SMARTDECISION: A ROUTE CHOICE APP BASED ON ECO-FRIENDLY CRITERIA

Sérgio Ramos Pereira, MSc.
Research Assistant, Mechanical Engineering
University of Aveiro
Dept. Mechanical Engineering / Centre for Mechanical Technology and Automation (TEMA)
Campus Universitário de Santiago, 3810-193 Aveiro - Portugal
Phone: (+351) 234 370 830, Fax: (+351) 234 370 309,
E-mail: sergiofpereira@ua.pt
(corresponding author)

Tânia Fontes, PhD.
Post-Doctoral Researcher, Mechanical Engineering
University of Aveiro
Dept. Mechanical Engineering / Centre for Mechanical Technology and Automation (TEMA)
Campus Universitário de Santiago, 3810-193 Aveiro - Portugal
Phone: (+351) 234 370 830, Fax: (+351) 234 370 309,
E-mail: trfontes@yahoo.com

Jorge M. Bandeira, PhD.
Research Assistant, Mechanical Engineering
University of Aveiro
Dept. Mechanical Engineering / Centre for Mechanical Technology and Automation (TEMA)
Campus Universitário de Santiago, 3810-193 Aveiro - Portugal
Phone: (+351) 234 370 830, Fax: (+351) 234 370 309
E-mail: jorgebandeira@ua.pt

Paulo Fernandes, MSc.
PhD Student, Mechanical Engineering
University of Aveiro
Dept. Mechanical Engineering / Centre for Mechanical Technology and Automation (TEMA)
Campus Universitário de Santiago, 3810-193 Aveiro - Portugal
Phone: (+351) 234 370 830, Fax: (+351) 234 370 309
E-mail: paulo.fernandes@ua.pt

Margarida C. Coelho, PhD.
Assistant Professor, Mechanical Engineering
University of Aveiro
Dept. Mechanical Engineering / Centre for Mechanical Technology and Automation (TEMA)
Campus Universitário de Santiago, 3810-193 Aveiro - Portugal
Phone: (+351) 234 370 830, Fax: (+351) 234 370 309
E-mail: margarida.coelho@ua.pt

July 2014
Submitted for consideration for publication and presentation at the 94th Annual Meeting of the Transportation Research Board, January 11-15, 2015.

Total number of words: 5924 (text) + 6 (figures/tables) = 7424 words (Max 7500 words).

ABSTRACT

The main goal of this paper is to validate the SmartDecision app, a route-choice application which provides the best route between two points based not only in the conventional criteria parameters (as distance or time) but also taking into account the pollutant emissions and fuel consumption considering some vehicle characteristics and the route choice preferences of the user.

To perform this evaluation, emissions and travel time were analyzed in four different Origin-Destination (O/D) pairs. For this purpose, two GPS-equipped vehicles, which left the departure point at the same time and followed different trajectories, were used. The first vehicle followed the recommended route by Google Maps, and the second followed the indication of an eco-friendly route provided by the SmartDecision app. To estimate the emissions the EMEP/EEA methodology was used. In addition, the information collected in the Applications for the Environment Real-time Information Synthesis (AERIS) research program was used to monetize the emissions in one cost variable.

Using experimental data, it was found that the route defined by SmartDecision app can provide a 15%-32% reduction in health and social costs when compared with the recommended Google route. Despite this reduction, in only one case study, the route defined by the application presents a higher travel time when compared with the defined route by Google Maps (6%). Thus, this tool can be used not only as a solution to improve the fuel efficiency of road vehicles but also may contribute to reduce the pollutant emissions with relevant health and social impacts.

Keywords: Emissions, Route choice, Smartphone, Travel time.

1. INTRODUCTION AND OBJECTIVES

Since the 90s, the road transportation sector has been one of the main contributors of atmospheric emissions, especially in cities (e.g. hydrocarbons – HC, carbon monoxide - CO, nitrogen oxides - NO_X and particles matter - PM). To promote a more sustainable use of existing road infrastructures the implementation of eco-routing systems has been pointed out as a promising approach to minimize traffic impacts. Extensive research has been conducted assessing the potential and applicability of a correct route selection as a way for minimizing emissions.

In general all studies suggest that eco-trip assignment can lead to significant system emissions savings. Sugawara and Niemeier (*1*) developed an eco-assignment model which allow CO emissions savings over user equilibrium (UE) up to 25%. Similarly, Ahn & Rakha (*2*) found that is possible to minimize 7% in carbon dioxide (CO_2), 50% in CO, and 15% in NO_X over the traditional UE assignment. In addition, Frey et al (*3*) analyzed empirically several routes over different periods showing that is possible to minimize 24% of NO_X emissions if a driver selects an optimal path. Bandeira et al (*4*) corroborates this findings demonstrating that both during off peak and peak periods, the selection of an appropriate route can lead to significant emissions reduction: CO_2 up to 25%, and local pollutants (such as HC, CO, NO_X) up to 60%. Apparently route choice has shown to be more impact on local pollutants than CO_2 in fuel use (*2, 4*). Additionally several authors have recognized that often the optimal speed profile to minimize fuel use cannot be considered ecologically optimal due to increases in local pollutants emissions, such as CO and HC (*5, 6*). To overcome this trade-off, Gazis et al (*7*) proposed a set of different methods to identify the best eco-routes based on multiple pollutants present in traffic emissions namely in (i) economic cost, (ii) health and social impact, and (iii) atmospheric pollutant concentrations.

Usually the impact of route choice on emissions is performed by applying different categories of traffic-emissions models. Numerous case studies (*8-10*) applied emissions models based on average speed to estimate the emission impacts of eco-routing strategies. However, recently there has been a growing tendency to employ instantaneous emissions models to assess the influence of route choice in terms of emissions and fuel consumption (*3, 6-8, 10-16*).

