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Game Theory-based Human-Assistant Agent Interaction Model: Feasibility Study for a Complex Task

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ABSTRACT

As road traffic is becoming increasingly dense, new needs in terms of intelligent human-machine interaction are emerging for their control by human operators. One avenue of research consists in assisting them in their control task by an assistant agent. This paper presents a feasibility study in this field, involving interactions between humans and an assistant agent. For this purpose, a game theory-based model is proposed in order to be able to model a context-sensitive system for the cooperative realization of complex tasks. In this case, the participants of the game are human operators and an assisting agent interacting within the framework of the realization of a control task. Thus, each participants can choose an action between two possible ones (to cooperate or not). Then, the proposed utility functions allow to build the context-sensitive payoff matrix at each observation cycle of the human-machine interaction. To validate our model, we have implemented a simulated control situation; it concerns the regulation of traffic through intersections; this involves two human operators and an assistant agent. Thus, the assistant agent uses the game payoff matrix for its decision-making in using Nash equilibrium. This paper describes a feasibility study, focusing on an analysis of the results obtained during the execution of the simulation. Different research perspectives arise from this study in order to improve and generalize the proposed model.

CCS CONCEPTS

- Human-computer interaction (HCI)
- Interaction design
- Collaborative and social computing

KEYWORDS

Human-Computer Interaction, assistant agent, game theory, control task, context sensitivity, road traffic

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1 Introduction

Since the progressive exploitation of artificial intelligence in human-machine interaction since the late seventies [1, 2, 3], research on the so-called adaptive or intelligent human-machine interaction now induces a sub-domain dealing with human-agent interaction. In particular, intelligent agents are taking an increasingly important place in the design of intelligent interactive, recommender or assistance systems. In more and more cases of practical uses, it becomes possible for these agents to take initiatives [4].

In the case of cooperation with human beings, in carrying out complex tasks, several interaction models and assistant agents have already been proposed. For example, Levin and colleagues propose a stochastic interaction model for assistant level decision making [5]. In [6], the authors use a markovian model for predicting human trust behaviour in the framework of human-agent interaction. An interaction model is proposed in [7], with the objective of describing intelligent agents that can teach human operators working in groups. In an assistance framework, Azaria *et al.* propose a so-called social agent which can give advice to a human being in case the decision making seems complicated [8]. To our knowledge, among the approaches of artificial intelligence using game theory [9] and the notion of Nash equilibrium [10], there is not yet an approach directly involving several human beings (our first work focusing on a single human [11]) and one or more assistant agents, as

players, with a view of intelligent human-machine interaction. Thus, the participation of human beings in the game, in the sense of game theory, is not yet formally expressed in the literature for this purpose of interaction.

This paper focuses on a human-agent interaction model based on the definition of a repeated (or iterated) multi-player game. This paper is structured as follows. The second section first sketches a state of the art on human-agent interaction models. Then it addresses the problem of applications using agents for road traffic control; indeed such domain is considered in the feasibility study. In the third section, an interaction model based on game theory is proposed, explaining the formulation of the Nash equilibrium search. The fourth section presents a traffic simulator involving two human operators and an assistant agent, who collaborate for the purpose of traffic light control. This is implemented thanks to the possibility of participatory simulation in Netlogo. The analysis of the simulation results is presented in the fifth section; it illustrates the effectiveness of the proposed interaction model. The paper concludes with a discussion, a conclusion and research perspectives.

2 State of the art

This state of the art focuses primarily on human-agent interaction in a complex task setting. It then focuses on the exploitation of agents in traffic simulation; indeed this application field is used for the instantiation and validation of the interaction model proposed in this paper.

2.1 Human-agent interaction models

2.1.1 Agent-based approaches. When performing a complex or sometimes dangerous task, collaboration and cooperation between artificial agent or software agent and human operators proves to be a promising solution. For example, in the case of industrial process supervision, Le Strugeon *et al.* [12] propose an intelligent agent model to assist a human operator in a collaborative way to optimize industrial process control. In addition, Badeig *et al.* [13] describe the construction and design of a collaborative system using a multi-agent model. To improve the efficiency of assistance, Mandiau *et al.* [14] propose an assistance approach based on the agent concepts of beliefs and intentions. In [15], the authors propose a model of human-agent interaction with the objective of improving artificial intelligence with the support of human business expertise. For this goal, they use the iML interactive learning machine technique based on a principle of ant colony optimization (with possible human influence on constitutive agents). Finally, a recent study proposes a formal definition of explicability in the context of human-agent interaction using Machine Learning techniques. This approach takes into account information from the context, in particular the user's workload level and performance [16].

