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ELECTRIC VEHICLE ROUTE RECOMMENDER SYSTEM

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Abstract: This paper presents a recommender system responsible for processing information that will help the driver in the daily use of his Electric Vehicle (EV), minimizing the problem of range anxiety through a personalized range prediction and by presenting in real time relevant information about the charging stations that can be reached within the range autonomy. Given the success of recommendation systems on automatic delivery of relevant information in numerous areas of usage, this type of systems can also be applied in the electric mobility scenario, with the objective of maximizing the relevance of the information presented to the driver, which should be the strictly needed data for the driver to make important decisions, filtering out the unnecessary information.

1. INTRODUCTION

Aiming the electric mobility in Smart Grids (SG), mainly electric vehicles and the driver habits, in this paper is proposed a recommendation system that aims to present to the users the recommended charging point according to their preferences, with their usual choices and according to the data collected from public transportation, traffic information and charging places. The recommendation system is also used to present to the user sites and services near of the charging point or typical services associated with mobility in large urban areas. The system communicates with the vehicle system to obtain information of the battery status and the range prediction estimation (Ferreira, 2010). The integration of information recommendation systems with information of the Smart Grids energy systems in conjunction with the interface with the EV allows deliver alerts to the driver during the normal vehicle use. Control the vehicle's range and indicating the nearest point of charging through geographical positioning information, use the user profile to indicate the direction of the planned route, loading preferences between fast or slow charge, identifying the proximity to public transportation scheme, are the main objectives of the proposed recommendation system. The system provides to the driver several points of interest (e.g. loading points, interface with public transport, parking lots with charging or tourist areas of interest), based on a recommendation system, based on the profile and the preferences of the driver. The system will target a mobile device that may be a Personal Data Assistant (PDA) or a device integrated into the EV, taking into account the specifics of these devices which have advantages such as mobility and integration with geographic positioning systems and disadvantages such as limitation of processing capacity and size of the graphic interface.

2. RECOMENDER ENGINE AND SYSTEM

Given the success of recommendation systems in automatically delivering the relevant information in numerous areas of usage, it can be applied in this scenario as well, with the objective of maximizing the relevance of the information presented to the driver, which should be the strictly needed for him/her to make decisions, filtering out the unnecessary one.

Based on the available information (charging points, traffic and public transportation information, and EV range autonomy), the recommendation system will choose (recommend) the 'right' information, based on user pre-defined preferences expressed in their profile. This system uses *n* dimensions to calculate utility function (information relevance measurement) for all input information: user D_1, information D_2 and context D_3. A diversity of recommendations is displayed. So, a recommended function has a new dimension *d* (means context), and is a three dimensional vector *u* (user, item, and context), see Figure 1:

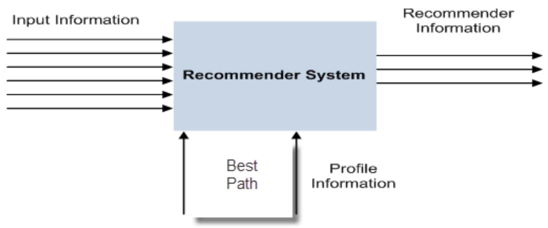

Figure 1: Overview of the Recommender System.

Input Information: Is the available information and represents charging places and other information related to EV driver.

Best Path: Is the algorithm implemented to define the best travel to be performed.

Driver Profile: Represents past user options in a three dimensional matrix based on selected information. In our implementation this field has only two values: value 1 represents a user choice, and value 0 signifies user disagreement. It is used to improve recommender system performance, based on the fact that user preferences change based on the context. For example, in a tourism recommender system, the year period changes the user's preferences, among others. Several authors, (Gediminas, 2005) and (Tuzhilin, 2001), suggest that context information is used based on a bi-dimensional space, (User, Information), in a multidimensional matrix, *u* (utility): $u{:}D_1 \mathrm{x} D_2 \mathrm{x} \ldots D_n \rightarrow R$. Each *D* dimension is represented by an information vector and the algorithm to find the best tuple (*d1*,…,*dn*), that maximizes the utility function (Gediminas, 2005). Our implementation uses as context information based on four main types:

(1) function mode: "leisure" or "direct";

(2) day period: "morning", "afternoon" or "night";

(3) destination: "home" or "work";

(4) trip status: "starting" "middle" or "ending".

