

Enhancing the Urban Road Traffic with Swarm Intelligence: A Case Study of Córdoba City Downtown

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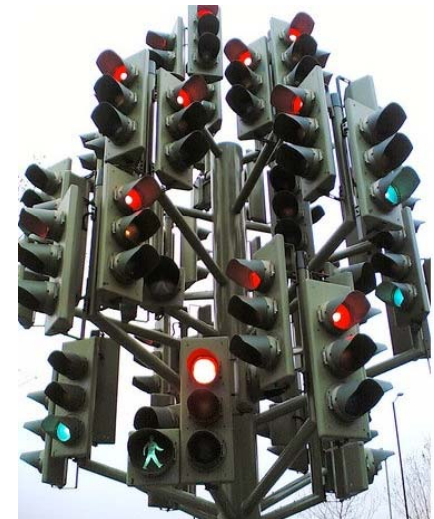
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Introduction

- Nowadays, the **excessive vehicular traffic** in current cities provokes severe problems related to: pollution, congestion, security, noise, and many others
- Improving the flow of vehicles is a **mandatory task**
- Traffic lights are **configurable devices** that **partially control the flow** of vehicles
- Nevertheless, the **increasing** number of traffic lights require a highly **complex scheduling**
- A **great number of combinations** (color states and phase durations) appear that should be considered (explored) by experts



Motivation:

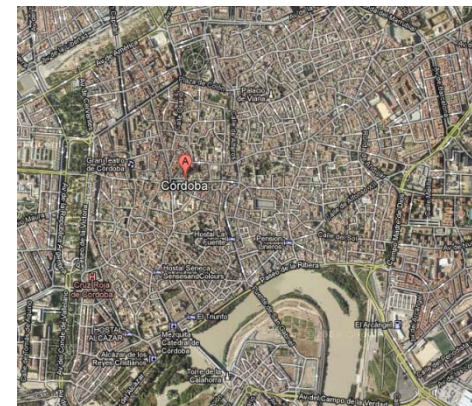
Providing the experts with **automatic intelligent tools** to obtain optimized traffic lights schedules for large urban areas

Introduction

Hypothesis:

Metaheuristics approaches (concretely PSO) **can find** successful schedules of traffic lights for **heterogeneous urban scenarios** in **reasonable time**

- **Our proposal:** A Swarm Intelligence approach (Particle Swarm Optimization) coupled with SUMO (Microscopic Simulator of Urban Mobility), to **automatically search quasi-optimal solutions** (traffic lights schedules)
- **Case Study:** realistic metropolitan area in the city center of **Córdoba**



The Problem: Optimal Cycle Programs of TLs

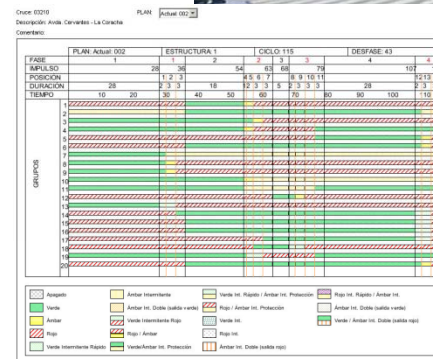
- All traffic lights located in the same intersection are governed by a common program, e. g., the combination of color states during a cycle period is kept valid (it must follow specific traffic rules of intersections)
- **Main objective:** find optimized cycle programs (CP) for all the TLs in a given area. CPs are referred to the **time span (or phase duration)** a set of TLs, in a given intersection, keep their color states

