EVS30 Symposium
Stuttgart, Germany, October 9 - 11, 2017

Smart-Cities urban mobility management architecture for electric vehicles

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Summary

Improving efficiency is one of the most important objectives of the Smart Cities standards, and Electric Vehicles (EVs). TICS can help to soften one of their main limitations –autonomy– planning efficient driving strategies. This paper evaluates the physical variables that have an impact on the EV consumption and presents an electronic architecture to monitor them in an Experimental Ultralight Electric Vehicle. This system includes a set of very low cost sensors integrated with a data logger and a GPRS transmission system that can connect, in real time, with a control center where a route-finding reinforcement-learning algorithm that helps to find the most-effective route and reduce the time spent on urban environment tips.

Keywords: city traffic, efficiency, electric drive, GPS, light vehicles

1 Introduction

Currently, cities demand more than 75% of the world's energy production and generate 80% of all the greenhouse gas emissions [1]. In order to avoid that these values continue to increase, the concept of Smart Cities has been developed. It proposes an urban model based on the sustainability and optimization of the resources available through the application of the new ICTs. Among other things, the Smart Cities model seeks to improve efficiency both in the generation and use of energy resources, through the enhancement of renewable energies and improved energy efficiency of buildings, as well as in urban mobility [2].

Improving the efficiency of urban mobility is one of the main challenges in the Smart Cities model. The following data show the current panorama of urban transport in Spain [3]:

- 50% of all the journeys travel less than 3 km and a 10% are of less than 500 m
- More than 75% of trips are made with a single occupant. The average rate is 1.2 persons per vehicle.

The lines of action to improve mobility and air quality in cities are based on the progressive reduction of the use of fossil fuels in the means of transport and the electric vehicle (VE) is presented as the main alternative. The massive implementation of VEs as the main means of transport in the urban environment presents a series of difficulties. One of the main problems is its reduced autonomy compared to conventional vehicles. The immediate solution would be the implementation of a network of fast charging points with sufficient capacity to meet growing demand.

However, another perspective to face the problem is represented by a more efficient management of urban mobility. An efficient management of the parameters of the vehicle and the environment where it drives can generate strategies that make it possible to carry out urban transfers with the lowest energy cost.

2 Methodology

We propose a working strategy within this second philosophy based on the use of Ecologic Low Budget Electric Vehicle (ELBEV) [4]: Tricycle -two directional front wheels and a rear- single occupant and weight less than 100 kg with Speed limited of 70 - 80 km/h.

A prototype similar in performance to the one described above, although with a 45 km/h speed limitation, the VEIR14, was designed and developed by the AERO EV Racing Team of the Engineering School of the Universidad de Malaga and is used in this study. See figure 1.

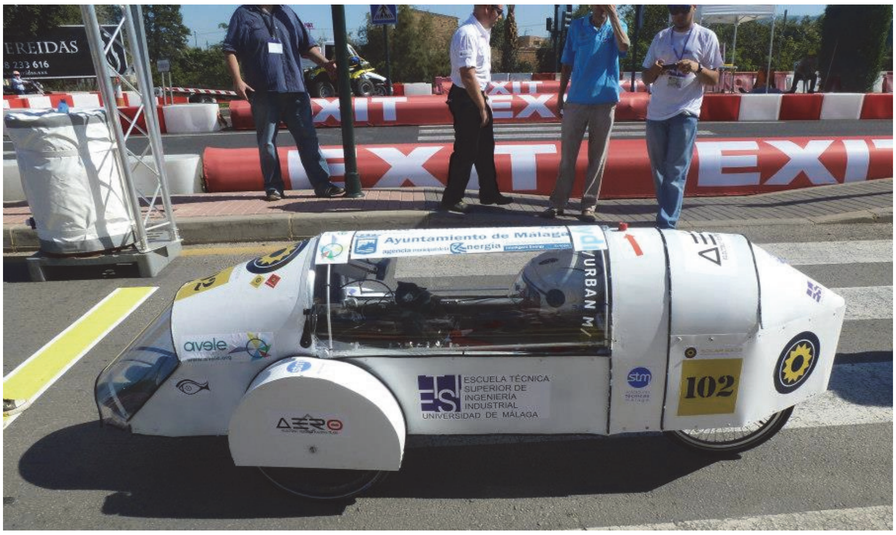

Figure1: The VEIR14 ELBEV by the AERO EV Racing Team

This vehicle has been the environment to implement a low-cost monitoring device made with distributed sensors that allow measuring both internal and external variables: instantaneous consumption, speed, inclination, GPS location, battery charge status, speed of the air, ... All these data can be saved and transmitted in real time. This allows its integration into IoT (Internet of Things) platforms.