2.1.2 Game Theory Approaches. In our previous work, we proposed a first interaction model between a human and an assistant agent [11]. Moreover, in [17], the authors use the game

theory approach to study a strategic behavioural interaction between a human and an autonomous agent. In fact, this work focuses on the agent's behaviour using two principles: negotiation and deliberation. Regarding human-robot interaction, in [18], the authors exploit the game theory model to develop an interactive robot controller capable of physically interacting with one human being. In addition, game-theoretical approaches are proposed in various application domains, such as the Internet of Things (IoT) and Bitcoin technology, in the case of resource and task sharing (see for example [19]). However, human participation and context awareness are most often not explicitly addressed.

2.2 Agents in our case study: road traffic control

2.2.1 Agent-based approaches. Several works deal with the study and simulation of road traffic in terms of agent-based modelling. For example, in [20], the authors exploit the advantage of using the anticipatory behaviours of agents in multi-agent coordination for the simulation of traffic at intersections. In [21], a constructivist learning control model is proposed to facilitate traffic regulation. For traffic flow optimization, Ksontini *et al.* [22] propose a model based on an egocentric representation of the traffic environment that exploits the heterogeneity of vehicles and the drivers' behaviours. In [23], the authors propose a reactive agent model for traffic microscopic simulation. With a view of organization of traffic light control, [24] describe a self-organizing control in case of intersection signals's failure. In order to improve traffic control, [25] introduce a control model based on traffic history. With the same objective, an agent-based modeling is also proposed by [26], using inference engines taking in input values related to temporal traffic situations. Finally, [27] propose a division of the global traffic network into a set of sub-networks in order to facilitate the control task by implementing a multi-agent system. To conclude, a brief (but not exhaustive) state of the art of multi-agent road traffic models has been presented. But the involvement of human operators in these agent-based or multi-agent approaches has not yet been explicitly formalized in the literature.

2.2.2 Approaches using game theory. Some work focuses on the application of game theory for the organisation and simulation of road traffic. This is the case in ARCHISIM platform [28]: game theory has been proposed for resolving conflicts between vehicles at intersections. A two-player game model has been proposed in [29] in the case of conflict resolution between two motorcycle drivers. However, these approaches consider only vehicle or vehicle-driver participants. No game-theoretical approach explicitly involves one or more human operators and assistant agents interacting in a traffic control task.

3 Proposal of an interaction model exploiting the principle of game theory for the purpose of assistance

The game theory-based interaction model can be started with the case where an assistant and a human being (i.e. a human

operator) interact. However, it is possible to propose a generalization of the model towards an interaction between several agents and several human beings (users). In this paper, we illustrate the proposed approach with one human and one agent, then two humans and one agent. Let us recall that to be able to define a game [9], it is necessary to specify at least the following elements: (i) the participants in the game who are called players, (ii) the rules of the game, (iii) the possible actions for each of the players, (iv) the utility functions allowing to calculate the gains of all the participants for the creation of the game payoff matrix. For a given game, a combination of the possible actions of all players is called a *strategic profile*. Thus, game theory modeling consists in finding the solutions of the game. The most commonly used approaches are the search for the best answers and the search for equilibrium. For this feasibility study, we will use the Nash equilibria [10].

3.1 Formalization of multi-player game with two possible actions for each player

For formalization, we can consider the case where several human beings (users) interact with one or several assistant agents. In the following, we choose to use the *C* & *D* usual notation (coming from the prisoner's dilemma, stated in 1950 by the mathematician Albert W. Tucker) for the actions of the different entities: *C* for Cooperate, *D* for Defect (knowing that in our case, *D* actually means for an agent that it chooses not to cooperate, cf. below).

For human beings, we choose the following notations:

1. The human being asks the assistant for help : *C*.
2. He or she does not require any help: *D*.

Concerning the assistant, it can respond to the request of one of the human beings (if there is at least one request) or inform/warn human beings of important information if there is no request: *C*.

The assistant can also let human beings work autonomously [which is also in line with the principle of *learning by doing* [30]: *D*.