This information is stored on information repository and is obtained by interaction with the driver, (1) plus (3), and (2) plus (4), by the system based on pre-defined rules. So, day period is pre-defined on system, morning is until 12 am, afternoon from 12 am to 19 pm, and night in the remaining hours. Trip status is based on target distance, the first 25% km is considered starting and the last 25% km are considered ending.

Recommender Information: Generates new system output information, ordered by a utility function. In this pre-release phase the proposed system takes care of the charging point.

Each information type is represented by a vector, with class values. The PCSs (Public Charging Stations) are based on:

- Charging Modes: Slow, Fast;
- Operator: "MOBI.E", "Better-Place", "EDP";
- Location Type: "Street", "Small Station" and "Big Station";
- Services: "Without Services", "Reservation", "Washing Services" and "Others":
- Public Transportation Interface: "1","0";
- Nearby Points of Interest (POI): "1","0" – only if operator mode is on travel mode.

Utility (*u*) Calculation

User recommendation is based on utility function (*u*), where only three items are showed to the user (this is a configurable parameter). After distance measure is introduced (Manhattan distance, others could be implemented), it is calculated the utility based on context information, for each piece of input information, item I_i: $I_i = \{I_{1i}, I_{2i}, I_{3i}, I_{4i}, C_{1i}, C_{2i}, C_{3i}\}$. Where $\{I_{1i}, I_{2i}, I_{3i}, I_{4i}\}$ are the characteristics of input information I_i and $\{C_{1i}, C_{2i}, C_{3i}\}$ are the context characteristics.

The utility function is based on the nearest neighbor algorithm, see Figure 2, where it includes context and distance function. For details see (Pereira, 2010).

μ = utility; α = distance; c = user; S = selected items (candidates); d = context

H = context list (past data); $R(\mu, item)$ = list of items with u measure

1. Start $R(\mu, item) = \{\}$
   1.1. For each S item:
      1.1.1. Add context information = $S(i) + d$
      1.1.2. Start $\mu = 0$
         1.1.2.1. For each H item:
            1.1.2.1.1. Calcule distance α to $H(i)$
            1.1.2.1.2. Calcule $\mu' = \begin{cases} 1 \text{ se } \alpha = 0 \\ \frac{1}{d} \text{ se } \alpha \neq 0 \end{cases}$
            1.1.2.1.3. If $\mu' > \mu$ then $\mu = \mu'$
      1.1.3. Insert $(\mu, item)$ in R
2. Sort R from highest value to the lowest
3. Return three highest elements of R

Figure 2: Nearest Neighbour Algorithm used to calculate the function utility.

3. DRIVER PROFILE

Initial driver profile is manually created by the driver, with the following information (Table 1):

Table 1: Driver profile of an Electric Vehicle (EV).

Propriety	Description
User login information	User name and password
Home Address	GPS position of home address
Work Address	GPS position of Drivers work
Car Information	Model, Year, Battery type and power
Trip information	Work days or week-end + holidays, start time, finish time, distance (km), SOC level

This profile, later receives information about driver trip (time, duration and km travelled) from the tracking system. A resume of EV parameters (speed, SOC level, travelled distance) is also stored and associated with this profile for later range prediction.

Driving range (see section 4) is intensively related to the driving style or mode. This happens in all types of vehicles, but on EV, due to the weakness related to the amount of energy stored on-board, this relation is much clearer. Thus, changing driving style and driving habits may be a considerable factor on energy saving and on extending vehicle autonomy. Considering the actions or driving habits that can bring significant energy saving to the vehicle operation, it is important to evaluate how receptive EV drivers will be in changing their driving style and driving habits towards the achievement of the intended energy saving. The study of this receptivity for change will be addressed through a set of surveys made over a group of potential EV drivers with different profiles, from gender, age, education, job, etc. These surveys will allow the identification of correlations between the driver profile and new driving habits. Under these surveys another factor that will be evaluated relates with the acceptance for automated actions performed by the vehicle control system. This type of actions may be accepted for some of the driving process but not for all driving process. For example, one driver may accept the vehicle control system to automatically turn off the air-conditioning under certain conditions, but will not accept the system to limit his driving speed. Part of this study will create and store for further analysis a Driving Profile. Driver profiles will play an important role to determine the EV range, since range prediction will be based on the assessment of the drivers' usual behaviour. An initial Driver profile can be identified by the system, after being created manually by the driver with the information presented in Table 1.