This monitoring system can be adapted to any other type of VE and its total cost is, approximately, 115 €.

3 Vehicle monitoring

The main factor related to EV´s efficiency is the performance of its engine. However, there are other factors that also contribute, with a greater or lower extent, to the total energy consumption of the vehicle: rolling resistance, aerodynamics, slope, internal frictions … Each of these variables is associated with parameters that can be controlled to optimize the autonomy of our vehicle.

The objective of developing an EV monitoring system is to be able to know the evolution of the most significant variables related to consumption in real conditions. Because of this, several sensors are placed in the LEV (see figure 2) to measure the following significant parameters:

- Speed and distance: A rotation sensor mounted on the vehicle wheel is used to measure the angular velocity of the wheel. The distance travelled is obtained integrating the speed measured.
- Energy consumption: This is calculated integrating the instantaneous power in the time. It measure the voltage and the current of the battery. Multiplying these two measures calculates the instantaneous power used. The state of charge of the battery is obtained integrating the current and subtracting it to the initial charge

- **Road tilt:** A motion sensor is used (MPU-6050) with an accelerometer to measure linear acceleration and a gyroscope to measure angular velocity in the three axis (x, y, z) with high precision. The sensor itself does not return the angle of inclination but can be inferred by trigonometric calculations. [5]
- **Wind speed:** An anemometer that compares the dynamic and static air pressure is used: A Pitot-Prandtl tube. It is used widely in aeronautical applications [6] and in competition vehicles like F1.
- **GPS:** It localize and temporize all the collected data and characterize any route that the vehicle execute to determine the points of greater consumption, speed and to be able to compare different driving strategies to know which one is the most efficient. The sensor used is integrated in a mobile device, which adds GPRS connectivity and ports to connect peripherals like a microphone.

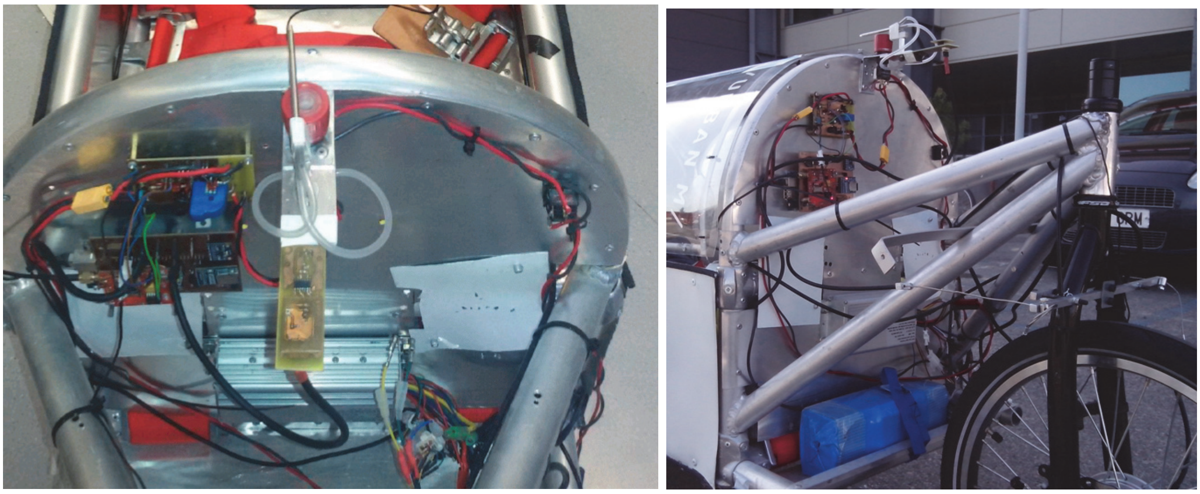

Figure 2. Electronic CPU and main sensors placed in the LEV.

