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Signal priority for improving fluidity and decreasing fuel consumption

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Abstract

Signal priority is a strategy to handle traffic that adjusts the timing of a traffic signal phases to achieve a mobility goal, typically to reduce congestion or waiting time. This strategy enables increased mobility and is usually used in public transport operations; it works by making small modifications to the phases of a cycle in order to delay the green phase or anticipating the end of the red phase. We build a detailed simulation of the city center where an industrial partner operated and introduce signal priority handling to improve operations and mobility for their heavy-duty vehicles. The idea is that when these vehicles stop at red signs, they incur high consumption to regain speed, and cause conges-tion on the traffic behind them due to their lower acceleration. Detailed computational experiments demonstrate that this strategy generates significant gains for the partner fleet and has a side benefit of also improving fluidity for the surrounding traffic.

1 Introduction

Traffic congestion is a major issue in many cities. Dense urban areas as well as those within city centers are prone to congestion, which leads to many adverse effects: noise, pollution, decreased mobility, increased risks of accidents, etc. This is particularly important when heavy-duty vehicles must traverse these areas. This is often the case when industrial parks are located within city limits. In this paper, we present a case study of such a city, and with access to large databases of terrain data, including the latest origin-destination survey of the geographical area, detailed LiDAR counters, and connected onboard devices on a partner's fleet, we design transit signal priority rules in order to alleviate many of these issues.

Signal priority is a strategy that modifies the schedule of traffic lights on signal-controlled intersections. The goal is to improve fluidity of the axis of interest, without any major disruption on the surrounding traffic [8]. This strategy is well-known in transit systems, typically for vehicles in service, allowing them to decrease their travel time as well as improving the adherence to their schedules [4]. Different strategies and parameters have been tested, mostly related to the operational performance of bus systems [6]. Using signal priority to alleviate the congestion caused by heavy-duty vehicles and to decrease their fuel consumption does not seem to have been largely tested.

In our case study, we collaborate with the city administration and with an industrial partner who allowed their heavy-duty vehicles to be equipped with GPS and real-time communication devices. The goal is to design signal preemption rules in order to prevent these heavy vehicles from stopping too often within the city center due to red lights, giving them priority if required to ensure congestion is avoided and that their fuel consumption is then optimized. In order to achieve these goals, we make use of four large datasets:

1. road network and traffic signal phases,
2. origin-destination matrices of people movement in the metropolitan area,
3. camera counters of traffic,
4. detailed GPS traces and fuel consumption data from the partner fleet.

These different sources of data and how we adjusted them to obtain a representative simulation in SUMO [1] are described in Section 2. In Section 3 we described how we managed the traffic lights. In Section 4 we present several relevant statistics of the simulation including total fuel consumed by the fleet of interest and by all the vehicles of the simulation, the time lost in traffic, among others. Section 5 concludes the paper and suggests future research directions.

2 Data description and adjustments

In this section we describe the data available to us, and how we have adjusted the simulation parameters to ensure that the simulation model is representative of the real life.

2.1 Road network

The road network of the area of interest was first imported from OpenStreetMaps [7]. This area covers the territory of the Origin-Destination survey provided to us as presented in the next section. After several rounds of corrections such as lane numbers, connections, traffic lights, speed limit, and edge geometry, the graph contains 17 194 segments for 4 643 km and covers 1 965 km^2, for a population of about 175 000 inhabitants. A snapshot of the complete region [7] is provided in Figure 1.

2.2 Detailed Origin-Destination information

We had access to detailed data from the 2011 origin-destination (O-D) survey on travel habits conducted by the Transport Systems Modeling Department from the *Ministère des transports du Québec* [5]. This survey covers the Trois-Rivières census metropolitan area which encompasses 18 municipalities. Each line of this survey represents a number of movements containing information regarding the origin, destination, departure and arrival times, mode of transportation, along with socio-demographic information. This large file was obtained from interviews, and was also treated by statisticians who determine that each one of these trips represents a number of trips actually happening. So for example, one trip from a given residential area (a street or a block) toward a commercial area (also as small as a street or a block) is representative of, as an example, 15 such trips over the same O-D pair, the same approximate time, and the same mode of transportation.

