals with aspects like human (or team) state or behaviour which the machine can be aware (Lyons, 2013). The level of transparency would also influence the trust that humans would place in the machine, the higher the level of transparency, the higher the trust level would increase (Chen, 2014). The relationship between human and machine is also influenced by the know-how to cooperate. While know-how is defined as the skills, i.e. abilities of an operator to interact with the process to achieve the task or function requested, the know-how to cooperate (KHC) focuses rather on the interaction of the operator with another agent (human or technical) interacting itself with the same process (Millot & Lemoine, 1998). Other works have sought to explore the CWA approach to design dynamic function allocation for sociotechnical systems by identifying impossible allocations and best configuration (Rauffet et al., 2015). Finally, Lintern (2010) has focused on the use of the CWA method and especially Decision Ladder modelling tool to position assistance on the decision-making process, whether in the processing or presentation of information.

2.2 WDA, ConTA and SOCA phases of CWA

CWA 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). In this paper, we presented the three phases developed: WDA, ConTA and SOCA.

WDA allows to define the functions of the work domain but also the physical objects that can provide data. As Vicente (1999) stated, a domain is a description of the work independently of any particular worker, automation, event, task, goal or interface. The WDA phase is associated with a modelling tool, the Abstraction Hierarchy (AH). Thus, an AH is context- and resource-independent, i.e. it does not deal with any specific worker, event, or assistance solutions. AH tool enables the description of a work domain in terms of five levels of abstraction: 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 in order to achieve the functional purpose), object-related processes (processes and capabilities characterizing the objects used by the general functions), and physical objects.

The ConTA phase is related to the activity required for achieving a system's purpose. This phase is associated with a modelling tool, the Rasmussen's Decision Ladder (DL) that models cognitive decision-making processes. These activities could be carried out by humans or by automation (in our study, by one of the four categories of technologies for industry 4.0 – cf. Table 1)

SOCA addresses the constraints governing the distribution of work demands, communication, and cooperation amongst the different resources or actors (humans, machines) of the system under investigation). Jenkins et al. (2010) propose to map actors (represented by means of a colour code) onto the AH and more precisely onto the functions described at the levels of the purpose-related function and of the object-related processes (SOCA-AH). In the same way, we can map actors onto the decision-making processes to carry out in the system (SOCA-DL). The remainder of this paper will use SOCA-AH and SOCA-DL on the specific case study of the ordering picking system to model function allocation between humans et machines, by placing the different type of technologies 4.0 that could cooperate with the human operator, by supporting his/her cognitive work.

3 PROPOSAL: UNDERSTANDING THE BENEFITS OF INDUSTRY 4.0 WITH CWA

To illustrate how the technologies 4.0 can support the cognitive work of smart factories' operators, a case study was designed and analyzed using the first CWA stages described above (WDA, ConTA and SOCA). This case study focuses on the system of order picking, in which the symbiosis between operator and cyber-physical system (CPS) would allow to give new margins for controlling and improving the activity of filling parcel boxes (by providing operators with more important supervision capabilities on their execution tasks). The order picker could thus have the possibility of planning, reordering and reorganizing his/her activity: at the tactical level, for instance by changing the order of completion of orders over a half-day; at the operational level, by changing the order of filling parcels, or by changing production resources, i.e. tool type or parcel box type.

To design and model this order picking system 4.0, a workgroup was constituted, bringing together researchers with a practice of the CWA method and student-engineers specialized in industrial engineering. A first modeling was proposed by this group and was then submitted to field experts for improvement and validation. The models, presented in the following paragraphs, have been discussed with operators who assembly customized carpentry products (e.g. windows and glass sliding doors), within an industrial company having adopted the paradigm of empowering companies and lean management (thus leaving considerable control margins to operators).

