OACTS: Mathematical Model for Optimizing the Active Control of Traffic Signals Parameters

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Abstract

The vehicle fleet circulating in Brazilians' city centers has increased significantly, but the mobility public policies have not been sufficient to follow this growth. The consequence of it is the increase of vehicular traffic on roads leading to congestion. Given this scenario, there are several works in the literature on the construction of smart cities by the use of Computational Intelligence techniques. Among the strategies used, stands out the reactive traffic signals. In this context, this paper presents a new mathematical model called: OACTS - Optimization of the Active Control of Traffic Signals. This model associates the use of Genetic Algorithm (GA) to optimize the following traffic signal parameters: green time, cycle time, phase sequence and offset. For this, the model uses a new proposal of delay time function to evaluate the solutions of the algorithm. For testing the applicability of OACTS, a case study is developed in which real vehicles demand data of a Belo Horizonte region - Brazil (actual data collected by the city transport company - BHTrans) are loaded in the AIMSUN traffic simulator. This simulator is calibrated previously to better represent the real conditions of the study region. The OACTS model receives these demands from AIMUSUN and, based on the application of GA, defines, in real time, a good set of the traffic parameters that meets the demand in order to reduce the delay of vehicles in the intersections. The experiments were statistically analyzed and the results show that the OACTS was able to find better solutions to the problem when compared to other models that optimize a smaller set of parameters and to the traffic plan currently used by BHTrans.

Keywords: Traffic Signal Programming; Genetic Algorithm; Active Traffic Management; Traffic Simulation; Intelligent Transport Systems.

1. Introduction

Due to the increase in the vehicle fleet in Brazil in recent years, defining an efficient vehicle traffic system has been a major challenge for public mobility policies in Brazilian urban centers. According to the annual survey by the Parts Manufacturers Union (SINDIPEÇAS, 2022), the circulating fleet of vehicles in Brazil, in 2021, was approximately 46.6 million units in circulation.

One of the main reflection of this large number of vehicles traveling on the roads is traffic congestion, which has consequences for the population's quality of life, associated with economic, social and environmental damages. In view of this, many studies have been carried out on strategies to define an efficient mobility plan for urban centers within a context of smart cities.

According to Tonon (2018), smart cities are cities that use technology to improve urban infrastructure and make urban centers more efficient and better to live in. Among the various areas that can be invested to make a city smarter, the use of smart traffic signals through Intelligent Transport Systems (ITS) and Computational Intelligence (CI) stand out. These traffic signals are able to perceive movements on the roads and automatically change their configuration in real time to meet demand, in order to increase vehicle fluidity and reduce delay times.

One of the major areas of ITS is the Advanced Travel Management Systems (ATMS) (BAZZAN et al., 2007). One of the ATMS control strategies is active traffic control. This type of control has the ability to dynamically manage recurring and non-recurring congestion based on existing traffic conditions, affirm Mirshahi et al., (2007).

According to Grant (2007), the active traffic control is a traffic signal control technique that has already been implemented in several European countries and in the United States and several benefits have been observed, such as reduction in congestion and in the emission of pollutants; reduction in the average travel time and in the average delay time of vehicles; the improvement in security; between others.

The use of this technique is also promising in Brazil and although there are not many public policies for mobility and investment culture in active traffic control in the country, some studies have already been made about this strategy. In the work of Loureiro et al. (2002), the performance of traffic management with fixed-time plans of the software TRANSYT is compared with the real time control of the SCOOT system, evaluating the indicators of average delay and volume in each approximation of the intersections under study. Meneses et al., (2003) present a discussion on the performance indicators for a real time traffic control system called ATCS for the city of Fortaleza - Brazil.

Based on the state-of-the-art study carried out in this paper, it can be seen that, although there are many works in the literature addressing CI techniques for the control of traffic signals at intersections, there is still a lack of a complete model that optimizes, at the same time, all the main parameters of traffic signal control, automatically and in real time, that is, according to the demand of vehicles on the roads. And that this model is independent of simulation to evaluate the solutions of the algorithms, generic and scalable and, therefore, faster and easier to be deployed in real-world situations.

In view of the above, the objective of this work is to present an innovative proposal of a mathematical model for the optimization of traffic signal control, called Optimization of the Active Control of Traffic Signals (OACTS), which is an extension and evolution of the Leal et al. (2016) and Leal et al. (2017) studies, aiming to overcome the limitations observed in the literature and in those works, such as: the lack of model calibration to better represent the real conditions of the study regions and the use of a reduced number of parameters in the optimization process (in those studies only green time was used). From the experiments carried out in this article, it can be observed that these limitations influence the optimization result.

In this work, OACTS was used with an evolutionary algorithms of CI - the Genetic Algorithm (GA), but the model is independent and can be associated with other CI technique. OACTS associates the use of CI to determine, in real time, a good configuration of traffic signal parameters that minimize the average delay of vehicles in a network of intersections, according to the real traffic demand. The “delay time” performance measures the wait caused to vehicles due to traffic signals.

Evolutionary algorithms have also been used in traffic control systems to optimize travel times (TEKLU et al., 2006), to reduce vehicle delay time Vilarinho et al. (2014), to maximize the capacity of the network (YIN, 2000) and minimize the performance index of the network (CEYLAN and BELL, 2004), among other objectives. The studies made by (OHAZULIKE and BRANDS, 2013), Costa, Leal, Almeida and Carrano (2018), (WANG et al., 2014), ZHOU and CAI, (2014) use the multi-objective evolutionary approach to solve traffic control problems.

For the case study of this paper, OACTS associated to GA uses real traffic data from a network of intersections in the city of Belo Horizonte - Brazil, designed in the AIMSUN simulator, to optimize traffic signals parameters. The details of the proposed modeling, the experimental results obtained and the statistical analyses will be presented in the next sections.

2. Related Work

In recent years, several studies have been carried out to improve urban mobility conditions, as the precursor control systems have failed to find solutions for the increasing vehicle demand in urban centers, according to the review of Noaeen et al., (2022). Many of these studies use CI techniques to optimize traffic control and find more effective and, on the other hand, less costly strategies. Among these works, some are highlighted in this paper for their relevance and the way in which the problem was approached.

Mao et al., (2021) use machine learning to improve GA for traffic control optimization and Masterton and Topiwala, (2018) apply agent-based techniques and GA to enable the optimization of traffic control in a network of intersections. Turky et al. (2009) also use GA in traffic control and pedestrian crossing system to provide intelligent responses from interval to green time using dynamic traffic loads.

Slowik, A., Kwasnicka, H. (2020) and in the work of Kwasnicka and Stanek (2006), traffic data from simulation are input to the evolutionary techniques. The objectives of the GA used are: to minimize the time lost and to maximize the average speed of vehicles. In this work, the authors used the simulation as a fitness function, which can make the convergence of the algorithm slow.

Singh et al., (2009) presented a GA-based real-time traffic control strategy to promote good performance at an intersection. The developed intelligent system was able to make real-time decisions to modify the green times for a set of traffic signals. In addition, the authors developed an emulator to represent traffic conditions at an isolated intersection. In the work, Ata et al., (2021), the authors explore the use of IoT (Internet of Things) empowered for intelligent road traffic congestion control system using supervised machine learning algorithm.

