energies

Review

Prediction of Electric Vehicle Range: A Comprehensive Review of Current Issues and Challenges

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Abstract: Electric vehicles (EV) are the immediate solution to drastically reducing pollutant emissions from the transport sector. There is a continuing increase in the number of EVs in use, but their widespread and massive acceptance by automotive consumers is related to the performance they can deliver. The most important feature here (a hot topic at present in EV research) is related to the possibility of providing a more accurate prediction of range. Range prediction is a complex problem because it depends on a lot of influence factors (internal, external, constant, variables) and the present paper aims to investigate the effect of these factors on the range of EVs. The results and aspects of current worldwide research on this theme are presented through the analysis of the main classes of influence factors: Vehicle design, the driver and the environment. Further, the weight and effect of each potential factor which influences EV range was analyzed by presenting current issues. An exhaustive and comprehensive analysis has made it possible to identify future research and development directions in the EV research field, resulting in massive future and immediate EV penetration in the automotive market.

Keywords: electric vehicle; range prediction; energy; efficiency; model

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1. Introduction

It is now widely accepted that electric vehicles (EV) are the solution for sustainable transport in the future, at least in terms of passenger cars and light transport vehicles. This is due to the zero local emissions feature of the cars, which reduces (and even removes totally in certain areas) the pollutant emissions caused by transport processes inside of large urban agglomerations, also making an essential contribution to reduce greenhouse gas emissions, especially CO_2. However, there is still a problem with the energy mix used to power/charge the batteries of an EV. It is a mix that can indirectly lead to a high level of total CO_2 emission, caused by the electric energy production process required for the operation/use of an EV [1].

With the accomplishment of numerous studies to increase the competitiveness of EVs over similar vehicles equipped with internal combustion engines (ICE), it has been observed over the last few decades that a growing number of manufacturers have adopted electric propulsion technology (pure electric or hybrid) and have proposed more and more EV models in the automotive market (including passenger cars and also electric buses) [2,3].

However, the technological development relating to the energy source of propulsion for EVs is still far from providing advanced and/or energy-efficient technical and technological solutions, and some immediate issues need to be addressed in this regard [4–8]:

- Costs associated with production and their correlation with the purchasing power of customers;
- Identifying a battery technology that provides the best power/weight capacity ratio, low charging time, high lifecycle, safety in operation (eliminating the risk of self-ignition due to thermal load), reduced production prices;
- Calculation of well-to-wheel emissions, due to the energy mix used in the battery charging process;

The aspects mentioned above are some of the actual barriers to massive penetration of the car market by EVs, but besides these aspects, the perception and attitudes of customers also have a central role. There have been various studies on the perception of clients and users regarding the adoption and acquisition of an EV [9–13]. The main factors considered in the studies performed were:

- Range satisfaction;
- Intention to recommend;
- Purchase intentions;
- Vehicle purchase price;
- Maintenance costs;
- Reduced greenhouse gas emissions;
- Cost of exploitation.

It can be seen from the results obtained from these studies that the issue of autonomy (range) is an important element in the attitudes and perceptions of consumers in the automotive market, mainly due to the level of technical knowledge of the consumers regarding the amount of energy stored in an EVs batteries and the overall energy efficiency of an EV [9,14–16]. It is not surprising that the predictability of the possible distance to be achieved by an EV is directly related (and has a major weight in the perception and attitude of consumers towards the EV) to the vehicle's energy capacity. The battery is a central element in the construction and operation of the powertrain group of an EV.

Recent research and progress in the technological development of batteries used in the construction of an EV has shown that in past few decades, their energy capacity has increased from 80–100 Wh/kg to 200–250 Wh/kg, with an important drop in the production price of a battery pack from 450–600 USD/kWh to 250–300 USD/kWh [2,6].

Power sources based on lithium-ion (Li-Ion) technology are the most used energy sources in EV construction and are made up of several electrochemical cells. Each electrochemical cell consists of a graphite anode, a lithium oxide cathode and an electrolyte (based on lithium salt and an organic solvent). Lithium is a rational choice for the construction of an electrochemical cell due to its many functional advantages. Its electrode has high potential (-3.04 V), resulting in a high operating voltage (which influences both the power and energy stored in the electrochemical cell; specific energy 90–240 Wh/kg (200–500 Wh/L) on cell level), high discharge rate (up to 40 °C), fast charging capable, low self-discharge rate (<5% per month, depending on storage/rest temperature), no memory effect, no reconditioning needed and tolerates micro-cycles.

Generally, for automotive applications, a lithium-ion battery pack needs to be made up of tens and thousands of individual cells packed together in several modules to provide the voltage, energy, and power required to operate the vehicle at the required parameters.

It should be noted, however, that there are a number of standard minimum requirements for lithium-ion batteries used as an energy source for EVs:

- High lifetime (8–15 years);
- Cycle life (2000–5000 @ 80% DOD—depth of discharge);
- Operating/exploitation effectively at a temperature range between -20 °C and 60 °C;
- Resistance to vibration effects (caused by the vehicle-road interaction and by the EV's powertrain).

It is considered that the implementation of a general and reliable method to estimate the electric energy available in the battery pack of an EV as accurately as possible, also correctly predicting EV autonomy, can alleviate the driver's range of anxiety and improve driving safety [17].

Through the study of the scientific literature, the authors have not found a work that presents in totality the integration and magnitude of the factors (majors and minors) that can influence the EV range prediction in a single mathematical model. This paper aims to make a comprehensive review of the problems raised by the prediction of the autonomy of electric vehicles (EV), the research carried out so far on the predictability of the range/autonomy that can be traveled by an EV, the interference between different factors influencing the current research results and directions, as well as issuing conclusions that will provide indications on future directions to solve the current issues related to this topic.

2. Influence Factors on Range Prediction

2.1. General Considerations

The prediction of possible EV range generally depends on three major classes of influence factors: Vehicle design, driver and exploitation environment (Figure 1). Research on this topic shows that each of these classes depends on the variation of direct or indirect parameters [17–20]. Some of the parameters have a constant value (e.g., vehicle type, transmission type, number of seats, mass, weight, battery type, road infrastructure, availability of battery charging infrastructure, loading time, etc.) and other parameters are variable (battery state of charge—SOC, battery state of health—SOH, driver behavior [21], traffic flow [22], EV dynamic performance, battery management system (BMS), external weather/environmental factors [23], interior of the cabin, etc.), all of them influencing the EV's range performance (Figure 2). However, most of the work in the field that studies and deals with these issues is directly related to the linear estimation of the maximum that can be achieved by an electric vehicle based on real-time SOC battery estimation [24].

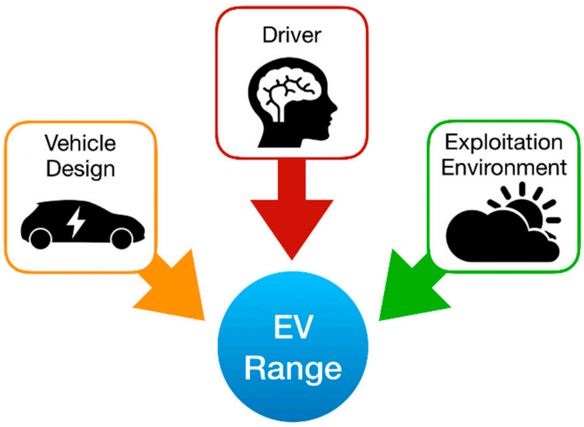

Figure 1. Classes of factors that influence an electric vehicle's (EV's) range.

2.2. Electric Vehicle

2.2.1. Vehicle Design

The influence of the construction/design of an electric vehicle on the overall energy efficiency of an EV is directly related to a multitude of factors, factors that are required by general laws and regulations as well as by the specific requirements of consumers from the automotive market. Generally, these are the overall dimensions, passenger capacity, body type, volumetric luggage capacity, rolling train, specific front area, tire type and shape, type of HVAC (heating, ventilation and air conditioning) system, etc. The design and subsequent construction of an electric vehicle starts from physical relations in accordance with Newton's second law of motion, by considering all forces acting on the vehicle in motion (Figure 3).