A good deal of research has documented the importance of considering the vehicle type in the implementation of eco-routing systems. Using GPS data and Portable Emissions Measurements Systems (PEMS), Frey et al (*3*) have shown that both intra and inter vehicle variability are significant sources of overall variation in emission rates. Ahn & Rakha (*2*) have also demonstrated that the fleet composition should be cautiously examined before executing emissions-optimized assignments which is in line with Nie & Li (*17*) who have numerically demonstrated that vehicle characteristics influence path choice in eco-routing. Boriboonsomsin et al (*18*) introduced an eco-friendly route system comprised a historical and real-time traffic information and an energy/emissions operation parameter for a wide range of vehicles types and characteristics based on the Dijkstra algorithm. The validation of the system in a freeway route in Los Angeles (California) resulted in some errors in the trip fuel consumption and emissions estimation due to data aggregation, model inputs or emissions data base. In Anderson et al (*19*), an Eco-Tour system was developed to select different routes from a pre-defined Origin-Destination (O/D) based on time, distance and vehicular fuel consumption.

The academic research on the eco-routing along with the exponential growth of new communication technologies has brought new opportunities for people to be more informed about their impacts. Specifically, the integration of Intelligent Transportation Systems (ITS) with smartphones is becoming noteworthy. According with Gartner (*20*), for the first time, in 2013, the worldwide number of sold smartphones exceeded the number of feature phones. Furthermore, smartphones represent a growing of 42.3% related to the number of sales in the same period of the previous year. Thus, with this increasing popularity, new opportunities are emerging with regard to new applications in particular in the transportation sector.

Smartphone applications (apps) can simultaneously fulfill the roles of multiple existing technologies, as the common GPS devices (*21*). Some apps have been developed in order to indicate the most sustainable route for a certain purpose. Usually, the route is selected choosing some parameters such as travel time (some of them with real-time traffic), costs (fuel and/or tolls), and more recently the CO_2, which is directly related with the vehicle fuel consumption. Websites and smartphone application, such as hittheroad (*22*) and Transport Direct (*23*), enable users to plan a public transportation trip assessing their selected route in terms of CO_2 emissions reduction in comparison to undertake the same route in a car.

However, to the authors' best knowledge, existing eco-routing apps do not consider pollutants that having direct health and social impacts. Also the environmentally friendly route is commonly provided for a generic vehicle (or with basic information about the fuel type), in popular pre-trip information websites (e.g. via Google Maps, Bing Maps, Here, ViaMichelin) and on board information devices (e.g. TomTom, Garmin). These limitations are even more evident when implemented on smartphone apps. Therefore, this paper has two main objectives:

1) To introduce an eco-routing application architecture for smartphone;

2) To validate the results of the eco-routing application, by comparing the predicted results and observed results by modeling the real word driving cycles of routes recommended by a widely used routing software and routes recommended by the eco-routing application;

3) To include local pollutants assessment (responsible for human health and social impacts) in eco-routing applications.

The paper is organized as follows. Section 2 explains the development of the SmartDecision app focusing the methodology, both used in the SmartDecision app as in the case studies analysis, for the emissions estimation and the calculation of the environmental costs was presented. In Section 3 the case studies are presented. Analysis results are presented and discussed in Section 4. This paper finishes outlining the main conclusions in Section 5.

2. SMARTPHONE APPLICATION DEVELOPMENT

The SmartDecision is an application for Windows Phone 8$^+$ developed to determine an optimal route according to several optimization criteria. The user can choose between the options in order to minimize distance, travel time, vehicle fuel consumption or pollutant emissions (CO_2, HC, CO, NO_X and PM). Regarding to pollutant emissions minimization, it is possible to select one or a group of pollutants. In order to describe the overall application, section 2.1 presents the software architecture while section 2.2 describes the emissions estimation as well as the calculation of the environmental costs.

2.1 Software development

The application was written in C# and xmal using Visual Studio 2013 (*24*), which provides facilities for writing, testing and debugging Windows Phone applications, as well as the integration of an emulator of Windows Phone devices. The Windows Phone 8 Maps

Application Programming Interface (API) based on Nokia's cartography was used in the development. As this Maps API is different from the Bing Maps API available in Windows Phone 7/7.5, the application is only compatible with Windows Phone 8^+ devices. The SmartDecision app was tested in the Visual Studio emulator as well as in a Nokia Lumia 920 device.

In addition to the available criteria in the Maps API (minimize distance and time), other optimization route criteria were considered. The EMEP/EEA methodology was used to obtain the vehicle fuel consumption and pollutant emissions (CO_2, HC, CO, NO_X and PM) (*25*). The emission factors considered by the app are function of the vehicle type (European emission standard, fuel, engine capacity or weight) and speed. While the data related with the vehicle type is provided by the user, the predicted link-based average speed is given by the Windows Phone 8 Maps API. According to the location, link average speeds can be entered into the emission model using real-time data (if available) or assuming a constant predetermined value. The EMEP/EEA methodology is explained, with more detail, on section 2.2.

The application was organized using a three tier architecture: (i) data access, (ii) business model and (iii) graphical interface.

In the business model tier the emissions are estimated by pollutant and link using speed by applying the EMEP/EEA methodology. The required information to apply this methodology is stored in a local database, and its manipulation was made using the LINQ to SQL in the first tier. LINQ to SQL provides object-relational mapping capabilities that enable your managed app to use Language Integrated Query (LINQ) to communicate with a relational database. With this communication is possible to obtain the optimal route in terms of fuel consumption and pollutant emissions (CO_2, HC, CO, NO_X and PM) in order to be displayed in the graphical interface, taking into account the vehicle and route parameters selected by the user.

