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Dynamic Range Prediction for an Electric Vehicle

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Abstract

Electric Vehicles (EVs) have limited energy storage capacity and the maximum autonomy range is strongly dependent of the driver's behaviour. Due to the fact of that batteries cannot be recharged quickly during a journey, it is essential that a precise range prediction is available to the driver of the EV. With this information, it is possible to check if the desirable destination is achievable without a stop to charge the batteries, or even, if to reach the destination it is necessary to perform an optimized driving (e.g., cutting the air-conditioning, among others EV parameters). The outcome of this research work is the development of an Electric Vehicle Assistant (EVA). This is an application for mobile devices that will help users to take efficient decisions about route planning, charging management and energy efficiency. Therefore, it will contribute to foster EVs adoption as a new paradigm in the transportation sector.

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

1 Introduction

The increase in fuel prices encourages the development and the integration of electric mobility. Hence Electric Vehicles (EV) are being presented as a sustainable solution to reduce Greenhouse Gases (GHG) emissions and oil dependency.

The EV presents many advantages when compared to vehicles with Internal Combustion Engine (ICE). It has lower energy consumption and emission rates, it is rather silent and it has lower operating costs. However, the EV also presents disadvantages since it have limited autonomy. The long charging times, the limited charging stations and the undeveloped smart grid infrastructures demands for a hard planning of the daily use of the EV. Based on the available energy sources, currently, the EVs cannot compete with the conventional vehicles in terms of driving range and initial cost.

The main goal of the presented work, based on Information and Communication Technologies (ICT), is the interaction between the driver and the EV. This is done aiming planning the trip of the EV and their usage optimization, including the energy use and the battery charging process. Through the developed solution, the EV driver can interact with the EV battery charging system using the information of the charging points. This information is related with the charging point position, the availability, the energy price, and the reservation with the associated parking place. The integration of this information associated with driver interaction devices and applications to be developed, will contribute for a better trip planning and energy usage. Consequently, it is reduce the range anxiety of the EV driver. In this research work we describe a personalized range prediction in a mobile application.

After obtaining an estimation of EV range, it is started the calculation of the route optimization based on the 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 Data Mining (DM) approach to estimate the EV range. The DM approach uses a regression model to find the best fitting estimation. This is done based on the current battery State-of-Charge (SoC) level, the past driver behaviour (battery SoC level, weather information related with wind and temperature, EV average speed, and traffic information). The output of this approach is an individual range prediction based on past driving data combined with external factors like traffic information and weather (sky conditions and temperature). This output is obtained through a Naïve Bayes approach, where it is fitted the past driver behaviour to current situation in order to estimate a more accurate EV range based on driver behaviour. This range prediction, represented on a map, could be a useful information for the driver. Therefore, it is possible check if the desirable destination could be reached with or without extraordinary driving optimization actions (e.g., range could be increased with air-conditioner turned off or reduced, smooth driving, among others). Also this approach can be used to estimate the EV battery State-of-Health (SoH) in terms of battery SoC based on past charging experience and lifetime in a similar process. In the user interface, checkboxes and user-defined entries could be added in order to manually specify trip features (e.g., air-conditioning will be used, what is the desired cruising speed).

The mobile application to a personalized range prediction and its representation, as well as the integration and interaction with charging systems, is called Electric Vehicle Assistant (EVA). A small implementation detail is described in appendices A. Thus, EVA is a mobile application used to increase the driving autonomy through the reduction of energy consumption and driving efficiency. Through the integration and interaction with the charging infrastructure, the EV drivers can plan his journey considering the charging points position, and booking a charging point for a specific time period. Therefore, the distance that the driver can drive comfortably without fearing running-out the battery is increased. The main application modules of the EVA, illustrated on Figure 1, are:

1. EV charging functions, divided in Home Charging (HC) and Public Charging Stations (PCS).
2. Vehicle Interface System (VIS), where we developed a basic electronic unit that can accommodate the different interfaces required for this system (CAN-bus, Bluethooth, 3G, Wifi).
3. Driver Behaviour, where we create and store in a SQL Server database the driver's profile, and check the main EV energy consumption parameters.
4. Range Prediction Process.
5. Extended Range Navigation (ERN), which is an application to give to the driver information about a combined navigation strategy between consumption optimization and travel speed.
6. External System Interface to public transportation, energy market and points of interests (POI).

2 Charging Functions

This application is oriented for two main charging processes: Home Charging (HC) and Public Charging Station (PCS).

