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Integrating agent transparency adaptation mechanisms into Human Machine Cooperation

L. Simon, C. Guérin, M.-P. Pacaux-Lemoine, P. Rauffet

Abstract— This paper proposes to model the dynamic management of dialogue in human-machine cooperation. It seeks to articulate a generic model of human-machine cooperation, based on two complementary abilities of agents (the Know-How-to-Operate and the Know-How-to-Cooperate), with 2 prominent models of agent transparency (SAT and HRT model). Modeling is applied to a specific Human-Machine Cooperation, a cyber-physical system assisting a human for planning decisions of maintenance operations. Dialogue management mechanisms filter the information displayed on the interface, from the agent's analysis of the supervised process to the team's performance and cooperation activities. This dynamic dialogue management contributes to the calibration of trust and optimisation of cooperation.

I. INTRODUCTION

In the context of Industry 4.0, we observe an increased use of new technologies (digital twin, cobotics, virtual and augmented realities, machine learning) to optimize, customize and make flexible the processes of execution, supervision or planning [1][2].

The introduction of these technological revolutions therefore allows us to manage highly complex processes, thanks to autonomous and intelligent cyber-physical systems. However, these emerging capabilities also challenge rethinking decision-making processes and the distribution of work between humans and machines.

To characterize the evolution of these hybrid human-system teams, and to develop new ways of thinking about the mechanisms of cooperation within these entities [3], the Human-Autonomy Teaming (HAT) paradigm has recently emerged [4]. Unlike Human-Automation Interaction [5], HAT is characterised by greater interdependence between agents [6], and the fact that the autonomous agent is considered as a teammate, and no longer as a simple tool [7].

In order to ensure optimal cooperation in these new hybrid teams, [8] talk about the importance of having two mechanisms for controlling and regulating cooperation: the *broker agent* (function to manage the sharing of work and authority) and the *interface agent* (function to manage the human-machine dialogue).

- The broker agent has long been considered in models of human-machine cooperation, and already in HAI (Human-Machine Interaction) field, with the question of

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levels of automation [9] and dynamic allocation of functions [10].

- On the contrary, human-machine dialogue management is an important and significant issue in the context of HAT [11][12]. It becomes crucial to further investigate how this dialogue can be dynamically managed.

The aim of this paper is therefore to formalize the interface agent, and to integrate it into models of human-machine cooperation. We will illustrate this modeling approach in the case of a specific human-machine cooperation, that of CPS-assisted decision-making in the context of an "Industry 4.0" predictive maintenance activity.