Part of this driver profile will be based on a tracking application running on a driver's mobile device. This application will update driver profile with travel distances, time and SOC levels, weather information, etc. as showed in Figure 3.

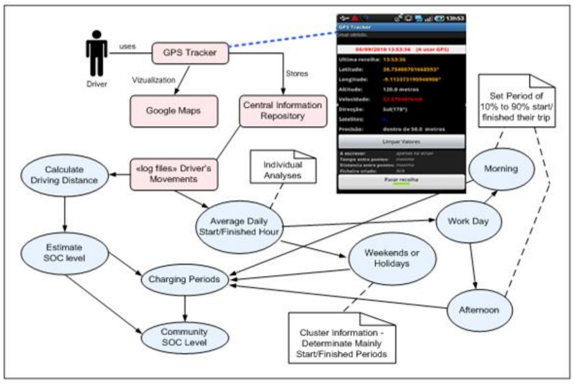

Figure 3: Main module of the driver's tracking system in a mobile device with GPS and with information created from the Drivers Movements database.

4. RANGE PREDICTION

Range prediction is the process of estimation the EV range based on three main dependency types:

1) The EV with its main variables: the model of the vehicle (mainly its performance under different scenarios, speed, and acceleration), the chemical technology of the batteries (as lithium-iron-phosphate, lithium-titanate, or nickel-metal-hidride) the batteries characteristics (mainly, variation of SOC, temperature, lifespan, performance, specific power, specific energy, and safety), and the EV powertrain (electric motor and its power converter, as well as the other electric parts, as batteries charger, controllers, and power cables). This data is stored on an information repository on a central server. All of these parts will influence the SOC and consequently the range prediction. The batteries SOC, and other relevant parameters, are provided to the main control system through CAN-bus communication, and then these information's are stored in a data base (DB), in order to predict the available range.

2) The driver behavior: speed and acceleration information are taken from EV through the CAN-bus communication, and the driver past behavior

(e.g., SOC level versus travelled distance achieved), are stored in a DB. Weight is a manual input, and driving directions are acquired based on the GPS information.

3) Environment: current location, traffic conditions (taken from a web service), road information (in a distance graph), weather information (wind and temperature, taken from a web service), and altitude, taken from GPS.

The range prediction procedure is in a first step based on the batteries SOC level, and using driving behavior (relation of SOC level versus travelled distance achieved, from past experience, stored in a central information repository). This distance is tuned based on weather information: if it is hot, a percentage of the energy stored in the batteries is taken for air-conditioning; if it is raining, a percentage of energy is taken for the window cleaning process. For night drive, also a percentage of energy is taken for light services. A web service brings traffic information, and based on past experience (e.g., information about driving times and traffic information), a driving range is predicted. Current driving behavior (e.g., driving speed and accelerations) are taking into account in this process. Once it is achieved the EV range estimation, it is started the calculation of the possible reachable points based on current position.

Most of these estimation processes were performed based on simple heuristics (Ferreira, 2010). For example, if the weight is above a configurable threshold, a percentage of reduction is applied on the range (this value should be tuned from past experience data and depending on EV parameters). Also altitude was taken into consideration, using Google maps to obtain the altimetry of the desirable path, again several levels were configured, and also is applied a percentage of reduction in the range, in function of the altitudes to overcome in the path. Temperature is an important parameter, because of the relation with air-conditioning. The temperature was divided in five classes range: (1) less than 5ºC; (2) from 5ºC to 15ºC; (3) from 15ºC to 25ºC; (4) from 25ºC to 30ºC; and (5) above 30ºC. For classes 1 and 5 it was assumed that all drivers use air-conditioning, for class 3 no usage is performed, and for classes 2 and 4 it is considered that a percentage of drivers use air-conditioning (initial profile parameter, but past data can tune this behavior). Traffic information is used again as a parameter that can reduce range, because possible starts/stops on traffic jams increase consumption.

4.1 Range Representation

Once a range prediction is achieved, a topographical search starts with the current driver position, based in Figure 4. Main road nodes are used to check distances from current position and a polygon representation is achieved (see Figure 5 and Figure 6) based on Google API usage. A zone of uncertainty can be marked, based on the uncertainty parameters used to estimate the drive range (see Figure 7).

