Emotional Factor Forecasting based on Driver Modelling in Electric Vehicle Fleets

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Abstract: Until recently, the automotive industry focus has been safety, comfort, and user experience. Now, the focus is shifting towards human emotion for driver-car interactions, autonomy and sustainability; all of them are increasing concerns in recent scientific literature. On the one hand, the growing role of emotion in automotive driving is empowering human-centred design coupled with affective computing in driving context to improve future automotive design. It is resulting in emotional analysis being present in automotive. This requires real-time data processing that involves energy consumption in the vehicle. On the other hand, electric vehicle fleets and smart grids are technologies that have provided new possibilities to reduce pollution and increase energy efficiency looking for sustainability. This paper proposes the emotional factor forecasting according to data gathered from electric vehicle fleet, based on the application of K-means algorithm. The results shows that is possible to forecast the emotional status that takes negative effect in the driving. Additionally, the Cronbach alpha variation analysis provides an interesting tool to select features from samples.

1 INTRODUCTION

For different reasons and purposes, the number of studies related to include emotional analysis in cars is growing in the scientific literature (Akamatsu et al., 2013; Braun et al., 2019; Izquierdo-Reyes et al., 2018; Khan & Lee, 2019; Nass et al., 2005; Schuller et al., 2006). User-centred design coupled with affective computing is resulting in emotional analysis being present in cars.

In vehicles that consider the emotional indicators of passengers, it is necessary to perform several analyses (signal processing, feature extraction, emotional classification and behaviour for reaction). That processing requires energy consumption from on-board computer. In the case of electric vehicles (EV), it is interesting to forecast the consumption of said processing in order to know how this can affect to the autonomy of the vehicle and to the longest route that can be made without recharging.

EVs represents a new research field in smart grid (SG) ecosystems. Currently, the new generation of EVs provides different technologies which can be integrated in SGs. However, these new technologies make difficult the distribution of grid management. In particular, EVs and the infrastructure needed to charge them have resulted in a great quantity of new standards and technologies.

Currently, there are several research lines related to EVs: fast charging networks, battery performance modelling, parasitic energy consumption, EV promotional policies, increasing the range of the battery in EV, etc.; and other research lines related to EV energy management: contract models for consumption vehicle, market model to adopt EVs, distributed energy resources management systems

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(DERMS), distributed energy resources (DER) standards, faster charging technologies, demand response management systems (DRMS), the role of aggregators in V2G (vehicle-to-grid), energy efficiency, customer support, driver support, etc.

Additionally, all these lines are influenced by the current regulation and may different greatly between countries (for example, the regulation between United States (Lazar, s. f.) and Europe (CEER, 2019) is very different regarding energy management).

The charging infrastructure affects SG on several levels (Guerrero, Personal, García, et al., 2019; Guerrero, Personal, Parejo, et al., 2019). These levels concern the transmission, distribution, and retailer levels. The main affected frameworks inside these levels are: energy management (EM), distribution management (DM), and demand response (DR). The EM systems include several functions, one of which is the control of energy flows. The charging of an EV can be made at any point on the grid which has a charging unit. If the system has information about the expected use of the charging unit, the energy flow will be easier to manage. The DM is related with Distribution System Operators (DSO). Usually, the charging infrastructure is overseen by the DSOs. Thus, the DSOs must manage these facilities and maintain information about them. Finally, the demand response concerns retailers and DSOs, and the main problem is demand curve flattening and price management. Nevertheless, the new paradigm proposed by standard organizations, including National Institute of Standards and Technology (NIST), International Electrotechnical Commission (IEC), among others, related with V2G proposed that EVs could charge or discharge batteries. Thus, the EV is a power source in specific scenarios. In these cases, the distributed resource management is affected by the new V2G technologies as a distributed power resource in low voltage without total availability, like some renewable energy resources, for example, wind and solar energy.