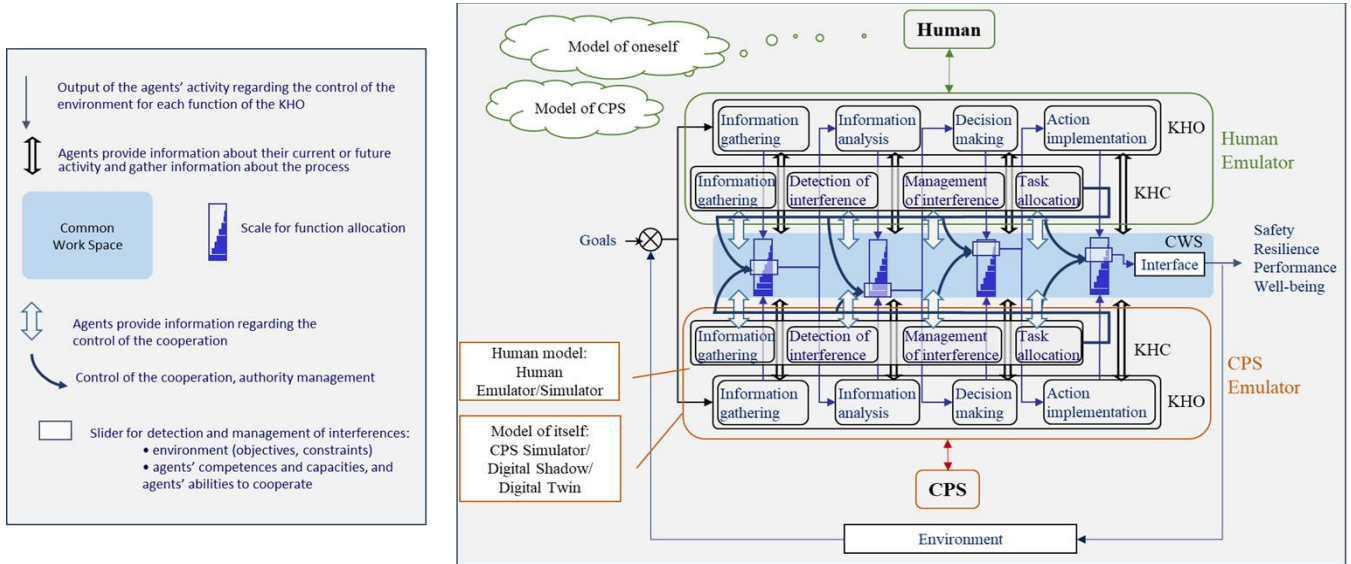
II. RELATED WORK

A. Modelling Human-Machine Cooperation

Pacaux-Lemoine proposes a generic model of cooperation to support the design of cooperation between heterogeneous agents like human and artificial entity such as a cyber-physical system (CPS). The model has been firstly used to evaluate cooperation between air traffic controllers and expert system [13], in car driving [14], then it has been also used to design human-machine systems, in robotics [15], in manufacturing [16], in railway [17]. Each type of cooperation and domain of application contribute to its improvement. This model is useful to combine task work to team work, two types of activities that are usually analyzed independently [18].

Both agents could be partly autonomous to control an environment like production system, but need the assistance of a cooperative partner for safe and efficient control of the overall environment. The approach based on the model of cooperation uses a similar digital model to represent human and CPS. A digital representation of human is implemented for human to provide accessible and understandable information to CPS, and for CPS to provide precise and intelligible information to human. Information is organized in a way that both human and CPS address similar steps of the reasoning process when cooperation is needed. The digital representation could be an emulator of the agent, directly fulfilled by the same agent or indirectly inferring from the agents' actions through the Human-Machine Interface. However, it could also be a simulator when rules support the dynamics of the model according to the situation of the environment. The digital representation of human is a rudimentary representation of what can be done by human, but the objective is only to provide information to CPS with or without direct control by human.

Figure 1. Generic model of cooperative agents and cooperative activities (from [18])



The digital representation is split into two complementary abilities of agents, the Know-How-to-Operate (KHO) and the Know-How-to-Cooperate (KHC). Agents cooperate on the control of an environment (or a process) according to their KHO, and on the control of the way they cooperate according to their KHC, through a Common Work Space. These concepts are quickly explained in the next parts [18]. The figure 1 presents the control loop of the environment managed by two cooperative agents, i.e. a human and a CPS.

Know-how-to-operate (KHO). The KHO is the ability based on agent expertise and experience that supports problem-solving process regarding the control of the environment (thin blue arrows on Fig. 1) to attend objectives (e.g. maintenance of the ship). The simple representation of the KHO presented on the Figure 1 is defined according to the model proposed by [19]. The reasoning process is decomposed into four main functions: Information gathering on the environment, Information analysis, Decision making and Action implementation. However, if agents are skilled, actions could be directly implemented after information gathering.

Know-how-to-cooperate (KHC). The KHC is the ability to cooperate with a partner. It is based on the definition proposed by [20]. The four KHC functions presented on the Figure 1 are: Information gathering on/from the partner (and not on the environment as for the KHO), Detection of interference (analysis of the activity of the partner regarding self-activity), Management of interference (decision making about the way to cooperate), Function allocation (implementation of decision by the agent who has the authority). Interference is positive when the action of one agent can help in achieving another agent's goals, or is negative when the actions of one agent may obstruct another agent's plans.

Common Work Space (CWS). The CWS supports cooperative activities between agents when they do not use common language (e.g. human and artificial entity) or they cannot communicate directly (different localizations). The CWS helps agents to build and maintain a Common Frame of Reference by providing information about/from their KHO

(double black arrow), their KHC (double blue arrows), and their decision regarding the way to cooperate (thick blue arrow and slider).

