A GAME THEORETICAL FRAMEWORK TO ASSESS COMMUNICATION STRATEGIES IN C-ITS

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ABSTRACT
In Cooperative Intelligent Transport Systems, road users and traffic managers share information for coordinating their actions to improve traffic efficiency allowing the driver to adapt to the traffic situation. Its effectiveness, however, depends on the user's decision-making process, which is the main source of uncertainty in any mobility system, and depends on the ability of the infrastructure to communicate timely and reliably. It is expected that cooperation will perform optimally when no uncertainties are present in the system, i.e. there are no communication failures, the information is clear, the sender is trustworthy and the receiver adopts the information unconditionally. However, uncertainty is inherent to the road traffic domain, populated by boundedly rational agents in a dynamic environment. To cope with such a complex scenario, this paper proposes a game theory perspective based on the *n*-Person Prisoner's Dilemma as a metaphor to represent the uncertainty of cooperation underlined by communication infrastructures in traveller information systems. The traveller information system is thus one of the participants together with N-1 vehicles in a binary road network setting. Taking place in a dynamic environment, with en-route path recommendations, the emergence of cooperation and changes in agents' behaviour are analysed, as well as the effect of information percolation in both flawless and malfunctioning transmission situations. Results highlighted a close relationship between the emergence of cooperation and network performance, as well as the impact of the communication failure on the loss of cooperation sustainment, which was not recovered after the system was re-established.

Keywords: *n*-Person Prisoner's Dilemma, Advanced Traveller Information System, communication strategies, information percolation, Cooperative Intelligent Transport Systems, agent-based simulation, Multi-Agent Systems

INTRODUCTION

The accelerating phenomenon of rural exodus that characterizes contemporary society has been accompanied by an increasing need for mobility in city and town centres, as well as for inter-urban connections. The imbalance between transport demand and network capacity gives rise to traffic congestion, with significant consequences for transport infrastructure. Inefficiencies have economic, environmental and social impacts.

Cars are becoming directly or indirectly networked devices. Interaction with each other and with the road infrastructure enables the exchange of information, which is used to coordinate management actions and help drivers in their decision-making, the main source of uncertainty in a mobility system. This is why Cooperative Intelligent Transport Systems (C-ITS) solutions, assisted by an inter-vehicle and vehicle-to-infrastructure communications platform, will play a crucial role in improving traffic efficiency, safety and security of the public, and the management of road infrastructures.

A transport network is the backbone of urban activities, designed to accommodate the circulation of people and goods in metropolitan areas. The dynamics of cities and their consequences on traffic flows imply a continuous updating and readjustment of the system. This must obtain and provide the most appropriate information to the exact users in a timely manner, at the appropriate place and to the intended recipient, in order to enable informed decision-making and to influence users towards an optimal system condition.

This work contributes with a study of information percolation strategies, with both flawless and malfunctioning transmission situations, allowing us to shed light upon the effects of information on the coordination mechanisms. It takes into account the topology of the road network, the characteristics of communication networks and routing algorithms, and the composition of transport demand. The proposed approach is leveraged on the assumption that the effectiveness of information is highly dependent on the user's decision-making process, which is the main source of uncertainty in any mobility system. It also depends on the ability of the infrastructure to communicate timely and reliably, which is not always guaranteed. Considering cooperation will perform optimally when no uncertainties are present in the system, i.e. there are no communication failures, the information is clear, the sender is trustworthy and the receiver adopts the information unconditionally, such an ideal scenario becomes rather an utopia.

However, uncertainty is inherent to the road traffic domain, populated by boundedly rational agents in a dynamic environment. To cope with such a complex scenario, we propose a game theory perspective based on the *n*-Person Prisoner's Dilemma as a metaphor to represent the uncertainty of cooperation underlined by communication infrastructures in traveller information systems. The traveller information system is thus one of the participants together with N-1 vehicles in a binary road network setting. It takes place in a dynamic environment, with a strategy to predict and disseminate the recommendation of the Advanced Traveller Information System (ATIS) en-route, towards an optimal and fair system state. A simulation framework was implemented to test and evaluate those strategies, as well as to analyse their impact on the network performance, including the failure of the information service, allowing to observe the system degradation and the agents' behavioural changes. For the sake of simplicity, in this work social behaviour refers to whether agents are prone to cooperation or defection, whereas the economic behaviour is associated with the payoff balance in terms of travel time costs and their equal distribution among the agents in the population.

The remainder of the paper is organized as follows. The next Section reviews the relevant literature. The Section entitled "Methodological Approach" presents the formalization in the context of Game Theory, and describes the experimental framework. Section "Results and Analysis" summarizes the results of these experiments. Finally, in "Conclusion" the results and future directions are discussed.

LITERATURE REVIEW

It is possible to identify a social dilemma in the relationship between Game Theory and the study of car traffic, which explains the stable condition of User Equilibrium with the natural behaviour of drivers, even though a System Optimum is rarely reached without the intervention of an information service (*1, 2*). However, even if User Equilibrium is optimal for the user, this does not necessarily mean that it is optimal for the system.

Increasing road capacity is not a viable solution for reducing congestion, as the Braess's Paradox has shown (cf. 3), hence the importance of rational and efficient management of existing resources. Selfishness is an innate characteristic of human beings (*4*), whereby pure rationality threatens social dilemmas. However, while consistent with selfishness, so is rationality with altruism (*5*). In (*6*) authors have shown cooperation in social dilemmas without external controls, suggesting that their origin lies in human nature, but also that its emergence rate has a strong causal link with payoffs (*7*).

Selfish, rational behaviour leads to suboptimal outcomes. The Nash Equilibrium in the Prisoner's Dilemma, obtained with a mutual defection strategy is not socially efficient. However, it is possible for the system to reach an optimum, given the concept of partial cooperation, in which some players are induced to behave cooperatively, while the rest opt for the rational action of defection. Implemented iteratively, decision alternation leads to a Pareto-efficient solution, although in finitely repeated games this is not an equilibrium state, as players are tempted to abandon the strategy (*8*). this is also empirically verified in a route choice experiment (*9*), with an alternating cooperation emerging between players, previously informed that by coordinating their actions they would be able to achieve maximum time savings. After a certain period of adaptation, the players learned to coordinate their actions, suggesting that through the gradual acquisition of information cooperation between small groups can emerge spontaneously (cf. 10). Furthermore, an experiment with public goods games also showed that the greater the heterogeneity of the group, the lower the degree of cooperation (*11*).