Overall, the 58 084 lines of this O-D survey represent a total of 471 530 movements (396 523 of them being vehicle movements, others may be bicycle or buses trips for example) per day in the regions of Ville de Trois-Rivières, Bécancour, Batiscan, Champlain, Grand-Saint-Esprit, Nicolet, Notre-Dame-du-Mont-Carmel, Saint-Barnabé, Saint-Célestin, Saint-Étienne-des-Grès, Sainte-Geneviève-de-Batiscan, Saint-Luc-de-Vincennes, Saint-Maurice, Saint-Narcisse, Saint-Sévère, Wôlinak and Yamachiche. The data from this O-D survey gives a general overview of the traffic sources and profiles.

We input this data into SUMO by using the attribute *fromLonLat* and *toLonLat* on a trip file. Thereby, each route was created from the latitudes and longitudes of origin and destination

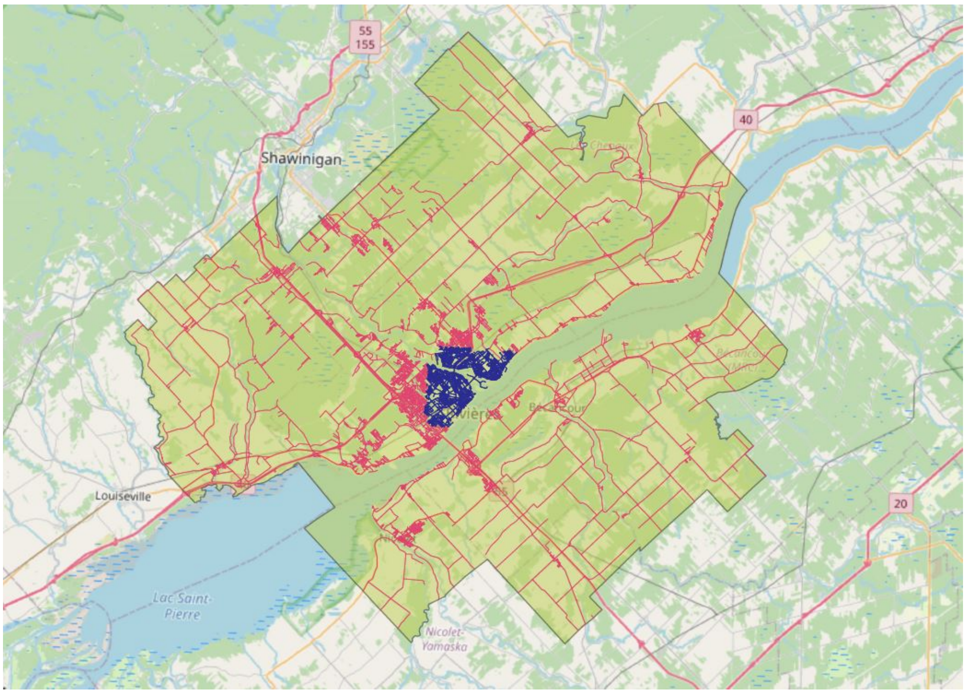


Figure 1: Interest zone

and we created a complete 24 hours model. To be representative of the types of vehicles, we used seven different types of vehicles (we generated 75% of passenger vehicles, 15% of sport utility vehicles, 3% of light vehicles, 1% of light delivery vehicles, 2% of buses, 1% of tractor trailers type 1, 1% of tractor trailers type 2, and the individual vehicle's trips of the fleet of our partner). These proportions were obtained from the city officials which use cameras with LiDAR technology. These cameras are able to identify the type of vehicles like regular cars, light trucks, heavy trucks, buses and tractor trailers. Data come from 18 different intersections which are representative of the heavy circulation in this area. Note that we did not model real bus lines. We carefully selected the best SUMO consumption model to be representative of the vehicle's consumption rates reported by the manufacturers.