3.1 Abstraction Hierarchy of order picking system and positioning of technologies 4.0

First, a work domain analysis (WDA) for order picking 4.0 was conducted with the aid of the abstraction hierarchy, to capture the means-end relationships between the physical objects and the system's overall purposes (cf. Fig. 1). At the highest level, the functional purpose was defined as a mix of operational and tactical functions, where the order picking must be carried out by assembling products into parcel boxes to meet the customer demand without damaging the production resources, but also by planning the preparation of the different orders. The system is then evaluated as the second upper level against its ability to enact this purpose, with different criteria related to the customer demand (delivery time, quality and quantity of the goods packaged relatively to the specifications), to the internal objectives of the plant (optimization of resources and time, customer relationship management policy), or to the compliance with internal or external rules and standards (focusing on operator safety or product trackability). These different criteria may sometimes be in conflict and should be balanced by the system to reach a trade-off. With the aid of these criteria, the purpose related functions can be modelled to explain what it is required to perform the functional purpose. The studied system must thus carry out functions for spatially and temporally organizing order picking (flow mapping and workplaces implantation, scheduling), for controlling the inputs, outputs and environment of the picking activity, as well as for operationally achieving the activity (workstation settings, parcel boxes filling). Finally, the two lowest levels describe the different physical objects (products, information listing, equipment, parcel boxes) and the processes to handle these ones, to perform the previous purpose-related functions.

Based on the SOCA stage, this abstraction hierarchy were also used to model the static function allocation, by placing the different type of technologies 4.0 that could cooperate with the human operator on the purpose related functions (cf. coloured square boxes in Fig. 1). For instance, the scheduling or the spatial organization of the picking activity could be

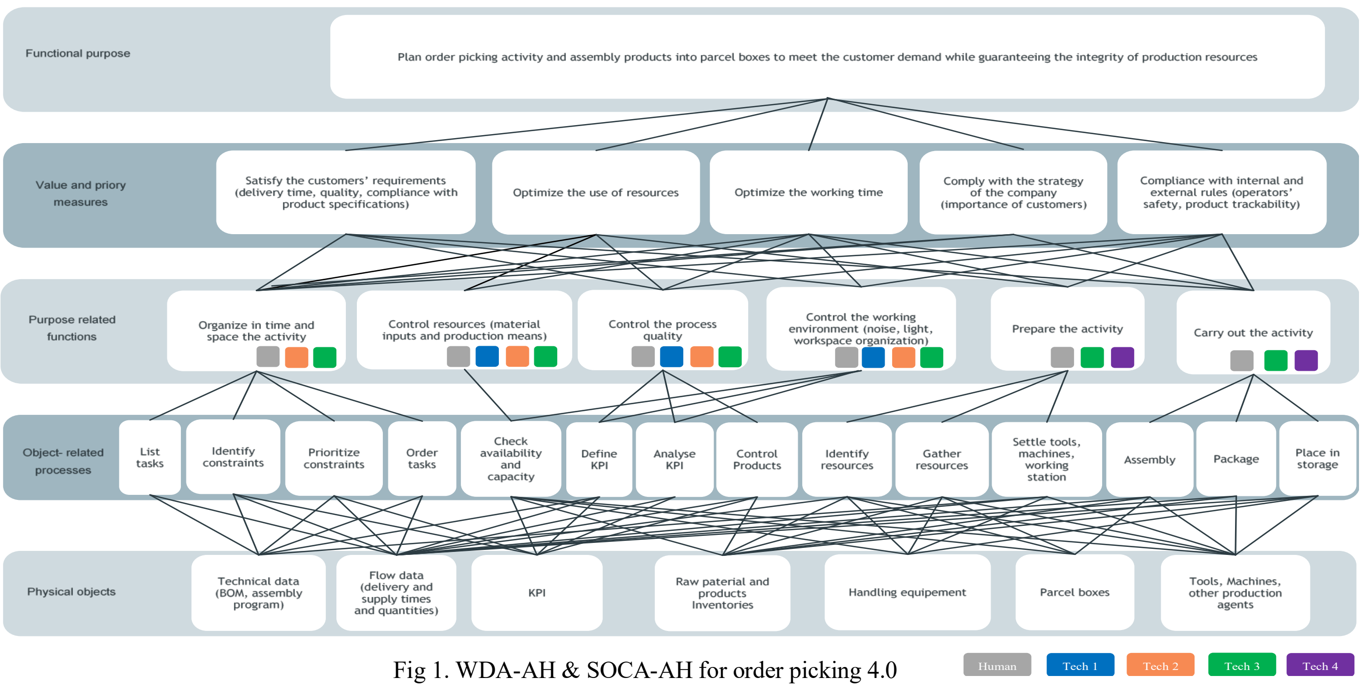

Fig 1. WDA-AH & SOCA-AH for order picking 4.0

improved with Tech 2 coloured in orange (i.e. with big data, models and machine learning supporting manufacturing planning and process simulation tools) and Tech 3 coloured in green (i.e. with Augmented Reality and Personal Digital Assistant helping operator for better contextualizing the information resulting from Tech 2 tools, and to request additional information).