Our researching group has proposed a distributed charging prioritization methodology based on the concept of virtual power plant without considering emotional factors consumption (Guerrero, Personal, García, et al., 2019; Guerrero, Personal, Parejo, et al., 2019). In these papers, we describe the Driver Modelling module which is one of the elements of the distributed charging prioritization methodology. Additionally, we get advantage from the driver pattern to stablish an emotional analysis based on the deviation from the driver pattern.

Firstly, background of this study is presented. Secondly, the methodology including emotional factors consumption is described and finally some conclusions and future work are outlined.

2 BACKGROUND

2.1 Electric Vehicle Fleets and Related Technologies

The introduction of EVs provides several advantages, but it is necessary to have additional energy sources in order to include the associated infrastructure (Meissner & Richter, 2003; Tie & Tan, 2013). The new generation of EVs has several requirements not only in power but also infrastructure (Francesco Marra et al., 2011). SGs have provided a good scenario to integrate EV and its charging infrastructure.

Dielmann & Velden (2003) propose Virtual Power Plant (VPPs) as a new solution for the implementation of technologies related to SGs, and several applications were developed to show the advantages of VPPs. The FENIX European Project (Kieny et al., 2009) delved into the concept of VPP and considered two types of VPP: the commercial VPP (CVPP), that tackles the aggregation of small generating units with respect to market integration, and the technical VPP (TVPP), that tackles aggregation of these units with respect to services that can be offered to the grid. Mashhour & Moghaddas-Tafreshi (2009) described a general framework for future VPP to control low and medium voltage for DER management. You et al. (2009) presented a case study which shows how a broker GVPP was developed based on the selection of appropriate functions. The EDISON Danish project (Binding et al., 2010) described an ICT-based distributed software integration based on VPPs and standards to accommodate communication and optimize the coordination of EV fleets. Jansen et al. (2010) proposed an architecture for EV fleet coordination based on V2G integrating VPP. Musio et al. (2010) analysed the possibility of using EVs as an energy storage system (V2G) within a VPP structure. Skarvelis-Kazakos et al. (2010) considered the EV as a mobile load and described a VPP containing aggregated microgeneration sources and EV, but is cantered around minimizing carbon emissions. Raab et al. (2011) proposed and discussed three approaches for grid integration of EVs through a VPP: control structure, resource type, and aggregation. Sanduleac et al. (2011) presented a solution for integrating EVs in the SG through unbundled smart metering and VPP technology dealing with multiple objectives. Marra et al. (2012) addressed the design of an EV test bed which served as a multifunctional grid-interactive EV to test VPP or a generic EV coordinator with different control strategies.

The common point of these references is the utilization of the VPP concept in a simulation, but they only simulate the VPP which aggregates the information of EV. The present paper additionally analyses the impact in VPP of higher levels, and how the distribution of charging is made.

Additionally, some researchers have studied the impact of HEV and plug-in HEV (PHEV) (He et al., 2012). In this sense, decentralized algorithms for coordinating the charging of multiple EVs have gained importance in recent years. Mansour et al. (2015) compared several approaches based on centralized, decentralized, and hybrid algorithm, with the latter showing better results. Hiermann et al. (2016) introduced the electric fleet size and mix vehicle routing problem with time windows and recharging stations (E-FSMFTW) to model decisions to be made with regards to fleet composition and vehicle routes, including the choice of recharging times and locations. Hu et al. (2016) presented a review and classification of methods for smart charging of EVs for fleet operators, providing three control strategies and their commonly used algorithms. Additionally, they studied service relationships between fleet operators and four other actors in SGs.

All these works did not consider behaviour or emotional parameters to forecast charging requirements in EV. In the next section we describe how emotional factors are present in automotive industry and how their impact has evolved.

2.2 Emotional Factors in Automotive

Over time, automotive industry has evolved by changing the approach based on technological developments and user needs. For highly automated vehicles where the driver still has an active role and control is shared between the automobile and the driver, the role of human-automobile interaction is highly significant (Weber, 2018).