By studying the O-D survey data, we observed that departure times were often rounded up to 15 minutes. To avoid a jagged generation, we took each observation and spread its departure time to more or less 5 minutes. In the O-D data, each individual observation is associated with a multiplication factor $Fact$. This factor means that each line in the sample represents $Fact$ similar trips in the population. Then we generate $Fact$ movements uniformly distributed around the departure time within an interval of 10 minutes (5 minutes before and 5 minutes after). In addition, in order to avoid that all trips depart and arrive from exactly the same coordinates, we also used a buffer of 500 meters around the departure and arrival locations, and generated $Fact$ different departure locations and $Fact$ different arrival locations within this radius.

At this step, the 24h simulation has 396 523 trips and takes 88 341 seconds to run without the Graphical User Interface, on a computer equipped with Intel® Core™ i9-9900K CPU @ 3.60GHz and 64GB of RAM. At this stage we keep all the information (location and time) on the movements of each original trip even if the simulation was not yet calibrated and adjusted, and it contained a number of teleports, traffic jams and waiting time.

2.3 Area of interest

We have then reduced the geographical area of O-D survey to concentrate on the Trois-Rivières city center. In this smaller graph, we have 5 480 edges for a length of 659.85 km and it covers 39 km^2. In order to have all vehicle trips passing thought the interest zone, we have analyzed each of the 396 523 original vehicle trips of the O-D survey to consider only the part of their path that travels through the area of interest. The function *duarouter* was used to facilitate the process. This is depicted in Figure 2, where the area of interest is shown as the white polygon within the complete map. This region is illustrated in blue in Figure 1. An example of a trip starting at O and ending at D outside the zone of interest is shown. For this trip, the departure time at O and the arrival time at D were obtained from original simulation over the complete O-D zone. When the trip enters the interest zone, we noted its exact location O' and entering time $t(O')$. The trip continues and exits the interest zone at location D'. Thus, in the smaller simulation we have a trip starting at $t(O')$ from O' to D'. For an improved visualization of this zone, we use satellite image tiles from Google Maps [3].

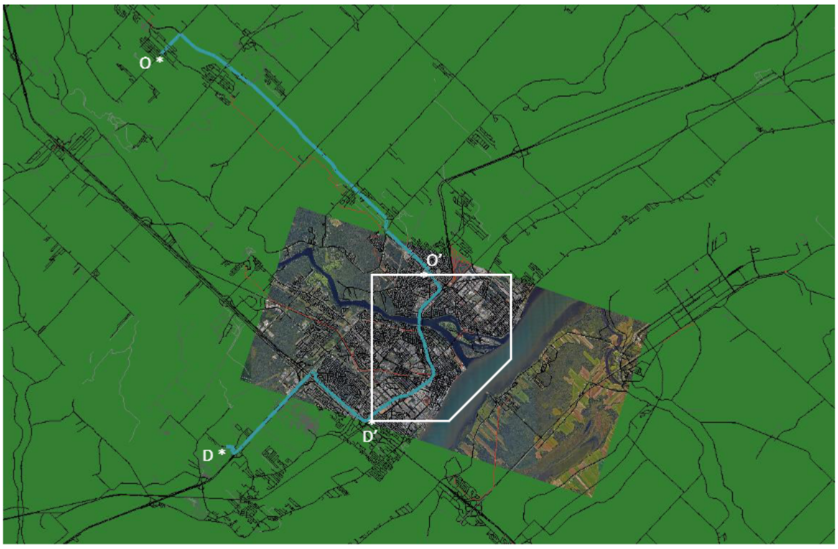


Figure 2: Zone of interest and trips interception

Note that trips originating and ending outside the zone of interest, for which no part of the trip travelled through this zone, are then not considered. Obviously, trips that are completely within the zone of interest remain unchanged. The function *cutRoutes.py* was used to generate the reduced trips files. These two procedures (decreasing the zone of interest, and intercepting the trips within this zone) decreased the size of the graph from 17 194 to 5 480 segments. Moreover, the number of vehicle trips now considered in the simulation decreased from 396 523 to 262 393.

