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Evolutionary Computation Applied to Urban Traffic Optimization

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1. Introduction

At the present time, many sings seem to indicate that we live a global energy and environmental crisis. The scientific community argues that the global warming process is, at least in some degree, a consequence of modern societies unsustainable development. A key area in that situation is the citizens mobility. World economies seem to require fast and efficient transportation infrastructures for a significant fraction of the population.
The non-stopping overload process that traffic networks are suffering calls for new solutions. In the vast majority of cases it is not viable to extend that infrastructures due to costs, lack of available space, and environmental impacts. Thus, traffic departments all around the world are very interested in optimizing the existing infrastructures to obtain the very best service they can provide.
In the last decade many initiatives have been developed to give the traffic network new management facilities for its better exploitation. They are grouped in the so called Intelligent Transportation Systems.
Examples of these approaches are the Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS). Most of them provide drivers or traffic engineers the current traffic real/simulated situation or traffic forecasts. They may even suggest actions to improve the traffic flow.
To do so, researchers have done a lot of work improving traffic simulations, specially through the development of accurate microscopic simulators. In the last decades the application of that family of simulators was restricted to small test cases due to its high computing requirements. Currently, the availability of cheap faster computers has changed this situation.
Some famous microsimulators are MITSIM(Yang, Q., 1997), INTEGRATION (Rakha, H., et al., 1998), AIMSUN2 (Barcelo, J., et al., 1996), TRANSIMS (Nagel, K. & Barrett, C., 1997), etc. They will be briefly explained in the following section.
Although traffic research is mainly targeted at obtaining accurate simulations there are few groups focused at the optimization or improvement of traffic in an automatic manner — not dependent on traffic engineers experience and "art".

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One of the most important problems in traffic optimization is traffic light cycles[1] optimization. This is a hard Combinatorial Problem which seems not to have a known deterministic solution at the present time.

In our group we have been working on the optimization of traffic lights cycles for the better performance of urban traffic networks. As shown in (Brockfeld, Elmar, et al., 2001), traffic light cycles have a strong influence in traffic flow results. For that reason we decided to focused on that problem. We have combined a Genetic Algorithm (GA) as optimization technique with a traffic microscopic simulator running on a scalable MIMD multicomputer[2].

We have tested the fore mentioned three pillar model with some works (Sánchez, J. J. et al., 2004), (Sánchez, J. J. et al., 2005 A), (Sánchez, J. J. et al., 2005 B), (Sánchez, J. J. et al., 2006), (Sánchez, J. J. et al., 2007) and (Sánchez, J. J. et al., 2008).

The rest of this chapter is organized as follows. In section 2 we give a wide survey of the current State of the Art. In 2.4 we briefly expose our own contribution to the matter. In section 3 we explain with some detail the proposed methodology. In section 4 we outline the achieved goals obtained with the explained methodology. Finally, section 5 gives some ideas of research foreseeable trends.

2. State of the art

In this subsection we want to give a survey o some significant works in the area. We have categorized works in three classes: those mostly related to Advanced Traveler Information Services (ATIS); those mainly about Advanced Traffic Management Systems (ATMS), and in a third subset we have called Advanced Traffic Optimization Systems (ATOS), those where traffic is not just managed but optimized — or tried to be optimized — in an automatic manner, without human interaction.

2.1 Advanced traveler information services

Advanced Traveler Information Services are those services that can potentially help drivers to make better decisions in order to reduce their travel time. There are many initiatives in this area. Here we show some examples.

In (Florian, D. G, 2004), this thesis provides an empirical study of the impact of ATIS on transportation network quality of service using an application of DynaMIT (Dynamic network assignment for the Management of Information to Travelers). The main results are that the provision of dynamic route guidance can simultaneously benefit the individual performance of drivers, both guided and unguided, as well as the system performance of existing transportation infrastructure.

In (Hafstein, S. F., et al., 2004) a high resolution cellular automata freeway traffic simulation model applied to a Traffic Information System. They provide a simulation for current traffic zones without loop detectors, and 30 min. and 60 min. future traffic forecasts. They run a java applet in a web page in order to give the network users this useful information.

[1] Traffic light cycle: the finite sequence of states — e.g. green, orange, etc. — that a traffic light runs iteratively.

[2] MIMD: Multiple Instruction Multiple Data: A type of parallel computing architecture where many functional units perform different operations on different data. For example a network of PC's working in parallel.

2.2 Advanced traffic management systems.

Advanced Traffic Management Systems are those systems that help engineers to better manage traffic networks. There are many works around this topic, most of them focused on traffic simulation. Some examples are the following.

The INTEGRATION model has been used to simulate traffic for the Salt Lake Metropolitan Area (Rakha, H., et al., 1998).The objective of this paper is threefold. First, the feasibility of modeling a large-scale network at a microscopic level of detail is presented. Second, the unique data collection challenges that are involved in constructing and calibrating a large-scale network microscopically are described. Third, the unique opportunities and applications from the use of a microscopic as opposed to a macroscopic simulation tool are described.

The MITSIM model (Yang, Q., 1997) has been used to evaluate aspects of both the traffic control system and the ramp configurations of the Central Artery/Tunnel project in Boston. It explicitly incorporates traffic prediction, time variant traffic information, and dynamic route choice.

AIMSUN2 has been used to simulate the Rings Roads of Barcelona (Barcelo, J., et al., 1996). Uses parallel computers to shorten the execution time.

Traffic simulation using CA models has also been performed on vector supercomputers to simulate traffic in shortest possible time (Nagel, K. & Schleicher, A., 1994).

The INTELSIM model is used in (Aycin, M. F. & Benekohal, R. F., 1998) and (Aycin, M. F. & Benekohal, R. F., 1999). In those works a linear acceleration car-following model has been developed for realistic simulation of traffic flow in intelligent transportation systems (ITS) applications. The authors argue that the new model provides continuous acceleration profiles instead of the stepwise profiles that are currently used. The brake reaction times and chain reaction times of drivers are simulated. As a consequence, they say that the good performance of the system in car-following and in stop-and-go conditions make this model suitable to be used in ITS.