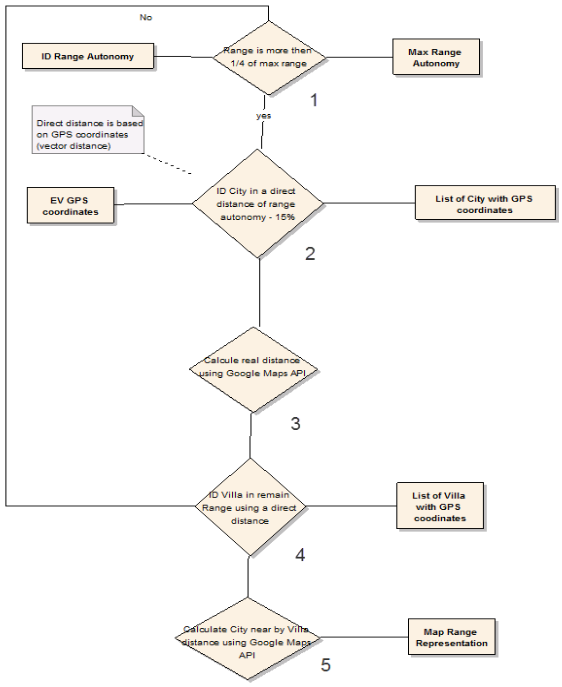

Figure 4: Range representation process using Google Maps API.

If the SOC level is below 25 % (available range should be around 30 km-40 km) it is calculated every road option with guidance to the nearest charging point. Taking into account Figure 5, it was considered Lisbon as the starting point. Since the available range for the EV is around 160 km, the implemented process starts to look for main destinations in a radius of 130 km to 160 km. This distance calculation is based on GPS coordinates of correspondent places. For Lisbon as the starting point, the process identified the following cities (Figure 4, process (2)): Pombal, Leiria, Marinha Grande, Ourem, Tomar, Évora, Grandola, Santiago do Cacém and Sines. Then, the distances are calculated based on Google Maps query (Figure 4, process (3)), and the process identifies that Pombal are out of the EV range. The distances calculated to the other locations are within the available range of the EV. For example, the distance from Lisbon to Évora is 134 km, so the process (4) (Figure 4) looks nearby villas, and process (5) (Figure 4), identifies the ‘real’ distance. In the case of the present example (Figure 6) and using the city of Évora as destination, it is available more 26 km, which allows increasing the range representation around Évora with a radius of 20 km. The output of this iterative process is represented in Figure 6. For every 5 km of EV movement this map is again calculated and represented. The web range estimator represents range by the connection of main distances and putting the polygon together. To do so, our application uses Google maps API and shows the polygon on a mobile device display, as showed in Figure 5 and Figure 6.

Figure 5: Range estimation of a trip from Lisbon to north, where four different cases are shown.

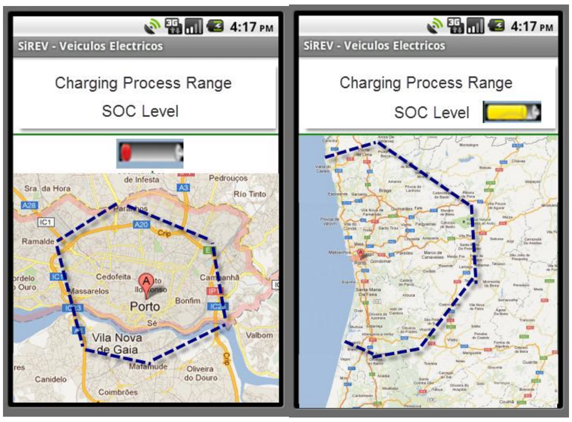

Figure 6: Representation of the charging range for different SOC levels, with a charging process performed in a public charging station in the centre of Porto city. On left, with a low SOC level, a small area is achieved. On right, with almost 90% of SOC level, a large area is achieved.

For the charging process, the range prediction and their representation is performed in the same way. Based on the charging level (SOC information) the application predicts the range based on previous driving parameters (past relations of SOC levels and distances achieved stored in driver profile) and based on this information represents using Google Maps the regions that is possible to reach with that charging level. System is prepared to generate alerts about charging levels needed to reach a charging station (it is assumed that a charging process is always performed in a charging station, in the driver’s home or in the work place). The range prediction process has several uncertainty factors that reflect driving behaviour and external condition (e.g. traffic, road topology and weather). These factors showed in Figure 4 can be used to estimate a safe range (green shadow in Figure 7) and a maximum range. The red shadow in Figure 7 is a range that is possible to achieve but the driver needs to perform driving optimization (air condition off and avoid big accelerations). This could be helpful information because driver can customize his behavior function of the range it needs to achieve in their trip. This process is can be continue updated and when SOC level is low this uncertain gets low.