In order to facilitate the identification of some contributions and the limitations of the literature, Table 1 is presented below. In this table there is a summary of the comparison between some of the most relevant works found in the literature review and the OACTS model proposed by this paper. The following parameters are considered for each bibliographic reference in the table: traffic control strategy; performance measure or fitness function used in experiments; decision variables considered by the authors; CI techniques that were used in the papers and evaluation method of the generated solutions (when mentioned). The decision variables are represented by: *c* for cycle time; *g* for green time; *p* for phase sequence and *o* representing offset.

Table 1. State of the Art Comparative Table.

Reference	Traffic Control Strategy	Fitness Function	Decision Variables	CI Technique	Evaluation
GONG and ZHANG, (2012)	active in roundabouts	queue and delay	p	Fuzzy Logic	-
WANG and JIANG, (2012)	fixed at isolated intersection	-	c, g and p	-	-
YANG and LUO (2013)	active at isolated intersection	delay time	-	GA and SA	-
ZHOU and CAI, (2014)	fixed at isolated intersection	delay, polution and fuel	g	GA	Simulation
Vilarinho et al. (2014)	active at isolated intersection	delay time	g	GA	Simulation
Leal et al. (2017)	active in intersection network	delay time	g	GA	Model
OACTS model	active in intersection network	delay time	c, g, p and o	GA	Model

From this literature review, it can be seen that the OACTS model optimizes all the main parameters of traffic signal control. To this end, the model estimates the real time feedback of the control system at network intersections, meeting the objective of minimizing the delay time of vehicles in the network. In addition, OACTS does not depend on simulation to evaluate the solutions of the problem, which is an advantage of this work, since this is one of the major problems in previous approaches because it makes the algorithms search process slow and difficult to adapt and use in the real world.

3. OACTS - The Model Proposed by This Paper

In the OACTS model, at each cycle time interval, the CI technique used (GA) receives the flow data of the roads and determines the traffic signal parameters, for this period, based on the actual traffic condition. The traffic strategy adopted is the network control, in which the traffic signal plan is defined for a traffic network working together. This strategy aims to optimize the global traffic of the network and not only isolated intersections and is a predominant feature in real cases of traffic signal control. The general scheme of OACTS can be seen in Figure 1 and is described as follows:

- **Start**: The start of the model execution;
- **Calibrating the Simulation Model**: In this step, a GA is used as an optimization technique to calibrate the model - find an optimized set of behavioral and vehicle parameters for the traffic simulation model (AIMSUN).

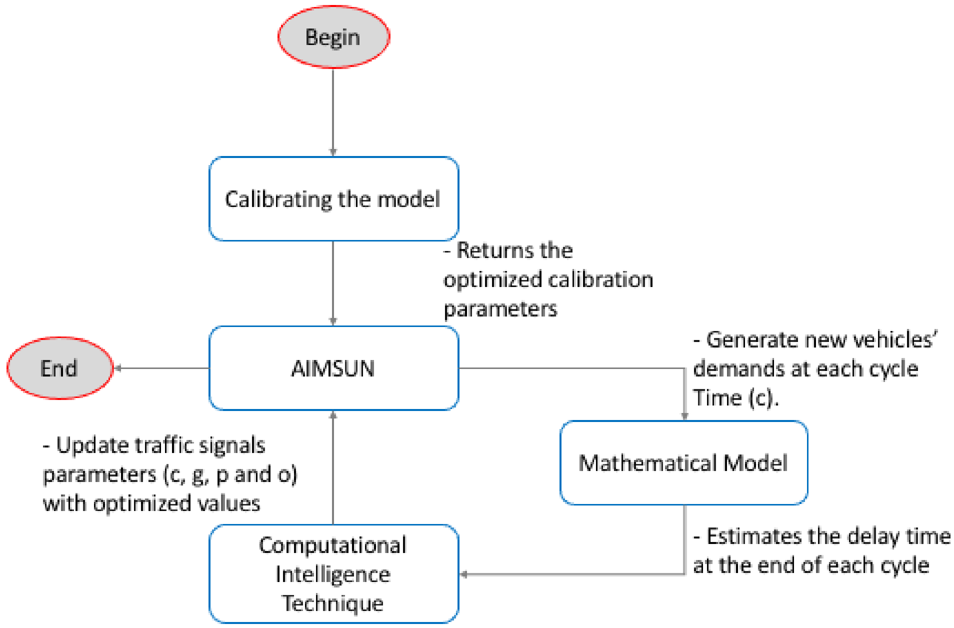

Fig. 1. General scheme of the OACTS optimization model.

The calibrating process used in this paper was proposed by Leal et al. (2020). This paper uses the same network of intersections used by Leal et al. (2020). Since the main objective of this paper is to present OACTS model associated to GA to optimize traffic signal parameters, details of GA applied to the calibrating process will not be shown here, however, further information can be found in the work of Leal et al. (2020);

- **AIMSUN**: The optimized configuration of behavioral parameters found in the calibration process is loaded into AIMSUN simulator. Soon after, the traffic network inserted in AIMSUN generates traffic demand for the execution of the experiments with OACTS model, at each cycle time interval. This demand loaded in the simulator is based on real data provided by the transport company of Belo Horizonte city - Brazil (BHTrans) and it will be presented in more details in section 5, however the proposed method can be implemented in a real network by replacing the simulator with real-time data collected by sensors installed int the transport infrastructure;
- **Mathematical Model**: OACTS receives input data from AIMSUN and estimates average delay time. In order of defining which delay time estimation function should be used in this paper, among the most referenced in the literature, an additional experiment is performed in this step and will be presented in the Experimental Results section of this paper;
- **Computational Intelligence Technique**: In this step, GA is used as a CI test technique in the process of optimizing traffic signals parameters. It is worth mentioning that the model presented in this work is generic, it is a framework in which different computational heuristics can be applied and, therefore, other CI techniques can be explored as solutions in the model. This optimization consists in finding a good set of the traffic signal control parameters (cycle time - c, green time - g, phase sequence - p and offset - o) for the traffic network that minimizes the estimated delay time calculated by the mathematical model in the previous step;
- **AIMSUN**: The optimized configuration of traffic signals parameters obtained using the CI technique is loaded into AIMSUN. Figure 2 shows the network designed in AIMSUM for the experiments of this paper, in which vehicles are circulating on the roads respecting the optimized traffic signal plan indicated by OACTS and GA. Then, a new cycle starts in which the previous steps are repeated (except the model calibration that is done only once at the beginning of the general scheme) until the total time of simulation and execution of the experiments is finished.
- **End**: Finishing the model execution and generating reports for statistical analysis.