8 TLs with a common CP in intersection:

Paseo de la Victoria/Ronda de los Tejares

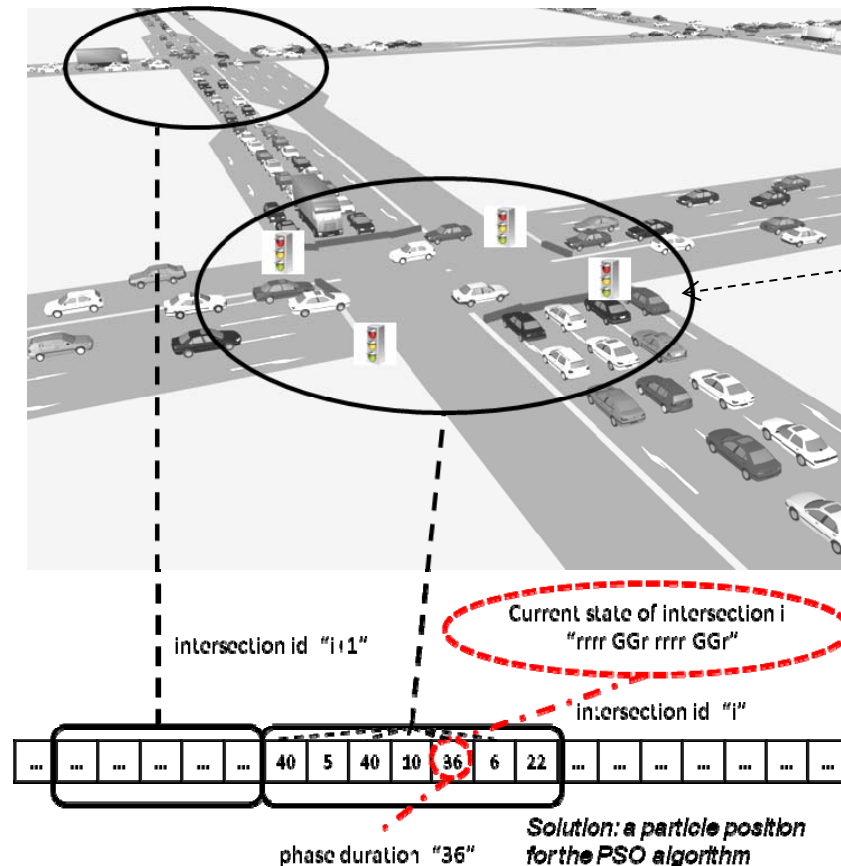


- As in **real schedules**, CPs are designed for established time periods with certain vehicle densities and speeds (rush hours, nocturne periods, etc.)



The Problem: Optimal Cycle Programs of TLs

- **Solution encoding:** vector of integers where each element represents a phase duration of one state of TLs in intersections (SUMO structure of CPs)



- **Adjacent intersections** have to be also coordinated in order to improve the global flow of vehicles

The Problem: Optimal Cycle Programs of TLs

- Fitness function: maximizing the number of vehicles that reach their destinations and minimizing the global trip time of all the vehicles, during the simulation time

$$fitness = \frac{TT + SW + (NV * ST)}{V^2 + P}$$

Values collected during the simulation process

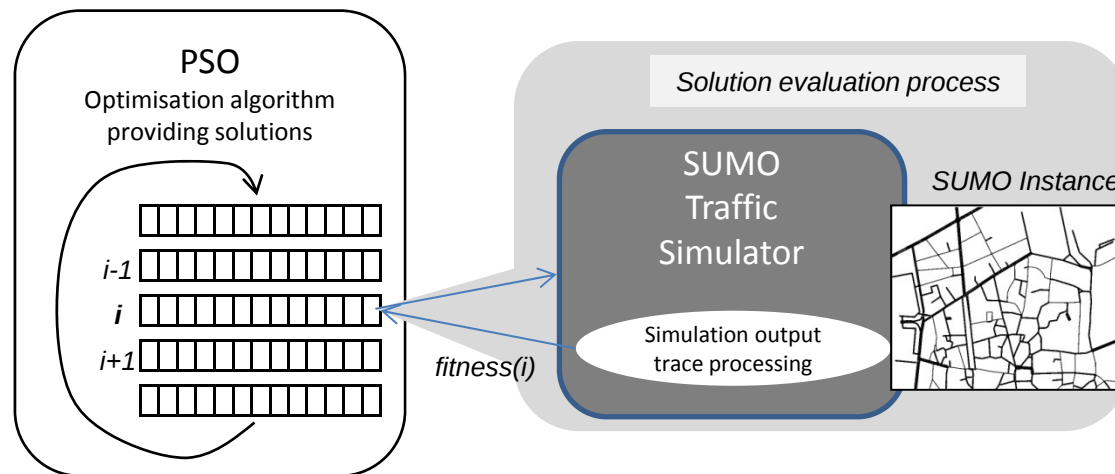
V : Number of vehicles that reach their destinations
TT: Global trip time of all the vehicles
ST: Simulation time
NV: Vehicles that do not reach their destinations
SW: Mean time each vehicle must stop and wait
P: Proportion of colors in each phase and intersection

$$P = \sum_{k=0}^{tl} \sum_{j=0}^{ph} s_{k,j} * \left(\frac{G_{k,j}}{r_{k,j}} \right)$$

tl : Intersection
ph: phase
G: Number of traffic lights in green
r: Number of traffic lights in red
S: phase duration

