Decentralized Intersection Control Using Bayesian Game Theory

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***Abstract*—Future smart cities are expected to have efficient control of vehicular traffic to provide satisfactory mobility and transportation of people and goods. Reliable and efficient control schedule design for signalized intersections is needed to alleviate vehicular congestions and improve the overall road network management. In the present paper, we propose an approach based on game theory to design a decentralized intersection traffic controller, able to adaptively react to changing traffic conditions and minimize the waiting time of the cars in queue. We adopt a Bayesian dynamic game framework, which is able to improve the existing state of the art alternatives by reducing the amount of data exchanged from monitoring roadside units. Moreover, we also introduce a tunable sharing factor that is a design element available to the traffic planner controlling the priority of access and allowing for prioritization. Finally, the proposed solution is extensively evaluated via simulation in different scenarios.**

***Index Terms*—Game theory; smart cities; road traffic control; scheduling algorithms.**

I. Introduction

Modern cities are often subject to traffic congestion, defined as a state of traffic flow with a high number of vehicles moving at low speed, often caused by a demand for urban roads that exceeds their capacity [1], [2]. Traffic congestion causes productivity losses, energy wastes, pollution, and decreased quality of life [3], [4].

With the advent of the Internet of Things (IoT), application to smart cities and intelligent transportation systems are envisioned [5], [6], and traffic regulations can be made smarter. Signalized intersections are key infrastructures, where the schedule for switching the traffic lights plays an important role. This can be controlled either singularly, using local information on the traffic conditions, or in groups, based on the road network characteristics [7]. A first method of controlling signalized intersections is based on fixed schedules, or on sets of fixed schedules to chose among in response to real-time traffic measurements [8]–[10]. This approach is often dictated by the limited technology deployed at intersections. Thanks to current technological advances in sensors and control hardware, adaptive schemes can be implemented, possibly exploiting game theory as we propose here.

Game theory is the discipline that models the interaction between rational decision makers in situations of conflict [11]. A decision maker (or player) is considered to be rational if it acts to maximize its own wellbeing, as quantified by a utility (or payoff) function. The payoff is function of the actions of all the decision makers participating in the game. A Nash equilibrium (NE), i.e., an operating point where every agent chooses a best response, i.e., a local optimum of the payoff, is generally seen as the natural result of this interaction.

The problem of controlling signalized intersections received several proposals with diverse underlying assumptions. In [12], a linear model is advanced to design a proportional-integrative-derivative (PID) controller with the goal of achieving a desired traffic state, defined in terms of queue lengths. The authors of [1] employ a state-space model to cast the design of the intersection schedule into an optimal control problem. The authors propose different objective functions based on queue length and average vehicle delay. A comprehensive survey on such traffic control theory is presented in [2].

Another possible approach to traffic control makes use of computational intelligence paradigms, for example: fuzzy systems, artificial neural networks, evolutionary computing and swarm intelligence, and reinforcement learning [9]. A thorough survey of the research made in the field of computational intelligence for traffic control is presented in [10].

Many other approaches share similarities with ours. The authors of [7] model the traffic at each road of the interesection as a Markov chain and design a Markovian non-cooperative game for the scheduling of the traffic lights. An ϵ-NE is found, using an iterative optimization algorithm. In [13], a model of an intersection with IoT-empowered vehicles is presented, and the control schedule is designed according to a Cournot game or a Stackelberg game in the case of controlling prioritized traffic. Both [14] and [15] propose game theoretic approaches to control a network of intersections. The former paper employs fictitious play to minimize the average travel time. The latter develops a decentralized coordination scheme through evolutionary game theory.

Our objective is to present an adaptive scheduling for signalized intersections that makes use of game theory. The idea is to model each traffic light as a rational decision maker, charged with the task of choosing its allotted time for controlling the intersection. The proposed algorithm is suitable for a decentralized implementation [16] and does not require information about the overall state of traffic at the intersection.

With respect to the existing literature, we introduce the following advancements. First, the information about current traffic condition at the roads converging to the intersection are taken into account by considering a Bayesian type [17]. The required common knowledge elements of the Bayesian game (such as the prior of the traffic distribution, e.g., at a given time of day), are relatively easy to gain. The resulting decentralized implementation is lightweight, as for scalability and generality reasons, it is key not to require data-intensive exchanges.

