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## Swarm intelligence for traffic light scheduling: Application to real urban areas

J. García-Nieto a,\*, E. Alba a,1, A. Carolina Olivera b

- <sup>a</sup> Dept. de Lenguajes y Ciencias de la Computación, University of Málaga, ETSI Informática, Campus de Teatinos, Málaga 29071, Spain
- <sup>b</sup> Departamento de Ciencias e Ingeniería de la Computación, Universidad Nacional del Sur, Av. Alem 1253, 8000 Bahía Blanca, Argentina

#### ARTICLE INFO

Available online 20 May 2011

Keywords:
Traffic light scheduling
Particle swarm optimization
SUMO microscopic simulator of urban
mobility
Cycle program optimization
Realistic traffic instances

#### ABSTRACT

Congestion, pollution, security, parking, noise, and many other problems derived from vehicular traffic are present every day in most cities around the world. The growing number of traffic lights that control the vehicular flow requires a complex scheduling, and hence, automatic systems are indispensable nowadays for optimally tackling this task. In this work, we propose a Swarm Intelligence approach to find successful cycle programs of traffic lights. Using a microscopic traffic simulator, the solutions obtained by our algorithm are evaluated in the context of two large and heterogeneous metropolitan areas located in the cities of Málaga and Sevilla (in Spain). In comparison with cycle programs predefined by experts (close to real ones), our proposal obtains significant profits in terms of two main indicators: the number of vehicles that reach their destinations on time and the global trip time.

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#### 1. Introduction

Nowadays, most cities in the world suffer from an excessive vehicular traffic that provokes severe problems like pollution, congestion, security, parking, and many others. Since changes in the urban area infrastructure are usually not possible researchers often agree in that a correct scheduling of traffic lights can help to reduce these problems by improving the flow of vehicles through the cities (McCrea and Moutari, 2010; Sánchez et al., 2008; Spall and Chin, 1997). At the same time, as traffic lights are installed in cities and its number grows, their joint scheduling becomes complex due to the huge number of combinations that appear, and hence, the use of automatic systems for the optimal cycle programming of traffic lights is a necessary choice.

Current initiatives are focused in the use of simulators (Hewage and Ruwanpura, 2004; Karakuzu and Demirci, 2010; Lim et al., 2001) since they provide an immediate and continuous source of information about the traffic flow. Recent studies in the literature about traffic simulation focused on both, macroscopic (McCrea and Moutari, 2010) and microscopic (Sánchez et al., 2008; Tolba et al., 2005) traffic views. In the last few years, the main efforts are directed towards an accurate microscopic modeling of traffic flow (Karakuzu and Demirci, 2010; Sánchez et al., 2008) and the programming of convenient cycles of traffic lights (Brockfeld et al., 2001; Nagatani, 2010).

In this sense, the use of intelligent methods have demonstrated their usefulness to the optimization of cycle programs of traffic lights (Angulo et al., 2008; Sánchez et al., 2008). However, authors in general have addressed specific urban areas with few intersections and small number of traffic lights (Brockfeld et al., 2001), and most of them apply ad-hoc algorithms designed only for one specific instance (Angulo et al., 2008; Sánchez et al., 2008). The use of intelligent techniques for large and heterogeneous cases of study is still an open issue (Nagatani, 2010; Rouphail et al., 2000).

All these motivations drive us to propose an optimization strategy here based in a particle swarm optimization (PSO) algorithm (Montes de Oca et al., 2009; Kennedy and Eberhart, 2001) that can find successful cycle programs of traffic lights. Several features led us to use PSO instead of other evolutionary methods: first, the PSO is a well-known algorithm shown to perform a fast converge to suitable solutions (Clerc and Kennedy, 2002). This is a highly desirable property for the optimal cycle program of traffic lights, where new immediate traffic light schedules should be required to face updating events in traffic scenarios. Second, the canonical PSO is easy to implement, and requires few tuning parameters (Clerc and Kennedy, 2002; Montes de Oca et al., 2009; Kennedy and Eberhart, 2001). Third, PSO is a kind of Swarm Intelligence algorithm that can inform us on future issues to deal with this problem using independent agents in the system for online adaptation (a future line of us).

A microscopic traffic simulator is then coupled with our PSO for the evaluation of cycle programs (codified as vector solutions) for the traffic lights that control the flow of vehicles through a

<sup>\*</sup> Corresponding author.

E-mail addresses: jnieto@lcc.uma.es (J. García-Nieto), eat@lcc.uma.es (E. Alba), aco@cs.uns.edu.ar (A. Carolina Olivera).

given scenario instance. In this particular work we use SUMO (simulator of urban mobility) (Krajzewicz et al., 2006).

As a first contribution of this work, our proposed PSO is tested with real data of two large and heterogeneous metropolitan areas with hundreds of traffic lights located in the cities of Sevilla and Málaga, in Spain. The results are analyzed under different road conditions. Secondly, in comparison with predefined cycle programs close to real ones, our PSO will be shown to obtain quantitative improvements in terms of two main objectives: the number of vehicles that reach their destinations and their global trip time.

The remaining of this article is organized as follows. In Section 2, a review of related works in the literature is presented. In Section 3, our optimization approach is described. Section 4 presents the experimental methodology used and the results obtained. Conclusions and future work are given in Section 5.

