Decentralized Optimization of the Flow in a Traffic Network of IAVs

Mohamed Tlig, Olivier Buffet, and Olivier Simonin

***Abstract*—The InTraDE project is concerned with optimizing the transport of containers using intelligent autonomous vehicles (IAVs) within container sea ports. Due to the large number of moving vehicles, an important issue —which we are considering here— is to make the traffic flow as fast/smooth as possible, which involves taking care about intersections. The present paper proposes an approach that aims at reducing the need for slowing down vehicles by alternating them through intersections and optimally synchronizing them. Experiments on a simulated environment have been conducted to evaluate the approach through its ability to spare energy and time.**

Keywords*—*traffic management; intelligent autonomous vehicles (IAV); flow optimization

I. Introduction

The InTraDE project is concerned with optimizing the transport of containers using intelligent autonomous vehicles (IAVs) within container sea ports. Due to the large number of moving vehicles, an important issue —which we are considering here— is to make the traffic flow as fast/smooth as possible, which involves taking care about intersections.

In the past, traffic optimization in a network has mainly focused on the case of non-autonomous vehicles. The few approaches involving IAVs rely on negociations or reservations, and thus optimize the traffic around each intersection without optimizing it at the scale of the network. Here, we present an approach that aims at improving the traffic for the whole network while exploiting the capabilities of IAVs.

The present work relies as a building block on a previous approach [1] that prevents vehicles from stopping at an intersection by (1) alternating vehicles from different flows, and (2) adapting the speed profile in the vicinity of the intersection. The approach we propose synchronizes intersections through a factored/decentralized local search algorithm, which allows improving the flow by reducing the need for most vehicles to slow down (which wastes both time and energy).

II. Two Approaches for Stop-Free Intersections

A. Alternating Strategy

As in [1], we model our traffic network as follows:

- We consider traffic networks made of roads —each with two opposite lanes— and their intersections. The intersections (illustrated by Fig. 1) allow crossing a road but not turning. Two roads intersect at an intersection i and under some angle θ_i.
- Each lane l has its own flow W_l (measured in vehicles.minutes^{-1}).
- The network can thus be seen as a graph $(\mathcal{V}, \mathcal{E})$ where the vertices in $\mathcal{V}$ are intersections and the edges in $\mathcal{E}$ are lane segments $i \rightarrow j$, where i and j are neighboring intersections.

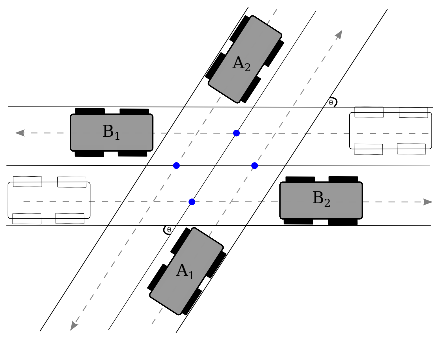

Fig. 1. An example intersection with two 2-lane roads

In [1], we introduce a control agent at each intersection i so as to ensure that vehicles from both roads alternately cross the intersection (at default velocity V). To that end, an optimal crossing period $T_{min}(i)$ has to be computed as a function of V and of the geometric parameters such as the intersection's angle θ_i. Two vehicles, one from each lane, shall pass at time steps $t = kT_{min}(i)$ for one road ($k \in \mathbb{N}$), and at $t = (k + \frac{1}{2})T_{min}(i)$ for the other. To that end, the control agent of the intersection tells incoming vehicles — as soon as they enter a control zone of radius R— when they should enter the crossing area of radius r_0 (at speed V), which requires them to compute an appropriate speed profile between R and r_0 (during which they temporarily decelerate). Fig. 2 illustrates this alternating principle of half-period $T_c = \frac{T_{min}(i)}{2}$ (the minimum time needed to pass a single vehicle through the intersection).

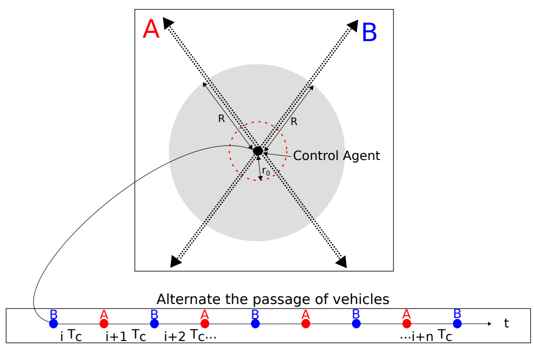

Fig. 2. Alternating principle of an intersection for two roads A and B

B. First-Come First-Served Strategy

The above Alternating (Alt) strategy may waste time at some intersection i when a group of vehicles would like to pass on one lane while no vehicles are going through orthogonal lanes. We thus also consider another strategy

Author 1 and 2 are with INRIA and Université de Lorraine, Nancy, France. E-mail: firstname.lastname@loria.fr

Author 3 is with Université de Lyon and INSA Lyon - CITI Lab., Lyon, France. E-mail: olivier.simonin@insa-lyon.fr which still lets the vehicles go through at the same time instants (every half-period $T/2$), but does not constrain to alternate vehicles from one road and the other. To that end, the vehicles book the time instant when they traverse. This *First-Come First-Served* (FCFS) strategy is inspired by Dresner and Stone's reservation strategies [2], [3].