Cooperation between car and driver needs that interaction happens on an affective level to create a successful control loop. To keep the human informed, car must understand and respond to human behaviour and emotions (Braun et al., 2019). Therefore, a high level of understanding of drivers is required (Khan & Lee, 2019).

For instance, Nass et al. (2005) studied whether characteristics of a car voice can affect driver performance and affect concluding that when user emotion matched car voice emotion (happy/energetic and upset/subdued), drivers had fewer accidents, attended more to the road (actual and perceived), and spoke more to the car. They also discussed implications for car design and voice user interface design. Schuller et al. (2006) introduced novel concepts and results considering the estimation of a driver’s emotion by focusing on acoustic information. Izquierdo-Reyes et al. (2018) proposed a multiagent-based framework called ADMAS (Advanced Driver Monitoring for Assistance System). This system considers the typical stages in affective computing, including data acquisition (signals from wearable, images from cameras, audio from microphones), signal processing (computer vision, natural language processing, audio mining) for feature extraction and emotional classification using an emotional model and machine learning to predict emotional behaviours.

Shaikh & Krishnan (2012) proposed a framework to combine empirical models describing human behaviour with the environment and system models. They analysed the design for safe vehicle-driver interaction and showed a case study involving semi-autonomous vehicles where the driver fatigue were factors critical to a safe journey.

Videla & Kumar (2020) presented an approach to detect person fatigue using image processing with machine learning. In particular, they combined two methods: face recognition with Histograms of Oriented Gradients (HOG) and Support Vector Machine (SVM) and off-the-shelf face detectors and facial landmark detectors together with a novel eye and mouth metric.

Silva & Analide (2019) considered that comfort evaluation depends on environment attributes, physical attributes and also emotion recognition. They proposed a multiagent-based computational sustainability platform which manages contexts supported by principles of computational sustainability and the assurance of sustainable scenarios. They consider social indicators based on mood analysis.

In all cases, artificial intelligence processing applied in affective computing, above all regarding machine learning techniques, requires substantial energy consumption (Strubell et al., 2019). In the case of electric vehicles this impacts in their autonomy. Therefore, modelling driver behaviour and emotion is useful to further refine the prediction of vehicle power consumption.

3 ARCHITECTURE VIEW

A solution for EV Fleet Management Platform based on the concept of a VPP and using distributed evolutionary computation algorithms to optimize the prioritization of EV fleets at different levels of SG ecosystems has been proposed in previous works. The proposed architecture and methodology are described in detail in (Guerrero, Personal, García, et al., 2019; Guerrero, Personal, Parejo, et al., 2019). Additionally, this reference treats only one of the modules related to Charging Prioritization Module, which is based on several Artificial Intelligence Algorithms:

- Genetic algorithm (GA).
- Genetic algorithm with evolution control (GAEC) based on fitness evolution curve.
- Swarm intelligence based on particle swarm optimization (PSO).

The objective of the present paper is to describe in detail the process of driver modelling, from the acquisition to the modelling stage. Additionally, the driver model is applied in a local application to determine the alteration of driver pattern, recommended different actions according to the forecasting emotional status.

The viewpoint of the proposed solution treats vehicles as a mobile load. In this manner, the system must have data about these loads and the charging prioritization. Thus, the system will have information about the expected consumption or the expected generation of the resource (in the case of a fault in the grid), such as a battery.

The proposed system works as a service for large companies with EV fleets. Knowledge about the state and prioritization of vehicles and driver patterns may minimize the impact of charging loads. These services provide new tariffs for retailers and new policies for energy price management.

The conceptual architecture of the proposed solution is shown in

, where several VPPs are included. The information is aggregated on the lower level. Then, the aggregated information is sent by each lower VPP to a higher level. In this manner, each VPP aggregates the data and services from lower VPPs to higher VPPs. Each level may have one or more VPPs depending on the needs at each level and the power grid.

