Traffic Signal Optimization in "La Almozara" District in Saragossa Under Congestion Conditions, Using Genetic Algorithms, Traffic Microsimulation, and Cluster Computing

Javier J. Sánchez-Medina, Manuel J. Galán-Moreno, and Enrique Rubio-Royo

***Abstract*—Urban traffic congestion is a pandemic illness affecting many cities around the world. We have developed and tested a new model for traffic signal optimization based on the combination of three key techniques: 1) genetic algorithms (GAs) for the optimization task; 2) cellular-automata-based microsimulators for evaluating every possible solution for traffic-light programming times; and 3) a Beowulf Cluster, which is a multiple-instruction–multiple-data (MIMD) multicomputer of excellent price/performance ratio. This paper presents the results of applying this architecture to a large-scale real-world test case in a congestion situation, using four different variables as fitness function of the GA. We have simulated a set of congested scenarios for "La Almozara" in Saragossa, Spain. Our results in this extreme case are encouraging: As we increase the incoming volume of vehicles entering the traffic network—from 36 up to 3600 *vehicles per hour*—we get better performance from our architecture. Finally, we present new research directions in this area.**

***Index Terms*—Cellular automata (CA), genetic algorithms (GAs), intelligent transportation systems, microsimulation, traffic congestion, traffic modeling.**

I. Introduction

WE are currently undergoing a global energy and environmental crisis. The scientific community argues, providing solid and sound scientific reasons, that the global warming process is, at least partially, a consequence of the high energy expenditure in developed modern societies. A key area in this situation is citizen mobility, as world economies require fast and efficient transportation infrastructures for a large part of the population.

The continuous upsurge in demand on traffic networks calls for new solutions. In the vast majority of cases, it is not viable to extend current infrastructures due to cost, lack of available space, and environmental issues. Thus, traffic departments around the world are interested in optimizing their existing infrastructures to obtain the very best service that they can provide.

Manuscript received June 6, 2008; revised December 15, 2008, May 14, 2009, August 12, 2009. First published November 3, 2009; current version published March 3, 2010. The Associate Editor for this paper was M. Chowdhury.

The authors are with the Universidad de Las Palmas de Gran Canaria, 35017 Las Palmas, Spain (e-mail: javier.sanchez.medina@gmail.com; mgalan@dmat.ulpgc.es; erubio@cicei.com).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITS.2009.2034383

A key topic for traffic optimization is traffic-light cycle[1] optimization. This is a hard combinatorial problem that, at present, has yet to be solved. Our group has done some research on this topic since, as shown in [1], such devices seem to have a strong influence on the resulting traffic flow.

Our optimization proposal can be described, in summary, as a *combination of a genetic algorithm (GA)—as an optimization technique—and a microscopic traffic simulator running on a scalable multiple-instruction–multiple-data (MIMD) multicomputer*.[2] Although the idea of combining GAs with microsimulation is not completely new [2], [3], we have presented a highly scalable approach due to the combination of GA and Beowulf Clusters. Moreover, our cellular automata (CA)-based traffic simulator has been improved by including traffic common traffic situations, such as overtaking and multiple-lane streets.

Our aim here is to study the performance and possible drawbacks of our model in a large congested traffic network.

We were provided with traffic data by the city authority of Saragossa, Spain, for a district called "La Almozara." In the first stage, we used the statistics supplied to infer the traffic inflow in our simulated environment. In the second phase, we increased the traffic inflow beyond the current statistics, performing optimization of traffic-light cycles. The results seem to indicate that our model may also be applied for optimizing congested traffic networks.

This paper is organized as follows: In the next section, we give a survey of the current state of the art, ending with a brief presentation of our own contribution. In Section II, we explain our methodology in detail. In Section III, we describe the experiments performed, specify our assumed restrictions, and show our results. In Section IV, we discuss those results and their implications. Final conclusions and ideas for future research are given in Section V.

A. State of the Art

In this section, we will give a brief survey of some significant research in traffic simulation and/or optimization, particularly those where an attempt is made not only at managing traffic but

[1]Traffic-light cycle: finite sequence of states, e.g., green, yellow, etc., that a traffic signal iteratively runs.

[2]MIMD: type of parallel computing architecture where many functional units perform different operations on different data.

also at optimizing it in an automatic manner, minimizing human supervision.

The Transportation Analysis Simulation System project uses CA models to simulate traffic for the city of Fort-Worth–Dallas, TX, using parallel computers [4]. This paper presents a day-to-day rerouting relaxation approach for traffic simulation. Starting from an initial plan set for the routes, route-based microsimulation is carried out, and its results are fed into a rerouter, which reassigns a certain percentage of all trips. This model is similar with ours in that it can also simulate roads with more than one lane. Very often, in urban scenarios, streets have several lanes. Therefore, this feature makes microsimulators adapt to many realistic traffic layouts.

An ad hoc architecture was used in [3] to optimize a nine-intersection traffic network. It uses GAs as an optimization technique running on a single machine. The Corridor Traffic Simulation Model (CORSIM) is used within the evaluation function of the GA. However, in this work, scalability is not addressed; the authors acknowledge that it is a customized *nonscalable* system. Our system, on the contrary, incorporates a scalability feature due to the intrinsic scalability of the Beowulf Cluster and the parallel processing of the evaluation function within the GA engine.

In [6], the concept of the optimal green time algorithm was proposed. Its aim was to reduce the average vehicle waiting time while improving the mean vehicle speed using fuzzy rules and neural networks. Through computer simulation, this method has been proven to be much more efficient than using fixed-time cycle signals. The fuzzy neural network will consistently improve the average waiting time, vehicle speed, and fuel consumption. Although this work only considers a very small number of traffic signals—two close intersections—in the cycle optimization, we do coincide with them on the unsuitability of using fixed cycles.

A very interesting combination of GAs and traffic simulation was investigated in [2]. In this work, a routing and scheduling system for freight carrier vehicles was presented. Taniguchi and Shimamoto used a GA engine to minimize travel cost. A dynamic vehicle-routing algorithm was proposed and checked against a test road network, but its implemented traffic simulation model was macroscopic.

Another interesting work was presented in [7]. A dynamic system optimal (DSO) traffic-assignment model was formulated for a congested urban network with a number of signalized intersections. Varia and Dhingra also combined traffic simulation with GAs. The aim of this work was to build a traveler-route assignment. A GA was used to minimize the total user travel time. A macroscopic model was used for the estimation of traffic delays. The DSO problem was solved with fixed signal timings and with the optimization of signal timings.