3.2 Decision Ladder of order picking and positioning of technologies 4.0

After studying the goals and functions of the system in the WDA stage, it is necessary to study the recurrent cognitive activities that may exist, by using the Control Task analysis (ConTA). The Decision Ladder (DL) presented in Figure 2 thus describes the cognitive processes that the human operator can implement within the system. The DL can be followed in a linear way if the operator is novice passing through all the states of knowledge (circles in Figure 2) and the processes of information processing (square boxes in Figure 2), or by using shortcuts if the operator is expert (see links between the two ladders in Figure 2). In the case of the order picking system, a certain number of dynamic situations can be encountered, caused by the appearance of unexpected or incidental events (specific product during the production of a series of standard packages, product breakage, low level of stock), or nominal variations (the arrival of a new customer orders that must be integrated into the picking activity). The case of a low level of parcel boxes stock is kept in the rest of the paper to illustrate the benefits of industry 4.0 technologies on the cognitive activity of operators.

These situations can then cause a diagnosis activity in the operator (who will eventually seek additional information) to arrive at a representation of the state of the system, which can here correspond here to the identification of root causes according to the Ishikiwa's 5M method (related to Material, Machine, Manpower, Method, and Medium / Environment causes). The perception of a low level of parcel boxes stock in a given format can for example lead to diagnose a risk of stock-out. This state of the system is then evaluated by an operator according to his/her goals (oriented by the criteria defined in WDA at the functional level of the values and priority measures). This allows the selection of:

- Options on the system target state: should one consider or not the stock-out of parcel boxes, depending on the progress of production (if the production of a product series is almost done, low level of stock may be normal)?
- Tasks: should one go to resupply parcel boxes by interrupting the current filling, or could one reschedule the production to make products that are packaged in boxes in different format while waiting for resupply by the storekeeper?
- Procedures: Does one have to physically and digitally process an operation of boxes removal in the main store, or should one rather set up a visual Kanban system to improve communication with the storekeeper and avoid a low level of stock?

Based on the SOCA stage, the different technologies 4.0 were also positioned on the DL to explain how they can support the cognitive work of the human operator. Tech 1 (in blue) supports the process of activation on the Decision Ladder, since the integration of new IoT sensors could help the human to perceive more signals from his/her environment, from the machines he/she has to supervise, or even from the operator itself (with biofeedback sensors). Tech 4 (in purple) assists operator in the physical implementation of action, with customized mechanical aids (e.g. an exo-skeleton following and powering the movement of operator, or a cobot learning then replicating alone the movement of operator). Tech 2 (in orange, with big data and machine learning technique) helps for carrying out all the different implemented processes to analyse and diagnose the system state, as well as to elaborate or choose an option of action to implement onto the system. Finally, Tech 3 (in green, with augmented reality, virtual reality, PDA) supports the representation of the state of knowledge, by contextualizing and customizing alerts, relevant information or proposal of one or several decision choices.