Different driving strategies based on the data generated have been evaluated and the results have been selected which are more efficient and therefore increase the autonomy of the VE. A few examples are given on figure 3, 4 and 5.

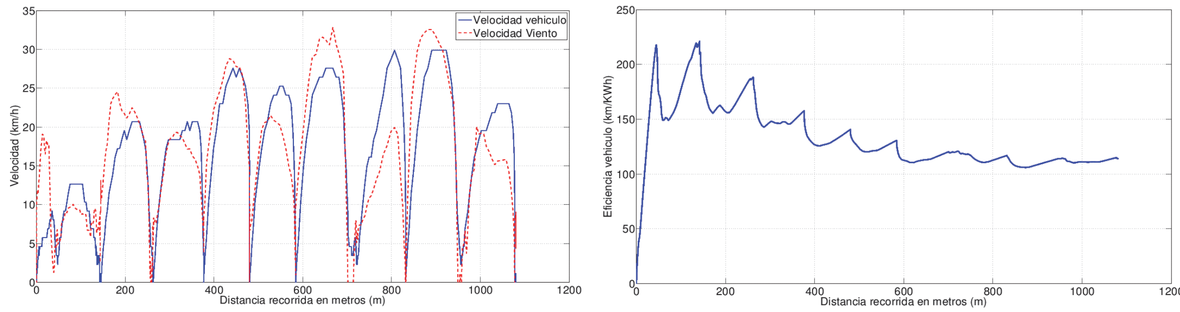

Figure 3: (Left) Speed of vehicle Vs Speed of wind. (Right) EV efficiency in different moments of a road test.

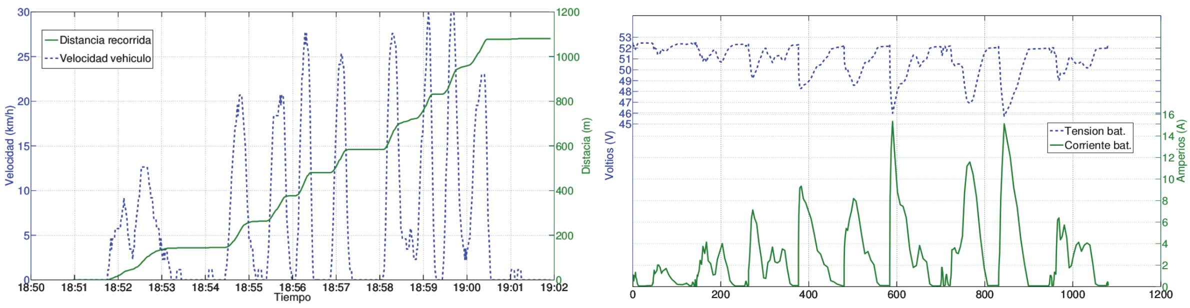

Figure 4: (Left) Speed of vehicle and distance travelled. (Right) Evolution of the current output and voltage of the battery of the vehicle.