1. Through the HC it is possible to control the battery charging process, in which the charging system permits the interaction through remote control communication. Therefore, it is

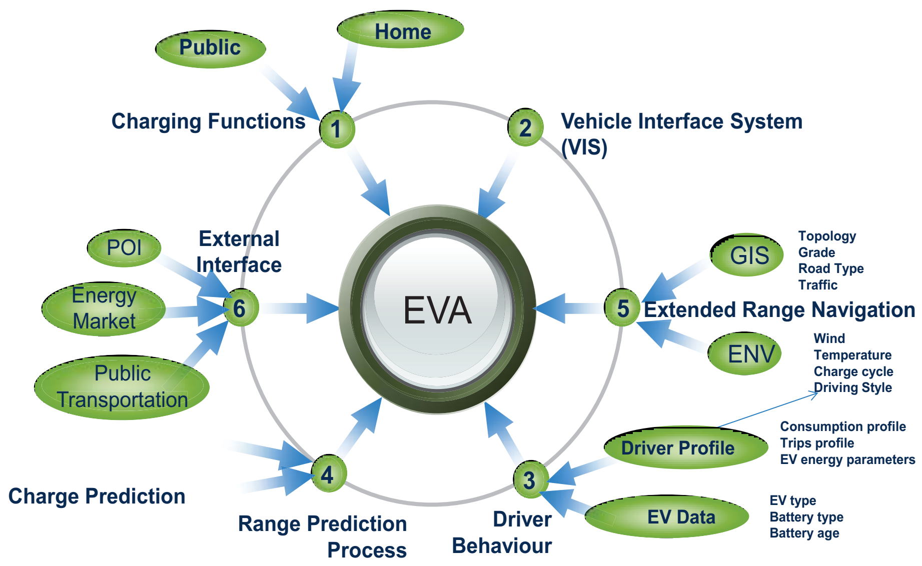

Figure 1: Electric Vehicle Assistant (EVA) main application modules.

possible to establish a smart battery charging strategy, taking into account the current limitations of the power grids, in order to support EVs integration in large scale [1]. In [2][3] is studied a smart battery charging process which takes into account the power limitations of the distribution network and driver's home. It also allows choosing the best price periods to perform the battery charging process. The proposal of Collaborative Broker also deals with local micro generation [4].

2. In PCS, the main goal is the driver guidance towards the nearest PCS, and the enable of online advanced booking of charging spots. Based on battery SoC level, driver profile, and remaining distance, the system can find the minimum value of energy to charge the batteries (see the charge prediction process in sections 5 and 6). This charging is done in order to make possible reaching the desired destination.

3 Vehicle Interface System

Taking into account all the necessary data transfer between the vehicle and the external system, the complexity of the inner-vehicle architecture must be abstracted from the high-level applications. In order to accomplish this goal, we are working in a definition of a common API for "Vehicle2Infrastruture" (V2I). At this moment we have an On-Board Unit (OBU), that provides locally (in the EV) and remotely (to mobile devices applications) relevant data communications. The OBU device is based on a microcontroller that integrates CAN-bus communication, Bluetooth, GSM/GPRS (Global System for Mobile communications / General Packet Radio Service) and GPS (Global Positioning System). In this way, the implementation of the CAN-bus protocol allows requesting and receiving data from the vehicle. With the available OBU wireless communication interface, it is possible to report both locally and remotely the data through Bluetooth and/or GSM/GPRS technologies, respectively. Moreover, Bluetooth allows the OBU integration with mobile equipment, such as mobile/smart phones.

The OBU interacts through the Battery Management System (BMS), which is an equipment that allows to analyse 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 battery SoC level. This parameter is useful to determine the range prediction of the EV.

This VIS (Vehicle Interface System) allows measuring the key performance indicators from each event driven by the vehicle through a CAN-bus on-board data collection system. Then those variables are crossed with publicly available historical meteorological data, in order to build a driver profile and to find the most important parameters related with driver efficiency.

4 Driver Behaviour

The driver can be educated to understand how the EV works regarding energy consumption. It is important to adapt the message given to the driver, so that he or she can easily assimilate the different strategies for the optimization of energy saving. The main idea is to store their behaviour in a driver profile that can be used for range prediction or for alerts towards energy savings.

The driver profile plays an important role in the range prediction process, and is based in three main components:

1. Drivers trip information, such as data/time (work days, weekend, holidays, start time, finish time), distance (in km), battery yoC level;
2. EV characteristics, like model, year, battery type and capacity;
3. EV driving style.

4.1 EV Driving Style

Any time a driver starts and stops a voyage, an on-board recording system records the accumulated distances travelled, energy consumption, time travelled per engine rotation band, etc. From these variables the following ratios were defined: (1) Energy spent per 100 km; (2) Time percentage of engine rotation in green band; (3) Time percentage of engine rotation in yellow band; (4) Time percentage of engine rotation in red band; (5) Excessive acceleration events per 100 km; (6) Excessive braking events per 100 km; (7) Inertial distance travelled percentage; (8) Time percentage of inertial movement; (9) Brake usage per 100 km; (10) Air conditioner usage; (11) Lights usage; and (12) Accelerator usage per 100 km. All this data is related with EV driving consumption parameters.