In the graphical interface the user can select several parameters. To configure that, it is recommended that the user accept the access and use of your location (only used to find the start point of the route). Following that, the user location is signalized with a dot in a map (that allowing the rotation and the pitch in/out). To start the app, the user needs to specify the vehicle characteristics: brand, model, category, year, and fuel type and engine capacity. The specifications of the vehicle must be specified only one time, nevertheless the user can store the characteristics of different vehicles. In the route menu some parameters can be chosen, such as the shortest travel time, the fastest route, the low-cost route, lower pollutant emissions. Figure 1 presents some configuration menus.

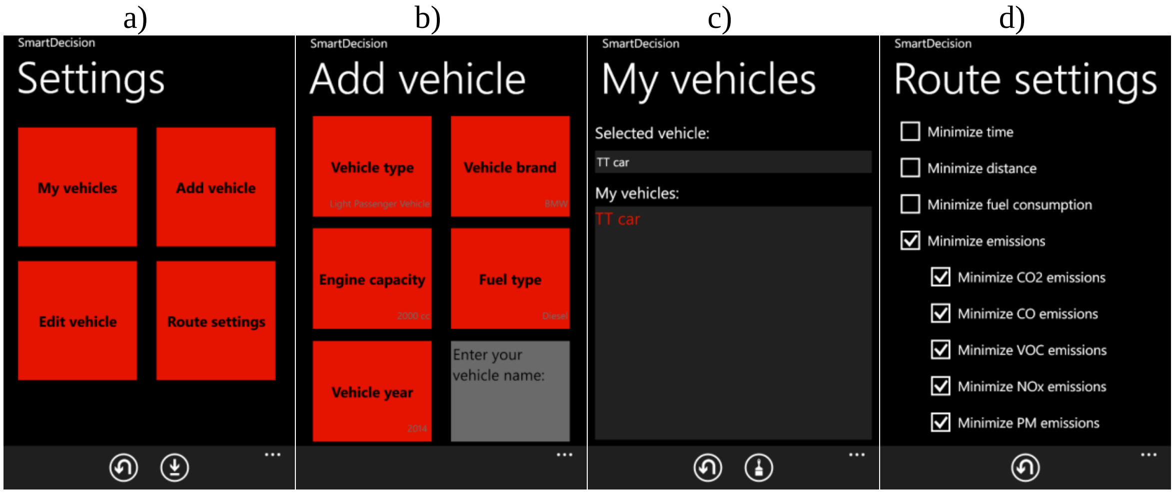


FIGURE 1 Representation of the settings (a), add vehicle (b), my vehicle (c) and route settings menus (d) of the SmartDecision app.

After these previous configurations (which must be performed at least one time, since then will be saved), the user can now input the destination. Considering all the inputs, the app will inform the user not only about the route but also the distance, time and fuel/emissions/ health and social impacts.

2.2 Emission modelling

The EMEP/EEA methodology (*25*) was used in the SmartDecision app to estimate pollutant emissions (CO_2, HC, CO, NO_X and PM) and fuel consumption. This methodology can be used with three different methods: Tier 1, Tier 2 and Tier 3. In the SmartDecision app Tier 3 was considered, since it is the most detailed and precise method when there is detailed information available (*25*). In such method, the exhaust emissions are calculated using a combination of technical data (such as emission factors) and activity data (such as travel distance). To obtain emission factors, several characteristics of the vehicle (European emission standard, fuel type, engine capacity or vehicle weight, speed) and the road are needed. The speed attributed by the Windows Phone 8 Maps API for each link is used to obtain road classes (rural, urban, highway) and to select the correct equation for the emission factor. In this case the speed obtained is an average value by link. The used equations as well as the values for the coefficients of these equations can be found elsewhere (*25*).

In the case of SmartDecision app, the average speed of each link is given by the Windows Phone 8 Maps API.

Previous research found that the optimization of different pollutants based on route choice can dictate different paths. Furthermore, the emissions impacts of different pollutants per unit of mass are not easily perceptible by drivers. In this context, the SmartDecision app allows that the impacts of each pollutant can be monetized by a common measure. Therefore, total emissions costs were monetized based on the information collected in the Applications for the Environment Real-time Information Synthesis (AERIS) research program who have presented a framework for conducting a benefit-cost analysis of real-time information systems (*26*). Although other methodologies can be used to quantify such impacts (e.g. as the Disability Adjusted Life Years – DALY (*27*)), in this app the main goal was to provide to the user a unique measure to integrate human health and social impacts of emissions (CO_2, HC, CO, NO_X and PM) in an easy way to understand. Regarding these considerations, the information collected by AERIS research program can be used to inform the user to the human health and social cost of the pollutant emissions in one variable. This approach applies different techniques based on social cost of carbon (for CO_2), social benefits (HC) and contingent valuation (CO, NO_X and PM). The monetary value changes over time in accordance with the source information's predicted values by year. In this app data from 2012 are used. This is as primary approach to ponder the health and social impacts of different pollutants using a common methodology regardless the driver's location. Further developments of the application must consider the real effect of each pollutant at a higher spatial resolution. The costs associated with each pollutant are: HC – 0.008271 $/g; CO – 0.00416 $/g; NO_X – 0.0248 $/g; PM – 0.2292 $/g and CO_2 – 0.00007 $/g (*26*).

3. SMARTDECISION APP TESTING

Several case studies were assessed by using a microscopic approach in order to compare emission estimations produced by following a route suggested by the SmartDecision app (RSD) with a route suggested by a conventional route planner software, Google Maps (RG), and assess to what extent the predicted link-based speeds considered by the SmartDecision app affect the quality of the emissions provided. Thus, section 3.1 introduces the case studies, section 3.2 the experimental procedure followed and section 3.3 the emission modelling approach.