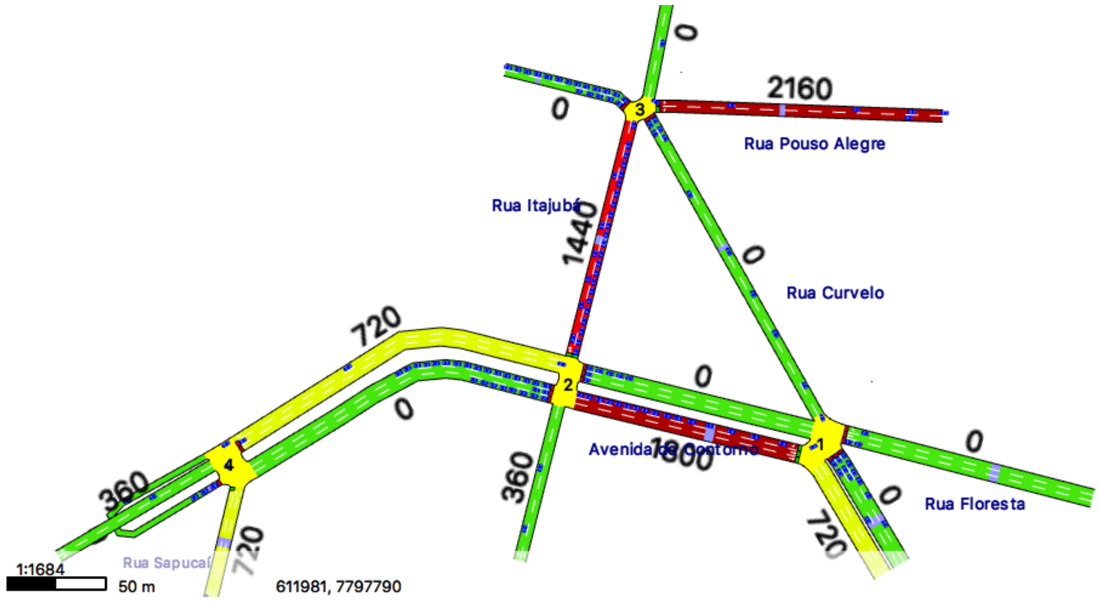

Fig. 2. Vehicles circulating on the roads during the simulation.

In summary, OACTS model is executed at each cycle time in which there is the process of feedback to the system with actual traffic demand data, generating valid and good solutions through CI techniques and updating the traffic signal plans of the traffic network, responding in real time to changes in demand. Therefore, the model operantes in active traffic control in which the set of optimized parameters for the next cycle is based on current vehicle demand data and there isn't any traffic demand forecast involved.

In the next section, the general aspects of the GA associated to OACTS are presented. In order to use this CI technique, it is necessary to decide the computational representation of the decision variable and how the treatment of constraints will be carried out. In addition, it is required to define the fitness function, objective function and the genetic operators.

4. Genetic Algorithm (GA)

GA is a CI algorithm inspired by simplified models of natural evolution. GA process an initial set of possible solutions to a problem (initial population). The elements that constitute this population are designated by individuals (decision variables) that are transformed and evolved over successive generations.

According to Pacheco (2007), these transformations occur as follows:

- The fittest elements of a generation are selected (evaluated by a fitness function) to serve as progenitors of the solutions that will appear in the next generation;
- The transformation operators or genetic operators (crossover and mutation) act on the individuals, generating new solutions and trying to guarantee an adequate level of diversity.

Due to the selection mechanism, individuals that constitute a new population tend to be better than individuals from previous generations, that is, they represent a better solution to the problem.

4.1. Decision Variable

In this traffic signal optimization problem using GA, the decision variable is represented by a vector. Table 2 presents an example of a decision variable for a traffic network with four intersections:

Table 2. GA - Decision Variables.

Decision Variable	Representation	Initial Value	Research Space
g - green time	real	[[25.0, 65.0], [53.0, 75.0], [35.0, 41.0, 14.0],[49.0, 41.0]]	15.0 - 140.0
c - cycle time	real	[90.0]	90.0 - 140.0
p - phase sequence	integer	[1]	1, 2, 3, 4, 5
o - offset	real	[15.0, 15.0, 15.0]	0.0 - 20.0

Each position of GA decision variable's vector corresponds to a vector that contains the values of each traffic signal parameter. At each experimental interval, the cycle time found by optimizing is set to the same value at each intersection, i.e. it's unique. The phases sequence is encoded by integer values between 0 and 5, in which each value corresponds to the encoding of a phase sequence: 0 = [0, 1, 2], 1= [0, 2, 1], 2= [1, 0, 2], 3= [1, 2, 0], 4= [2, 0, 1] and 5=[2, 1, 0], for example.

The phases sequences size is equal to 3 due to the fact that the traffic network of the case study in this work has a maximum of three phases, but the proposed model is easy to change for implementation in a network with more phases.

The offset is represented by a real value between 0.0 and 20.0 for the $N-1$ intersections of the region (the offset value is equal to zero for the first intersection, as the offset is calculated from the relation of the first intersection with the others).

Since the cycle time is equal to the sum of the green times and between greens (an equality constraint imposed by the problem), modifying the values of a green time would inevitably result in the total cycle time being different from the predefined cycle time. As this is not desirable, the strategy of mobile partition was adopted, as described below.

4.1.1. Mobile Partition Strategy

This strategy uses $N-1$ partitions to represent N decision variables, according to Abrao et al. (2013). To explain how this strategy works, consider as an example a simple intersection with 1 cycle traffic signal programming with 3 phases. For each phase, GA would calculate its green time. Therefore, the number N of decision variables would be equal to 3. Using this strategy, instead of using a variable to represent each of the 3 solutions, $N-1$ partitions would be used, ie 2 partitions. This way, the objective of GA becomes to find the positions of these $N-1$ partitions, instead of finding optimal N green times.

Using this approach, in addition to automatically meeting the equality constraint of the problem, one less dimension is needed to represent the solutions, which facilitates the search for the optimization algorithm as the number of intersections increases.

4.2. Fitness Function

As seen in the previous section, solutions must be adjusted to find the cycle time correctly. Furthermore, to avoid unfeasible solutions, the green time has to be greater than zero ($g > 0$), so there cannot be repeated partitions (repeated partitions can represent a value of $g = 0$).

To handle this restriction of overtaking partitions, a penalty function F_P was added to the fitness function of the individual (in this work, the fitness function corresponds to the objective function itself F_O). Obviously, individuals will avoid off-limits areas due to the low fitness they reach when they do not meet the established restriction.

Using this strategy, the fitness s of the individual x is given by:

$$s(x) = \frac{1}{F_O(x) + kp * F_P(x)}, \tag{1}$$

on what:
$F_O(x)$ is the value of the objective function for the individual x;

$F_P(x)$ is the value of the individual in the penalty function for the individual x;
kp is the applied penalty constant and
x is the individual (decision variable).

4.3. Objective Function and Problem Formulation

In the new delay estimate model proposed by this paper (OACTS), it is intended to extend a delay estimate used in the literature to a more complete delay model, in which all the main traffic signal parameters are considered as decision variable in the delay time estimation process.

This delay estimate from the state of art, used as a basis for the OACTS model, is defined from an additional experiment in the next section (experiment $E2$), in which the most used functions in the literature to calculate the delay time are compared, in order to define which one presents the best estimate for this performance measure and, thus, define which will be used by OACTS.