The remainder of this work is organized as follows. Section II describes the game designed to model the interaction among traffic lights. Section III proposes a solution to the game and presents the implementation of the control schedule. Section IV discusses the results of simulations performed with MATLAB. Section V concludes the work.

II. System Model

We provide a generic description of road traffic at an intersection, and then we discuss strategic aspects that can be useful for framing the problem into an approach based on Bayesian game theory [17]. The model takes after the formulation presented in [12].

For the intersection, the following assumptions have been made. First, each converging road is modelled as a queue [18], If the road has multiple lanes, this assumption is still sensible in case all lanes allow travel in the same direction. Otherwise, the assumption can be relaxed by controlling each lane with a different agent. Also, we assume that only one traffic light can be green (or amber) at the same time. However, the setup of the game can be easily extended to account for the control of *phases* [8], i.e., a set of lanes whose traffic lights can be green at the same time given that they allow travel in non-conflicting directions. Moreover, the traffic lights turn green in a fixed order. While a traffic light is amber vehicles cannot engage the intersection, the only vehicles that are moving are those clearing the intersection. The duration A of the amber phase is assumed to be equal for all traffic lights. Each street is characterized by an arrival and a service Poisson process of cars, with rates $\lambda_i \in \mathbb{R}_+$ and $\eta_i \in \mathbb{R}_+$, respectively [19]. It is assumed that $\eta_i > \lambda_i$. Moreover, the queues of each road do not have a maximum capacity, and overflow is neglected.

We consider an intersection with N incoming lanes. Each traffic light is assigned a time-slot of duration $\tau_i \in \mathbb{R}_+$ and the length of its queue is $l_i(k) \in \mathbb{R}_+$ at the end of the k-th round.[1] Let $\Delta l_i\left(\{\tau_i\}_{i=1}^N\right)$ be the difference between the numbers of cars entering the ith queue and leaving it during the round. Thus, omitting the dependence on the τ_is,

$$\begin{aligned}\Delta l_i &= \lambda_i \sum_{i=1}^{N} \tau_i - \eta_i \tau_i + \lambda_i N A \\ &= (\lambda_i - \eta_i)\tau_i + \lambda_i \sum_{j \neq i} \tau_j + \lambda_i N A\end{aligned} \tag{1}$$

and in principle $\Delta l_i \in \mathbb{R}$. The length of the queue at the end of the $(k+1)$-th round is therefore

$$l_i(k+1) = \max\{l_i(k) + \Delta l_i, 0\}. \tag{2}$$

Remark 1: It is assumed that the time-slots' durations and the flow rates are expressed with respect to the same unit of time. So, if the τ_is are expressed in seconds, then the arrival and service rates λ_is and η_is represent the number of ingoing and serviced cars per second.

The interaction among the traffic lights of the intersection is modeled as a *repeated Bayesian* game [17]. Even though a model of the intersection controllers interacting during their whole activity would apparently require an infinite-horizon repetition, traffic conditions usually exhibit a periodic character over the day and on a seasonal scale [20]. Thus, a finitely repeated game can be employed over a period. According to the repeated game framework, a Bayesian static *stage-game* is played at each round. The players choose the lengths of their green light period for that round. It is assumed that players do not precisely know the arrival rate of cars in the queue of their opponents; thus, the game is Bayesian.

Formally, the stage-game is defined by the following elements. **Players**: they are the traffic lights controllers, that is, the devices charged with switching the traffic light of a road at the appointed time. **Actions**: available to each player is the choice of intersection time to occupy during the current round, that is, $\tau_i \in [0, +\infty)$. **Types**: these are the numbers of cars entering each queue during the round, λ_i. The underlying assumption is that a player has access only to data about the flow of cars through its own queue, with which it is able to estimate λ_i. To obtain these data it is possible for instance to use *inductive loop sensors* [21], [22]. It is in principle possible to transmit the estimated λ_is to each traffic light–in which case the game would collapse to a perfect information game–but it would require a larger number of transmissions than with this formulation. Moreover, it is assumed that the flow of cars is constant during the game. This is realistic if the traffic changes on a larger time-scale than the duration of the stage-games. **Priors**: players are characterized by the arrivals in their queue. The underlying assumption, used as the prior, is that the arrivals λ_i in the queue of player i are modelled as a Poisson process with rate Λ_i. Actually, the prior distribution of Λ_i is assumed to be Poisson truncated at η_i, since λ_i must be less than η_i [23] and it is assumed that the distributions are all independent of each other. The priors can be derived from historical observations of the traffic flow at the intersection of interest. **Payoffs**: each utility function comprises two terms. The former depends on the overall number of cars that transit through the queue, and increases when τ_i increases. The latter is a "penalty term" that accounts for the increase in the queue length for i's opponents caused by the choice of τ_i. Formally the payoff function is