4.2 EV Energy Consumption

The aim of this task is to look at the different EV systems under the energy consumption

perspective, in order to provide information for a realistic range prediction of the travel. Models for the energy consumption of the vehicle, as well as regenerative braking potential, will be developed for the different operating conditions. Two types of energy consumptions should be characterized: electrical and mechanical. In terms of electrical energy consumption, the various powertrain components (batteries, BMS, inverter, controller and motors) and auxiliary systems (air conditioner, lights and other electric-driven devices) were analyzed from CAN-bus data. In terms of mechanical energy consumption, the analysis was performed from the data available of driving style, and were studied the most influential parameters for the energy losses during driving. This study was performed based on real data taken from an EV developed at ISEL, in the Lisbon area: the electric vehicle VECCO [www.veeco.pt]. Additionally, historical meteorological data was obtained from the site Weather Underground [wunderground.com], assuming a unique point as representative of the regions of Lisbon. Collected variables examples are: temperature, visibility, wind speed, rainfall, and weather events (storm, heavy rain, etc).
All data collect from VIS interface and weather information were stored in Microsoft SQL Server Analysis. It was used a CRoss Industry Standard Process for Data Mining (CRISP-DM) methodology [5]. From this approach was possible to identify key energy consumption actions for each driver. From this type of analysis, the system identifies actions to reduce energy consumption, and automatically alerts the driver. However, no automatic actions are performed, because the ultimate decision of reducing or not energy expenses is made only by the driver. Thus, the driver may accept or not the advising to turn off the air-conditioning or to reduce his driving speed. All data regarding alerts and driver's response is stored in a driver profile. Taking into account the data available, the key parameters that influence the energy consumption are shown in Figure 2. From this analysis, the highlighted top four key influences are: the utilization of air conditioner, the observation of optimal engine rotation, the minimum engine idling, and the inertial movement. This data is also used for driver profile, charge prediction and for range prediction. Using this approach a deep study was performed for bus drivers and bus routes in Lisbon [6].
Energy saving alerts are produced through the EVA application, taking into account the energy consumption study performed. For example, if the desirable destination is in the limit of the predicted range, the system can detect that the air conditioner is on, and suggests the driver to turn it off, or he will have to perform a battery charging operation during the trip.

5 Range Prediction Process

Range prediction has already taken the attention of scientific community, with several published

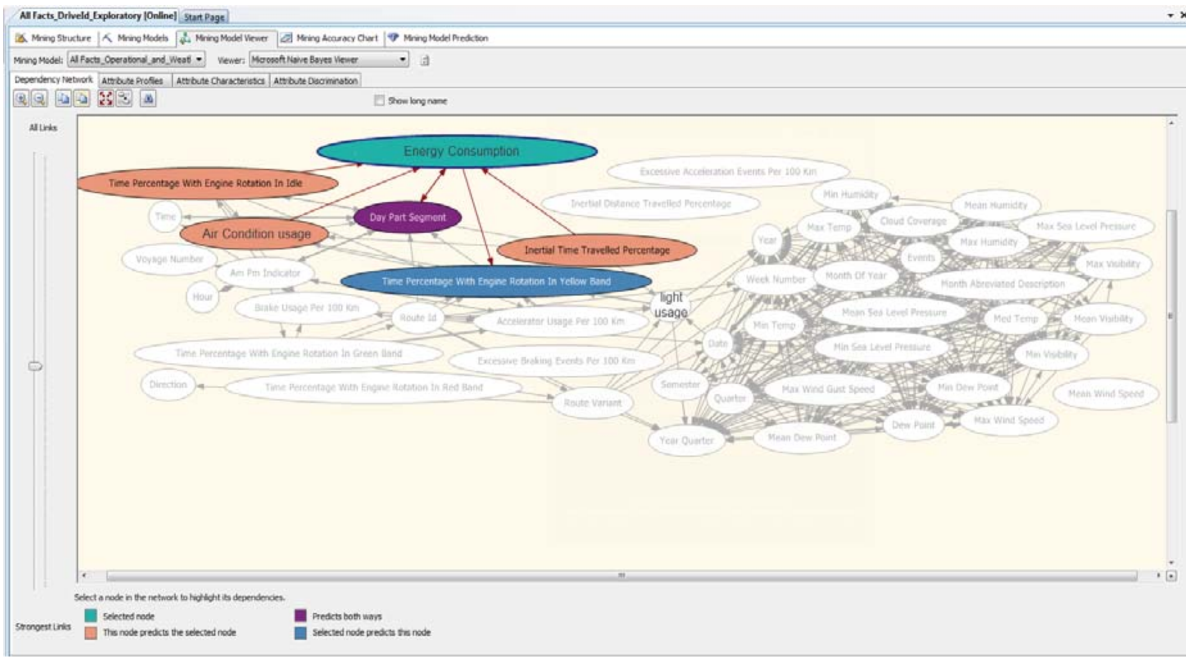

Figure 2: Average Energy Consumption key influencing factors.