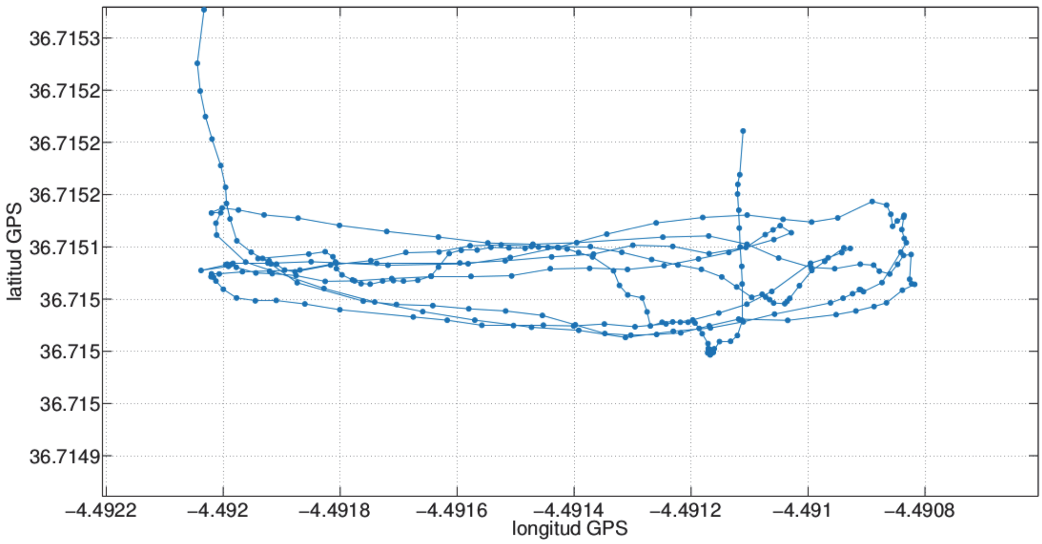

Figure 5: (Left) GPS location of the electric vehicle that is running in an oval track.

A software application has been built to receive all the information generated and sent though the GPRS communication channel to make it visible in a simple way, along with storing all of it and creating a log file with several graph options. See figure 6.

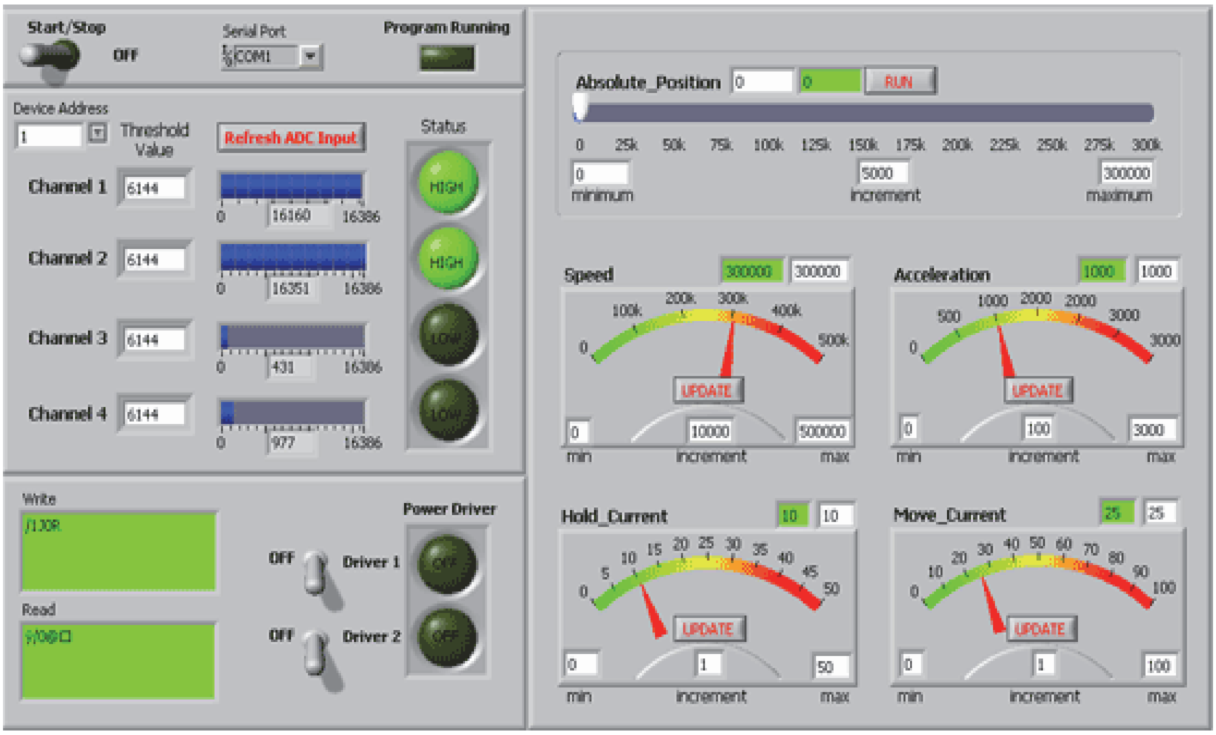

Figure 6. Overview of the data acquisition software application.