In the original formulation of the Prisoner's Dilemma, with two participants in a binary choice of different cost and congestion-sensitive routes, User Equilibrium occurs when both players choose the lowest cost route. However, the social optimum only exists when one player is on the lowest cost route and the other on the complementary route, something hardly achievable by two rational players in a one-shot game. With repetition, in turn, if players learn to cooperate by alternating between faster and slower routes and share time-saving equally among themselves, partial cooperation can become a game equilibrium (*2*).

Successive interactions of the same commuter community, by way of social encounter, can define a repeated game (*9*), which, by promoting cooperation to alternately use better and worse routes, can make each driver's travel costs lower, on average, than in User Equilibrium (*12*). With a certain degree of altruism and a sufficient number of route alternations between drivers, there is a self-organizing formation of a fair equilibrium capable of maintaining the network in an optimal state (*13*).

One of the strategies to influence drivers towards altruistic behaviour for small-scale deviations for the benefit of the common good, with suggestions to achieve a System Optimum, is to inform them in advance about the objectives of traffic management. The result of survey and simulator studies showed an increase in compliance rate (*14*), however they are not directly transferable to real traffic as they focused on one-time interactions in a laboratory environment, and drivers' behaviour may be different. Another approach in a simple binary network was to let the agents know about the overall daily travel time of the system. When their last action had increased it, they responded with a change of route (*15*). The result was a stable and equitable optimal system in which everyone contributed to the common good. However, this model assumed a completely altruistic society, something quite difficult to maintain with human drivers.

The benefits of providing rational travellers with journey time information would depend on their knowledge and ability to predict times based on external factors (*16*), enabling them to make optimal choices, thereby contributing to reducing traffic congestion and improving the level of service provided by road infrastructure (*17*). Nevertheless, there are three adverse impacts on the network resulting from the prevailing travel information: oversaturation, overreaction and concentration (*18*).

In reality, many travellers rely on information to make their choices, both for its cognitive and affective value, whether in selecting routes or modes of transport (*19–21*) However, increasing the informational burden at the individual level leads to a state of User Equilibrium (*22*), as rational agents with full knowledge will compete for the least cost paths on the road network (*23*). On the other hand, because of the rational traits and cognitive limitations associated with human behaviour, not all drivers would comply with the recommendations (*24*), particularly when achieving a sub-optimal result (*25*). As Roughgarden noted (*26*), route selection is a selfish act, with no thought of the consequences of such a choice for others, since it is made in order to reach the destination as quickly as possible.

The advent of ATIS has made it easier to provide current or even predictive information on traffic flow to road users (cf. 27). However, not only the quantity and validity of the information is important, but its nature also plays a relevant role (*28*). Traffic density is pointed out as the best criterion for control purposes, helping to optimize the flow, to the detriment of travel time, which introduces not only concentration but also oscillations in the system and is consequently not a good indicator.

Perfect information draws road networks closer to the User Equilibrium state, but this is generally sub-optimal and quite different from the System Optimum, which minimizes the aggregation of travel times for all travellers. Nevertheless, if widely accepted by road users, ATIS can contribute to the road network converging towards the System Optimum rather than User Equilibrium by providing the most optimal route for the system (*1*).

In addition to external information, travellers also generate data during their usual trips based on the experience of previous journeys, which can be disseminated through information sharing services. This model shows a positive correlation between percolation rate and convergence to User Equilibrium (*29*).

The study of the effects of providing traffic recommendations on driver behaviour, in particular their impact on implicit cooperation in self-interested agents, has demonstrated that optimized route recommendations and extrinsic incentives (rewards for compliance) in a simple binary road network led to more efficient emergence of cooperation (*22*). However, although recommendations were a condition of cooperation, with incentives increasing the acceptance rate, in a realistic road network, the need for some kind of coordination was suggested, as indifferent participants were observed to have maintained route preference even when severely penalized. When all agents follow the ATIS recommendations, coordinating actions will allow System Optimum to be achieved by changing suggestions to ensure that all drivers receive the best and worst routes with approximately the same frequency. They will thus be able to learn to cooperate without incentives, although these are useful when cooperation between agents requires a change in behaviour against natural propensities (*2*). However, drivers may mistrust strategic routing heavily relying on incentives (*30*).

In this work we explore the use of a well-known game theoretic framework to assess the degree of cooperation between driving agents and an ATIS agent, when the latter acts as information provider to the former. To the best of our knowledge previous works do not consider ATIS as participant of a game. Here we will use the formalization of the n-Person Prisoner's Dilemma to evaluate the effectiveness of the information percolation strategies adopted by the ATIS to foster cooperation in the other participants.

METHODOLOGICAL APPROACH

The decision-making model is implemented based on the n-Person Prisoner's Dilemma and the payoff matrix was grounded in the social dilemma of the "tragedy of the commons". The participants in the game are the driving agents constituting the population (the independent variable) and an information service (ATIS agent), in the form of a road side unit (RSU), which provides a route recommendation to lead the system to an optimal state. Both driving agents population and ATIS agent follow the Multi-Agent System (MAS) paradigm. With a game played between the information system and the driving agents, the two possible actions of *Cooperation* or *Desertion* correspond, respectively, to the options of *Accepting* or *Rejecting* the suggestion provided by the ATIS agent.