It is important to note that, in practice, there are other possible actions than: *to cooperate* and *not to cooperate*. These two actions have been chosen to facilitate the search for equilibrium (using Nash equilibrium) and adaptation with a view to a generic assistance system.

Thus, Figure 1 shows an example of a graphical representation of possible cases. H_i is one of the human beings involved and A_1 designates an assistant. Thus, the outcomes of the game are the paths: *CCC*, *CCD*, *CDD*, *DCD*, etc. For example, *CCC* means that the two human beings H_1 and H_2 simultaneously ask for help and the assistant intervenes.

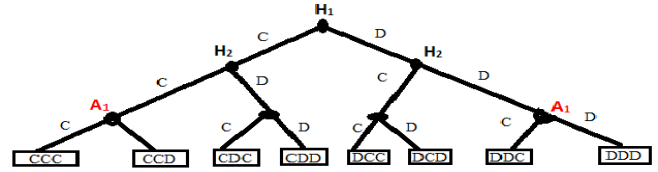


Figure 1: Graph showing the outcome of the game (case of two humans and one assistant agent)

In the decision-making process, the assistant has one of the following strategies at its disposal:

1. To act or not to act randomly (without intelligency)
2. To act or not, while trying to maximize its gain for each move in the game (the assistant is selfish [31]).
3. To act or not to act, while considering the maximum gain for human beings (it is more altruistic [32]) with human beings).
4. To act or not to act according to Nash equilibrium [10] considering the optimal gain for everyone.

3.2 Payoff of human beings and assistant agent

3.2.1 *The Human beings's payoff.* If a human being asks for help, his or her gain depends on the responses of the assistant agent and the choices of other humans: his or her gain decreases with his or her workload level. This gain also decreases with his or her profile because the higher experience level and the lower workload, the less the human being should ask for help from the assistant agent (who should then be able to take care of other tasks for example). Thus, the gain of each human also depends on the other human beings: if the human asks for help, his or her gain increases with the sum of the workloads of all humans, and with the criticality level. But the gain decreases with his or her experience level. If the human being is autonomous, his or her gain decreases with the intervention of the assistant and especially if he or she does not have a high level of workload. But in fact, the criticality level can significantly influence the choice of the human being, to be autonomous or not.

3.2.2 *The assistant's payoff.* The assistant(s)'s payoff depends on the choices of the human beings. In addition, the numerical values of the payoff take into account the information relevant to the user context, i.e. the human's workload and the experience level. The assistant is an intelligent agent capable of intervening if human beings need help. In terms of game theory, the agent and the human beings who need help, share the same payoff value, because if the assistant intervenes, it justifies by its payoff that its intervention is necessary; this payoff also increases with the criticality level of the situation. In case of non intervention, the values can be chosen according to two cases: (1) When human beings do not need help, the assistant agent must not react (i.e. respond to their request) at the risk of unnecessarily wasting time (which could be spent on other tasks); (2) When humans have asked for help (and the assistant does not intervene), the assistant's payoff may increase because

it has much more time to deal with other tasks, but it will not be very useful from the human point of view [33], especially if the human really needs the help because of a high level of workload, for example.

3.3 Proposal of utility functions to build payoff matrix at each iteration during the task

According to the principles related to payoff, stated above, we can propose the following functions in the context of the creation of the game payoff matrix for the case of an assistant agent and m human beings:

3.3.1 *Calculation for Assistant agent gain.* If the assistant has reacted (i.e. it plays C):

$$u_A(C, \bar{x}_j) = c_h \sum_{i=1}^m w l_i - \sum_{i=1}^m u s r l_i - d_h \times c r t \quad (1)$$

with:

$c r t$ designates the criticality level of the situation, according to [34]

c_h means the number of human beings requesting assistance.

d_h means the number of human beings who are self-sufficient: no need for assistance.

$w l_i$ refers to the workload level of a human being of index i [35].

$u s r l_i$ is the experience level of the user of index i [36].

m is the total number of human operators.

In this formula, the assistant's payoff increases with the number of humans requesting assistance, and with their workload level. This shows the importance of the assistant's intervention. However, this gain decreases with the sum of their experience's levels because if all humans are experts, the assistant does not need to intervene.