3.1 Case studies

To identify the energy and emission impacts two different study domains located in Portuguese cities, Aveiro and Oporto were selected. Thus, four O/D pairs (two in each domain) were defined taking into account emblematic locations in the both cities. These two domains were selected in order to allow the choice of routes with different characteristics including a wide range of geometric configurations (arterials, freeways, and urban streets) and traffic conditions. The considered case studies were the following:

- Case study 1 (CS1) - located in Aveiro city, links the local exhibition center - A (in "Padaria" street) and the city center -B (in "São Sebastião" street);
- Case study 2 (CS2) - located in Aveiro city, connects the city center - B ("São Sebastião" street) with the local exhibition center - B (in "Padaria" street);
- Case study 3 (CS3) - located in the Oporto city, links the Casa da Musica exhibition hall - C (in "Ofélia Diogo da Costa" street) with the Dragão Football Stadium - D (in "Alameda das Antas" street);
- Case study 4 (CS4) - located in the Oporto city, connects the Dragão Football Stadium - D (in "Alameda das Antas" street) with "Nossa Senhora de Fátima" street – E.

Figure 2 outlines the routes suggested by SmartDecision app and Google Maps for each one of the case studies. In addition, Table 1 provides information of the case studies, namely the type of road, traffic data and total number of intersections with conflicting traffic and number of traffic lights and roundabouts.

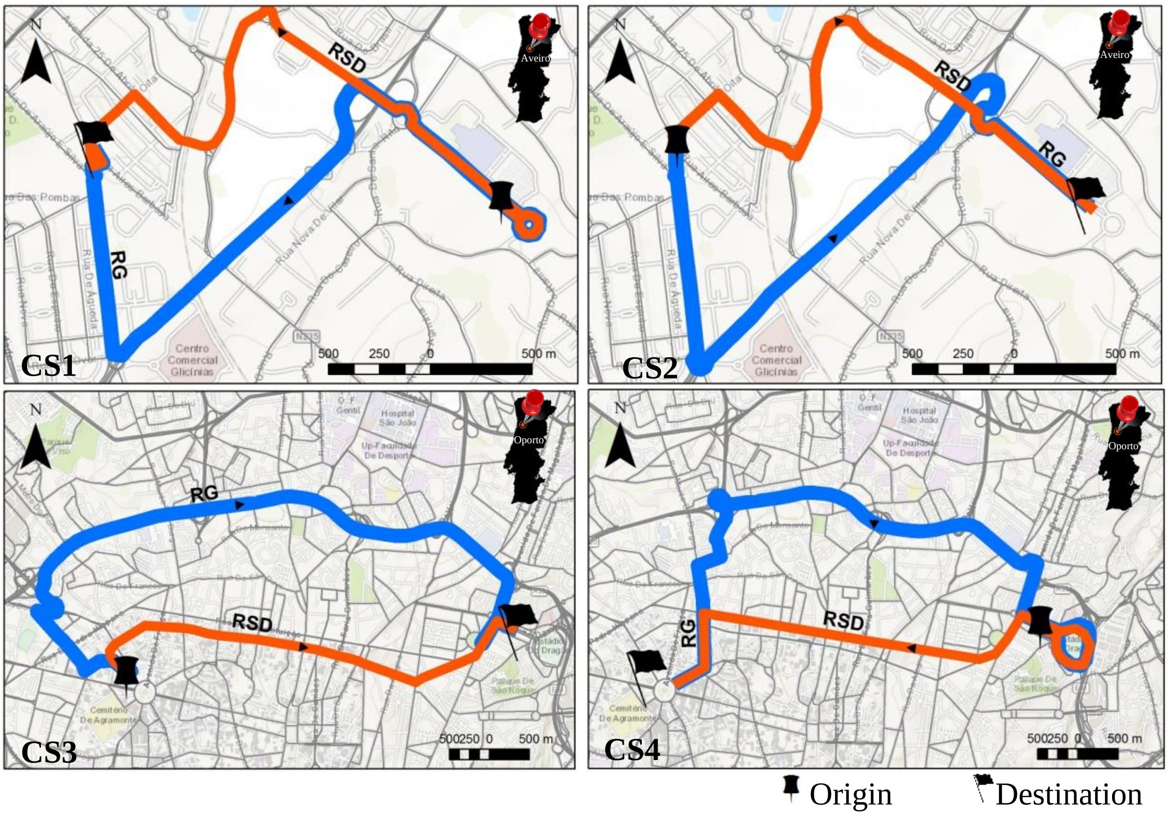


FIGURE 2 Routes suggested by the SmartDecision app (RSD) and by Google Maps (RG) for each one of the case studies.