B. Transparency model

Agent transparency is the ability of a technological agent, such as a CPS, to communicate its capabilities, intentions and constraints to human [21]. Research suggests that allowing humans to agents' inner workings provides a better understanding of how it works and thus to have appropriate trust and improve cooperation [22].

Two models are widely cited in the literature [22][23][24]. The Human-Robot Transparency HRT model [25] and the Situation Awareness-Based Agent Transparency SAT model [21], that are prescriptive (prescribe a set of information to be communicated by the agent) and unidirectional (the sender is an agent, and the recipient is a human).

HRT model. This model is based on the two dimensions robot-TO-Human (rTOh) and robot-OF-Human (rOFh). rTOh corresponds to the information that the agent will transmit about its control of the environment (its intention, its tasks, its reasoning, the environmental constraints it considers). rOFh deals with information about the human (e.g. work overload) and the team (e.g. task allocation), communicated by the agent.

SAT model. This model proposes three levels of transparency. At level 1, the agent communicates about its processes or tasks it performs, enabling the human to perceive how it behaves. At level 2, the agent communicates about its reasoning (e.g., data analyzed, constraints considered), to better understand why it behaves in this way. At level 3, the agent communicates its future projections (e.g., the risks associated with this future, or the probabilities of success or failure), to appreciate the quality and reliability of the information communicated.

Following [26], HRT and SAT can be combined. Level 1 (what is performed), level 2 (how and why it is performed) and level 3 (reliability of performance) from the SAT model

can be applied to the rOF and rTOh dimensions of the HRT model to define more precisely the information transmitted by the agent.

C. Research question

In this article, we seek to specify how an agent interface can dynamically manage the dialogue within a human-machine cooperation. On the one hand, [18] models HMC from two complementary abilities of agents KHO and KHC. On the other hand, agent transparency is an ability to communicate different types of information to human [21][25]. Our research question is as follows: how may articulate transparency models and HMC model to define configuration settings of interface agent for human-machine dialogue. From this articulation, how may specify the closed communication loops between human and agent to regulate and control the dialogue in order to manage information flow.

III. PROPOSAL OF AN INTERFACE AGENT TO MANAGE DIALOGUE WITHIN HUMAN-MACHINE COOPERATION

A. A specific Human-Machine Cooperation : Agent Assisted Decision-Making

Focus on a specific cooperative activity. We focus on a specific class of human-machine cooperation to model and illustrate the dynamic management of human-machine dialogue. This class of cooperative activities corresponds to the agent-assisted decision-making, where the CPS makes a proposal to the human who has the final decision to accept or refuse this CPS recommendation.

This CPS' proposal, based on its ability to collect and analyze data about the supervised process, corresponds to the output of the function Decision Making (DM) of agent's KHO (cf. Figure 2, dialogue box ①). This recommendation in turn activates the human's Information Gathering (IG) function of KHO.

The human can then analyze the situation to verify the machine's proposal (debative cooperation [27]) and/or take into account other information or criteria in his/her analysis (integrative cooperation [27]). By doing this, the human Information Analysis (IA) function of his/her KHO is activated by processing the data related to the supervised process. Moreover, it should be noticed that this implementation of IA function is driven by the Interference Detection (ID) function of the human's KHC (e.g. the human would verify the CPS' proposal if he/she has not enough shared Situation Awareness (SA) or trust in CPS).

Finally, the human decides to accept or refuse the CPS' proposal on the decision to make on the process (cf. Figure 2, dialogue box ②). Again, there is an intricate relationship between the human's KHO and KHC functions. Indeed, the human decision corresponds to the implementation of Decision Making (human's KHO DM) for the supervised process, but also to the implementation of Interference Management (human's KHC IM). Making the decision can therefore indicate if the CPS' proposal is accepted or not, based on the level of trust or shared SA the human can have with the agent.

Application on a study case: the Seanatic project. We have studied this particular class of cooperative agent-assisted decision-making in the Seanatic project, which aims to implement predictive maintenance in a maritime context. This project involved the implementation of sensors, the development of artificial intelligence algorithms (the agent) and the design of Human-Machine Interface (HMI) to communicate with operators of maintenance [28]. Several HMI were designed. HMI-1 presents a list and dates of maintenance operations are displayed. HMI-2 displays data processed by the agent from a set of sensors positioned on the maritime diesel engine (pressure, temperature, speed). Data were displayed on graphs showing recorded data and a projection of these data into the future. HMI-3 enables communication of the agent proposal, the reliability of the proposal and a projection of risky consequences.

