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Data Mining Approach for Range Prediction of Electric Vehicle

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ABSTRACT: Our work proposal is based on the past driving data that are stored in a driver profile, and using real time information about the Electric Vehicle parameters (e.g. speed and energy stored in the batteries), combined with external parameters (e.g. conditions of roads, traffic, and weather), determine the range autonomy accurately, taking into account the historical driver behavior. The driver profile is based on the stored data, which acts as training set for a Data Mining approach, in order to estimate the Electric Vehicle range. The Data Mining approach uses a regression model aiming to find the better range autonomy, which is used to represent the current Electric Vehicle range autonomy on a map.

Keywords: Range Prediction, Data Mining, Driver Profile, Range Anxiety Problem, Electric Vehicle.

1 Introduction

The upcoming reality of electric mobility, in conjunction with the new paradigm of Smart Grids and the electrical power grids markets, will bring a diversity of advantages to the final users, however, it will be required several technological developments in order to facilitate the electric mobility integration, in special Electric Vehicles (EVs) and Plug-In Hybrid Electric Vehicles (PHEVs), which are seen as one of the most promising means in order to improve the sustainability of the transportation and energy sectors.

Nowadays, EV has a limited energy storage capacity and the range is strongly dependently of the driver behavior. Consequently, and due to the fact that the batteries cannot be quickly recharged during a journey, it is essential that a precise range prediction is available to the driver of the EV, in order to check if the desirable destination is possible to be reached without charging, or even if to reach this destination a driving optimization, must be performed (e.g., by reducing travel speed, by cutting the air-conditioning system, etc). As shown in Fig. 1, the range prediction is based on three main dependency types:

The EV with its main variables: the model of the vehicle (mainly their performance under different scenarios, taking into account the speed and the acceleration), the chemical technology of the batteries (as lithium-iron-phosphate, lithium-titanate, or nickel-metal-hydride), the batteries characteristics (mainly variation of State-of-Charge - SoC, lifespan, performance, specific power, specific energy, and safety), and the EV powertrain (electric motor and their power converter, as well as the other electric parts, as batteries charger, controllers, and power cables). All of these variables of the EV will influence the SoC and consequently the range prediction. The batteries SoC and others relevant parameters, are provided to the main control system through CAN-bus communication, and then these information is stored in a Data Base (DB), in order to predict the range available.

The driver behavior: speed and acceleration (taken from EV through the CAN-bus communication), the driver past behavior (e.g. SoC level versus achieved distance – which is stored in a DB), weight (that is a manual input), and driving direction (that is acquired based on the GPS information).

Environment: current location, traffic conditions (taken from a web service), road information (obtained through a distance graph), weather information (wind and temperature - taken from a web service or from an EV sensor), altitude (taken from the GPS device).

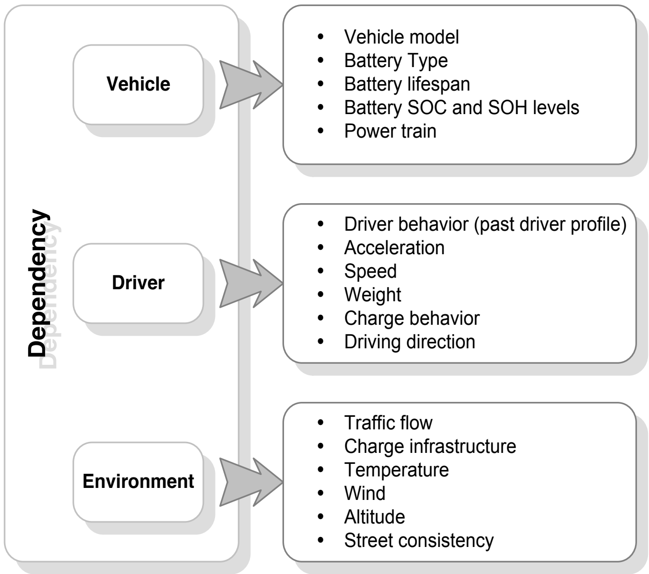

Figure 1: Main parameters for range prediction

In this context, our work proposal is based on past driving data, collected from a tracking application to run in an off-line mode (to avoid communication costs) in a mobile device with GPS device [1]. This tracking application mainly stores times, GPS coordinates and user identifications. From the GPS coordinates it is easy to calculate travel distances that is combined with SoC levels. Driver profile is based on this data that acts as a training set for a Data Mining (DM) approach to estimate the EV range. The DM approach uses a regression model to find the best fitting estimation based on current SoC level, past driver behavior (SoC level, weather information - wind and temperature, average speed, traffic information, etc) based on a CRISP-DM methodology [2]. Our approach was implemented with a freeware data mining product [3]. Range prediction already catch the attention of scientific community with the works [4, 5].