Figure 7: Range estimation based on the uncertainty factors shown in Figure 4.

5. REAL TIME INFORMATION AND BEST PATH

Real time information is available from road concessionaries, but outside these organizations the access to this information is most of times denied. There are technical issues to solve because each organization has its own data format, and data integration is a real problem. During current research work several approaches were performed to have access to these data (with the Municipal Chambers of Lisbon and Loures, and with the company Brisa), but all the requests have been denied. The problem was contoured with the creation of a web crawler to pick traffic information from specialized sites by pre-defined heuristics, and a XML file with traffic information was created (Fontes, 2008). The XML file is an approach of future data integration from different source providers. In Figure 8 is illustrated the process of XML file with road information oriented to a geo-reference graph.

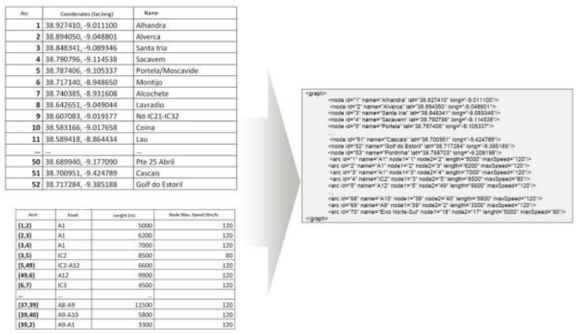

Figure 8: Semi-automatic creation of a XML file with road information to be used for graph creation.

The Crawler (WebNews, version 1.0) was configured to pick traffic information from TVI web site [http://www.tvi.iol.pt/transito.php] and also a Web service from Sapo was implemented. Information about nodes were checked against a heuristic table, where a conversion factor (CVF) reduces the node speed traffic (if the rode is blocked, with no traffic flow, the CVF is zero). Figure 9 illustrates this process. The result is stored in an adjacency matrix, where the number *aij* represents the cost of going from *i* to *j*. This process creates a graph representing the map, where the arcs represent roads and nodes represent intersections or traffic areas. To determine the best path between two points on a map an algorithm could be applied to this graph to find the path with less weight between the two desired points.

The weight of an arc is basically the average time in seconds that it needs to be traveled, for this it is used the equation:

Time = (*L* / *V*) * 3600,

where *L* represents the size of the graph in km and *V* is the top speed allowed. For all arcs there is a speed limit which serves as the basis for the weight of the cases in which there is no traffic information. When there is traffic information for a particular arc, the weight of this arc is affected because the traffic influences the speed. For example, if an arc with heavy traffic has a speed limit of 90 km/h, given the existing traffic, the reduction factor of the maximum speed has a value set between 0 and 1, based on current traffic information, causing the increase of the time required for this arc to be traversed, as much as its weight increases. If the transit is cut off, the factor of speed reduction assumes the value 0, and the maximum attainable speed is set to 0 km/h, what causes this arc to have an infinite weight.

If traffic is proceeding smoothly, without any problems, the factor of speed reduction has a value equal to 1, and the maximum attainable speed becomes equal to the speed limit, which makes this arc to assume the lowest weight possible, what is translated in a reduction in the mean time the arc needs to be traversed. This weight can integrate also public transportation information and a price associated with CO_2 emission of private transportation. Users can choose the impact parameters based on their strategies, in order to save money, to satisfy conveniences, or even to save time. For a complete description see (Fontes, 2008).

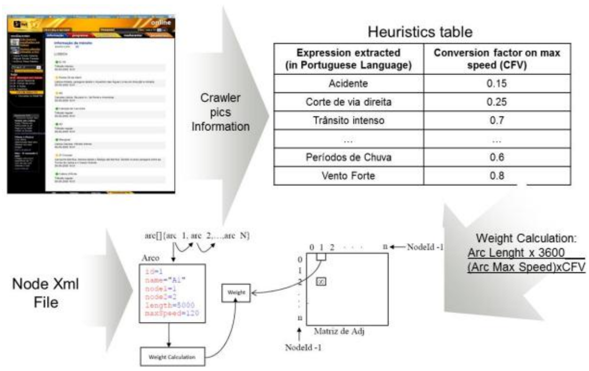

Figure 9: Graph node weight calculation based on traffic information from web sites (traffic information in Portuguese language).