We will now study and formalize how transparency can be integrated into the framework of human-machine cooperation (section B), and how it can evolve dynamically (section C).

B. Interface agent configuration settings: articulation of transparency models with KHO/KHC

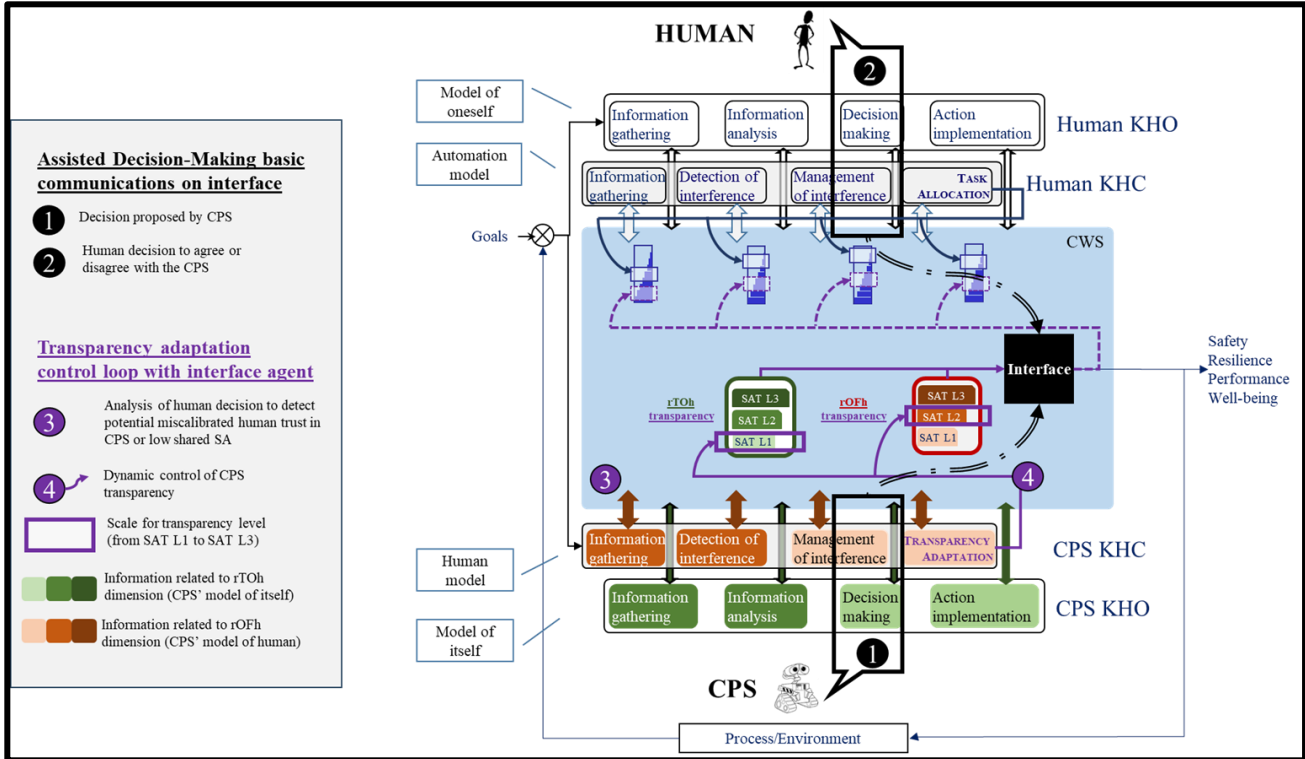
Transparency settings and CPS's know-how-to-cooperate by communicating to human. In an agent assisted decision-making cooperation, the agent communicates on its KHO: Decision Making (proposal), Information Gathering (sensor data collection) and Information Analysis (sensor data analysis). Here, the agent informs about its processes of controlling the environment, which corresponds to the rTOh dimension of the HRT model. The level of transparency about rTOh can be set according to the SAT model (table 1). At level 1, it communicates only its proposal, enabling the human to perceive this decision proposal. At level 2, it can communicate the reasoning that led to its proposal (the data collected and analyzed). At level 3, the agent can qualify the information it communicates by specifying the level of reliability of its proposal.

