Traffic Lights Control with Adaptive Group Formation Based on Swarm Intelligence

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Abstract. Several traffic control approaches address the problem of reducing traffic jams. A class of these approaches deals with coordination of traffic lights to allow vehicles traveling in a given direction to pass an arterial without stopping. This paper presents an approach where each traffic light behaves like a social insect, having coordinated signal plan as task to be performed. This is done without any centralized task allocation mechanism. In our study, we focus on the group formation dynamics and how agents decision processes can be influenced by others.

1 Introduction

Approaches to reduce traffic jams have been proposed in several disciplines like transportation engineering, physics, and artificial intelligence, among others. A classical one is to *coordinate or synchronize* traffic lights so that vehicles can traverse an arterial *in one traffic direction*, with a specific speed, without stopping. 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. There are several reasons why this approach may fail.

In traffic networks without well-defined traffic flow patterns like for instance morning flow towards downtown and it similar afternoon rush hour, that approach may not be effective. This is clearly the case in big cities where the business centers are no longer located exclusively downtown. Also, in some cities, "secondary" streets turned as important as traditional arterials due to the saturation of these. Traffic patterns can also be affected by accidents, floods, snow, etc. Finally, 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.

These issues show that simple offline optimization of the synchronization in *one arterial* alone cannot cope with changing traffic patterns. This happens because traffic is a highly dynamic process, thus the currently optimal signal plan can hardly be determined in advance. With an increasing volume of traffic, this situation becomes more and more unacceptable. Thus, flexible and robust approaches are not only attractive, but necessary.

Our approach seeks to replace the traditional arterial green wave by "shorter green waves" in *segments* of the network. Of course in some key junctions conflicts may appear because in almost all practical situations, a signal plan do not allow synchronization in more than one traffic direction. However, our approach dynamically deals with the question of which traffic direction shall be synchronized.

Decentralized systems, and especially swarm intelligence offer more flexible solutions. This paper presents an approach in which each junction (plus its traffic lights) behaves like a social insect that grounds its decision-making on mass recruitment mechanisms found in social insects [3, 10]. Henceforth we use the terms crossing, junction, and traffic light indistinctly.

Signal plans are seen as tasks to be performed by the insect. Thus, following the social insect metaphor, in our approach the ability of changing tasks in order to suit the colony needs is located in each crossing or junction. Stimuli to perform a task or, sometimes, to change tasks, are provided by the vehicles that, while waiting for their next green phase, continuously produce some "pheromone", as well as by the number of insects in the coordination area performing the task. Thus the volume of traffic coming from one direction can be evaluated by the agent, and this may trigger some signal plan switching. This paper is an extension of our previous model, presented in [9], discussed in sub-section 2.2.

The next section presents some traffic signal coordination methods. In the third section, the proposed approach is described while section 4 presents and discusses the results. In the last section we make some conclusions about our work.

2 Traffic Signal Coordination

2.1 Synchronization in arterials: basics

Signalized 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. Several plans are normally required for an intersection (or set of intersections in the case of a synchronized system) to deal with changes in traffic flow. The goal of coordinated or synchronized systems is *to synchronize the traffic signals along an arterial* in order to allow vehicles, traveling at a given speed, to cross the arterial without stopping at red lights. Besides the parameters mentioned above, the synchronized 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 synchronized).

Well designed signal plans can achieve acceptable results in *un-congested streets in one flow direction.* However synchronization in two opposing directions of an arterial cannot be achieved 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. Synchronization 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 optimize a weighted combination of stops and delays, a measure of the density (vehicles/unit of length) in the road or network, or travel time. Here we are focused in how the coordination is working, so we measure the number of coordinated agents and the number of groups.

2.2 Approaches for Traffic Signal Coordination

The Traffic Network Study Tool (TRANSYT) [11] is one well-known algorithm for traffic lights synchronization. It runs off-line and aims at optimizing the bandwidth of an arterial via the design of phases and offsets from one intersection to the adjacent one. Similar tools are SCATS and SCOOT. However these are both based on online traffic volume information coming from loop-induced detectors installed in the roads. SCATS (*Sydney Coordinated Adaptive Traffic System*) [6] was initially developed for the Sydney area. It is a real-time control system, based on a decentralized architecture. It optimizes the length of cycle time and offsets, and allows some phases to be skipped at times. SCOOT (*Split Cycle and Offset Optimization Technique*) [5] is a centralized traffic control system developed by the *Transportation Road Research Laboratory* (UK). SCOOT also optimizes cycle and offset, as well as saturation rate. Although both deal with real time data, their concept is still based on synchronization in one main path.