System Optimality

Based on Wardrop's first principle (*31*), no driver can unilaterally reduce its own travel costs by shifting to another route. This behavioural assumption leads to a deterministic User Equilibrium (UE).

$$
\begin{aligned}
\underset{X}{\text{minimize}} \quad & Z = \sum_a \int_0^{x_a} t_a(x_a)\mathrm{d}x \\
\text{subject to} \quad & \sum_k f_k^{rs} = q_{rs} : \forall (r,s) \\
& x_a = \sum_r \sum_s \sum_k \delta_{a,k}^{rs} f_k^{rs} : \forall a \\
& f_k^{rs} \geq 0 : \forall k,r,s \\
& x_a \geq 0 : \forall a \in A
\end{aligned}
$$

In a link a, the variable x_a is equilibrium flows, t_a is the travel time, f_k^{rs} the flow on path k connecting an origin/destination pair $\langle r,s \rangle$, and q_{rs} the trip rate between r and s.

According to Wardrop's second principle (*31*), an optimal traffic assignment pattern, called the System Optimum (SO), drivers cooperate with each other in order to minimize the total journey time of the system.

$$\begin{aligned}
\underset{X}{\text{minimize}} \quad & Z = \sum_a x_a t_a(x_a) \\
\text{subject to} \quad & \sum_k f_k^{rs} = q_{rs} : \forall (r,s) \\
& x_a = \sum_r \sum_s \sum_k \delta_{a,k}^{rs} f_k^{rs} : \forall a \\
& f_k^{rs} \geq 0 : \forall k, r, s \\
& x_a \geq 0 : \forall a \in A
\end{aligned}$$

n-Person Dilemma

In the n-Person Prisoner's Dilemma game each of n players has a choice between two actions: to cooperate with the others for the "common good"; or to defect, pursuing their own short-term selfish interests. The participants—who can be individuals, organizations, or other types of agents—, receive a reward or punishment (the *payoff*) that depends simultaneously on their choice and that of all the others. This paradox of decision-making illustrates that the rational collective acting in self-interest is the opposite of the socially optimum.

For the purpose of this project, the dilemma is formulated as a normal-form game, in which driving agents make a binary decision to *accept* or *reject* the suggestion of the ATIS agent, and the payoff function is based on the socially beneficial outcomes that result from choosing a higher cost route, thus contributing to reduce the total cost to the system.

Mathematical Concepts

Within the framework of non-cooperative game theory, the following definitions shall apply:

Definition 1. A finite normal-form game is a tuple $\mathcal{G} = \langle \mathcal{I}, \mathcal{A}, (u_i)_{i \in \mathcal{I}} \rangle$, where:

- $\mathcal{I} = \{1, 2, \ldots, n\}$ is a finite set of n players, with $n \geq 2$;
- $\mathcal{A} = A_1 \times \cdots \times A_n$, where A_i is a non-empty finite set of actions available to player $i \in \mathcal{I}$, whereby $a = (a_1, \ldots, a_n) \in \mathcal{A}$ is an action profile;
- $u = (u_1, \ldots, u_n)$, where $u_i : \mathcal{A} \to \mathbb{R}$, is a real-valued utility function for player $i \in \mathcal{I}$.

Definition 2. Let A_i be the the action profile of player i, let $a_i, a_i' \in A_i$ be two actions of player i, and let A_{-i} be the set of all action profiles of the remaining players. Then, a_i strictly dominates a_i' if $\forall a_{-i} \in A_{-i} : u_i(a_i, a_{-i}) > u_i(a_i', a_{-i})$. An action is strictly dominant if it (strictly) dominates any other action.

Definition 3. A player i's best response to the action profile $a_{-i} = (a_1, \ldots, a_{i-1}, a_{i+1}, \ldots, a_n)$ is the action $a_i^* \in A_i : u_i(a_i^*, a_{-i}) \geq u_i(a_i, a_{-i}), \forall a_i \in A_i$. An action profile a is a Nash equilibrium if, for each player i, a_i is a best response to a_{-i}. An outcome of a game is any action profile $a \in \mathcal{A}$.

Definition 4. Let $\mathcal{G}$ and $a', a \in \mathcal{A}$. Then an action profile a' Pareto dominates action a if $u_i(a') \geq u_i(a), \forall i \in \mathcal{I}$, and $\exists j \in \mathcal{I} : u_j(a') > u_j(a)$

Assumptions

Assumption 1. The participants in the game—the driving agents, in this case—, are *boundedly rational,* meaning that individual players will do what is profitable to them and try to maximize their expected value.

Assumption 2. The common resources are the routes of the road network. Each traveller/player may choose either to travel in a direct route or use an alternative route, thereby not contributing to congestion.

Assumption 3. The resource is limited, but since each player is rational, they are expected to behave selfishly towards its use.

Assumption 4. There always exists a communication channel that allows the ATIS agent to communicate with the driving agents.

Assumption 5. Driving agents have only the knowledge they have gathered through their journeys on the infrastructure, and solely about travel times and rewards received. They have no information about the current status of the network other than the information provided directly to them by the infrastructure (ATIS agent).

Assumption 6. Each driving agent has a predefined preferred route, which corresponds to the route with the lowest cost, the one with the shortest travel time at free-flow speed.

Assumption 7. There is a society of $n \in \mathbb{N} : n \geq 2$ uncooperative players induced with a shared-resource, which is open-access to all.

Assumption 8. In a game-theoretical context, each traveller represents a rational player who has two possible actions, namely D (defect) by rejecting the suggestion provided by the infrastructure and following his preferred/predefined route, or C (cooperate) by accepting the recommendation and taking the proposed route.

Assumption 9. The ATIS is also a participant in the game, playing against all driving agents with a fixed strategy to cooperate (C). The payoff depends on the action of the other players accepting or rejecting its recommendation.

Assumption 10. All players receive a benefit (utility) $b \in \mathbb{R}_{>0}$ for their decision to accept the ATIS agent's recommendation and contribute to the social optimum.

Assumption 11. As choosing the preferred route is a selfish choice, and exploits the resources of the common good, each player who decides to reject the suggestion pays a cost $c \in \mathbb{R}_{<0}$.