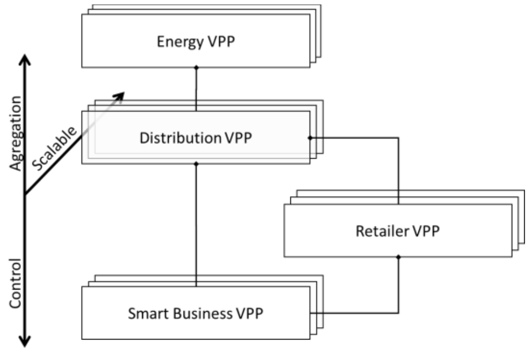

Figure 1: Scalability properties and information flow between different VPP layers.

The information representation at different levels was based on an extension of the common information model (CIM) from IEC 61870, 61968, 62325, and eMIX (Energy Market Information Exchange). The interface information is based on the component interface specification (CIS) from the IEC and OpenADR from OASIS (Open Association for System and Information Standards). The information representation and interface description are beyond the scope of this paper.

Each higher VPP can perform evolutionary algorithms to generate commands or instructions to modify the queues from lower VPPs. Additionally, lower VPPs can perform the same evolutionary algorithms to request resources from other VPPs to prioritize the charging of vehicles that cannot be charged at their charging stations.

The artificial intelligence is based on data mining algorithms or techniques. Each level runs the data mining algorithms depending on the available computational resources or option configured in the corresponding VPP. The level at which the VPP is performed determines the availability of services and data. In this paper for the platform, four levels are proposed:

- Smart business VPP (SBVPP). This is the lowest level. At this level, all information about vehicles, routes, and drivers from the same company is available. Thus, the charging prioritization of the charging stations and driver patterns of the company is treated at this level. The state of charge (SoC) is also calculated at this level.
- Distribution VPP (DVPP). At this level, information is aggregated from lower levels, and information about retailers and the presence of charging stations is stored. This information is sent to higher levels, such as an energy VPP (EVPP). Additionally, the

restrictions from an EVPP to the corresponding retailer and SBVPP are addressed at this level.

- Retailer VPP (RVPP). At this level, a retailer needs to know when vehicles require charging at any point outside of the company points. The retailer can use this information to offer different tariffs to a company.
- Energy VPP (EVPP). In this paper, the vehicles represent mobile loads. Thus, if an energy management system has information about the expected charging stations, it may take advantage of this information to improve the load flow forecasting algorithms.

The prioritization process is performed in several stages to aggregate information for the upper layers and to control lower layers.

The lowest levels implement functions that are related to consumers. The medium levels implement functions that are related to energy distribution and commercialization. The higher levels implement functions to guarantee the quality and continuity of a power supply. This architecture is highly scalable, increasing the interoperability between different enterprises and integration of heterogeneous ecosystems. The VPPs include data mining algorithms and some capabilities in the corresponding driver modelling modules which makes the driver pattern modelling quicker and easier:

The data mining algorithm in an SBVPP. This algorithm sorts the vehicles with their drivers according to the SoC and expected route. If the algorithm cannot model any driver, the algorithm classifies the driver as an external model and sends the request to higher VPPs. The SBVPP can receive commands and warnings from the DVPP and RVPP, and it downloads general driver patterns. The higher VPP commands and warnings are considered as external restrictions. The external driver patterns are considered as general models with low priority level, and they will be replaced by the models generated in the first route. Additionally, the RVPP commands and warnings can take effect over different elements of customer power facilities when the customer that implements a SBVPP has contracted additional services from a retailer to manage the customer power facilities.

The data mining in a DVPP. The DVPP gathers all requests from all SBVPPs. In the prioritization module, this information is employed in an evolutionary algorithm to prioritize charging in available charging stations. In case of driver modelling module, the data mining algorithm takes advantage form different modules generated in the SBVPP, providing a generalized classification of the different models or patterns. The generated models are the basis for the driver models in the SBVPP level.

The EVPP does not gather any information from driver modelling, but this level takes an important role in the charging prioritization.