TABLE 1 Generic information about each one of the case studies

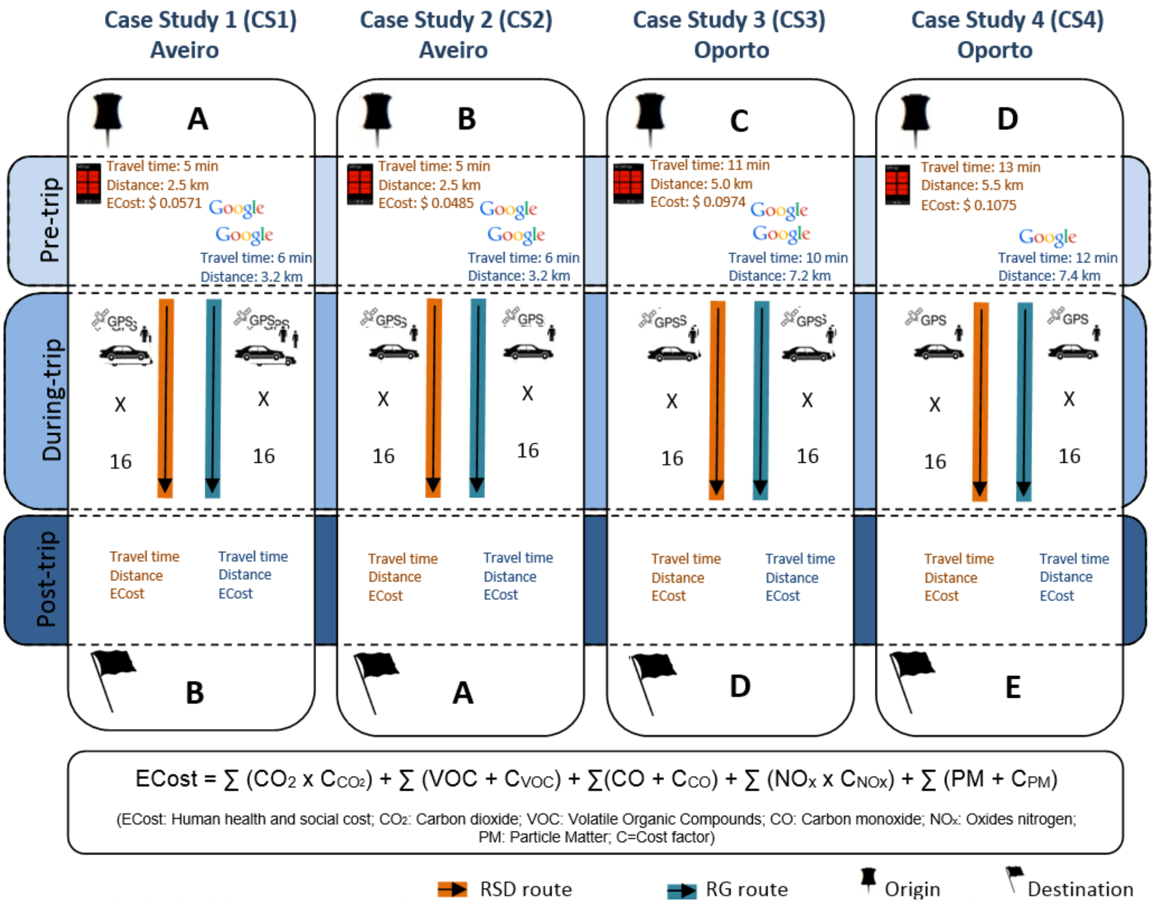
Case study	Route	Road type (km)			Max Average Daily Traffic	Intersections		
		Urban	Arterial	Motorway		N	Traffic lights	Roundabouts
CS1	RG	1.8	1.4	0	9240	6	1	4
	RSD	2.5	0	0	3820	7	1	3
CS2	RG	1.8	1.4	0	6390	6	1	3
	RSD	2.5	0	0	2745	7	1	2
CS3	RG	2.5	0	4.7	20000	28	9	1
	RSD	5.0	0	0	12848	32	18	0
CS4	RG	3.7	0	3.7	20000	36	10	1
	RSD	5.5	0	0	7533	41	17	0

3.2 Experimental setup

Although the developed application has the ability to use real-time speed data on each link, in the majority of the Portuguese road network this information is not yet available. Field experiments were performed in off-peak periods (10:00 a.m. – 5:00 p.m.) in order to analyze the inherent characteristics (typical speed profiles) of the routes without the influence of significant changes in traffic. Thus, to identify the energy and emission impacts of the routes suggested by the RSD and the RG, GPS second-by-second data were collected in each case study. The tests were performed during weekdays under dry weather conditions and using two similar light diesel passenger vehicles (LDPV), Toyota Auris 1.4 l with the same European emission standard (EURO V). To reduce systematic errors, three different drivers were used, each one performing an identical number of trips on each route. The drivers were composed of two men and one woman with ages between 26 and 34 years. Each one of the routes has been traveled 15 times. According to Turner et al (*28*) this sample size is predicted to allow a combination of confidence level higher than 95%

and an acceptable relative error lower than 10% taking into account the characteristics of the analyzed routes.

For all O/D pairs both vehicles departed simultaneously from the same starting point but following two different routes, i.e. one vehicle followed the route recommended by Google Maps, while the another traveled along the route recommended by the SmartDecision app. Each driver and vehicle traveled alternately along each route. Figure 3 outlines the pre-trip information (predicted travel time, distance and human health and social costs (in the case of RSD); the number of tests performed on each route, and the parameters analyzed post-trip (travel time, distance and human health and social cost caused by emissions), along the four analyzed O/D pairs.



Legend: A is the local exhibition center (in "Padaria" street); B is the city center (in "São Sebastião" street); C is the Casa da Musica exhibition hall (in "Ofélia Diogo da Costa" street); D is the Dragão Football Stadium (in "Alameda das Antas" street) and E is in the "Nossa Senhora de Fátima" street.

FIGURE 3 Overall methodology summarizing the pre-trip, during-trip and post-trip information analyzed for each case-study.

After the road field tests, total emissions and its respective costs produced on each route were estimated based on the second-by-second GPS speed data gathered during the experiments, in order to compare with the predicted data given by the routing application.

3.3 Emission modeling

The methodology used to compare routes, considering emissions and human health and social costs, is the same implemented by the SmartDecision app which is described on Section 2.2. Nevertheless, in the post-trip analysis the second-by-second speed recorded by GPS was used, instead of the average link speed by link given by Windows Phone 8 Maps API. In this case every stop is considered, since a second-by-second speed data are being used. The use of a second-by-second travel speed data allows the description, with high accuracy, of the traffic dynamics along routes with higher variability of speed patterns (e.g. high number of traffic lights) such as the case studies in the Oporto domain (CS3 and CS4).