In [8], a real-time traffic signal control model was proposed. Using a combination of multiagents and fuzzy neural networks as main techniques, Srinivasan *et al.* presented some challenging simulated results from Singapore.

In [9], a very interesting approach for optically detecting vehicles on a road was proposed. Akanegawa used the power network and the led lights of traffic signals to reduce the needed budget.

Fang and Elefteriadou [10] described an application programming interface (API) for the classic microsimulator AIMSUN, extending its capabilities by allowing users to interact with, in progress simulations, varying driver behaviors, vehicle characteristics, control strategies, etc.

Finally, we would like to cite some works on an upsurging research topic: short-term traffic simulation/prediction. First, in [11], a model based on the combination of time-series prediction models and neural networks was proposed. The time-series prediction models used were moving average (MA), exponential smoothing, and autoregressive MA (ARIMA). The predicted parameter was the traffic flow volume that was collected in a day.

In another work [12], Ghosh *et al.* introduced a structural time-series model in its multivariate form for short-term traffic prediction. They argued that the proposed model avoids the huge computational complexities derived from extending existing univariate time-series models.

1) Our Contribution: It is not a new idea to combine traffic microsimulation and GA [2], [3], [7]. However, we have defined and tested a new approach for two main reasons. First, we developed a *new* CA-based traffic microsimulator. It may simulate situations such as overtaking and multiple lanes. We then used a Beowulf Cluster as MIMD, which makes our system highly scalable, in combination with the GA. The combination of all these elements is what makes our methodology completely new.

In this section, we have included our contribution to the "art." In [13], we present our methodology for the optimization of traffic-light cycles in a traffic network. The very good results of a parallel speedup study convinced us that it was advisable to use a "Beowulf Cluster" as a parallel computing system.

In [14], we compared two versions of our microscopic traffic simulator, i.e., a stochastic versus a deterministic traffic simulator. There were three main differences between them: 1) cell-updating order; 2) new vehicle creation time; and 3) acceleration probability.

From that study, we concluded that the *stochastic simulator* is a suitable—convergent—statistical procedure for use as an optimization pattern. We were also able to show that the *deterministic simulator* outputs are highly linearly correlated with the stochastic simulators. Therefore, our deterministic simulator can arrange the population ranking in order of fitness at least, as well as the stochastic simulator, but with a remarkably *lower computing time*. In that project, we achieved a speedup factor of 70.87.

At Eurocast 2007 [15], we presented a study considering three candidate criteria as a first step toward extending our fitness function toward a multicriteria fitness function. We will comment on this in detail in Section II-B1.

Finally, we have also carried out some other research using this methodology, such as that presented in [16]. In this case, we studied another traffic network located in Santa Cruz de Tenerife, Spain. Although the scale of that network is not as large as that considered in this paper, the results were very promising and encouraging as well.

II. Methodology

A. Optimization Model

The architecture of our system comprises three main elements: 1) a GA as a nondeterministic optimization technique;

2) a CA-based traffic simulator inside the fitness evaluation routine of the GA; and 3) a Beowulf Cluster as MIMD multicomputer. Through this section, we will give a wider description of the GA- and the CA-based traffic simulator used in our methodology. Finally, a brief description of the Beowulf Cluster will also be provided.

B. GA

In this section, we will describe the GA utilized.

1) Optimization Criterion—Fitness Function: For this research, we have tested four different fitness functions.

1) Number of vehicles (NoV): This variable is simply calculated by counting the total number of vehicles that left the network during the whole simulation run. During the traffic simulation, many new vehicles are created as if they were arriving at the inputs of the network. Furthermore, during the simulation, many vehicles reach their destination point and leave the network. The number of vehicles that reach their destination point easily illustrates how the simulation behaved and consequently helps us to compare a particular cycle combination with any other.
2) Mean travel time (MTT): This variable means the average time, i.e., time steps, it takes a vehicle to leave the network once it is inserted at any traffic input. It seems a reasonable variable to be minimized by the GA.
3) TOC/SOC (TS): There are two parameters in the literature called time of occupancy (TOC) and state of occupancy (SOC). Through the simulation, we obtained the average SOC, which has the same value as the average TOC (see Appendix A). This is why we label this obtained variable "TOC/SOC."
4) Global mean speed: To calculate this variable, we count the number of movements of vehicles during each time step of the simulation; then, we obtain the average value. This is a new parameter. We want to test it, because it is time and space independent. We can use it for any time period and any traffic network size.

We are also testing other criteria related to the total number of vehicles that left the network, such as greenhouse gas (GHG) emissions. The following have been published in [15]:

1) Exit probability: To compare that parameter with the relative parameters *emissions* and *occupancy*, it is necessary to derive a new relative parameter. Thus, for this study, we defined the exit probability as

$$\text{exit probability} = \frac{N_v^l}{N_v^i}. \qquad (1)$$

The exit probability is the number of vehicles that left N_v^l over the number of vehicles that entered the network N_v^i once the simulation finishes.

2) Total emissions (TEs): In [17], it is shown that CO and NO_x are mostly linearly correlated with the speed of vehicles. This fact may clearly be observed in [17, Figs. 4 and 5]. With this in mind, we defined a new parameter *emission factor* as the value of the speed of every vehicle at each simulation time step. This very low computing consuming parameter will give us an approximate idea of the volume of GHGs *emitted* during the simulation.

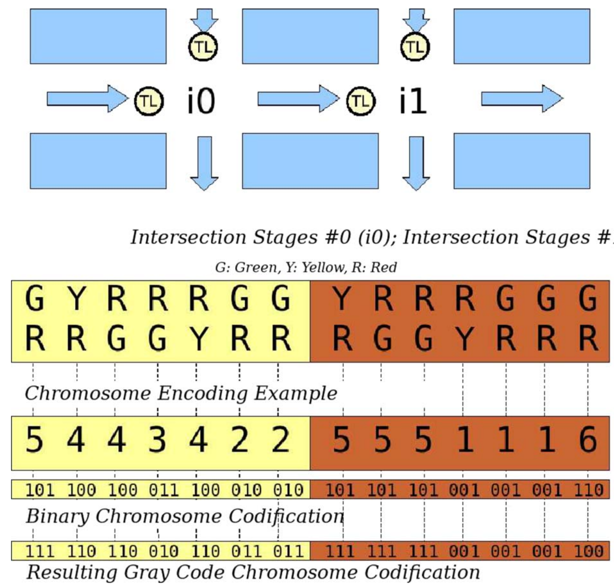


Fig. 1. Chromosome encoding.