Output of this approach is an individual range prediction based on past driving data combined with external factors, like traffic information, weather (wind and temperature) with a regression approach, where we fit past driver behavior with the current situation, in order to estimate a more accurate EV range. This range prediction, represented on a map, can be an useful information for the driver in order to check if the desirable destination can be reached with or without driving optimization (e.g. range can be increased reducing or turning-off the air-conditioned, or smoothing the driving profile, among others). This approach can also be used to estimate EV batteries life charging capacity, based on past charging experience and lifetime, in a similar process.

The range prediction application modules are illustrated on Fig. 2: (1) Range prediction, see section 4; (2) tracking application, see section 3; (3) drivers profile, is one of the most important parameter in the use of the EV. Mainly, in the profiles should be included: the traveled distances; the time available to charge the EV taking into account the use of the EV, and the power available to charge the EV according with the contracted power for each case (4) SoC level through CAN-bus, see section 2. This information is obtained through the Battery Management System (BMS), equipment that allows analyze the performances of the batteries. There are several topologies of BMS with different characteristics and functions; however, the main function provided by the BMS is the State of Charge (SoC) of the batteries bank, normally in percentage. With this parameter is useful to the range prediction of the EV. The communication with the BMS, to provide the SOC information, is done with through CAN-bus; (5) Google Maps, for information visualizations; (6) EV type, a data base with EV descriptions, weight, battery type; (7) weather information (e.g. temperature, wind, weather conditions) pick from a web site (www.meteo.pt); (8) the charging station, for location and guidance and also to handle reservation charging slots, see [6]; and (9) Data Mining algorithms, see section 3.

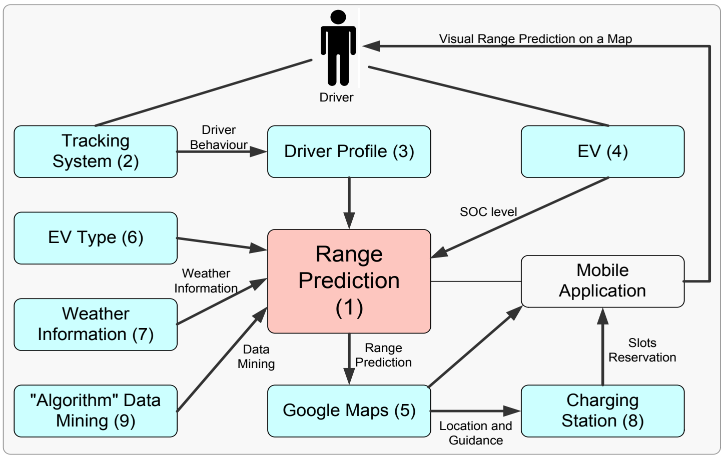

Figure 2: Main range prediction interaction modules

2 INFORMATION EXTRACTION

This section describes two equipment, with wired and wireless communications interfaces, allowing access information for two different scenarios/systems: EV and Home Charger Device. Providing relevant data from EV and charging spots to the platform, these devices integrate Charger Systems and EVs with the Mobi-System, enabling intelligent and opportunistic EV charging management, and providing useful information for each driver according to her/his needs. Main information extraction is the charging log file performed by charging devices, the information from EV and the commands to the charging device (Fig. 3).