The RVPP gathers all information about vehicles that may have contractual relationships with a retailer. The retailer can use this information to offer new services to clients. If any problems arise in the client contract, the retailer can send a command or alarm to change the prioritization for one or more vehicles and/or charging stations. In case of driver models, the RVPP gather information about the best driver pattern (in terms of energy efficiency), and the RVPP could offer new services or advantages related to the correspondence with the driver pattern.

All information about driving is gathered from vehicle and transmitted to the SBVPP when the driver cellular connects to the acquisition system. The information about the current route and data from the vehicle is stored in the Driver Modelling. This information is used to update the driver model or pattern.

Any algorithm for the SBVPP and DVPP is possible because the algorithm works independently of other layers. Thus, several algorithms were tested in this paper, and a final configuration is proposed based on the results of the tests. However, the algorithms can be configured according to the resources of each level.

3.1 The Electric Vehicle Fleet Management VPP

The Electric Vehicle Fleet Management VPP or Node (EVFMN) is the generic system implemented in each VPP. The architecture of Electric Vehicle Fleet Management Platform (EVFMP) is shown in Figure 1, and it is formed by the replication of EVFMN between different VPPs, enabling or disabling certain functionalities according to the level of VPP. The EVFMN is shown in Figure 2. Each module has specific functions:

- Asset Management System. The asset management system is based on the predictive maintenance of vehicles and charging stations.
- Driver Modelling. This module executes a modelling process of driver behaviour. This module provides a driver pattern which is used to schedule the routes and, in this case, to forecasting the driver's emotional context.
- Energy Efficiency. This module applies different techniques to optimize the energy consumption

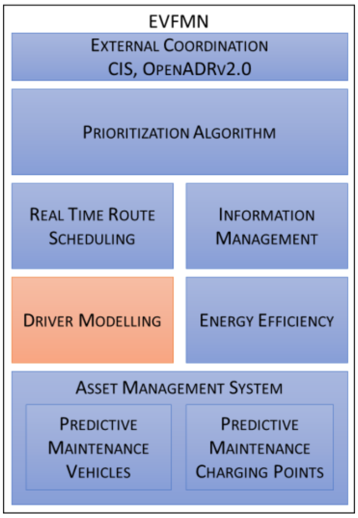

Figure 2: Modules of distributed evolutionary prioritization framework.

and reduce the maintenance periods and economic impact.

- Real-Time Route Scheduling. This module manages all information about vehicles, routes, drivers, and external conditions to establish better prioritization in each charging station.
- Information Management. This module manages all information of this VPP for reporting and visualization.
- Prioritization Algorithm. The prioritization algorithm in this layer is based on swarm intelligence.
- External Coordination. This module sends information to higher layers and gathers information about external requirements or vehicles to charge.

The external coordination is provided by the interoperability with higher VPP layers.

Some modules, such as external coordination, prioritization algorithm, and the SoC module, are available for all VPPs. The other modules depend on the available information in the VPPs. For example, the SBVPP has all information about the EV fleet; however, the SBVPP may have additional services of energy efficiency if it shares the information with the RVPP (in this case, the RVPP would use the energy efficiency module).

In case of Driver Modelling, it is not included in the EVPP level, and it optionally could be included in RVPP, depending on the services provided by this level.

3.2 Information Acquisition from Electric Vehicle

The information is gathered from ODB-II system (Road vehicles—Diagnostic systems—Part 2: CARB requirements for interchange of digital information, 1994), a standardized CAN-bus based protocol, designed for cars monitoring. This bus was introduced in 1995 in North America, being mandatory in all cars since 2008 (Taha & Nasser, 2015). Similar situation happens in Europe, being mandatory in all gasoline vehicles since 2001 and diesel since 2003.

Therefore, according to different regulations all modern relies on embedded computers, called engine control units (ECUs) (Moore et al., 2017), designed to control different subsystem of the vehicle as motor control, lights, braking subsystem, etc., most of them using standardized messages.