$$u_i\left(\{\tau_i\}_{i=1}^N; \{\lambda_i\}_{i=1}^N\right) = -\Delta l_i - \gamma \tau_i^2 \sum_{j \neq i} \lambda_j$$

which gives, substituting the expression written in (1) and omitting the dependences,

$$u_i = (\eta_i - \lambda_i)\tau_i - \lambda_i \left(\sum_{j \neq i} \tau_j + NA\right) - \gamma \tau_i^2 \sum_{j \neq i} \lambda_j. \tag{3}$$

The parameter $\gamma \in (0, 1]$ that weighs the penalty term can be thought of as an "altruism coefficient" that quantifies the

[1] *Round* hereafter refers to the interval of time during which all the traffic lights turn green once. It will coincide with the duration of a stage-game.

willingness of a player to shorten its time-slot to benefit the opponents [24]. The structure of the game as well as rationality of the players is assumed to be *common knowledge*.

Remark 2: For the limit case of $\gamma = 0$ the utility of player i is monotonically increasing with the intersection time chosen, and therefore the best response is to choose $\tau_i \to +\infty$. Notice that γ can be in principle different for each player.

The interaction between the players is modeled as a (possibly infinitely) repeated game. It is assumed, in order to define a more flexible control scheme, that the priors of the players change at each stage-game. The utility of each player in the game is the sum of the discounted payoffs received at each stage-game. The discount parameter is $\delta \in [0,1]$, with $\delta = 1$ being admissible only in the case of finitely repeated game.

Remark 3: In the definition of the game it is assumed that the prior distributions for a player over the different stage-games are independent and different from each other. To justify this assumption, think of a day as divided in intervals of m minutes, each interval characterized by a distribution that reflects the typical traffic conditions at that time of day. It is possible to assign to each stage the priors that are associated with the interval the stage begins in. If the stage-games have a duration shorter or at most comparable to m, this approach will handle the varying traffic conditions throughout the day.

III. Solution of the Game

This section presents first the derivation of the *Bayesian NE* of the stage-game. The Bayesian NE extends the idea of everyone playing a best response, including the beliefs about the types of the other players. Formally, it is defined as the strategy profile $(\tau_1^*, \tau_2^*, \ldots, \tau_N^*)$ where, for any player i and any action τ_i,

$$\begin{aligned}\mathbb{E}_{\lambda_{-i}}\left[u_i\big(\tau_i^*, \{\tau_j^*\}_{j\neq i}; \{\lambda_i\}_{i=1}^N\big)\Big|\lambda_i\right] \geq \\ \mathbb{E}_{\lambda_{-i}}\left[u_i\big(\tau_i, \{\tau_j^*\}_{j\neq i}; \{\lambda_i\}_{i=1}^N\big)\Big|\lambda_i\right].\end{aligned} \tag{4}$$

From (3), the expected utility for player i is computed as

$$\begin{aligned}&\mathbb{E}_{\lambda_{-i}}\left[u_i\big(\tau_i, \tau_{-i}; \lambda_i, \lambda_{-i}\big)\big|\lambda_i\right] = \\ &= \mathbb{E}_{\lambda_{-i}}\left[(\eta_i - \lambda_i)\tau_i - \lambda_i \sum_{j\neq i}\tau_j - \lambda_i NA - \gamma\tau_i^2 \sum_{j\neq i}\lambda_j\Big|\lambda_i\right] \\ &= (\eta_i - \lambda_i)\tau_i - \lambda_i \sum_{j\neq i}\tau_j - \lambda_i NA - \gamma\tau_i^2 \mathbb{E}_{\lambda_{-i}}\left[\sum_{j\neq i}\lambda_j\Big|\lambda_i\right]\end{aligned}$$

where the properties of the expectation have been applied, and the shorthand notations λ_{-i} and τ_{-i} are used to denote the set of types and actions of i's opponents, respectively.