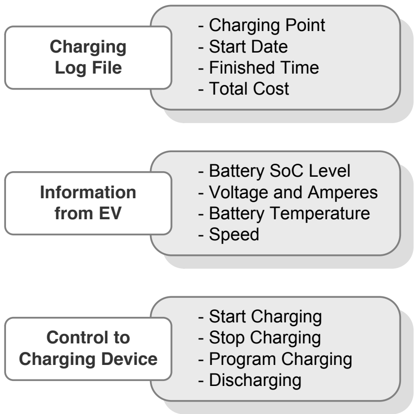

Figure 3: Main information to extract and commands to perform on charging device

Analyses of transactions data can be useful information for future charging or discharging processes, taking into account a smart charging strategy to combine distribution network limitation and low prices. All this information is stored on the information repository on the central server. If internet communication is available, the driver can check remotely the home charging process, and interact with it if he wants to.

2.1 Development of the On Board Unit (OBU)

The On Board Unit (OBU) is installed on-board in the EV, providing telematics both locally (in the EV) and remotely (to our information repository). The device is based on a microcontroller that integrates CAN, Bluetooth, GSM/GPRS (Global System for Mobile communications / General Packet Radio Service) and GPS (Global Positioning System). The implementation of CAN protocol allow requesting and receiving data from the car. With the available OBU wireless communications interfaces, it is possible to report both locally and remotely the data being received from the EV through Bluetooth and/or GSM/GPRS technologies, respectively. Moreover, Bluetooth allows the OBU integration with mobile equipment, such as a mobile/smart phones. Additionally, and by having knowledge of the EV current coordinates (GPS receiver), the OBU is able to make the best decisions through the platform. GPRS allows the development and implementation of the OBU update over the air, increasing the easiness with which software updates are made.

Also, this task was not easy to be performed due to missing information provided by the electric motor manufacturer company. This work was part of a student final year project in ISEL (Instituto Superior de Engenharia de Lisboa – Lisbon Superior Institute of Engineering) where Fig. 4 shown the main results achieved: the extraction and visualization in real time using Buddy 09 (Fig. 5).

Figure 4: Visualization of Buddy 09 extracted information to an android mobile device

In this process real timing information is crucial and it must be extracted from EV. Here a main barrier may arise once each vehicle model or each Original Equipment Manufacturer (OEM) does not release the information for this data acquisition process. Considering this, an open source vehicle under development at CEIIA (www.ceiia.com), which may prove the benefits from that by creating synergies with other data systems and create useful information in real time for the EV driver. CEIIA has already developed two complete full electric vehicles, one on production at Norway, Pure Mobility Buddy 09

(Fig 5). As CEIIA does not represent any specific vehicle manufacturer, but has the ability and experience to develop a vehicle using open source technology.

Figure 5: Pure Mobility Buddy 09

2.2 Charging Device

The batteries charging device is a power electronics equipment that converts the AC voltage from the electrical power grid into a controlled DC voltage or current in order to charge the batteries. Besides the charging, this equipment allows discharge the batteries, delivering part of the stored energy in the batteries back to the electrical power grid. In both modes of functioning the power quality is preserved through a sinusoidal current consumption with unitary power factor.

In Fig. 6 is shown the developed charging device. As referred before, this equipment, with the proper control, allows charging the batteries with different algorithms as constant voltage, constant current, constant current followed by constant voltage, or other.

