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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 19s 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 andreliably. To cope with such a complex scenario, this paper proposes a game theory perspective based on the n-Person Prisoner 19s Dilemma as a metaphor to represent the uncertainty of cooperation underlined bycommunication infrastructures in traveller information systems. 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.

Assessing Communication Strategies in C-ITS using n-Person Prisoner's Dilemma

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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 current traffic situation. Its effectiveness, however, depends on the i) user's decision-making process, which is the main source of uncertainty in any mobility system, and on the ii) ability of the infrastructure to communicate timely and reliably. 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. Results highlight a close relationship between the emergence of cooperation and the 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: Game Theory · n-Person Prisoner's Dilemma · Advanced Traveller Information System · Cooperative Intelligent Transport Systems · Agent-based Simulation

1 Introduction

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.

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 two-route network setting. 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 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.

The remainder of the paper is organized as follows. The next Section reviews the relevant literature. Section 3 presents the formalization in the context of Game Theory, and describes the experimental framework. Section 4 summarizes the results of these experiments. Finally, the main results and future directions are discussed in Section 5.

2 Literature Review

Increasing road capacity is not a viable solution for reducing congestion, as the Braess's Paradox has shown (cf. [2]), hence the importance of rational and efficient management of existing resources. Selfish, rational behaviour leads to sub-optimal 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 [10,11]. This is also empirically verified in a route choice experiment [7], with an alternating cooperation emerging between players, previously informed that by coordinating their actions they would be able to achieve maximum time savings.

In the original formulation of the Prisoner's Dilemma, with two participants in a binary choice of different cost and congestion-sensitive routes, 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 [11].

Successive interactions of the same commuter community, by way of social encounter, can define a repeated game [7], 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 [8]. 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].

The benefits of providing rational travellers with journey time information would depend on their knowledge and ability to predict times based on external factors [5], enabling them to make optimal choices, thereby contributing to reducing traffic congestion and improving the level of service provided by road infrastructure. 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 [1] However, increasing the informational burden at the individual level leads to a state of User Equilibrium [9], as rational agents with full knowledge will compete for the least cost paths on the road network. On the other hand, because of the rational traits and cognitive limitations associated with human behaviour, not all drivers would comply with the recommendations [14], particularly when achieving a sub-optimal result [4].

The advent of ATIS has made it easier to provide current or even predictive information on traffic flow to road users (e.g. [18]). 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 [10]. 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 in a simple two-route network led to more efficient emergence of cooperation [9].

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 [11]. Accepting the recommendations can be implemented in form of smart contracts, registered by a management blockchain-based infrastructure, and confer reward-based incentives, such as tradable credits to be exchanged for services offered by local administrations [16]. Nonetheless, drivers may mistrust strategic routing heavily relying on incentives [12].

Dissemination of information by the infrastructure to allow drivers to make informed decisions is essential for the performance of the system. It is therefore important to optimize the frequency of message delivery and the efficiency of communication between roadside and on-board units, also articulating its location with key decision points in the network, but based on a strategy that simultaneously privileges the maximization of coverage and the minimization of transmission failures [3].

In this work, we explore the formalization of the n-Person Prisoner's Dilemma 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 in the game.

3 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 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.

3.1 n-Person Prisoner's 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 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 work, 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.

Within the framework of non-cooperative game theory, the following definitions 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* $n \in \mathbb{N} : n \geq 2$*;*
- $\mathcal{A} = A_1 \times \cdots \times A_n$*, 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 payoff function for player* $i \in \mathcal{I}$*.*

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

Definition 3. *A player i's best response to the action profile $a_{-j} = (a_1, \ldots, a_{j-1}, a_{j+1}, \ldots, a_n)$ is the action $a_j^* \in A_i : u_i(a_j^*, a_{-j}) \geq u_i(a_j, a_{-j}), \forall a_j \in A_i$. An action profile a is a Nash equilibrium if, for each player i, a_j is a best response to a_{-j}. 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 profile a' if $u_i(a) \geq u_i(a'), \forall i \in \mathcal{I}$, and $\exists i' \in \mathcal{I} : u_{i'}(a) > u_{i'}(a')$*

3.2 Assumptions

Assumption 1 *The participants in the game—the driving agents, in this case—are boundedly rational, meaning that individual players don't have perfect information about the others and try to maximize their expected value.*

Assumption 2 *The ATIS is 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 3 *The common resources are the routes of the road network with limited capacity. Each traveller may choose either to travel in a direct route or use an alternative route, thereby not contributing to congestion.*

Assumption 4 *The communication channel for ATIS agents to communicate with the driving agents is reliable and non-lossy.*