TABLE I. INTERFACE AGENT SETTINGS OF TRANSPARENCY RELATED TO HUMAN-MACHINE COOPERATION

		Information related to... [18]		Level of transparency [21]	
				SAT L1 or SAT L2 (Output)	SAT L3 (Value or Quality about output)
Dimension of transparency [25]	rTOh	CPS' KHO	Information gathering Information analysis Decision making Action implementation	SAT L2	SAT L3
	rOFh	CPS' KHC	Information gathering Detection of interference Management of interference TRANSPARENCY ADAPTATION	SAT L2 SAT L1	SAT L3

The agent can also communicate what it perceives about the human (e.g. a state of fatigue or the task he is carrying out)

Figure 2. Modeling interface agent within human-machine cooperation: transparency adaptation settings and control loop



and how the team works (e.g. how tasks are divided up), thus demonstrating its ability to cooperate with a partner. This information about the rOFh dimension of the HRT model corresponds to the agent's KHC ability. The agent can communicate information gathered about its human partner (e.g. accept or refuse its proposal), whether its partner's activity may generate interference (e.g. by communicating the associated positive or negative consequences) and what decision is taken to manage this interference. The agent can also set the transparency level of the rOFh dimension according to the SAT model (table 1). At level 1, it communicates what it perceives about the cooperation (e.g. the human's decision following its proposal, e.g. an acceptance rate too high in relation to the reliability). At level 2, it communicates its understanding of cooperation (e.g. the acceptance rate is too high because the human doesn't know enough about its abilities). At level 3, the agent can communicate the consequences that a decision may have on cooperation (e.g. the division of tasks may not be adapted to the new situation).

Application to the Seanatic project. For rTOh level 1 transparency modality, the agent communicates (HMI-3) "here's my proposal to bring forward the maintenance of operation 12 by one week". At level 2, HMI-2 justifies the proposal "I'm making this suggestion because, according to the data I've analyzed, the filter clogs up faster than expected.". Finally, at level 3, the agent transparency is "my proposal is 90% reliable". When the agent needs to communicate about its rOFh dimension of transparency (level 1), the list of maintenance operation displayed suggests "the team's workload smoothed" (HMI-1). At level 2, the HMI-1 displayed "This smoothing is the result of calculating the balance between workload (number and duration of

maintenance operations) and capacity (number of operators in the team)". Finally, at level 3, the agent transparency is "According to the expert operators' rules, if you refuse the proposal, the operators' workload is likely to be high".

C. Interface agent control loop: dynamic Transparency Adaptation within Human-Machine Cooperation

The closed communication loops [29] that pass through the interface between human and CPS correspond to the questions 1 and answers 2 illustrated by black dialogue boxes in figure 2 (CPS proposes a decision, and human accepts or refuses).

These exchanges can be regulated by a control loop, this mechanism corresponding to what Romero et al. (2017) call the agent interface in human-CPS cooperation. In the context of assisted decision-making, the human will therefore have authority over the allocation of tasks (and will thus play the role of broker agent defined by Romero), while the CPS will have authority over the information communicated on the interface (thus playing the role of interface agent). This interface control loop will consist of dynamically adapting the various levels of CPS transparency (both rOFh and rTOh dimensions), depending on the level of human acceptance (representing the human's trust behavior as perceived by the CPS).