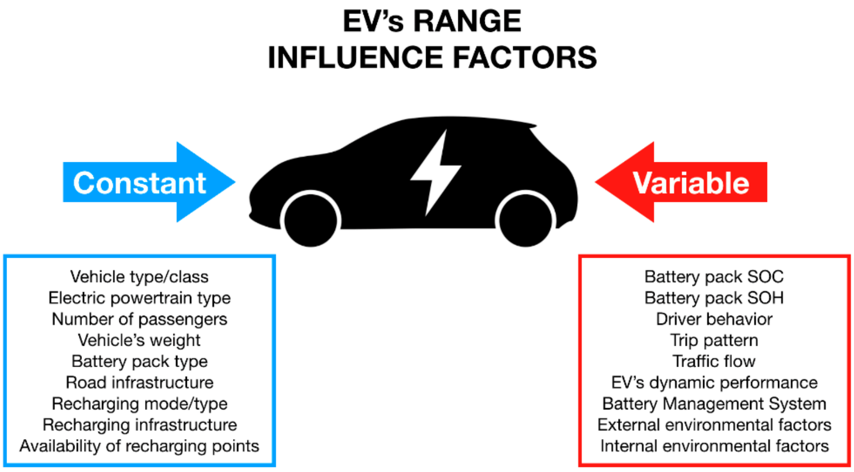

Figure 2. The main influence factors on EV's range (constants and variables).

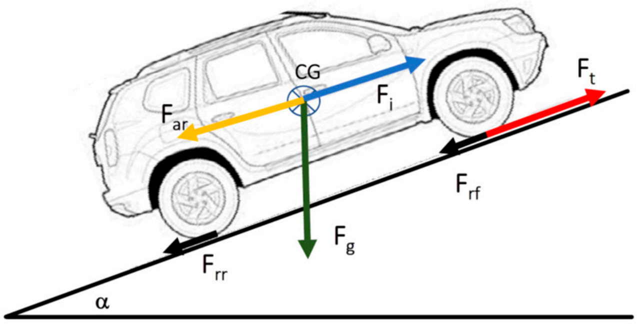

Figure 3. Forces acting on a moving vehicle (F_i, inertial force; F_t, tractive force; F_g, gravitational force; F_{rr}, rear rolling resistance force; F_{rf}, front rolling resistance force; F_{ar}, aerodynamic (air) drag; CG, center of gravity; α, the road slope).

The tractive force (F_t) necessary to propel a vehicle forward consists of gravitational force (F_g), rolling resistance ($F_r = F_{rr} + F_{rf}$) and aerodynamic (air) drag (F_{ar}), which is calculated as:

$$F_t = F_g + F_{ar} + F_r = mgsin\alpha + \frac{1}{2}\rho_a C_d A\left(v + v_{fw}\right)^2 + mgc_r \quad (1)$$

where m is the mass of the vehicle, g is the gravitational acceleration, ρ_a is the air density, C_d is the drag coefficient, A is the vehicle's frontal area, v is the speed, v_w is the frontal wind speed and c_r is the rolling resistance coefficient.

The necessary power delivered by an engine such that the vehicle maintains a desired acceleration and speed is given by the following equation:

$$P_e = \frac{1}{\eta_{eng}} \cdot F_t \cdot v \quad (2)$$

where P_e is the engine power and η_{eng} is the engine (powertrain unit/group) efficiency.

It is noticed that starting from this initial physical relationship, the sizing and selection process of a battery pack and the electric powertrain group that will later equip an electric vehicle is directly related to the characteristic design parameters of the electric vehicle. It should also be mentioned that the body shape of an electric vehicle influences air drag resistance through the specific front area (generally with major influence for speeds higher than 36 km/h [25]), which implies the necessity of creation for a body that has a low aerodynamic coefficient. The current tendency of major manufacturers in the automotive industry is to adapt an already existing body shape to an electric powertrain, meaning that the aerodynamic coefficient is not significantly improved. However, given that certain EV models will be (are) designed for urban pre-use, this can be neglected, because in most urban agglomerations, the average speed (traffic) is well below 36 km/h (Table 1).

Table 1. Average traffic speed of traffic in urban agglomerations [26].

City	Average Traffic Speed (km/h)
Seoul	22.4
Tokyo	21.4
London	19.0
Copenhagen	15.5
New York	12.5
Los Angeles	12.4
Beijing	12.1
New Delhi	3.1

In addition to the power calculation required to be developed by the powertrain unit of an EV, there is a feature of the operation of an EV which allows the generation of energy during the braking or deceleration process (due to particularities of the electric powertrain), providing energy to be directed and used for partial charging of the battery pack. This is known as the regenerative braking process [19,27]. The energy balance of a battery pack is given by Equation (3):

$$P_{bp} = k \cdot \eta_t \cdot \eta_{em} \cdot P_t + P_{aux}, \tag{3}$$

where P_t is the mechanical tractive power at the wheels, P_{bp} is battery pack's electrical power, η_t is the transmission efficiency, η_{em} is the electric motor efficiency, P_{aux} is the cumulative power of the auxiliary equipment and k represents the energy reconversion factor.

The regenerative process caused by the brake and/or deceleration process of the vehicle is obtained for the condition $P_t \leq 0$.

To define regenerative braking energy efficiency, an energy reconversion factor (k) is used, which can be represented by a function dependent on the vehicle's acceleration (a) (Equation (4)) or speed (v) (Equation (5)), thus [27,28]:

$$k = \begin{cases} \left(e^{\frac{0.0411}{a}}\right)^{-1} & a < 0\ \mathrm{m/s^2} \\ 0 & a \geq 0\ \mathrm{m/s^2} \end{cases} \tag{4}$$

$$k = \begin{cases} 0.5 \cdot v & v < 5\ \mathrm{m/s} \\ 0.5 + 0.015(v - 5) & v \geq 5\ \mathrm{m/s} \end{cases} \tag{5}$$

The method of estimating the k factor by considering the EV's acceleration/deceleration regime (Equation (4)) is a more accurate method, because it directly considers the deceleration effect of the vehicle at the moment of braking (and the automatic start of the energy regeneration system).

However, in practice, it is more challenging to obtain instantaneous data of a vehicle's acceleration, and it is, therefore, preferable to use a method that considers the EV's speed in calculating the efficiency of the energy regeneration process (Equation (5)). The information on the current speed of the EV can be obtained easily from the data provided by the control and command systems of the EV (on-board computer).

It should be noted that both previously presented estimation methods of k factor are empirical methods based on the analysis of data obtained from experiments on particular types of EV (e.g., the Nissan Leaf and Chevy Volt [28]) and do not offer a generalized application of an EV range prediction model for any constructive type of EV.

However, under the actual operating conditions of an EV, there are two major factors that influence the power requirement to ensure that the vehicle has a constant speed on the road, namely: The total weight of the passengers (the number of passengers transported varies the total weight of the vehicle) and the optimum pressure in tire (which influences the vehicle's rolling resistance). Research studies have shown that an important parameter of EVs that directly affects the range characteristics is their weight [20,28–30], but these studies focused mainly on the effect of battery pack weight (depending on the technologies used in the electrochemical cell construction) and the type and complexity of the BMS and BTM (battery thermal management) systems. Future studies should also consider the fact that a load of 5 passengers on the electric vehicle leads to an increase of approximately 15–25% in its total mass. Consequently, by extrapolation, it can be said that the increase in the number of passengers transported (and implicitly the total mass of the electric vehicle) increases the EV's energy consumption.

Also, by matching with studies conducted on ICE-equipped vehicles, maintaining optimal tire pressure can result in a saving in fuel consumption (and sequentially the energy needed for traction) of up to 10.08% (for a speed of 40 mph) [31]. Therefore, for this reason, these two major factors must also be considered in the development of specific tools to evaluate an EV's prediction of range.

2.2.2. Battery Management System

The battery management system (BMS) is designed and used to manage all control and command operations of the battery pack and energy transfer from the battery pack to the powertrain by [31]:

- Battery charging and discharge control based on the energy demand of the powertrain and the available energy load;
- Protection of electrochemical cells against over-charging and/or over-discharging phenomena;
- Monitoring and balancing electrochemical cell voltage;
- Equalization of charging between battery cells;
- Monitoring the input and output voltage and current;
- Monitoring and controlling the battery temperature;
- Control and command of electrical and electronic systems;
- Diagnose, evaluate and display faults and malfunctions.