Moreover, in (Aycin, M. F. & Benekohal, R. F., 1999) they compare many car-following methods with their proposed method, and with field data.

In (Bham et al., 2004) they proposed a ``high fidelity'' model for simulation of high volume of traffic at the regional level. Their model uses concepts of Cellular Automata and Car-Following models. They propose the concept of Space Occupancy (SOC) used to measure the traffic congestion. Their aim is to simulate high volume of traffic with shorter execution time using efficient algorithms on a personal computer. Like in our case, they based their simulator on Cellular Automata concepts. Although their model could be more accurate than the one of ourselves, in our work we go further using our simulator inside a GA for optimizing the traffic — not just for simulating traffic.

In (Tveit, O., 2003), Dr. Tveit, a senior researcher with *SINTEF*[3], explains that a common cycle time[4] for a set of intersections is a worse approach than a distributed and

[3] SINTEF means The Foundation for Scientific and Industrial Research at the Norwegian Institute of Technology.

[4] Common cycle time: This is a very simple way of programming traffic lights in an intersection or groups of intersections. All the traffic lights share a cycle length. The starting point of each one of the states or *stages* in the particular cycle of every traffic light may be different, but the cycle period is the same for all of them.

individualized one. His conclusions appear sound and convincing, so we consider them in our approach. In our system every intersection has independent cycles.
In (Smith, M. J., 1988) the use of responsive signals[5], with network capacity (rather than total travel cost) as a control criterion is argued. The capacity of the network is maximized if the signals operate to equalize traffic density on the most occupied parts of the network. This is another example of multiple local optimizations instead of a global optimization, like the one of ours.
In (Logi, F. & Ritchie, S.G., 2001) a knowledge based system is presented for traffic congestion management. The proposed model comprises a data fusion algorithm, an algorithm for selection the suitable control plan, and it presents the proposed plan with an explanation of the reasoning process for helping the traffic operators decisions. They presented also a validation example for displaying the ability of their system to reduce congestion. From our point of view, although this seems a very interesting approach to the matter, both the selection of control strategies and the estimation of future traffic are based on the experience of traffic engineers. In spite of this, in our methodology we use the combination of two widely accepted and trusted techniques. We use a more accurate estimation of future traffic — thought a microsimulator — and a genetic algorithm for the optimization of the traffic flow.

2.3 Advanced traffic optimization systems

TRANSIMS project used CA models to simulate traffic for the city of Fortworth-Dallas using parallel computers (Nagel, K. & Barrett, C., 1997). This paper presents a day-to-day re-routing relaxation approach for traffic simulations. Starting from an initial plan-set for the routes, the route-based microsimulation is executed. The result of the microsimulation is fed into a rerouter, which re-routes a certain percentage of all trips.
In (Wann-Ming Wey, et al., 2001), an isolated intersection is controlled applying techniques based on linear systems control theory to solve the linear traffic model problem. The main contribution of this research is the development of a methodology for alleviating the recurrent isolated intersection congestion caused by high transportation demand using existing technology. Again this work deals with very small scale traffic networks — one intersection.
In (Schutter, B. De & Moor, B. De, 1997) the authors present a single intersection — two two ways streets — model describing the evolution of the queue lengths in each lane as a function of time, and how (sub)optimal traffic switching schemes for this system can be determined.
In (Febbraro, A. Di, et al., 2002) Petri Nets are applied to provide a modular representation of urban traffic networks. An interesting feature of this model is the possibility of representing the offsets among different traffic light cycles as embedded in the structure of the model itself. Even though it is a very interesting work, the authors only optimize the coordination among different traffic light cycles. Our cycle optimization methodology is a complete flexible one because we implicitly optimize not only traffic light offsets but also every *stage length.*

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[5] Responsive signals: Traffic signals capable o adapting their state to the current traffic situation near them.

Another interesting work using Petri Nets is (Li, L et al., 2004) where they are applied to control a single intersection by means of programmable logic controllers (PLCs). They compare three methods for modeling the traffic lights at an intersection and found out that the more suitable is the one that combines Petri nets with PLCs. Again, in this research just one intersection is optimized, and not a whole traffic network.

In (Spall, J.C. & Chin, D.C., 1994) the author presented a neural network (NN) approach for optimizing traffic light cycles. A neural network is used to implement the traffic lights control function. The training process of the NN is fed exclusively with real data. This being so, it would only be useful in systems with an on-line data acquisition module installed. However, so far such systems are not common at all.

The “offset-time”[6] between two traffic lights is optimized using Artificial Neural Networks (ANNs) at (López, S., et al. 1999). Although our system does not treat explicitly the offset time parameter we think that our system faces traffic optimization in a much more flexible manner.

In (GiYoung L., 2001) a real-time local optimization of one intersection technique is proposed. It is based on fuzzy logic. Although an adaptive optimization may be very interesting — we checked out this in (Sánchez, J. J. et al., 2004) — we believe that a global optimization is a more complete approach to the problem.

In (You-Sik, H. et al., 1999) authors present a fuzzy control system for extending or shortening the fixed traffic light cycle. By means of electrosensitive traffic lights they can extend the traffic cycle when many vehicles are passing on the road or reduce the cycle if there are few vehicles passing. Through simulation they presented efficiency improvement results. This work performs a local adaptation for a single traffic light instead of a global optimization.

In (Rouphail, N., et al., 2000) an “ad hoc” architecture is used to optimize a 9 intersection traffic network. It uses Genetic Algorithms as an optimization technique running on a single machine. The CORSIM[7] model is used within the evaluation function of the GA. In this work scalability is not addressed. Authors recognize that it is a customized non scalable system. Our system has the scalability feature thanks to the intrinsic scalability of the Beowulf Cluster and the parallel execution of the evaluation function within the GA.

