Reducing Traffic Jams with a Swarm-based Approach for Selection of Signal Plans

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Abstract. Several approaches tackle the problem of reducing traffic jams. A class of these approaches deals with synchronisation of traffic lights in order to allow vehicles travelling in a given direction to pass an arterial without stopping at junctions. In short, classical approaches, which are mostly based on offline and centralized determination of the priorized direction, are quite unflexible since they cannot cope with dynamic changes in the environment (traffic flow) and/or depend too much on communication which can be costly or unavailable. More flexible approaches have been proposed but can be demanding to realise if based on techniques of game theory, for instance. The present paper proposes an approach where each traffic light behaves like a social insect. The signal plans are seen as tasks to be performed by the insect without any centralised control or task allocation mechanism. The stimulus depends on the number of cars waiting or passing the traffic lights, among other things. We implemented this approach in a microscopic traffic simulator which permits the modelling of each individual object – vehicles, traffic lights, etc. The scenario is taken from the city of Porto Alegre in Brazil, with real flow and signal plan data. We have simulated the flow of vehicles in an arterial and its vicinity under different situations: without any coordination between traffic lights, with fixed coordination, and with our approach. In all cases we have measured the density of vehicles in the arterial. The results show that our swarm-based approach is more flexible: traffic lights adapt to the current flow of vehicles by selecting the appropriate signal plan, thus reducing the density in the arterial.

1 Introduction

Approaches to reducing traffic jams has been proposed in several disciplines like transportation engineering, physics, and artificial intelligence, among others. A classical approach is to coordinate or synchronise traffic lights so that vehicles can traverse an arterial *in one direction*, with a specific speed, without stopping [1]. Thus, coordination here means that if appropriate signal plans are selected to run at the adjacent traffic lights, a "green wave" is built so that drivers do not have to stop at junctions.

This approach works fine in traffic networks with defined traffic flow patterns like for instance morning flow towards downtown and it similar afternoon rush hour. However, in cities where these patterns are not clear, that approach may not be effective. This is clearly the case in big cities where the business centers are no longer located exclusively downtown.

Beside, a priori determination of the appropriate signal plans for the different times of a day is a complex task that requires a lot of knowledge about dynamic traffic flow. Thus, flexible and robust approaches are not only attractive, but necessary. Multiagent systems, and especially swarm intelligence offer more flexible solutions. In [2, 3] a multi-agent based approach is described in which each traffic light is modelled as an agent. Each of them has pre-defined signal plans to coordinate with other agents in the neighbourhood. Different signal plans can be chosen in order to coordinate in a given direction or during a pre-defined period of the day. This approach makes use of techniques of evolutionary game theory: intersections in an arterial are modelled as individually-motivated agents or players taking part in a dynamic process in which, due to the reward, not only their own local goals but also a global one has to be taken into account. Moreover, each agent possesses only information about their local traffic states.

The benefits of this approach are threefold. First, it is not necessary to have a central agent to determine the direction of the coordination. Second, agents can build subgroups of synchronisation which meet their own local and current needs in terms of allowing vehicles to pass in one given direction. Third, it avoids communication between agents when they have to decide which direction to priorise, i.e. there is no explicit communication or negotiation.

However, payoff matrices (or at least the utilities and preferences of the agents) are required, i.e these figures have to be explicitly formalised by the designer of the system. This makes the approach time consuming when many different options of coordination are possible (for example all four directions: south, north, east, and west) and/or the traffic network is complex (for instance, not only a main arterial has to be considered but also many transversal and parallel streets).

Therefore, in order to meet this need, this paper presents an approach in which each crossing with a traffic light behaves like a social insect that grounds its decision-making on mass recruitment mechanisms found in social insects [4, 5]. Henceforth we use the terms crossing, junction, and traffic light indistinguily. This is so because in fact in each crossing or junction only one *signal plan* runs in a set of traffic lights (despite the fact that one sees two or three of these) so that the set of traffic lights must be seen as a single entity.

The signal plans are seen as tasks to be performed by the insect. Thus, in our approach the ability of changing tasks in order to suit the colony needs (both at local and global levels) are located in each crossing or junction. Stimuli are provided by the vehicless that, while waiting for their next green phase, continuously evaporate some “pheromone”. Thus the volume of traffic coming from one direction can be evaluated by the agent, and this may trigger some signal plan switching. No other information is available for the intersection agents.