Finally we ran the dynamic user assignment procedure *one-shot.py* on the 262 393 routes with a travel-time updating intervals of 30 seconds to better balance the users' routes.

2.4 Camera counters

To make sure that the simulation reproduces the city traffic, we used again up-to-date camera counters from LiDAR technology, thank to the city officials. These counters were available from nine intersections and cover 24 road segments on the city's main boulevard where our partner's trucks circulate. These city counters report a total of 88 529 vehicles. They indicate with very high precision the number and type of vehicles traveling, their speed, direction and cornering information, among others. At this point, our simulation reports 68 698 vehicles passing through the same roads, which is about 78% of the observed traffic. This gap can be explained by the fact that the O-D survey was conducted in 2011 and that the city camera counts were taken in 2021.

Based on these information, we have calibrated the simulation using the *calibrator* functions of SUMO which allow dynamic adaptation of traffic flows, speeds and vehicle parameters. The *calibrator* removes vehicles in excess of the specified flow and it inserts new ones to try and match the counts. We used hourly flows for the calibration. Several iterations were carried out in order to adjust the simulation counts. The routes of the partners trucks remained unchanged in the calibration simulations. At the end of the calibration process, we have 87 351 vehicles passing through the studied intersection, which represents 98.66% of 88 529 trips reported by the LiDAR counters. To obtain these values, 26 729 trips were added by the *calibrator* for a total of 289 122 trips which is now the basis of the initial simulation (see Table 1).

Figure 3 shows the complete traffic profile of the O-D study and the traffic profile over the simulated region. We can see that both profiles follow the same hourly profile. The simulated traffic is very close to the O-D one especially outside the peak hours. Both profiles differ in the peak hours because we do not consider the vehicle movements outside of our region, as discussed.