This paper assumes that this emission methodology (*25*) has been already validated by previous research. In fact, the emissions factors considered by the app have been deduced on the basis of a large number of experimental data, i.e. vehicles which have been measured over a wide range of laboratories in Europe (*25*). Moreover, it should be highlighted that the uncertainty/degree of confidence of emission estimation will depend on the type of vehicle and pollutant evaluated. However, this subject is beyond the scope of this paper.

4. RESULTS AND DISCUSSION

Figure 4 presents the average travel time and speed during the travels in each recommended route (by Google Maps and SmartDecision app) in each one of the four case studies.

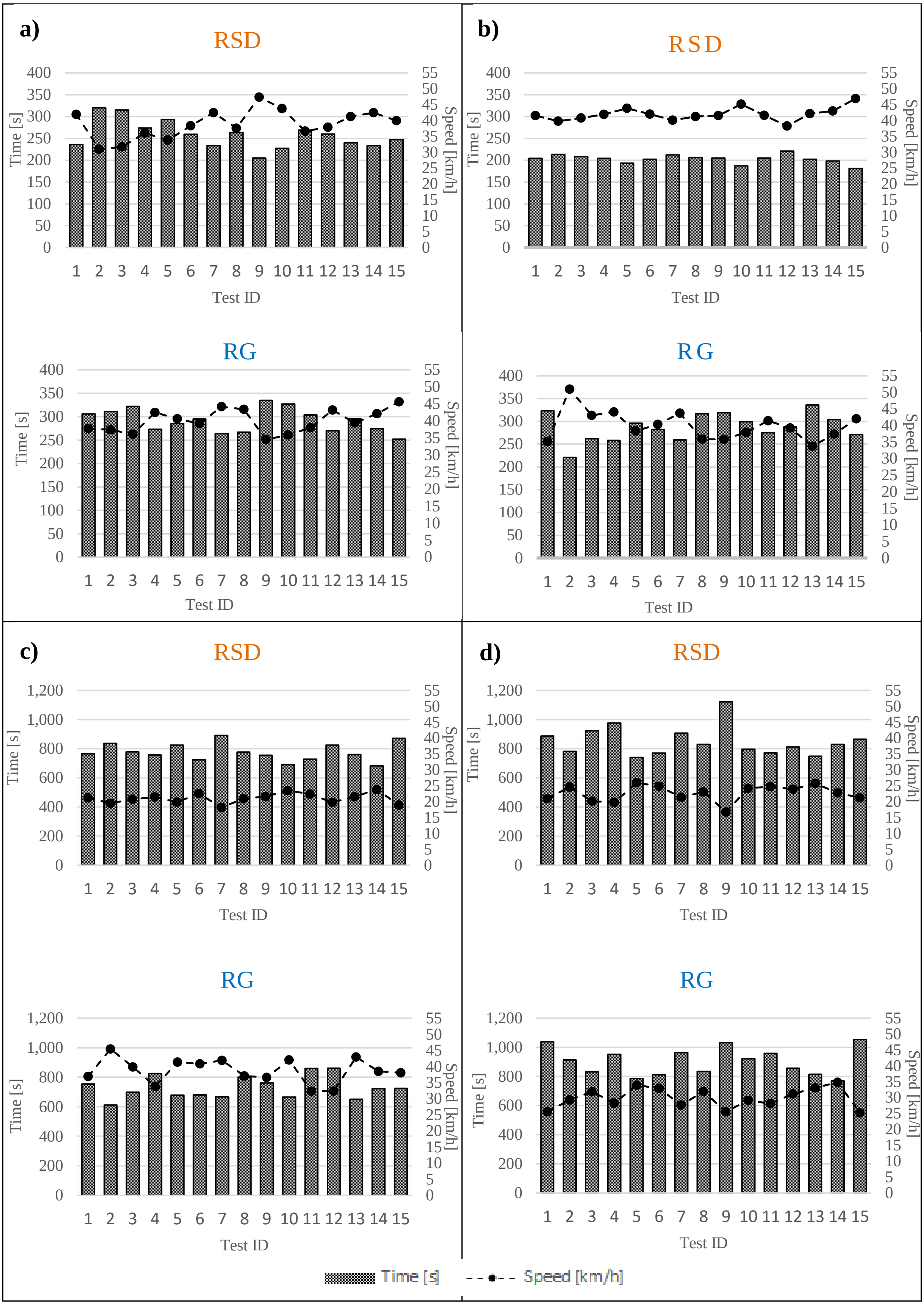


FIGURE 4 Observed travel time (s) and average speed (km/h) during experimental tests in CS1 (a), CS2 (b), CS3 (c) and CS4 (d), for the routes suggested by Google Maps (RG) and SmartDecision app (RSD).

In first case study (Figure 4.a), the average measured travel time in the RSD was 258 ± 31 s, which represents 14 % less than the pre-trip time indicated by the SmartDecision app (see Figure 3). These differences are explained by the fact that in this case study the SmartDecision app does not had the real-time average speed on each link. Although there is no big difference in the travel time among the three drivers (the higher coefficient of variability (CV) was 0.12), the data collected for each driver is not sufficient to reach a conclusion that the driving patterns do not influence. Nevertheless, the same situation is observed in RG, when the average measured travel time was 291 ± 25 s and the information given by Google Map before the trip represent 19% more in travel time. Despite RSD presents a 3% lower average speed than RG (38.8 ± 4 km/h vs 40.1 ± 3 km/h), the average travel time was 11% lower in CS1.