Our approach was realized on a microscopic traffic simulator. This is necessary in any swarm-based approach since it is desirable that the objects can be modelled at individual level. Thus, the next section presents some basic concepts about the simulator and traffic simulation regarding synchronisation of traffic lights. Section 3 then discusses our swarm-based model of the traffic scenario, while Section 4 presents the scenario we simulated as well as the results of these simulations. Section 5 summarises the contributions and discusses future extensions.

2 Description of the Simulator and Synchronisation of Traffic Lights

We use the Nagel–Schreckenberg model [6] which is a microscopic model for traffic simulation originally based on cellular–automata (CA). In short, each road is divided in cells with a fixed length. This permits the representation of a road as an array where on the discrete positions vehicles may be positioned. Each vehicle travels with a speed which is represented by the number of cells it currently may advance at each time step. The vehicle behavior is expressed by some rules that represent a special form of car following behavior. This simple, yet valid microscopic traffic model can be implemented in such an efficient way that it is good enough for real time simulation and control of traffic.

As for the network representation, each road is described as a composition of nodes representing junctions (also called intersections, crossings) and edges. The expression edge is used to refer to directed edges representing one direction of motion on a road, i.e., one road usually consists of two (oppositely directed) edges.

In the urban traffic scenario, more elements were added such as traffic lights and more complex types of intersections. Thus, the simulation tool we developed consists of different elements like lanes, edges, vehicles, sources and sink (of vehicles), sensors and detectors, traffic lights. The topological configuration and parameter for the simulation dynamics are stored in a database. This database can also be used for save the status of all objects in the simulation.

Basically, the simulator checks the static and dynamic network data read from the database for consistency and initialises the scenario. During the simulation it receives and updates dynamic data like vehicle counts, etc. and handles the simulation output, as well updates the vehicle motions, traffic light, and data for statistics.

More details can be obtained in the paper which describes the structure of the simulator and the database [7]. Here, we focus on the traffic light since it is the main object for the coordination. Each (signalised) junction has an agent which is in charge of deciding which signal plan to run. In this paper we assume that all main junctions have traffic lights.

Signalised intersections are controlled by signal-timing plans which are implemented at traffic signals. A signal-timing plan (henceforth signal plan for short) is a unique set of timing parameters comprising basically the cycle length (the length of time for the complete sequence of the phase changes), and the split (the division of the cycle length C among the various movements or phases).

The criteria for obtaining the optimum signal timing is that it should lead to the minimum overall delay at the intersection. This is usually achieved by using simulation or optimisation programs. Several plans are normally required for an intersection (or set of intersections in the case of a synchronised system) to deal with changes in traffic flow.

The goal of coordinated or synchronised systems is *to synchronise the traffic signals along an arterial* in order to allow vehicles, travelling at a given speed, to cross the arterial without stopping at red lights. Besides the parameters mentioned above, the synchronised plans also need an *offset* i.e. the time between the beginning of the green phase at two consecutive traffic signals (only when they are synchronised).

Well designed signal plans can achieve acceptable results in *un-congested streets in one flow direction.* However synchronisation in two opposing directions of an arterial is difficult to achieve, if not impossible, in almost all practical situations. The difficulty is that the geometry of the arterial is fixed and with it the spacing between adjacent intersections. Only in very special cases the geometry allows progression in opposite directions. Synchronisation in four directions is, for practical purposes, impossible. Therefore an agent at a junction must *select* which plan to carry out, in analogy to a task selection.

As a measure of effectiveness of such systems, one generally seeks to optimise a weighted combination of stops and delays or a measure of the density (vehicles/unit of length) in the road or network. Here we use the latter.

The average density $\bar{\delta_k}$ of a lane k during a given simulation horizon T is thus computed by:

$$\bar{\delta_k} = \frac{\sum\limits_{T} \sum\limits_{L} N}{T \times L} \tag{1}$$

where:

L is the length of the lane in number of cells
N is the number of vehicles

If the time horizon T is 1 time step (as it is usually the case), then we do not need to consider the sum over T. Moreover, the density δ is always between 0 and 1 since a cell is occupied by at most one vehicle. Also, an average density value for a set of lanes or for the whole network can be computed by simply weighing each $\bar{\delta_k}$ by each length L_k.

We measure the average density in the network and also the density in some key roads. The former gives the engineer an idea of the whole performance but is of little use because it may compensate heavy loads in some roads with lower ones, giving the false figure that *on average* the flow of vehicles is satisfactory. More details are given in Section 4.1.

