Glossary

INSTITUTO SUPERIOR DE ENGENHARIA DE LISBOA

Área Departamental de Engenharia de Electrónica e Telecomunicações e de Computadores

Electric Vehicle X Driving Range Prediction – EV X DRP

David Alexandre Sousa Gomes Albuquerque

Licenciado

Projecto Final para obtenção do Grau de Mestre
em Engenharia Informática e de Computadores

Orientadores : Doutor David Pereira Coutinho
Doutor Artur Jorge Ferreira

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Acknowledgments

TODO: acknowledgements

Abstract

The increase of electric vehicle (EV) use as a reliable and eco-friendly means of transportation has increased rapidly over the past few years. When choosing an EV, the vehicle's performance is a decisive factor to be taken into account. An EV's driving range prediction depends on multiple factors that must be factored in to accurately infer results. As machine learning has become a widely used approach for finding suboptimal solutions on complex mathematical problems, EV's driving range prediction through machine learning could become an accurate enough solution for any vehicle. Previous work has covered a history-based method on an adaptive model for EV's driving range prediction. The present project explores the implementation of a machine learning based model to learn from existing data, adapting with changes and aiming to provide more real and accurate results.

Keywords: electric vehicle; range prediction; energy consumption; machine learning

Resumo

TODO: resumo em português

Palavras-chave:

TODO: Palavras-chave do resumo em português

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Acronyms

DT Decision Tree. 6

EV Electric Vehicle. 1, 2, 3, 5, 6
EVs Electric Vehicles. 1, 5

KNN K-Nearest Neighbor. 6

RF Random Forest. 6
RTs Regression Trees. 6

SOC state of charge. 1, 3, 6
SOM Self-Organizing Maps. 6

Glossary

big data TODO - bigData

. 1

dataset A structure containing data for a model. 2, 3, 5

eRange electric range. 1, 2, 3, 5, 6

LightGBM Light Gradient Boosting Regression Tree. 6

machine learning a branch of AI focused on learning from data. 1, 2, 3

python programming language. 5

time series series of data points indexed by time. 2

XGBoost Extreme Gradient Boosting Regression Tree. 6

1

Introduction

On today's day and age, the global concern on climate change has been a major focus on recent international agreements, such as the Paris Agreement (*Paris Agreement* 2015), incentivizing many car manufacturers to introduce Electric Vehicles (EVs) as the eco-friendly solution for sustainable transport for the future.

EVs have been growing in popularity in recent years and as a result, car manufacturers have increased competitiveness on vehicle's performance (Figenbaum *et al.*, 2015), a decisive factor for consumers (Egbue and Long, 2012).

The Electric Vehicle (EV)'s autonomy also known as eRange, allows consumers to know an estimate of the remaining driving distance for the existing EV battery power, easing driver's anxiety for the duration of a trip to a charging station (Smuts *et al.*, 2017; Song and Hu, 2021).

The eRange can be estimated through many driving data parameters, such as vehicle design, driver's behavior, whether, road inclination and state of charge (SOC) estimation. The eRange accuracy allows consumers to rely on its vehicle for longer travel time and efficient charging plans, eRange estimation however, is a complex problem with multiple influencing factors (Varga *et al.*, 2019), fueling previous studies in the past to provide a solution for this challenge.

The rise in popularity of machine learning (Amershi *et al.*, 2019) has demonstrated its effectiveness in the past with a variety of fields such as big data (Condie *et al.*, 2013; Zhou *et al.*, 2017), pattern recognition analysis and data mining (Bose and Mahapatra, 2001). This is due to its nature of learning from previous data to gradually achieve better results making it a widely recognized tool for complex problems (Mitchell, 2006). As a result, machine learning, has been chosen in the past as one of the adopted solutions for the eRange estimation problem, making it a more accurate solution.

This project approaches the eRange estimation problem through the use of a machine learning based model, being comprised by three distinct phases: the dataset generation phase, the learning phase and the estimation phase.

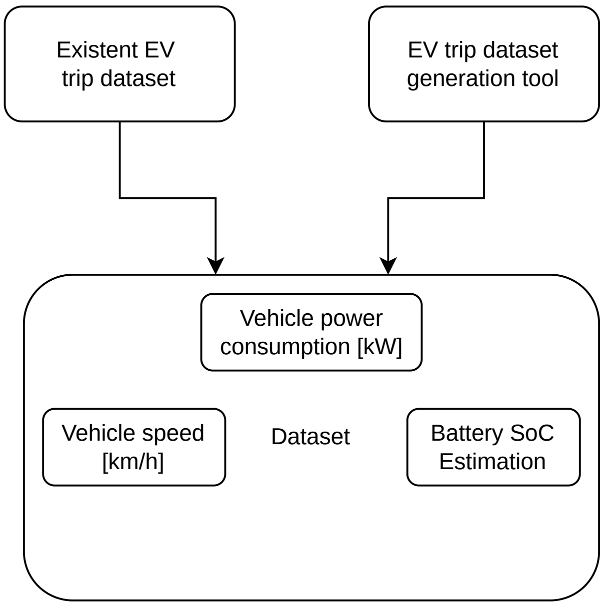

Figure 1.1: System overview - Dataset generation.