4 Self-adaptive route planning

With the purpose of getting the optimal route, the EV can connects to server and makes a planning order to go from A to B. This paper introduces a new method of generating routes that, at the same time, is being able to minimize the travel time of each user, avoiding traffic through dangerous areas of dense traffic, and adapting to the dynamism of today's cities [7]. LEVs users select their route in order to reduce the length of the trip and its urgency [8]. Based on these factors, we have developed a search algorithm for the shortest route to develop the system, using time as a feedback factor to reinforcement learning inspired by the Q-learning methodology [9] and designed for a multiuser network in which the learning process is accelerated.

The developed system consists of a local application, executed in an electronic CPU installed in the vehicle of the user, and a central server in which the general processing program and an associated database are executed. From the application, the user connects to the server and requests a route between a source point and a destination. This calculates the most suitable route according to the circumstances of each moment [10]. Likewise, the user, as it is circulating through the selected route or any other route, sends the server the time spent running through each segment of the path.

The server sends back the most suitable route according to the current environment's conditions obtained by the data collected within a Smart City environment: Goodness levels of segments of urban roads are updated in the database, considering time/day of the week in which they were gathered. The data base is checked when any other user order a new route, so the original path could be modified if previous users report problematic sections with large period of time or energy needed to complete them. See figure 3.

With these values of location and times sent by the users, the server adjusts the levels of goodness of each segment involved, represented these levels by what we call values 'Q'. These values are stored in the database, accessible only by the server, and classified in tables according to the time and day of the week. This information is available to calculate the best routes for future users.

The great advantage of this method compared to the current systems is the adaptation to the changes that occur in dynamic population nuclei. Thus, the system is allowed to recognize problematic sections by dense traffic, high concentration of pedestrians or other circumstances, as well as recommended sections for the absence of these same events at certain times of the day.

The simulation and experimental results show that, with few feedbacks, the system is able to interpret traffic-relevant incidents, allowing it to trace alternative routes to these conflicting stretches. The fact that they are multiple potential users that are able to collaborate in the updating of a common database allows to accelerate this process of learning. It has been proven that, once the Q values have been adjusted for all segments of the map, alternative routes allow the user to reach their destinations in less time. Moreover, through the simulations we have verified how the system also seeks the proper balance between length and unevenness accumulated in the route.

The system also attends the flows of journeys that occur at peak times, allowing a better organization of the traffic. Because the Q-values are separated in different segments that discriminate between time zones and days of the week, it is possible to detect when an event occurs in isolation at a particular time or time of day, and to plan the route accordingly. In this sense, routes on working days are not generated under the same considerations as others generated, for example, on holidays. In this way, structuring Q-values implies a longer learning process, but significantly more effective.

Figure 7. Basic route scenario

It is also worth highlighting the benefits of having chosen the time as a feedback parameter for the learning algorithm, since all events that may occur during the course of the route are a direct cause of variations in this factor. Through the consultation of time in each segment we know the ease to move through it. Apart from the simulated situations, any other circumstance of nature that is and that obstructs the circulation would have the same effect on the algorithm.

In short, the success of the results supports the feasibility of applying reinforcement learning techniques to route generation systems. This work opens the door to broad lines of future work centered on a possible real implementation of the algorithm on a much larger scale.

In order to verify the operation of the algorithm, three situations that could arise in a real map have been simulated in a limited node map around the Enginiering School of the Universidad de Málaga See figure 7.

In that scenario, it is assumed that a school is located on one of the tracks 12. It is expected, therefore, that the traffic of cars and pedestrians is much greater in this segment for the selected time zone. The purpose of the route generator user is to move from node N0 to node N12. See figure 8

