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A linear programming approach for adaptive synchronization of traffic signals

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Abstract

As traffic congestion during rush hours is a growing problem for most cities, there is an increasing need for more effective management of traffic signal control and traffic assignment systems. We present here a new adaptive system based on a linear programming model for the signal-control problem. The objective is to minimize the total length of the queues of vehicles waiting at each intersection. The model is based on traffic information provided by real-time sensors installed at each intersection. In order to compare the performance of our program with the current scheduling designed by the transit office of Buenos Aires city, we used a traffic simulation system and real traffic flow data of two pilot areas of the city. Preliminary results are very promising.

Keywords: urban traffic control; adaptive signal control; signal timing; linear programming

1. Introduction

Traffic signal control systems are used to synchronize the timing of traffic signals in an area of a city. These systems minimize the delay experienced by vehicles traveling through a network of intersections. Despite all the research done in this field since five decades, there is still an increasing need of tools for more effective management of traffic control.

A cycle of a traffic signal is the sum of the time period of the green and "not green" phases. Therefore, the main decisions in signal-control strategies at urban areas are to determine the duration of the whole cycle, duration of green lights at each direction of every intersection, and gap (offset) between the starting time of a green phase at one signal and starting time of the green phase at an adjacent one.

Our goal was to develop an automatic system that determines, in real time, the cycles of the traffic signals in a region of the city in order to improve traffic conditions. The system is continuously fed with information provided by sensors (on-street detectors embedded in the road) installed at each road intersection. Optimization is done by means of a linear programming (LP) model. The objective is to minimize the total length of the queues of vehicles waiting at each intersection. Part of our model was derived from some of the equations of the pioneer Robertson model for the platoon dispersion (Robertson, 1969; see also Wey, 2000). We adapted the equations describing the number of vehicles waiting at the queues.

Robertson's constraints relating neighbor intersections are not included in our model. We added constraints that bind the "not green" and green lights at each intersection. Bounds that prevent sudden changes on the length of the cycles and green lights are also defined. Several cycles of the traffic signals are considered at each run of the optimization program. Based on the results of the optimization, the signal planning is automatically modified.

This paper is organized as follows. Section 2 presents a review of the literature on traffic signal control systems. In Section 3 our linear programming model is introduced and the scheme of the overall system is described in Section 4. Computational results are reported in Section 5 and Section 6 summarizes the conclusions.

2. Literature review

On reviewing the literature, we have not found a system able to solve the complete traffic signal control optimization problem for broad urban areas. As this is a very difficult problem, authors address only part of it or propose hierarchical models, which implies dividing and solving each part of the problem independently. Most studies focus on small regions or a single intersection. Several mathematical and computational approaches have been proposed, most of them are based on heuristics. The existing exact models for traffic signal control are very limited in scope, but they are useful for providing insight into the problem and examining the performance of heuristics.

Most of the currently used traffic control systems may be grouped into the following categories:

- Off-line or fixed-time strategies that are derived using pretimed timing plans based on historical data. No information on the actual traffic conditions is taken into account (Robertson, 1969).
- Traffic-responsive strategies that make use real-time measurements to calculate in real time, the suitable signal settings. Vehicle-actuated controllers operate in real time based on traffic demands provided by traffic detectors. The signal-control decision is made according to a set of rules. The time period of green phase can vary between a minimum and maximum duration depending on traffic flow. No optimization is attempted (Sims and Dobinson, 1980; Hunt et al., 1982; Bretherson et al., 2004).
- Adaptive systems that apply optimization algorithms with the purpose of creating optimal timing plans based on real-time measurements. Instead of matching current conditions to an existing timing plan, the system uses an online computer to create an optimal timing plan (Farges et al., 1983; Gartner, 1983).
- Predictive strategies that are based on off-line and online information. They use a combination of current real-time information and timing plans based on historical data to predict future arrivals (Mirchandani and Head, 2001).

It is not possible to survey here all the research done in this vast area, so we will mention only a few selected references. A more exhaustive review can be found in Papageorgiou et al. (2003). Also other authors (Cheng et al., 2006; Dotoli et al., 2006; Wey, 2000) present an overview of available traffic control methods.

Some of the approaches are already implemented in real life while others are under research or in development stage. Among the commercial systems we can mention TRANSYT, which was first developed by Robertson (1969) and was substantially improved later. The last version includes local search and a genetic algorithm as optimizer options. It uses historical information and computes signal-control schemes off-line.