Since it is desired that every vehicle circulating in the intersections has the minimum possible delay time, OACTS model has an optimization formulation which is described as follows:

$$minimize \left\{ A = a_{Initial} + \sum_{i=1}^{n-1} (a_i + (a_i \times (\sum_{j=0}^{i-1}(g_j) + o[h]))) \right. \tag{2}$$

$$subject\ to: \begin{cases} c = \sum\limits_{i=1}^{v} g_i, \\ 15.0 \le g \le 140.0, \\ 90.0 \le c \le 140.0, \\ p = \{0, 1, 2, 3, 4, 5\}, \\ 0.0 \le o \le 20.0. \end{cases} \tag{3}$$

In this equation, a_i is the average delay function defined by experiment $E2$. In the literature delay models compared in $E2$, green time and cycle time are already considered as parameters. Now it is up to determine how to introduce the phase sequence and the offset as decision variables as well. To this end, the function A presented above (the OACTS delay function) is calculated as follows:

- Initially, the delay value of $a_{Initial}$ is calculated for the initial phase of the traffic signal;
- Afterwards, the delays a_i are calculated for the next phases i up to $n-1$. The value of a_i is obtained by multiplying the delay a_i by the sum of the green times of the previous phases (up to $i-1$) plus the offset value o of intersection h.

Thus, the decision to use a certain traffic signal phase (give the right of way or "green time" for the movements of this phase) will have an increase in the value of the green time of the previous phases plus the offset value of the intersection, in order to to determine whether the sequence of phases (in which the right of way is given) interferes with the average delay of vehicles at the intersection. Therefore, the objective is to minimize the sum of average delays of each phases.

For future work, it is intended to consider a weighted averaging of delays as an alternative fitness function to observe if the disparity in traffic demand across phases can affect the results and compare it with the actual fitness function.

4.4. Genetic Operators

For simplicity and for having demonstrated good performance in the previous approaches Sun et al. (2003), Kwasnicka and Stanek (2006), Costa, Leal, Almeida and Carrano (2018), the genetic operators used in this paper by GA are presented below. Details about these operators can be found in these references here quoted.

- **Selection**: Tournament method;
- **Crossover**: One point of cut;
- **Mutation**: Gaussian mutation.

In addition to the operators, to use GA it is also necessary to define a set of values for this algorithm parameters. To this end, for simplification (since the main objective of this paper is the development of the OACTS model - a generic mathematical model applied to any CI technique and not the in-depth study of variations in the behavior of GA) and for presenting good results in Leal et al. (2016), Leal et al. (2017), the set of values used for the experiments in this paper was:

- **Population size**: 50 individuals;
- **Crossing Rate**: 80%;
- **Mutation Rate**: 4%.

Another contributions of this paper is the usage of the convergence of the evaluation function as the stopping criteria for the algorithm, that is, GA stops when, over several generations, there is no more significant improvement in the results. This was a limitation found in this papers authors recent studies, since they used the maximum number of generations as stopping criteria for GA and this approach limits the research space for finding more promising solutions.

5. Experimental Results

In this section, the experiments carried out in this paper are presented, according to the planning of experiments suggested in Table 3.

Table 3. Design of experiments and abbreviations used.

Abbreviation	Experiment
$E1$	AIMSUN Simulator Calibration
$E2$	Definition of the Literature Delay Function
$E3$	Optimization using the OACTS Model (Main Experiment)
$E4$	Comparison of the OACTS Model results to the current BHTrans solution
$E5$	Traffic Oscillation Simulation

The solution proposed in this article was implemented in the Python language (version 2.7.5). The AIMSUN simulator (version AIMSUN Next 8.2.2) has an Application Programming Interface (API) for Python, which facilitates the development of algorithms and their integration with simulations.

The simulation period set is of 2 hours and the execution time of each simulation step is 1 second, much less than the cycle time, which suggests the practical ability of the OACTS model to be adapted and implemented in the real world. The computer used to carry out the experiments is a MacBook Air, with the macOS High Sierra operating system, a 1.6 GHz Intel Core i5 processor and 4 GB of RAM.

5.1. Data collection and the traffic network modeling

The traffic network designed in AIMSUN and used in the experiments was presented in Section 3 of this thesis (Figure 2). It is a network of intersections from the Floresta neighborhood in Belo Horizonte (Brazil). Belo Horizonte is the capital of the state of Minas Gerais, with about 4 million inhabitants and a fleet of more than 1.2 million vehicles. Traffic congestion is a major problem in this study area because it's surrounded by commerce, schools, banks, bars, and residential areas. The vehicle flow data uploaded into the simulator is based on data collected by BHTrans from 08:00 to 10:00 for a period of one month (July).

The network from Figura 2 is composed by 4 signalized intersections with the following number of traffic signals' phases:

- Contorno with Curvelo: 3 phases
- Contorno with Itajuba: 2 phases
- Pouso Alegre with Curvelo: 2 phases
- Contorno with Sapucai: 2 phases

Thus, the optimization process of this network consists of, from the OACTS model, obtaining the green times of the 9 phases of the traffic signals of these intersections, the cycle time, the phase sequence for the intersection with 3 phases and the offset for each intersection.

BHTrans provided vehicle demand data from these intersections for a period of one month to be uploaded in AIMSUN for the experiments. The company also provided the traffic signal control plan currently used at the studied network for comparison purposes and which is used with one of the individuals in the initial GA population.

5.2. E1 - AIMSUN Simulator Calibration

The calibrating process used in experiment $E1$ was proposed by Leal et al. (2020). $E1$ is an initial experiment to calibrate the behavioral and vehicle parameters of the AIMSUN simulator, in which GA is used to find a good set of these parameters that minimizes the mean absolute normalized error (MANE) between the delay time estimated by AIMSUN and the delay observed in the network under study.

For this experiment, the set of values found by GA for calibrating the simulator is shown in Table 4. With this set, GA reached a minimum value of MANE around 0.027, which means that the absolute value of the difference between the real network delay time and the delay time obtained by optimizing the calibration parameters is almost 3%. This value shows that the model outputs are similar to the observed data.

Table 4. Design of experiments and abbreviations used.

Calibration Parameter	Optimized Values found by GA
Reaction Time	1.02s
Reaction Time at Stop	1.87s
Traffic Signal Reaction Time	1.65s
Maximum Desired Speed for Vehicles	86km/h
Maximum Vehicle Deceleration	4.0m/s
Vehicle Acceptance Speed	0.94km/s
Minimum Distance between Vehicles	2.0m

To verify if this MANE value is good, an experiment was carried out using AIMSUN standard calibration parameters in the traffic network, in which a MANE value of 0.1189 was found. Thus, the application of the solution found by GA (Table 4) in the traffic simulation model provided a MANE value of 0.027, that is, approximately 78% lower than using the simulator's default values.

This result shows that the calibration process is important, as it ensures that the simulation more accurately reflects the real experiment environment, so that strategic decisions about traffic management for the analyzed network are better informed and more realistic.