works [7][8]. Also Data Mining (DM) approaches have been applied for the estimation of energy consumption [9][10]. Driving range is intensively related with the driving style or mode. This happens in all types of vehicles, but on EVs, 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 the EV autonomy. Considering the actions or driving habits that can bring significant energy savings to the vehicle operation, it is important to evaluate how receptive EV drivers will be towards the achievement of the intended energy saving. 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-conditioner under certain conditions, but will not accept the system to limit his driving speed. Part of this study will create and store a Driver Profile for further analysis. These Driver Profiles will play an important role on the project, since range prediction will be based on the assessment of the drivers' usual behaviour. The range prediction is based on three main dependency types [11]:

- 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 the battery SoC level, lifespan, performance, specific power, specific energy, and safety); The EV powertrain (electric motor and power converter, as well as the other electric parts, as battery charger, controllers, and power cables). All of these EV variables will influence the battery SoC, and consequently the range prediction. The battery SoC and other relevant parameters are provided to the main control system through CAN-bus communication. The provided information is stored in a database (DB), in order to predict the available range autonomy.

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

- Environment: Current location of the EV; Traffic conditions (taken from a web service); Road information (obtained through a distance graph); Weather information (wind and temperature that is taken from a web service or from an EV sensor); Altitude of the current location of the EV (taken from the GPS device); and traffic information taken from a traffic web service.

From the GPS coordinates it is easy to calculate travel distances, which are combined with battery SoC levels. Driver profile is based on this data that acts as a training set for a Data Mining (DM)

Figure 3: Prediction Model Web Service developed in Java.

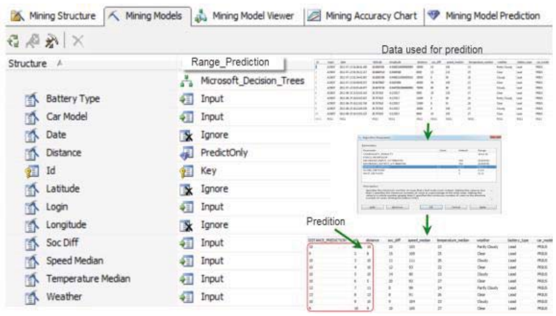

Figure 4: Implemented Prediction Process, from raw data using mining models to prediction range.

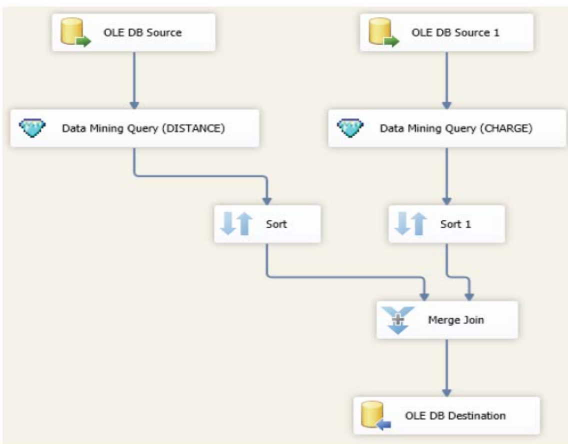

Figure 5: Data flow of used data mining process.

approach to estimate the EV range autonomy. The DM approach uses a regression model to find the best fitting estimation based on current battery SoC level, past driver behaviour (weather information of wind and temperature, average speed, traffic information, among others). Range Prediction was implemented through a Naïve Bayes, using past data available that has a training set and Charge Prediction by Microsoft decision tree algorithm, both available in the Microsoft SQL Server Analysis.
Figure 3 shows the prediction web service, developed in Java, and Figure 4 shows the mining models used for the prediction, which employs the available data of the driver profile and weather information. Range prediction is based on data mining (Microsoft Decision Trees). Figure 5 shows the flow of information, where we correlate several input variable (battery SoC, vehicle speed, temperature of the vehicle, weather conditions, battery type and the distance travelled - see Figure 4 for the case of distance prediction). More details are presented in [4]. The DISTANCE_PREDICTION and the CHARGE_PREDICTION are the two main prediction variables.
The output of this approach is an individual range prediction based on past driving data combined with external factors, like traffic information and weather conditions of wind and temperature. Therefore, it was used a regression approach, where it is fitted the past driver behaviour with the current situation, in order to estimate a more accurate EV range autonomy. This range prediction, represented on a map, can be a useful information for the driver in order to check if the desirable destination can be reached with or without driving optimization. For instance, the range can be increased by reducing or turning-off the air-conditioner, or by smoothing the driving profile. This approach can also be used to estimate the EV battery lifetime, based on the past battery charging experience, in a similar process.

6 Extended Range Navigation

This module takes into account the necessity of suggesting consumption efficient routes, and/or routes that considers the charging needs for the specific EV. At computing the shortest and the fastest route, the best economic routing strategy is to use a mixture of both. For EVs it may be important to optimize the route by energy consumption. This Extended Range Navigation (ERN) specification addresses mainly there different tasks:

1. Range Prediction - This application estimates the range of EV based on current battery SoC level and historical data. A green prediction range is calculated based on worst scenario data available in driver profiles. A yellow range prediction is calculated based on average data available on driver profile. A red range is calculated based on all possible optimization performed to save energy.
2. Charging Prediction - For a given desirable destination, this application based on historical data calculates the battery charge necessary for the EV to reach the destination.
3. Extended Navigation Representation (ENR) - This process is performed in three main approaches: (1) from current position and with the range prediction calculation, a circular range is represented; (2) using current position and based on Google Maps API, a polygon range is represented based on Figure 6; (3) the same as in the second approach, where we take into account current traffic, weather condition and road topology.