SCOOT (Hunt et al., 1982; Bretherson et al., 2004) includes a network model that is fed with real data. It runs repeatedly in order to make frequent and small changes to signal control parameters such as cycle length, phase duration, and offset based on the actual traffic flow variations. The adjustment of the parameters is based on a traffic model that predicts delays and halts resulting from different signal timing plans. Changes are implemented if they prove to be beneficial.

SCATS (Sims and Dobinson, 1980) selects the best phase durations and offsets from some predefined plans (Bullock and Abbas, 2001) based on real-time traffic flow conditions. It consists of a hierarchical system structure with three levels. The lowest level is based on the local controllers at each intersection. The middle level includes regional masters, which form the core of SCATS. Each regional master controls up to several hundred local controllers, and these controllers are further grouped into systems and subsystems. Subsystems usually consist of several intersections and are the smallest control elements on the multi-intersection level. The highest level is the control center that monitors the entire system.

RODHES (Sen and Head, 1997; Mirchandani and Head, 2001), PRODYN (Farges et al., 1983), and OPAC (Gartner, 1983) include more rigorous model-based traffic responsive strategies. RODHES and PRODYN solve, in real-time, optimization problems by means of dynamic programming and OPAC through exhaustive enumeration. All three of them are feasible in real time for only one intersection and end with decentralized optimal strategies coordinated heuristically by a superior layer. In TUC (Diakaki et al., 2002; Dinopoulou et al., 2006), a store-and-forward strategy is implemented. The main idea is to simplify the model in order to describe the traffic flow process without using discrete variables. The optimization part of the system requires solving a quadratic programming problem.

Among academic work, Wey (2000) presents an integer linear model for the network-wide signal optimization problem and a modification of the network simplex algorithm to solve it. The model is tested in a five-intersection area and compared with the exact solution of the mixed-integer linear programming (MIP) model. Lo (2001) models the traffic flow conditions using a cell transmission model (CTM) based on hydrodynamic concepts. The resulting model for the dynamic signal-control problem is a mixed-integer linear programming program. A two-intersection network is used to show applicability of the formulation. Lin and Wang (2004) also propose an enhanced 0-1 formulation based on the CTM model and He et al. (2010) propose heuristics based on the linear relaxation of CPM-based MIP formulations. They test their approach on instances of one or two intersections.

Barisone et al. (2002) propose an elaborated real-time nonlinear optimization model. They successfully tested their model in an urban area of Genova consisting of 18 links. Dotoli et al. (2006) modify this model to take into account the presence of pedestrians, different levels of traffic congestion, vehicle classification, etc. Their case study is an area of two consecutive intersections with heavy traffic.

Cheng et al. (2006) present a parallel off-line algorithm for the problem of finding optimal coordination of signal timing plans for a large area based on game theory. They test their algorithm in a real area of 75 intersections, and claim that they found a signal planning in less than 10 minutes using 1000 CPUs.

Aboudolas et al. (2009) propose a methodology based on store-and-forward traffic model, mathematical optimization, and optimal control for real-time signal control in congested large-scale urban traffic networks. Porche and Lafortune (1999) propose a decentralized adaptive traffic signal control method called ALLONS-D based on a branch-and-bound algorithm.

There are several other heuristic approaches based on genetic algorithms, ant colony optimization, Markov processes, fuzzy logic, and neural networks. We mention here a few of them.

Zang et al. (2009) describe a genetic algorithm applied to the coordination of signals in an urban network based on real-time traffic information. They evaluate their approach on a 12-intersection area, using the CORSIM traffic simulation software (http://mctrans.ce.ufl.edu/featured/tsis), and report that they reduce average delay times by 15%. Park et al. (1999) propose a genetic algorithm, which they assure is able to handle oversaturated signalized intersections. Results are compared with those of TRANSYT-7F (Robertson, 1969) in a region of two signalized intersections. The genetic algorithm provides better signal timing plans in terms of queue times. An ant colony algorithm for one signalized intersection is presented in Renfrew and Yu (2009) and compared with a full-actuated control algorithm.

