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Energy Consumption Estimation for Routing EVs based on Driver Behavior

Niklas Schwertner and Gretchen A. Macht, Ph.D.
Mechanical, Industrial and Systems Engineering Department
University of Rhode Island
Kingston, RI, 02881, USA

Abstract

There has been a significant increase in the sales of electric vehicles (EVs) in the United States and abroad in the last few years. Nevertheless, the overall adoption of these vehicles is hindered by range limits of EVs in conjunction with long charging times. In this context, it is essential to determine current energy demands and to predict future demand. This paper presents approaches for predicting energy consumption of EVs and discusses their eligibility for this purpose. Four modeling approaches (i.e., dynamic systems, neural networks, statistical models, physics-based models) have primarily been used in recent literature. In order to predict an EV's energy demand, several modeling techniques are combined to give an accurate prediction of the future energy consumption. For the battery EVs a combination of physics-based modeling and statistical modeling have shown to be an effective and efficient choice.

Keywords
Optimization, Sustainability, Electric Vehicles, Driving Behavior

1. Introduction

Sales for electric vehicles (EVs) in the United States (US) have increased from 73,000 in 2012 by more than 600 percent to 542,000 in 2016 [1]. In other industrialized countries, the number of EVs has also risen considerably [2, 3]. Electrification and on-demand services are two of the main driving forces within the current global automotive sector [4]. Increasing urbanization and stricter environmental regulations require a redesign of existing transportation systems [5]. The future of mobility systems must combine high-quality service for the customer with a minimal environmental footprint [6]. Improving information and communications technologies (ICTs) can form the basis for intelligent route choice in order to reduce miles traveled [7]. In addition, both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) can contribute to significantly decreasing emissions and BEVs can specifically help to maintain zero local emissions [6, 8]. Despite recent developments and the great potential of EVs, the market penetration rate of EVs is still very low, potentially due to the discrepancies between range, charging time, and consumer expectations [9, 10].

EV energy consumption prediction for a specific route is an important basis for several of these discrepancies, such as range prediction, charging duration, and charging location. There is a range of energy prediction models for internal combustion engine (ICE) vehicles and hybrids [11, 12, 13]. The residual range can be predicted by estimating the future energy demand in relation to the energy remaining in the battery [11]. Estimating energy consumption is used for EV navigation functions similar to ICE vehicle eco-routing, which is a navigation strategy for finding the route that consumes the least fuel or produces the least emissions, or for finding ways to reduce energy consumption [9]. However, it is debated which of the many ICE vehicle eco-routing approaches can be utilized for BEV energy estimation since the modeling is not dependent on the energy source or power unit [9, 13]. This paper presents state of the art energy consumption prediction models eligible for BEV energy estimation and discusses their further benefit in route optimization.

2. State of the Art

Based on existing literature, research on energy consumption estimation divides current approaches into 1) dynamic systems, 2) neural networks, 3) statistical models, 4) physics-based models [10] and 5) agent-based models. This section reviews the similarities and differences of these types of modeling approached. For detailed energy consumption estimation, however, a combination of these models can and is often used.

Predicting energy consumption for EVs presents particular challenges since there are numerous variables that often vary over time [9]. Unique characteristics of EVs include range limitation, long battery charging time, and recuperation of deceleration energy if equipped with a recuperative braking system (RBS) [14]. Therefore a precise prediction of EV range estimation is necessary for greater consumer acceptance [15]. EV range can be increased in various ways, most of which focus on improvement of battery capacity [16], the design of gearing configurations [17], or the application of vehicle RBS [18]. In addition to optimizing the EV itself, efforts can be put into optimization of charging infrastructure [19] and energy efficient route planning [12]. Zhang and Yao [10] assert that energy consumption analysis is the basis for studying location of charging infrastructures, ICE vehicle eco-driving behavior, and energy-saving route planning, which all contribute to extend EV range. ICE vehicle eco-driving behavior and energy-saving route planning are addressed in this research paper.