#### 2. Literature overview

Recently, metaheuristic algorithms (Blum and Roli, 2003) have become very popular as optimization methods for solving traffic light scheduling problems. A first attempt corresponds to Rouphail et al. (2000), where a genetic algorithm (GA) was coupled with the CORSIM (Holm et al., 2007) microsimulator for the timing optimization of nine intersections in the city of Chicago (USA). The results, in terms of total queue size, where limited due to the delayed convergence behavior of the GA.

In Teklu et al. (2007), the impact of signal time changes with respect to the drivers were analyzed. More precisely, authors considered the problem of determining optimum signal timings while anticipating the responses of drivers as an instance of the network design problem (NDP). In order to solve the traffic equilibrium problem they used the SATURN package (simulation-assignment modeling software, Van Vliet, 1982). Authors applied a macroscopic point of view of the traffic flow and they employed a GA to compute the signal setting NDP (cycle time, offset, and green light times for stages). It is important to note that the chromosome (grey-code) encoding was done differently for each particular instance under study. The algorithm was tested with the city of Chester in UK, mainly addressing a complete GA parameter analysis, not actually the traffic problem.

In Sánchez et al. (2008), following the model proposed in Brockfeld et al. (2001), the authors designed a GA with the objective of optimizing the cycle programming of traffic lights. This GA was tested in a commercial area in Santa Cruz de Tenerife (Spain). In this work, every intersection was considered to have independent cycles. As individual encoding they used a similar binary (greycode) representation to the one used in Teklu et al. (2007). The computation of valid states was done before the algorithm runs, and it strongly depended on the scenario instance tackled.

Turky et al. (2009) used a GA to improve the performance of traffic lights and pedestrians crossing control in a unique intersection with four-way two-lane. The algorithm solved the limitations of traditional fixed-time control for passing vehicles and pedestrians, and it employed a dynamic control system to monitor two sets of parameters.

A few works (three) related to the application of particle swarm optimization for the schedule of traffic lights also exist. One of the most representative was developed by Chen and Xu (2006), where they applied a PSO for training a fuzzy logic controller located in each intersection by determining the effective time of green for each phase of the traffic lights. A very simple network with two basic junctions was used for testing this PSO.

More recently, Peng et al. (2009) presented a PSO with isolation niches to the schedule of traffic lights. In this approach, a custom microscopic view of the traffic flow was proposed for

the evaluation of the solutions. One single academic instance with a restrictive one-way road with two intersections was used to test the PSO. Nevertheless, this last study was focused on the capacity of isolation niches to maintain the diversity of the PSO population, and was not very involved with the problem itself.

Finally, in Kachroudi and Bhouri (2009) a multiobjective version of PSO is applied for optimizing cycle programs using a predictive model control based on a public transport progression model. In this work, private and public vehicles'models are used performing simulations on a virtual urban road network made up of 16 intersections and 51 links. Each intersection is then controlled by a traffic light with the same cycle time of 80 s.

All these approaches focused on different aspects of the traffic light scheduling. However, three common weak points can be found in all of them:

- They tackled limited vehicular networks with very few traffic lights and a small number of other elements (roads, intersections, directions, etc.). In contrast, our PSO can find optimized cycle programs for large scenarios with hundreds of traffic lights, vehicles, and other elements.
- They were designed for only one specific scenario. Some of them studied the influence of the traffic density. Our approach can be easily adapted to different scenario topologies.
- They were not compared against other techniques. Our PSO is compared here against two different approaches: a Random Search algorithm and the cycle program generator provided by SUMO.

#### 3. PSO for traffic light scheduling

This section describes our optimization approach proposed for the optimal cycle programs of traffic lights. It details the solution encoding, the fitness function, and finally the global optimization procedure. Previous to this, basic notions about the PSO algorithm are given.

#### 3.1. Particle swarm optimization

Inspired in the social behavior of birds within a flock, particle swarm optimization (Montes de Oca et al., 2009; Kennedy and Eberhart, 2001) is a population-based metaheuristic initially designed for continuous optimization problems. In PSO, each potential solution to the problem is called particle *position* and the population of particles is called the *swarm*. In this algorithm, each particle position  $x^i$  is updated each iteration g by means of

$$\chi_{g+1}^i \leftarrow \chi_g^i + \nu_{g+1}^i, \tag{1}$$

where term  $v_{g+1}^i$  is the velocity of the particle, given by the following equation:

$$v_{g+1}^i \leftarrow w \cdot v_g^i + \varphi_1 \cdot UN(0,1) \cdot (p_g^i - x_g^i) + \varphi_2 \cdot UN(0,1) \cdot (b_g - x_g^i). \tag{2}$$

In this formula,  $p_g^i$  is the best solution that the particle i has seen so far,  $b_g$  is the global best particle (also known as the leader) that the entire swarm has ever created, and w is the inertia weight of the particle (it controls the trade-off between exploration and exploitation). Finally,  $\varphi_1$  and  $\varphi_2$  are specific parameters which control the relative effect of the personal and global best particles, while UN(0,1) is a uniform random value in [0,1] which is sampled anew for each component of the velocity vector and for every particle and iteration.

Algorithm 1 describes the pseudo-code of PSO. The algorithm starts by initializing the swarm (Line 1), which includes both the positions and velocities of the particles. The corresponding  $p^i$  of

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