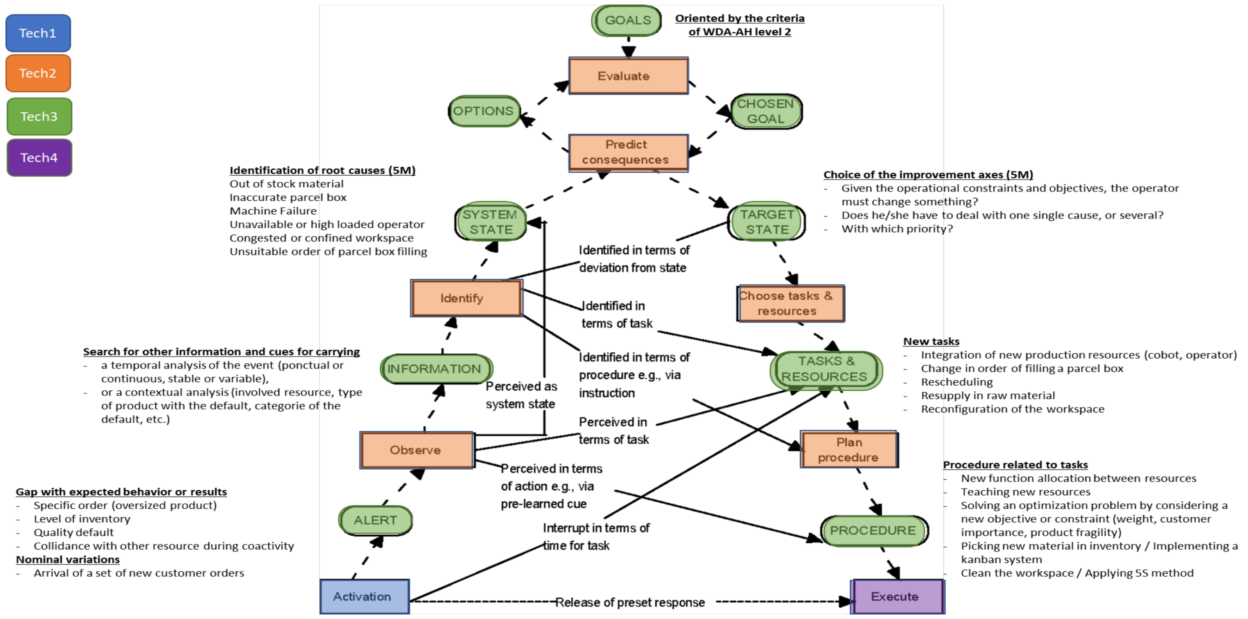

Fig 2. ConTA-DL & SOCA-DL for order picking 4.0

3.3 Decision Ladder shorcuts and interface/broker agents

In addition to the positioning of technologies 4.0 on the processes and the states of knowledge modelled within the Decision Ladder template, it is also important to understand how these technologies can enhance the operators' cognitive activity, by helping them to bypass the linear information processing by taking the shortcuts mentioned in Figure 2. These shortcuts can result from the experience and the expertise of the human operator, as internal references of knowledge, but could also triggered off by the use of CPS Components. As mentioned in Romero et al. (2017), the cooperation between human agents and CPS agents are driven by two mediating sets of rules, i.e. broker and interface agents.

On the one hand, the broker agent allows for tuning the allocation of functions to human or CPS components, according to some rules based for instance on the levels of automation (LOA, Sheridan and Verplank, 1978), or on the form of cooperation (Schmidt, 1991). The chosen case of a perceived low level of boxes stock within the order picking system may trigger different function allocations. Two examples are depicted in Figure 3: in both configurations, the process of activation is shared by human and Tech 1 (i.e. the problem can be perceived by the human operator or by some IoT sensors placed in the store containing the parcel boxes) in a debative form of cooperation, whereas the execution of action is allocated to Tech 4, carried out by a cobot (i.e. a collaborative Automated Guided Vehicle that picks the missing parcel boxes in the main storage and bring them to the operator). Nevertheless, the two configurations vary on the automation of the processes to analyse information and to make decision.

- In the first configuration (Fig. 3, left), human and machine cooperate in an integrative form all along the Decision Ladder: only the diagnosis of the situation is allocated to Tech 2 (simulation and planning tools), after a request from the operator having perceived the low level of stock, then the operator evaluate options and choose the task and procedure according its goals. This configuration allows operators for taking shortcut A (cf. Fig. 3).
- In the second configuration (Figure 3, right), the LOA is higher, the tech2 makes the diagnosis but also propose one or several tasks to the operator, for example between resupplying of boxes or rescheduling production. This configuration may thus enable the shortcut B (cf. Fig. 3).

On the other hand, the interface agent supports the dialogue between human and CPS agents. This dialogue can be managed according to some rules base for instance of the information transparency of Chen et al. (2014) and Lyons (2013). Indeed, the quality of the dialogue - in terms of display of information resulting from the machine processing, request of complementary information by operator, or transmission of an order from one agent to another - is dependent from the level of SAT (Situation Awareness-based agent Transparency) that the machine can provide but is also dependent from the knowledge of the artificial agent on the state and the behaviour of the human operator.

- The dialogue can be improved by the possibility to transmit an order in a natural language rather a programming language, or by the contextualization of an information making it more understandable for the operator. In the case of a low level of box stock, the risk of stock-out can be expressed through an augmented reality device (Tech 3) to locate the risk on the specific line of box storage (augmenting the perception and the understanding of the situation by the operator). Moreover, the display of this information can be enriched by providing the number of customers order that can be achieved with the existing stock, or even the time remaining before the stock-out computed according to the production rate (augmenting thus the projection of the situation by the operator).
- The dialogue can be also improved in the evaluation part of the DL, by displaying criteria and priority measures as external reference to help operator to better make a decision (Figure 3, left), or by enabling to parameter the most important criteria (Figure 3, right), for example to propose a