6.1 Examples

Once a range prediction is achieved, a topographical search starts with the current driver

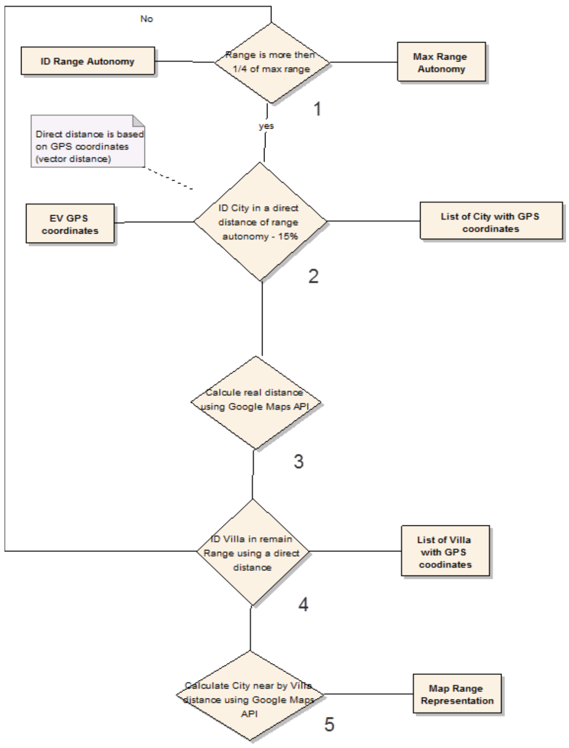

Figure 6: Range representation process using Google Maps API.

position, based in Figure 6. Main road nodes are used to check distances from current position, and a polygon representation is achieved (see Figure 7) based on Google API usage. If battery 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 7, 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 6, 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 6, process (3)), and the process identifies that Pombal is 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 6) looks nearby villas, and process (5) (Figure 6), identifies the 'real' distance. 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 7.

The approximation (3) is challenging to implement, because it is difficult to establish a direct relation of traffic and energy consumption. Our approach is based on past data stored, relating this parameters for a range prediction tuning. Basically, this methodology uses a DM approach with a regression (a continuous approach, since we use data without any change), or Naïve Bayes algorithm (discrete approach, since we divide data in classes - groups) for related past date (traffic, weather and road topology), with real consumption compared against the predicted one. Past behavior (Driver Profile data) is used to find the impact of these factors in the range prediction process.

Figure 7: Range estimation of a Lisbon trip to north. Four different cases are showed.

Charge Prediction is applied on charging process and we change the prediction process to use distance as input factor and battery SoC level as the estimate parameter. This DM algorithm creates a series of splits in the tree, where the nodes represent battery SoC level as discrete variables. Profile data with the desirable distance determinates the best node (charge prediction).

6.2 Implementation detail

Since a mobile device has a limited process capacity, most of these complex calculations are performed remotely, in order to get the user of an EV as fast as possible, and in the most reliable way, to his/her desired destination, based on the Cloud services of:

1. Geographic Information Server (GIS), which is responsible for the data representation of the 3D topography, the vertex/node abstraction.
2. Environment Server (ENV), which is responsible for the weather data, like current temperature, wind and traffic information picked from a web service, but also that is responsible for the computing and delivering of the battery charge cycles and the driving style. Residing on the Integration Platform, it uses all the data and computes all the results.

As result, the extended Range Navigation develops an approach on how to best match the data coming from the EV and the Cloud services residing on the Integration Platform, how to compute them, and finally display the best route and optimized range to the EV user.

7 External System Interface

This functionality is related to a data integration of different information sources, such as:

1. Energy market functions, like electricity prices, broker for energy transactions, and EV aggregation platform for electricity market participation [12].
2. Public transportation data [13].

3. Information related with Points of Interest (POI), preloaded on the system, such that the driver can perform a quick search for POI near the present location. This information is also used for guidance on the EV battery charging points that remain at a predefined distance [13].

These systems were already described in previous publications of the authors [11][13][14].

8 Use Cases

In this section are shown some screens of EVA application to illustrate the usage of this application in different situations.

Figure 8 illustrates the range prediction process developed for mobile applications in this work. Figure 8 (a) shows the starting of a range prediction, where the application presents the location of the EV. The option of specifying layers is shown in Figure 8 (b). In this case, the user chooses the range prediction process, and the results are illustrated in Figure 8 (c). A safe range is shown in green, in yellow a range which the driver is able to reach with driving optimization, and in red a range that is not guaranteed to be achieved. This range information can be complemented with the location of POI and Charging Stations (CS), illustrated in Figure 9 (a). In Figure 9 (b) is shown an example of alert of insufficient charge for the EV to reach a desired destination. In this case the proposed route is showed, the information about insufficient battery SoC is highlighted, and recommendations about actions to reduce energy consumption can be suggested. The application can also show options of the nearest CS in the proposed route.