Assumption 5 *Driving agents have only knowledge about their experienced travel times and reward.*

Assumption 6 *Each driving agent has a predefined preferred route, which corresponds to the route with the lowest cost.*

Assumption 7 *Each traveller has two possible actions; D (defect) by rejecting the suggestion provided by the infrastructure or C (cooperate) by accepting the recommendation and taking the proposed route.*

Assumption 8 *All players receive a benefit $b \in \mathbb{R}_{>0}$ for their decision to accept the ATIS agent's recommendation and contribute to the social optimum, otherwise pay a cost $c \in \mathbb{R}_{<0}$.*

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

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

Considering the payoff-matrix based on the formalization of the n-Person Prisoner's Dilemma (cf. Table 1) for modelling a collective behaviour when users have to compete for the road infrastructure with incomplete information, 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 9

1. *The payoff difference* $\alpha = f(D,h) - f(C,h)$ *is positive and constant for all values of* $h = \{0, 1, ..., n-1\} \subset \mathbb{N}$*;*
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 9, any player i will get a better payoff by selecting defection (D) than by choosing cooperation (C), regardless of what all other players select, i.e. the dominant action for each player is defection. 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 third condition, if all players choose the dominant defection one 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:

$$Benefit > (Benefit + Cost) > 0 > Cost$$

for n players, with $n \in \mathbb{N} : n \geq 2$, in view of the general case of a compound symmetric game [6], the following payoff functions result:

$$\begin{aligned} f(C,h) &= \frac{h \cdot (Benefit + Cost) + (n-h) \cdot Cost}{n} \\ f(D,h) &= \frac{h \cdot Benefit + (n-h) \cdot 0}{n} \end{aligned} \tag{1}$$

From Assumption 9:

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

where the unique integer 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.

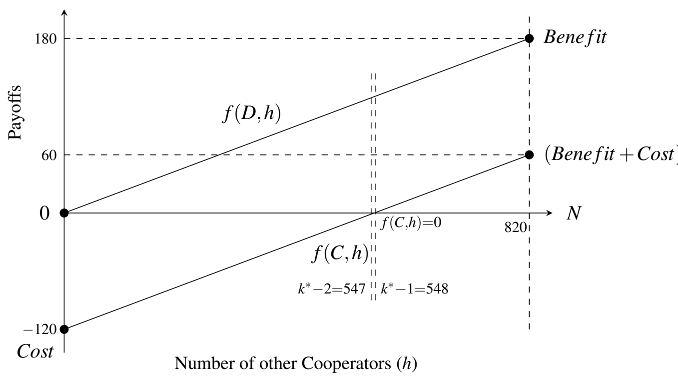


Fig. 1: Graph of the payoff functions for defectors (D) and cooperators (C).

One of the best-known and studied models in game theory, the Prisoner's Dilemma can transition from 2-person to n-person by replacing the two-dimensional matrix by payoff functions [6] (cf. Equation 1), which can be plotted on the graph in the Fig. 1, along with k^* obtained from Equation 2.

Parameter setting. The payoffs chosen were based on the cost of the routes from their travel times in free flow, considering a $Cost = -120$ and a $Benefit = 180$. Given the above formalization and relating it to the outcomes of the original Prisoner's Dilemma matrix, *Punishment* is 0, i.e. not get the benefit nor bear the cost. *Sucker's payoff* is the cost of taking the alternative route, hence the negative value -120. *Temptation,* getting the benefit without bearing the cost (180), is significant for the slope of the payoff functions and, consequently, for the cooperation rates. *Reward*, getting the benefit with a cost, has a value of 60. It results, then, $k^* = 549$ for 820 driving agents plus the ATIS agent, which always cooperates, its payoff being a reflex of the driving agents' cooperation.

3.3 Recommendation algorithm

The algorithm employed to build the suggestion calculates, for each route, the product 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 (see. Algorithm 1). The weights calculated are then used by the RSU to compose the route recommendations, disseminated in order to distribute the vehicles among routes and lead the system to an optimal state.

Algorithm 1: Calculation of the weight of the routes for recommendation build and dissemination by the RSU.

Input: R – Set of routes, N – Number of vehicles plus ATIS, ρ_r – Occupancy of route r, $\overline{\Delta t}_r$ – Average of last n travel times for route r, h – Number of other cooperators,
Output: w_r – Route weight

forall $r \in R$ **do**

$$w_r = \frac{\frac{\rho_r}{\sum_{e=1}^{R} \rho_e} \cdot \frac{\overline{\Delta t}_r}{\sum_{e=1}^{R} \overline{\Delta t}_e}}{\frac{h}{N}}$$

end

3.4 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 [17] was implemented (see Algorithm 2). Driving agents choose an action from the set of actions A, which, by Assumption 7, are *Cooperate,* accepting the recommendation provided by the infrastructure, or *Defect,* rejecting that suggestion.