Multiagent systems, and especially swarm intelligence offer more flexible solutions. In [1] a multi-agent based approach is described in which each traffic light is modeled as an agent. Each agent has pre-defined signal plans to coordinate with other agents in the neighborhood. Different signal plans can be chosen in order to coordinate in a given traffic direction or during a pre-defined period of the day. This approach uses techniques of evolutionary game theory: intersections in an arterial are modeled 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 can 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 synchronization 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 give priority, i.e. there is no explicit negotiation. However, payoff matrices (or at least the utilities and preferences of the agents) are required, i.e these figures have to be explicitly formalized by the designer of the system. This makes the approach time consuming when many different options of coordination are possible (for example all four traffic 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).

In our previous work, [8], the control was decentralized using a technique from distributed constraint optimization: one agent is selected to mediate. This mediation thus is not decentralized: group mediators communicate their decisions to the mediated agents in their groups and these agents just carry out the task. Also, the mediation process can take long in highly constrained scenarios, this having a negative impact in the coordination mechanism. Therefore, in order to address this shortcoming, a decentralized, swarm-based model of task allocation was proposed to select synchronized signal plans. Our first swarm based model was presented in [9]. It was tested in a microscopic simulator and our objective was to analyze the impact on traffic, so that we have not collected and analyzed information about the group formation. The dynamic group formation without mediation is the object of the present model (next section). It combines the advantages of those two previous works (decentralization via swarm and dynamic group formation).

3 Using Metaphors of Task Allocation in Colonies of Social Insects Create Coordinated Groups

3.1 Models of Task Allocation

In Bonabeau et al. [2], a mathematical model is presented that formalizes a hypothesis of how the division of labor may happen 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 for each task to be performed. That means, at individual level, each task has an associated stimulus, like for instance 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. 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 (Eq. 3). 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 specialized individuals.

These concepts are used in our approach in the following way: each agent (traffic light/crossing) has a social insect behavior. It 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 agents at the junction. This metaphor is realistic since many junctions have loop induction sensors which detect the counting of vehicles (and sometimes speed). We also consider that an agent can receive direct information from agents in its area, and that is also a feature that is being introduced in modern traffic control systems using communication among related traffic lights. This communication is a form of direct communication, as defined in [7] (quoted by [12]).

3.2 Computation of Stimulus

The pheromone dissipates in a pre-defined rate along time and its intensity indicates how high is the traffic volume in the street portion. The pheromone trail can be considered as a stigmergic communication among 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 neighbor.

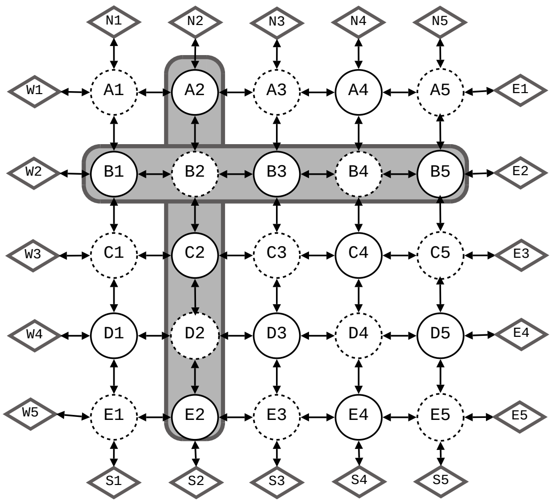

Fig. 1. The gray area represents the visibility are of the agent B2.

Each particular task in the Bonabeau et al. model [2] has one associated stimulus. The intensity of this stimulus can be related to 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 lanes (incoming and outgoing).

The accumulated pheromone in a lane, $d_{l,t}$, is the pheromone trail accumulated in the lane l at time t. While the vehicles are waiting for the green light they remain releasing pheromone so its amount increases. However the pheromone also dissipates at a rate β.

$$d_{l,t} = \frac{\sum_{t=0}^{w} \frac{w-t}{\beta}(d_{l,t})}{\sum_{t=0}^{w} \frac{w-t}{\beta}} \quad (1)$$

where:

w time-window size
β pheromone dissipation factor for each lane l

The stimulus s of the plan j is based in a weighted sum of accumulated pheromone in each phase of this plan and the number of agents in the area of coordination of the signal plan. In Figure 1, the gray area represents the visibility for the agent B2: In this case, the stimulus of the signal plan that gives more priority to NS/SN directions is influenced by the agents in the "B" row, while the plan that gives priority to the other direction is influenced by the agents in the "2" column. Each phase has a time share ($\Delta_k = (time_{end} - time_{begin})/time_{cycle}$), that indicates how much green time the plan allows to a phase. A higher time interval indicates a priority for a particular phase in that plan.