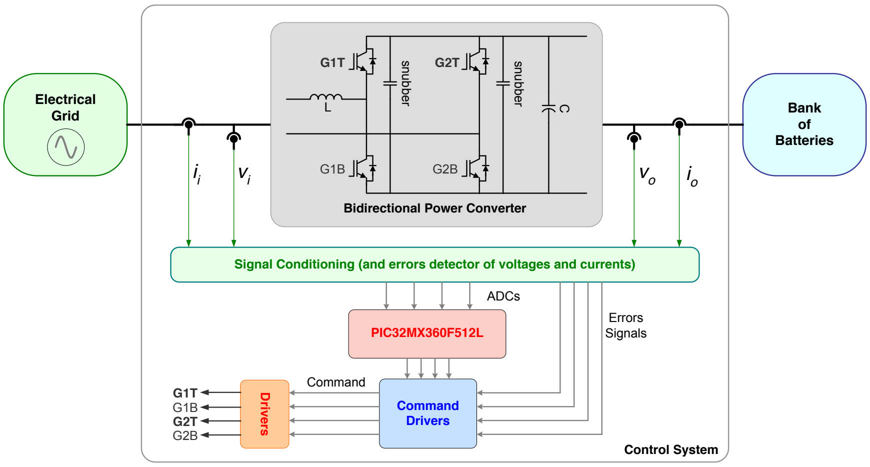

Figure 6: Conceptual diagram of the developed charging device

The charging device is composed by main parts: the power electronic converter and the control system. The power converter consists is a bidirectional converter that uses four power semiconductors (IGBTs FGA25N120ANTD 25 A – 1200 V), two snubber capacitors (1 uF – 400 V), an inductance (5 mH – 10 A) to interface with the electrical power grid side (AC side), and a capacitor (4.7 mF – 450 V) in the batteries side (DC side). The developed control system is composed by a microcontroller (PIC32MX360F512L), the Digital Analog Converter (DAC – DAC712P), voltage and current sensors (LEM – Hall Effect Sensors), the IGBTs command circuit and drivers, and the circuits of the signal conditioning and errors detector.

Currently, a charger system is equipment which only has in consideration the EV batteries charge level. However was developed a RSU (Road Side Unit) which interacts with the different blocks that constitute the charger system to provide more information to the EV driver and to the mobile device. It can provide the SoC, the charge remaining time, the efficiency of the charging, as well as other data. The RSU is a prototype that includes hardware and software to be attached to the charger system, providing telematics, both locally and remotely. The RSU device integrates Bluetooth, GSM/GPRS and charger information. The available RSU wireless communications interfaces allow to report locally and remotely the charger system information data. As for the OBU, Bluetooth allows the integration of RSU with mobile equipment, such as a mobile/smart phone, and GPRS allows the development and implementation of the RSU update over the air, increasing the easiness of software updates.

The microcontroller, located on the control system of the charging system, has as main function, control the process of charging or discharging. The data associated with this process, as the evolution of the voltage, the current and the temperature, are managed by the microcontroller and can be provided to the RSU in order to provide more information to the EV driver and consequently to the mobile device. Nevertheless the RSU also communicates with the microcontroller in order to define the start and stop of the charging process, the charging program (to define the charging algorithm), and to control the discharging process. The interface between the control system of the charging device and the RSU, not described in this paper, can be done through RS-232 communication.

2.3 Information Repository

The Central Information Repository stores the information related with the EV, namely: (1) EV drivers profile; (2) electricity transactions of EV; (3) electricity prices; (4) weather information; (5) driving parameters; and (6) other EV related information. For detail information see corresponding Sections. This Central Information Repository is based on XML files and a Mysql DB implementation. Since our goal was the creation of a prototype, not a commercial application, this subject was not tuned for best system performance, but only for testing purposes. Initial driver profile is manually created by the driver, with the following information (Table 1):

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.

Table 1: Driver Profile of an 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, road type, traffic information, weather

3 DRIVER BEHAVIOR

Driving range is intensively related with the driving style or mode. This happens in all types of vehicles, but on electric vehicles, due to the weakness related with 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.

Main idea is based on a tracking system to acquire data for a diversity of drivers and achieve a discrete driver profile, based on pre-defined class, related with EV consumption to achieve an average driving behavior function of external parameters: weather, road topology (discrete variable representing urban driving, mountain, motorway), driving mode (e.g. work or leisure), day period (morning, afternoon, night).

A Naïve Bayes (NB) classifier can be used classify driver behavior in pre-defined class based on external data to relate past driver consumption with external information, such as weather information (temperature and raining information), average speed, traffic information, road type, EV age and type, drive mode (work or leisure) and drive period (morning, afternoon, night), a small example is shown in Table 2. Driver behavior is divided in n classes (configurable number, get from clustering analyses of past data). In our implementation $n = 10$ and classes are defined based on percentage of SoC level decreasing from the ideal driver (class zero); class 0 ideal driver no change on SoC level; class 1 is performed a decrease until 5%; class 2 from 5% to 10% decrease; class 3 from 10% to 15% decrease; class 4 from 15% to 20%; class 5 from 20% to 25% decrease; class 6 from 25% to 30% decrease; class 7 from 30% to 40% decrease; class 8 from 40% to 50% decrease; and class 9 more than 50%, where is applied a 60% decrease. This decrease values are determinate by the: SoCc/(SoCi-SoCf), where SoCi is the SoC measurement in the trip begin and SoCf is the SOC measurement in the end of the trip. SoCc is the theoretical calculation of SoC level taking into account the distance and EV efficiency.