3 Model of task allocation in the traffic scenario

Theraulaz et al. [8] present a mathematical model that resembles a hyphothesis of how the division of labour may be organised in colonies of social insects. Interactions among members of the colony and the individual perception of local needs result in a dynamic distribution of tasks. Their model describes the colony task distribution using the stimulus produced by tasks that need to be performed and an individual response threshold related to each task. Each individual insect has a response threshold to each task to be performed. That means, at individual level, each task has an associated stimulus (e.g. the perception of waste as a stimulus for cleaning behavior). The levels of the stimulus increase if tasks are not performed, or not performed by enough individuals, etc. An individual that perceives (e.g. after walking around randomly) a task stimulus higher than its associated threshold, has a higher probability to do this task. This model also includes a simple way of reinforcement learning where individual thresholds decreases when performing some task and increases when not performing. This double reinforcement process leads to the emergence of specialised individuals.

These concepts are used in our approach in the following way: Each traffic light has a social insect behavior. This traffic light has different tendencies to execute one of its signal plans (each signal plan is considered an available task), according to the environment stimulus and particular thresholds. Besides these individuals, this approach also considers that each vehicle leaves a pheromone trace that can be perceived by the traffic light at the junction This metaphor is realistic since many junctions have sensors of type loop induction detectors which detect the counting of vehicles (and sometimes speed).

3.1 Computation of Stimulus

The liberated pheromone dissipates in a pre defined rate in time and its intensity indicates the vehicle flow in the street section. The pheromone trail can be considered as a stigmergic communication among the adjacent traffic lights. The increase of the accumulated pheromone in a certain direction can be seen by the insect as a change in a task selection executed by its neighbour.

Each particular task in the Theraulaz et al. model [8] has one associated stimulus. The intensity of this stimulus can be associated with a pheromone concentration, a number of encounters between individuals performing the task, or any other quantitative cue sensed by individuals. The traffic light stimulus is the average of the accumulated pheromone of all the lanes (incoming and outgoing).

The accumulated pheromone in a lane, $d_{i,t}$, is the pheromone trail accumulated in the lane i at time t. While the vehicles are waiting for the green light they remain releasing pheromone so the amount of pheromone increases.

$$d_{i,t} = \frac{\sum\limits_{i=0}^{n} \beta^{-i}(d_{i,t})}{\sum\limits_{i=0}^{t} \beta^{-i}} \tag{2}$$

where:

n time-window size

β pheromone dissipation rate of the lane

The stimulus s of the plan j is based in a weighted sum of accumulated pheromone in each phase of this plan. Each phase has a time share $((time_{end} - time_{begin})/time_{cycle})$, that indicates how much time the plan spends with a phase. A higher time interval indicates a phase priority in the plan.

$$s_j = \sum_{i=0}^{n} ((1-\alpha) d_{in_{i,t}} + \alpha d_{out_{i,t}}) \Delta t_i \tag{3}$$

where:

n number of phases of the signal plan j
$d_{in_{i,t}}$ is the accumulated pheromone trail in the input lanes in phase i at time t
$d_{out_{i,t}}$ is the accumulated pheromone trail in the output lanes in phase i at time t
Δt_i is the time fraction of the phase i
α constant employed to set different priorities to the input and output lane densities

3.2 Actual Plan Allocation

Behavioural flexibility of changing plans is a consequence of environmentally induced changes in stimulus and threshold. Every signal plan possess associated stimuli according to the direction towards this signal plan is biased. Individuals may change task because high levels of stimulus related to a direction exceed their response threshold. Equation 4, defines the response function (the probability of chose the plan j as a function of stimulus intensity s_j) of the individual i.

$$T_{\theta_{ij}}(s_j) = \frac{s_j^2}{s_j^2 + \theta_{ij}^2} \tag{4}$$

where:

θ_{ij} is the response threshold for the individual i for executing the task j.
s_j is the stimulus associated with the task j.

3.3 Reinforcement

We use the specialisation model [9], where the threshold is updated in a self reinforced way. Each individual in the model has one response threshold to each task. Those thresholds are updated (increasing or decreasing) according to two different coefficients. The response threshold θ is expressed as units of intensity of stimulus. The response threshold θ_{ij} of an individual i when performing task j during time interval of duration Δt is:

$$\theta_{ij} = \theta_{ij} - \xi \Delta t_{ij} \tag{5}$$

where:

ξ learning coefficient
$\varDelta t$ time interval

The response threshold θ_{ij} of the agent i when not performing method j during time interval of duration $\varDelta t$ is:

$$\theta_{ij} = \theta_{ij} + \rho \varDelta t_{ij} \tag{6}$$

where:

ρ forgetting coefficient

According to Gordon [10] the real ants are directly influenced by its success in performing a given task. Successful ants are motivated to stand performing a task and unsuccessful ants are motivated to change or stop performing the task. We have extended the Bonabeau et al. [9] model in order to include a success function as the coefficient that describes learning and forgetting at the same time (when the l is negative the agent is forgetting). Equation 7 defines this extention.

$$\theta_{ij} = \theta_{ij} - l \varDelta t \tag{7}$$

where:

l is the learning/forgetting coefficient.
$\varDelta t$ is a normalised discrete time interval.