Likewise, in the CS2 routes (Figure 4.b), the travel time values measured in RSD were 30% lower than RG. Nonetheless in this case the average recorded speed in RSD (42.0 ± 2 km/h) was 6% higher than the collected in RG (39.8 ± 4 km/h). The travel time predicted by Google Maps was 25% higher than the collected in experimental fields (288 ± 30 s). On the other hand, the observed average time to cover the RSD was 203 ± 10 s which is 33% higher than the information obtained before the trip. In this route the traffic is relatively constant, since the standard deviation for the average speed and travel time was 50 % and 67 % lower, respectively, than in the RG. Although in CS2, both RSD and RG routes only have one traffic light, their mode of operation is distinct. In RSD, the signal is green or is blinking, so when there is small traffic volumes, the vehicle does not stop at the traffic signal which reduces their travel time. In contrast, in the RG, the traffic light is often red. In addition, the RG is 28% longer than RSD, which explains the difference in measured travel times.

In CS3, in Oporto study domain, the RG (with 720 ± 86 s) showed 6% lower travel time than the time observed in RSD (768 ± 70 s). This is the only case study examined where the route recommended by Google Maps presents less average travel time than the route recommended by the SmartDecision app. This difference is justified with the average speed of the routes. Despite this, the RG is 44% longer than RSD and 65% of its length is conducted in a motorway which allows increase the average speed of this route (21.3 ± 2 km/h). The RG average speed is 84% higher than the RSD.

Regarding the CS4, some similarities are observed with the previous case studies. Although this case study was conducted in the same domain than CS3 (Oporto), in this case, a similarity with the one recorded in Aveiro domain were observed. RSD recorded an average travel time 6% lower than the RG (896 ± 96 s). It happens because RG is 35% longer (see Table 1 and Figure 3). However 50% of its length is performed in motorway, so the average travel time is higher than in RSD. Notwithstanding the evidence, the average measured speed is 32% higher in RG (30.1 ± 3 km/h) than in RSD (22.8 ± 3 km/h).

The results presented in Figure 4 demonstrated that there is no substantial differences in the measured travel time in each case study. In summary, there is no substantial variation in travel time along the trips in each case study and on each one of the routes (the higher CV was 0.12 in the CS4 for RSD). Note that in the Aveiro study domain, the collected travel time were 14-32% lower than those given by Google Maps and the SmartDecision app. On the other hand, in the Oporto study domain, the collected travel time were 8-24% higher than those obtained by the two platforms before the trip. The high number of traffic lights and the intensity of traffic contributes to these results. The Google Maps and SmartDecision app (since it is based on Nokia's cartography) allows to access at real-time traffic information's. For Portugal this information is very limited and only available for freeways and major urban centers. The majority of the areas under study do not include such information.”Thus the differences in travel time are justifiable. In the case of Aveiro study domain, the low intensity of traffic (see Table 1) allows lower travel time. In the Oporto study domain, the intensive traffic flow (see Table 1) along with the presence of illegal parking on urban roads leads to higher travel time than the predicted pre-trip information. In the urban section of the Oporto study domain is common to find incidents, namely, vehicles parked in the second row that affect the travel time and consequently the average speed.

However, in order to assess the route provided by the SmartDecision app (route given in terms of human health and social costs), the human health and social costs will be analyzed taking into account the data collected for the RSD and RG (with the post-trip data). Figure 5 shows the human health and social costs for each one of the case studies, taking into account the data collected for the different routes.