Temperature is also discretized in a pre-defined class (class 1 temperature is below 0ºC, class 2 temperature is between 0ºC and 8ºC, class 3 temperature is between 8ºC and 15ºC, class 4 temperature is between 15ºC and 25ºC, class 5 temperature is between 25ºC and 30ºC and class 6 temperature is above 30ºC. These classes are related with range that can influence the usage of air condition of heating system. Time is also a discrete variable (morning, afternoon and night). Table 2 shows a small example how NB algorithm works, showing the probability of an event happening. In this case we want to know the driver behavior (defined by the ten classes) based on past data taking into account the external parameters that could influence their driving energy pattern consumption.

Table 2 NB (Naïve Bayes) classifier approach for a small example. Drive mode: W (work) and L (leisure); Drive Period: M (morning), A (afternoon), N (night); Road Topology: U (urban path profile), Mw (motorway path profile), Mt (mountain path profile), D (default road path profile). In this table we show only example for one driver, but on information repository there is several drivers. DC means driver class, RT - road topology, W- weather, T – Temperature, DM - drive mode.

Driver	Weather	Road Topology	Temp	Drive Period	Drive Mode	Driver Class
1	Sunny	Mw	2	M	W	3
1	Rainy	Mt	1	A	W	4
1	Rainy	Mw	4	A	L	2
1	Sunny	U	6	A	W	9
1	Sunny	Mt	3	N	L	4
1	Rainy	U	1	M	L	1
1	Cloudy	Mw	3	A	W	2
1	Cloudy	Mt	4	N	W	5
1	Rainy	U	3	N	W	3
1	Sunny	Mw	3	A	L	4
1	Sunny	Mt	2	A	2	To determinate

P (DC) = 0.1 (10 classes)
P (sunny|DC=3) = 1/2 (appears one in two examples of DC=3)
P (sunny|DC=4) = 2/3 (appears two in three examples of DC=4)
…the same for the others examples

P (DC=1|W=sunny + T=2 + DP=N+DM=L+RT=U) = P(p1) x P(sunny|DC=1) x P(T=2|DC=1) x P(RT=U|DC=1) x P(DP=N|DC=1) x P(DM=L|DC=1) x P (DC)

P (DC=2|W=sunny + T=2 + DP=N+DM=L+RT=U) = P(sunny|DC=2) x P(T=2|DC=2) x P(RT=U|DC=2) x P(DP=N|DC=2) x P(DM=L|DC=2) x P (DC)

…

P (DC=9|W=sunny + T=2 + DP=N+DM=L+RT=U) = P(sunny|DC=9) x P(T=2|DC=9) x P(RT=U|DC=9) x P(DP=N|DC=9) x P(DM=L|DC=9) x P (DC)

Based on historical data (in case 10 events) NB shows the probability for p1 to p10. For more details see [6]. Other important aspect of driver profile is the driver education towards energy saving. 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. 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 EV range, since range prediction will be based on the assessment of the drivers' usual behavior. An initial driver profile can be identified by the system, after being created manually by the driver with the information presented in Table 1.

The driver will be allowed to perform the operations presented on Fig. 7 This profile will receive information about driver trip (time, duration and km performed) from tracking system. A resume of EV parameters (speed, SoC level, distance) is also stored and associated with this profile for later range prediction. 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 Fig. 8.