Figure 10 (a) shows the remaining battery SoC level with the daily historical of battery SoC. Figure 10 (b) shows several route paths near of the limit of the EV range autonomy with indication of CS and POI. Figure 11(a) shows the detailed information about the CS market to perform the battery charging process. Figure 11 (b) shows the information about a specific POI.

The EVA application stores all events and can be used for the driver to understand how certain factors can affect the EV consumption. In order to assess the various daily events it is necessary to use the screen of history, as shown in Figure 12. Looking at the various points on the map, the driver can get information about the battery SoC level and distance travelled. The driver can also list specific peaks of consumption, with specific consumptions circumstances of the day, such as traffic event, the fact that rained, having performed a particular travel in a faster way, among others. Thus, it is possible to determine empirically some behaviours of the driver that lead to higher efficiency utilization of the EV.

9 Conclusions

The main goal of the current work was to minimize the driver range anxiety problem through two variables. The first one consists in an accurate EV range prediction based on past driver behaviour, battery SoC and external parameters, like road characteristics, traffic conditions and weather. The second one consists in a range prediction representation on a map, taking into account the current driver position with an uncertainty associated with driver behaviour. Other

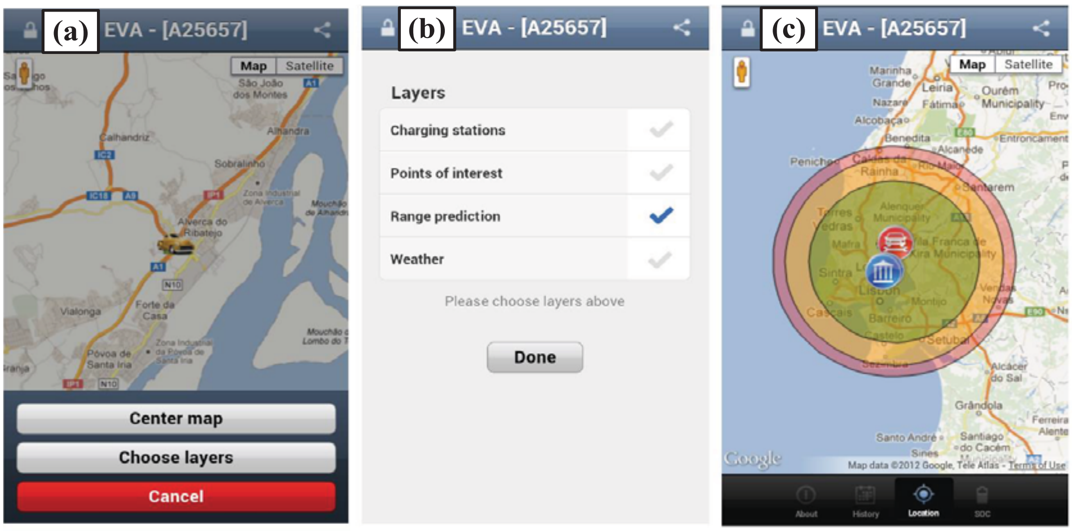

Figure 8: Range prediction interaction process: (a) EV position; (b) Available functions; (c) Range representation.

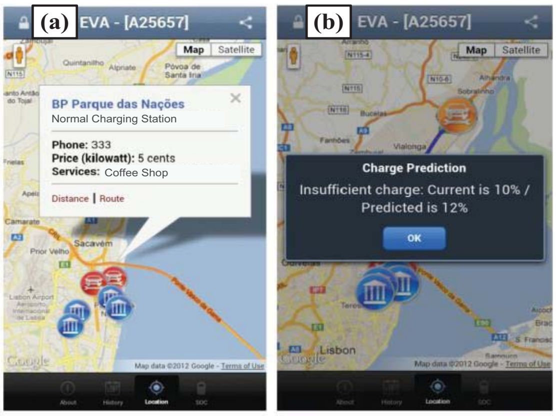

Figure 9: Screens of the EVA mobile application: (a) Guidance to Charging Stations (CS) and Points of Interest (POI); (b) Alert of insufficient charge to reach a desired destination.

important output of this work is the historical driver profile data that can be used to establish profiles of driver communities (drivers with similar behaviour). Therefore, from this information, it is possible the driver education towards energy savings.

This work is integrated under the 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; and (3) Interaction with public transportation and charging stations.