If the assistant leaves it up to the human operators to work autonomously (D):

$$u_A(D, \bar{x}_j) = c_h \sum_{i=1}^m u s r l_i - \sum_{i=1}^m w l_i \quad (2)$$

Here, the assistant's gain increases only with the sum of the values of the human experience levels. But the assistant's payoff decreases with their workload level, and especially with the criticality level (because non-assistance can lead to a loss).

3.3.2 *Calculation for Human (Hk) gain.* If the human of index k (called H_k) asks for help (C):

$$u_{H_k}(C, \bar{x}_k) = c_a \sum_{i=1}^m w l_i - u s r l_k - d_a \sum_{i=1}^m w l_i \quad (3)$$

with: c_a the number of assistant agents which choose act, d_a designates the number of assistant agents which choose not to intervene (i.e $c_a, d_a \in \{0,1\}$ in our case); \bar{x}_k are the actions for other players (the assistant and non-humans of index k).

In this formula, the human being's payoff asking for help increases with the sum of the workloads of all the human beings. But it decreases with this human being's experience level (here indexed by k).

If the k -index human being is autonomous (D):

$$u_{H_k}(D, \bar{x}_k) = -c_a \sum_{i=1}^m w l_i + u s r l_k - (c r t + w l_k) \quad (4)$$

with: H_k refers to the human of index k and $u s r l_k$ the experience level of k -index human being.

In this case, the gain decreases with the sum of the workloads of all human beings. And since the human being (of index k) is autonomous, it is only his or her experience level that will have a positive impact on the value of his or her payoff. However, with a high criticality level and a high workload level, his or her payoff should decrease accordingly.

If the agent acts, the payoff of humans asking for help are greater than the payoff of those who are self-reliant. If the agent does not respond, the payoff of humans asking for help are less than the payoff of autonomous humans. If the human is autonomous, the payoff of the agent in case of intervention is lower than in case of non-intervention. If the human asks for help, the intervening agent's payoff is higher than that in case of non-intervention.

3.4 Total payoff calculation over N iterations

As we have considered a repeated game of several players, we propose to calculate each player's payoff by the following formulas:

$$\text{For human beings: } G_{H_k} = \frac{1}{N} \sum_{i=1}^N u_{H_k}(x_k, \bar{x}_k)_i \quad \text{with: } u_{H_k}$$

designates the utility function of each human operator. For the

$$\text{assistant: } G_A = \frac{1}{N} \sum_{i=1}^N u_A(\bar{x}_k, x_k)_i \quad \text{with: } (\bar{x}_k, x_k)_i \text{ designates}$$

the strategic profile in the i -th iteration and u_A the utility function of the assistant agent.

These formulas make it possible to evaluate each player's payoff by studying the Nash equilibrium of each iteration. For the assistant, we have assumed that it takes charge of other tasks apart from assisting the human operator(s).

3.5 Equilibrium search

After building the utility functions for the players, we will now proceed to the resolution of the game. The Nash equilibrium in pure strategy corresponds to a situation in which none of the players has an interest in unilaterally changing the strategy [10]. However, this equilibrium does not always exist. Alternatively, there is also another type of equilibrium called mixed-strategy equilibrium which uses a probability distribution over the set of

possible actions for each of the players to determine the equilibrium.

Our formulation leads to a non-zero sum game, i.e. the sum of the payoffs of the different players is not equal to 0. In our case, the following conditions must be met for a strategic profile to be a Nash equilibrium in pure strategy. Let a strategic profile rated s^* such that:

$$s^* = (s_1^*, s_2^*, \dots, s_k^*, s_{k+1}^*, \dots, s_m^*, s_A^*) = (s_k^*, s_{-k}^*, s_A^*)$$

So, s^* is a Nash equilibrium in pure strategy if $\forall i \in [1, m]$

$$\begin{cases} u_{H_i}(s^*) \geq u_{H_i}(s_1^*, s_2^*, \dots, s_{i-1}^*, s_i, s_{i+1}^*, \dots, s_m^*, s_A^*) \\ u_A(s^*) \geq u_A(s_1^*, s_2^*, \dots, s_k^*, s_{k+1}^*, \dots, s_m^*, s_A) \end{cases}$$

with: s_i^* designates an action performed by the human of index i at the equilibrium, s_i for any action of the latter. Thus, s_A^* an action performed by the assistant at the equilibrium, and s_A designates any action of the assistant.