Optimisation Strategy

➤ Optimization algorithm (PSO) with Simulation procedure (SUMO)



Algorithm 1 Pseudocode of Standard PSO 2007 for OCP

```

1: initializeSwarm()
2: while  $g < \text{maxIterations}$  do
3:   for each particle  $x_g^i$  do
4:      $b_g^n = \text{bestNeighbourSelection}(x_g^i, n)$ 
5:      $v_{g+1}^i = \text{updateVelocity}(w, v_g^i, x_g, \varphi_1, p_g, \varphi_2, b_g^n)$  //Eq. 4
6:      $x_{g+1}^i = Q(\text{updatePosition}(x_g^i, v_{g+1}^i))$  //Eqs. 3 and 5
7:      $\text{evaluate}(x_{g+1}^i)$  //SUMO Simulation and Eq. 1
8:      $p_{g+1}^i = \text{update}(p_g^i)$ 
9:   end for
10: end while
  
```

Mid-Thread quantisation

$$Q(x) = \Delta \cdot \lfloor x/\Delta + 0.5 \rfloor$$

Scenario Instance: Córdoba

- Scenario generated from actual information in real digital maps
- A urban area of approximately 0.75km² comprising: Ronda de los Tejares, Alfaro, Claudio Marcero, and Cervantes street
- 30 intersections each one of them including from 4 to 16 TLs. A total number of **152 TLs** (solution dimension). **Simulation time 500 s**
- Three scenario versions with **traffic densities: 100, 300, and 500** vehicles

Google Map view



OpenStreetMap view



SUMO capture view



Córdoba
Ronda de los
Tejares Avenue
Spain

Experimental Setup

- Comparison of Standard PSO 2007, Differential Evolution (DE), Random Search (RAND), and SCPG (deterministic cycle program generator provided by SUMO according to human expert information)

Implementation in C++ MALLBA Library [online available]

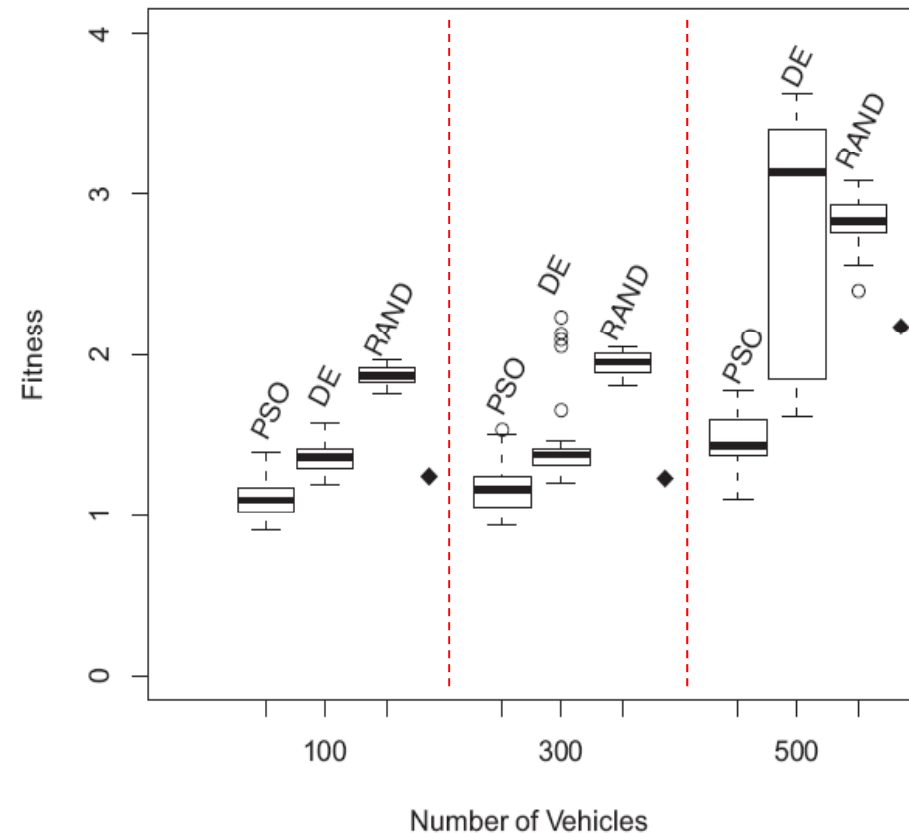
- Standard PSO and DE, with populations of 100 vector solutions and performing 200 iteration steps, e. g. total number of 20.000 function evaluations (simulations)
- Random Search also performing 20.000 function evaluations