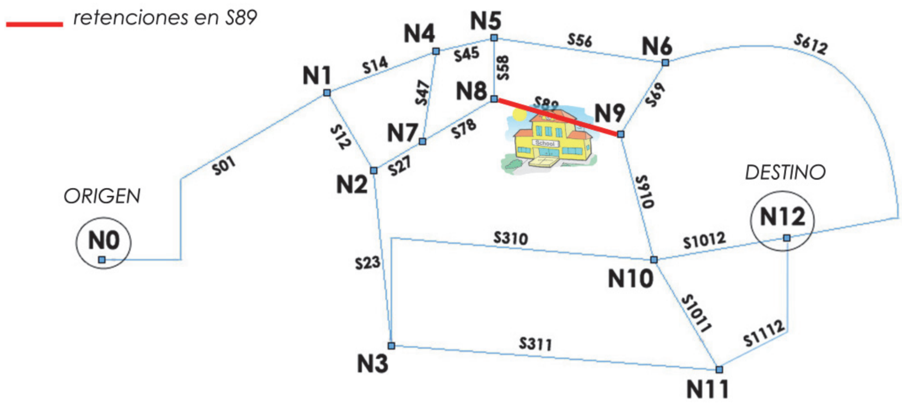

Figure 8. Simulation scenario 1, with the conflicting segment trough a school.

We run the generator with the Q values initialized to zero. The route obtained coincides with the shortest route (N0-N1-N2-N5-N7-N9-N10-N12) using the maximum allowed speed in each segment. As we see, the route passes through the segment S89 in which there was the conflict. The Q value corresponding to this segment is updated with a negative value after the end of the first transit. Also the average speed, originally 3 ud / s, is set at 2.7889 ud / s. The total time to travel from origin to destiny it has been 827s.

If other users run the route twice more. In the third execution the route recommendation changes. The Q value of S89 is negative enough for the generator to consider that it is better to take an alternate, longer but probably faster path. The path chosen in this case is N0-N1-N4-N5-N6-N12. We verify that it has been carried out in a total time of 779s, smaller than the previous route. See figure 9

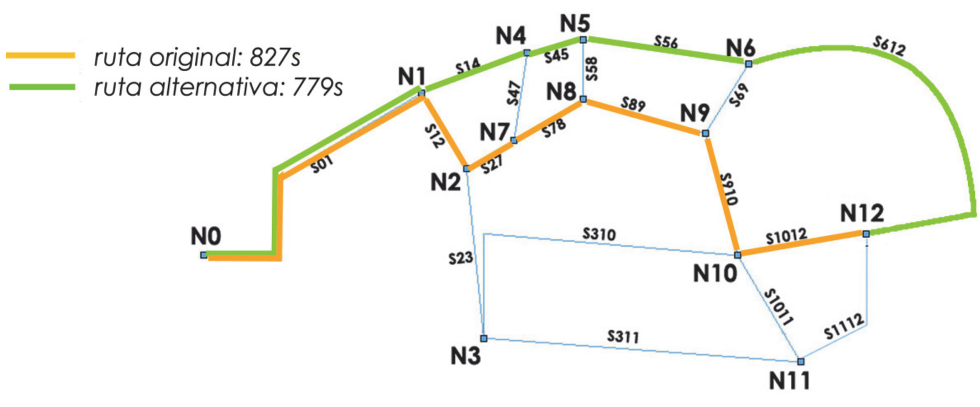

Figure 9. Summary of the changes that occurred in the case of simulation 1

Below is a second example we simulates a scenario with unevenness in its tracks. It is intended to illustrate the effect of this type of circumstance on the algorithm. The N0-N12 route is considered again and positive slopes are created in segments S14, S45, S56, S27, S78, and S89 and negative in S612 and S910. Figure 10 illustrates the slopes on the stage.

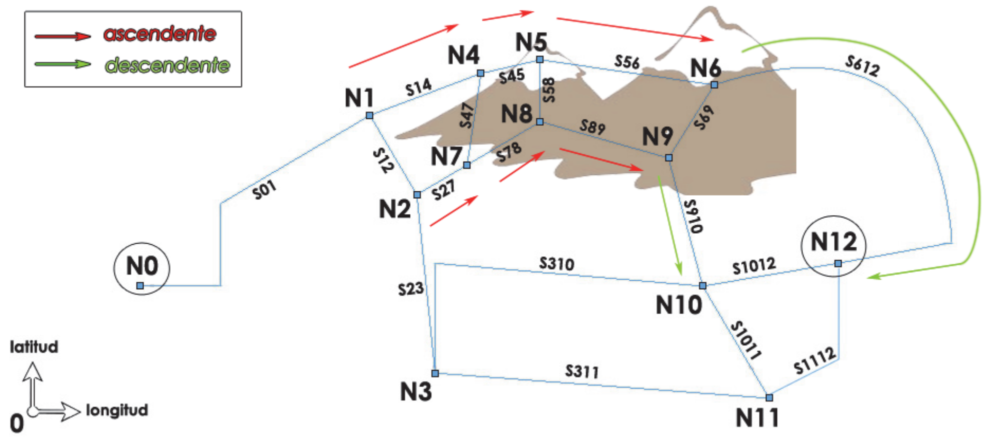

Figure 10. Simulation scenario 2, with unevenness in some of its tracks.