It would be possible to choose other methods. But Nash equilibrium has been chosen particularly as we are considering an assistant agent (considered rational and cooperative) which can take over other occupations: it can become an assistant for one or more other tasks. Thus, the Nash equilibrium allows to obtain an optimal gain for each participant (humans and agent). For Nash equilibrium search, we use the algorithm described in [37]. If the algorithm does not find a Nash equilibrium, we have taken by default the action D for the assistant agent.

4 Feasibility study: road traffic control task involving one and then two human operators assisted by an assistant agent

Traffic control is one of the complex tasks that can involve human beings, who have to deal with regulation at every intersection. In this feasibility study, we use Netlogo to simulate the road traffic control environment. Netlogo is an open source simulation platform created by Ury Wilensky [38, 39]. It is easy to use in modelling and simulation of complex systems, such as natural, social or engineering systems. Netlogo uses an agent-based approach.

The assistant agent is intended to assist the human being(s) in carrying out these control tasks with two actions: to take special care of an intersection or to leave the task to the human being(s) for the control of the traffic lights located at each intersection.

To this end, certain rules of expertise could be evoked to justify the importance of the intervention or not of the assistant agent through each of the intersections:

1. It can search for an intersection that has the maximum number of vehicles waiting to enter it (for example, vehicles stopped by the red traffic lights in front of them). In this

case, it can change the signal control (i.e. colours of the lights) in this intersection.

2. It can select an intersection that has the minimum number of vehicles waiting to enter the intersection (stopped by the red traffic lights).

4.1 Description of the participative traffic simulation application under Netlogo

The hubnet server allows a so-called participative simulation [40]. In this simulation, clients (human operators) can participate in a cooperative way in the management of traffic lights in order to obtain maximum fluidity.

The three participants (later referred to as P1, P2 and P3) in this first feasibility study are undergraduate students in physics or economics (average age: 25 years; two men and one woman). The main selection criteria for choosing participants are: Have good eyesight, be able to use a computer, be able to work in a team, not be subject to dizziness (which can be caused by vehicle movements on a screen). All the people solicited in the framework of this first feasibility study agreed to take part in it, but the health situation related to Covid-19 did not make it possible to have more participants (no access to the buildings).

In addition, an external observer (evaluator) is appointed for the initial configuration of the traffic model by setting the speed limiter, number of vehicles, etc. The observer also sets the duration of an iteration, starts and stops the simulation. For the implementation, the protocol in Figure 2 is followed.

1. Answering a questionnaire (age, gender, visual ability, left/right-handedness, level of education, knowledge level in road traffic, knowledge of using Netlogo as a traffic simulator)
2. Demonstration of using Netlogo for traffic simulation (vehicles, traffic lights) and the user interface of the hubnet client (choice of experience level, workload estimation, other commands useful for traffic control)
3. Explanations about assistant agent and its principle of intervention; description of the objective of human-agent cooperation with regard to traffic control task
4. Launch of the simulation by using a large screen; each participant tries to optimize the traffic in his or her occupation area on his or her own screen (duration: about 1h30).
5. Answering a questionnaire after the simulation (usability, effectiveness of the assistance, opinion on it)

Figure 2. Protocol followed by participants

In terms of functionalities, the use case diagram visible in Figure 3 shows the different types of actors: human operator, simulating a road traffic controller (one, then two human operators); assistant agent; external observer (evaluator).

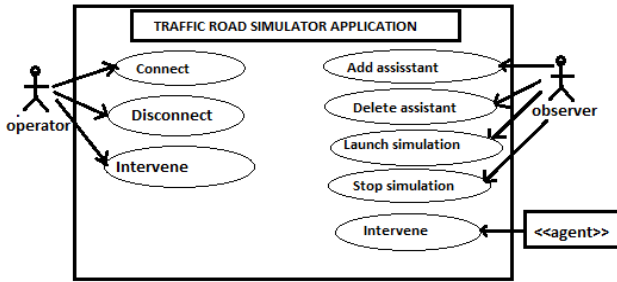


Figure 3: Use Case Diagram

Figure 4 shows a screenshot used by participant P2 (case of two humans P2 and P3 involved in the traffic control task). Each participant is connected via a Hubnet client. Each client displays a user interface with a set of commands to intervene on road traffic.