In (You Sik Hong, et al., 2001) the concept of the optimal green time algorithm is proposed, which reduces average vehicle waiting time while improving average 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 average waiting time, vehicle speed, and fuel consumption. This work only considers a very small amount of traffic signals — two near intersections — in the cycle optimization. We do agree with them about the non-suitability of fixed cycles.

An interesting combination of Genetic Algorithms and Traffic Simulation is published in (Taniguchi, E. & Shimamoto, H., 2004). In this work a routing and scheduling system for freight carrier vehicles is presented. They use Genetic Algorithms as optimization technique. The objective of the GA is the minimization of the costs of travel. A dynamic vehicle routing

[6] Offset-time: the time since a traffic light turn green until the next traffic light — for example, in a boulevard — turns also green.

[7] CORSIM: Corridor Traffic Simulation Model (Halati A. et al., 1997).

algorithm is proposed and tested with a test road network. The implemented traffic simulation model is macroscopic.
Another very interesting work is presented in (Varia, H.R. & Dhingra, S.L., 2004). A dynamic system-optimal (DSO) traffic assignment model is formulated for a congested urban network with a number of signalized intersections. They also combine traffic simulation with Genetic Algorithms. The aim of this work is to assign any traveler a route. A GA is used to minimize the users total travel time. A macroscopic model is used for the estimation of traffic delays. The DSO problem is solved with fixed signal timings, and with the optimization of signal timings.
In (Vogel, A. et al., 2000) every intersection is optimized considering only local information. Moreover, it can be adapted to short and long term traffic fluctuations. In our case we perform a global optimization instead of multiple local optimizations. We think that our approach may be a more efficient exploitation of the traffic infrastructure.
A very interesting work is published in (Wiering, M. et al., 2004). In this work, traffic is regarded as formed by a set of intersections to be optimized in a stand alone manner. They proposed to use reinforcement learning algorithms to optimize what they consider a multi-agent decision problem. We do not agree with them. Although a local optimization can obviously reduce average waiting times of cars — as it seems to happen with simulated tests at this work — we think that a global optimization taking into account every intersection in a zone should be more profitable.

2.4 Own contribution.

In this subsection we have included our contribution to the art. In (Sánchez, J. J. et al., 2004) we presented our methodology for the optimization of Traffic Light Cycles in a Traffic Network. The very good results of a parallel speed-up study convinced us that it was advisable to use a "Beowulf Cluster" as parallel computing system.
In OPTDES IV[8] we shared a scalability study on that architecture. We ran tests using four networks from 80 up to 1176 cells. In that work we found out that our system had a very good performance for all cases.
In (Sánchez, J. J. et al., 2005 A) we compared two versions of our microscopic traffic simulator: a stochastic versus a deterministic traffic simulator. There were three differences between the stochastic and the deterministic version: The cells updating order; the new vehicle creation time and the acceleration probability. From that work we realized that the stochastic simulator is a suitable — convergent — statistical process to compare with; and we demonstrated that the deterministic simulator outputs are highly linearly correlated with the stochastic ones. 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 the research presented for CIMCA2005 (Sánchez, J. J., Galán, M. J., & Rubio, E., 2005 B) we described the difference between two sorts of encoding, yielding different crossover and mutation strategies. The main achievement in that work was to demonstrate — by means of a wide set of tests — that, at least for our particular case, a bit level crossover combined with a variable mutation probability means a great saving of computing time. Besides, we noticed

[8] Optimization and Design in Industry IV, Tokyo, Japan, (September, 26-30th, 2004)

how that choice lets the algorithm cover the solution space faster due to a bigger gene variability between generations. This combination seems to avoid premature convergence.

In ECT2006 we delivered a research (Sánchez, J. J. et al., 2006) that included two goals. First, we introduced a new methodology – such a visual one – helping those practitioners occupied tuning a GA by giving them much deeper knowledge of how the GA is doing than they had before. Furthermore, we tried this new methodology with a wide set of tests. We used it for tuning the genetic algorithm within our traffic optimization architecture applied to a particular network.

We presented another research in Eurocast 2007 (Sánchez, J. J. et al., 2007). In that communication we shared a study considering three candidate criteria as a first step toward extending our fitness function towards a multicriteria one. The criteria where related to the total number of vehicles that left the network, the occupancy of the network and greenhouse gases emissions. We performed a correlation study and, although conclusions where not definitive, we obtained some interesting conclusions about the relationship among those parameters.

Finally, soon we will publish an optimization research (Sánchez, J. J. et al., 2008) for another traffic network situated in Santa Cruz de Tenerife, Spain. Although the scale of that network is not as large as the one treated for the current paper, results are promising.

3. Methodology

3.1 Optimization model

The architecture of our system comprises thre items, namely a Genetic Algorithm (GA) as Non- Deterministic Optimization Technique, a Cellular Automata (CA) based Traffic Simulator inside the evaluation routine of the GA, and a Beowulf Cluster as MIMD multicomputer. Through this section we will give a wide description for the GA and the CA based Traffic Simulator used in our methodology. Finally, a brief description of the Beowulf Cluster sill also be provided.

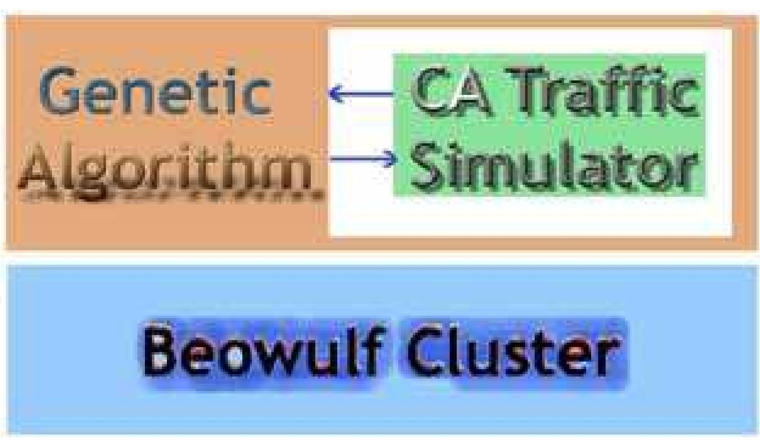

Fig. 1. Model Architecture

3.1.1 Genetic algorithm

In this subsection we will describe the genetic algorithm utilized.