Energy consumption prediction for electric vehicles is determined by various influencing factors that are strongly interactive and vary over time. These factors can be classified into three major categories: internal vehicle-specific elements, external environmental elements, and individual driver-specific elements. The internal vehicle-specific parameters include mass, rolling resistance, aerodynamics, powertrain efficiency, the operational strategy (e.g., degree of RBS), and auxiliary energy (e.g.,heating or air-conditioning). External parameters are inherent attributes of a chosen route, such as road type, topography, and traffic conditions. Individual driver-specific elements include a driver's individual style of driving based on their skills and attitude, all of which can strongly affect the energy consumption. To determine the effects of these parameters on the estimate of state of charge (SOC), as well as to test a model's accuracy, empirical data is needed. To consider all relevant impact factors, many different data sources are needed, however, not all current or historical data sources might be available due to accessibility and errors. Grubwinkler [9] addresses this challenge by developing a modular and dynamic model. Dividing the model into subordinate parts which use different data sources ensures a prediction of energy consumption even with limited availability of data in one or more section without affecting the accuracy of the other parts. The dynamic part addresses the temporal variability of the data so that a prediction based on current data is possible [9].

Common modeling techniques for predicting energy consumption include statistical models, physics-based models, and dynamic systems. Neural networks do not appear often in the literature, but since a lot of approaches include machine learning, neural networks are considered here as a primary modeling technique. Zhang and Yao [10] distinguish recent energy analysis models of EVs into similar types. An overview of the relevant literature in major prediction modeling techniques and the energy consumption of BEVs is delineated in Table 1.

Table 1: Recent literature on predicting BEVs energy consumption, classified by major modeling technique.

Literature		**Modeling Technique**				
		Dynamic Systems	***Neural Networks***	***Statistical Models***	***Physics-based Models***	***Agent-based Models***
Grubwinkler	2013 [9]	✓		✓	✓	
Krashl-Krischmann	2012 [13]			✓	✓	
Masikos	2014 [23]		✓			
Zhang	2015 [10]			✓		
Wager	2014 [17]			✓	✓	
Jäger	2017 [4]	✓		✓		✓

2.1 Dynamic Systems

A dynamic system is a defined, time-dependent functional unit interacting with its environment through signal inputs and outputs [20]. The basic concept of this modeling approach is to model continuous systems. It is commonly used in technical fields such as mechanical, electrical, and chemical engineering. Behind this modeling approach there are mathematical models which consist of a number of state variables and algebraic differential equations of various forms over these variables. The variables are directly related to physical measures (e.g., location, velocity, acceleration). Common computer programs for such calculations include Matlab Simulink or AnyLogic [21]. Grubwinkler & Linekamp [9] finds that because of the high number of energy influencing factors and the variability of some of these factors, an accurate prediction for the entire route from the beginning of the trip is not possible. Instead, they advocate the adaptation of the dynamic model to the current situation is necessary throughout the entire model and across other modeling approaches.

2.2 Neural networks

Computational intelligence or machine learning is a generic term for gaining knowledge and experience based on an artificial system. Generally, this process can be divided into supervised learning and unsupervised learning. Supervised learning means the algorithm is given a pair of inputs and outputs, and the algorithm can check its response with the actual response. In unsupervised learning the algorithm creates a model based on a given number of inputs, which allows for description and prediction [22]. In the context of EVs, machine learning engines are used by Masikos et al. [23] to predict the energy consumption and travel time for a road segment, based on direct vehicle-related data as well as additional data like traffic and weather. Based on the energy consumption per road segment, they find the optimal route involving the least energy consumption by using existing and well-researched shortest path algorithms. The energy prediction function is built on two factors that determine the energy consumption for each road segment. One factor is the energy consumption that can be predicted based on the previous amount of energy needed to travel through the same road segment. The other factor is the energy overhead that may occur based on unexpected traffic events at later times.