Yu and Recker (2006) develop a stochastic adaptive traffic signal control model. Authors model traffic signal control as a Markov decision process (MDP) and solve it with dynamic programming. MDP is a discrete time stochastic process characterized by a set of states, actions, a reward function, and a state-transition function. In the context of intersection traffic signal control, the state variables are the queue lengths of all approaches, the action variables are the control actions that can be taken for each state, the reward function tells the immediate reward of each action under specific state, and the state-transition probability function is time-varying and dependent on actual traffic arrivals. They report good results on a single intersection and five-intersection region.

Several studies apply fuzzy logic to traffic signal control (Pappis and Mamdani, 1977; Trabia et al., 1999; Niittymaki and Pursula, 2000; Murat and Gedizlioglu, 2005). All approaches use queue lengths and traffic arrivals as input, and the control action is determined based on a number of fuzzy rules. An obvious advantage of using fuzzy logic for traffic signal control is that it needs minimal computational resources. Other approaches using distributed artificial intelligence technologies such as multiagent systems are explored, for example, in Gershenson (2005).

Also Srinivaan et al. (2006) develop a multiagent distributed system based on neural networks. They carry on a simulation with PARAMICS (http://www.paramics.com) in order to compare their results in an area of 25 intersections in Singapore with those of the actual plans provided by the SCATS traffic algorithm (Sims and Dobinson, 1980). Results show significant reduction in the mean delay of each vehicle.

We were not able to find a benchmark for traffic signal control problems. Systems already implemented in real life can be evaluated through the improvement of traffic conditions in cities or areas where they are installed. Other approaches are difficult to be compared among themselves, as they show results in different small real areas, generated *ad hoc* case studies, or simplified scenarios.

3. Model formulation

As we mentioned above, we propose an adaptive system based on a LP model that is intended to be fed with traffic information provided by sensors. In this section, we describe the LP model in detail.

We consider an area that consists of a set $\mathcal{N} = \{1 \dots N\}$ of intersections. At each intersection, there is a variable number of $J(n)$ directions from which traffic flow arrives, so there are $J(n)$ signals that have to be regulated.

The temporal horizon of the model is a predetermined number H of complete cycles of the signals. The optimization program is run with the information of the previous H cycles. When new data are received from the sensors, the oldest cycle is discarded.

Each cycle is divided into two phases, "not green" (red and yellow) and green. Each phase of the cycle is divided into I smaller time intervals, $\mathcal{I} = \{1 \dots I\}$.

We need to distinguish directions (n, j) at which signal is green at the beginning of the temporal horizon and those that are "not green," therefore we define

$$RS = \{(n, j)/\text{first cycle at } (n, j) \text{ starts in "not green"}\}.$$

For each (n, j), we also define the set of indexes $\mathcal{H}(n, j)$ to denote the cycles of the temporal horizon that have "not green" phase. If the first cycle starts in "not green," then $\mathcal{H}(n, j) = \{1 \dots H\}$. Otherwise we have $\mathcal{H}(n, j) = \{2 \dots (H + 1)\}$.

3.1. Variables

The decision variables of the model are the durations of the green and "not green" lights in each direction at each intersection.

Variables related to time are as follows:

- $V_{n,j}^h$: length of the green at intersection $n \in \mathcal{N}$, direction $j \in J(n)$, and cycle $h \in \{1 \dots H\}$.
- $R_{n,j}^h$: length of "not green" at intersection $n \in \mathcal{N}$, direction $j \in J(n)$, and cycle $h \in \mathcal{H}(n, j)$. If $(n, j) \notin RS$, variable $R_{n,j}^{H+1}$ appears in the model and $R_{n,j}^1$ does not.

Then $C_n^h = R_{n,j}^h + V_{n,j}^h$ for any direction $(n, j) \in RS$ is the total length of cycle $h \in \{1 \dots H\}$ at intersection $n \in \mathcal{N}$.

Variables related to number of vehicles are as follows:

- $LV_{n,j}^{h,i}$: queue length at the beginning of interval $i \in \mathcal{I}$, intersection $n \in \mathcal{N}$, direction $j \in J(n)$, cycle $h \in \{1 \dots H\}$ (green light).
- $LR_{n,j}^{h,i}$: queue length at the beginning of interval $i \in \mathcal{I}$ at intersection $n \in \mathcal{N}$, direction $j \in J(n)$, cycle $h \in \mathcal{H}(n, j)$ ("not green" light).
- $Q_{n,j}^{h,i}$: outcoming flow of vehicles during interval $i \in \mathcal{I}$, intersection $n \in \mathcal{N}$, direction $j \in J(n)$, cycle $h \in \{1 \dots H\}$.