3.1.1.1 Optimization criterion. Fitness function

After testing several criteria we found out that we obtained the better results just by using the absolute number of vehicles that left the traffic network once the simulation finishes.

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 was, and consequently helps us to compare a particular cycle combination with another.
Other optimization criteria tested are the following:

- Mean time at the network – Mean Elapsed Time, MET. During the simulation, the arrival and departure time of every vehicle is stored. With these values we can easily calculate the number of iterations (or seconds) it takes any vehicle to leave the network. Once the simulation finishes the average time at the network is calculated.
- Standard Deviation values of vehicle times at the network.
- A linear combination between the MET and the Standard Deviation of vehicle times at the network.
- A linear combination between the MET and the total number of vehicles that have left the network during the simulation.
- The traffic network mean occupancy density. To calculate this parameter we divided the network into small sections and counted the number of vehicles inside every section.

As we search the optimization criteria for our system we encountered an unexpected problem. If we included the minimization of the MET in a multicriteria evaluation function we provoked a very undesirable effect. The chromosomes that blocked the network faster were the best marked. That is because only a few vehicles were able to leave the network (in a small amount of iterations) before it collapsed. Hence, we obtained very "good" values but caused by "false" optimal cycle combinations. Therefore, we resigned to include that criterion in our fitness function.

3.1.1.2 Chromosome encoding

In figure 1 we present the chosen encoding used in our methodology. In this figure we represent a chromosome example for a very simple traffic network. It consists of only two intersections and two traffic lights for each intersection.

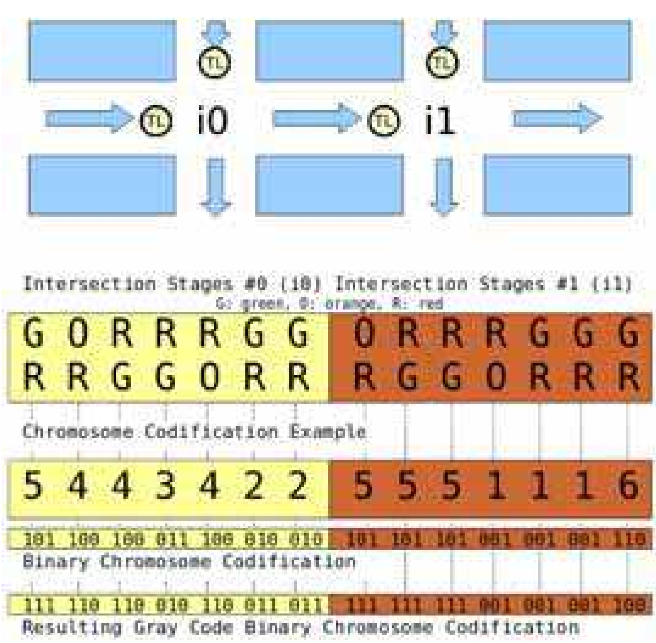

Fig. 2. Chromosome Codification

Below the traffic network we have put the *stages*[9] of each traffic light separated in two different color regions, one for each one of the two intersections. The traffic light state at each *stage* may be green (G), orange (O) or red (R).
This stages sequence is preestabilished, and wil 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) in order to get the very best traffic behavior from the network under study.
In figure 1 a chromosome encoding example I included. It can be seen that through several translation steps we obtained a binary Gray Code encoding (Black, P. E., 2005). We have proven out this methodology to be very efficient for our case in (Sánchez, J. J. et al., 2005 B).
We use Gray Code because it is designed in such a manner that when a bit changes its value — when mutation occurs — the *stage length* value only increases or decreases one unit. This is a desirable feature because it makes the search space to *conform* with the "Hamming Distance Metric".

3.1.1.3 Initial population

Before the GA starts we created an initial population. Initially we set a time range for every preestablished *stage*. Each individual is created by choosing a random value within its corresponding range.

3.1.1.4 Random number generation

For the random number generation we have employed the MT19937 generator of Makoto Matsumoto and Takuji Nishimura, known as the "Mersenne Twister" generator. It has passed the DIEHARD statistical tests (Matsumoto, M. & Nishimura, T., 1998). The seeds for that algorithm were obtained from the ``/dev/urandom'' device provided by the Red Hat 9 operating system.

3.1.1.5 Selection strategy

We have chosen a Truncation and Elitism combination as selection strategy. It means that at every generation a little group of individuals — the best two individuals in our case — is cloned to the next generation. The remainder of the next generation is created by crossovering the individuals from a best fitness subset — usually a 66 percent of the whole population.
This combination seems to be the most fitted to our problem among a set of selection strategies tested. However, we do not discard to change it if better results seem attainable.
Other selection strategies previously tested — and discarded — for this problem are succinctly explained as follows:

- Elitism: The population is ordered by fitness and a small set with the best individuals (elite) is cloned to the next generation.
- Truncation: The population is ordered by fitness. Then the population is divided into two sets, one to survive and the another one is simply discarded.
- Tournament: Small groups of individuals are chosen at random. The best fitness individual of each one of them is selected.
- Random Tournament: Like the Tournament Selection but the best individual is not always selected. It will depend on a probability value.
- Roulette Linear Selection: Every individual has a survival probability proportional to its fitness value.
- Elitism plus Random Tournament.

[9] Stage: Every one of the states associated to an intersection, that contains a set of traffic lights.

3.1.1.6 Crossover operator

We have tested some different crossover operators: Uniform Crossover, Two Points Crossover at fixed points and Two Points Crossover at random points. We reached the conclusion that for our case the better one was the third one.