Recalling that the types of the players are independently drawn from Poisson distributions with mean Λ_i, $i = 1, \ldots, N$, it follows that

$$\begin{aligned}&\mathbb{E}_{\lambda_{-i}}\left[u_i\left(\tau_i, \tau_{-i}; \lambda_i, \lambda_{-i}\right)\Big|\lambda_i\right] = \\ &\quad = (\eta_i - \lambda_i)\tau_i - \lambda_i \sum_{j\neq i}\tau_j - \lambda_i NA - \gamma\tau_i^2 \sum_{j\neq i}\Lambda_j.\end{aligned} \tag{5}$$

Once the values $\tau_j,\ j \neq i$ have been set, the expected utility is a parabola in τ_i with downwards opening and intersection with the vertical axis at $-\lambda_i\left(\sum_{j\neq i}\tau_j + NA\right)$. This suggests that the best response for player i can be computed as the value of τ_i that attains the single maximum of (5). Imposing the first-order necessary condition on the derivative of (5) with respect to τ_i yields

$$\tau_i^* = \mathrm{BR}_i\left(\lambda_i\right) = \frac{\eta_i - \lambda_i}{2\gamma\sum_{j\neq i}\Lambda_j}. \tag{6}$$

Therefore, the best response of player i does not depend on the actions of i's opponents. Once the type of player i is fixed, the best response is uniquely determined.

Remark 4: The observation in Remark 2 is confirmed by the best response function tending to infinity for $\gamma \to 0^+$ and decreases as γ approaches 1.

Once the types of the players have been drawn, the unique Bayesian NE of the stage-game corresponds to the profile of actions $(\tau_1^*, \ldots, \tau_N^*)$. Since the stage-game has a unique Bayesian NE, also the whole multi-stage game has a single NE as the sequence of the stage-games NEs.

The game defined in the previous section relies on a simplified model, and therefore the efficiency of the proposed solution might decrease when it is implemented. However, such a simple model allows us to define a game with computationally lightweight solution, which is fundamental if the algorithm is deployed on simple hardware. This characteristic is missing, for instance, in the approaches presented in [7], [14], which require solving a complex optimization problem. Moreover, the choice of a utility function that only depends on the flow of vehicles allows for the use of simple sensors, such as inductive loop sensors [22]. Many previous works, on the other hand, assume the availability of complex visual systems that would be necessary to estimate for instance the lengths of the queues or of the possibility of communication between infrastructure and vehicles, as in [13] or [26].

The structure of the game allows for a decentralized implementation of the control scheme, which is especially useful in a vehicular network context [16]. Indeed, the traffic lights are assumed to turn green in a fixed order, therefore it is necessary to transmit only the length of the green for the traffic light that currently has control of the intersection to the next in line. Furthermore, the stage-game is Bayesian, and hence the information that a player needs is minimal. In particular, assuming the traffic conditions to be periodic, it is sufficient to store the prior distribution of types over the period, which is also easy to infer.

For the structure of the game to be common knowledge, no exchange of information is required among the players during the game. Indeed the game is static, so that a player chooses its action without the need to know the time that was allotted to the players with turns before its own. Finally, the best response of a player does not depend on the type of its opponents and hence it is not necessary to transmit such informations.

IV. Simulation Results

We present numerical results obtained in Matlab for an intersection with two approaching roads. The performance

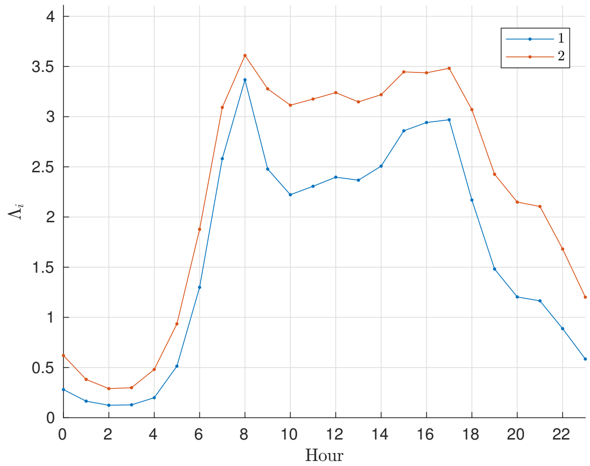

Fig. 1. Means of each hourly distribution for the two players.