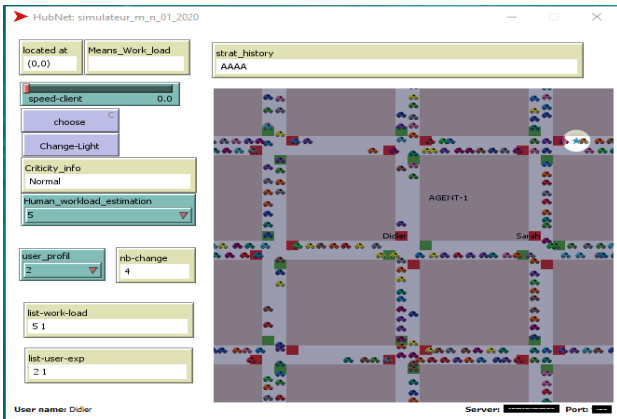


Figure 4: Hubnet Client interface (participant P2)

4.2 Hubnet client description

On the client's user interface, the human being connected to the simulator server has the choice to take the initiative on an intersection he or she can choose: he or she can change the corresponding traffic lights or wait for the help of the assistant agent set up to help them control the lights of the whole traffic. Thus, each human operator can also consult information about the workload level of the other operators and their experience levels; this information may help his or her decision-making. For example, it can be seen that the workload level of the other human is equal to 1 (very low workload) and his or her experience level is equal to 5 (very high level).

In addition, humans can control the maximum vehicles's speed limit. They can choose the intersection concerning the lights they want to intervene on.

5 Results of the feasibility study with 1 agent and 1 human then 2 humans

An initial feasibility study has yielded a set of promising results. These make it possible to highlight the impact of decisions taken by the players on the overall traffic behaviour. This impact is in terms of average traffic speed, number of vehicles waiting, evolution of the average waiting time of vehicles.

The proposed simulator has been used in situations involving 200 vehicles to give meaning to the cooperation between human beings and the assistant in the context of traffic control using traffic lights.

Each participant used the Netlogo simulator for about 1 hour and 30 minutes. This period included a series of simulator runs, with short breaks in between (to approximate working conditions in a control room [41]). For this feasibility study, an execution lasts 180s for a number of iterations equal to 60, to obtain the following results: Average speed, number of vehicles waiting and vehicle waiting time for both cases: (1) one human being and one assistant, (2) two human beings and one assistant. The curves below show usage sequences of 60 cycles only (for good readability of the curves presented for representative purposes, in relation to this feasibility study). These sequences occur after approximately one hour of use; each participant had the opportunity to master the commands of the user interface.

5.1 Numerical Results

Figure 5 shows the average vehicle speeds calculated for each cycle in the simulation. At the beginning of the simulation, all the vehicles move with a random initial speed, and a peak is obtained for the average speed. Afterwards, due to the traffic density, a decrease in the average speed will be observed. Indeed some vehicles have to stop or slow down depending on the situation of the vehicle ahead: presence of a red traffic light or waiting for a vehicle that crosses the intersection first.

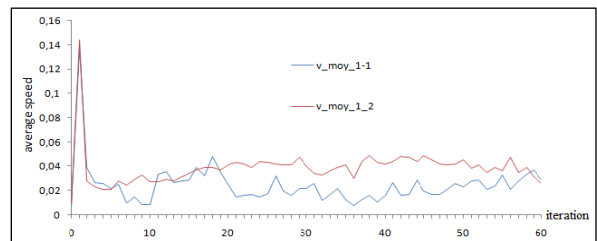


Figure 5: Evolution of the average speed of the vehicles

In Figure 5, $v_{moy_1_1}$ refers to the evolution of the average speed of vehicles in the case of one human being (P1) and one assistant agent; $v_{moy_1_2}$ refers to the case of two human beings (P2 and P3) and one assistant. For the two simulation cases mentioned above, Figure 6 shows the evolution of the total number of vehicles stopped during each of the cycles. After the start of the simulation, almost all the vehicles are running at initial speeds, which justifies the low value of this number at the start.

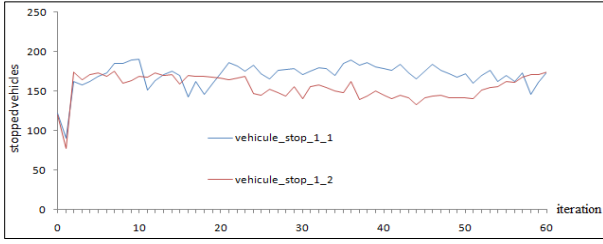


Figure 6: Evolution of number of stopped vehicles

In Figure 6, *vehicule_stop_1_1* refers to the number of vehicles stopped in the case of one human and one assisting agent; *vehicule_stop_1_2* refers to the case involving two humans and one assisting agent.