$$s_j = \alpha \sum_{k=0}^{n} (d_{in_{k,t}}) \Delta_k + (1-\alpha)\frac{a_j}{\mathcal{A}} \quad (2)$$

where:

n number of phases of the signal plan j
$d_{in_{k,t}}$ is the accumulated pheromone trail in the input lanes in phase k at time t
Δ_k is the time share of the phase k
α is the influence coefficient
a_j is the number of agents performing plan j in the area
$\mathcal{A}$ is the number of agents in the area that can perform signal plan j

3.3 Actual Plan Allocation

Behavioral flexibility of changing plans is a consequence of environmentally induced changes in stimulus and threshold. Every signal plan is associated with a given stimulus according to the direction towards this signal plan is biased. One individual may change task/plan when the levels of stimulus for a given direction exceeds its response threshold. Equation 3 defines the response function (the probability to select the plan j as a function of stimulus intensity s_j) of the individual i.

$$T_{\theta_{ij}}(s_j) = \frac{s_j^2}{s_j^2 + \theta_{ij}^2} \quad (3)$$

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

3.4 Reinforcement

We use the specialization model [2], where the threshold is updated in a self reinforced way. Each individual in the model has one response threshold to each task. These 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:

$$\theta_{ij} = \theta_{ij} - \xi \Delta t_{ij} \tag{4}$$

where ξ is the learning coefficient and Δt is the time interval.

The response threshold θ_{ij} of the agent i when *not* performing task j during time interval of duration Δt is:

$$\theta_{ij} = \theta_{ij} + \rho \Delta t_{ij} \tag{5}$$

where ρ is the forgetting coefficient.

According to Gordon [4], real ants are directly influenced by their success in performing a given task. Successful ants are motivated to remain performing a task and unsuccessful ants are motivated to stop performing the task and change to another one. We have extended the Bonabeau et al. [2] 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 6 defines this extension.

$$\theta_{ij} = \theta_{ij} - l \Delta t \tag{6}$$

where l is the learning/forgetting coefficient and Δt is a normalized discrete time interval.

The success degree of an individual is given by Equation 7, where a higher standard deviation of accumulated pheromone σ (Equation 8, where n is the number of street sections) leads to a smaller degree of success.

$$l = 1 - 2\sigma \tag{7}$$

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

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} (d_i - \overline{d})^2} \tag{8}$$

where:

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

The whole system tends to remain stable. However, if there is a change in the traffic flow, there must be an adaptation to the new situation in the environment. Traffic lights in the same street with an intense traffic flow in a certain direction tend to adopt the synchronized plans and give priority for this direction.

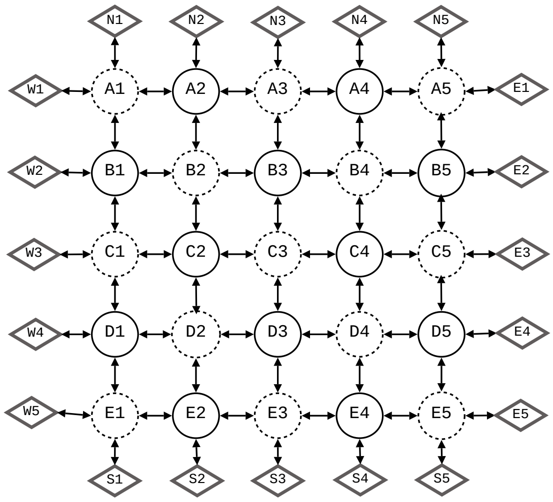

Fig. 2. A network of 25 Intersections (dotted and full-line circles show intersection with SN/NS and EW/WE signal plans respectively)

4 Scenario and Experiments

4.1 Scenario

We use the scenario depicted in Figure 2, representing a traffic network which is a 5x5 Manhattan-like grid, with a traffic light (ant/agent) in each junction. A very similar scenario was used in [8], in order to create groups using cooperative mediation. In our previous work, all agents in the scenario should be capable of sending and receiving information for any other agent in the scenario. This need of wide communication would demand a complete interconnection between all traffic lights in a network and this communication process could also take several minutes, due information losses and delays.