of our contribution is compared with the proposal of [13], where the overall game is split in intervals of fixed duration T and at the beginning of each interval the players need to chose the time that will be allocated to them. The authors propose a static game of perfect information based on the Cournot duopoly game [27]. However, the formulation of the game requires that the queue lengths and the arrival rates of all players be common knowledge. Our analysis instead just requires an estimate on their probability.

To assess the performance, the *share ratio* metric will be used, denoted as R and defined as the average over all stages of the ratio between the time reserved to player 1 in the round and the total duration of the round. Let K be the number of stages of a game and τ_i^k the action of player i at round k, then the share ratio is

$$R = \frac{1}{K} \sum_{k=1}^{K} \frac{\tau_1^k}{\tau_1^k + \tau_2^k}. \tag{7}$$

Notice that an equivalent definition can be given for player 2, and the two ratios complement to one.

This first experiment was carried out in order to compare the performance of our proposed algorithm and that of [13]. A simulation was devised to test the algorithms when faced with a realistic profile of priors. The means used for the Poisson arrival distributions are depicted in Fig. 1, one for each hour of the day. This profile of priors is meant to emulate the typical traffic during a work-day, with two rush hours around 7:00 am and 6:00 pm [21]. Moreover, we assumed service rates $\eta_1 = 12$ and $\eta_2 = 13$, and for the Bayesian stage-game the “altruism coefficients” were $\gamma_1 = \gamma_2 = 0.75$. For both games, the amber phase was neglected. The length of the Cournot stage-games was set to be equal to the corresponding Bayesian stage-game, once the latter was solved.

The data employed to model the prior distributions of the players were taken from the hourly traffic intersection volumes in Adelaide City, published by the Adelaide City Council [28], where an hourly traffic profile is available for each day of the year. Therefore, an average profile was computed over all the workdays of the year, and the resulting profile was rescaled to estimate the rates per second.

The simulation performed 1000 stage games, i.e., 1000 simulations of a daily traffic control schedule. Each game is a sequence of stage-games that span the arc of a day, but the number of these stages depends on the actual types that are drawn. In particular, at the beginning of each stage the types are drawn from the distribution relative to the current hour and independent of what drawn in the previous stages. Hence, based on the actual draws each game had a different number of stages. The queue lengths at the beginning of a round were those observed at the end of the previous round; the initial rounds started without vehicles in the queues.

The average queue lengths μ_i, average standard deviations σ_i and peak queue lengths P_i of the two players for the two games are reported in Table I.

TABLE I
AVERAGE AND STANDARD DEVIATION OF QUEUE LENGTHS.

	μ_1	σ_1	P_1	μ_2	σ_2	P_2
Bayesian	0.85	2.9	21	0.35	1.7	15
Cournot [13]	0.03	0.29	3.5	0.06	0.42	4.5

Thus, our proposed algorithm is slightly worse for what concerns the mean number of vehicles in queue at any given time. However, μ_1 and μ_2 are very small for both games, meaning that on average both schedules manage to service the most part of the vehicles that arrive at the intersection.

From inspection of the simulations, off the rush hours the queue lengths are very close to zero, meaning that the intersection is cleared at the end of the stage-games. However, during the rush hours the player experiences some saturation, meaning that part of the vehicles arriving in a stage-game are serviced in the following round or (rarely) after two rounds. This is reflected by the standard deviations reported in Table I, that are larger for the Bayesian game. Finally, the maximum queue lengths reached over all the repetitions P_i are much larger in the Bayesian case, further highlighting that overflowing might be an issue for the proposed algorithm.

One last remark can be made about the share ratio of the games. In particular, the Bayesian game shows an average share ratio of 0.42, while the Cournot game of [13] an average of 0.51. This shows that the Bayesian game is more sensitive to the characteristics of the players and effectively allocates an amount of time to players that is related to their mean arrival rate. Indeed in this case the share ratio is skewed in favour of player 2 because on average it has a larger mean arrival rate 2.2, against 1.6 for player 1.