Figure 7 shows the cumulative waiting time of vehicles during the 60 cycles. *wait_time_1_1* shows the evolution of the waiting time for vehicles at each iteration (case involving one human being and one assistant agent); *wait_time_1_2* refers to the case involving two human beings and one assistant.

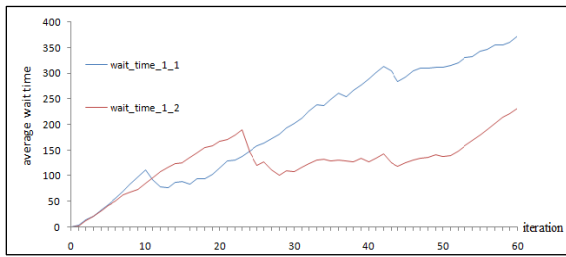


Figure 7: Evolution of average vehicle waiting time over iterations

Concerning the number of interventions (expressed, for example, by the number of colour changes at traffic lights), Figure 8 shows the evolution of the number of interventions by human beings (in both cases considered) while Figure 9 shows the evolution of the number of interventions by assistant agents.

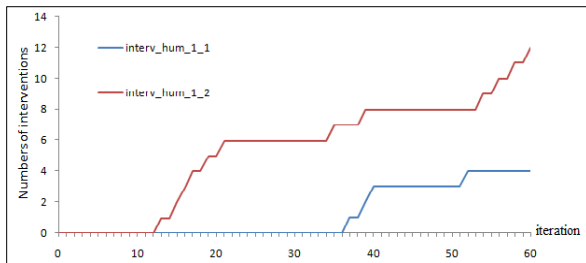


Figure 8: Evolution of the human's intervention numbers

In Figure 8, *interv_hum_1_1* refers to the evolution of interventions of human beings in the case of one human being (P1) and one assistant agent; *interv_hum_1_2* refers to the case of two human beings (P2 and P3) and one assistant.

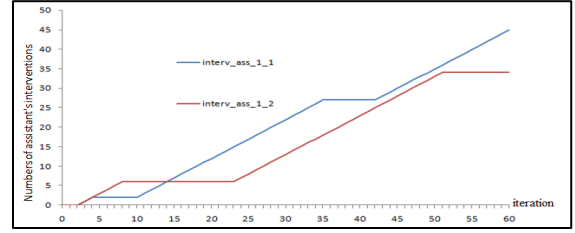


Figure 9: Evolution of the intervention of the assistant agent depending on the Nash equilibria

In Figure 9, *interv_ass_1_1* refers to the intervention of the assistant agent in the case of one human being (P1) and one assistant agent; *interv_ass_1_2* refers to the case of two human beings (P2 and P3) and one assistant.

The description of the interventions of the assistant and the human beings during the 60 cycles is as follows: 35 interventions of the assistant and 12 for the human beings (case: 1 assistant, 2 human beings); 45 interventions of the assistant and 4 for the human being (case: 1 assistant, 1 human being). This can be explained by the fact that with only one human being, the assistant has to increase the frequency of the interventions in order to contribute to the fluidity of the traffic.

5.2 Qualitative results

The answers of the 3 participants to the questionnaire after the performance of the control task (during 60 iterations) assisted by the agent, are visible in Table 1. For evaluation purposes, each of the participants answers the question on the usability of the proposed simulator, the effectiveness of the agent assistant in assisting and the opinion on the mode of assistance. Each response is measured using the 5-value Likert scale [42]. The values are 1 (Strongly Disagree), 2: (Disagree), 3 (Neither Disagree nor Agree), 4 (Agree), 5 (Strongly Agree). The first results regarding participants' opinions are provided in Table 1. They show a first positive trend, which is promising for this first feasibility study. This will have to be confirmed in the context of other studies involving more participants.

Table 1: Opinions of the three participants involved (Case 1-1: one human being (P1) and one assistant agent; Case 1-2: two human beings (P2 and P3) and one assistant).