This dynamic adaptation of transparency is therefore the output of the CPS' KHC, which consists of analyzing human decisions to detect possible interference of miscalibrated trust or poor SA (circle ③ in figure 2), then adjusting the CPS transparency (purple circle ④) to manage and solve these human-CPS interferences:

- **Information Gathering about cooperation:** the human's decision-making (dialogue vox), responses to proposals issued by the CPS (agreement or refusal, dialogue box), can be collected by the CPS over time, in order to determine the human's behaviour (and thus to consolidate the CPS model of the human).
- **Interference Detection:** this profiling will be used to measure whether the human has too much or too little trust in the CPS (the CPS will thus infer on the human's model of the CPS).
- **Interference Management:** the detection by the CPS of poorly calibrated human trust will enable the most appropriate transparency settings to be defined, on either the rOFh or rTOh dimensions, and following Chen's SAT levels (1, 2 or 3).
- **Transparency Adaptation:** these transparency settings will be implemented in the CWS in the form of filters, and will make it possible to add or remove information to improve human-CPS trust and thus optimize cooperation.

This transparency adaptation loop will influence human (purple dotted arrows between interface and function allocation scales in figure 2). That may possibly change their trust behavior, i.e. their decisions ② on whether or not to accept the CPS's proposals ①. Moreover, that can also have an impact on how humans reallocate tasks within the cooperative activities (playing their role of broker agent). For instance, they could verify the CPS information process by collecting data on their own, or analyzing by themselves the data collected by CPS to confirm or not the CPS decision. In return, this change in human behavior may change the evaluation of the human's trust as perceived by the CPS.

Application to the Seanatic project. We illustrate how processes have been implemented in the Seanatic project:

- **Information Gathering about cooperation:** the agent is able to know the acceptance rate of its proposals by the human. To do this, it collects data linked to the human's decision-making process (accept or refuse).
- **Interference Detection:** the agent infers on the human's model by comparing its reliability rate and the acceptance rate of its proposals. The agent considers that an human with an acceptance rate of over 90% has an inappropriate model and overestimates the agent's skills. Conversely, if the human's acceptance rate is below the 30% threshold, the agent considers that the human has a model that underestimates its abilities.
- **Interference Management and Transparency adaptation:** when the agent's model is underestimated by the human the agent reduces its level of transparency on its rOFh: from level 3 (projection) to

level 2 (reasoning). If the human overestimates the agent's abilities, then it can reduce its level of transparency on its rTOh from level 3 (reliability) to level 2 (reasoning) (see section III. B. Application to the Senatic project).

IV. CONCLUDING DISCUSSION

This paper has investigated the way we can consider the management of human-machine dialogue in cooperative activities, through the dynamic management of CPS transparency. To this end, we have integrated the notion of agent transparency (based on the models of Chen [21] and Lyons [25]) into the Pacaux-Lemoine's model of cooperation. This emphasizes more clearly the dialogue mechanisms (management rules that Romero [8] calls the "interface agent"), which filter the elements of the CWS that will be communicated on the interface by the CPS to the human.

Modeling the transparency mechanisms also makes it possible to explain the ability of the CPS to communicate with the human, which is an important part of its know-how-to-cooperate (KHC [18]), complementary to the ability to manage the allocation of tasks (what Romero [8] calls the "broker agent").

As we have shown, this transparency management can concern elements related to the analysis by the CPS of the supervised process (thus to its KHO, by managing the level of rTOh transparency [25]), but also elements related to the analysis by the CPS of the team's performance and its cooperative activities (thus to its KHC, by playing upon the level rOFh transparency [25]).

We have also emphasized, and illustrated in the example of SEANATIC project, that this transparency can be dynamically managed, based on the CPS interactions with the human. Analyzing the human's decisions to accept or reject the CPS' recommendations allows us to assess his/her level of trust or acceptance of the CPS. This is in line with the work of Akash [30] and Okamura Yamada [31], who have recently sought to operationalise this dynamic transparency.

Nevertheless, this current work on articulating transparency management with the modeling of cooperative activities and agents is currently limited to a particular class of cooperation: that of CPS-assisted decision-making, which is asymmetrical by nature. In these situations, the CPS proposes, the human decides, and the dialogue is adapted according to the human's decisions, possibly reflecting poorly calibrated trust or incomplete situational awareness. In terms of future prospects, we therefore need to think about the generalization of the approach, considering, as suggested by Akash [30] and Chen [32], a more symmetrical dynamic management of transparency. For instance, the human could also explain to the CPS the reasons for his/her acceptance or refusal, that can be helpful to improve both human and CPS know-how-to-cooperate (KHC) within these human-autonomy teams.

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