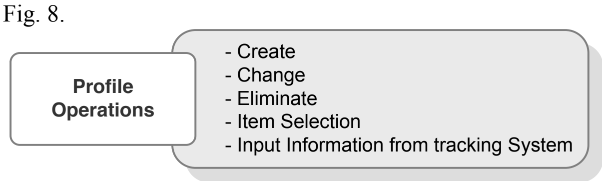

Figure 7: User Profile Operations

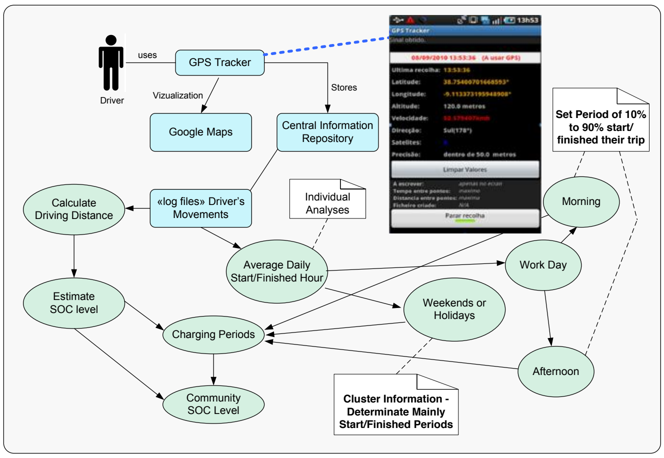

Figure 8: Main module of driver's tracking system in a mobile device with GPS and information created from Drivers Movements database

4 RANGE PREDICTION

The progress in digital data acquisition and storage technology has resulted in the growth of huge databases. This happens in several areas such as supermarket transaction data, credit card usage records, telephone call details, molecular databases, medical records and government statistics to others. The interest has grown in the possibility of tapping these data, of extracting from them information that might be of value to the owner of the database. The discipline concerned with this task has become known as data mining.

The process of seeking relationships within a data set— of seeking accurate, convenient, and useful summary representations of some aspect of the data—involves a number of steps: (1) determining the nature and structure of the representation to be used; (2) deciding how to quantify and compare how well different representations fit the data (that is, choosing a "score" function); (3) choosing an algorithmic process to optimize the score function; and (4) deciding what principles of data management are required to implement the algorithms efficiently.

The prediction procedure is based on a data mining approach using a multi-dimensional regression model using information repository data as a training set for regression parameters estimation. First step the determination of variables used on current approach: SoC level, EV speed, a discrete variable representing the usual driver behavior (section 3) and traffic information. This distance is tuned based on weather information, if it is hot a percentage of energy is taken for air condition, if it is raining a percentage of energy is taken for the window cleaning process. In night drive also a percentage of energy is taken for light services. Also a web service provides traffic information and based on past experience (e.g. information about driving's times and traffic information) a driving range is predicted. Current driving behavior (e.g. driving speed and accelerations) are taken into account in this process. Once we have an estimation of EV range we start calculation based on current position. For route optimization this process may be iterative. This approach can be complemented with a personalized one using a driving profile that acts as a training set for a DM approach to estimate the EV range. The DM approach uses a regression model to find the best fitting estimation based on current SoC level, past driver behavior (SoC level, weather information (wind and temperature), average speed) and traffic information (traffic is quantified in a discrete variable with n class ranging from no traffic to no traffic through). The Output of this approach will be an individual range prediction based on past driving data combined with external factors, like traffic information, weather (wind and temperature) with a regression approach, where we fit past driver behavior to current situation in order to estimate a more accurate EV range based on driver behavior.

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. 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.

Traffic information is used again as a parameter that can reduce range, because possible starts/stops on traffic jams increase consumption. This range prediction represented on a map could be a useful information for the driver in order to check if the desirable destination could be reached with or without extraordinary driving optimization measures (e.g. range could be increased with air condition turned off or reduced, smooth driving, among others). Also this approach can be used to estimate EV battery health in terms of charging capacity based on past charging experience and life time in a similar process. In the user interface, checkboxes and user-defined entries could be added in order to manually specify trip features (for instance, whether or not air conditioning will be used, what is the pretended cruising speed). EV weight (this is estimated based on driver input of number of passengers and a check list of possible baggage).

4.1 Range Representation

Once a range prediction is achieved, a topographical search starts with the current driver position, based in Fig. 9. Main road nodes are used to check distances from current position and a polygon representation is achieved (Fig. 10 (left and right picture) and Fig. 11) based on Google API usage. A zone of uncertainty can be marked, based on the uncertainty parameters used to estimate the drive range.