In our tests, we registered, time step by time step, the global sum of emissions, i.e., TE, as shown in

$$\mathrm{TE} = \sum_{c=0}^{N_{\text{cells}}-1} \left(f_{\mathrm{EF}}(i,c)\right). \qquad (2)$$

In this equation, N_{cells} is the number of cells in the traffic network, and f_{EF} is the *emission factor* of the vehicle at cell c and time step i. Obviously, when the cell is not occupied, the f_{EF} value is set to 0.

We realize that only one variable, like the absolute number of vehicles leaving the network, could be a weak objective. That is why we are searching for other criteria to build up a robust multicriteria fitness function for all cases and scenarios. In addition to this, we would like to consider the common effects of traffic networks, such as queue spill back blockages.

On the other hand, we have found that the extra load on computer time for considering other parameters for the fitness function is not significant. The most important part of the computing time of our optimization is the simulation itself. This is why we are still confident about future upgrades for our objective function.

2) Chromosome Encoding: In Fig. 1, we present the encoding used in our methodology. In this figure, we represent a sample chromosome for a very simple traffic network, which consists of only two intersections and two traffic signals for each intersection.

Shown below the traffic network are the stages[3] of each traffic light, separated in two different color regions, with one for each of the two intersections. The traffic signal state at each *stage* may be green (G), yellow (O), or red (R).

This *stage* sequence is previously established and will cycle *ad infinitum* or until we stop the corresponding simulation. The objective of our system is to optimize the duration of each *stage* (in seconds) to get the very best traffic behavior from the network under study.

[3]Stage: each one of the states associated with an intersection that contains a set of traffic lights.

In Fig. 1, a chromosome encoding example is included. It can be seen that, through several translation steps, we obtain a binary Gray Code encoding [18]. We have proven that this methodology is very efficient for our case in [19]. We use Gray Code, because it makes the *search space conform* to the *chromosome space* by means of the *Hamming Distance metric*.

3) Initial Population: At the GA start, we create an initial population. Initially, we set a time range for every pre-established *stage*. Each individual is created by choosing a random value within its corresponding valid range.

For this research, we included within the initial population another individual that was not randomly created. This individual contains in its chromosome the combination of cycle times currently used by the Saragossa Traffic Department.

4) Random Number Generation: For the random number generation, we have employed M. Matsumoto and T. Nishimura's MT19937 generator, which is also known as the "Mersenne Twister" generator. It has passed the Diehard statistical tests [20]. The seeds for that algorithm were obtained from the "/dev/urandom" device provided by the Red Hat 9 operating system.

5) Selection Strategy: We have chosen a truncation and elitism combination as selection strategy. This means that, for every generation, a reduced group of individuals, which, in our case, pertains to the two best individuals, is cloned to the next generation. The remainder of the next generation is created by crossing the individuals from the best fitness subset, which is usually 66% of the whole population.

6) Crossover Operator: We have used a standard two-point crossover operator. At random points, for a pair of *parent* chromosomes, it selects two random points, cuts them at these positions into three pieces, and then interchanges the central chunk.

7) Mutation Operator: When an individual is chosen to be mutated, according to the mutation probability, the value stored at a randomly chosen position of its chromosome is changed.

The mutation probability is not fixed. It starts with a high mutation probability that will progressively decrease until it reaches probability values near the inverse of the population size at the end of the planned number of generations.

C. Traffic Simulator

Traffic simulation is known to be a very complex task. Nowadays, microscopic simulators are widely used. One of the main reasons for this is that they can model the discrete dynamics that arise from the interaction among individual vehicles [21]. CA is usually faster than any other traffic microsimulator [22], and as stated in [23], *the computational requirements are rather low with respect to both storage and computation time, making it possible to simulate large traffic networks on personal computers*.

We have developed a traffic model based on the SK[4] model [24] and the SchCh[5] model [25]. The SchCh model is a combination of a highway traffic model [26] and a very simple city traffic model [27]. The SK model adds the "smooth braking" to avoid abrupt speed changes. We decided to base our model on the SK model due to its better results for all the tests shown in [28].

[4]SK stands for S. Krauss, the author of [24].

[5]SchCH stands for A. Schadschneider and D. Chowdhury, the authors of [25].

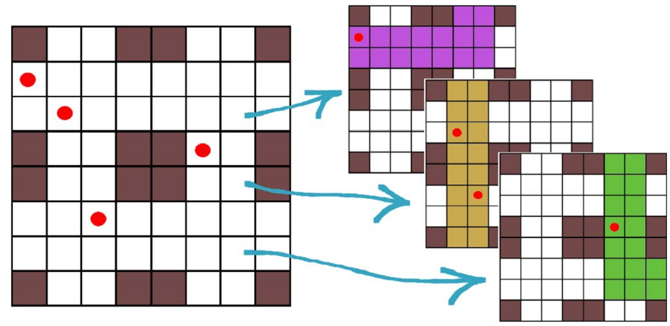


Fig. 2. Paths in our improved CA model.

Based on the CA model, we have developed a nonlinear model for simulating traffic behavior. The basic structure is that used in CA. However, in our case, we add a new level of complexity by creating two new abstractions: "Paths" and "Vehicles."

"Paths" are overlapping subsets included in the CA set. There is one "path" for every origin–destination pair. To do this, every "path" has a collection of positions, and for each one of them, there exists an array of allowed "reachable" positions. This idea is shown in Fig. 2.

"Vehicles" consist of an array of structures, each one of them having three properties.

1) Position: Situation at the CA. Note that every cell may be occupied by only one vehicle.
2) Speed: the current speed of a vehicle. This is the number of cells it moves over at every time step.
3) Path: In our model, every vehicle is related to a "path."

The rules applied to every vehicle are given here.

1) A vehicle ought to accelerate up to the maximum speed allowed if it has no obstacle in its way (another vehicle or a red traffic signal). It will accelerate at a rate of 1 point/time step for every time step.
2) If a vehicle can reach an occupied position, it will have to reduce its speed and will occupy the free position just behind the preceding vehicle.
3) If a vehicle has a red traffic signal ahead, it will stop.
4) Smooth braking: Once the vehicle position is updated, then the vehicle speed is updated as well. To do this, the number of free positions from the current position ahead is taken into account. If there is not enough free space for the vehicle to move forward on the next time step going at its current speed (hypothetically, since, in the next time step, the traffic situation may change), it will reduce its speed by one unit.
5) Multiple lanes: When a vehicle is trying to move on or update its speed, it is allowed to consider positions on other parallel lanes. For every origin–destination couple (path), at every point, there exists a list of possible "next" positions. The first considered is that straight ahead; if this one is not available, there may be more possible positions in parallel lanes that will need to be considered. Of course, this list of possible "next" positions is created by taking the basic Spanish Highway code into account.