All the variables of the model are allowed to take noninteger values.

3.2. Relationship among directions

As there are several types of intersections in a city, we provide the following definitions:

- $JVR(n, j)$ is the set of directions related to the intersection n, for which green lights do not overlap and jointly define the time when light of direction (n, j) is red. The simplest and more typical situation is an intersection with two crossing directions j and k. In this case, we have $JVR(n, j) = \{k\}$ and $JVR(n, k) = \{j\}$. If $(n, j) \in RS$, we will have $R^h_{n,j} = V^h_{n,k}$; otherwise, $R^{h+1}_{n,j} = V^h_{n,k}$.
- Analogously, $JVV(n, j)$ is the set of directions related to the intersection n in which green light times do not overlap and jointly define the time when light (n, j) is green. In this case, a typical situation is to have two opposite directions in a two-way street, which are usually green simultaneously. $JVV(n, j)$ can be empty for some j, but j must belong to some $JVR(n, k)$ or $JVV(n, k)$ for another direction k.
- Finally, $JRR(n, j)$ is a set of directions related to the intersection n, in which "not green" light times are nonoverlapped and jointly define the time when light of direction (n, j) is red.

3.3. Coefficients

- $\widehat{ER^{h,i}_{n,j}}$ is an estimation of the number of vehicles arriving to direction j at intersection n, during interval i of "not green" light of cycle h. This is the information that would be provided by sensors if the signal planning obtained at previous run of the model was executed.
- $\widehat{EV^{h,i}_{n,j}}$ is the same estimation for green lights.
- $CI_{n,j}$ represents the length of the queue at direction j at the beginning of the period to be optimized.
- $S_{n,j}$ is the flow capacity of a street section (number of lanes).
- α is a positive parameter of the objective function.
- δ_V (δ_R) is a bound to the variation of the length of green (not green) lights between consecutive cycles.
- V_{Min}, V_{Max} are lower and upper bounds for green light lengths, and R_{Min}, R_{Max} for "not green" light lengths.

3.4. The model

We propose the following linear programming formulation:

$$\min \sum_{n=1}^{N} \sum_{j=1}^{J(n)} \sum_{i=1}^{I} \sum_{h \in \mathscr{H}(n,j)} LR^{h,i}_{n,j} + LV^{h,i}_{n,j} - \alpha Q^{h,i}_{n,j}$$

subject to the following constraints $\forall n \in \mathscr{N}, j \in J(n)$:

$$LR^{h,1}_{n,j} = LV^{h-1,1}_{n,j} + \frac{\widehat{ER^{h,1}_{n,j}}}{I} R^h_{n,j} \qquad \forall h \in \mathscr{H}(n, j), h \geq 2, \tag{1}$$

$$LV_{n,j}^{h,1} = LR_{n,j}^{h,1} + \frac{\widehat{EV_{n,j}^{h,1}}}{I} V_{n,j}^{h} - Q_{n,j}^{h,1} \qquad \forall h \in \{1 \ldots H\} \cap \mathscr{H}(n, j), \tag{2}$$

$$LR_{n,j}^{h,i} = LR_{n,j}^{h,i-1} + \frac{\widehat{ER_{n,j}^{h,i}}}{I} R_{n,j}^{h} \qquad \forall h \in \mathscr{H}(n, j), i \in \{2 \ldots I\}, \tag{3}$$

$$LV_{n,j}^{h,i} = LV_{n,j}^{h,i-1} + \frac{\widehat{EV_{n,j}^{h,i}}}{I} V_{n,j}^{h} - Q_{n,j}^{h,i} \qquad \forall h \in \{1 \ldots H\}, i \in \{2 \ldots I\}, \tag{4}$$

$$LV_{n,j}^{1,1} = CI_{n,j} + \frac{\widehat{EV_{n,j}^{1,1}}}{I} V_{n,j}^{1} - Q_{n,j}^{1,1} \qquad \forall (n, j) \notin RS, \tag{5}$$

$$LR_{n,j}^{1,1} = CI_{n,j} + \frac{\widehat{ER_{n,j}^{1,1}}}{I} R_{n,j}^{1} \qquad \forall (n, j) \in RS, \tag{6}$$