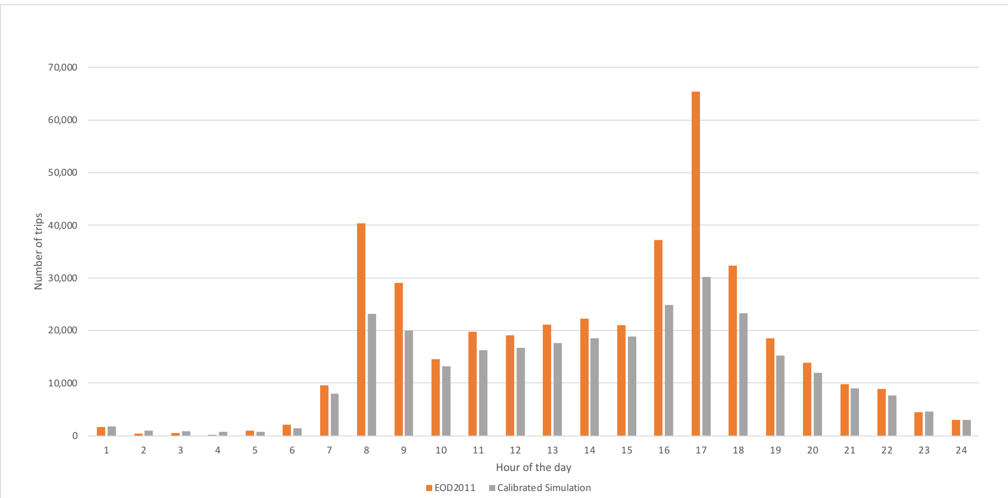


Figure 3: O-D and simulated traffic profiles

2.5 GPS traces and fuel consumption data

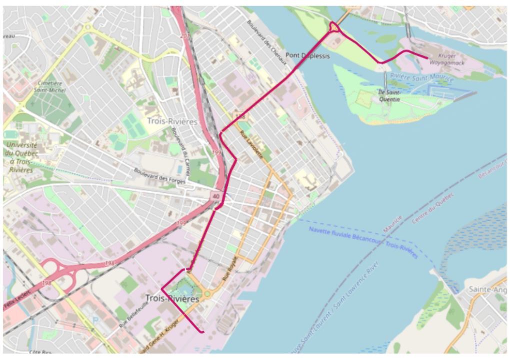
The trucks of our industrial partner are all equipped with high-frequency GPS devices that stores their location and instantaneous speeds, providing a detailed understanding of their trips, average speeds, acceleration and deceleration patterns, and how often they stop at red lights along the way. Moreover, these high-frequency devices are connected to the on-board computer of the vehicles and also provide us with detailed fuel consumption, acceleration rates, among other useful data.

The company's trucks perform many round trips, each for 11.74 km and facing a total of 26 traffic lights. Their trucks travel fully loaded, weighting around 50 tons, and return empty, with a curb weight of around 25 tons. To better model the vehicle consumption we use two different SUMO consumption classes (PHEMlight/HDV-TT-D-EU6 and PHEMlight/HDV-TT-D-EU4) for an average consumption of 119.4 l/100 km when loaded and of 113.8 l/100 km unloaded. These values are representative of the consumption levels reported by the company. Figure 4a depicts the path traveled by the company's vehicle.

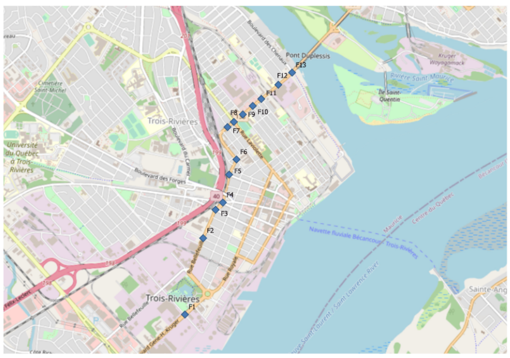
2.6 Traffic signal phases

Finally we also obtained from the city the traffic signal phases of all traffic lights in the path of our partner's vehicle (see Figure 4b). These phases were carefully implemented in SUMO. These were corroborated by field observations and video recording of several trips. All others traffic lights are set to *actuated*.

At this step we have a simulation based on the data of the O-D survey, where the hourly profile matches the survey and LiDAR-obtained vehicle counts. Traffic on the main street of interest was validated with the city counters and the fuel consumption corresponds closely either to the manufacturer specifications or to our partner's consumption data. The final simulation takes 12660 seconds to run without the Graphical User Interface.



(a) Detailed vehicle trip



(b) Traffic lights location

Figure 4: Vehicle route and traffic lights (images from [2])

3 Managing the traffic lights

In order to obtain simulation results that can yield significant savings without affecting too much the surrounding traffic or changing too much the signal phases, we establish several signal priority strategies to be simulated. Our goal is to provide the city officials with strategies that can be used to improve fluidity in the city center, allow fuel economy for the partner and not cause any disruption on the surrounding traffic.

To dynamically manage the traffic lights, we positioned a number of sensors on the path followed by the trucks of our partner. To interact with these sensors we use the Traffic Control Interface (TraCI) which allows us to retrieve the state of the simulation and change the value of some simulation parameters according to different sets of rules. Despite the synchronization of the green wave, city officials confirm that traffic on this boulevard is recognized as being problematic. This is a very busy boulevard and the succession of very close traffic lights causes several problems.

We positioned 24 sensors on 13 locations on the forward path and 24 sensors on 13 locations of the truck's return path. As we will see, the good positioning of each sensor is crucial to enhance the performance of the simulated network. If the sensor is too close to the traffic light, the truck may not reach it if too many cars are waiting at the red light. If the sensor is too far, the light may have time to turn red before the truck has crossed the intersection. In the following we tested a number of strategies.