By means of these rules, we can have many different paths and vehicles running in the same network. This model may

Fig. 3. Bird's eye view of "La Almozara."

be seen as a set of $N_{\rm paths}$ traditional CA networks working in parallel over the same physical grid.

D. Justification of the Use of a CA-Based Microsimulator Fitness Function

CA microsimulation has given us a basis for implementing a flexible microsimulator where we can simulate things such as overtaking and multiple-lane streets. We can also sample individual statistics, for instance, to estimate the individual vehicle GHG emissions. From our point of view, these benefits widely compensate for not explicitly addressing other relevant effects, such as queue spill back blockage and stop-and-go waves. However, we do not discount considering such problems in multiobjective fitness functions in future works.

For the current methodology, we do not consider the inclusion of path changes. Although dynamic traffic assignment (DTA) is a key topic in the state of the art, in the current system, we take a static approach, considering traffic statistics as input from the real-world situation and fixed paths for vehicles. However, we are currently working on the adaptation of our methodology to a scenario of sensor data inputs and dynamic traffic optimization, where DTA can profitably be implemented, maybe through some advanced traffic information system (ATIS).

E. Beowulf Cluster

The architecture of our system is based on a Beowulf Cluster, due to its price/performance relationship and the possibility of employing open-source software on it. This is also a very scalable MIMD computer, which is a very desirable feature in solving all sorts and scales of traffic problems.

For this research project, we set up an eight-node cluster, with each node consisting of an AMD Opteron64. The nodes were connected through a gigabit Ethernet backbone. Every node had the same hardware, except the master node, which had an extra gigabit Ethernet network card for "out world" connection.

Every node had installed CentOS—Kernel 2.6.9-78.0.13.ELsmp. For parallel programming, the installation of Open MPI (openmpi-1.2.9-1) was also necessary.

In our application, there were two kinds of processes, i.e., *master* and *slave* processes. There was only one master process running at each test. At every generation, it sends the chromosomes (MPI_Send) to slave processes, receives the evaluation results (MPI_Recv), and creates the next population. Slave processes are inside an endless loop, waiting to receive a new chromosome (MPI_Recv). Then, they evaluate it and send the evaluation result (MPI_Send) to the master process.

III. Results

A. Tests Performed

In Fig. 3, Saragossa district number 7—"La Almozara"—is shown. The statistics for the zone are the following:

1) number of cells after zone discretization: 2753;
2) number of "input cells": 16;
3) number of "output cells": 18;
4) number of possible paths: 288 (16×18);
5) number of traffic signals optimized: 17;
6) number of intersections: 7.

The parameters of the GA and the traffic microsimulator employed are listed here.

1) for each test case, the GA was run ten times, and the average values were calculated;
2) population size: 200 individuals;
3) number of generations: 400;
4) selection strategy: truncation + elitism;
5) fraction of the population selected: two thirds;
6) fraction of the population cloned: two individuals;
7) mutation probability: We have employed a variable mutation probability. It started with a very high probability (0.9990), which is decreased generation by generation by a factor of 0.9875;
8) simulation time steps: 4000;
9) time step versus time relationship: $1(\mathrm{s}) \equiv 1(\mathrm{ts})$.

It is important to highlight the large scale of the zone under study, as shown in Fig. 3. In Appendix B, we enumerate the

TABLE I
CURRENT SITUATION TRAFFIC INPUT

Input	Vehicles per Hour
0	8.93
1	8.93
2	8.93
3	8.93
4	124.14
5	50
6	17.91
7	21.05
8	21.05
9	21.05
10	13.53
11	13.53
12	13.53
13	41.38
14	41.38
15	41.38

TABLE II
TRAFFIC INPUT TESTED

Situation	Vehicles per Hour
#0	3600
#1	1800
#2	1200
#3	900
#4	600
#5	360
#6	180
#7	120
#8	90
#9	36

streets and/or street sections included or withdrawn, for the sake of simplicity, from our model.

We have performed a wide set of tests with this zone with two objectives. The first aim was to optimize the traffic light cycles for the current traffic situation. Then, we were also interested in checking how our system worked in a congested or overloaded scenario. To do so, we have created ten hypothetical test cases by varying the network traffic inflow.

In Table I, we represent the current—real—traffic input. For every traffic entrance, the *vehicle-per-hour* ratio is shown. These times are derived from traffic statistics supplied by the Saragossa City Traffic Department.

Table II shows the traffic volume entering the network for the ten hypothetical test cases. Note that the same traffic volume is injected to every traffic entrance in the network. It may be observed that, for situation 0, there is a new vehicle in each input cell at every simulation time step, which is the worst possible test case for our model.

During the optimization process and for every individual, we have obtained the fitness value and also calculated the mean TOC/SOC, as described in Section II-B1.

B. Results

Figs. 4–7 represent the maximum and average fitness obtained once the GA ends its work for each one of the four different fitness functions used and the 11 traffic situations listed in Table II.

The obtained simulated value for every fitness function using the current traffic signal programming and the supplied incoming traffic volume (see Table I) is also displayed with a blue line. Note that, for Fig. 5, the inverse of the variable used (MTT) is represented since, in that case, the GA performed a minimization, instead of a maximization, of that value.

In Fig. 8, we have plotted the maximum and average improvement of fitness through the GA evolution—in percentage and using a logarithmic scale for each one of the four used criteria. It may be observed that, except for the TOC/SOC case, it seems to reach higher improvements for the most congested test cases (shown on the left).

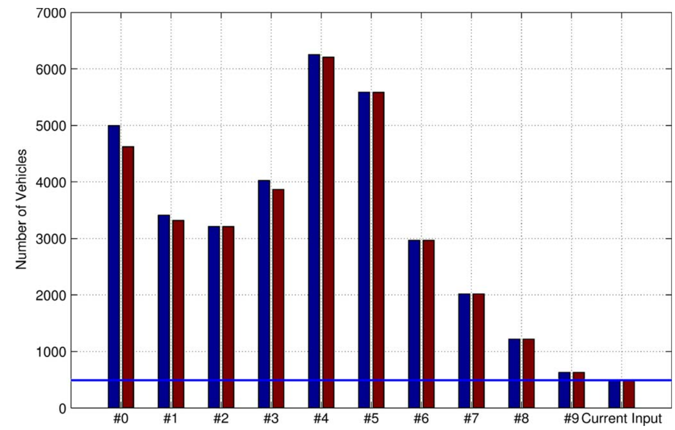


Fig. 4. Maximum and average fitness obtained for the 11 situations using the variable NoV as fitness function.