We run the generator on the Linux console with the Q values initialized to zero and the average speed to 3ud / s. As in the previous case, the route we obtain is N0-N1-N2-N7-N8-N9-N10-N12. During the follow-up of the route we observed that, as expected, the reward for segments S27, S78 and S89 is negative because the user runs uphill, and positive for S910 on the descent. The Q values of the mentioned segments are updated in accordance with the rewards obtained, and the average speed is reduced to 2.65 ud / s.

In the following executions, the system tests with different routes. It is from the sixth execution when the Q values have been adjusted in such a way that the algorithm is able to interpret the unevenness introduced in the map. Then the optimal route changes to N0-N1-N2-N3-N11-N12, as shown in Figure 18. We know that the user travels faster on this route as the average speed rises again. Also, the time taken to reach the target falls from 1,021 s to only 876 s thanks to the new route planning layout. See figure 11

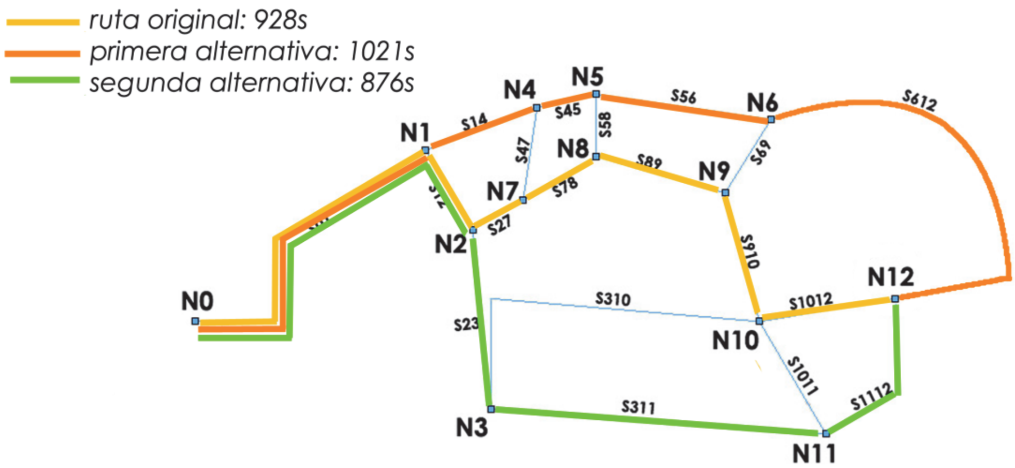

Figure 11. Summary of the changes that occurred in the simulation case 2.

Finally, a last case of simulation is exposed. This time there are different segments that are traveling at different speeds, and in turn, two users making different paths (N2-N11 and N3-N9 respectively) and updating the database simultaneously.

The program has been run with the Q values of the initialized database to zero. Each user has received his route, initially, taking care of the shortest path, and each one has contributed the corresponding feedback to the server that updates the database.

Once the Q values are adjusted accordingly to the situation reflected by the map, the system offers an alternative route to users 1 and 2, which, as we can see in Figures 12, is faster than the previous route.