Strategy 0: This strategy is the *status quo* where the sensors are not used. These results are used as a basis for improvement.

Strategy 1: Under this strategy each sensor is located at 150 meters of the light that it controls. When a truck reaches the sensor, the light is automatically switched to green.

Strategy 2: In this strategy, the position of the sensor follows a function of the duration of the green light phases d_g and the allowed speed (in meters per second) on the segment towards it, s. The sensor is located at $\frac{d_g}{2s}$ meters of the traffic light. For a 20 seconds green light and a 50 km/h speed limit (13.88 m/s), the sensor will be located at 138 meters. The light turns green as soon as the truck reaches the sensor.

Strategy 3: Under strategy 3 we do not automatically give a green light to the truck but rather consider the current phase of the traffic light. When the truck reaches the sensor, we have three cases:

i) if the light is red, we change the lights of the other direction to yellow for α seconds and then the truck is given a green light;

ii) if the light is green but for less than β seconds, we extend the duration of the green such that it lasts β seconds; and,

iii) if the light is green for more than β seconds, or if the light is yellow, no action is taken.

These rules are applied to the sensor positioning of Scenario 1. Indeed, as the speed limit is the same all along the vehicle's path, the use of a fixed β implies that all the sensors are positioned at the same distance from the traffic lights. Results are presented in the next section.

4 Simulation results

At this step, the simulation provides a representative digital twin of the city, with a particular emphasis in the city center where the fleet of trucks of our industrial partner often affect traffic, and is impacted by the large number of traffic lights. Our goal is to evaluate how much can be saved in terms of time, congestion, and fuel, if traffic lights are operated in a coordinated way, considering the real-time location of the trucks.

Table 1 presents the results of the simulation under the initial Strategy 0. We present the number of trips, consumption in liters (column Cons.), the distance traveled in kilometers, and the consumption rate in liters/100 km. This table also presents a column Trips % which shows for each vehicle type, its percentage of trips with respect to the total number of trips. We can see that the proportion of generated vehicle of each type closely respects the percentages presented in Section 2.2. For all vehicle types, the generated percentages are within 0.05% except for passenger vehicles which is 0.17%. This deviation mainly comes from the calibration process where the added vehicles to respect the camera counters are of the *Passenger vehicle* type.

We detail the findings for each vehicle type: buses, articulated buses, tractor trailers, passenger vehicles, sport utility vehicles, light vehicles, light delivery vehicles, tractor trailers, and Partner (standing for our partner's vehicles). In this simulation, 289 590 vehicle trips were inserted and only 383 teleports were reported by the simulation (this is reported in Table 5). The simulation provides a consumption of 166 liters for the company's trucks and of 195 265 liters for the whole set of 289 122 trips. We can see that the simulation returns realistic consumption rates for all vehicles.

Table 1: Initial simulation results under Strategy 0

Vehicle types	Nb. trips	Trips %	Cons. (liters)	Dist. (km)	Cons. (l/100 km)
Buses	5 674	1.96%	19 191	25 259	76.0
Articulated buses	5 679	1.96%	19 374	25 232	76.8
Tractor trailers	2 758	0.95%	15 099	12 177	124.0
Passenger vehicle	217 320	75.17%	92 826	883 234	10.5
SUVs	43 260	14.96%	27 634	191 076	14.5
Light vehicle	8 697	3.01%	6 282	38 013	16.5
Light delivery vehicle	2 931	1.01%	4 523	12 789	35.4
Tractor trailers	2 792	0.97%	10 170	12 170	83.6
Partner	11	0.00%	166	129	128.7
Total	289 122	100.00%	195 265	1 200 078	16.27