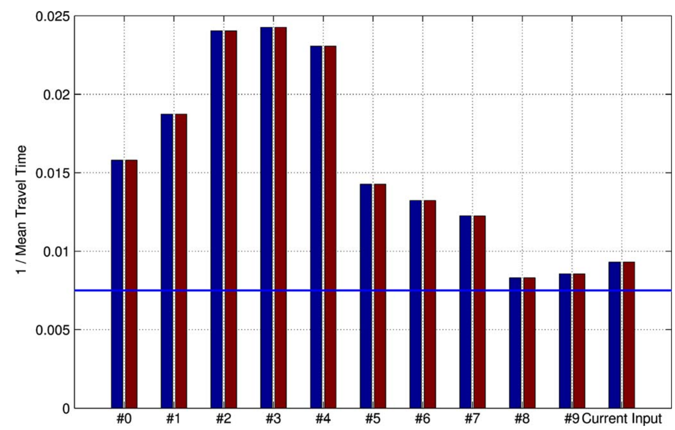


Fig. 5. Maximum and average fitness improvement for the 11 situations using the inverse of the variable MTT as fitness function.

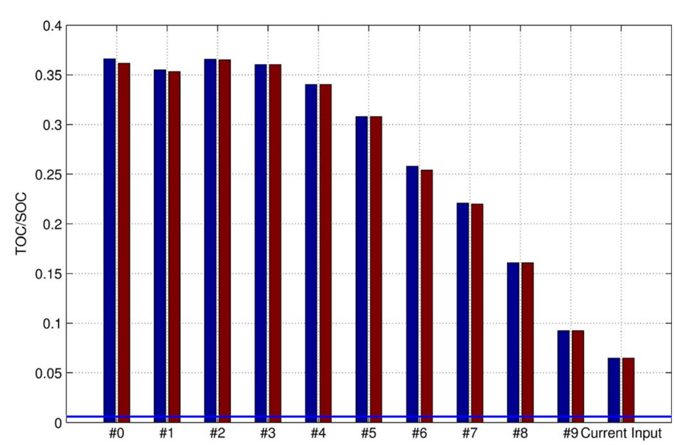


Fig. 6. Maximum and average fitness obtained for the 11 situations using the variable TOC/SOC as fitness function.

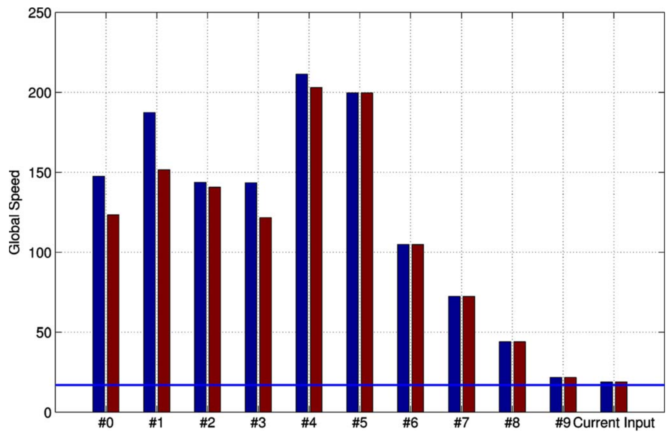


Fig. 7. Maximum and average fitness obtained for the 11 situations using the variable *global speed* as fitness function.

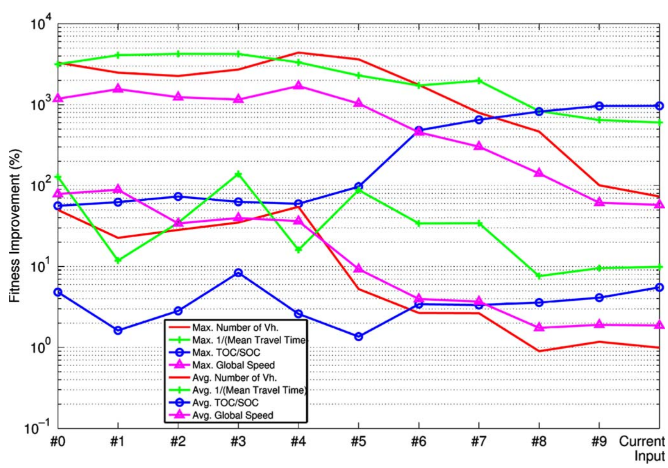


Fig. 8. Maximum and average improvement of fitness obtained for the 11 situations.

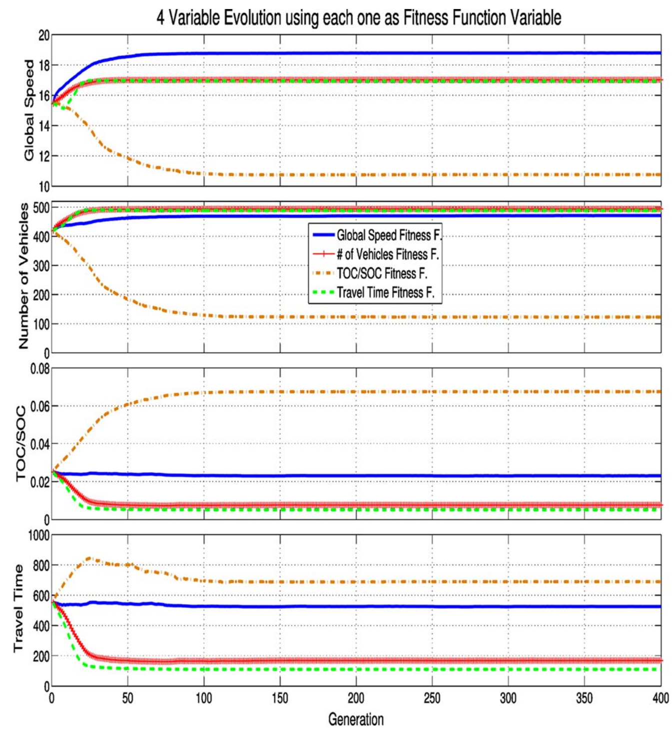


Fig. 9. Variable evolution comparison.

Finally, by means of Fig. 9, our aim is to represent the evolution of the four studied variables, choosing each time one of them as fitness function criterion. Our purpose is to display any possible similarity or correlation among the evolution of each variable as the GA evolves.

In the first row, we represent the evolution of global speed using the four variables for the fitness function of the GA. With four curves, the evolution of global speed as the GA maximized the global speed itself, the NoV, the TOC/SOC, and minimized the travel time, respectively, is represented.

In the second, third, and fourth rows, we represent equivalent curves for the evolution of the other three variable under observation.