For a couple of parents, it simply chooses two random points at each one of the two chromosomes, cut them into three pieces and then interchanges the central chunk of them.

3.1.1.7 Mutation operator

The value of a randomly chosen bit in the chromosome is just flipped.

The mutation probability is not fixed. It starts with a very high mutation probability that will decrease multiplied by a factor value in the range (0,1) until it reaches probability values near to the inverse of the population size as approaching the end of the planned number of generations.

3.1.2 Traffic simulator

Traffic Simulation is known to be a very difficult task. There are mainly two different traffic simulations paradigms. The first one is the Macroscopic model. Macroscopic simulators are based on Fluid Dynamics, since they consider traffic flow as a continuous fluid. The second paradigm is the one that includes Microscopic simulators. For them, traffic is considered as a collection of discrete particles following some rules about their interaction. In the last decade there has been a common belief about the better performance of Microscopic simulators to do Traffic Modeling. One Microscopic model widely used is the Cellular Automata Model.

There has been a large tradition of macroscopic approaches for traffic modeling. In the 50's some “first order” continuum theories of highway traffic appeared. In the 70's and later on some other “second order” models were developed in order to correct the formers' deficiencies. References (Helbing, D., 1995); (Kerner, B. S., & Konhäuser, P., 1994); (Kühne, R. D., et al., 1991); (Kühne, R. D., 1991); (Payne, H. J., 1979) and (Witham, G. B., 1974) may illustrate some of these models. However, in (Daganzo, C. F., 1995) “second order” models are questioned due to some serious problems like negative flows predictions and negative speeds under certain conditions.

Nowadays the microscopic simulators are widely used. One reason for this fact is that macroscopic simulators can not model the discrete dynamics that arises from the interaction among individual vehicles (Benjaafar, S., et al., 1997). Cellular Automata are usually faster than any other traffic microsimulator (Nagel, K., & Schleicher, A., 1994), and, as said in (Cremer, M. & Ludwig, J., 1986) “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”

3.1.2.1 The cellular automata as inspiring model

Cellular Automata Simulators are based on the Cellular Automata Theory developed by John Von Neumann (Neumann, J. von, 1963) at the end of the forties at the Logic of Computers Group of the University of Michigan. Cellular Automata are discrete dynamical systems whose behavior is specified in terms of local relation. Space is sampled into a grid, with each cell containing a few bits of data. As time advances, each cell decides its next state depending on the neighbors state and following a small set of rules.

In the Cellular Automata model not only space is sampled into a set of points, but also time and speed. Time becomes iterations. A relationship between time and iterations is set. For instance, 1(sec.) ≡ 1 (iteration). Consequently, speed turns into “cells over iterations”.

In (Brockfeld, E. et al., 2003) we can find a well described list of microscopic models and a comparative study of them. Although conclusions are not definitive, this work seems to demonstrate that models using less parameters have a better performance.
We have developed a traffic model based on the SK[10] model (Krauss, S., et al., 1997) and the SchCh[11] model (Schadschneider, A. et al., 1999). The SchCh model is a combination of a highway traffic model (Nagel, K. & Schreckenberg, M., 1992) and a very simple city traffic model (Biham et al., 1992). The SK model adds the "smooth braking" for avoiding abrupt speed changes. We decided to base our model in the SK model due to its better results for all the tests shown in (Brockfeld, E. et al., 2003).

3.1.2.2 Our improved cellular automata model

Based on the Cellular Automata Model we have developed a non-linear model for simulating traffic behavior. The basic structure is the same as the one used in Cellular Automata. However, in our case we add two new levels of complexity by creating two new abstractions: "Paths"and "Vehicles".
"Paths" are overlapping subsets included in the Cellular Automata 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 next positions. In figure 2 we try to illustrate this idea.
"Vehicles" consists of an array of structures, each one of them having the following properties:

1. Position: the Cellular Automaton where it is situated. Note that every cell may be occupied by one and only one vehicle.
2. Speed: the current speed of a vehicle. It means the number of cells it moves over every iteration.
3. Path: In our model, every vehicle is related to a "path".

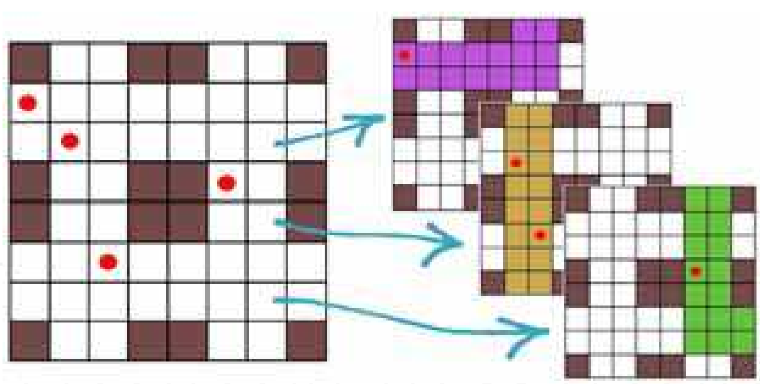

Fig. 3. Paths in our Improved Cellular Automata Model

These are the rules applied to every vehicle:

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 light), it will accelerate at a pace of 1 point per iteration, every iteration.
2. If a vehicle can reach an occupied position, it will reduce its speed and will occupy the free position just behind the preceding.

[10] Stephan Krauss, the author.
[11] Andreas Schadschneider and Debashish Chowdhury, the authors.

3. If a vehicle has a red traffic light in front of, it will stop.
4. Smooth Braking: Once the vehicle position is updated, then the vehicle speed is updated too. 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 iteration going at its current speed (hypothetically, since in the next iteration the traffic situation may change), it will reduce its speed in one unit.
5. Multi-lane Traffic: When a vehicle is trying to move on, or update its speed, it is allowed to consider positions on other parallel lanes. For every origindestination couple (path), at every point there exists a list of possible next positions. The first considered is the one straight forward. If this one is not free, there may be more possible positions in parallel lanes that will be considered. Of course, this list of possible next positions is created taking the basic driving rules into account.