Appendice

In this appendice is presented the implementation details of the Electric Vehicle Assistant (EVA). The EVA is divided in three main components: (1) Portal; (2) Web Server; and (3) Application server. This platform is based on the standard HTML5 and WebKit platform, including platforms Sencha Touch and Sencha Touch Charts. These platforms provide a set of JavaScript libraries that enable more convenient and structured robust built applications, and looking quite appealing. Figure 13 shows a standard programming MVC (Model View Controller), where the logic is implemented in three distinct categories, namely the presentation layer, application logic and the components that represent data objects. The format of messages exchanged between the portal and the server are in JSON format, which allows quickly serializing and de-serializing a Java object / Javascript into a textual representation, easily sent via the HTTP protocol. Javascript is used on the Sencha library

Figure 10: Screens of the EVA mobile application: (a) Route paths near of the limit of the EV range autonomy; (b) Remaining battery SoC level with the daily historical of battery SoC.

Figure 11: Screens of the EVA mobile application: (a) Details about Charging Stations (CS); (b) Points of Interest (POI).

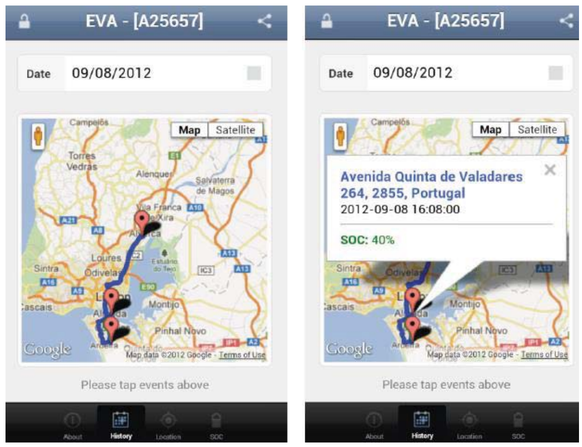

Figure 12: Screens of the EVA mobile application getting old information from historical events data.

to do the conversion, while Java is used in the library google Gson. Figure 14, shows the models: (1) Charge Prediction; (2) Charging Station (CS) – locations and type of CS; (3) Event – location

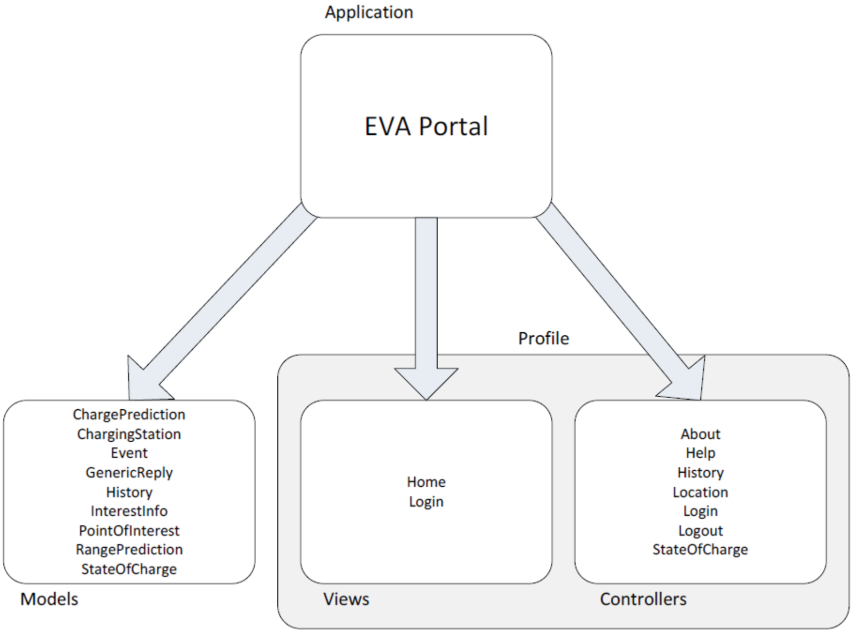

Figure 13: EVA Portal in MVC (Model View Controller) approach.

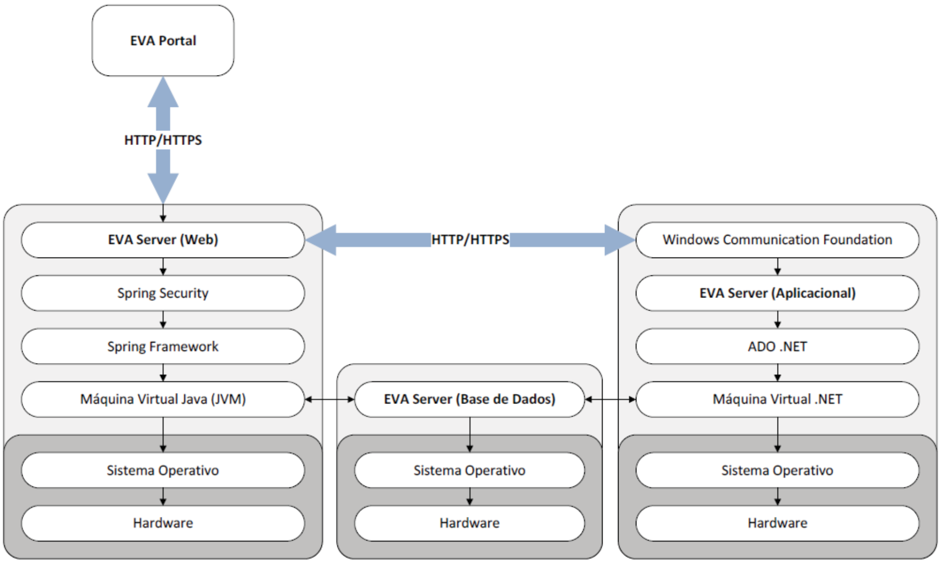

Figure 14: EVA Server and Application architecture.