Fig. 3 (where $T = T_{min}(i)$) illustrates the FCFS approach where two roads A and B (lanes A_1, A_2, B_1 and B_2) cross at intersection i. It indicates, at each time step, to which lane the passing vehicles from a random execution belong.

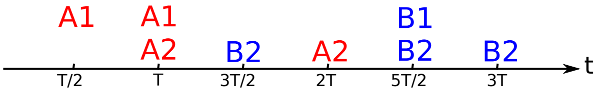

Fig. 3. Illustration of the First-Come First-Served approach at the intersection of roads A and B. As for Alt, only vehicles from the same road —but from opposite lanes (either A_1 and A_2, or B_1 and B_2)— can go through the intersection at the same half-period

III. How to Create Green Waves

As can be noted, the two control strategies presented in the previous section let each intersection have its own period $T_{min}(i)$. Yet, green waves require that all intersections on the same lane share the same period. This typically implies that all intersections in the network should share the worst period: $T_{max} = \max_{i \in \mathcal{V}} T_{min}(i)$.

Given the above Alternating approach, the only control variable left is the phase (offset) $\phi_i \in [0, 2\pi)$ of each intersection's periodic signal (which was omitted in the previous section). As shown in Fig. 4, an intersection i directly interacts with its neighbors (here i's neighborhood is $N(i) = \{j, k, o, p\}$), their phases constraining the duration of the traversal of each segment. For example, one can obtain a desired average speed $V_{i,j}$ on segment $i \to j$ by tuning the phases ϕ_i and ϕ_j appropriately. Yet, each of the 8 segments represents a different constraint to satisfy (/criterion to optimize) while only 5 parameters can be set, meaning that, even on this small example, compromises will be required.

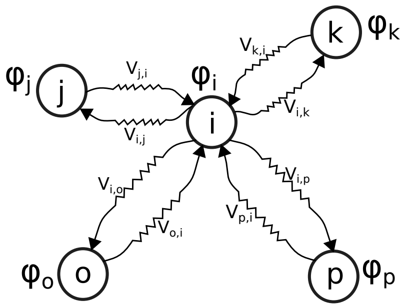

Fig. 4. The optimal phase ϕ_i for intersection i depends on the phases of its neighbors

A. Separable Optimization Criteria

Let us note $\vec{\phi}$ the vector of all the network intersection phases. We focus here on two objectives, which will be considered independently:

1) minimizing the travel times, i.e., the sum of the travel times $t_{i,j}$ on each lane segment $i \to j$, weighted by the flow $W_{i,j} = W_l$:
$$t_{global}(\vec{\phi}) = \sum_{(i \to j) \in \mathcal{E}} W_{i,j} t_{i,j}(\vec{\phi}), \text{ and}$$
2) minimizing the total energy consumption, i.e., the sum of the kinetic energy $E_{i,j}$ on each lane segment $i \to j$, weighted by the flow $W_{i,j}$:
$$E_{global}(\vec{\phi}) = \sum_{(i \to j) \in \mathcal{E}} W_{i,j} E_{i,j}(\vec{\phi}).$$

An important point is that these criteria are separable (one term per intersection), which will allow factoring/decentralizing the optimization.

B. Hill-Climbing Based Algorithm

Various local search algorithms could be considered such as hill-climbing, gradient descent (when the gradient of the evaluation function can be computed), tabu search, or simulated annealing [4]. Here we consider a simple hill-climbing approach. At each iteration t, for each intersection i, the algorithm locally searches for the best phase given the phases of neighbouring intersections $j \in N(i)$, and assigns this value to intersection i: $\phi_{t+1}(i)$. To that end, for each intersection, it is easy to derive a local optimization criterion from any of the two criteria introduced in Section III-A that only relies on the intersection's own phase and its neighbors' phases. Details can be found in [5].

The resulting algorithm can be adapted to run on-line, each intersection continuously estimating the flows going through it and adapting its own phase with respect to the phases of its neighbors. The flows are estimated using an exponential moving average with parameter $\alpha \in (0, 1)$.