In terms of internal organization, a BMS system is formed by a hardware module (consisting of sensors and actuators, thermal management elements, protection circuits, communication network etc.) and a software module (with models for the prediction, estimation and calculation of SOC, SOH, cell balancing and fault detection) [32].

The IT (information technology) solutions implemented in the BMS function control the operation of the hardware elements/subsystems and estimate the operational state of the battery cells. Balancing control of the cell load/discharge, actuators' control and safety circuitry are performed by the BMS's implemented software. The specific software implemented within a BMS system also performs data analysis for the continuous process control and update of battery functions, in order to estimate the in-service (currently operational) status (which is a key factor for successful battery operation), permanently helping to identify possible failures.

The assessment of the functional state of the battery is performed mainly by analyzing two basic parameters: The battery charge level (SOC) and the internal degradation level of the cells (SOH). The SOC parameter is calculated using information about the voltage, current and operating temperature, and the SOH parameter is calculated based on the degradation of the electrochemical process performance in the battery cells (which reduces the charging/discharging capacity and available energy). Because the battery discharge and charge processes involve complex chemical and physical processes, it is not an easy task to estimate the value of the SOH parameter accurately. The calculation process of SOC and SOH is done using different mathematical models and algorithms: Conventional, non-linear, hybrid, neural networks, fuzzy logic, etc. [32].

Currently, there have been multiple studies and attempts to develop and implement different methods to estimate/calculate SOC, and generally, they can be classified into five major categories (Figure 4):

- Conventional methods (CM);
- Adaptive filter algorithm (AFA);
- Learning algorithm (LA);
- Non-linear observer (NO);
- Hybrid methods (HM).

The prediction of range for an EV directly depends on the accuracy of the SOC prediction. This is because it provides primary information about the amount of available energy to be used by the EV's powertrain. Therefore, the accuracy of prediction (the magnitude of prediction errors) is an important factor in choosing and implementing a SOC estimation method within an EV's systems.

By comparison, the advantages and disadvantages, along with the prediction errors of the main SOC estimation/calculation methods are presented in Table 2.

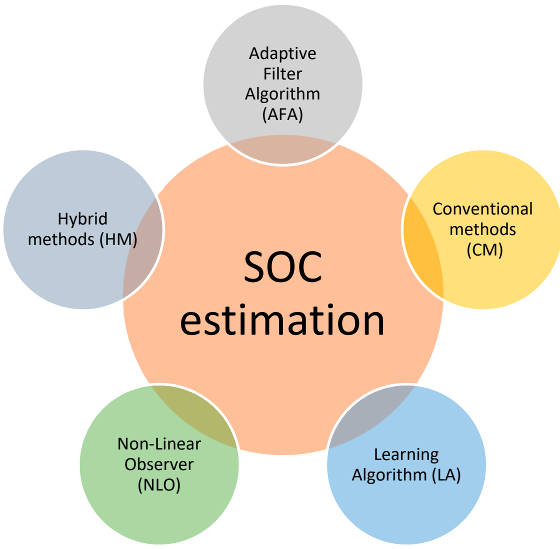

Figure 4. State of charge (SOC) estimation methods.

2.3. Driver

The influence of drivers on the energy efficiency of operating an EV in real traffic conditions can be delimited in two major ways. First, the energy efficiency of an EV depends on how it is exploited, by the so-called "driver aggressiveness". Driver aggressiveness mainly refers to how the acceleration pedal is operated (vehicle acceleration variation/gradient) and research by [20] has found that an EV's range is not influenced only by design parameters, but also influence of the driver. Simulations have been carried out using real driving cycles to determine how these factors influence the range of EVs.

Four acceleration cases were taking into consideration for comparison, the initial condition being the on-going departure of the vehicle until it reached 50 km/h after 10, 15, 26 and 36 s. In terms of the energy consumed, there was a difference between the fastest and slowest acceleration by approximately 4% at the EV's considered weight of 1000 kg, and 2.7% at the EV's considered weight of 1500 kg.

Secondly, it is the human factor (psychological factor) of the driver through the existence of the psychological perception of distances that can be achieved by an EV (range anxiety) [33]. It has been shown that range and range of anxiety are closely related concepts and users actively avoid critical range situations by reserving a substantial range of safety buffers (on average only about 80% of their actual range available). The results obtained by researchers [16] indicate that experienced EV drivers have significantly less negative range ratings and lower range stress than inexperienced EV drivers. Therefore, driving the experience of the EV driver seems to have a direct effect on range anxiety at the cognitive, emotional, and behavioral levels.

Table 2. General methods for SOC estimation [32].

Category of SOC Estimation Method	Estimation Average Error	Advantages	Disadvantages
Conventional Methods (CM)	±2–8%	Simple, easy-to-use, high-precision method and consumes few hardware and software resources (relatively low costs to implement).	Difficulties in determining the initial state of SOC in time (the internal resistance of the battery undergoes changes over time due to specific chemical processes).
Adaptive Filter Algorithm (AFA)	±1–4%	Good estimation by eliminating "noise" caused by external factors of the system that defines the energy source. Good accuracy achieved in low time.	Using complex mathematical calculations that offer the possibility of errors due to particularities of used algorithms.
Learning Algorithm (LA)	±2–5%	High accuracy in estimation of battery energetic capacity by considering as parameters: SOC, SOH and working temperature. Can be applied to batteries operating under non-linear conditions of energetic processes.	It requires for implementation of large computational memory for complex mathematical calculations.
Non-linear Observer (NLO)	±1–4%	Good, reliable and fast estimate of SOC.	Requires a good choice and programming of the controller, with limitations due to the use of the specific matrix to reduce/eliminate errors.
Hybrid Methods (HM)	±1–8%	Relatively accurate and stable estimate of SOC obtained with relatively low implementation costs.	Errors in estimation of the SOC marginal values, due to the correlation and implementation of several/different SOC estimation methods.

Other direct factors of influence (with a minor impact on the energy consumption/energy efficiency of the EV's battery pack) of the driver's behavior on the energy efficiency of an EV are those related to how the driver uses the vehicle in different traffic conditions. This involves proper use of regenerative braking, aggressiveness in traffic, specific trip pattern and the use of auxiliary equipment in the electric vehicle (air conditioning, open windows, use of lights, entertainment systems, etc.).

Taking into account that the behavior of the driver is determined in particular by the individual psychological reactions specific to each individual, it is difficult to create specific algorithms that accurately determine the influence of these factors on an EV's prediction of range. However, based on the data on this issue that can be collected and stored, there is a possibility that it can be predicted (and considered) for example, by the driver's pattern of starts or acceleration processes in different traffic/road conditions.

2.4. *Environment*

The range of an EV is directly influenced by the external environment (outside ambient temperature, precipitation, wind, etc.) as well as by the internal environment (temperature in the passenger compartment, use of auxiliary systems and electric consumers, etc.). Also, the existence of minimal thermal comfort in the operation of an EV is a major condition for rapid and massive acceptance of this technology by customers, and in terms of this, it is necessary that EVs are equipped with HVAC systems. The total thermal load of an EV is the sum of the thermal loads due to the environment (inner and outer) in which it is operated (Figure 5). The mathematical formulation of the thermal loads of a vehicle, according to Figure 5, can be expressed as:

$$Q_{tot} = Q_{ven} + Q_{rad} + Q_{amb} + Q_{itl} + Q_{AC} \quad (6)$$

where Q_{tot} is the total heat gain encountered by the cabin, Q_{ven} is the ventilation load, Q_{rad} is the solar radiation load, Q_{amb} is the ambient load, Q_{itl} is the internal thermal load and Q_{AC} is the thermal load generated by the HVAC system. The internal thermal load (Q_{itl}) considers the thermal load generated by the passengers' bodies due to metabolic processes (55–85 W/m^2 [34]) (Q_{met}) and the thermal load caused by the heat radiation of the inner surfaces from the passengers' space (dashboard, door panels and the area, material and surface type of seats, etc.) (Q_{shr}).