IV. Discussion

Figs. 4–8 are enlightening. They show that the system behaves very well for all cases, including the most demanding cases (left).

However, for the current—supplied—traffic situation, limited results were obtained. Everything seems to indicate that, when the traffic input is that low, regardless of the combination of traffic light times, the network has similar outputs. In other words, a nearly empty traffic network is not likely to be optimized.

From Fig. 9, a strong linear relationship between TOC/SOC and MTT seems to exist. Regardless of the criterion used to guide the GA, the two variables evolved with very similar curves.

A kind of relationship between the global speed and TOC/SOC and between TOC/SOC and NoV also seems to exist. The less-related couple may be global speed with MTT and with NoV.

Further research would be needed to determine with precision the relationships among the four used variables. As we explained in Section II-B, we plan to design a multicriteria fitness function, maybe using some of the variables studied in this research. However, we will need to carefully study the variables to be included in, granting, as far as possible, functional independence between them.

A final comment about the performance of the system needs to be added. The whole set of tests performed took about 1 100 000 s (12.7 days). This may be seen as a handicap for future dynamic implementation of our model. However, we have to highlight that those results were obtained with an eight-node AMD Opteron cluster. A valuable virtue of our methodology is its scalability, due to the combination of the Beowulf Cluster and the GA. Therefore, to reduce those times by several orders of magnitude, it would only be necessary to extend the Beowulf Cluster with more nodes.

V. Conclusion and Future Research

Throughout this paper, we have described our positive experience with the optimization of traffic light cycles in a real city area. A distinctive feature of this paper is the large scale of the underlying grid. Using the supplied maps and statistics, we have simulated the present-day traffic behavior. Additionally, we have optimized the traffic signal times, yielding better results with regard to several predefined parameters.

Moreover, we have successfully performed a simulated overload or congestion study. We have designed and tested a set of congestion scenarios, observing a good performance of our system for all test cases. Another remarkable achievement of this research deals with the overload study. Many wide or in-depth studies dealing with this topic does not seem to exist in the literature. For this research, we have defined ten hypothetical congestion situations. The results seem promising since we observed a very good performance of our system, even for the toughest cases. We believe this is a key feature of our methodology since congested networks are the ones more urgently requiring optimization.

We intend to develop this research project, first by extending the architecture to a dynamic optimization context. The current version was designed in a static manner, considering traffic statistics and without the possibility of including path changes. Although DTA is a key topic in the state of the art, in the current system, we take a static approach, considering traffic statistics as input and fixed paths for vehicles.

However, we are currently working on an adaptive version of our methodology for a scenario of sensor data inputs and dynamic traffic optimization. In the new version of our methodology, DTA can profitably be implemented, maybe through an ATIS.

To achieve that objective, first we will have to solve a problem. In this research, run times were too long to be adapted to a dynamic scenario. However, the used methodology is highly scalable due to the intrinsic parallelism of GAs and the easy expandability of Beowulf Clusters. Therefore, run times can drastically be reduced, for instance, just by adding nodes to the cluster.

We have also planned to modify our single-criterion fitness function to a multicriteria fitness function. In this research, we have used four different variables for the fitness function. In future research, we plan to combine two or more variables into a multicriteria fitness function for the sake of robustness.

CA microsimulation has given us a basis for implementing a flexible microsimulator where we can simulate things such as overtaking or multiple-lane streets that help us to sample individual statistics, for instance, for estimating the individual vehicle GHG emissions. From our point of view, these benefits widely compensate for not considering other relevant effects such as queue spill back blockage and stop-and-go waves. However, we plan to consider such problems in potential multiobjective fitness functions in future works.

Finally, we want to remark a virtue of our methodology. In our system, the run time will not be affected by the use of multicriteria fitness functions since the most demanding part of the software is the simulation task, which is separately performed in parallel *slave processes*.

APPENDIX A
TOC/SOC AVERAGE DEMONSTRATION

SOC and TOC were defined in [29] and [30], respectively. In (3) and (4), we represent both parameters. About (3), N_c^o is the number of cells occupied by a vehicle, and N_c^T is the total number of cells in the treated network. In (4), N_{ts}^o is the number of simulation time steps that a particular cell is occupied by any vehicle, and N_{ts}^T is the total number of time steps that the simulation lasts.

TABLE III
ORIGIN–DESTINATION PROBABILITY MATRIX EMPLOYED

Outputs	**00**	**05**	**07**	**08**	**12**	**34**	**42**	**43**
	3.83	3.83	33.10	10.68	19.51	10.68	10.68	7.68

As can be inferred from the following:

$$\mathrm{SOC} = \frac{N_c^o}{N_c^T} \tag{3}$$

$$\mathrm{TOC} = \frac{N_{\mathrm{ts}}^o}{N_{\mathrm{ts}}^T} \tag{4}$$

$$\overline{\mathrm{SOC}} = \frac{\sum_{i=0}^{N_{\mathrm{ts}}^T} \frac{N_c^o(i)}{N_c^T}}{N_{\mathrm{ts}}^T} = \frac{\sum_{i=0}^{N_{\mathrm{ts}}^T} N_c^o(i)}{N_c^T * N_{\mathrm{ts}}^T} \tag{5}$$

$$\overline{\mathrm{TOC}} = \frac{\sum_{c=0}^{N_c^T} \frac{N_{\mathrm{ts}}^o(c)}{N_{\mathrm{ts}}^T}}{N_c^T} = \frac{\sum_{c=0}^{N_c^T} N_{\mathrm{ts}}^o(c)}{N_c^T * N_{\mathrm{ts}}^T} \tag{6}$$

the average SOC across the simulation time steps and the average TOC across the cells in the network have the same value. In other words, the mean value of the average occupied cell ratio across all the simulation time steps is equivalent to the mean value of the average number of occupied time steps for a particular cell across all the cells in the traffic network.

APPENDIX B
STREETS TAKEN INTO ACCOUNT AND STREETS WITHDRAWN FROM OUR MODEL

These are the streets under consideration for this work.