Payoff Matrix

The payoff matrix is based on a formalization of the n-Person Prisoner's Dilemma (cf. Table 1), founded on the social dilemma of the "tragedy of the commons", to model a collective behaviour when users have to compete for a shared but limited resource—the road infrastructure—, open to all but with incomplete information, anticipating a selfish behaviour regarding the usufruct of road capacity.

	more than n choose **C**	n or fewer choose **C**
C	$C+B$	C
D	B	0

TABLE 1 Payoff matrix structure, where C and D stand for C*ooperate* and D*efect* respectively, just as *B* and *C*, in turn, mean *Benefit* and *Cost*. Payoffs are ordered $B > (B+C) > 0 > C$, assuming a cost C represented by a negative number. Relating to the original matrix of the Prisoner's Dilemma, Temptation means getting the benefit (B) without cost, Reward is gaining the benefit with a cost ($B+C$), Punishment is not obtaining either (0), and Sucker is paying a cost without realizing the benefit (C).

The payoff function of player i is given by:

$$f_i(a_i,h), a_i = C_i \text{ or } D_i,\ h = \{0,1,...,n-1\} \subset \mathbb{N}$$

where a_i is player i's action and h is the number of other cooperators.

In the payoff functions it is assumed:

Assumption 12.

1. The payoff difference $f(D,h) - f(C,h)$ is positive and constant for all values of $h = \{0,1,...,n-1\} \subset \mathbb{N}$, and denoted by α;
2. $f(C,h)$ is monotonically increasing in $h = \{0,1,...,n-1\} \subset \mathbb{N}$;
3. $f(C,n-1) > f(D,0)$.

By the first condition of the above assumption, any player i will get a better reward by selecting defection (D) than by choosing cooperation (C), regardless of what all other players select, i.e., defection is the dominant action for each player. The payoff difference α is interpreted as the player's incentive to defect. The second condition means that the payoff of a cooperator becomes increasingly larger as more players select cooperation. By the last condition, if all players choose the dominant defection you will have a non-cooperative equilibrium that will be Pareto-inferior to the outcome if they select the cooperative dominated actions.

Considering the payoffs hold the condition $T > R > P > S$, with $n \in \mathbb{N} : n \geq 2$, the following utility functions result:

$$\begin{aligned} C(h) &= \frac{h \cdot R + (N-h) \cdot S}{h} \\ D(h) &= \frac{h \cdot T + (N-h) \cdot P}{h} \end{aligned} \tag{1}$$

From assumption 12:

$$\exists! k^* (2 \leq k^* \leq n) \in \mathbb{N} : f(C, k^* - 2) < f(D,0) \leq f(C, k^* - 1)$$

where k^* is the minimum number of cooperators that guarantees that the cooperative payoff can be greater than or equal to the non-cooperative payoff in case no one selects cooperation, i.e, that the overall utility of cooperators is greater than the utility of those who reject suggestion, hence the social dilemma in this context of traffic recommendation and route selection.

One of the best-known and studied models in game theory, the Prisoners' Dilemma can transition from 2-person to n-person by replacing the two-dimensional matrix by utility functions (*32*), which can be plotted on the graph in the Figure 1, where k^* is the minimum number of cooperators that guarantees that the cooperative payoff can be greater than or equal to the non-cooperative payoff in case no one selects cooperation, i.e, that the overall utility of cooperators is greater than the utility of those who reject suggestion.

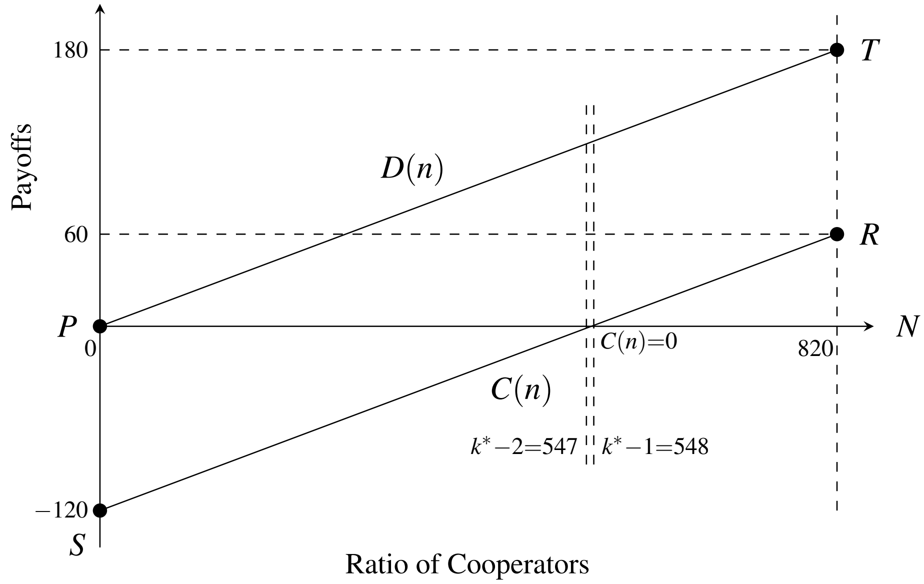

FIGURE 1 Reward/punishment functions for defectors (D) and cooperators (C).

The payoffs chosen were based on the cost of the routes, taking into account their travel times in free flow, considering a *Cost* $C = -120$ and a *Benefit* $B = 180$. In view of the formalization above, the Punishment value is $P = 0$. The Sucker is the cost of taking the alternative route, hence the negative value $S = -120$. The value of Temptation is significant for the slope of the payoff functions and, consequently, for the cooperation rates. $T = 180$, that give $R = 60$, obtaining $k^* = 549$ for 820 driving agents plus the ATIS agent, which always cooperates, its payoff being a reflex of the driving agents' cooperation.

Recommendation algorithm

Taking place in a dynamic environment, where both routes were susceptible to congestion, the ATIS agent provided a route recommendation to driving agents whose goal is to lead the system to an optimal state. The algorithm employed to build the suggestion calculates a proportion from the products of the normalization of occupancies and the average travel time of the last n trips, and reinforces its weight according to the cooperation rate as measured by the RSU (vd. Algorithm 1), then used to disseminate in multicast routing, for two groups of vehicles.

Algorithm 1: Weight calculation for suggestion build and dissemination.