5.3. E2 - Definition of the Literature Delay Function

In this experiment, a statistical comparison is performed (using $MANE$ function) between the delay value obtained in the field for the traffic network used in this paper and the most used time-dependent delay models in the literature, which are:

- Australian delay model proposed by Akcelik in AKCELIK (1980) and AKCELIK (1981) - a_A
- American delay model proposed by the Highway Capacity Manual (HCM) in HCM (2000) - a_{HCM}
- Canadian delay model proposed in TEPLY (1991) - a_C

The objective of this experiment is to define which model presents a delay estimate closer to reality and can be used as basis in the calculation of the delay time proposed by the OACTS model. The experimental results obtained from the execution of $E2$ experiment can be seen in Figure 3.

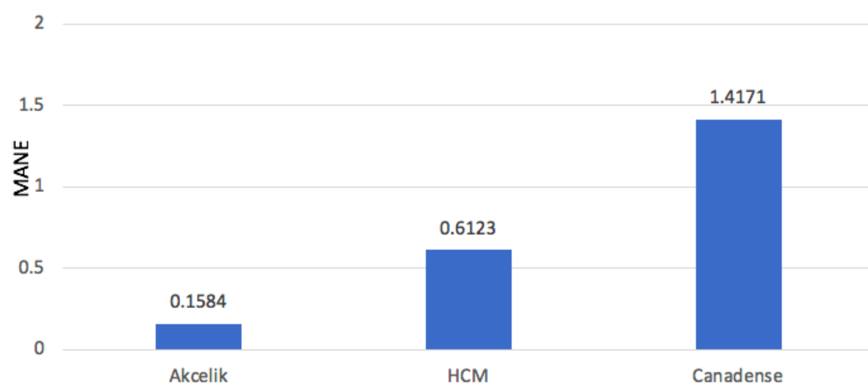

Fig. 3. E2 - Definition of the Literature Delay Function

From this graph, it is possible to observe that the delay model that generated a lower $MANE$ value was the Australian delay model, with a $MANE$ value equals to 0.1584. Thus, it can be stated, statistically, that Akcelik's delay estimation model is better than others to estimate this measure and can be the delay estimate used by OACTS.

5.4. E3 - Optimization using the OACTS Model (Main Experiment)

The mathematical model OACTS, focus of this work, presents a proposal for estimating the delay time (an extension of the function defined by the experiment $E2$), considering, as decision variables in the optimization process, the main parameters of traffic signal control (green time, cycle time, phase sequence and offset).

In $E3$ experiment, OACTS is implemented and optimized by GA to determine, at each cycle time, the values of these parameters that minimize the average delay of vehicles in the intersection network, according to the actual traffic demand loaded in AIMSUN.

To validate whether the optimization of the four traffic signal parameters by OACTS model really contributes to the minimization of the delay time, in $E3$, the settings for the decision variable considered by the delay model, in the optimization process, are presented in Table 5.

Table 5. Configurations of the decision variable for E3 experiment.

Configuration	Decision Variable
$C1$	green time
$C2$	green time - cycle time
$C3$	green time - cycle time - phase sequence
$C4$	green time - cycle time - phase sequence - offset

In the $C1$ configuration, only the green time is optimized, the other parameters are kept with constant values obtained in the field, according to the approach proposed by Leal et al. (2016). In $C2$, the green time and cycle time are optimized, leaving the phase sequence and offset constant. In $C3$ only the offset is constant, as the other variables are optimized. Finally, in $C4$ - complete configuration of OACTS model, all traffic signal parameters are optimized simultaneously.

Thus, these configurations are compared in order to statistically determine whether the optimization of the four traffic signal parameters from OACTS model ($C4$ configuration) presents lower delay values for the vehicles than the other configurations that consider fewer parameters in the process of optimization.

The experimental results of $E3$ can be seen from the graph of the average convergence curve in Figure 4. This graph shows the average rank of the best individual of the population in the objective function for all generations, based on 30 GA runs using the settings $C1$, $C2$, $C3$ and $C4$ as decision variables for OACTS model. Analyzing the experiment, it can be seen that the curves of the graph decrease towards smaller and smaller values of the objective function (delay time). This fact supports the hypothesis that GA can be used to find good traffic signal parameter settings that minimize the delay time of vehicles at intersections.

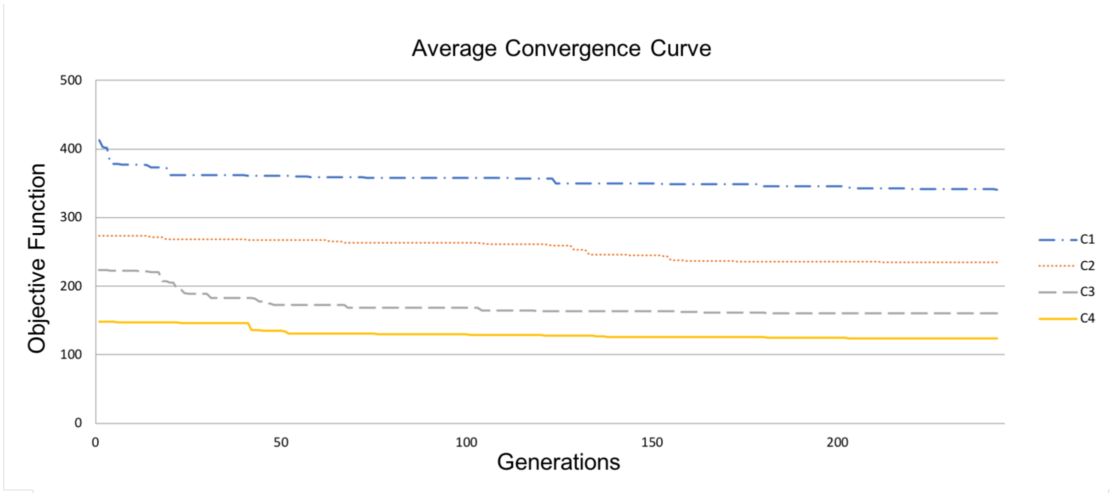

Fig. 4. E3 - Optimization using the OACTS Model

The simulation period used is 2 hours, as it is considered sufficient time for the network to reach a steady state regime. For each cycle time interval of this period, the simulator receives a new traffic signal from GA. It would be unfeasible, in this paper, to show the average convergence curve graph for all traffic signals' plans generated during 2 hours. Thus, experiment $E3$ was performed using an instance of the problem, that is, a specific simulation interval chosen randomly.

From the analysis of Figure 4, it can be seen that the optimization of all traffic signal parameters proposed by configuration $C4$ converges to smaller values of delay time than the other configurations. In experiment $E3$, with 220 generations, GA using $C4$ converges to a minimum value of 123.85 seconds of delay time, while using $C1$, $C2$ and $C3$ the values found for the delay time, with 220 generations, are 340.84, 234.36 and 160.03 seconds, respectively.

However, to statistically compare these samples, a hypothesis test must be performed. For this, it is necessary to verify the assumptions of traditional tests to decide which test procedure to use: parametric if the assumptions are met or non-parametric if not. One of the most important assumptions is the normality of data and, to check this assumption in this paper, the *Shapiro-Wilk* test was used through the software R. The null hypothesis of this test is that the sample comes from a normal population, which, when applying the test to this paper's data, was rejected because the p-value of the test was lower than any adopted significance level.