There are 25 nodes and 60 edges or sections. Each of these sections has a capacity of 30 vehicles (in each traffic direction). The actual number of vehicles inserted in the sources, depicted as diamonds in Figure 2, in each simulation cycle, is given by an insertion parameter. Upon arriving at the borders of the network, vehicles are removed from it.

Traffic lights normally have a set of signal plans (for different traffic conditions and/or time of the day). We consider here only two plans, each allowing more green time to a given traffic direction. These signal plans have two phases, one allowing more green time to direction north-south(NS)/south-north(SN) and other to east-west(EW)/west-east(WE). Agents can select a new plan at every 10 minutes, so the agent can perceive the influence of its last decision on the traffic situation before changing to another plan. All signal plans have cycle time of 60 seconds and phases of 40 and 20 seconds. Therefore, the smallest unit of time we consider in the simulation is one-third of the cycle time (20 seconds).

Table 1. Insertion rate values according to the simulation time.

Time (min)	Insertion in N1-N5 and S1-S5 in Figure 2	Insertion in E1-E5 and W1-W5 in Figure 2
0	20	10
60	10	20
180	20	10
300	10	20
480	20	10
660	10	20

The graphs shown in this section all depict the time interval in minutes. Speed and topology constraints are so that 30 vehicles can pass the junction within 60 seconds, for each direction.

4.2 Experiments

At the beginning of all simulations, agents A1, A3, A5, B2, B4, C1, C3, C5, D2, D4, E1, E3, and E5 (Figure 2) are set to use the NS/SN plan while others are set to use the other plan. This initial and arbitrary configuration makes all agents start with neighbors with different plans, so that no group is formed a priori.

We define a coordination group as two or more adjacent agents in a given traffic direction running the same task/plan at the same time. An agent can only be in a group with agents in its visibility area (Figure 1). For example, in this scenario, if an agent is in a NS/SN group it has to coordinate at least with one of its direct neighbors located in North or South.

In all simulations we use the insertion rate according to Table 1. This insertion rates emulates *unexpected* changes in the scenario. Using historical data, a traffic engineer can at most predict general patterns and thus program the coordination of traffic lights accordingly. Our idea was to create a scenario in which this kind of coordination would not be able to cope with unexpected situations. For example, consider that the engineer had designed the groups coordinated to NS/SN from time 0 to time 359 and to EW/WE from 360 to 720. This configuration would potentially increase the travel time in the periods where the traffic was not behaving as expected.

We have performed two different experiments: in the first, the stimulus from each task is not influenced by other agents actions ($\alpha = 1$, in Equation 2); in the second experiment, agents are influenced by the actions of the agents in his visibility area (see Figure 1), so α is a value different from 1. Different values of α were tested but here we discuss only the values 1 and 0.5, due their relevance. The pheromone dissipation rate is set to 10%, $\beta = 10$ (Equation 1), in all experiments. In our previous work the dissipation rate was 50% per minute. This led to agents taking decisions considering almost only instantaneous information. Now this value is set to 10% per minute.

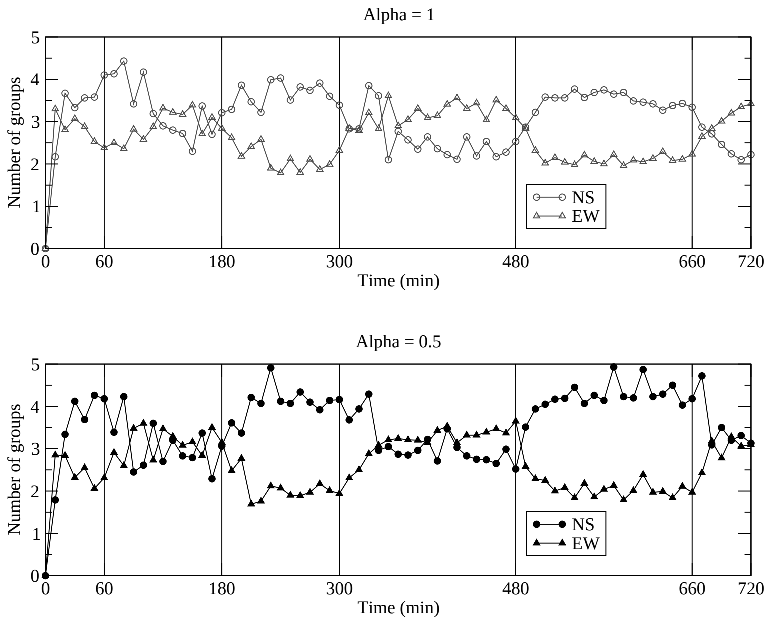

Fig. 3. Changes in the number of groups during the simulation time.