The success degree of the individual is given by the Equation 8 and Equation 9, where a greater standard deviation of the densities σ (Equation 10, where n is the number of street sections) leads to a smaller degree of success.

$$l = 1 - 2\sigma \tag{8}$$

$$l = 2e^{(-5\sigma)} - 1 \tag{9}$$

σ is the standard deviation of accumulated pheromone trail in the sections.

$$\sigma = \sqrt{\frac{1}{n-1} \sum\nolimits_{i=1}^{n} (d_i - \overline{d})^2} \tag{10}$$

where:

n is the number of street sections.
$\overline{d}$ is the mean accumulated pheromone trail in n sections.

The whole system tends to stay stable and suited to the traffic flow but can change in order to adapt to a new environment situation. Traffic lights in the same street with an intense traffic flow in a certain direction tend to adopt the synchronised plans and give priority for this direction.

4 Description of the Scenario and Results of the Simulations

4.1 Scenario

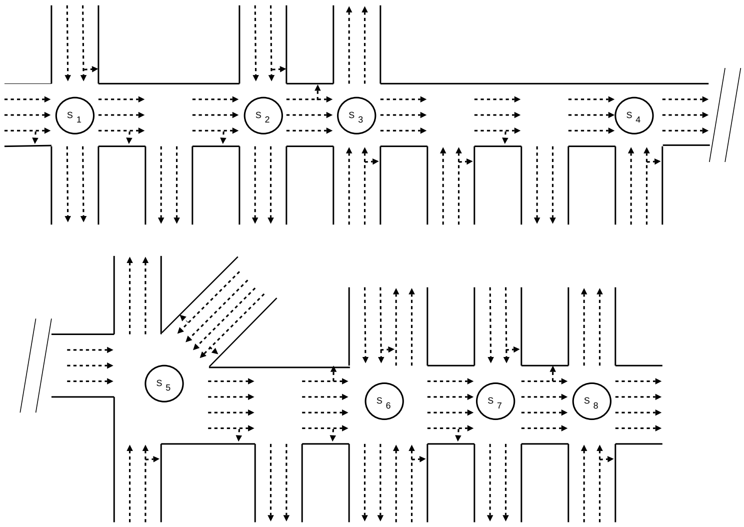

Fig. 1. Network and the traffic light location (numbered circles)

The scenario, showed in Figure 1 in a simplified schema, is part of a real network situated in the city of Porto Alegre (Brazil). This set of streets were chosen due to the high traffic flow and availability of data regarding flow of vehicles and the signal plans.

The main street or arterial has eight traffic lights, each with two possible plans. Signal plan 1 gives priority to the main direction (WE) and it is synchronised with the adjacent traffic lights in this direction. Plan 2 is not synchronised with plans in neighouring junctions, and allocates equal share of green time for each direction, as we can see in Figure 2.

Regarding plan 1, the difference between this kind of plan running at two adjacent junctions is the offset. For instance, junctions S_2 and S_3 in Figure 1 have the same basic plans but S_3 has a 16 second offset. This indicates that vehicles departing at S_2 and travelling with the synchronisation speed V will be able to pass at S_3 16 seconds later without stopping.

Vehicles are inserted in the network by sources located at the borders of it. For instance, vehicles are inserted in the main street from a source located in the left corner (Fig. 1). This insertion happens with different rates in each street. We setup these rates according to real traffic flow information. Similarly, at the network borders, vehicles are removed from the scenario. Besides, each junction

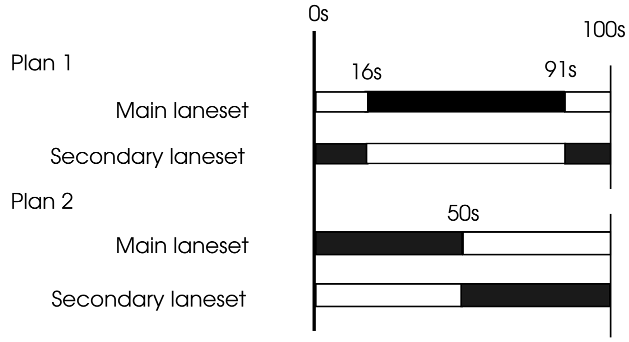

Fig. 2. Basic Signal Plans (the dark strip represents the time of green

has turning probabilities which can be computed from real data. Therefore, each vehicle either stays in the direction it is, or turns to another one.