Avda. de Francia	C. de Juan Bautista del Mazo	C. de Iriarte de Reinoso
Avda. de la Almozara	C.del Río Alcanadre	Puente de la Almozara
Avda. de Pablo Gargallo	C.de los Diputados	C.de Braulio Foz
Avda. de la Autonomía	Paseo de María Agustín	C. de Santa Lucía
Avda. Puerta de Sancho	Paseo de Echegaray y Caballero	C.del Lago

The streets removed from our model are the following:

C. de Mónaco	C.de Berna	C.del Monasterio de Sta. Lucía
C.Jardines de Lisboa	C.de Viena	C.del Reino
C.de Bruselas	C.de París	C.del Río Duero
C.de Berlín	C.de Bohn	C.del Río Ebro
C.de Amsterdam	C.Jardines de Atenas	C.de la Reina Felicia
C.de Oslo	C.de la Batalla de Almansa	C.de Hijar
C.de la Batalla de Arapiles	C.de la Batalla de Bailén	C.de Fraga
C.Ainzón	C.del Padre Consolación	C.del Río Cinca
C.del Padre Landa	C.de las Cortes	C.de Ribagorza
C.del Río Guadalope	C.del Río Aragón	C.de Santiago Dulong
C.de la Sierra de Vicor	C.del Río Esera	C.del Río Guadiana
C.del Río Guatizalema	C.de Monegros	C.de Dionisio Casañal

TABLE IV
STAGES SEQUENCES USED

Int #0																						
TS #0	0	0	3	1	0	0	0	0	0	0												
TS #1	3	3	3	1	0	0	0	0	0	3												
TS #2	0	0	0	0	0	3	3	1	0	0												
TS #3	0	0	3	1	0	0	0	0	0	0												
TS #4	1	0	0	0	0	0	0	0	0	3												
MSS	100	100	100	100	100	100	100	100	100	100												
mSS	0	0	0	0	0	0	0	0	0	0												
Int #1																						
TS #5:	3	3	1	0	0	0	0	3														
TS #6	3	3	3	1	0	0	0	3														
TS #7	1	0	0	0	3	3	3	3														
TS #8	0	3	3	0	0	0	0	0														
MSS	100	100	100	100	100	100	100	100														
mSS	0	0	0	0	0	0	0	0														
Int #2																						
TS #9	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	0	0
TS #12	3	3	3	3	3	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3
MSS	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
mSS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Int #3																						
TS #10	3	3	3	3	3	3	3	1	0	0	0	0	0	0	0	0	0	0	0	0	3	3
TS #11:	0	0	0	0	0	0	0	0	0	3	3	3	3	3	3	3	3	3	1	0	0	0
MSS	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
mSS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Int #4																						
TS #13	3	3	3	3	3	3	3	3	1	0	0	0	0	0	0	0	0	0	0	0	3	3
TS #14	0	0	0	0	0	0	0	0	0	0	3	3	3	3	3	3	3	3	1	0	0	0
MSS	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
mSS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Int #5																						
TS #15	0	0	0	0	0	0	0	0	3	3	3	3	3	3	3	3	3	3	3	1	0	0
MSS	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
mSS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Int #6																						
TS #16	3	3	3	3	3	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
MSS	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
mSS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Int = Intersection; TS = Traffic Signal; MSS = Maximum Stage Span; mSS = Minimum Stage Span

APPENDIX C
ORIGIN–DESTINATION MATRIX

In this Appendix, we show the origin–destination probability (see Table III). To do so, we assumed some approximations.

1) Traffic leaving district 7 en route to district 1 divides up into two equal parts, going along Paseo de Echegaray y Caballero and Calle de Santa Lucía.
2) Traffic leaving district 7 en route to district 3 divides up into three equal parts, going along Calle de Iriarte de Reinoso, Calle de los Diputados, and Avenida de Francia.
3) All vehicles leaving district 7 by Avenida de Francia go to district 3.
4) Each traffic input has the same destination probabilities.

To generate this matrix, we used average daily traffic[6] statistics between districts for a weekday.

APPENDIX D
STAGES SEQUENCES

In Table IV, we have represented the preestablished stage sequence used for tests in this work. In this table, "0" denotes a red light, "1" denotes a yellow light, "2" denotes a yellow intermittent light, and "3" denotes a green light.

[6]Average daily traffic: total traffic volume during a certain period of time in full days (longer than one day and shorter than one year) divided by the number of days in that period.

ACKNOWLEDGMENT

The authors would like to acknowledge the Saragossa Town Hall Traffic Department for their kind help and assistance, M. L. Sein-Echaluce Lacleta from the University of Saragossa for her help in obtaining the data from the Saragossa City Traffic Department, and Dr. S. Cranfield, who is an English Native Professor with the Translators Faculty of the University of Las Palmas de Gran Canaria, for her kind assistance in revising and editing this paper.

REFERENCES

[1] E. Brockfeld, R. Barlovic, A. Schadschneider, and M. Schreckenberg, "Optimizing traffic lights in a cellular automaton model for city traffic," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat.*, vol. 64, no. 5, p. 056132, Oct. 2001.

[2] E. Taniguchi and H. Shimamoto, "Intelligent transportation system based dynamic vehicle routing and scheduling with variable travel times," *Transp. Res. Part C: Emerg. Technol.*, vol. 12, no. 3/4, pp. 235–250, Jun.–Aug. 2004.

[3] N. Rouphail, B. Park, and J. Sacks, "Direct signal timing optimization: Strategy development and results," in *Proc. XI Panamerican Conf. Traffic Transp. Eng.*, Nov. 19–23, 2000, pp. 195–206.

[4] K. Nagel and C. Barrett, "Using microsimulation feedback for trip adaptation for realistic traffic in Dallas," *Int. J. Mod. Phys. C*, vol. 8, no. 3, pp. 505–525, 1997.