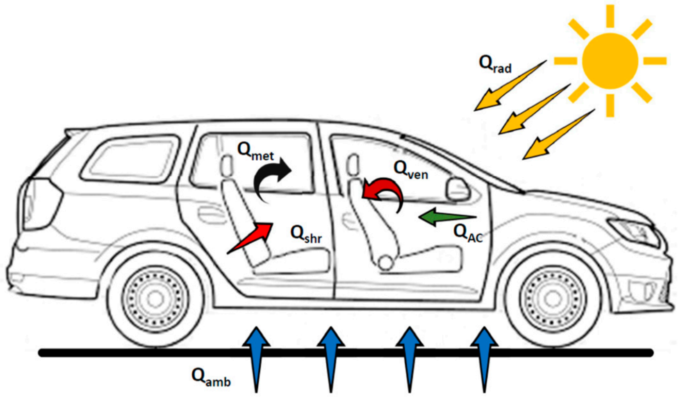

Figure 5. Thermal loads of a vehicle (schematic representation).

Studies have shown that climate control loads (Q_{AC}) will cause significant range reduction in both winter and summer. Under different simulation conditions, the cooling load in summer will cause a 17.2–37.1% range reduction, and in winter the heating load will cause a range reduction of 17.1–54.0% [34]. The effect of the HVAC system on EV's range, in the condition of variable ambient temperature, was investigated in the case of a Nissan Leaf [35]. Using experimental data, the authors conducted simulations for different driving cycles (NEDC—New European Driving Cycle, FUDS—Federal Urban Driving Schedule and SFUDS—Simplified Federal Urban Driving Schedule) considering extra urban, rural, and motorway driving profiles. The obtained results showed that the EV's range exceeds 150 km for an ambient temperature of 20 °C, while it reduces to 85 km at 0 °C and 60 km at −15 °C.

High values of range reduction due to this factor need to be considered in the development of predictive tools, along with the need to develop research in this direction (e.g., the use of heat pumps, the correlation of the BTM (battery thermal management) system with the HVAC system in the vehicle, the use of TEG (thermo electric generator)-based heat recovery systems and transformation into electric power, capable of being stored in supercapacitors, etc.). It is also possible to consider the possibility of using energy-independent auxiliary equipment from the EV energy source for the HVAC system of the vehicle. For this purpose, an independently fueled air heating system can be used for heating. However, the required performances of the HVAC system regarding the energy efficiency of the system vs. weight, ease of use and safety are perceived as barriers to the use of an EV by the consumer.

The external environment has a direct influence on the BTM of the battery pack by direct thermal loading (through its own operation) or indirectly (from other sources of heat through radiation). The heat generated by a running battery is directly proportional to the energy demand required by the powertrain group at a specific time. The higher the demand for energy, the higher the power delivered, and consequently the higher the temperature inside the battery pack. The overall conclusion that has been reached is that a limitation of the operating temperature of a battery pack is necessary and leads to an increased lifetime [24].

The cell's solid electrolyte interface (SEI) layer formation is a necessary part of the initialization process of the battery during the first charging cycles. The SEI layer protects the electrolyte material from further depletion and protects the charged anode from corrosion (the anode material reacts with the electrolyte material) [36]. Unfortunately, due to irreversible side reactions during the cell's cycling process, SEI layer growth will occur at the anode, being a major cause of fading battery capacity and power loss over time [37]. The SEI modification/growth reduces battery life (an aging process of battery) and is a mechanism that is dependent on the cell's functioning temperature. Low temperatures can cause problems at the level of the electrochemical cell (due to the intrinsic properties of the materials used) through the rapid increase in cell impedance, with growing contribution from charge transfer and SEI to the total cell's resistance [38]. It is also considered that a battery's fading capacity is accelerated at elevated temperatures (>60 °C), due to enhanced decomposition of the electrolyte solution, a growth of a solid electrolyte interface and also the non-uniformity of the SEI layer [39].

In those conditions, a problem arises regarding when the optimum moment is to charge an EVs battery, taking into consideration the climatic conditions (ambient temperature). It has been demonstrated for low ambient temperatures that the charge-transfer resistance significantly increases. Another major effect that appears is lithium plating. The polarization of anodes caused by low (cold) temperatures would slow down the Li-Ion intercalation process into the anodes during battery charging (aggregated lithium ions are deposited on the surface of the electrodes, causing a reduction in battery performance. Thus, the process of charging a battery is much more difficult if it is done at low temperatures (mainly due to the slow diffusion of lithium ions within electrodes) [40,41].

The effect of exposure to high temperatures on the battery cell's components is pregnant on two main cell components: The cathode and the current collector. The cathode is the transit center for both Li+ ions and electrons, and these materials are susceptible to undesirable phase transitions. Possible parasitic reactions at the electrode-electrolyte interface in deep-charged conditions can destabilize the cathode's structure. Exposing cells to high temperatures increases the extent of metal dissolution and oxygen evolution (processes which are generally irreversible), leading to performance degradation (loss of active mass) and instability in the structural composition. When copper is used as a material for the current collector, it is susceptible to oxidation by impurities in the electrolyte (a process accelerated beyond 50 °C), both by enhanced kinetics and the decay of LiPF6 into HF57 (the loss of passivation properties due to cracking and dissolution of its current collector components) [42]. A possible problem using aluminum as an anode current collector at elevated temperatures is the loss of passivation properties due to the cracking and dissolution of components [42].

For the issues presented above, the BTM system must ensure that the temperature inside the battery pack does not exceed certain limits in order to maintain the structural integrity of the electrochemical cells to be able to provide the maximum amount of energy demanded by the immediate operating conditions of the EV.

The construction and operation of the BTM system is achieved by two cooling methods: Passive and active. The active cooling method most efficient but increases the total mass of the battery pack. For the passive cooling method, the BTM system does not consume electric energy (maintaining the temperature inside the battery pack is achieved by transferring heat to the external air-to-air environment via a radiator). In the case of active cooling systems, additional components (electric consumers) are needed to achieve transfer of heat generated by battery pack operation to the outside environment (ventilation and/or liquid cooling systems).

The BTM system plays an important role in the behavior of Li-Ion based batteries, and studies on this issue have shown that the battery's energy capacity is proportional to the ambient temperature (Figure 6) [43]. The effects of temperature on the electrochemical cells that form a "battery pack" have been studied and presented in numerous scientific papers [24,44].

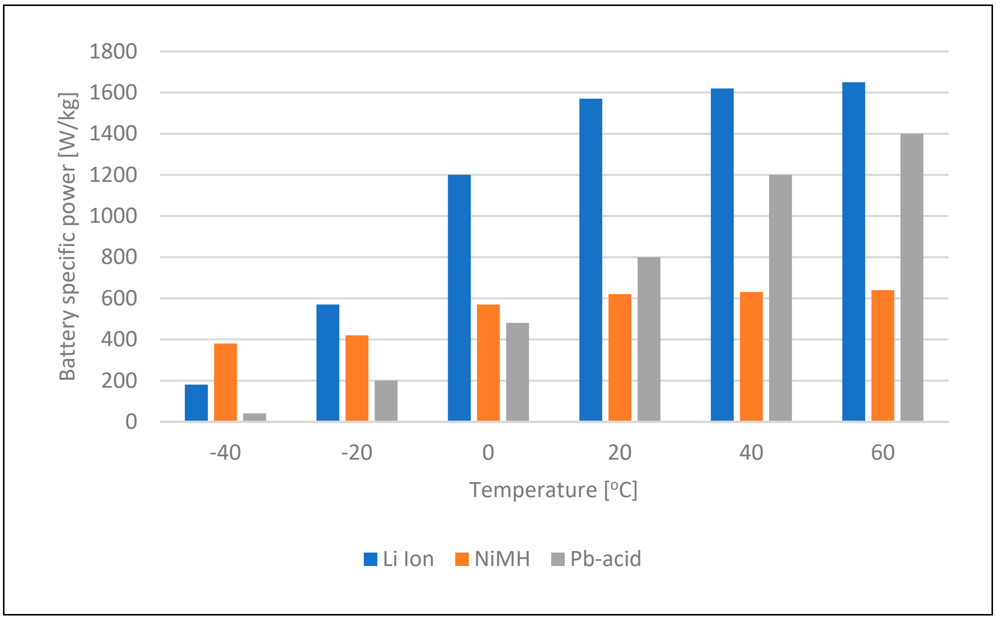

Figure 6. Influence of temperature on the energy performance of different types of batteries [43].