Input: ρ_i Occupancy of route i
$\overline{\Delta t}_i$ Average of last n travel times for route i
k Number of cooperators
R Set of routes
N Number of vehicles plus ATIS

forall $i \in R$ **do**

$$w_i = \frac{\frac{\rho_j}{\Sigma_{j=1}^{R} \rho_j} \cdot \frac{\overline{\Delta t}_i}{\Sigma_{j=1}^{R} \overline{\Delta t}_j}}{\frac{k}{N}}$$

end

Agent Behaviour

As driving agents make several passes through the network, and to observe social and economic behaviour, they were modelled as learning agents, whose probability of electing a particular action changes by an amount proportional to the reward or punishment they received from the environment. If the action is followed by a satisfying state, then the agent's propensity to choose that particular action is reinforced. The Modified Roth-Erev Reinforcement Learning algorithm (*33*) was implemented (vd. Algorithm 2).

The learning model proposed by Roth and Erev (*34*), used in sociological theory, leads to the Matching Law (*35*), which, in the context of social dilemmas, predicts that players will learn to cooperate until the payoff for cooperation exceeds that for defection, only possible, given *Reward* > *Punishment*, if both players cooperate and defect at the same time (*36*).

Algorithm 2: Modified Roth-Erev Learning Algorithm

Require: $\varepsilon \in (0,1)$ Exploration rate
$\phi \in (0,1)$ Recency
A Set of actions

Input: a_j Current action choice
$q_{nj}(t)$ Propensity for action a_j at time t
a_k Last action chosen
$R_k(t)$ Reward for action a_k at time t
N Number of actions

Parameters: $q_{nj}(0)$ Initial propensity
ε Experimentation
ϕ Recency

t $\leftarrow$ 0
initialize $q_{nj}(0) \leftarrow 1$, for all $j \in E$
repeat
  t $\leftarrow$ t + 1
  $\left\{ p_{nk}(t) = \frac{q_{nk}(t)}{\sum_{j=1}^{N} q_{nj}(t)} \right\}_{k \in A}$
  choose action $X_t \leftarrow k \in A$ randomly, using the probabilities $p_{nk}(t)$
  collect reward $R_t(j)$
  $q_{nk}(t+1) \leftarrow (1-\phi)q_{nk} + R_k(t)(1-\varepsilon)$
  forall $j \neq k$ **do**
    $q_{nj}(t+1) \leftarrow (1-\phi)q_{nj} + q_{nj}(t)\frac{\varepsilon}{N-1}$
  end
until *termination*;

The sensitivity tests with the parameters *Recency* and *Experimentation* of Roth-Erev algorithm evidenced its impact during the initial period on the promptness with which cooperation emerges and the plateau around the analytically calculated value of k^* was established. Therefore, since it was studied the variation of cooperation in case of a system failure, the values $\phi = 0.5$ and $\varepsilon = 0.5$ were chosen, for which the plateau was reached more quickly.

Simulation setup

This is an empirical work, based on simulation methods for the implementation and on quantitative methods for the analysis of the results. A microscopic simulation was chosen, using SUMO for traffic modelling (*37*), externally controlled by modules written in Python, through the TraCI traffic control interface, allowing access to the ongoing traffic simulation, obtain values of the simulated objects and manipulate their behaviour in simulation time. Moreover, this program had also implemented the decision models of driving agents and road infrastructure, as well as the C-ITS service.

Scenario design

Following a principle of simplification, the designed scenario consists of a binary network (see Figure 2), with two routes of different cost in free-flow, the one with lower cost being the preferred one for the driving agents. The network is coupled with a 300 m feedback loop and buffer zone, to reintroduce the simulated vehicles and be able to maintain a network overload. The two routes between the origin-destination pair are: the *main*, designated *direct* (lower cost), with 6000 m, and the *alternative* (higher cost), with 9000 m. The RSU sector and feedback edge are two-lane roads, while the direct and alternative roads are single-lane. The default maximum speed on the network is $25\,\mathrm{m\,s^{-1}}$ ($90\,\mathrm{km\,h^{-1}}$).

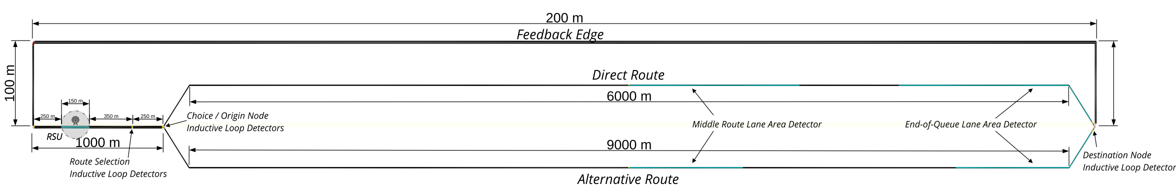

FIGURE 2 Network diagram of the scenario, with the two monitored routes (direct and alternative, with 6000m and 9000m, respectively), the initial zone where the RSU and inductive loop detectors for route selection are located, and the edge for feedback loop. *(Diagram is not to scale.)*

Before the choice node, marked as origin for timing, there is a 1000 m section on which the RSU is located, with a coverage of 150 m, whose zone starts at 250 m of this sector. At 750 m there is an inductive loop detector to carry out route selection, as already chosen by the driving agent. This initial configuration was due to the need to have an area to study the RSU dissemination and, on the other hand, to create a traffic merging zone, allowing the vehicles to change to the most appropriate lane for the chosen route, without causing too much parasitic noise in the simulation.

On the destination node side, there are 1000 m lane areas for monitoring traffic density, in the middle of the route and for end-of-queue assessment, as well as inductive loop detectors to record intermediate travel times (in the middle of the route) and time to destination (at the destination node). The feedback edge has lane change prohibition to mitigate parasitic noise in the simulation due to premature vehicle insertion manoeuvres that could lead to significant instantaneous speed changes.