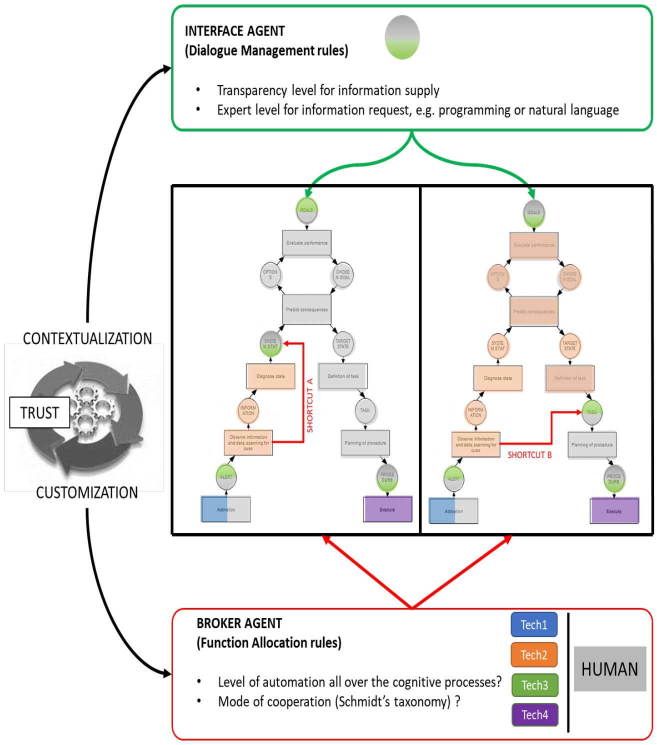

Fig 3. Broker and interface agents as support for cognitive shortcuts. The middle part illustrates some shortcuts in the decision ladder between cognitive processes (square boxes – see fig. 2) and/or states of knowledge (circles – see fig. 2)

4 DISCUSSION

This work opens new questions to design the assistances provided by CPS components to the operator of Industry 4.0.

4.1 Relationships between interface and broker agents

Interface and broker agents are seemingly interdependent. As pointed out on Figure 3, the efficiency of the function allocation between man and machine, piloted by the broker agent, may be conditioned to the quality of dialogue management and the level of information transparency, driven by the interface agent. That can explain why the broker agent could switch between the first and the second configuration of function allocation, if the information provided by the artificial agents is sufficiently explained or relevant, or if there is enough possibility to question the artificial agent and to explore the underlying sources of processed information, or the reasoning and evaluation mechanisms. In some extent, this relationships between interface and broker agents can be therefore brought closer to the concept of Know-How to Cooperate (Millot and Lemoine, 1998). Indeed, as claimed in this approach, the know-hows of each agent (human or artificial) are not sufficient to efficiently cooperate, it is necessary to develop the ability to facilitate goals and manage interferences by improving the dialogue between agents.

4.2 Evolution and adaptation of interface and broker agents

Function allocation and cooperation could be affected by the quality of the communication. By developing a common code of communication and models of oneself and the partner, interface and broker agents' rules will thus evolve. In a positive way, this meta-cooperation level allows adaptation to new situations, by customization or contextualization of rules. Situations of interaction can then be anticipated and, according to the knowledge of the agent, some decisions can be adjusted. On the contrary, a lack of access to data can lead to forms of "circumvention" of cooperation and a decline of trust that built up gradually by observation of the behavior of the agent can lead to misuses. The design of future work must consider these drifts by proposing adjustments of the interface/broker agents according to the use (on the degree of transparency to bring, on the degree of automation, etc.).

5 CONCLUSION

The use of CWA, and especially the modelling of Abstraction Hierarchy and Decision Ladder within the three stages of WDA, ConTA and SOCA, allows to position and think the design of technologies 4.0 as cognitive assistances for operator. The different types of technologies, listed by Romero et al. (2016, 2017), were thus positioned according to how they support the work functions of a sociotechnical system (Abstraction Hierarchy of the order picking system), and how they support the cognitive processes of the operator (Decision Ladder). The technologies 4.0 can indeed play upon on the way information is processed, on the way knowledge of system state is represented, and on the way cognitive shortcuts be taken by operator with the aid of these technologies, considered as external references. Two kinds of agents ruling the interaction between men and machines: broker and interface agents. The first mainly consists in allocating functions between operator and technologies 4.0, while the second is used to manage the dialogue between man and machine, by for instance setting the transparency level of the information provided by technologies 4.0. Since broker agent and interface agent are the key mechanisms to support the human-machine cooperation, further work is needed to model them and define principles for tuning them.

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