The analysis showed that the proposed algorithm has on average performances only slightly worse than the Cournot game, suffering however from oversaturation issues in some cases. What is worth remarking, though, is that the Cournot game was developed in [13] with a connected intersection in mind. That is, all traffic lights can communicate with each other and moreover the vehicles themselves alert the intersection controller of their arrival. This makes a huge

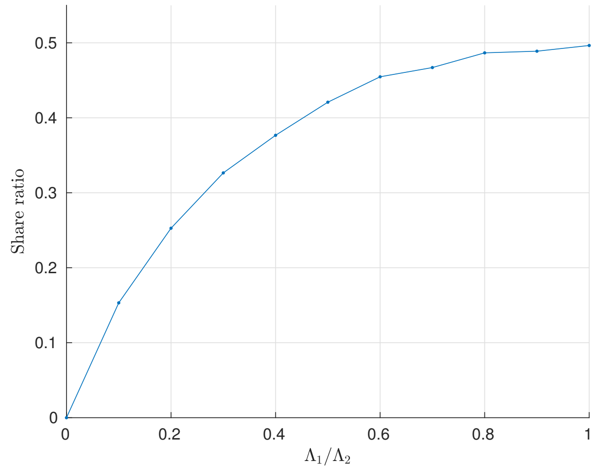

Fig. 2. Share ratio as a function of the arrival rates ratio.

amount of data available, such as the queue length and the arrival rate, to all the players involved. On the other hand, the formulation presented in this work does not require the same amount of information, since traffic light controllers do not need to communicate but just release control to the next one. Furthermore, the Bayesian formulation does not require that players be aware of the arrival rates of their opponents. Therefore, the proposed schedule achieves a performance very close to a Cournot game but with much fewer information exchanges among players.

The results above show that players experiencing average thinner traffic flows are allocated less time during each round. This follows from the fact that τ_i inversely depends on Λ_j, see (6), and hence a player with larger traffic flows induces smaller τ_is in its opponent. To evaluate this phenomenon, a set of simulations were carried out, changing the parameter Λ_1 in $[0, 5]$, while Λ_2 remained constant at 5. Moreover, $\eta_1 = \eta_2 = 12$ and for both players $\gamma = 0.75$. For each value of Λ_1, 100 independent stage-games were played, and the average share ratio computed.[2] Fig. 2 depicts the results. The share ratio increases steadily as the ratio Λ_1/Λ_2 increases, reaching 0.5 when the two players have the same characteristics.

Recall that the utility function in (5) includes a penalty term weighted by γ, and the action at the equilibrium depends on its inverse. Thus, it is interesting to evaluate the share ratio as a function of the penalty coefficient, which was the aim of the following simulation. In this case the arrival and service parameters of the stage-games were chosen to be constant, and are reported in Table II. Moreover, $\gamma_2 = 0.75$, while γ_1 took values in $[0.1, 1]$ distanced by 0.05. Fig. 3 depicts the average share ratio as a function of the different values of the altruism coefficient. The figure was obtained by drawing the types of the players and then simulating a stage-game for each value of γ_1, repeating this procedure 1000 times and then averaging. Notice that the time share of player 1 decreases steadily as its "altruism" increases, as was expected. Moreover, given that the traffic flow of player 1 is lower, the share ratio falls below 0.5 even before γ_1 becomes larger than or equal to γ_2.

[2]'Independent stage-games' means that, for each stage, types are independent, and the queue lengths are reset to 0 and not related through (2).

TABLE II
PARAMETERS FOR THE STAGE-GAME.

i	Λ_i	η_i
1	5	12
2	8	13

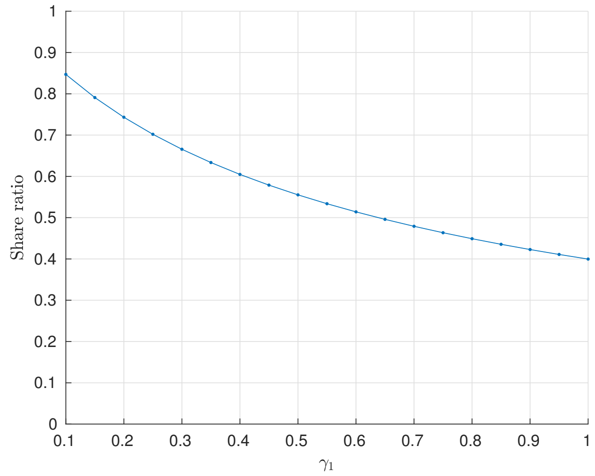

Fig. 3. Share ratio as a function of the "altruism coefficient".