As the assumption of normality was rejected, a non-parametric alternative was chosen. The test used is called the *Kruskal Wallis* kw_0 test, which does not consider normality as an assumption, as observed in Pires (2018).

Furthermore, the assumption of homoscedasticity (which is the term to designate constant variance of residuals), analyzed from the *Bartlett test* in R, was also not observed for the distributions of this experiment, only the independence test (from the test analysis of residues). Therefore, the non-parametric test kw_0 is adequate for the analysis in question.

In this work, the null hypothesis of the hypothesis test bellow establishes that the difference between the treatment effects τ_{C1}, τ_{C2}, τ_{C3} and τ_{C4} of the responses of each configuration, respectively, is equal to zero, that is, there is no difference between the effects. The alternative hypothesis establishes that there is difference between the effects.

$$\text{Hypothesis Test } kw_0 = \begin{cases} H_0 : \tau_{C1} = \tau_{C2} = \tau_{C3} = \tau_{C4}, \\ H_1 : \tau_{C1}, \tau_{C2}, \tau_{C3} \text{ and } \tau_{C4} \text{are not all the same.} \end{cases} \tag{4}$$

Setting a confidence level of 95%, that is, significance level $\alpha = 0.05$ and knowing that $k = 4$ (number of samples, ie configurations), the critical value corresponds to the point $Q_{0.95} = 9.48$ for the test. As the value of kw_0 calculated for the experiment $E3$ was equal to 910.5, we have that $910.5 > 9.48$ and a $p - value$ less than $2.2e - 16$, that is, less than the α significance level. A low $p - value$ suggests that the sample provides enough evidence to reject the Null Hypothesis for the entire population. Therefore, with this result, the null hypothesis is rejected and it can be stated, statistically, that at least one of the configurations is different from the others.

As the *Kruskal-Wallis* test was significant, a *post-hoc* analysis can be performed to determine which configurations differ from each other, since this test does not present this information. In this sense, the *Wilcoxon-Mann-Whitney* test was used in R, for multiple comparisons, according to Pires (2018).

This test allows to verify if the problem using $C4$ (main configuration proposed by this work) presents answers statistically different from the solutions given by the configurations $C1$, $C2$ and $C3$ separately. Additionally, demonstrating that the answers or solutions are statistically different, it can also be verified if the configuration $C4$ is better than the others. To this end, using the *Wilcoxon-Mann-Whitney* test, the hypothesis tests cm_1, cm_2 and cm_3 were performed:

$$\text{Hypothesis Test } cm_1 = \begin{cases} H_0 : \tau_{C4} - \tau_{C1} = 0, \\ H_1 : \tau_{C4} - \tau_{C1} < 0. \end{cases} \tag{5}$$

$$\text{Hypothesis Test } cm_2 = \begin{cases} H_0 : \tau_{C4} - \tau_{C2} = 0, \\ H_1 : \tau_{C4} - \tau_{C2} < 0. \end{cases} \tag{6}$$

$$\text{Hypothesis Test } cm_3 = \begin{cases} H_0 : \tau_{C4} - \tau_{C3} = 0, \\ H_1 : \tau_{C4} - \tau_{C3} < 0. \end{cases} \tag{7}$$

In all tests, the $p - values$ found were lower than $2e - 16$, that is, $p - values < 0.05$ (significance level). With these results, the null hypotheses of equality between the solution proposed by the configuration $C4$ and the other configurations are rejected. Therefore, it can be said that, with a confidence level of 95%, the proposed configuration $C4$ for the optimization problem of this paper is different from the others and, therefore, presents smaller final values of delay time, being the most appropriate solution to the problem.

The traffic signal plan obtained by optimizing the OACTS model with GA using the decision variables from $C4$, can be seen in Figure 5. Using this traffic signal plan for the network of intersections under study, an average delay time of 123.85 seconds was obtained.

In addition to the green time values for each traffic signal group of intersections (indicated in the figure by the abbreviation TSG - traffic signal group), it can be seen from Figure 5 that the sequence of phases obtained for the first intersection was equal to $[1, 2, 0]$, where: initially, there is **phase 1** in which the traffic signal group $TSG2$ has the right of way (first green time indication for the traffic signals in the figure with the value of 21 seconds of effective green time, which correspond to 18 seconds of green time plus 3 seconds of yellow time). Soon after, in the next phase

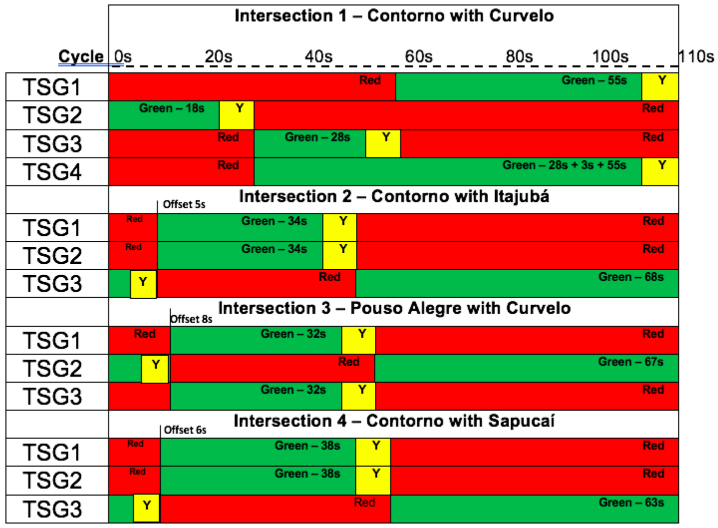

Fig. 5. Traffic signals plan obtained by OACTS optimization with the configuration C4.

(**phase 2**), the traffic signal groups $TSG3$ and $TSG4$ have 31 seconds of effective green time and in the last phase (**phase 0**) the traffic signal groups $TSG1$ and $TSG4$ have the right of way with 58 seconds of green time.

Furthermore, it can be seen in the figure that the offset for the intersections 2, 3 and 4, in relation to the first intersection, obtained by the OACTS optimization was equal to 5 , 8 and 6 seconds, respectively, and the cycle time c was equal to 110 seconds for all intersections.

5.5. E4 - Comparison of the OACTS Model results to the current BHTrans solution

The $E3$ experiment was performed using only one given traffic signal plane obtained in a specific simulation interval, that is, using only one instance of the problem. For this instance, OACTS model using GA in the optimization of all traffic signal parameters (configuration $C4$) presented better final values of delay time than the other configurations with a smaller number of parameters.

In the experiment $E4$, the total network delay time obtained by the optimization of OACTS model, during the entire simulation period (2 hours), is compared to the estimated network delay when the active control is not being used, that is, when the network is being operated with the traffic signal plan currently used by BHTrans and without optimization. The *box plot* statistical comparison method was used to compare the results as shown in Figure 6. This method is useful for comparing different sets regarding their homogeneity and trends.

In the *box plot*, using the OACTS associated with GA, the lowest value of total delay was obtained for all the intersections of the network. As there is no intersection between the quartiles of the graph, it is possible to statistically prove that OACTS provides the best solution to the problem in the time period considered for this comparison.