$$Q_{n,j}^{h,i} \leq \frac{S_{n,j}}{I} V_{n,j}^{h} \tag{7}$$

$$-\delta_V \leq V_{n,j}^{h} - V_{n,j}^{h-1} \leq \delta_V \tag{8}$$

$$-\delta_R \leq R_{n,j}^{h} - R_{n,j}^{h-1} \leq \delta_R \tag{9}$$

$$V_{Min} \leq V_{n,j}^{h} \leq V_{Max}, \tag{10}$$

$$R_{Min} \leq R_{n,j}^{h} \leq R_{Max} \tag{11}$$

$$R_{n,j}^{h} = \sum_{k \in JVR(n,j)} V_{n,k}^{h} \qquad \forall h \in \{1 \ldots H\}, (n, j) \in RS, \tag{12}$$

$$R_{n,j}^{h} = \sum_{k \in JVR(n,j)} V_{n,k}^{h-1} \qquad \forall h \in \mathscr{H}(n, j), (n, j) \notin RS, \tag{13}$$

$$V_{n,j}^{h} = \sum_{k \in JVV(n,j)} V_{n,k}^{h} \qquad \forall h \in \{1 \ldots H\}, \tag{14}$$

$$R_{n,j}^{h} = \sum_{k \in JRR(n,j)} R_{n,k}^{h} \qquad \forall h \in \mathscr{H}(n,j), \tag{15}$$

$$V_{n,j}^{h},\ R_{n,j}^{h},\ LR_{n,j}^{h,i},\ LV_{n,j}^{h,i},\ Q_{n,j}^{h,i} \geq 0. \tag{16}$$

The main objective is to minimize the sum of the queue lengths. α is a parameter of the model included to force outgoing flow of the vehicle at each intersection. This helps to make constraint (7) as tight as possible.

Constraints (1)–(6) define the new queue lengths for every interval by adding the vehicle arrivals, and subtracting the outgoing flow of vehicles, to the previous length. These equations are inspired in part by Robertson's model (Robertson, 1969). However, instead of using information of neighbor intersections, arrivals are computed by multiplying estimations of the number of arriving vehicles per second by the length of the time interval. Constraints (1) and (2) define the length of the queues for interval $i = 1$, which is the first time interval for the current light color. Constraints (3) and (4) compute the length of the queue in contiguous intervals corresponding to the same light color. Finally, (5) and (6) set initial values of the queues.

Constraint (7) sets a bound, based on street capacity, for the outgoing flow from direction j at intersection n. Constraints (8) and (9) impose smoothness in the changes of light schedules. Quality of estimators $\widehat{ER_{n,j}^{h,i}}$ and $\widehat{EV_{n,j}^{h,i}}$ is also guaranteed by these constraints taking small values of δ_V and δ_R.

Constraints (10) and (11) set bounds on light duration and constraints (12)–(15) establish the necessary coordination among traffic lights in different directions at each intersection. Depending on each intersection structure, some of the equations, (12)–(15), can be redundant. For the sake of clarity, we chose to write the model as above instead of using a more complicated notation to avoid this redundancy.

The number of variables and constraints of the model grow linearly with the number of intersections of the region. This implies that the system can be successfully scaled to optimize the traffic signal control in a broad area.

4. Adaptive system

The model presented in the previous section is the core of an adaptive system intended to run indefinitely. It can be described as follows.

(1) Sensors measure the traffic flow entering every street section at every instant.
(2) For every interval i of a cycle h, $\widehat{ER_{n,j}^{h,i}}$ and $\widehat{EV_{n,j}^{h,i}}$ are estimated using the data collected in step 1.
(3) The LP model presented in Section 3 is solved using these $\widehat{ER}$ and $\widehat{EV}$ estimators.
(4) Traffic light plan changes. Return to step 1.

Note that the $\widehat{ER}$ and $\widehat{EV}$, computed at step 2, are calculated using the data collected from sensors at step 1. They are estimators of the values that would be measured if current traffic control

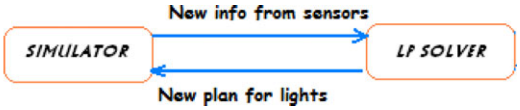

Fig. 1. Adaptive system scheme.

plan would be the one obtained at step 3. Besides safety reasons, a smooth change of light plan is required to ensure good quality of these flow estimators.