For example, there is a dramatic decrease in the energy capacity of $LiPF_6$ batteries when the temperature reaches below −20 °C (phenomena that increases the electrochemical cell's internal resistance [45–47]), but also under the operating conditions of high battery pack temperatures (60–80 °C), reducing the life of the battery and increasing the risk of the so-called "catastrophic failure". Thus, for reasons of safe operation and the optimal power performance of the Li-ion type battery, the battery should operate inside a thermal safety zone. Experiments have shown, for example, that for a battery charging process, the BMS system has to maintain a temperature range between 15–50 °C to increase the life cycle of the battery (Figure 7) [48].

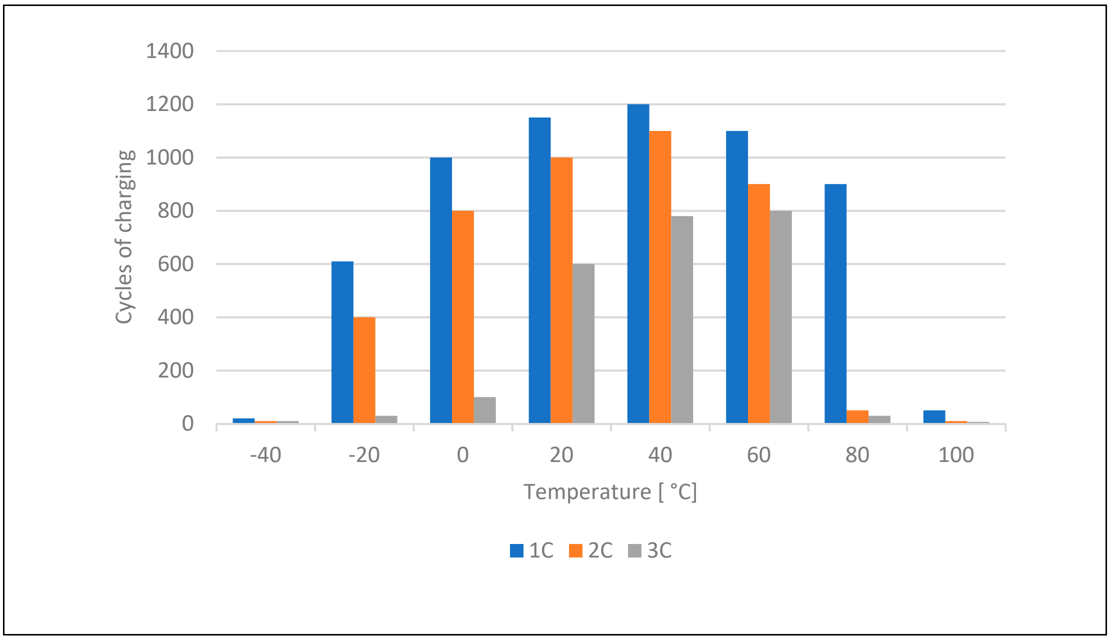

Figure 7. Effects of the charging process characteristics over battery life and temperature [24].

The operating temperature of a battery (also related to the ambient temperature in which the EV is used) has a direct influence on another parameter considered as an operating factor for EVs: The SOH. When a battery pack deteriorates to a certain level, it is no longer efficient and economical to be used in EVs [49], that is why an accurate SOH estimation (a parameter that can reflect the aging level and health condition of the batteries) is essential to be also implemented for a safe and high-efficiency operation of EVs [50–52].

Degradation of battery consists mainly in irreversible capacity loss (capacity fade) and increase in cell impedance both due to fatigue caused by cell operation (operational cycles), as well as aging phenomena occurring at storage [53]. Aging during storage (or rest for a long period of time) has a negative influence on some electrochemical parameters such as capacity loss, impedance rise, potential change, state of charge (SOC) and state of health (SOH) [54].

An important issue is also the way the battery is charged (the charging process). A fast battery charging process takes place over a relatively short time, but with the significant effect of an increased thermal load on the cells (with the negative effects shown above). At higher SOCs and an elevated temperature, the SEI layer becomes unstable and can cause a severe reduction in battery performance (especially in output power). At the same time, a slow battery charging process reduces the thermal effect on cells, increasing battery life and equalizing the electrical potential of the cells (through the BMS system). In the opinion of the authors, a future integrated EV energy management system must take into account the geographic position of the vehicle and climatic information (as the ambient temperature can influence the charge pattern and efficiency). If an EV is used in the urban environment, then the driver will be informed about the need for recharging based on the daily EV user profile. In this case, the charging process can be slow. If the vehicle is operated over longer distances, outside of the urban environment, then the most efficient solution (from the point of view of user comfort) is the use of a fast charging station. Future studies should be carried out to determine whether a charging process at low ambient temperature must be done only when the battery internal temperature does not drop below 20–25 °C (alternatively, studies on the identification of an optimally differential temperature range) in order to increase the life span of EV batteries.

3. Methods and Approaches for EV Range Prediction

The estimation of EV autonomy is known as a range prediction problem. Accurate range prediction provides confidence in using the vehicle and is more important information for the end user than information about the SOC parameter. However, the issue of range prediction is a much more complex and challenging problem in comparison with SOC estimation/approximation. It aggregates, besides SOC, many other independent parameters (which are presented in previous chapters) in different mathematical models. As the use of mathematical models can lead to errors in estimating values at the end, we will present and analyze some of the methods and current studies in predicting EV range, focusing on two main points of interest: Parameterization of driver behavior and a methodology combining multiple factors in a single model.

3.1. Methods for Parametrization of Driver Behavior

One way to tackle driver behavior is to use a discretization scheme, where drivers are classified into different efficiency levels. In other words, levels of deviation from an "ideal" driver are introduced [55,56]. There are 10 levels which imply a 0% to 60% range reduction. If a driver according to their trip history is categorized into level 10, then the range prediction is reduced by 60%. The category is based on driving style (e.g., velocity and acceleration) and preferences of using of an HVAC system. In our vision, such a discrete parametrization is not a proper way to model a driver behavior in real EV exploitation cases. In addition, the driver category is kept constant and is not considered to be a time-dependent variable (there may be different traffic and environment conditions that can alter the "aggressiveness" of the driver).

Another approach is to use a data-driven method to model certain driver's behavior. The authors of [57] learned personalized route preferences directly from the observed users' driving behaviors, using an inverse reinforcement learning technique [58]. As a result, the proposed model can predict routes according to driver preferences. Unfortunately, it does not predict the impact of HVAC system usage by the driver. However, this approach introduces a probabilistic map for possible destinations. For each destination point, the probability of reaching it is provided. In order to obtain such a map, the SOC parameter and EV's energy consumption are considered as random variables.

Data-driven methods have shown good accuracy of prediction and straightforwardness for usage. A data-driven energy consumption prediction method for EVs (used for the energy-efficient routing issue) was developed [59]. A feature of the model is that it makes it possible to distinguish between different energy consumption influencing factors (road characteristics, weather, altitude differences, etc.), making this approach suited for energy consumption prediction for any given road. It consists of a cascade of a neural network (NN) and a multiple linear regression (MLR) model. The MLR model is used to estimate the energy consumption (given several predictor variables), while the NN predicts the unknown predictor variables (inputs) of the MLR model. As obtained results, the proposed model predicts the energy consumption with a mean absolute error of 12–14% of the average trip energy consumption (of which 7–9% is caused by the energy consumption estimation of the MLR model).

There are also methods used to model the effects of the driver's behavior on the efficiency of EV use, considering a relatively small amount of experimental data (in contrast with the data-driven methods shown above). An approach to this can be found in the results obtained relating to the influence of driver behavior on reducing fuel consumption for an ICE vehicle, by developing and applying a control-based driving style model [60]. A semi-learning method was used to optimize the driver style-specific parameters, using the simplex method The key feature of the model is that it is proposed to be a driving style model for representing three different styles: Dynamic or aggressive driving (high acceleration and sudden braking with almost no anticipation), eco driving (driving with sufficient anticipation to avoid unnecessary acceleration and braking) and normal driving (an intermediate driving condition, considering driver aggressiveness as the main driver of effective vehicle use). The results obtained by simulation of the proposed model were validated experimentally, and the predicted errors were between -2.76% and 2.43% for the highway and between -8.82% and 0.43% for urban use, respectively. The researchers also showed that the model could be further improved to take account of the braking process, which is important for an EV due to the energy production by the regenerative braking process. By analogy, using the same above presented algorithm, a driver model can be developed to be implemented effectively in an EV energy management/range prediction system.