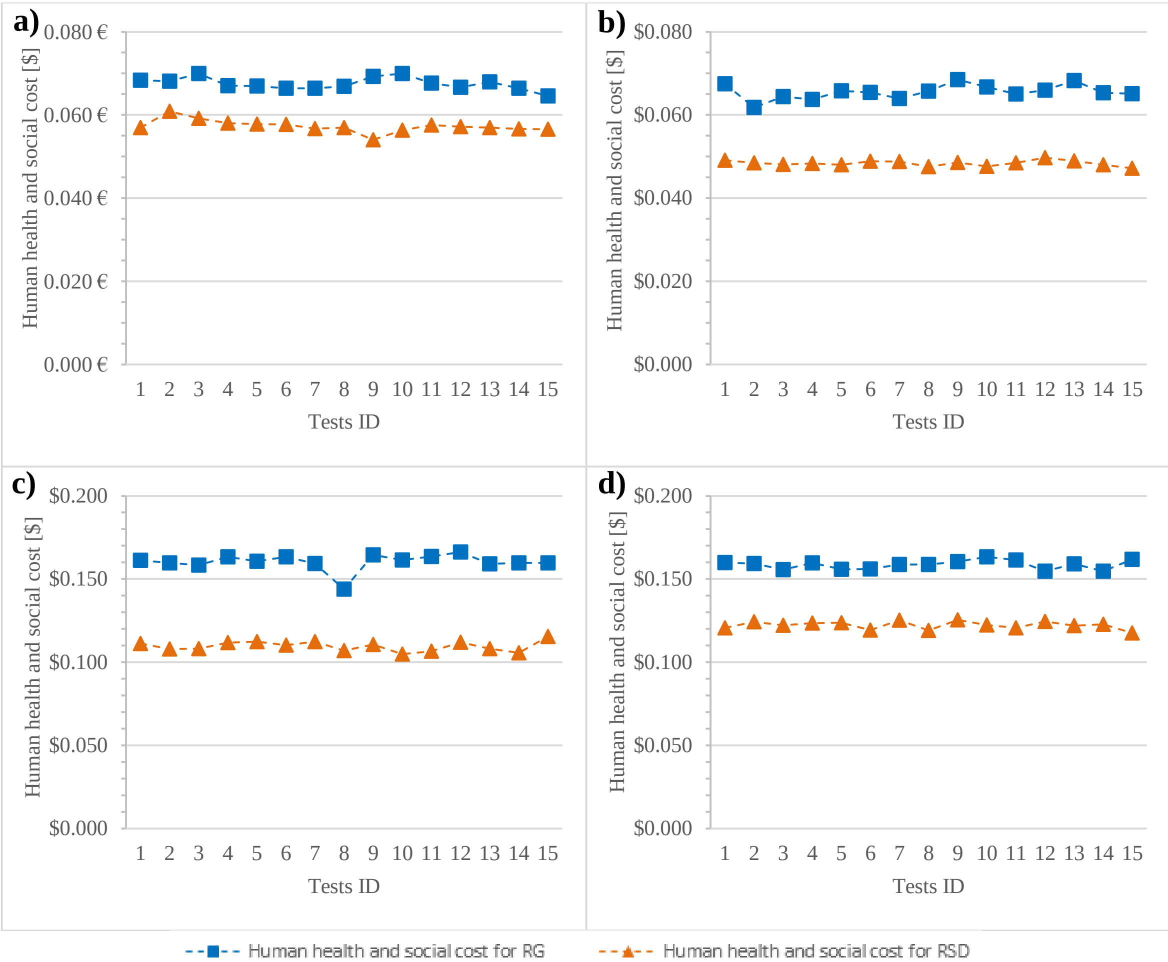


FIGURE 5 Human health and social costs during the travels in CS1 (a), CS2 (b), CS3 (c) and CS4 (d), for the routes suggested by Google Maps and SmartDecision app.

Taking into account the four analyzed case studies, the routes recommended by SmartDecision app shows consistently lower human health and social costs (see Figure 5). A first analysis demonstrates that for both study domains the SmartDecision app is correct when the selected criterion for route choice is “aggregate pollutants”, compared to the route recommended by Google Maps. A detailed analysis of these results shows that, as it happens with the travel times and the average speeds, the human health and social costs also have little fluctuations during the performed tests. In the Aveiro study domain, the RSD allowed human health and social costs to be reduced by15% and 26%, respectively for CS1 and CS2. The average human health and social cost for RSD was \$0.057 ± 0.001 in CS1 and \$0.048 ± 0.001 in CS2. On the other hand, in Oporto study domain, the average human health and social cost for RSD was \$0.110 ± 0.003 and \$0.122 ± 0.002 for CS3 and CS4, respectively. In CS3, the RSD presented 32% less human health and social average costs than the RG. Similar situation was verified in CS4, when RSD showed 23% less human health and social average costs than the RG.

Regarding the pre-trip information given by the SmartDecision app about human health and social costs, only in the CS1 and CS2 similar results were observed (difference lower than 1%). In the Oporto study domain, the human health and social cost given by SmartDecision app during the pre-trip information was 11% and 14% lower than the Google Maps platform for CS3 and CS4 respectively. This application also predicted a lower travel time and so for that a higher average speed than the measured values. The speed where the vehicle has lower fuel consumption and emissions is 65-70 km/h. Accordingly, the average speed value considered by the SmartDecision app is close to this ideal value, then the emissions and consequently the human health and social costs were lower than the measured values, during the field tests.

The shortest travel distance enables that the RSD has lower human health and social costs. Note that the emission factors in the RG are lower than in the RSD, since their average speeds are closer to optimal ones (65-70 km/h). However, the difference in the travel distance causes that in all case studies the costs are always lower in RSD.

5. CONCLUSIONS

In this paper, a smartphone application (SmartDecision app) for Windows Phone 8^+ was presented. This app, developed in a three tier architecture (data access, business model and graphical interface), allows the choice of different criteria for route selection. Besides the common criteria available in other route choice platforms (usually based on the minimization of distance and/or time) other optimization route criteria were included in SmartDecision app (such as the minimization of vehicle fuel consumption and/or pollutant emissions). To perform these estimates, the EMEP/EEA methodology was used as well as the information regarding human health and social costs to aggregate different pollutants.

Regarding the travel time, there is no substantial variation along the different travels in each case study and on each one of the routes (the higher CV was 0.12 in the CS4 for RSD). In Aveiro study domain the measured average travel time was 14-32 % lower than the pre-trip information. On the other hand, in the Oporto domain, due to the illegal parking on urban roads and the intensity of traffic the measured average travel time was 8-24 % higher than the pre-trip information.

The route recommended by SmartDecision app always presents lower values of human health and social costs lower (15-33%) than the route recommended by Google Maps. However, in terms of human health and social costs, just in one of the study domains (Aveiro), the predicted values by SmartDecision app before the trip were similar to the collected results (with a difference lower than 1%). On the other hand, in the Oporto study domain, the collected values for human health and social costs were higher (11-13%) than the pre-trip information given by SmartDecision app.

Despite in this paper the SmartDecision app has been used with the main aim of minimizing the aggregated pollutants, it allows the selection of other route choice parameters, such as to minimize the fuel consumption. This application has high potential for practical application as well as their actual utility for the user. Nevertheless SmartDecision app results were only validated for four case studies. In this context, as future work it should be evaluated in other countries with real-time traffic information, especially in areas with high congestion levels. In addition, other methodologies considering other parameters such as acceleration (e.g. the Vehicle Specific Power) can be used to estimate the vehicle pollutant emissions and fuel consumption, in order to analyze the collected data with higher detail.

ACKOWLEDGEMENTS

This work was supported by FCT (Portugal) under the R&D projects PTDC/SEN-TRA/122114/2010, PTDC/SEN-TRA/115117/2009 and to Strategic Project PEst-C/EME/UI0481/2014. The authors also acknowledge to Toyota Caetano Portugal, which allowed the use of vehicles. P. Fernandes acknowledges the support of FCT for the Scholarship SFRH/BD/87402/2012.

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