The sensitivity tests with the parameters *Recency* (forgetting) 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 $\epsilon = 0.5$ were chosen, for which the plateau was reached more quickly.

Algorithm 2: Modified Roth-Erev Learning Algorithm

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

Input: a_j – Current action choice, $q_{ij}(t)$ – Propensity for action a_j of player i at time t, a_l – Last action chosen, $P_l(t)$ – Payoff for action a_l at time t, M – Number of actions, $q_{ij}(0)$ – Initial propensity, ϵ – Experimentation, ϕ – Recency

$t \leftarrow 0$
initialize $q_{ij}(0) \leftarrow 1$, for all $j \in A$
repeat
  $t \leftarrow t + 1$
  // calculate the probability that player i chooses action l at time t
  $\left\{ p_{il}(t) = \frac{q_{il}(t)}{\sum_{j=1}^{M} q_{ij}(t)} \right\}_{l \in A}$
  choose action $a_l \leftarrow l \in A$ randomly, using the probabilities $p_{il}(t)$
  collect payoff $P_l(t)$
  // update the propensity of action l for player i at time $t + 1$
  $q_{il}(t+1) \leftarrow (1-\phi)q_{il} + P_l(t)(1-\epsilon)$
  // update the propensity of all actions j different from the last chosen action l, for player i, at time $t + 1$
  forall $j \neq l$ **do**
    $q_{ij}(t+1) \leftarrow (1-\phi)q_{ij} + q_{ij}(t)\frac{\epsilon}{M-1}$
  end
until *termination*;

4 Results and Analysis

4.1 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 [15], externally controlled by modules written in Python, through the TraCI traffic control interface, allowing

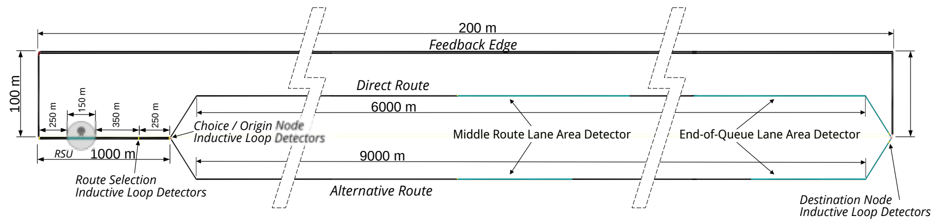


Fig. 2: Network diagram of the scenario, with the two monitored routes

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 Fig. 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: *i*) the *direct route* (lower cost) with 6000 m, and *ii*) the *alternative route* (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 $25\,\mathrm{m\,s^{-1}}$ ($90\,\mathrm{km\,h^{-1}}$).

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. 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).

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.

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

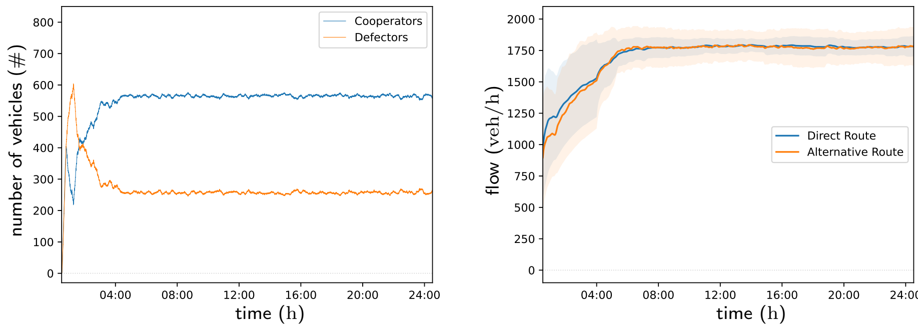
vClass (SVC)	Length Width Height (m)	a_{max} accel ($\mathrm{m\,s^{-2}}$)	b decel ($\mathrm{m\,s^{-2}}$)	b_e emergency decel ($\mathrm{m\,s^{-2}}$)	v_{max} maxSpeed ($\mathrm{km\,h^{-1}}$)	speed deviation	probability
passenger	4.3 1.8 1.5	2.9	7.5	9.0	180	0.1	0.70
motorcycle	2.2 0.9 1.5	6.0	10.0	10.0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

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.