2.3 Statistical models

Regression is one of the most commonly used multivariate analysis techniques. Linear regression models are used often throughout STEM disciplines since they conveniently need only a couple of requirements to be met, such as normality, significant sample size, goodness-of-fit (e.g., R-square, R-square adjusted, F-test) [22]. Depending on the driving state of the EV, the influence of energy-consuming factors might change. To predict the energy consumption of EVs, different combinations of variables (e.g., speed, acceleration) require different regression models to be used [10].

Kraschl-Hirschmann and Fellendorf [13] deliver an energy consumption prediction model based on a statistical approach. An estimation function for average acceleration and deceleration depending on traffic congestion, road type, and a gradient for every link calculates the driving force needed. Based on the factors mentioned above, an estimation function calculates the share of the different driving phases along the road (e.g., cruising, idling, acceleration and deceleration phase). The influence of different driving resistance forces differs with the share of driving phases, weighted respectively (e.g., roll resistance is irrelevant in idling phase) [13]. Speed profiles for certain sections along the route take into consideration speed limits, slopes, traffic lights, road signs, or traffic patterns on which the global speed profile is calculated. This approach allows a quick calculation of energy consumption, but Grubwinkler [9] considers it a relatively rough estimation. By contrast, Zhang and Yao [10] develop an energy consumption prediction model based on microscopic driving parameters collected in empirical experiments and evaluated by a statistical approach.

2.4 Physics-based models

Physics-based models are mathematical models where the model equations are derived from basic physical principles, foundational assumptions that cannot be derived from other assumptions. The physical equations are models themselves and are representations of those phenomena.. These models may not represent all aspects of a system and might be based on assumptions which constrain the use of the model. Incorrect assumptions or omissions might affect the usefulness of the models. In addition, they might suffer from invalid composition when simulations combine multiple physics-based models [20].

Kraschl-Hirschmann and Fellendorf [13] propose a model for energy estimation by deducing the actual energy consumption from classical mechanics and vehicle dynamics, to compute the power the engine must provide. Even though this model is typically used for predicting the energy consumption of ICVs, it can be easily used for predicting the energy consumption of EVs, since the model only predicts the energy needed to overcome resistance and does not consider how this energy is provided. Kraschl-Hirschmann and Fellendorf identify the main energy consumption factors of the vehicle as rolling resistance, aerodynamic drag force, acceleration force, inertia at gradients, and auxiliary energy, and they set up equations for these factors' energy consumption. Equation 1 shows this relationship. Auxiliary power (E_{aux}) is considered to be constant and independent from traveling speed (v), while rolling resistance (E_{roll}) and roadway gradience (E_{grade}) are independent from speed. The energy that is needed to overcome aerodynamic drag force and inertia at acceleration (E_{acc}) is dependent on speed. The model distinguishes between speed phases less than 50mph (80km/h), where the engine power is mainly needed to accelerate the vehicle, and speed phases greater than 50mph (80km/h), where the engine power is mainly needed to overcome aerodynamic resistance. They identify four driving phases: cruising time, idle time, deceleration time and acceleration time. All trips consist of all four driving phases, but might differ significantly in shares of time spent in each phase [13].

$$Eeng = Eroll + Eair + Eacc + Egrade + Eaux \tag{1}$$

The auxiliary power is considered to be constant. The other partial energy components are broken down based on physical laws in Equation 2-6. The coefficients Fr_0 and Fr_1 are determined by coast down tests.

$$Eroll = m * g * (Fr0 + Fr1 * v) * v * f \tag{2}$$

$$Eair = 0.5 * cw * \rho * A * (v)^2 * v * f \tag{3}$$

$$Eacc = m * a * v * f \tag{4}$$

$$Egrade = m * g * gradient * v * f \tag{5}$$

To be more suitable for energy consumption estimation in BEVs, this model could be expanded by a deceleration term which would include the relationships for energy recuperated during braking. This would depend on the effectiveness of the RBS as well as the operational strategy of the vehicle. An advantage of BEVs over ICVs is that the actual energy consumption can be measured directly at the battery without applying complex measurement methods. Predicted energy consumption and actual energy consumption could be compared in order to obtain an estimate for the overall powertrain efficiency and to improve the model.