Artificial population

To obtain a heterogeneous simulated population, four different classes of vehicles were inserted in the scenario, capable of travelling at full network speed, as shown in the Table 2, with their respective probabilities. The ceiling on the number of driving agents to be used in the simulation aimed to place the network in a state of congestion on the *main* (direct) route, with traffic moving at a pedestrian-like speed. Thus, the theoretical value were determined analytically considering the passenger class, and then verified in a sensitivity analysis by gradually increasing the number of driving agents, diverting all traffic to the direct route, until the average speed of the system dropped to $1.50\,\mathrm{m\,s^{-1}}$ ($5.40\,\mathrm{km\,h^{-1}}$).

After the sensitivity analysis, and also taking into account the mitigation of parasitic noise on the network, a ceiling of 820 driving agents was chosen. The launch speed, during the warm-up phase, is calculated as a function of density so as to obtain a stable traffic flow along the network and a balanced distance between vehicles, i.e. a stationary state, when origin demands, route choices ratio, and destination supplies are constant, time-independent (cf. 38). However, to avoid SUMO keeping some vehicles too long in backlog, making the process very time consuming, the launch phase is done for both routes, thus considering the whole length of the network.

vClass (SVC)	Length Width Height	a_{max} accel	b decel	b_e emergency decel	v_{max} maxSpeed	speed deviation	probability
passenger	4.3 m 1.8 m 1.5 m	$2.9\,\mathrm{m\,s^{-2}}$	$7.5\,\mathrm{m\,s^{-2}}$	$9.0\,\mathrm{m\,s^{-2}}$	$180\,\mathrm{km\,h^{-1}}$	0.1	0.70
motorcycle	2.2 m 0.9 m 1.5 m	$6.0\,\mathrm{m\,s^{-2}}$	$10.0\,\mathrm{m\,s^{-2}}$	$10.0\,\mathrm{m\,s^{-2}}$	$200\,\mathrm{km\,h^{-1}}$	0.1	0.10
truck	7.1 m 2.4 m 2.4 m	$1.3\,\mathrm{m\,s^{-2}}$	$4.0\,\mathrm{m\,s^{-2}}$	$7.0\,\mathrm{m\,s^{-2}}$	$130\,\mathrm{km\,h^{-1}}$	0.1	0.15
bus	12.0 m 2.5 m 3.0 m	$1.2\,\mathrm{m\,s^{-2}}$	$4.0\,\mathrm{m\,s^{-2}}$	$7.0\,\mathrm{m\,s^{-2}}$	$85\,\mathrm{km\,h^{-1}}$	0.1	0.05

TABLE 2 Different vehicle types used in the simulation, with their respective characteristics and probabilities.

Simulation Procedures

The simulation is launched with a warm-up period, for insertion of all driving agents in the network uniformly, after which they make a rolling start and run laps (events) during a simulated period of 24 h, with 0.1 s steps, to allow microscopic simulations in fractions of a second, required by both the RSU dissemination mechanisms and the vehicle insertion manoeuvres at lane changes.

Experiments started by determining a baseline, with constant dissemination, to observe the emergence of cooperation and its impact on the network. Then it was proceeded to a progressive degradation of the RSU dissemination, gradually increasing its transmission interval, reaching each time fewer driving agents. Finally, an abrupt increase of this interval was tested, restoring the initial, shorter interval, after a certain period, to analyse the behaviour of the driving agents when faced with a failure and the restoration of the system.

RESULTS AND ANALYSIS

In the baseline experiment, the emergence of cooperation and the establishment of the plateau occurred after about 5 h (Figure 3). The average vehicle speed on the network followed the increase in the number of cooperators, reaching a plateau around $10.5\,\mathrm{m\,s^{-1}}$ ($37.8\,\mathrm{km\,h^{-1}}$). Simultaneously, the traffic flow of both routes settled at about 1750 veh/h, in line with the travel times on each route, both at about $700\,\mathrm{s}$, a value corroborated by the average speeds on each route, about $8.5\,\mathrm{m\,s^{-1}}$ ($30.6\,\mathrm{km\,h^{-1}}$) on the direct route and $13\,\mathrm{m\,s^{-1}}$ ($46.8\,\mathrm{km\,h^{-1}}$) on the alternative route, which are, respectively, 6000 m and 9000 metre long.

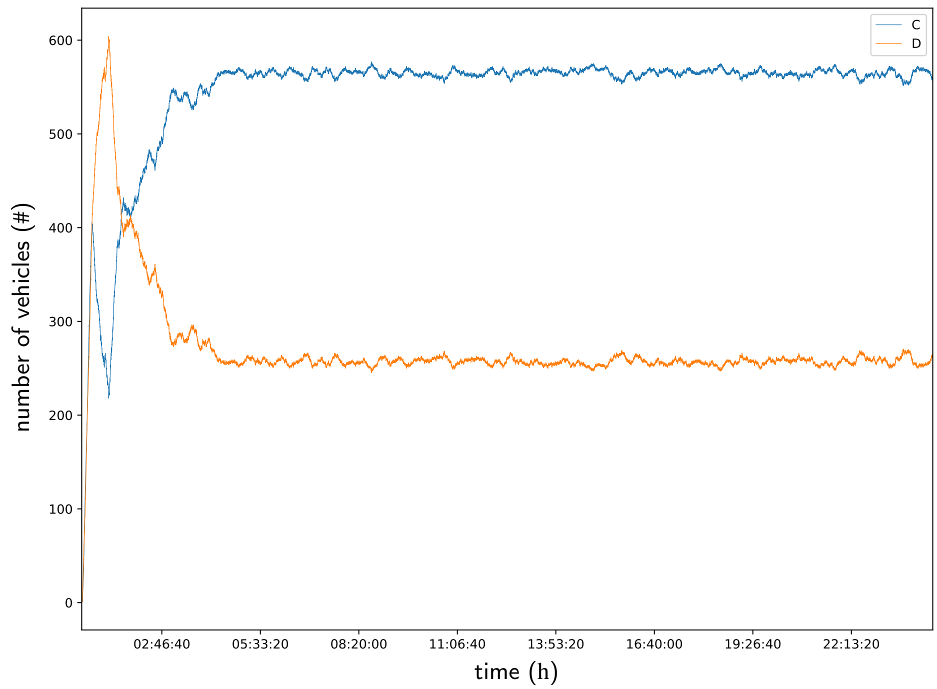

FIGURE 3 Evolution of the number of *Cooperators* and *Defectors*, over a 24 h **period, in which the RSU's dissemination time interval remained constant at** 5 s**.**

To analyse the effect of a degradation of the information service, simulations were conducted in which the dissemination time interval doubled every 4 h, in the sequence $\{5, 10, 20, 40, 80, 160\}$ s, during which an increasing number of driving agents stopped receiving suggestions and continued on their default preferred route.