4.2 Scenario analysis

Baseline Scenario. In the baseline experiment, the emergence of cooperation and the establishment of the plateau occurred after about 5 h (Fig. 3a). 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 (Fig. 3b), in line with the travel times on each route, both at about 700 s, a value corroborated by the average speeds registered on each route.

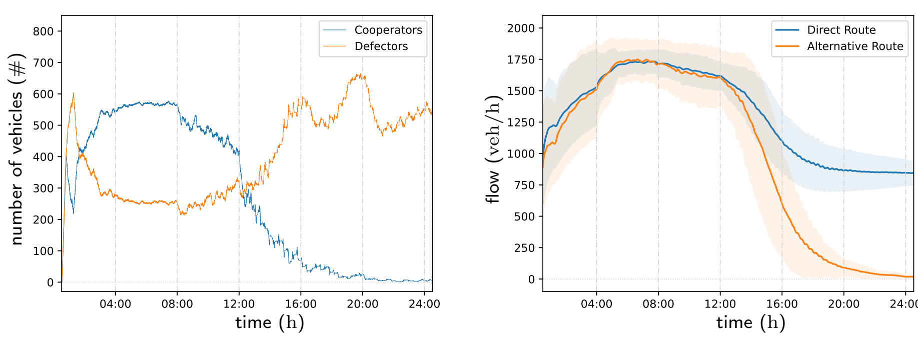
Progressive Degradation Scenario. To analyse the effect of a degradation of the information service, simulations were conducted in which the dissemination time interval doubled every 4 h, in the sequence $\{5, 10, 20, 40, 80, 160\}$ s, during which an increasing number of driving agents stopped receiving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



a) Number of *Cooperators* and *Defectors*. b) Traffic flow on each route.

Fig. 3: Evolution of the number of *Cooperators* and *Defectors,* and traffic flow on each route, in vehicles per hour (veh/h), 4 h Simple Moving Average, over a 24 h period, in which the RSU's dissemination time interval remained constant at 5 s.

During the first 8 h, the evolution was similar to the baseline, both in terms of cooperation emergence (Fig.4a vs. Fig. 3a) and traffic flow (Fig.4b vs. Fig.3b), 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 (Fig. 4b), which followed a drop in the number of driving agents in game (both cooperators and defectors decreased) (Fig. 4a). 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.



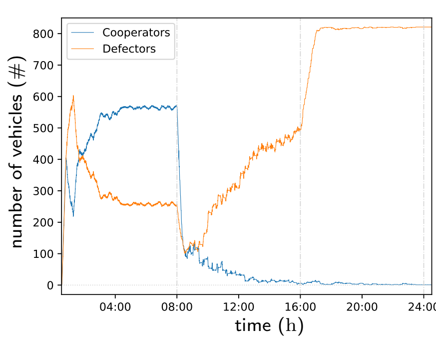
a) Number of *Cooperators* and *Defectors*. b) Traffic flow on each route.

Fig. 4: Evolution of the number of *Cooperators* and *Defectors,* and traffic flow on each route, in vehicles per hour (veh/h), 4 h Simple Moving Average, over a 24 h period, in which the RSU's dissemination time interval doubled every 4 h, in the sequence $\{5, 10, 20, 40, 80, 160\}$ s (dashed vertical lines).

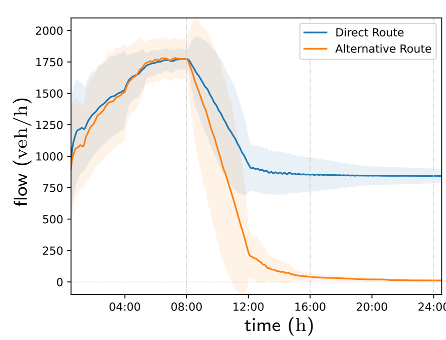
In subsequent interactions with the ATIS agent, the number of cooperators continued to decrease, tending towards zero, while that of defectors rose, with only part of the population, there being, however, two peaks, which can be explained with the reduction in speed due to the congestion that was forming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

Sudden Degradation Scenario. 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 (Fig. 5a). 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.



a) Number of *Cooperators* and *Defectors*.



b) Traffic flow on each route.

Fig. 5: Evolution of the number of *Cooperators* and *Defectors,* and traffic flow on each route, in vehicles per hour (veh/h), 4 h Simple Moving Average, over a 24 h period, changing the RSU's dissemination time interval, increased to 160 s at 8 h, and re-established to 5 s at 16 h (dashed vertical lines).

5 Conclusions

In this work, we simulated a binary road 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 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. 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. 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.

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