By means of these rules we can have lots of different path vehicles running in the same network. This model may be seen as a set of N_{paths} traditional Cellular Automata networks working I parallel over the same physical points.

Note that, so far, we are not considering a different behavior for the green and the orange state. However, our architecture is designed in such a manner that we can modify this whenever we want to, with a small effort.

3.1.3 Beowulf cluster

The Architecture of our system is based on a five node Beowulf Cluster, due to its very interesting price/performance relationship and the possibility of employing Open Software on it. On the other hand, this is a very scalable MIMD computer, a very desirable feature in order to solve all sort — and scales — of traffic problems.

Every cluster node consists of a Pentium IV processor at 3.06 GHz with 1 GB DDR RAM and 80GB HDD. The nodes are connected through a Gigabit Ethernet Backbone. Every node has the same hardware, except the master node having an extra Gigabit Ethernet network card for "out world" connection.

Every node has installed Red Hat 9 on it — Kernel 2.4.20-28.9, glibc ver. 2.3.2 and gcc ver. 3.3.2. It was also necessary for parallel programming the installation of LAM/MPI (LAM 6.5.8, MPI 2).

In our application there are two kinds of processes, namely *master* and *slave* process. There is only one master process running on 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*).

4. Achieved goals and future aims

The main goal obtain with this methodology is its application to two real world test cases in a simulated environment. To do so we have earned both collaboration agreements with Saragossa and Santa Cruz de Tenerife local governments.

4.1 La Almozara

In figures 4 and 5 the Saragossa district number 7 — "La Almozara"— is shown. We want to remark the large scale of the zone.

In our simulated environment we improve 10% fitness, in comparison with results obtained with the times currently used in the zone.

Fig. 4. Eye view of "La Almozara" in Saragossa (from Google Maps).

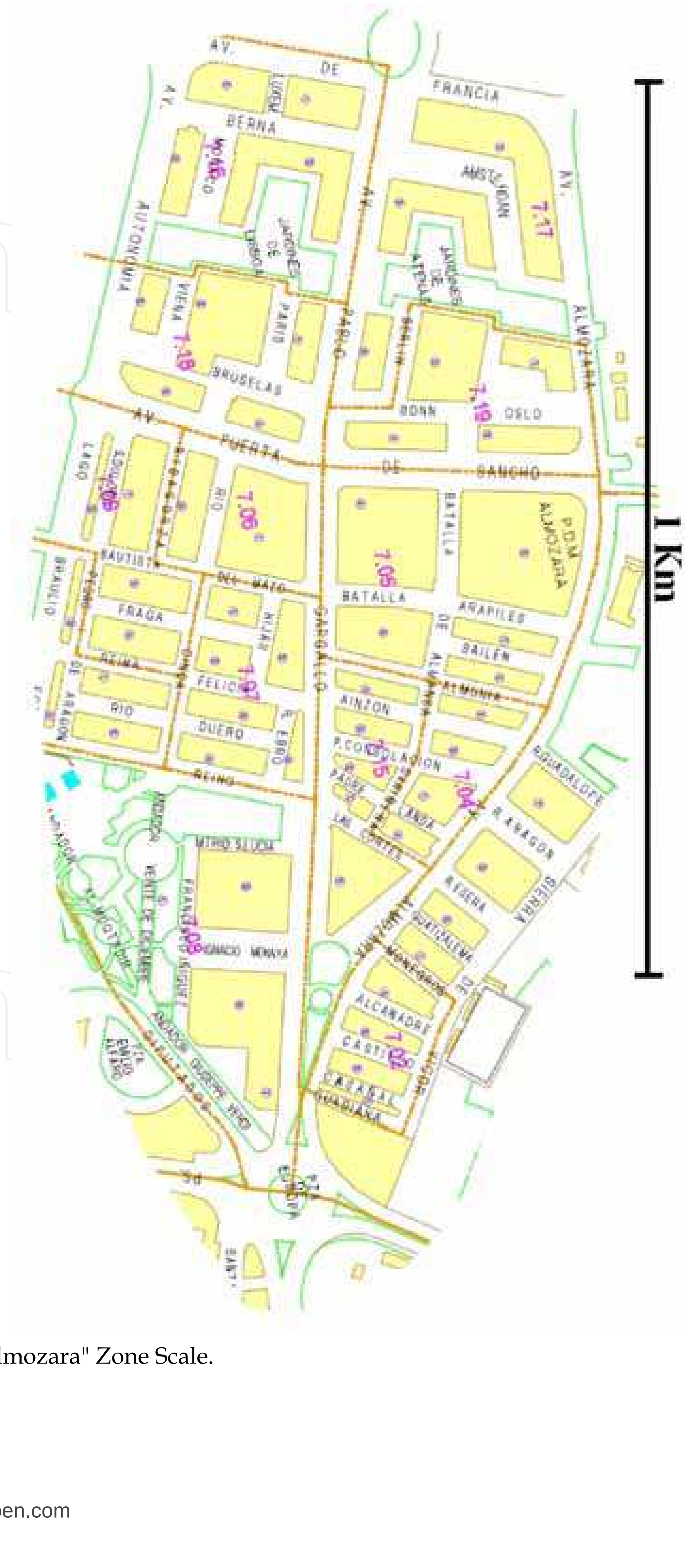

Fig. 5. "La Almozara" Zone Scale.

The statistics provided reflected a scarcely occupied network (under 10%). Everything seems to indicate that when the traffic zone is that empty, no matter what is the combination of traffic light times, the network would have similar outputs. In other words, a nearly empty traffic network is not likely to be improved just by optimizing traffic light times.
Nevertheless, we are carrying out a stud increasing the network occupation, and results seem really promising.