In many works on the subject, the amber phase of the traffic lights is neglected, as was done in the previous parts of this section. To develop an algorithm that can be deployed in practice, the amber phase needs to be accounted for. Hence, the following simulation was devised to test the proposed algorithm in the presence of amber phases. The parameters of the intersection were chosen according to Table II, with γ=0.75 for both players. The duration of the amber light varied between 0 and 1, with the same unit of measurement as for the arrival and service rates. Fig. 4 represents the mean queue length over 1000 independent stage-games for each value of A, drawing new types at each repetition. As the figure

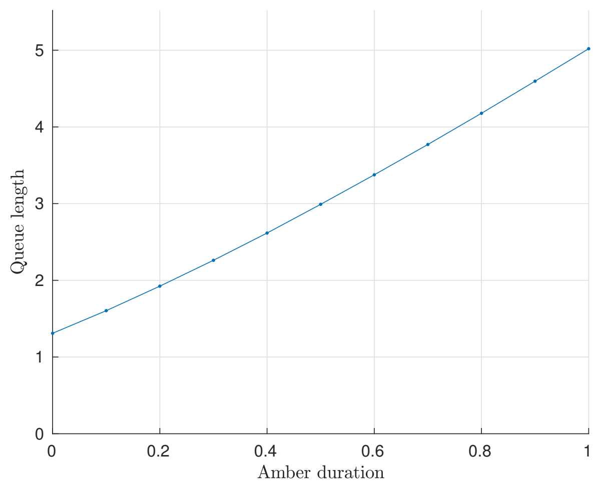

Fig. 4. Mean queue length for player 1 as a function of the amber duration.

demonstrates, the influence of the amber phase increases the mean queue length as it increases the span of time during which a player cannot service vehicles in the queue. However, the proposed algorithm proves to be reliable to this extended idle period, as the queue length, although increased, does not diverge. To give a gist of the performance of the proposed solution, the mean stage-game duration (amber excluded) was 1.3 during the simulation, which means that the amber phases tested reach up to 77% of its value.

V. Conclusions

We presented a game-theory inspired approach to adaptively and efficiently controlling an intersection in a smart city. The solution proposed is based on the repetition of a Bayesian static stage-game, used by the traffic controllers to assign the occupancy for the intersection. The game just requires limited information and is designed to encourage cooperation among the players so as to obtain a fair time sharing.

Our proposed approach is simple in both its definition and its solution, making it a good candidate for practical implementation that can be deployed even on hardware with limited functionalities. Moreover, the schedule relies on a Bayesian stage-game, which means that the information required for rational gameplay are very limited, avoiding the need for information exchanges with the other players, and possible strategic exploitations or error propagations [29].

Simulations were carried out to compare the proposed solution with the solution presented in [13]. We obtained good results with a considerably small amount of information. Other simulations were carried out to analyze the effect of the intersection characteristics on the division of the time allocated to each player. The proposed schedule fairly shares time considering the mean arrival rates of the players.

The formulation of the stage-game includes a parameter for players to sacrifice some of their allocations in favor of their opponents [24]. This is useful if the schedule needs to be modified, e.g., to account for prioritized traffic lanes. Finally, we analyzed the impact of the amber phase on the efficiency of the proposed schedule. The schedule proved to be robust to different local regulations of traffic light frequencies and reliable even in the presence of relatively large amber times.

Further work should seek increasing reliability in the presence of heavy traffic, to avoid oversaturation. Moreover, the same approach adopted in this work could be applied to more refined models of the intersection, e.g., including other road agents such as pedestrian and their safety issues [30], [31]. This way, the benefits of the proposed algorithms would combine with more accurate traffic modelling.

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