2.5 Agent-based Models

Agent-based modeling is used when a system of vehicles is researched and the interaction between those vehicles is of interest [21]. Jäger et al. [4] realize an approach investigating the behavior of an electric taxi fleet with a combined approach using stochastic modeling and an agent-based simulation. The modeling results are subject to dynamic decision making. However, their goal is not a prediction of the energy consumption of EVs but rather an understanding of how to manage mixed fleets of ICE vehicles and EVs. This modeling approach is indeed connected to EV-related problems, but is not appropriate for energy estimation; hence,why it is greyed out in Table 1.

3. Methods Comparison

This paper discusses the different approaches that exist for designing an energy consumption prediction model. Four major categories are used in recent literature: dynamic systems, neural networks, statistical models, and physical-based models. A fifth, agent-based modeling, is not relevant for energy estimation. Different models are preferred depending on the kind of research question and the scope of the research.

Dynamic Systems are part of many simulations and are used when time-variant systems are researched. Their structure is logical and they are demonstrative, since variables are representations of physical measures. However, relationships between the variables must be known in advance and strong biases might be possible if the relationships between the variables are misunderstood. This leads to high costs, since modeling all the relationships takes a lot of effort.

Neural networks work using statistical methods themselves, but they are considered to be their own category. Depending on the complexity of the problem, neural networks need a huge amount of data to give precise responses. Also, the calculation costs for complex problems can be very high [22]. Interpretation of the results from neural networks is more difficult than for statistical methods since a direct comparison of coefficients is not possible.

Neural networks are rarely used for BEV energy estimation but bear great potential for understanding complex effects which are difficult to model using one of the other approaches.

Statistical models are reasonable if experimental data from the system can be obtained economically with sufficient accuracy. Regressions are well understood and the the results gained from statistical analysis are easy to interpret. The focus of this approach is not on understanding the model but on understanding connections between relevant system factors. Also, statistical models can be easily expanded with more data to increase their significance.

Physics-based models can be used if the scope of the system is clearly defined, if there is already knowledge existing about the relationships between effects, and if the goal is to also obtain insights about the model itself. Furthermore, physics-based models are logically structured and can easily be extended or altered for further research. The downside of this modeling approach is that most physical equations are only allowed under idealized conditions and assumptions. Also, a combination of physical models can lead to inadmissible results.

Energy consumption prediction has been shown to rest on vehicle-inherent, external, and individual factors. The effects that influence the vehicle directly as well as the mechanisms in the vehicle are fairly understood. Therefore a physics-based model is a good choice for internal factors since this model is logically structured, clear to understand, and provides knowledge about the relationships in the model itself. The influences of external and individual factors are difficult to model in physics-based models since their relationship is not so well defined and their interaction and influence on the BEV is less understood. For these factors a statistical model is the adequate option. Speed profiles are a good way to include these effects without measuring them separately. For further research the model can be easily altered or expanded, and the database and the model are both easy to comprehend. In addition, for insights about the accuracy of the model the actual energy consumption can be measured at the battery and compared with the predicted energy consumption.

4. Conclusion

The goal of the paper was to research current energy prediction models for BEVs and give a recommendation for a suitable model for energy prediction of BEVs that would include driving behavior. This paper also categorizes energy prediction models based on existing literature. However, energy estimation models are typically not limited to one modeling approach, and the transitions between these categories are blurred. Recent attempts to predict energy consumption often combine several approaches for a higher accuracy. Speed profiles have been shown to be good ways to include driving behavior and traffic congestions without looking at them explicitly. However, the question remains how these effects can be separated from each other. For BEVs an approach combining a statistical model with a physics-based model is suggested, which would create an accurate model for energy consumption without being too complicated. The statistical part addresses relationships in the energy estimation process that are less understood, such as external and individual factors which need to be determined empirically, while the physics-based part addresses the internal factors that are well understood and delivers further insights on the multilateral influences of these factors.

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