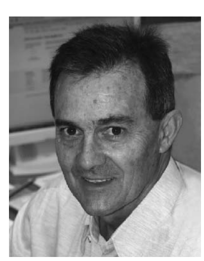
[5] A. Halati, H. Lieu, and S. Walker, "CORSIM—Corridor traffic simulation model," in *Proc. Traffic Congestion Traffic Saf. 21st Century: Chall., Innov., Oppor.*, Jun. 1997, pp. 570–576.
[6] Y. S. Hong, J. Kim, J. Kwangson, and C. Park, "Estimation of optimal green time simulation using fuzzy neural network," in *Proc. Fuzzy Syst. Conf., FUZZ-IEEE*, 1999, pp. 761–766.
[7] H. Varia and S. Dhingra, "Dynamic optimal traffic assignment and signal time optimization using genetic algorithms," *Comput.-Aided Civil Infrastruct. Eng.*, vol. 19, no. 4, pp. 260–273, Jul. 2004.
[8] D. Srinivasan, M. C. Choy, and R. Cheu, "Neural networks for real-time traffic signal control," *IEEE Trans. Intell. Transp. Syst.*, vol. 7, no. 3, pp. 261–272, Sep. 2006.
[9] M. Akanegawa, Y. Tanaka, and M. Nakagawa, "Basic study on traffic information system using led traffic lights," *IEEE Trans. Intell. Transp. Syst.*, vol. 2, no. 4, pp. 197–203, Dec. 2001.
[10] F. Fang and L. Elefteriadou, "Capability-enhanced microscopic simulation with real-time traffic signal control," *IEEE Trans. Intell. Transp. Syst.*, vol. 9, no. 4, pp. 625–632, Dec. 2008.
[11] M.-C. Tan, S. Wong, J.-M. Xu, Z.-R. Guan, and P. Zhang, "An aggregation approach to short-term traffic flow prediction," *IEEE Trans. Intell. Transp. Syst.*, vol. 10, no. 1, pp. 60–69, Mar. 2009.
[12] B. Ghosh, B. Basu, and M. O'Mahony, "Multivariate short-term traffic flow forecasting using time-series analysis," *IEEE Trans. Intell. Transp. Syst.*, vol. 10, no. 2, pp. 246–254, Jun. 2009.
[13] J. J. Sanchez-Medina, M. J. Galan-Moreno, and E. Rubio-Royo, "Genetic algorithms and cellular automata: A new architecture for traffic light cycles optimization," in *Proc. CEC*, 2004, vol. 2, pp. 1668–1674.
[14] J. J. Sanchez, M. J. Galan, and E. Rubio, "Stochastic vs deterministic traffic simulator. Comparative study for its use within a traffic light cycles optimization architecture," in *Proc. IWINAC*, 2005, pp. 622–631.
[15] J. J. Sanchez-Medina, M. J. Galan-Moreno, and E. Rubio-Royo, "Study of correlation among several traffic parameters using evolutionary algorithms: Traffic flow, greenhouse emissions and network occupancy," in *Proc. EUROCAST Conf.*, 2007, pp. 1134–1141.
[16] J. J. Sanchez-Medina, M. J. Galan-Moreno, and E. Rubio-Royo, "Applying a traffic lights evolutionary optimization technique to a real case: 'Las Ramblas' area in Santa Cruz de Tenerife," *IEEE Trans. Evol. Comput.*, vol. 12, no. 1, pp. 25–40, Feb. 2008.
[17] A. J. Kean, R. A. Harley, and G. R. Kendall, "Effects of vehicle speed and engine load on motor vehicle emissions," *Environ. Sci. Technol.*, vol. 37, pp. 3739–3746, Sep. 2003.
[18] P. E. Black, "Gray code," *From Dictionary of Algorithms and Data Structures*, P. E. Black, Ed., Gaithersburg, MD: Nat. Inst. Stand. Technol., 2005. [Online]. Available: http://www.nist.gov/dads/HTML/graycode.html
[19] J. J. Sanchez-Medina, M. J. Galan-Moreno, and E. Rubio-Royo, "Bit level versus gene level crossover in a traffic modeling environment," in *Proc. Int. Conf. CIMCA*, 2005, pp. 1190–1195.
[20] M. Matsumoto and T. Nishimura, "Mersenne Twister: A 623-dimensionally equidistributed uniform pseudorandom number generator," *ACM Trans. Model. Comput. Simul.*, vol. 8, no. 1, pp. 3–30, 1998.
[21] S. Benjaafar, K. Dooley, and W. Setyawan, "Cellular automata for traffic flow modeling," Intell. Transp. Syst. Inst., Minneapolis, MN, Tech. Rep. CTS 97-09, 1997.
[22] K. Nagel and A. Schleicher, "Microscopic traffic modeling on parallel high performance computers," *Parallel Comput.*, vol. 20, no. 1, pp. 125–146, Jan. 1994.
[23] M. Cremer and J. Ludwig, "A fast simulation model for traffic flow on the basis of Boolean operations," *Math. Comput. Simul.*, vol. 28, no. 4, pp. 297–303, Aug. 1986.
[24] S. Krauss, P. Wagner, and C. Gawron, "Metastable states in a microscopic model of traffic flow," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat.*, vol. 55, no. 5, pp. 5597–5602, May 1997.
[25] A. Schadschneider, D. Chowdhury, E. Brockfeld, K. Klauck, L. Santen, and J. Zittartz, "A new cellular automata model for city traffic," in *Traffic and Granular Flow: Social, Traffic, and Granular Dynamics*. New York: Springer-Verlag, 1999.
[26] K. Nagel and M. Schreckenberg, "A cellular automaton model for freeway traffic," *J. Phys. I France*, vol. 2, no. 12, pp. 2221–2229, Dec. 1992.
[27] O. Biham, A. A. Middleton, and D. Levine, "Self-organization and a dynamical transition in traffic-flow models," *Phys. Rev. A, Gen. Phys.*, vol. 46, no. 10, pp. R6 124–R6 127, Nov. 1992.
[28] E. Brockfeld, R. Kühne, A. Skabardonis, and P. Wagner, "Towards benchmarking microscopic traffic flow models," *Trans. Res. Rec.*, vol. 1852, pp. 124–129, 2003.
[29] G. H. Bham and R. F. Benekohal, "A high fidelity traffic simulation model based on cellular automata and car-following concepts," *Transp. Res. Part C: Emerg. Technol.*, vol. 12, no. 1, pp. 1–32, Feb. 2004.
[30] A. May, *Traffic Flow Fundamentals*. Englewood Cliffs, NJ: Prentice-Hall, 1990.

Javier J. Sánchez-Medina received the B.Sc. and M.Sc. degrees in telecommunications engineering, in 1998 and 2001, respectively, and the Ph.D. degree in computer science from the Universidad de Las Palmas de Gran Canaria (ULPGC), Las Palmas, Spain, in 2008.

He is currently an Assistant Professor with the ULPGC, where he has been doing research with the Centro de Innovación para la Sociedad de la Información, since 2002. He is also a reviewer of several international conferences and journals.

Manuel J. Galán-Moreno received the M.Sc. degree in mathematics from the University of Salamanca, Salamanca, Spain, in 1985 and the Ph.D. degree from the University of Las Palmas de Gran Canaria, Las Palmas, Spain.

Since 1994, he has been a Professor of mathematics with the School of Architecture, University of Las Palmas de Gran Canaria. He has extensive experience in systems resolution and genetic algorithms. He has authored or coauthored a genetic algorithms book.



Enrique Rubio-Royo received the M.Sc. degree in physics from the University Complutense de Madrid, Madrid, Spain, in 1971 and the Ph.D. degree from the University of La Laguna, La Laguna, Spain, in 1980.

Since 1990, he has been a Professor and is the Director of the Centro de Innovación para la Sociedad de la Información, which is a research center belonging to the Universidad de Las Palmas de Gran Canaria, Las Palmas, Spain. He has extensive experience in information society and technology.