As appear in the literature, this information can be used to estimate vehicle speed (Bagheri et al., 2018), or modelling the behaviour of the driver (Wang et al., 2018), as we need in our proposal.

In this case, we use an ODB-II to Bluetooth interface that sends the information to a mobile application that executes the proposed algorithm.

3.3 Driver Patterns

Driver behaviour is stored in driver patterns. The driver pattern is a model that takes effect over the consumption of a vehicle in route scheduling. The driver pattern affects the calculated SoC for each section of a route; it depends on the terrain topology and traffic data. Driver behaviour is calculated according to the historical data of a driver. If historical information about a driver is not available, this pattern will be calculated only with the emotional information.

The driver pattern consists of the deviation from the original predicted SoC. This pattern considers information about traffic, weather and previous emotional behaviour to explain the variation from the original predicted SoC.

Although a default driver pattern can be defined, information about driver patterns is currently unavailable. A default "average" driver pattern can be created when a system has adequate information. Currently, this pattern does not include the utility factor [39] because the EV fleets are treated as mobile loads and they do not include PHEVs.

The Driver Modelling process is based on Generic Rule Induction (GRI), Support Vector Machine (SVM) and K-Means clustering algorithm involving the Cronbach alpha variation analysis, which uses the information provided by acquisition system: accelerator and brake usage, average speed, variation of revolution per minute (rpm), usage of HVAC in the vehicle, brake energy restoration, etc. All this information provides a classification of driver pattern, which is translated into a set of typical values for different parameters in a different confidence ranges and correlation variation.

3.4 Real-time Route Scheduling

This module controls several conditions that can modify the current prioritization charging queues. This module notifies any change in the following conditions:

- Driver and EV availability.
- Route modifications.
- Traffic and roadwork.
- Weather conditions.
- Charging station availability.

3.5 SoC Module: Estimation of EV Consumption

The proposed solution is based on the instantaneous SoC value of each EV. These algorithms require an estimation of some consumption according to its planned route and alternative routes to reach different recharging spots. This consumption estimation is supported by a route planning tool. However, these estimations are not trivial and are related to the distance or time of the trip (Shankar & Marco, 2013; De Cauwer et al., 2015). Other factors (e.g., road (Park et al., 2009) and vehicle characteristics, traffic (Boriboonsomsin et al., 2012), driving style (Bingham et al., 2012), and weather conditions) are essential for this estimation.

4 DATA MINING ALGORITHMS

The data mining algorithms are based on the combination of three algorithm or techniques:

- Cronbach alpha variation analysis. This technique aids to classify the different parameters according to their variance related to other parameters, providing a map of the importance of different parameters in the driver pattern. The Cronbach alpha calculated for all parameters provided a general number, which describe the correlative variance between parameters. Additionally, the Cronbach alpha relative to each parameter p is calculated, providing a new value for Cronbach alpha corresponding to the new correlative variance, without the influence of the corresponding parameter p. If the value is greater than the general Cronbach alpha, the parameter p has a low level of relation with the driver pattern, and the variation of this parameter could provide erroneous patterns. If the value is lesser than the general Cronbach alpha, the parameter p has a high level of relation with the driver pattern, and the parameter is probably affected by emotional behaviour.
- K-means. Classifies the values according to the Cronbach Alpha stablishing classifications for each range of each parameter. Additionally, the algorithm is used to classify the different results of patterns, making groups according to the common characteristics of the driver behaviour. The method supposed that the driver drives with a pattern and this pattern is related to emotional context. Thus, the different groups describe different emotional status. In this case, it is not important to reveal the emotion. Thus, according to the distribution the emotions are named emotion1, emotion2, etc.
- Support Vector Machine. Classifies the driver pattern according to the other driver patterns.

This paper is centred in the results of K-mean algorithm to get different clusters which represents a classification of patterns based on emotions.