Table 2 shows the results when the control of the traffic lights is activated under Strategy 1. Here, whenever one of the partner's vehicles passes through the sensors, it is granted the green phase. We can see that 289 540 trips were performed during the simulation, an increase of 418 completed trips (less than 0.14%), and the number of teleports also slightly increases to 387. However the distance traveled increases by 13 629 km (1.1%). As the distances traveled was not exactly the same, we perform some adjustments to set the consumption on the same basis. For example, in the second simulation, the buses traveled 420 km less. In order to compare the results of two tables we need to increase the consumption accordingly, thus we added 420 km at the average consumption rate of 75.4 l/100 km for 316.92 liters. Thus the adjusted consumption is 18 908 liters. We can see that our partner's vehicle reduces its consumption by 9 litters from 166 to 157. For this scenario, the consumption of the partner's truck is 119.4 l/100 km when loaded and 113.8 l/100 km when empty. To this data we add 2.2 liters while the truck is running idle for a global consumption of 121.7 l/100 km. This is very close to the annual consumption level of 125.6 l/100 km reported by the company. For the overall vehicles, the second simulation reduces the total consumption by 2 893 litters (-1.48%). We can conclude that not only our partner's truck benefits from the traffic control but also many of the vehicles running on this congested road can also benefit from the added green light period. A second-hand benefit is that the trucks do not stop at red lights having then to slowly regain their speed, avoiding causing congestion for the vehicles behind them.

Table 2: Results with traffic light control under Strategy 1

Vehicle type	Nb. trips	Cons. (liters)	Dist. (km)	Cons. (l/100 km)	Diff. (km)	Diff. (liters)	Adjust. cons.	Cons. red. (liters)
Buses	5 665	18 591	24 838	74.8	-420	316.92	18 908	283
Articulated buses	5 702	18 812	24 886	75.6	-346	263.59	19 076	298
Tractor trailers	2 759	14 692	11 952	122.9	-225	277.85	14 969	130
Passenger vehicle	217 582	90 351	873 820	10.3	-9 414	981.38	91 332	1 494
SUVs	43 300	26 857	188 407	14.3	-2 669	383,27	27 241	393
Light vehicle	8 757	6 210	37 877	16.4	-136	22.38	6 232	50
Light delivery vehicle	2 948	4 411	12 565	35.1	-224	78.76	4 490	33
Tractor trailers	2 816	9 807	11 975	81.9	-195	160.99	9 968	202
Partner	11	157	129	121.7	0	0.00	157	9
Total	289 540	189 887	1 186 449	16.0	-13 629	2 485	192 372	**2 893**

Table 3 shows that further improvements can be obtained with an optimized positioning of the sensors. With these sensors the trucks of our partner reduce their consumption by 11 liters (6.6%) and for the whole vehicle fleet, the consumption reduces by 4 231 liters (2.17%).

Table 3: Results with traffic light control under Strategy 2

Vehicle type	Nb. trips	Cons. (liters)	Dist. (km)	Cons. (l/100 km)	Diff. (km)	Diff. (liters)	Adjust. cons.	Cons. red. (liters)
Buses	5 664	18 561	24 892	74.6	-366	275.55	18 836	355
Articulated buses	5 714	18 872	25 062	75.3	-169	128.86	19 001	373
Tractor trailers	2 756	14 878	12 086	123.1	-91	112.31	14 990	109
Passenger vehicle	217 429	89 331	871 530	10.2	-11 704	1214.81	90 546	2 280
SUVs	43 201	26 409	187 165	14.1	-3 910	558.65	26 967	667
Light vehicle	8 728	6 056	37 351	16.2	-663	108.49	6 164	118
Light delivery vehicle	2 945	4 311	12 444	34.6	-344	120.51	4 432	91
Tractor trailers	2 801	9 798	11 995	81.7	-175	144.77	9 943	202
Partner	11	155	129	120.2	0	0.00	155	11
Total	289 249	188 370	1 182 655	15.93	-17 423	2 664	191 034	**4 231**

Table 4 shows the results when we add the traffic light management rule with $\alpha = 3$ and $\beta = 15$ seconds. Here we were able to obtain an improved consumption reduction of 4 464 liters (2.2%). This scenario is also the one producing the most important consumption reduction for our partner fleet which is now 153 l instead of 166 l under the original scenario.