- Phase durations (variables) initialized in the range of [6,31]

Solver	Parameter	Value
PSO	Swarm Size	100
	Particle Size (N. Traffic Lights)	152
	Local and Social Coefficients ($\varphi_1 = \varphi_2$)	2.05
	Neighborhood size (n)	3
	Inertia Weight (w)	0.7213
DE	Population Size	100
	Individual Size (N. Traffic Lights)	152
	Mutation Constant (F)	0.5
	Crossover Probability (Cr)	0.9

Performance Comparison

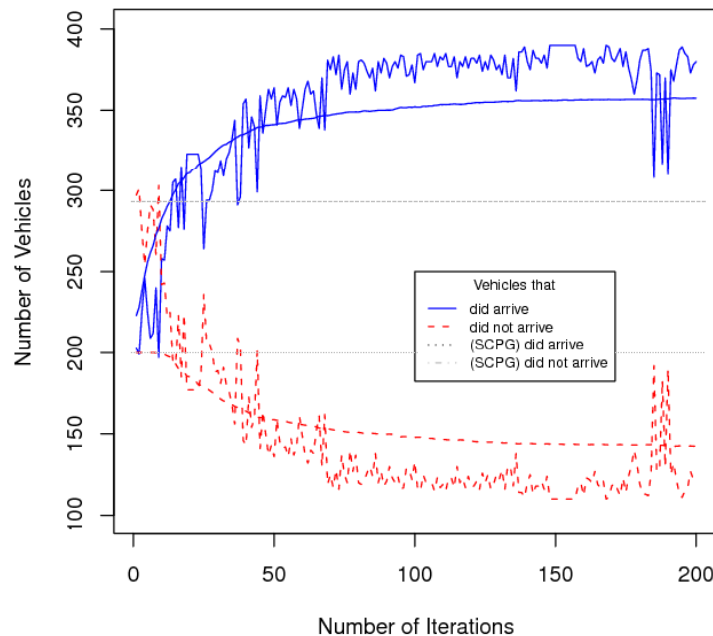
- PSO obtains the best results in general, followed by DE, SCPG (♦) and Random Search
- Statistically, each distribution pair (Wilcoxon) obtained significant differences ($\alpha=0.05$), excepting for DE and RAND with (500 vehicles)
- The higher the traffic density, the greater the benefits of using PSO



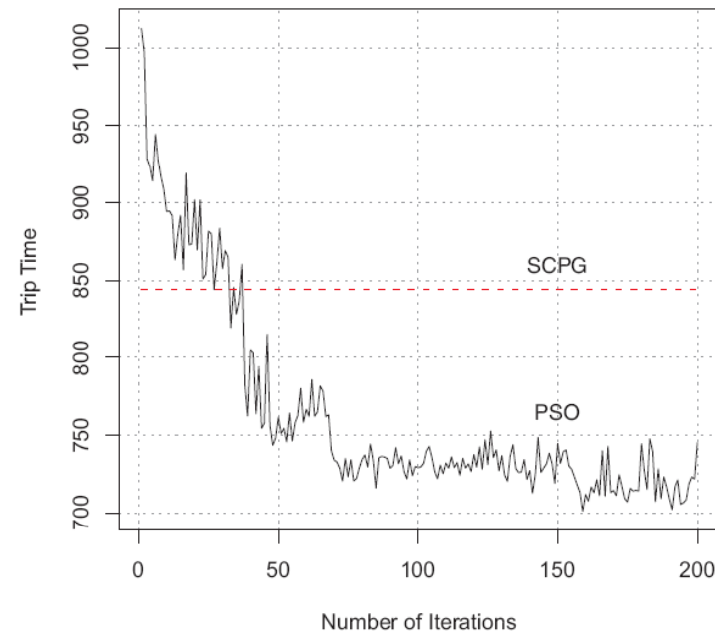
Performance Comparison

- The **global trip time** becomes shorter as the PSO approaches the stop condition (improvement of 17.45% respect to SCPG solutions)
- The **number of vehicles that reach their destinations** increases along with the search progress