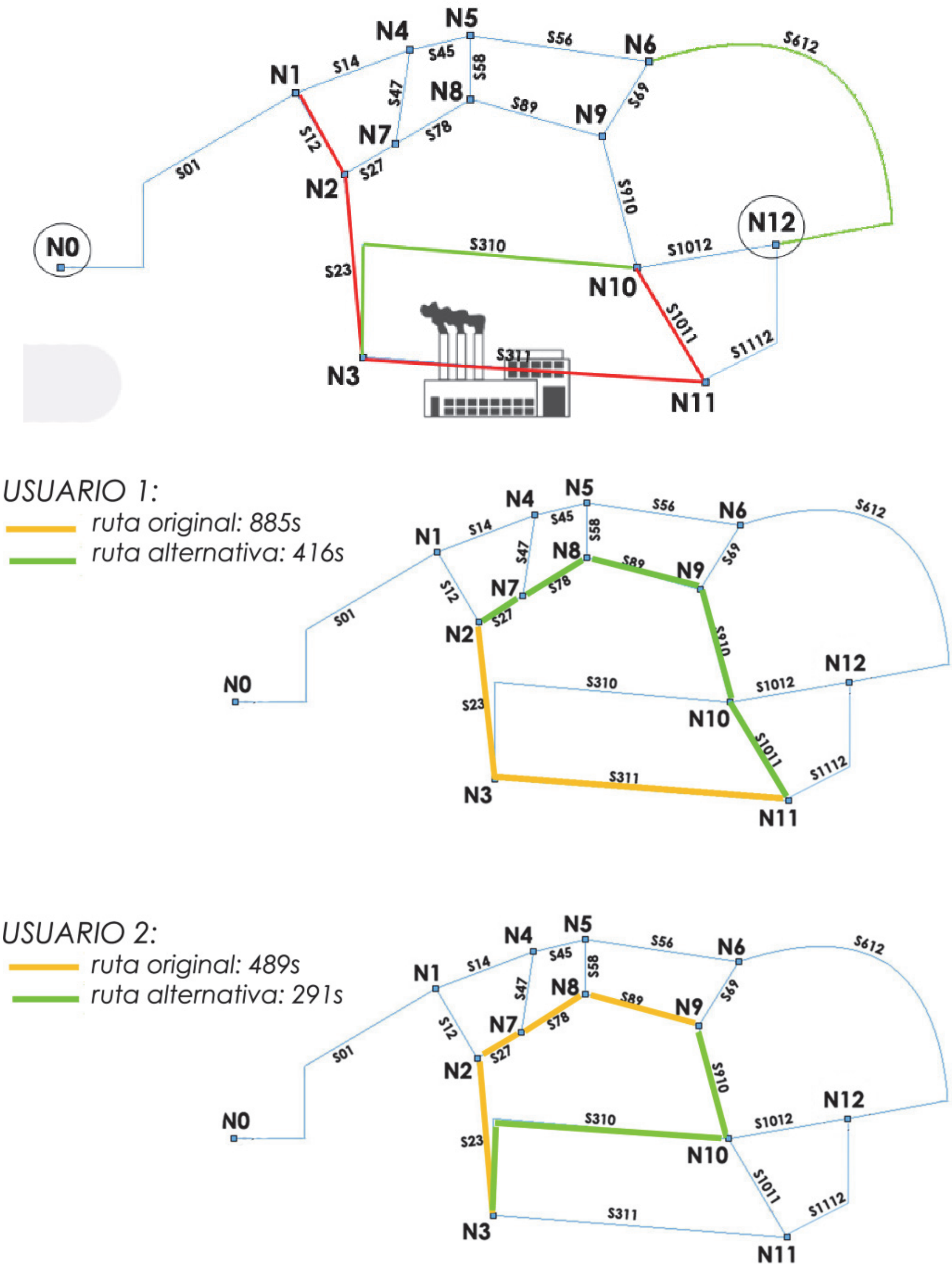

Figure 12. Summary of the changes that occurred in the simulation case 3 for both user 1 and 2 doing different routes but with trip nodes in common

5 Conclusions

We present the design and analysis low cost electronic architecture designed to improve efficiency and, therefore, optimize EV autonomy helping to adapt the driving mode depending on the conditions of the environment encountered on its way. This system can also connect itself to a Smart City control network, provide data of its trip and use information from other users to find the optimal route at any specific moment.

Acknowledgments

This work is part of an educational innovation project financed by the Universidad de Málaga within its programs 2013-2015 (PIE13-012) and 2015-2017 (PIE15-122)

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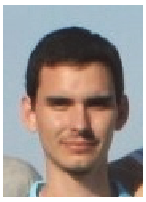

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