Example: Path A1 (Alhandra – Alverca). Maximum speed allowed on this section: 120 km/h (motorway), but traffic information shows average speed is 84 km/h. Distance is 5km, so *arc weight = (arc distance / average speed)* x 3600 s

= (5000/84000) x 3600 ≈ 214 *s.*

Let's consider, in this example, that public transportation takes more or less twice the time spent with private transportation (by car), consisting in a time of 400 s.

Transportation price is 1 € and car transportation is 2 €, including the price for CO_2 emissions and fuel price. If drivers choose the same weight factor for time and price, then the arc weight for car transportation is 214 x 2 = 428, and the transportation arc weight is 400 x 1 = 400. In this case these values approximately the same, but if the process takes care of parking price of the vehicle in the city, the system increases again the arc weight for private car, and then the system suggests the option of public transportation (PT), showing the next PT arriving to the nearest PT stop. System is able to provide orientation to the nearest PT stop.

To determine the best route or the quickest route was implemented a Dijkstra's algorithm, where its running time is proportional to N^2, with N being the number of nodes in the graph. The graph to be used by this Dijkstra's algorithm is represented by an xml file. The best way to apprehend the quickest way is determined using the Dijkstra algorithm. In our web application there is a class called Dijkstra, which is where the algorithm is implemented. For a complete description method sees (Fontes, 2008). Information exchanges with external systems are based on XML files.

6. CASE STUDY

EV create new paradigms to mobility due to its limited range and long recharging times, and inevitably have impact on the day-to-day of the drivers, who have to plan their journeys and stops for recharging. These problems will tend to decrease with the technological advances that increase the autonomy of the vehicles, and with the development of a network of battery charging places, with an increasing number of alternative sites, as well as with a larger geographical dispersion.

Current work shows scenarios that could be considered as representative for most types of electric vehicles in the near future. In Table 2 are presented the data used in the case study.

Table 2: Data used in the case study.

Characteristics	Values
EV Autonomy	150 km
Charging Points in Portugal	1,300
Slow Charging	6 Hours
Fast Charging	30 Minutes
Change Battery	10 Minutes

6.1 Case 1 - Day-to-Day Urban

This scenario shows the use of Electric Vehicle (EV) by a driver who lives on the outskirts of a big city, and uses the EV to go to the work. The driver takes the kids to school every day, and after the job, goes to a gym session before making the return trip. His typical driving day is:

- 07:30 - He leaves home with the EV fully charged, after charging during the night;
- 08:15 - He covers 30 km until reaches the school of the first son;
- 08:30 - He traverses 5 km to reach the school of the second child;
- 09:00 - He covers 10 km to came to his work place;
- 12:30 - He goes out for lunch in his EV covering a total of 10 km;
- 18:00 - He covers 10 km to the Gymnasium;
- 19:30 - He covers 10 km to the school of the child;
- 19:45 - He covers 5 km to the school of the other son;
- 20:30 - He covers 30 km in the way back home. The driver returns home with 25% of the EV battery capacity.

This is the optimal scenario, appointed by opinion builders to justify the viability of EV, vehicles even with the current state of autonomy. However in this scenario an extra utilization of the EV cannot exist, as leaving home in the evening for dinner, or visiting friends. Besides, in this scenario all EV owners have to be able to charge their vehicles at home overnight. For the vast majority of the population that lives in metropolitan areas, it is not possible to charge the batteries of the vehicles during the night, since the vast majority of them live in buildings without parking or garage that make possible the overnight charging. For these cases the batteries charging must be carried out during the day, or in the middle of a travel, as with today's vehicles powered by fossil fuels.

Thus, maintaining the same schedule, but removing the batteries charging during the night, the driver will enter the vehicle with 25% of the battery capacity. Figure 10 shows the main screen of the application with the indication of charging and battery life management system received from the battery through the adapter.

Figure 10: SiREV: Charging indication (SOC); EV estimated autonomy; A charging place identified (Better Place) at 20 km; and the Context Information (driver, mode, destination and day period) (in Portuguese language).

The vehicle's range is 40 km, however the trip will have a total of 45 km and it will be necessary to recharge the EV batteries to get to the destination.