IV. Experiments

We conducted experiments on a simulated traffic network with 12 intersections (Figure 5 is a screenshot[1]). Two groups of 6 lanes are created (one lane per road), and 4 traffic conditions are created by simply assign a high flow (15 vehicles.minute^{-1}) or low flow (5 vehicles.minute^{-1}) to all lanes in each group. These traffic conditions are noted 15–15, 15–5, 5–15, and 5–5.

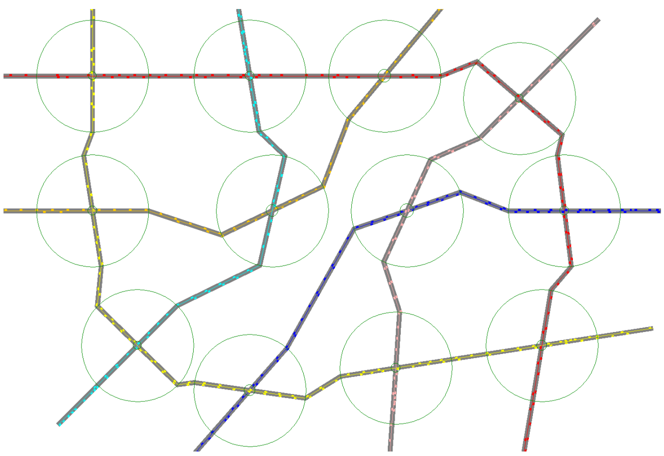

Fig. 5. Screenshot of a simulated 12 intersections network.

[1]A video showing the simulator can be viewed at http://www.loria.fr/~mtlig/videos/12_intersections.avi.

TABLE I. AVERAGE ENERGY CONSUMED PER VEHICLE USING ALT AND FCFS IN EITHER THEIR ASYNCHRONOUS, SYNCHRONOUS OR OPTIMIZED VERSIONS

Injections		$(10k\ veh)$ 15–15	$(7k\ veh)$ 15–5	$(7k\ veh)$ 5–15	$(3.5k\ veh)$ 5–5	Ave.
FCFS	async	137.6 ±2.4	104.6 ±2.1	102.3 ±2.2	**60.3** ±0.6	101.2
	sync	178.8 ±4.6	130.7 ±5.7	128.6 ±5.7	67.4 ±3.2	126.4
	optim	176.9 ±2.5	131.6 ±4.7	129.8 ±3.5	66.1 ±4.1	126.1
Alt	async	111.1 ±1.3	107.1 ±0.8	102 ±0.8	85.9 ±0.8	101.5
	sync	92.6 ±6.4	87.7 ±10.2	88.6 ±8.6	88.5 ±5.1	89.4
	optim	**83.8** ±7.4	**80.2** ±7.4	**74.7** ±5.6	83.7 ±12.4	**80.6**

TABLE II. AVERAGE ENERGY CONSUMED PER VEHICLE USING ALT WITH OFF-LINE OPTIMIZED PHASES, ALT WITH ON-LINE OPTIMIZED PHASES, AND FCFS WITH RANDOM PHASES

Alg.	Alt on-line				Alt off-line	FCFS
(α)	(0.05)	(0.1)	(0.2)	(0.3)		
Energy	78.2 ±4.3	77.1 ±4.7	**76.1** ±5	77.1 ±4.4	80.1 ±6.9	101.2

Table I considers an off-line setting, comparing the Alt and FCFS strategies depending on whether the phases non-synchronized, synchronized with random phases, and synchronized with optimized phases. As can be observed, our approach (Alt-optim) always improves on the other approaches, except when all lanes have low flows, in which case FCFS is more opportunistic and more efficient.

We also considered a 4-hour period during which the four traffic conditions used previously are applied 1 hour each, and compare:

- FCFS with local periods and random phases,
- Alt with phases optimized off-line using the average flow over 4 hours: 10–10, and
- Alt with phases optimized on-line using 4 values for parameter α.

The results presented in Table II show a clear benefit of using an on-line algorithm rather than optimizing phases off line.

V. CONCLUSION

In this paper we have first proposed an approach to optimize the flow of a traffic network in which (1) intelligent autonomous vehicles do not need to stop at intersections, and (2) at each intersection, vehicles from both roads cross alternately. This approach significantly improves on simply using independent stop-free intersections. It is also notably better than the more opportunistic First-Come First-Served strategy under dense traffic conditions. Moreover, the algorithm can be easily adapted to work on line, each intersection continuously estimating the local traffic conditions and optimizing its phase —only requiring to communicate this phase to its neighbors. This on-line version significantly improves on the off-line one, showing its adaptability to changing flows.

Ongoing work includes conducting further experiments to get a better understanding of the approach, and improving the local-search algorithm —e.g., using the Distributed Stochastic Algorithm, a variant of Hill-Climbing especially designed for such distributed settings [6].

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