3.2. Methods to Combine Multiple Factors in a Single Model

One way to handle multiple factors simultaneously is to assign them to a discrete road segment (a simple split of a road network/alleged route). Typically, such a discretization process is used in Google Maps. The road network then can be represented as a graph. Each road segment (graph edges) is assigned specific attributes, and for the range prediction problem, the attributes are the direct factors that influence an EV's range, such as as traffic intensity, air temperature, climbing or descending angle, etc. To perform computations efficiently, an algorithm to work with large-scale road networks was developed [61]. Further, other authors extended the algorithm to handle negative cycle costs caused by the recuperation of energy, specific to EV exploitation conditions [62]. For each considered road segment, the authors defined a cost function $f(arc)$, which is equal to the amount of energy necessary to travel the road segment *arc*. The sum of costs along the path is equal to the total amount of energy required to reach the destination. Unfortunately, this method does not take into account driver behavior, which makes it significantly less practical in many cases. However, the graph representation is efficient and commonly used to deal with road network related problems, such as mapping and route planning [61,63].

A model-based approach for range prediction (the RDR model—remaining driving range) was developed by combining a particle filter with Markov chains [64]. The range prediction is represented as a probability distribution function, approximated by a set of weighted particles. The model includes only detailed models of the battery, the electric powertrain and the vehicle dynamics, and considers different sources of uncertainty, such as variability of the driving profile, measurement noise and errors in the estimation of the battery state. The validation of the model was carried out through simulation, and the authors state that the proposed approach predicts the EV's residual range with acceptable accuracy and computational effort.

A fuzzy c-mean clustering algorithm was developed and presented in detail to predict the battery SOF (state of function) [65]. The SOF parameter indicates the power output capability of the battery and the capability to transfer to an electric powertrain group. The SOF parameter is closely related to SOC of the battery and can be considered an indirect parameter for the range prediction issue. The fuzzy prediction method was optimized by the fuzzy c-mean (FCM) algorithm using the three variables as inputs (SOC, SOH and charge-discharge rate). The average error of estimation was approximately 8.69% and authors conclude that the prediction algorithm has the advantages of being easy to implement, with a fast response and offering possibilities for future improvement.

4. Discussion

The prediction range of an EV is currently based (in most cases) on SOC estimation of the battery pack, a prediction that can display in real time EV autonomy. The errors that occur in the estimation of SOC by current methods are relatively small (1–8%), while errors in the distance traveled represent approximately 2–20 km (for an average range of an EV of 250 km) (Figure 8).

If more influence factors are taken into account in the complex mathematical models, the error predictions rise and vary from 12 to 15%, translating to a distance of approximately 40 km. These values are currently relatively large and could decide the possibility of reaching the destination or not. For a "safe" drive, due to the multitude of factors (direct or indirect) encountered in exploitation that may affect EV's range, it is necessary to develop more accurate mathematical methods and models that will inform the user in real time the EV's "geographic range", along with the continuous calculation of the possibilities to reach the intended destination (depending on the available charging infrastructure on the route the user wants to follow).

From an EV user's point of view, driver range anxiety can be reduced in the following major ways:

- The familiarity of the driver with the type and technical characteristics of the EV that it exploits for efficient energy usage.
- Creation of visual instruments (e.g., on-board maps) that delineate the area that can be covered by the electric vehicle (for example, the green area could be the potential area covered from existent battery pack energy, the yellow area possibly could cover the possible area of travel by taking measures related to adjusting driving behavior, while red area could indicate areas where there is not enough hardware/software resources to facilitate reaching the desired destination) [26]. Information that is calculated/determined can be visually displayed to the driver by means of specific instruments of the dashboard or on the entertainment system's display), or even on smartphone devices, which will be easily perceived and analyzed by any EV user and will eliminate "range anxiety".
- Besides interactive maps, if the destination point is known, a desirable solution should suggest an energy-efficient route and show available areas around the destination. Moreover, in case after reaching the destination the range is less than the distance to the closest charging point, the system should warn the driver about this issue and build a new route with a stop at a charging station.

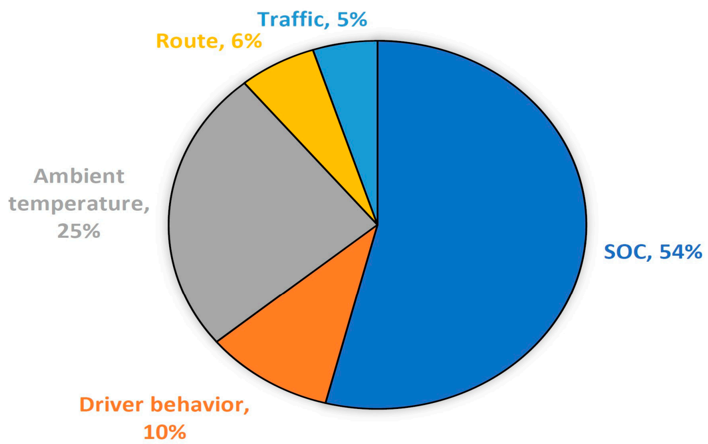

Figure 8. The importance of different parameters on EV range prediction (note that the values for ambient temperature consider using an HVAC system for air conditioning in summer or heating in winter).

As a future evolution of ideas on modeling driver behavior, a proposal would be to separate the driver's driving influence from the driver's preference to use HVAC (or other EV auxiliary energy-consuming systems) during the trip. The idea behind this statement is that these two EV exploitation conditions are relatively independent. The use of the HVAC system depends mainly on the weather conditions and the driver's personal comfort. Driving style (e.g., the rate of acceleration and the speed of the vehicle) depends mainly on the road, traffic and other conditional characteristics mentioned in previous chapters. This may also be the reason why many researchers focus only on researching one of these issues. Studies that consider the driver's complex behavior (from the perspective of the above) in a model do not provide excellent results. The advantage of separating these issues and the independent approach to this is given by the flexibility of the development process as well as the exploitation process.

However, in circumstances where it is necessary to increase the accuracy of predicting EV range, it can be considered that the solutions coming from the field of artificial intelligence are best suited for the complex modeling of parameters which define driver behavior. The immediate benefit of this is that there are no quantitative and qualitative requirements for the existing parameterizations and machine learning (ML) techniques can vary the number and properties of parameters to achieve better data matching with a reduction of errors in the final result.

5. Conclusions

There are currently many studies on the prediction of range for the efficient use of EVs. However, it can be observed that most of these studies were carried out by analyzing a single factor that influences EV range. Special importance is given to the range prediction by SOC estimation, and very few studies have been carried out with an aim to integrate (complex integration) the influences of all factors that determine an EV's range (driver behavior and environment) within a single mathematical model.

Future research should solve the optimal integration of EV hardware and software systems by creating and deploying complex range prediction tools based on advanced software solutions (for example, artificial intelligence-based solutions). These software solutions must consider all the factors (emphasizes the present work) involved and integrate the magnitude of their effect on EV range prediction, according to the momentary conditions of EV use/operation.

Additionally, it is necessary to correlate the battery pack thermal load with the EV's global thermal load to ensure the minimum required thermal comfort. This involves, besides the use of sensor systems, providing the most accurate data and the need for the common integration of BTM system(s) with the EV's HVAC system. Research should be maintained and continued to find solutions for improving the energy efficiency of HVAC systems, considering the major influence they can have on an EV's range and consumer perceptions. All issues and challenges presented in this article are necessary to be achieved in the near future, in order to counteract the "negative" characteristics of EVs compared to those of ICE vehicles, such as autonomy, stop time to battery charging, charging station density, fast charging technologies without a negative effect on the battery's life and time-performance, new technologies and/or new approaches for producing more energy efficient batteries, etc. The development and integration of such a complex model must also take into consideration the costs, which is one of the main barriers for rapid and massive EV penetration in the automotive market.