The SiREV presents an alert indicating the need to recharge the batteries, and shows the alternatives identified by the recommendation system. Since this is a trip to work, the goal will be to arrive as quickly as possible, so the recommendation system presents three alternatives for fast charging, and set the route, given the previous choices. The first step is to submit a recommendation to select the candidate items for the SiREV, and then it uses the information gleaned from smartgrid to create a list of all the charging points that can be reached by the vehicle. In this scenery the vehicle is in Odivelas, outside Lisbon, so the number of charging points is high. It is created a list of 30 possible charging sites. Then the list is sent to the component that manages the public transport information to validate the proximity of interfaces with different means of public transport. The component validates each of the candidate items and returns the updated list.

The next step is the processing of the recommendation. At the entrance of the recommendation system there is a list of 30 candidate items distributed as follows:

- 15 Points of slow charging: 5 of EDP; 5 of Better Place; 5 of Mobi.E.
- 10 Points of fast charging: 4 of EDP; 3 of Better Place; 3 of Mobi.E.
- 5 Points of drop-off (in which the batteries are replaced): 1 of EDP; 3 of Better Place; 1 of Mobi.E.

The driver of this studied case never chooses the drop-off sites, nor it is important for him to select locations near public transport. This driver has a clear preference for places of charging of EDP, followed by Better Place, and he never charges his EV at places of Mobi.E. The algorithm returns a recommendation to run the utility with more than three items after comparison with the history of the driver choices. The following screen is displayed to the driver, Figure 11:

Figure 11: Showing recommendation, regarding charging points that fits drivers' choices (in Portuguese language).

The driver selects the first recommendation of SiREV and sends the data on the location of the Public Charging Station (PCS) for the navigation system. Reached the PCS the charging process starts and SiREV presents progress and an indication that the vehicle performs in charging state. It is possible to visualize in a map the distance that the EV can reach with that charge. The driver can perform a charge until the desirable distance is reached (if less than the maximum range).

After the driver leaves the two children at school, SiREV continues to put a notification in the notification area that the vehicle's range is below the limit. Upon reaching the destination the driver selects the notice and recommendation system introduces three new options for charging, this time the system knows that the vehicle is at its destination because it is less than 5 km from the site displayed as a destination, so presents options for charging along three car parks within walking distance (see Figure 12-left). The batteries will charge while the driver is on his job.

After 4 hours, the driver receives an SMS notification on his phone, indicating that the batteries are fully charged (with 100% of energy storage capacity). The driver rests, assured that he can keep his routine the rest of the day, and that 150 km of EV autonomy are available until the next working day.

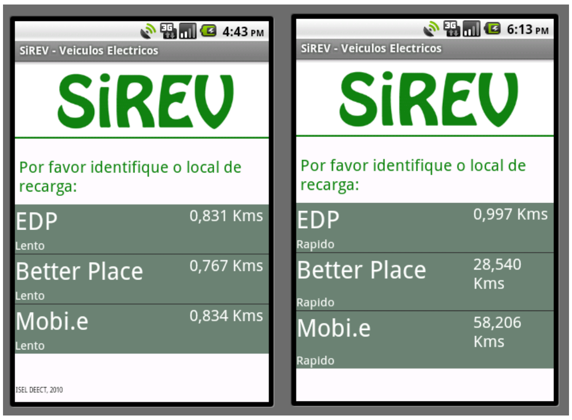

Figure 12: Recommendation of charging places nearby (left) and SiREV detects that EV range is below 30% of initial range (right) (in Portuguese language).

6.2 Case 2 - Long Distance Between Home and Work

This scenario presents the situation of a driver who lives at a considerable distance from his work place. The driver lives in a distant city but works in downtown Lisbon. The trip from home to work is 100 km. The driver lives in a building with a garage, but without a charging point for electric vehicle. A typical daily schedule of this driver is:

- 08:00 - Departure from home;
- 09:30 - He covers 100 km to his place of work;
- 13:00 - Out to lunch, traveling a total of 5 km;
- 19:30 - Return back home, covering 100 km.

This daily driver travel is 205 km long. Using the system SiREV, and assuming that, as in the previous case, in the morning the EV has 25% of its energy storage capacity. Upon entering the EV and after selecting the profile and identifying the destination the driver is alerted to the fact that he must charge his EV in a radius of 30 km. The system immediately displays the recommendations taking into consideration that the driver goes to his work place (see Figure 12-right).