During the first 8 h, the evolution was similar to the baseline, both in terms of cooperation emergence and traffic flow, i.e. up to 10 s interval the ATIS agent was able to deliver recommendation to all driving agents. However, starting at 8 h of simulation, with 20 s interval, there was witnessed a decreasing trend in the traffic flow (Figure 4), which followed a drop in the number of driving agents in game (both cooperators and defectors decreased) (Figure 5). The traffic flow on both routes, and consequently the mean speed on the network, had a steeper decrease after 12 h, when the interval was increased to 40 s, that of the alternative route tending to zero, as most of the traffic started to converge to the direct route. The cooperation, which had also been decreasing, suffered a strong decline and there was an inversion of trends with an increase in the number of defectors, although the sum diminished, since fewer driving agents were left in game.

In subsequent interactions with the ATIS agent, the number of cooperators continued to decrease, tending towards zero, while that of defectors rose, with only part of the population, there being, however, two peaks, which can be explained with the reduction in speed due to the

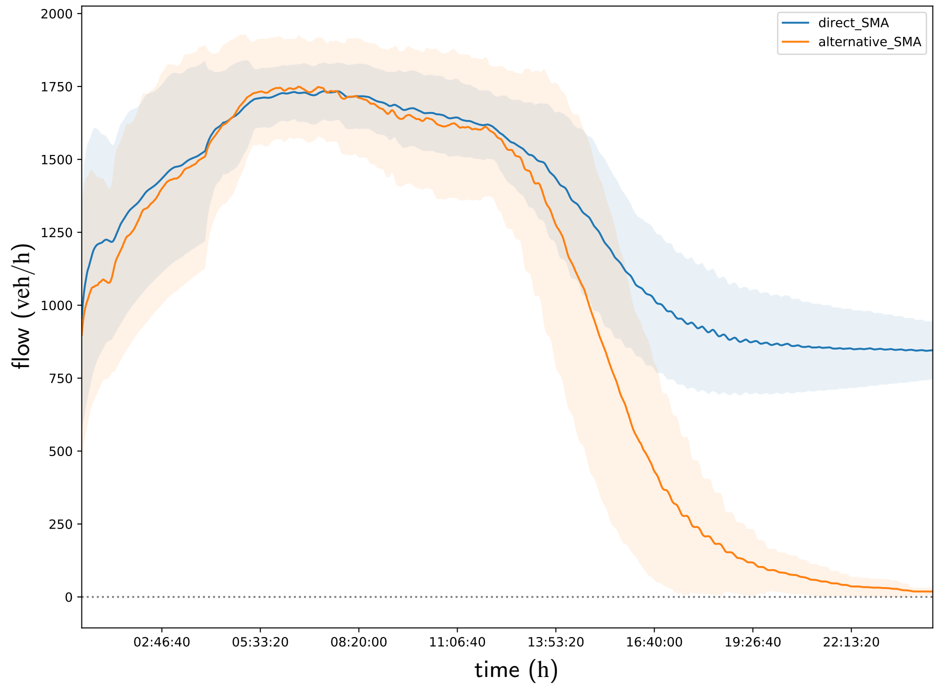

FIGURE 4 Traffic flow on each route, in vehicles per hour $(\mathrm{veh/h})$**,** $4\,\mathrm{h}$ **Simple Moving Average, over a** $24\,\mathrm{h}$ **period, in which the RSU's dissemination time interval doubled every** $4\,\mathrm{h}$**, in the sequence** $\{5, 10, 20, 40, 80, 160\}$ s**.**

congestion that was forming as more driving agents converged on the direct route. In fact, in simulations carried out with a smaller population, which did not generate congestion, after the inversion, the number of defectors reached a peak and then gradually descended in steps.

From what was observed, including by analysing the driving agents' individual history, as they began to receive increasingly sparse recommendations from the ATIS agent, they began to reject more often the few they did receive, even those that were mostly cooperative in the early hours.

Finally, a sudden degradation of the system was tested, at 8 h of simulation, with the established cooperation plateau, changing the dissemination intervals from 5 s to 160 s during an 8 h period. The driving agents made successive trips without receiving any suggestion, following the predefined route, and, as expected, there was a significant decrease in the number of participants in the game. Similarly to what had happened with progressive degradation, the cooperation status was reversed, with the number of cooperators decreasing, tending to zero. Meanwhile, the number of defectors began a steeper rise, due to the congestion that had commenced to form, keeping the vehicles very slow in the RSU coverage area and, therefore, the number of those who were receiving suggestions was increasing, even with the long transmission interval, also recovering the amount of participants in the game. However, the majority started to reject the suggestion, a behavioural trend confirmed after the 5 s dissemination interval was re-established, at 16 h of simulation, when they were again receiving recommendations at each passage and the number of participants in game grew to the population size.