event; (4) Generic Reply – Exchange message; (5) History – log file of events; (6) Interest Info – locations of points of interest; (7) Range Prediction; and (8) State Of Charge. Currently there are two relevant addresses, and the authentication of the main page is done in Spring Framework and redirected to the specific driver. There are two controllers implemented, one for home and the other for process asynchronous requests (AJAX). There is no need for a controller to implement the authentication page, taking into account that the platform Spring Security implicitly instantiates a controller that handles the processing required during the authentication phase. Complete details of the technical process can be found at [15].

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References

[1] João C. Ferreira, Alberto Silva and João L. Afonso. Agent based approaches for Smart charging strategy for Electric Vehicle. EVTEC 11 (1st International Electric Vehicle Tecnology Conference), 17-19 May 2011, in Yokohama, Japan.J.J. Romm, The hype about Hydrogen, ISBN 1-55963-704-8, Washington, Island Press, 2005.

[2] Vítor Monteiro, João C. Ferreira, , João L. Afonso, Smart Battery Charger for Electric Mobility in Smart Grids, 1st International Conference on Smart Greens, Porto-Portugal, April 2012.

[3] João C. Ferreira, Alberto Silva, Vítor Monteiro, João L. Afonso. Smart Electric Vehicle Charging System in proceedings of IEEE Intelligent Vehicles Symposium (IV 2011), June 5-9, 2011, in Baden-Baden, Germany.

[4] João C. Ferreira, A. Silva, Vítor Monteiro, João L. Afonso. “Collaborative Broker for Distributed Energy Resources,” in Computational Intelligence and Decision Making, 1st ed., A.Madureira, C.Reis, V.Marques, Ed. Springer, 2012, pp.367-378.

[5] CRISP-DM Process Model. Available http://www.crisp-dm.org/Process/index.htm.

[6] Jose Almeida, Joao Ferreira. BUS Public Transportation System Fuel Efficiency Patterns. 2nd International Conference on Machine Learning and Computer Science (IMLCS'2013).

[7] P Conradi. Advanced Mobile Information and Planning Support for EVs (MIPEV). (2010), Advanced Microsystems for Automotive Applications 2010, Springer.

[8] P Conradi, P Bouteiller. Dynamic Cruising Range Prediction for Electric Vehicles. (2011), Advanced Microsystems for Automotive Applications 2011, Springer.

[9] V.Figueiredo, F. Rodrigues, Z. Vale, J.B. Gouveia, (2010). An Electric Energy Consumer Characterization Framework based on Data Mining Techniques; IEEE Transactions on Power Systems; Vol. 20, n.2, pp. 596-602.

[10] J.H.Zhao, Z.Y.Dong, X.Li, K.P.Wong, (2007). A framework for electricity price spike analysis with advanced data mining methods, Power Systems, IEEE Transactions on Issue Date, vol 22, Issue 1, Feb. 2007, pp: 376 – 385.

[11] J. C. Ferreira, A. Silva and J. L. Afonso. “EV_Cockpit - Mobile Personal Travel Assistance for Electric Vehicles”. Ad. Microsystems for Automotive Appli-cations 2011. Smart Systems for Electric, Safe and Networked Mobility. Series:VDI-Buch. G. Meyer, J.Valldorf (Eds.) 1st Ed, 2011, X, 344 p. ISBN 978-3-642-21380-9.

[12] João C. Ferreira, João L. Afonso. A Conceptual V2G Aggregation Platform in proceedings of the EVS-25 -The 25th World Battery, Hybrid and Fuel Cell Electric Vehicle Symposium & Exhibition, 5-9 Nov. 2010, Shenzhen, China.

[13] João C. Ferreira, P. Filipe, Alberto Silva. Multi-Modal Transportation Advisor System in proceedings of the First IEEE FISTS Forum on June 29 - July 1, 2011 in Vienna Austria.

[14] João C. Ferreira and João L. Afonso. Mobi_System: A Personal Travel Assistance for Electrical Vehicles in Smart Cities in proceedings of the 20th IEEE International Symposium on Industrial Electronics (ISIES 2011), 27-30 June 2011, Gdansk University of Technology, Poland.

[15] Rui Nascimento. Determinação Dinâmica da Autonomia de um Veículo Eléctrico, MSc Dissertation, ADEETC-ISEL, 2012 in Portuguese.

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