4.2 Las Ramblas

Illustrations 6 and 7 show the treated zone in Santa Cruz de Tenerife — Canary Islands.
In figure 8 we represent the performance results using the solutions given to us by the Local Government — the first 9 points. The rest of the points represent the performance obtained using the solutions yielded by our method. One may observe that there is an obvious improvement using our times. Likewise, our 150 solutions seem to be more stable than theirs.
Figure 9 shows the improvement — as a percentage — of the mean, best and worst values of our 150 solutions against the 9 supplied.
This improvement (%) stays within a range fro 0.53 to 26.21. The smallest difference between the optimized results and the supplied simulated results is 12 vehicles — solution 43 with respect to supplied 'R1'. The biggest difference is 521 vehicles — distance from solution 69 to supplied 'R6'.
The improvement stays within a range from 0.53 to 26.21. The smallest difference between the optimized results and the supplied simulated results is 12 vehicles — solution 43 with respect to supplied 'R1'. The biggest difference is 521 vehicles — distance from solution 69 to supplied 'R6'.
One important conclusion is that we can clearl improve the supplied times in our simulated environment. So, we can seek optimal cycle time combinations for the traffic lights programming using our architecture with an appropriate amount of statistics. We have proven this with a real world test case (nevertheless, using a simulated environment).
This is useful as reducing travel times in a city clearly means saving money and reducing environmental impact.
It is important to note that our system is intrinsically adaptable to particularized requirements, such as "Path" preferences, minimum and maximum *stage length*, etc. In this sense, our system is flexible and adaptable.

4.3 Future work aims

Currently, we are planning to extend the model to a dynamic version. To do so we will need new agreements with traffic departments in order to obtain real time data.
On a second step we plan to validate our model running real traffic lights with times provided by us. This will require real commitment from any public institution, and we are convinced that we will earn that confidence soon.
Finally, we are considering the possibility of extending our model to take into account the "Pedestrians' Interaction" and including environmental aspects in the optimization criteria using a multiobjective approach.

5. Research trends

Forecasting research trends is always tricky. Fortunately, new discoveries surprise the scientific community every day, discarding common places and settled ideas.

Fig. 6. Eye View of "Las Ramblas", in Santa Cruz de Tenerife (from Google Maps)