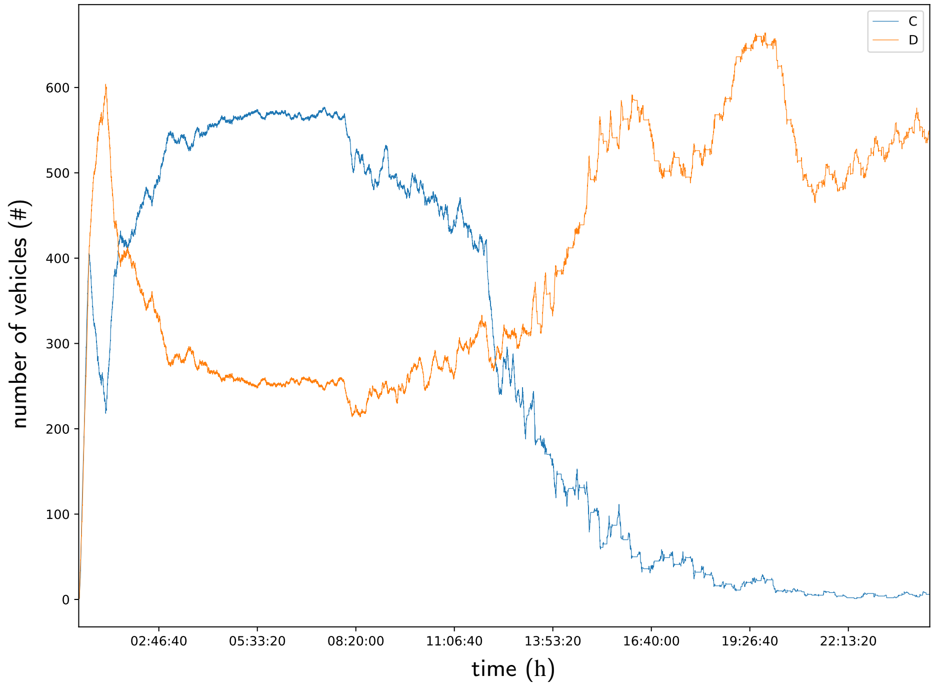

FIGURE 5 Evolution of the number of *Cooperators* and *Defectors*, over a $24\,\mathrm{h}$ **period, in which the RSU's dissemination time interval doubled every** $4\,\mathrm{h}$**, in the sequence** $\{5, 10, 20, 40, 80, 160\}$ s**.**

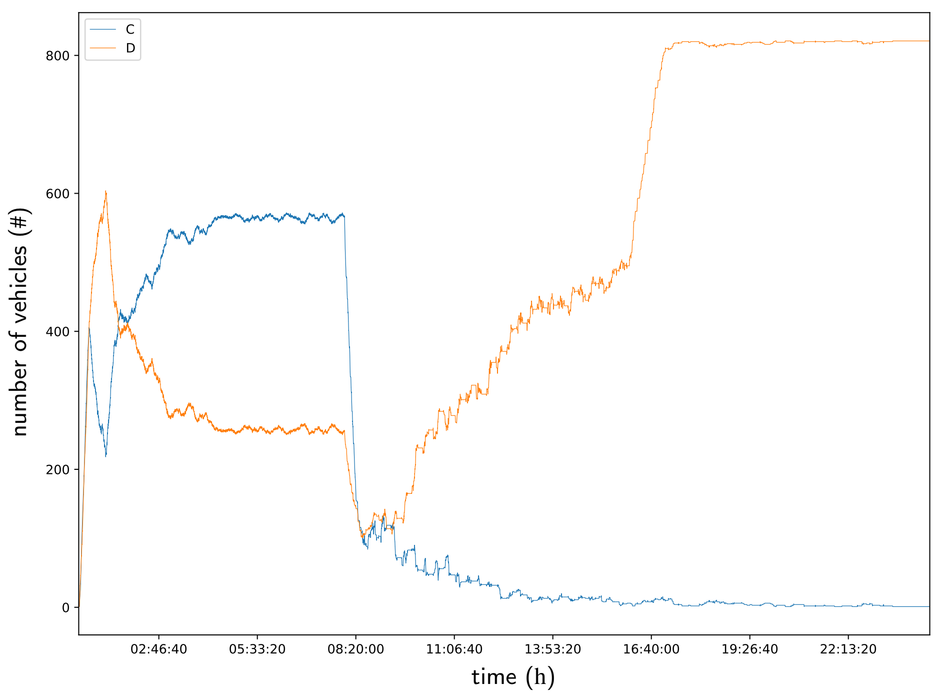

FIGURE 6 Evolution of the number of *Cooperators* and *Defectors*, over a $24\,\mathrm{h}$ **period, in which the RSU's dissemination time interval increased to** $160\,\mathrm{s}$ **at** $8\,\mathrm{h}$**, and re-established to** $5\,\mathrm{s}$ **at** $16\,\mathrm{h}$**.**

CONCLUSIONS

Some studies had already been devoted to the phenomenon of the emergence of cooperation between drivers and its impact on road traffic, mentioning the benefit of an ATIS to be able to bring the network closer to an optimal state. In this work we simulated a binary network, with routes of different cost, supported by an ATIS that makes en-route recommendations on the best path, based on Game Theory, with a formalization of the n-Person Prisoner's Dilemma, in which the ATIS is also a participant of the game along with the driving agents.

With a dynamic network, susceptible to congestion formation in both routes, it was possible to observe the correlation between the cooperation of the driving agents towards ATIS agent and the system performance, namely in the network average speed as well as in the traffic flows in both routes. By causing a degradation of that information service, with the increase of the dissemination intervals, there was a concomitant degradation of the system performance with the formation of congestion in the main route, accompanied also by a loss of cooperation, which tended to zero, and a generalized rejection of the suggestion by the remaining participants in the game. Testing full restoration of service after a failure, the trend of declining cooperation continued, even though the number of participants returned to population size, suggesting a loss of credibility of the ATIS.

The simplicity of this road network limits the ability to generalize to more complex networks. Further investigation with more simulations is needed with other traffic patterns and network topologies varying both in number of routes and origin-destination pairs. This extension will also necessitate proper calibration and validation of SUMO's simulation parameters. Another issue needing appropriate investigation concerns the scalability of this approach to cope with real-world scenarios and large-scale networks. Different approaches can be considered with this purpose, allowing for the comparison of the effect of one single global observer against strategies resorting to multiple local observers spotted on selected regions of the network, or other hybrid solutions exploring a hierarchy of observers.

On the other hand, it is important to account for the trustworthiness of all parties involved, which can be accomplished through modelling a trust factor in ATIS, to understand how cooperation could be restored after a system failure, for instance. Finally, we intend to explore this methodology in other scenarios, such as disruption and crisis management, in which appropriate information dissemination strategies play a crucial role.

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