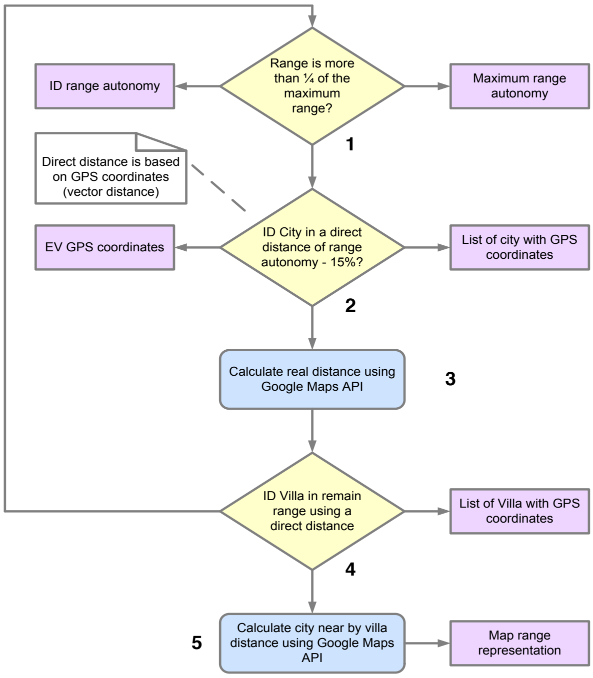

Figure 9: Range representation process using Google Maps API

If 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 10, 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 corresponding places. For Lisbon as the starting point, the process identified the following cities (Fig. 9, 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 (Fig. 9, 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) (Fig. 9) looks nearby villas, and process (5) (Fig. 9), identifies the 'real' distance. In the case of the present example (Fig. 10 –left picture) 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 (see Fig. 10-right pictu). The output of this iterative process is represented in Fig. 11. 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 Fig. 10 (left and right picture) and Fig. 11. For charging process the range prediction and representation is performed in the same way.

Figure 10: Range estimation of a Lisbon trip to north. Four different cases are showed (left picture) and Range estimation based on the uncertainty factors showed at Fig. 9 (right picture)

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 behavior and external condition (e.g. traffic, road topology and weather). These factors showed in Fig. 9 can be used to estimate a safe range and a maximum range. The red shadow in Fig. 10 (right picture) 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 S0C level is low this uncertain gets low.

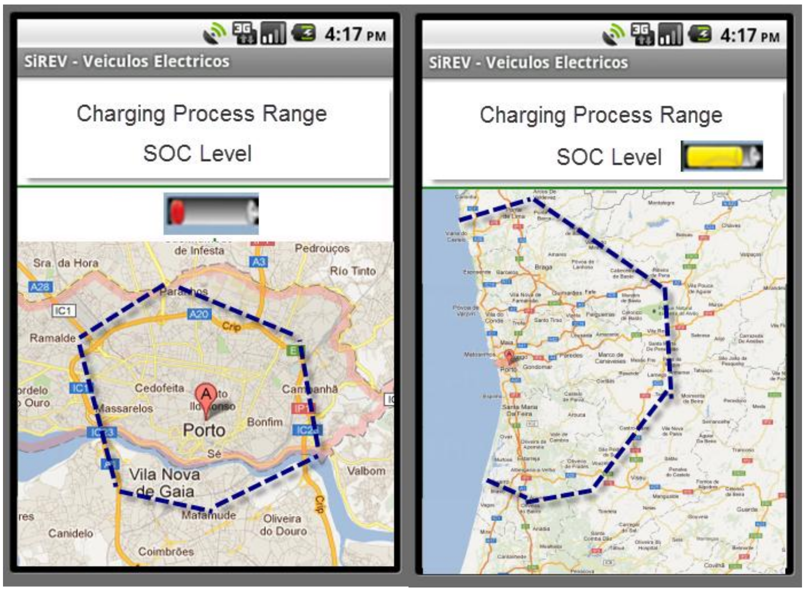

Figure 11: Representation of charging range for different SOC levels at a charging process

5 CONCLUSION

Current work goal was to minimize the driver range anxiety problem by: (1) an accurate EV range prediction based on past driver behavior, batteries SOC and external parameters like road characteristics, traffic conditions and weather; (2) range representation on a map taking into account current driver position with an uncertainty associated with driver behaviour. Other important work output is the historical driver profile data that can be used to establish driver communities profiles (Drivers with similar behaviour) and from this information start driver education towards the energy savings.

This work is integrated under a project MOBI.Cockpit system whose main mission is to display EV related and relevant information on a mobile device, such as: (1) Current traffic on the taken and planned trip; (2) Recommendation to take an alternative route according to the actual traffic status; (3) interaction with public transportation and charging stations.

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