All results in this section are averages over 100 simulations for each experiment. Figure 3 shows the changes in number of groups, with the agents having their stimulus calculated according to i) the influence from the group (black lines, in the plot with $\alpha = 0.5$), and ii) without this influence (gray lines, in the plot with $\alpha = 1$). As we can see, in both experiments, the agents were able to create groups of coordination and to coordinate in the direction with the higher traffic flow. For instance, between time 180 and 300, more vehicles come in the NS-SN directions and the traffic lights are coordinating in groups in these directions.

Figure 4 shows the number of agents that are part of a group of coordination, using the same colors and symbols used in Figure 3. One difference between the two stimuli types is that when agents are influenced by others they form smaller groups with more agents. We have verified that the average number of agents that join groups and the number of groups does not have a significant difference when the agents receive stimulus from other agents or not. The main difference is in how long this groups take to be formed, and in how long the agents take to change groups. This can be seen in Figures 3 and 4. When the insects are influenced by others, they tend to have a more persistent behavior. Thus the number of coordinated agents decreases and increases more smoothly. This particular behavior is more visible at the beginning of each change in the scenario, clearly seen in curves starting at time 660, in Figure 4.

The results shows that the proposed approach combines fully distributed coordination method and a more effective communication method than presented

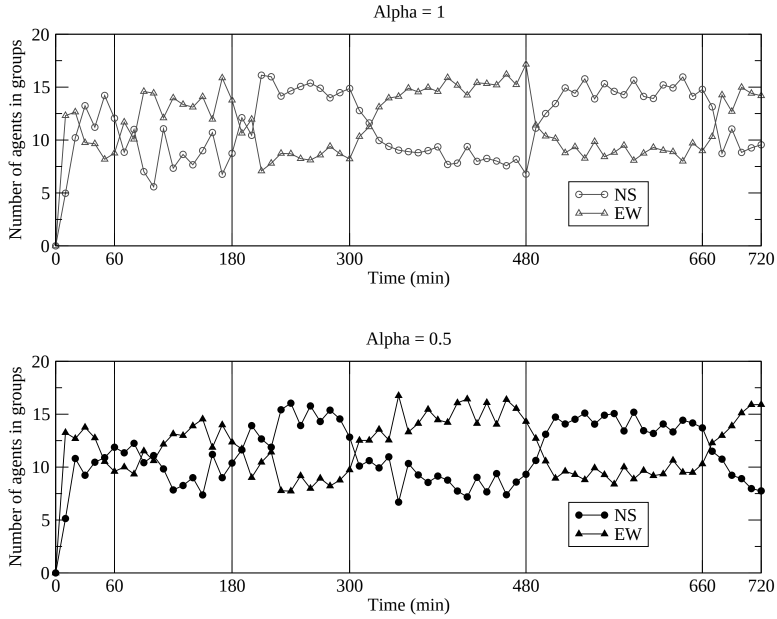

Fig. 4. Changes in the number of agents in groups during the simulation time.

in the cooperative mediation solution. Compared with traditional coordination systems, sub-section 2.2, the main advantage is the adaptation to changes in the traffic. Changes are perceived and the agents react to these changes is a fast and independent form, without any hierarchical organization.

5 Conclusions and Outlook

This paper proposes an approach to traffic lights group formation based on a swarm-inspired method of selecting signal plans. Some approaches to reduce traffic jams were presented, focusing on signal plan selection, either via classical approaches or via more flexible ones like those in [1, 8]. There is a clear need for more efficient and flexible approaches in which the preferences of the traffic lights regarding the coordination or synchronization do not have to be explicitly stated and/or communication among agents is reduced.

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 direct communication is restricted to the agents acting area, and the agent controls its behavior, without direct interference from others. Another important aspect is that when using swarm intelligence, agents have a very reactive and simple behavior, with low computational cost even in highly constrained environments, and low cost hardware could be used.

Quantitatively, when the agents are free to decide coordinating according to the swarm approach, the system behaves almost as if a central decision support were given. Our experiments show that the agents achieve synchronization without any management, indicating a successful swarm based application. Moreover, they are able to adapt to changes in the scenario, forming and dissolving coordination groups.

The present work foresees some extensions as for instance increasing the set of signal plans and more complex networks. 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.

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