From the statistical analysis of the graph for practical results, it can be said that using the model proposed by this paper in the process of optimizing the traffic control plane of the network under study, it is possible to obtain a reduction of approximately 75.5% in the total average vehicle delay time when compared to the BHTrans control plan. This means that vehicles will circulate through the region with a shorter average delay time, resulting in a decrease in traffic congestion, because vehicles will spend less time stopped at traffic signals.

Figure 7 presents the time graphs of the green times during the entire simulation for each intersection of the study region. It can be seen that there is an oscillation in the green times for the traffic signals groups of the intersections' phase, responding to the changes in the demand of vehicles during the simulation. The results obtained by the instance used in the experiment $E3$ (a point marked on the graph as "E3 Instance") can also be observed.

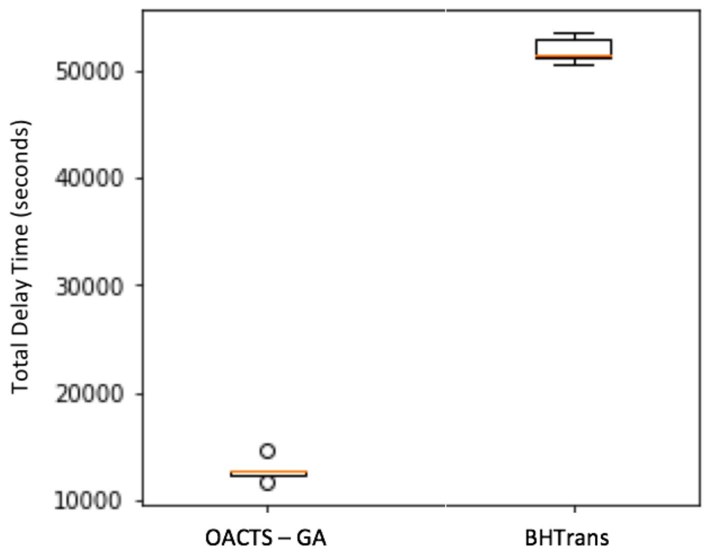

Fig. 6. E4 - Box plot diagram of comparison between solutions.

5.6. E5 - Traffic Oscillation Simulation

In $E6$ the traffic demand was increased by 50% in some movements of the traffic signal groups of the intersections, chosen at random, during 30 minutes (in the simulation interval from 1800 to 3600 seconds, that is, from 08:30 to 09:00), with the aim of verifying if OACTS is a sustainable model of traffic signal control and if the optimized traffic plan responds, in real time, to eventual oscillations that may occur in the number of vehicles traveling on the roads (increase in vehicles' demand).

The traffic signals groups randomly chosen to perform this 50% increase in the vehicle flow for the $E6$ experiment were:

- **Intersection 1**: Phase 2 was chosen with the traffic signals groups $TSG3$ and $TSG4$;
- **Intersection 2**: Phase 0 was chosen with the traffic signals groups $TSG1$ and $TSG2$;
- **Intersection 3**: Phase 1 was chosen with the traffic signal group $TSG2$;
- **Intersection 4**: Phase 1 was chosen with the traffic signal group $TSG3$;

In Figure 8, it is possible to observe the increase in the phase's green times of the intersections in which there was an increase in the demand of traffic in the movements of the traffic signals groups indicated above. From the analysis of this graph, it can be concluded that the OACTS model responds, in real time, to oscillations in traffic demand, indicating the green time needed to meet them.

Finally, Figure 9 presents, for the increase in demand proposed by this paper, the results obtained with the execution of the OACTS model and GA in the optimization of the traffic signal control compared with the results obtained using the current traffic signal plan of BHTrans, throughout the simulation.

From this graph, it is possible to verify that, given the increase in vehicle demand, OACTS still optimizes the traffic conditions in the region, producing better results than the solution currently used by BHTrans, that is, traffic signal plans that result in a lower total delay value for vehicles at network intersections during the entire simulation period.

Therefore, it can be concluded that by the usage of OACTS model in the traffic control plan optimization process, after the increase in vehicle demand, a reduction of approximately 85.8% of the total vehicle delay time is obtained when compared to the BHTrans's solution. Therefore, the increase in vehicle demand results in an even longer delay time using BHTrans's current traffic signal plan for the region under study. This result suggests that the current plan used in the region does not respond efficiently to traffic oscillation.

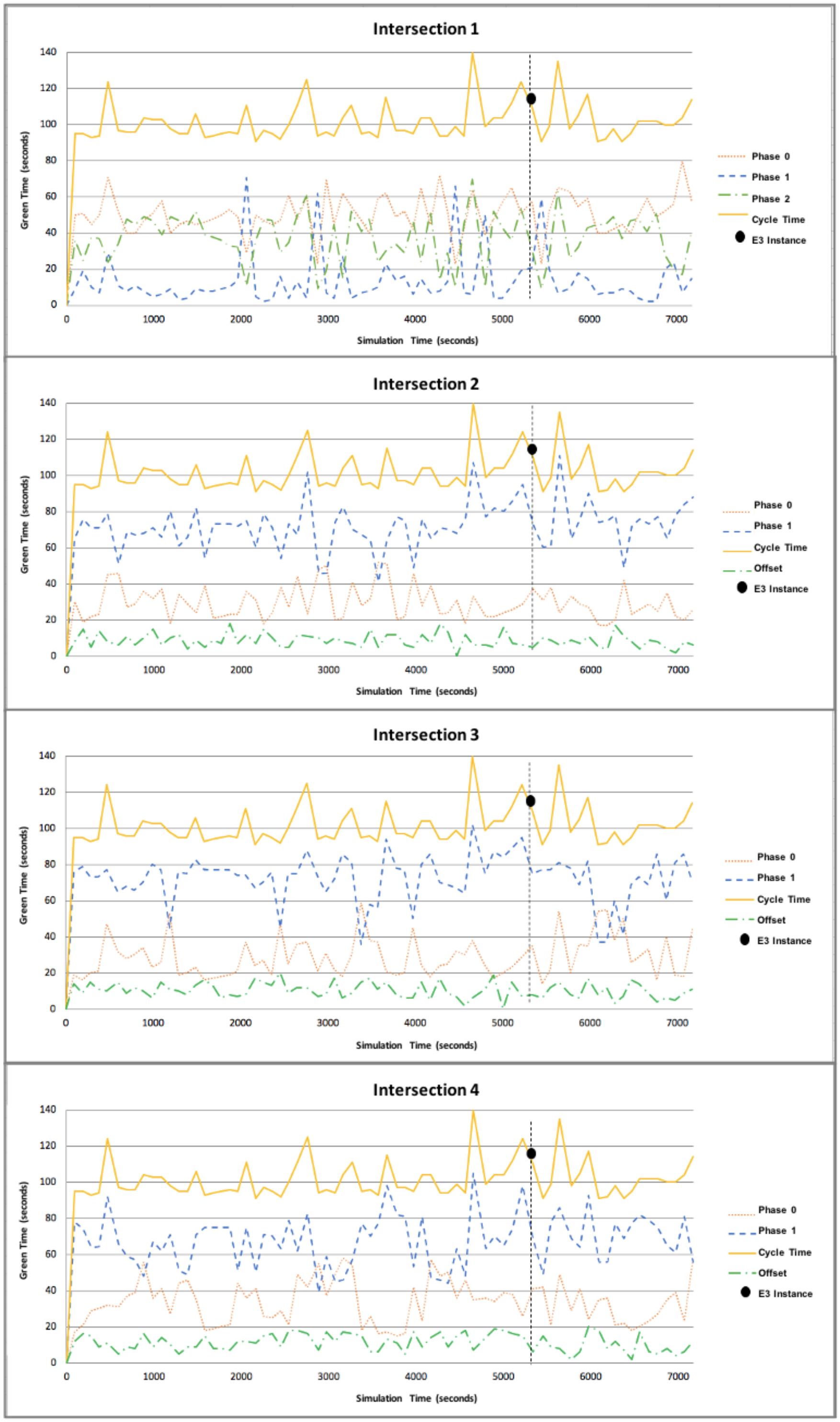

Fig. 7. E4 - Green Time Values during the simulation.