Participants	Usability of the simulator	Effectiveness of assistance	Opinion on the assistant agent
Participant P1 : Case 1-1	5	4	4
Participant P2 : Case 1-2	5	4	4
Participant P3 : Case 1-2	4	4	3

Several first impressions of the participants can be seen below:

« I think it's a good traffic simulator. In terms of performance, I've seen that the assistant offers effective help in controlling and detecting intersections with a lot of vehicles waiting to enter them. It really is a cooperative traffic management assistant » (Participant P1).

« I found the simulator easy to operate. About assistance, I found that the assistant acts efficiently on the most overloaded intersections when necessary. I have the impression that it can quickly determine the number of vehicles stopped at the entrance of the intersections to be prioritized and act on the traffic lights » (Participant P2).

« I think the simulator gives you some ideas about road traffic. I have the impression that the assistant acts appropriately when my workload is high. However, there is a limit in some intermediate cases where it does not intervene, even when my workload is high and the other person is not » (Participant P3).

6 Discussion

The discussion is focused on two points.

6.1 Equilibria considering only the intervention of the assistant

The Nash equilibrium proposes an intervention for the assistant in each iteration. In the case where the assistant agent takes over the control of all the junctions, the obtained results show a certain efficiency in the management of the junctions, in particular in terms of average traffic speed, number of vehicles stopped. At each iteration, the assistant is, therefore, obliged to act because the equilibrium allows it to intervene. To do this, the agent will consider successively during the same cycle, in its area of occupation, the number of vehicles stopped for each intersection in descending order: the assistant must first take care of the intersection or intersections with the maximum number of stopped vehicles. Thus, the number of interventions coincides with the number of iterations (remember that we have considered a number of iterations equal to 60).

6.2 Equilibria with or without the intervention of the assistant

The feasibility study shows us the interaction between an assistant agent and one and then two human operators in traffic control. Here, the assistant agent uses the Nash equilibrium principle [10] for decision making on all intersections (including those occupied by human operators). Simulation sequences over 60 cycles have been carried out, several of which have been illustrated to show the feasibility of the approach. Such a sequence duration allows to illustrate different interventions of the assistant agent, the human(s) involved, and the consequences of the interventions on traffic.

Thus, in the sequences selected and illustrated above, the assistant intervenes from iteration 10 to 35 (for the case: one

human and one assistant), and 25 to 50 (for the case: two humans and one assistant) (Figure 9). There is stability in the average traffic speed (Figure 5). Between iterations 35 and 40 (for the case: one human and one assistant) and 50 to 60 (for the case: two humans and one assistant) (Figure 9) during which the assistant has calculated the Nash equilibrium: the human beings have a lower workload level and with a high of expertise, the assistant does not act (given the equilibrium) hoping that the human beings have the possibility to act. In this period, the assistant does not intervene and there is a decrease in the average speed, despite the effort of the human beings (Figure 8).

Always considering Nash equilibrium, an optimization of traffic is also observed if the human beings have a high level of workload with a slightly lower expertise level: hence the importance of the assistant's intervention.

Finally, it can be noted that the traffic results do not depend on the number of iterations. We can go up to several hundreds or even thousands of iterations. Effectiveness depends essentially on the interventions of the human beings and the assistant throughout the execution, while taking into account the initial characteristics of the traffic.

7 Conclusion

In this paper, we proposed a game-theoretical model of human-computer interaction, involving an assistant agent and several human beings (two in the described study) who interact in a given interactive environment. This model supports decision making from the perspective of assisting, or not, based on information coming from the context, of human operators. The feasibility study was carried out on two cases: one human and one assistant agent; two humans and one assistant agent. These two cases concerned a complex traffic control task. They show the feasibility of the approach, and also give an insight into the effectiveness of the assistant agent. If the assistant does not intervene, a degradation of the traffic can be observed.

A first research perspective concerns the setting up of two user studies: the first with about ten participants for the case involving a single human; the second with about ten groups of participants for the case involving two humans and an agent. In these studies involving more participants, it will be possible to analyse their behaviour in detail. Another perspective concerns the explanation of the efficiency of the agents linked to a measure of satisfaction of human beings in terms of assistance. This measure can also be related to the principle of context awareness in the context of assistance. Finally, the comparison with other adaptation approaches, as well as with other agent-based approaches for traffic management, will be also envisaged.

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