The traffic control plans obtained from this iterative scheme adapt to changes in transit conditions (i.e., variations in the frequency of vehicles reaching every entry point of the system), as it runs indefinitely and new measurements are constantly obtained from sensors.

5. Experimental results

We implemented a C library that takes care of communication between the hub and signals and calls the LP solver. When the system will be operational, the hub will send sensors information to the library and receive next planning for every signal.

As sensors have not been installed yet, we tested our model with the traffic simulation software TSIS-CORSIM (http://mctrans.ce.ufl.edu/featured/tsis; Fig. 1).

Simulation tests were conducted with real traffic flow data of two pilot areas of Buenos Aires city and several scenarios. All LPs were solved with LP-solve (http://lpsolve.sourceforge.net) in a computer with an INTEL Core I7 860 processor. Full data of test instances (including links lengths, initial traffic flow for each sensor, phases for complex intersections, etc.) can be found at http://www.dc.uba.ar/Members/pfactoro/testsignals.txt.

5.1. Asamblea area

This area (Fig. 2) consists of 7 intersections, 18 links, some of which are one-way streets or two-way avenues. All streets in this area have two lanes except Vernet Avenue that has four, so $S_{n,j} = 2$ for every intersection (n, j) except for those corresponding to Vernet Avenue. Initial queue lengths, $CI_{n,j}$, were obtained by running a simulation with the current planning and real vehicle flow measured at afternoon rush hour.

In this area, we have tested our model with eight different scenarios that are obtained by varying green and "not green" lights lower bounds (15 and 30 seconds) and traffic flow rates (100%, 25%, and 50% of the real traffic flow). We fixed δ_V and δ_R values in 4 seconds.

We conducted tests with every combination of the following values for the parameters of the model: $\alpha \in \{0.033, 0.1, 0.5\}$; $H \in \{2, 3, 5\}$; $I \in \{4, 5, 6\}$. Although results were similar for most of the combinations, best results were obtained with $\alpha = 0.033,\ H = 2,\ I = 5$ ("configuration 2" in Fig. 3). Only when $H = 5$, in particular with $\alpha = 0.1,\ H = 5,\ I = 4$ results were significantly worse ("configuration 1" in Fig. 3).

In all scenarios, we iterated four times the adaptive scheme described in Section 4. Afterwards, we fed TSIS-CORSIM with the last plan provided by our optimizer and ran a simulation to evaluate the lengths of the queues.

Fig. 2. Asamblea pilot area.

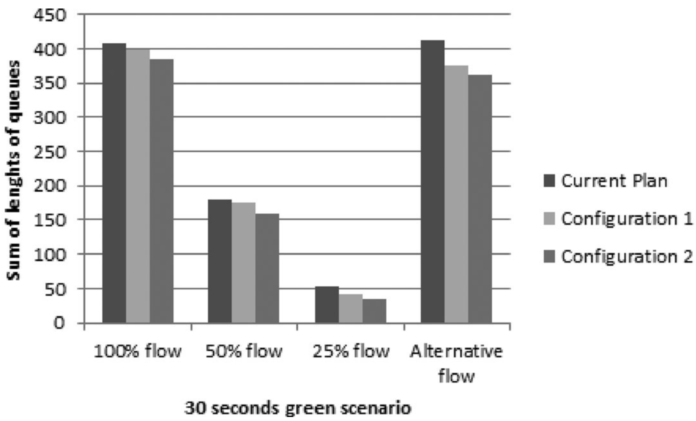

Fig. 3. Results on Asamblea pilot area.

We compared the performance of our algorithm with the current schedule designed by experts from the transit office of Buenos Aires city. With values of parameters as in “configuration 1,” results show that our optimization tool outperforms the current system reducing the average queue length by 4.17% at rush hours. On tests with 50% and 25% of this traffic flow, an improvement of 16.49% and 32.72%, respectively, was obtained. We have also tested the model with another modification of the real flow. We increased the flow at rush hour to 150% of the original one in N and E directions and decreased it to 66% in the S and W directions. In this way, we tried to represent the morning traffic in downtown direction (“alternative flow” in Fig. 3). All the LPs were solved in less that 0.1 seconds. Figure 3 shows the results of these experiments with green and “not green” lights lower bounds of 30 seconds.