30 Traffic Logics – 500 Vehicles

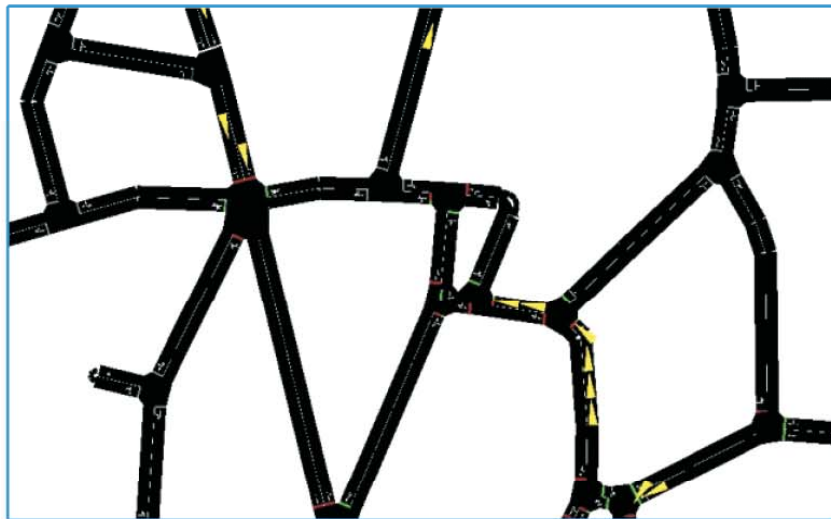


30 Traffic Logics - 500 Vehicles

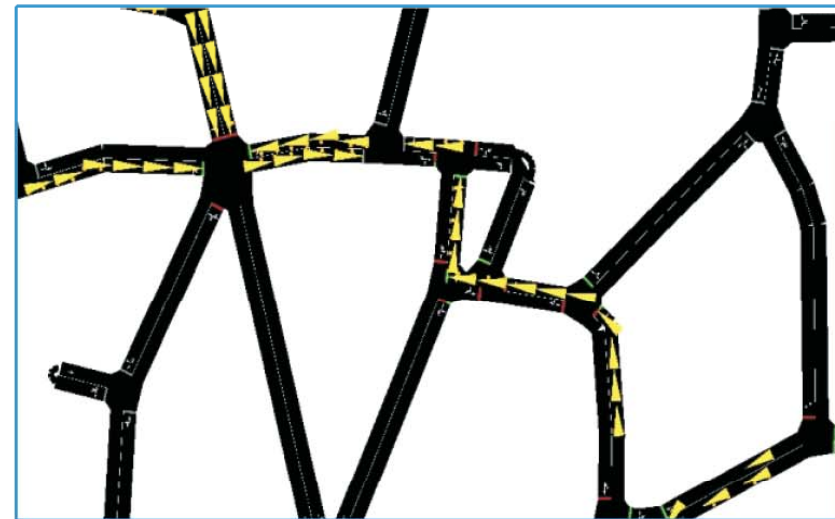


Performance Comparison

- Simulation snapshots of resulted cycle programs generated by PSO and SCPG with 500 vehicles (initial traffic density)
- A low traffic density can be observed in PSO's solutions, but traffic jams appeared in SCPG ones



PSO



SCPG

Conclusions

- We have proposed a Swarm Intelligent approach that, coupled with the SUMO traffic simulator, is **able to find successful cycle programs of traffic lights**. In concrete, we have focused on a metropolitan area of the of Córdoba city
- After the experimentation, we **test our initial hypothesis**:
 - Our proposal **performed efficiently** for the studied instance. In comparison with DE, Random Search, and SCPG, our PSO showed the best performance
 - PSO **scales adequately** in terms of traffic density with: 100, 300, and 500
 - Obtained CPs by PSO can improve both, the **global trip time** and the **number of vehicles that reach their destinations**
- Future work:
 - Tackling the problem with **other metaheuristics**
 - **New large instances** as close as possible to real scenarios of a whole city

Thank you so much!!