5 EXPERIMENTAL RESULTS

5.1 Sample Description

The sample provided comes from a real sample extracted from vehicles. However, this information was not extracted in real time, it was extracted by using a device to gather periodically information from vehicles, based on CAN-bus (Controller Area Network), specified by different standards (J2411, J2284, J1939, ISO 11898, etc.). The information is complemented by information of routing management and scheduling,

The extracted information comprises a sample with 2711 different routes. Each route is done by 32 different drivers during three months, around the same area.

The sample contains the following information: weather information, driver code, route code, route distance, number of stops in the route, route information, traffic information, doors, lights, brake, accelerator, gearbox, speed, voltage, distance travelled, current, and state of charge of the batteries. Additionally, there are some claims notified by clients about the drivers. This information is modelled by a parameter with the number of claims by route.

From Cronbach alpha variation analysis, two parameters are associated to each variable: the general Cronbach alpha, the correlation coefficient, and the Cronbach alpha if the corresponding parameter is removed from sample. These parameters are used to check the importance of parameters in the sample compared with the K-means results.

5.2 K-mean Results

The application of K-mean algorithm in the data provided by an electric vehicle fleet in distribution logistics, provided a basic classification of different patterns to drive, which take effect in the efficiency of driving.

The different clusters are corresponding to different driving types (figure 3). For example: the cluster-5 correspond to the emotion5, this emotion is like the great bag in which all the cases that are not possible to classify, including the 30% of claims (9 claims). However, the cluster-4 (emotion4) has 14,9 % of routes, and groups the drivers who has a very aggressive driving (this information is extracted from parameters of speed, accelerator, gearbox, and state of charge), including the 70% of claims (21 claims). Thus, using the information provided by vehicles and making this classification, it is possible to provide a forecasting about the influence of emotion in the vehicle driving, and could be notified to the system, in order to maintain a good level of efficiency in the consumption of vehicle. Cluster-2 and cluster-3 corresponding to drivers with careless driving pattern, according to the information from parameters. The cluster-1 groups all the patterns which provokes a high efficiency driving, decreasing the consumption and an understandable time invested in the route.

The size of smallest cluster is cluster-3 with 0,6% or 16 cases. The size of biggest cluster is cluster-5 with 53,9% or 1461 cases.

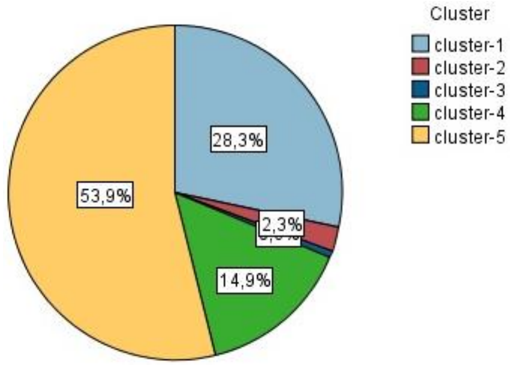

Figure 3: Sizes of Clusters obtained from the application of K-mean algorithm.

6 CONCLUSIONS AND FUTURE RESEARCH

The proposed platform can integrate information from electric vehicles to be considered as part of the electric vehicle fleet management platform to integrate the electric vehicle fleets in smart grids as mobile loads.

On one hand, the role of emotion in automotive driving is increasingly present, empowering human-centred design coupled with affective computing in driving context to improve future automotive design. The driver emotional status influence is modelling by the deviation of the driver pattern based on a Generic Rule Induction, Support Vector Machine and K-Means clustering algorithm involving the Cronbach alpha variation analysis, which provides a light-weight model to perform in low feature devices.

On the other hand, electric vehicle fleets and smart grids are technologies that have provided new possibilities to reduce pollution and increase energy efficiency looking for sustainability. The inclusion of driving data can improve the routing and charging prioritization forecasting, providing additional services to the different actors in the energy market, and other advantages for the better stability of the power grid.

The future works will be centred on provide more information about driver, including some devices to provide more information about emotional status of driver, based on biometric factors or emotional estimation by means of face image analysis. This information provides more possibilities to analyse the results presented in the present paper.

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