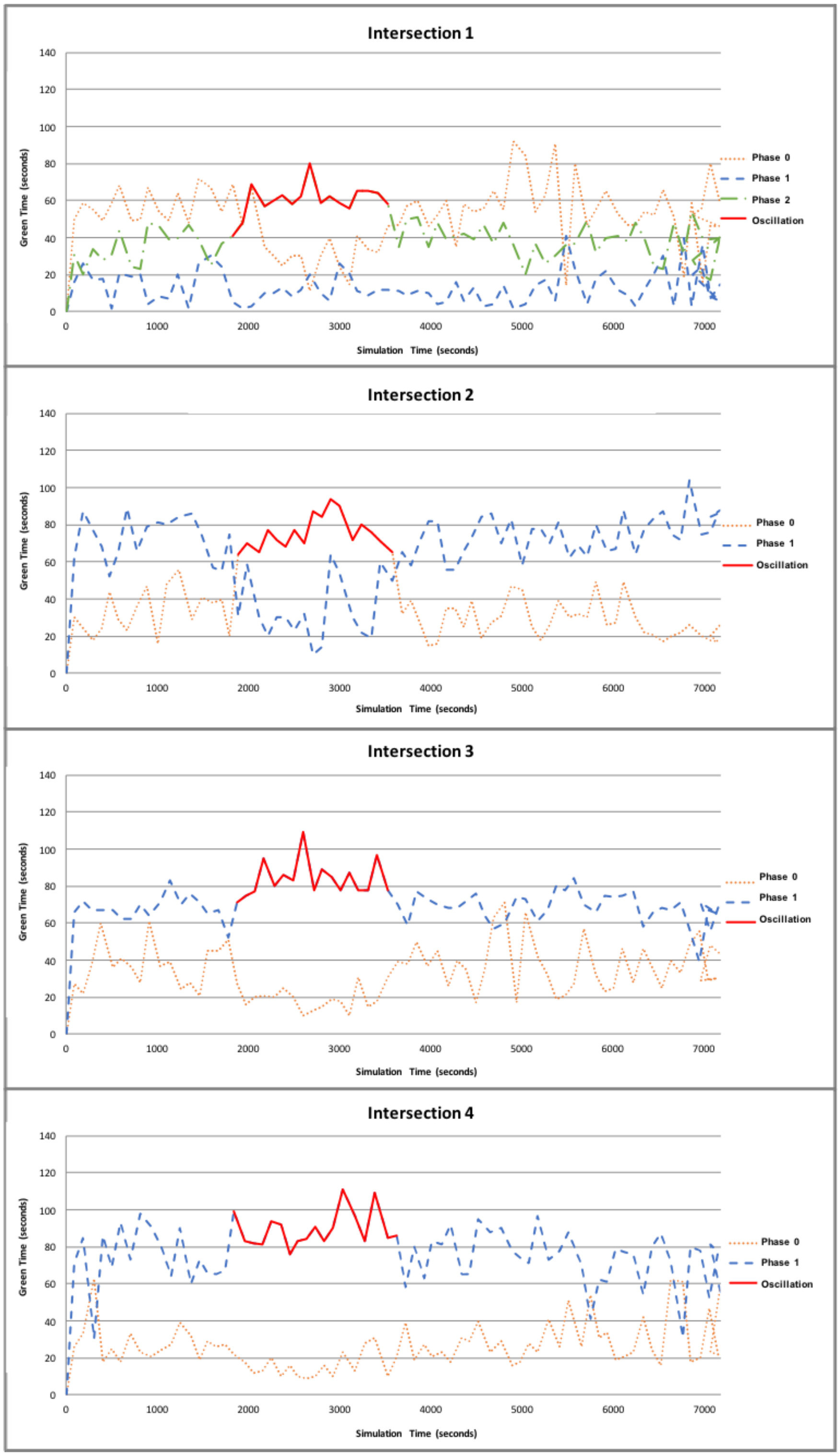

Fig. 8. E5 - Green Times Values Due to Traffic Oscillations.

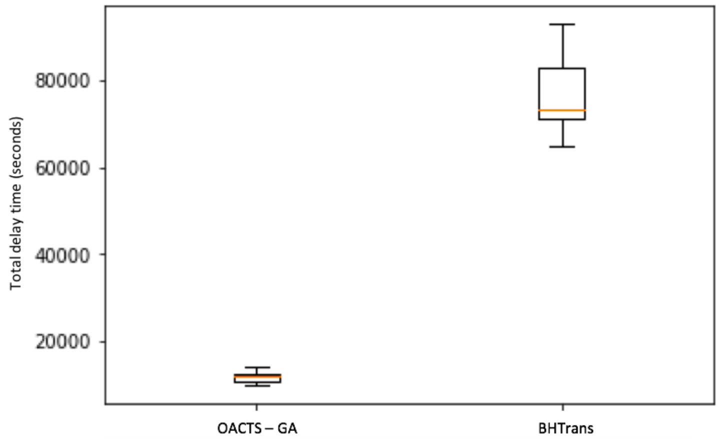

Fig. 9. E5 - Green Times Values Due to Traffic Oscillations.

6. Discussion and Conclusion

This paper presented a new proposal for active traffic control, called OACTS, which uses computational intelligence techniques (Genetic Algorithm) to optimize the traffic signal control of intersections, in real time, according to the demand obtained at each cycle time interval.

The work showed the practical feasibility of the proposal from a real case study in which the OACTS model, in the optimization of all the main traffic signal parameters, presented better values of delay time than using a smaller number of parameters in the optimization process. Furthermore, using the optimized control plan from OACTS, a lower delay time is also obtained when compared to the traffic signal control plan currently used in the intersection network under study.

This optimization of the traffic signal plans results in a greater fluidity of vehicles and, consequently, in the reduction of congestion and all the consequences provided by it in people's lives. In addition, efficient traffic signal control can optimize the road infrastructure as a whole, avoiding the construction of heavy infrastructure in the region (such as viaducts, for example) and contributing to the reduction of pollutant emissions into the atmosphere.

For future work, it is intended to consider a weighted averaging of delays as an alternative fitness function, applying the model in a network with more intersections in other regions and using other CI techniques.

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