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References

1. Varga, B.O.; Mariasiu, F. Indirect environment-related effects of electric car vehicles use. *Environ. Eng. Manag. J.* **2018**, *17*, 1591–1599.
2. Zhu, J.; Wierzbicki, T.; Li, W. A review of safety-focused mechanical modeling of commercial lithium-ion batteries. *J. Power Sources* **2018**, *378*, 153–168. [CrossRef]
3. Egbue, O.; Long, S. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy* **2012**, *48*, 717–729. [CrossRef]
4. EN21. Renewables 2015 Global Status Report. Available online: http://www.ren21.net/wp-content/uploads/2015/07/REN12-GSR2015_Onlinebook_low1.pdf (accessed on 16 December 2018).
5. Wu, G.; Inderbitzin, A.; Bening, C. Total cost of electric vehicles compared to conventional vehicles: A probabilistic analysis and projection across market segments. *Energy Policy* **2015**, *80*, 196–214. [CrossRef]
6. McManus, M.C. Environmental consequences of the use of batteries in low carbon systems: The impact of battery production. *Appl. Energy* **2012**, *93*, 288–295. [CrossRef]
7. Nykvist, B.; Nilsson, M. Rapidly falling costs of battery packs for electric vehicles. *Nat. Clim. Chang.* **2015**, *5*, 329–332. [CrossRef]
8. Park, O.K.; Cho, Y.; Lee, S.; Yoo, H.C.; Song, H.K.; Cho, J. Who Will Drive Electric Vehicles, Olivine or Spinel? *Energy Environ. Sci.* **2011**, *4*, 1621–1633. [CrossRef]
9. Franke, T.; Günther, M.; Trantow, M.; Krems, J.F. Does this range suit me? Range satisfaction of battery electric vehicle users. *Appl. Ergon.* **2017**, *65*, 191–199. [CrossRef] [PubMed]
10. Ramachandran, S.; Stimming, U. Well to wheel analysis of low carbon alternatives for road traffic. *Energy Environ. Sci.* **2015**, *8*, 3313–3324. [CrossRef]
11. Singer, M. Consumer Views on Plug-In Electric Vehicles—National Benchmark Report NREL. 2016. Available online: http://www.afdc.energy.gov/uploads/publication/consumer_views_pev_benchmark.pdf (accessed on 18 December 2018).
12. Labeye, E.; Hugot, M.; Brusque, C.; Regan, M.A. The electric vehicle: A new driving experience involving specific skills and rules. *Transp. Res. Part F Traffic Psychol. Behav.* **2016**, *37*, 27–40. [CrossRef]
13. Park, E.; Lim, J.; Cho, Y. Understanding the Emergence and Social Acceptance of Electric Vehicles as Next-Generation Models for the Automobile Industry. *Sustainability* **2018**, *10*, 662. [CrossRef]
14. Nilsson, M. Electric Vehicles: The Phenomenon of Range Anxiety. 2011. Available online: http://e-mobility-nsr.eu/fileadmin/user_upload/downloads/info-pool/the_phenomenon_of_range_anxiety_elvire.pdf (accessed on 12 December 2018).
15. Franke, T.; Krems, J.F. Interacting with limited mobility resources: Psychological range levels in electric vehicle use. *Transp. Res. Part A Policy Pract.* **2013**, *48*, 109–122. [CrossRef]

16. Eisel, M.; Nastjuk, I.; Kolbe, L.M. Understanding the influence of in-vehicle information systems on range stress–Insights from an electric vehicle field experiment. *Transp. Res. Part F Traffic Psychol. Behav.* **2016**, *43*, 199–211. [CrossRef]
17. Bi, J.; Wanga, Y.; Shaoa, S.; Cheng, Y. Residual range estimation for battery electric vehicle based on radial basis T function neural network. *Measurement* **2018**, *128*, 197–203. [CrossRef]
18. Kambly, K.; Bradley, T.H. Geographical and temporal differences in electric vehicle range due to cabin conditioning energy consumption. *J. Power Sources* **2015**, *275*, 468–475. [CrossRef]
19. Genikomsakis, K.N.; Mitrentsis, G. A computationally efficient simulation model for estimating energy consumption of electric vehicles in the context of route planning applications. *Transp. Res. Part D Transp. Environ.* **2017**, *50*, 98–118. [CrossRef]
20. Mruzek, M.; Gajdáč, I.; Kučera, L.; Barta, D. Analysis of Parameters Influencing Electric Vehicle Range. *Procedia Eng.* **2016**, *134*, 165–174. [CrossRef]
21. Sentoff, K.M.; Aultman-Hall, L.; Holmén, B.A. Implications of driving style and road grade for accurate vehicle activity data and emissions estimates. *Transp. Res. Part D Transp. Environ.* **2015**, *35*, 175–188. [CrossRef]
22. Wu, X.; He, X.; Yu, G.; Harmandayan, A.; Wang, Y. Energy-optimal speed control for electric vehicles on signalized arterials. *IEEE Trans. Intell. Transp. Syst.* **2015**, *16*, 2786–2796.
23. Yuksel, T.; Michalek, J.J. Effects of regional temperature on electric vehicle efficiency, range, and emissions in the United States. *Environ. Sci. Technol.* **2015**, *49*, 3974–3980. [CrossRef]
24. Rezvanizaniani, S.M.; Liu, Z.; Chen, Y.; Lee, J. Review and recent advances in battery health monitoring and prognostics technologies for electric vehicle (EV) safety and mobility. *J. Power Sources* **2014**, *256*, 110–124. [CrossRef]
25. Hucho, H. *Aerodynamics of Road Vehicles*, 4th ed.; SAE International: Warrendale, PA, USA, 1998.
26. Trigg, T. Cities Where It's Faster to Walk than Drive. 2015. Available online: https://blogs.scientificamerican.com/plugged-in/cities-where-it-s-faster-to-walk-than-drive/ (accessed on 18 December 2018).
27. Jiménez, D.; Hernández, S.; Fraile-Ardanuy, J.; Serrano, J.; Rubén Fernández, R.; Álvarez, F. Modelling the Effect of Driving Events on Electrical Vehicle Energy Consumption Using Inertial Sensors in Smartphones. *Energies* **2018**, *11*, 412. [CrossRef]
28. Fiori, C.; Ahn, K.; Rakha, H.A. Power-based electric vehicle energy consumption model: Model development and validation. *Appl. Energy* **2016**, *168*, 257–268. [CrossRef]
29. Hofer, J.; Wilhelm, E.; Schenler, W. Comparing the Mass, Energy, and Cost Effects of Lightweighting in Conventional and Electric Passanger Vehicles. *J. Sustain. Dev. Energy Water Environ. Syst.* **2014**, *2*, 284–295. [CrossRef]
30. Berjoza, D.; Jurgen, I. Effects of change in the weight of electric vehicles on their performance characteristics. *Agron. Res.* **2017**, *15*, 952–963.
31. Thomas, J.; Huff, S.; West, B. Fuel Economy and Emissions Effects of Low Tire Pressure, Open Windows, Roof Top and Hitch-Mounted Cargo, and Trailer. *SAE Int. J. Passeng. Cars-Mech. Syst.* **2014**, *7*, 862–872. [CrossRef]
32. Hannan, M.A.; Lipu, M.S.H.; Hussain, A.; Mohamed, A. A review of lithium-ion battery state of charge estimation and management system in electric vehicles applications: Challenges and recommendations. *Renew. Sustain. Energy Rev.* **2017**, *78*, 834–854. [CrossRef]
33. Rauh, N.; Franke, T.; Krems, J.F. Understanding the impact of electric vehicle driving experience on range anxiety. *Hum. Factors* **2015**, *57*, 177–187. [CrossRef]
34. Zhang, Z.; Li, W.; Zhang, C.; Chen, J. Climate control loads prediction of electric vehicles. *Appl. Therm. Eng.* **2017**, *110*, 1183–1188. [CrossRef]
35. Iora, P.; Tribioli, L. Effect of Ambient Temperature on Electric Vehicles' Energy Consumption and Range: Model Definition and Sensitivity Analysis Based on Nissan Leaf Data. *World Electr. Veh. J.* **2019**, *10*, 2. [CrossRef]
36. Buqa, H.; Würsig, A.; Vetter, J.; Spahr, M.; Krumeich, F.; Novák, P. SEI film formation on highly crystalline graphitic materials in lithium-ion batteries. *J. Power Sources* **2006**, *153*, 385–390. [CrossRef]
37. Pinson, M.B.; Bazant, M.Z. Theory of SEI formation in rechargeable batteries: Capacity fade, accelerated aging and lifetime prediction. *J. Electrochem. Soc.* **2013**, *160*, 243–250. [CrossRef]