Some relevant statistics of these simulations are presented in Table 5. We observe that for almost 300 thousand vehicles simulated, there were only 383 teleports in Scenario 0, for an average trip duration of 588 s. The time lost in traffic (waiting time) at speeds below 0.1 m/s was 186 s on average, and the total time loss due to driving below the ideal speeds, which is a measure of traffic incurred, averaged 313 s per trip. The same statistics for the simulation of

Table 4: Results with traffic light control and management rules, Strategy 3

Vehicle type	Nb. trips	Cons. (liters)	Dist. (km)	Cons. (l/100 km)	Diff. (km)	Diff. (liters)	Adjust. cons.	Cons. red. (liters)
Buses	5 626	18 079	24 547	74	-711	532.15	18 611	580
Articulated buses	5 690	18 581	24 755	75	-477	361.77	18 943	431
Tractor trailers	2 744	14 607	11 958	122	-219	269.61	14 876	223
Passenger vehicle	217 170	89 725	874 377	10	-8 857	919.82	90 645	2 181
SUVs	43 175	26 426	187 026	14	-4 050	578.91	27 005	629
Light vehicle	8 698	6 059	37 293	16	-721	118.12	6 177	105
Light delivery vehicle	2 953	4 320	12 460	35	-328	114.94	4 435	88
Tractor trailers	2 787	9 767	11 941	82	-229	189.45	9 956	214
Partner	11	153	129	118	0	0.00	153	13
Total	288 854	187 716	1 184 487	15.85	-15 591	3 085	190 801	**4 464**

Scenario 1 show a clear reduction on the time lost in traffic and on the waiting time. Scenario 2, with an optimized location for the sensors, demonstrated that a significant improvement is possible. Particularly, the number of teleports has decreased and the time loss and waiting time values have considerably decreased compared to the previous cases. Finally, the different timing control of the traffic lights as in Scenario 3 shows that the statistics of interest remain stable with respect to Scenario 2, indicating no signs of deterioration in the simulation as a result of the improved traffic signal handling.

Table 5: Simulation statistics

Statistic	Strategy 0	Strategy 1	Strategy 2	Strategy 3
Total vehicles loaded	292 965	293 475	292 708	292 593
Teleports	383	387	326	324
Duration (s)	588.3	563.01	551.41	553.45
Waiting time (s)	186	170	162	162
Time loss (s)	313.7	292.3	281.4	282.2

5 Conclusions

In this article we have proposed different strategies to manage traffic lights according to the movements of our partner's trucks while respecting a detailed simulation serving as a digital twin of a city. The objective was to improve the fluidity of the journeys of these heavily loaded trucks while not interfering with local traffic.

Using data from an Origin Destination survey and detailed counts from selected intersections, we have faithfully reproduced the traffic profile of the area studied and implemented the phasing of the city's traffic lights. The reference simulation generates 289 122 trips for a distance of 1 200 078 km and a consumption of 195 265 litres. The consumption of our partner's vehicle is 166 liters under this scenario.

Our results show that by carefully positioning the sensors it is possible to improve not only the consumption of our partner but also of all the vehicles. The best strategy proposed reduces the consumption of our partner's trucks by 13 liters per day and of all the simulated vehicles by 4 464 liters. These results show that the new method of traffic light management allows an overall improvement in improving the fluidity on the boulevard that the trucks traverse and where a significant part of the traffic of the city takes place.

The city is currently deploying cameras and sensors at the main intersections in its territory. On the city's main boulevard where our partner's trucks circulate, 9 cameras are already installed out of the 19 that would be needed. The other cameras will be installed shortly since they will also be used for fire vehicles and ambulances.

Acknowledgements

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