4.2 Results from Simulations

The simulations presented in this section were generated using the simulator discussed in Section 2 with the scenario presented in Section 4.1. In the beginning of the simulation the network is empty and some time is needed for vehicles to reach all the portions of the network. Thus, in order to have a stable situation in the network, with a representative number of vehicle, we do not consider the initial time window. The average density of the arterial is computed in each simulation step.

The aim of this experiment is to compare the density achieved in the network using both our approach and standard ones. Two situations are evaluated. In the first, there is no synchronisation (i.e. plans like Plan 2 in Figure 2 are used in each junction). In the second case, we compare our approach to the situation in which a synchronisation is present but it is fix, i.e. the designer or engineer decides that all traffic lights are synchronised in a fix way.

In each case, we also evaluate and compare the different possibilities of our extension of the specialization model (the success function). Thus, our approach was simulated in four diferent ways: one do not uses reiforcement (the tresholds do not change during the simulation); one uses the original idea about the threshold, updating the threshold with a learning and forgetting coefficients; one uses the linear function to update the threshold; and the last uses the exponential function to update the threshold.

In this paper we adopt $\alpha = 0.2$, $\beta = 0.5$ and θ starting with 0.5. When changing the threshold using the original idea we adopt $\xi = 0.5$ and $\rho = 0.05$. Our extension uses the linear function presented in Equation 8 and the exponential function presented in Equation 9.

As we can see in Figure 3, the swarm approach achieves the best result when we use our extension on threshold variation using Equation 9 as the success

Fig. 3. Change in densities over time for the simulations.

function. The manual synchronisation shows a slightly better result because, in this scenario, we are not changing significantly the traffic flow in the adjacent streets, so the main street has a more intense traffic. Besides, in the simulation beginning (from step 5,000 to step 6,000), when the main street has a lower traffic flow than the adjacent ones, we can see that the manual synchronisation shows worst results than our approach. It is happen because the traffic flow in the adjacents streets are growing while the main street stays almost empty. Our approach was able to perceive this difference and to adapt the traffic lights to priorize the grater traffic flow. A total lack of synchronisation among the agents shows the highest densities levels, as expected. The fixed threshold curve indicates lower densities than the original model of learning and forgetting and also the success based variation that uses Equation 8 as learning and forgetting coefficient.

5 Conclusions and Outlook

This paper proposes an approach to reduce traffic jams based on a swarm-inspired method of selecting signal plans. We have discussed some approaches to reducing traffic jams, focusing on signal plan selection, either via classical approaches or via more flexible ones like the one proposed in [3]. We also discussed the need for even more flexible approaches in which the preferences of the traffic lights regarding the coordination or synchronisation do not have to be explicitly stated.

The swarm approach is well suited here because it profits from the metaphor of vehicles leaving a pheromone trail when stopped at a junction. This metaphor is used as a kind of stigmergy between adjacent junctions.

The approach was realized in a microscopic traffic simulator, to which models of social insects were added. These insects thus perceive the pheromone trails and act accordingly which in this case means a selection of an appropriate signal plan.

The average density in the arterial was measured in order to compare the following situations: i) the traffic lights are not coordinated; ii) they are coordinated in the classical way, i.e., using a central decision component (normally the traffic engineer) which determines the unique synchronisation for all junctions; iii) they are free to decide, at local level, whether or not to coordinate. This last approach is more flexible and depends only on flow detectors installed at each junction.

Quantitatively, when the agents are free to decide coordinating according to the swarm approach the system behaves almost as if a central decision support was given. Our experiments shows that the agents achieve synchronisation without any management, that indicates a successful swarm based application.

This works foresees some extensions as for instance increasing the set of signal plans an insect has. Additional signal plans can be designed either to coordinate in other directions or to coordinate in the main direction with other shares of green time and offsets. To implement this we depend on the traffic engineer who has to design such plans.

Other possible extensions are the simulation of the enlarged network (which is currently being done and again, depends on the engineers) so to consider parallel streets and so on. The case in which both arterials crossing at junction S_6 (Figure 1 are allowed to coordinate is very interesting because both are important arterials in the city.

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