38. Zhang, S.S.; Xu, K.; Jow, T.R. Electrochemical impedance study on the low temperature of Li-ion batteries. *Electrochim. Acta* **2004**, *49*, 1057–1061. [CrossRef]
39. Haruta, M.; Okubo, T.; Masuo, Y.; Yoshida, S.; Tomita, A.; Takenaka, T.; Takayuki Doi, T.; Inaba, M. Temperature effects on SEI formation and cyclability of Si nanoflake powder anode in the presence of SEI-forming additives. *Electrochim. Acta* **2017**, *224*, 186–193. [CrossRef]
40. Liu, H.; Wei, Z.; He, W.; Zhao, J. Thermal issues about Li-ion batteries and recent progress in battery thermal management systems: A review. *Energy Convers. Manag.* **2017**, *150*, 304–330. [CrossRef]
41. Zhang, S.S.; Xu, K.; Jow, T.R. The low temperature performance of Li-ion batteries. *J. Power Sources* **2003**, *115*, 137–140. [CrossRef]
42. Rodrigues, M.-T.F.; Babu, G.; Gullapalli, H.; Kalaga, K.; Sayed, F.N.; Kato, K.; Joyner, J.; Ajayan, P.M. A materials perspective on Li-ion batteries at extreme temperatures. *Nat. Energy* **2017**, *2*, 17108. [CrossRef]
43. Weighall, M.J. Test requirements for 42 V battery systems. *J. Power Sources* **2003**, *116*, 151–159. [CrossRef]
44. Zhu, T.; Min, H.; Yu, Y.; Zhao, Z.; Xu, T.; Chen, Y.; Li, X.; Zhang, C. An optimized energy management strategy for preheating vehicle-mounted li-ion batteries at subzero temperatures. *Energies* **2018**, *10*, 243. [CrossRef]
45. Doughty, D.H.; Roth, E.P.; Crafts, C.C.; Nagasubramanian, G.; Henriksen, G.; Amine, K. Effects of additives on thermal stability of Li ion cells. *J. Power Sources* **2005**, *146*, 116–120. [CrossRef]
46. Li, J.; Yuan, C.F.; Guo, Z.H.; Zhang, Z.A.; Lai, Y.Q.; Liu, J. Limiting factors for low- temperature performance of electrolytes in LiFePO 4/Li and graphite/Li half cells. *Electrochim. Acta* **2012**, *59*, 69–74. [CrossRef]
47. Qian, K.; Zhou, C.; Yuan, Y.; Allan, M. Temperature effect on electric vehicle battery cycle life in Vehicle-to-grid applications. In Proceedings of the CICED 2010 Proceedings, Nanjing, China, 13–16 September 2010.
48. Dubarry, M.; Liaw, B.Y.; Chen, M.S.; Chyan, S.S.; Han, K.C.; Sie, W.T.; Wu, S.H. Identifying battery aging mechanisms in large format Li ion cells. *J. Power Sources* **2011**, *196*, 3420–3425. [CrossRef]
49. Andre, D.; Appel, C.; Soczka-Guth, T.; Sauer, D.U. Advanced mathematical methods of SOC and SOH estimation for lithium-ion batteries. *J. Power Sources* **2013**, *224*, 20–27. [CrossRef]
50. Sun, B.; Jiang, J.; Zheng, F.; Zhao, W.; Liaw, B.Y.; Ruan, H.; Han, Z.; Zhang, W. Practical state of health estimation of power batteries based on Delphi method and grey relational grade analysis. *J. Power Sources* **2015**, *282*, 146–157. [CrossRef]
51. Zhang, R.; Xia, B.; Li, B.; Cao, L.; Lai, Y.; Zheng, W.; Wang, H.; Wang, W.; Wang, M. A Study on the Open Circuit Voltage and State of Charge Characterization of High Capacity Lithium-Ion Battery under Different Temperature. *Energies* **2018**, *11*, 2408. [CrossRef]
52. Diao, W.; Jiang, J.; Zhang, C.; Liang, H.; Pecht, M. Energy state of health estimation for battery packs based on the degradation and inconsistency. *Energy Procedia* **2017**, *142*, 3578–3583. [CrossRef]
53. Hausbrand, R.; Cherkashinin, G.; Ehrenberg, H.; Gröting, M.; Albe, K.; Hess, C.; Jaegermann, W. Fundamental degradation mechanisms of layered oxide Li-ion battery cathode materials: Methodology, insights and novel approaches. *Mater. Sci. Eng. B* **2015**, *192*, 3–25. [CrossRef]
54. Vetter, J.; Novak, P.; Wagner, M.R.; Veit, C.; Moller, K.-C.; Besenhard, J.O.; Winter, M.; Wohlfahrt-Mehrens, M.; Vogler, C.; Hammouche, A. Ageing mechanisms in lithium-ion batteries. *J. Power Sources* **2005**, *147*, 269–281. [CrossRef]
55. Ferreira, J.C.; Monteiro, V.D.F.; Afonso, J.L. Data mining approach for range prediction of electric vehicle. In *Conference on Future Automotive Technology: Focus Electromobility*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 1–15.
56. Ferreira, J.C.; Monteiro, V.; Afonso, J.L. Dynamic range prediction for an electric vehicle. In Proceedings of the 2013 World Electric Vehicle Symposium and Exhibition (EVS27), Barcelona, Spain, 17–20 November 2013; pp. 1–11.
57. Bär, T.; Nienhüser, D.; Kohlhaas, R.; Zöllner, J.M. Probabilistic driving style determination by means of a situation-based analysis of the vehicle data. In Proceedings of the 2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC), Washington, DC, USA, 5–7 October 2011; pp. 1698–1703.
58. Ziebart, B.D.; Maas, A.L.; Bagnell, J.A.; Dey, A.K. Maximum Entropy Inverse Reinforcement Learning. In Proceedings of the AAAI, Chicago, IL, USA, 13–17 July 2008; Volume 8, pp. 1433–1438.

59. De Cauwer, C.; Verbeke, W.; Coosemans, T.; Faid, S.; Van Mierlo, J. A Data-Driven Method for Energy Consumption Prediction and Energy-Efficient Routing of Electric Vehicles in Real-World Conditions. *Energies* **2017**, *10*, 608. [CrossRef]
60. Javanmardi, S.; Bideaux, E.; Trégouët, J.F.; Trigui, R.; Tattegrain, H.; Nicouleau Bourles, E. Driving style modelling for eco-driving applications. *IFAC PapersOnLine* **2017**, *50*, 13866–13871. [CrossRef]
61. Delling, D.; Goldberg, A.V.; Pajor, T.; Werneck, R.F. Customizable route planning in road networks. *Transp. Sci.* **2015**, *51*, 566–591. [CrossRef]
62. Baum, M.; Dibbelt, J.; Pajor, T.; Wagner, D. Energy-optimal routes for electric vehicles. In Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, Orlando, FL, USA, 5–8 November 2013; pp. 54–63.
63. OpenStreetMap Contributors. Planet Dump. 2017. Available online: https://www.openstreetmap.org (accessed on 12 December 2018).
64. Oliva, J.A.; Weihrauch, C.; Bertram, T. Model-Based Remaining Driving Range Prediction in Electric Vehicles by using Particle Filtering and Markov Chains. *World Electr. Veh. J.* **2013**, *6*, 204–213. [CrossRef]
65. Wang, D.; Yang, F.; Gan, L.; Li, Y. Fuzzy Prediction of Power Lithium Ion Battery State of Function Based on the Fuzzy c-Means Clustering Algorithm. *World Electr. Veh. J.* **2019**, *10*, 1. [CrossRef]