The three options presented are of fast charging type, and have in common the fact that they are service areas that have cafeteria service. Whenever the driver needs to recharge the EV batteries in the morning, he chooses a service station with cafeteria service, because he takes the advantage of taking the breakfast as the car recharges. While having breakfast, the driver is alerted to the fact that the EV batteries are already charged. Back to the car, he follows his route to employment. Arriving at the entrance to Lisbon the battery pack is again with a low level of charge, with only 30% of stored energy, so that the driver is alerted to that fact.

The diver remains far from his destination, thus he is presented to all the fast charging options, and to an option of slow charging, but he is also near an interface to public transport, enabling the driver to put the car in a park covered with charging service, and continuing his journey by public transport. The driver chooses to deposit the car in the park, let the EV to be charged, and use public transport to go to the work.

After 6 hours the driver is notified that the EV batteries are fully charged, and so, he knows that can return home with his EV, because the energy stored in the batteries will be enough to cover the 100 km back.

6.3 Case 3 - Car Ride at Weekend

In this scenario, the same driver of the second scenario leaves home on a Saturday morning for a ride with the family in the western coastal zone of Lisbon. When entering the vehicle the driver identifies himself and indicates that he will shift into drive, with no predetermined destination.

After an hour of travel, the system notifies the driver that the autonomy of the vehicle reached the configured limit of 30 km, and displays an alert, as showed in Figure 13 (left).

In this situation the recommendation system will consider the following context: (1) Operating mode: leisure; (2) Time of day: morning; and (3) Destination: No destination.

The system has the following three charging station recommendations, see Figure 13 (left).

All recommendations are slow and charging points have in common the fact that they are near centers of tourist interest, with places to visit. The full charge will take about six hours, so the driver and family can visit the Points of Interest (nearby), lunch in one of several restaurants. Just four hours after the driver decides to return home. The vehicle's range is 70%, and will not reach the destination.

After walking 50 km of new drivers are notified that you have to carry the load of the vehicle. In this situation the recommendation system will consider the following context: (1) Mode of Operation: leisure; (2) Time of day: Afternoon; and (3) Destination: House.

By stating that the destination is home, the recommendation system provides fast charging points along the route (Figure 13-right), in this context because the driver always chooses this type of sites because they want to get home as soon as possible.

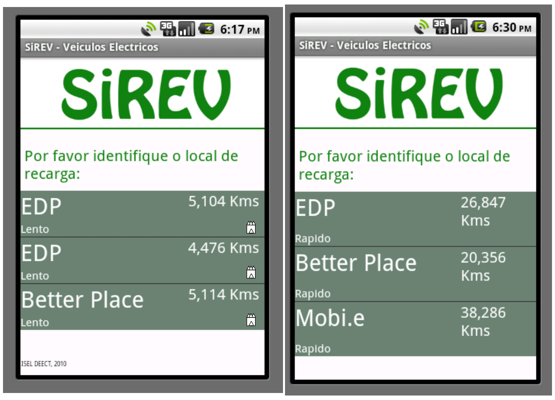

Figure 13: Recommendations given by the Recomender System, because SiREV detected that range is below the configured limit of 30 km: On left - recommendation for slow charging points; On right - recommendation for fast charging points (in Portuguese language).

7. CONCLUSIONS

The main objective of this work is to help drivers in the daily use of Electric Vehicles (EV), acting proactively and increasing the attractiveness of EV. However, EV technology is still under development, and so, all available information systems are necessary for a successful full integration of the Electric Vehicles in the transportation system. In this work it is proposed the integration of information from various areas that can be important in the successful implementation of a mobility model for drivers of Electric Vehicles. It is also necessary to ensure that the integration model is sufficiently generic and flexible to be adapted to different systems, having a low impact on the implementation of a Recommender System. On the other hand, it is easy to see that the technologies needed to develop a mobile system, capable of receiving position and geographic information, and able to establish connection to external devices or to the Internet, have a very advanced level of development. The Android system allows a very simple and efficient development of applications, with the advantage of being totally free of cost, both with regard to the licensing of their own API and developer tools, which are all based on free software. The ease of development, the integration with GPS, USB, Bluetooth, SMS, and the test execution, makes the implementation work very efficient.

The usage of the developed Recommender System showed only part of all its potential for application in the Electric Mobility context, It will be part of future work to deepen the study of a more complex model for the Recommender System, with the optimization of the scenario in question, demonstrating the validity and enforceability of this project in a real use, with its added value, in an attempt to identify functional requirements and possible ways for their implementation.

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