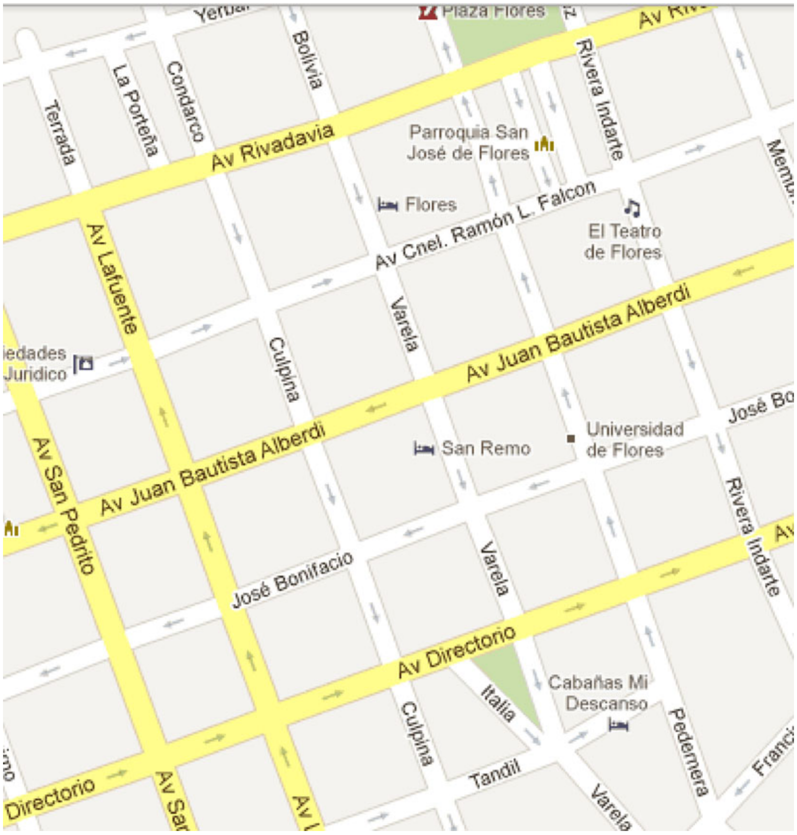

Fig. 4. Flores pilot area.

5.2. Flores area

We also tried our approach in a larger area of Buenos Aires city (23 intersections, 39 links, some of them were one-way streets or two-way avenues, see Fig. 4). In this area, streets have two lanes with the exception of Directorio (five lanes), Lafuente and San Pedrito (three lanes). So $S_{n,j}$ values were set accordingly.

We have tested our model with green and “not green” lights lower bound of 30 seconds and parameters of “configuration 2” defined in the previous section. We iterated five times the adaptive scheme described in Section 4. Data are from 10 a.m. traffic flow (morning rush hour).

In this case, our optimization tool outperforms the current light planning reducing the sum of the queue lengths from 1143 to 1091 vehicles (4.54%).

6. Conclusions

Traffic congestion is an increasing problem in towns and cities worldwide, but solutions are not easy to design. Traffic management requires making decisions on several issues. One of them is to design traffic light plans.

We developed an adaptive system based on a LP model for the synchronization of traffic signals in an urban area. The system is intended to respond automatically to fluctuations in traffic flow through the use of on-street detectors embedded in the road at each intersection. According to the results of the optimization, the system will automatically coordinate with traffic light lengths in an area of the city.

The model seeks to minimize the sum of the lengths of the vehicle queues at each direction of each intersection of an area of the city. It has constraints that determine the lengths of the queues at each intersection based on estimations of the number of arriving vehicles and the outgoing flow of vehicles. The objective function forces this flow to be the maximum allowed by the duration of green light and width of the street. Constraints imposing smoothness on changes of the signals schedule and relating the color of traffic lights of the directions of the same intersection are included. All variables are allowed to take real values.

Results in a simulation environment show that this approach can be integrated on an efficient tool for traffic congestion management. The LP model, core of the system, can be solved in a very short time by any standard linear programming software. Computational times are affordable in the framework of a real-time system for broad areas. This is the main advantage of our proposal.

Real-time implementation of the system requires one detector at each direction of a signalized intersection. Communication requirements are minimal. The proposed model is also suitable for implementation with information available from other means, as surveillance cameras.

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