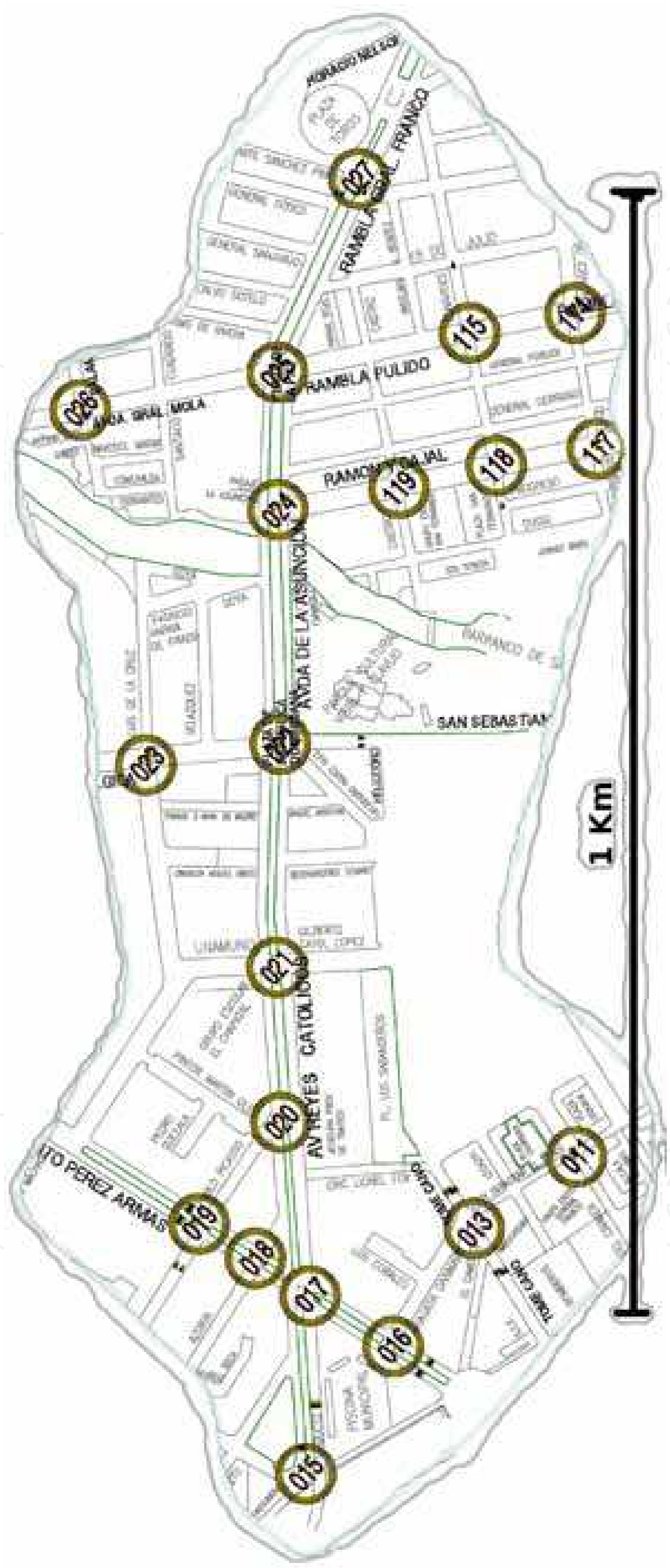

Fig. 7. "Las Ramblas" Zone Scale

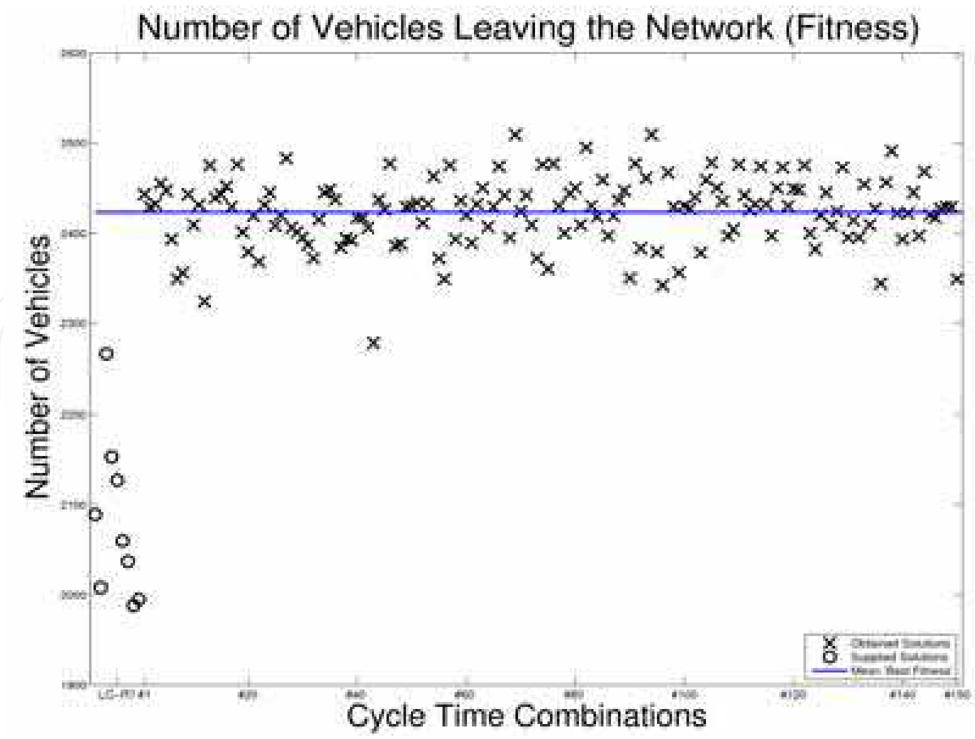

Fig. 8. Number of Vehicles Leaving the Network for the 9 Solutions Provided (on the Left) and the 50 Solutions Calculated by the System

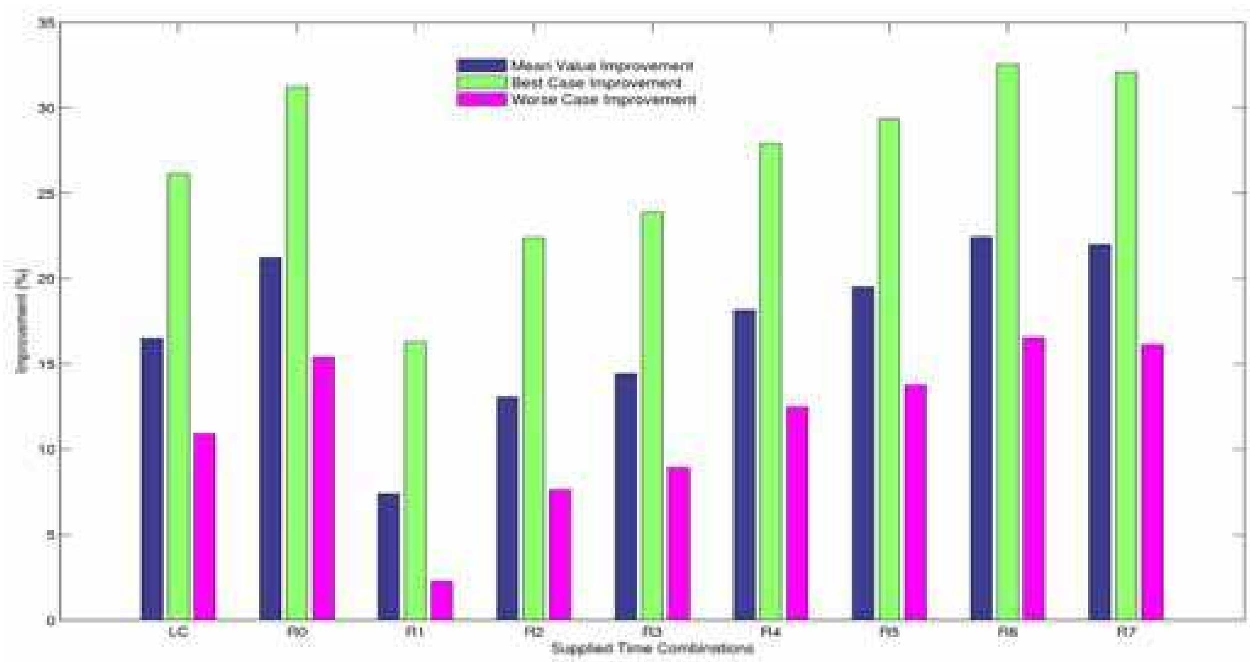

Fig. 9. Improvement of Fitness

However, everything seems to indicate that human control of traffic will be progressively replaced by automatic control systems, at least in crowded scenarios.

First, public traffic facilities, and then private vehicles, could be controlled by safe and automatic systems, maximizing the use of infrastructures, the safety of passengers, and minimizing the environmental impact of mobility.

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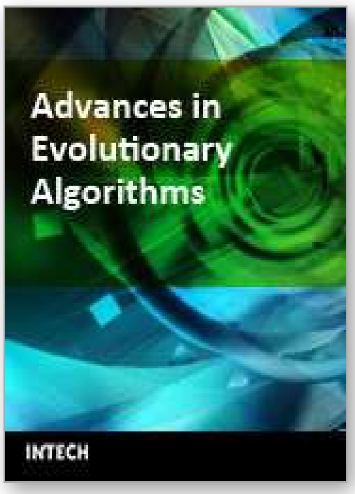

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