On the dataset generation phase (Figure 1.1) a dataset will be created from historical traffic dataset from personally recorded vehicle trips as well as external existing datasets such as *VED* (Oh *et al.*, 2019) as well *Emobpy*, an external library that provides the generation of EV trip and consumption time series (Gaete-Morales *et al.*, 2021). The resulting dataset contains multiple trips with their respective vehicle power consumption [kW] and the vehicle speed [km/h] in a time series format.

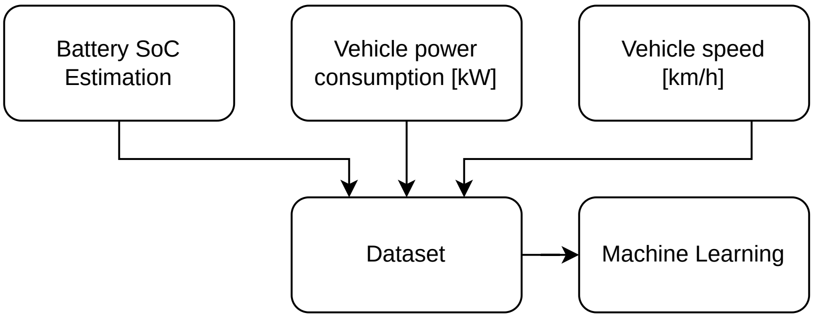

Figure 1.2: System overview - Learning phase.

This dataset will then be used to train the model on the learning phase through machine learning, allowing it to learn the estimation of the eRange for each trip on the dataset (Figure 1.2).

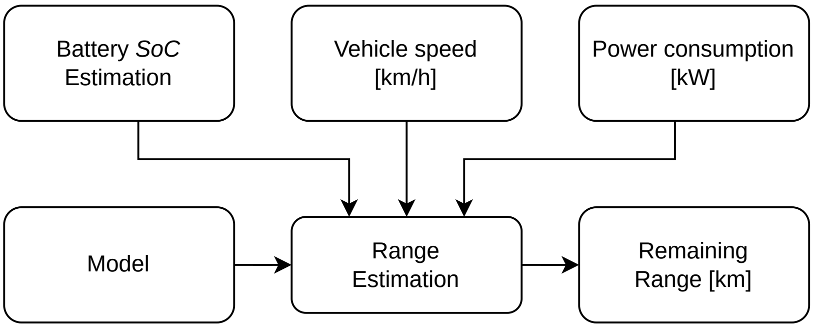

Figure 1.3: System overview - Estimation phase.

After training the model with the dataset, the estimation phase performs the eRange prediction on live SOC monitoring of a driving EV (Figure 1.3).

The remainder of this report is structured as follows: the referencing of existing solutions of the eRange estimation problem and their reliance on available datasets in Section 2.1. Section 2.2 mentions machine learning and its usability in existing eRange estimation solutions. On Section 3 will be discussed the future work and planning for the next stage in the development.

2

State of Art

2.1 EV Range prediction

Previous studies have already tackled various EV related topics, for example, the statistical measurement of charging EVs (Brighente *et al.*, 2021).

In today's day and age, the EV range prediction is an important EV feature to present to consumers as it reduces the driver's anxiety while driving. This problem has been previously studied before, prompting multiple ways to tackle the problem (Varga *et al.*, 2019).

When proving a solution to the eRange prediction problem, valid EV driving data in the form of a dataset is required to test the proposed model and compare it to existing alternatives, making it indispensable in determining the effectiveness of the chosen solution. citar

To this end, existing dataset solutions such as the *VED* dataset (Oh *et al.*, 2019) although providing sufficient EV driving data for estimation, there are only three dinstinct EVs present on the dataset, all from the same model 2013 *Nissan leaf*.

Mencionar datasets inválidos

Another dataset solution is the use of a python tool *Emobpy* (Gaete-Morales *et al.*, 2021) that generates multiple trips for charging and driving studies on EVs, providing a dataset based on empirical mobility statistics and customizable assumptions.

Existing work has demonstrated the use for this feature on EVs, showing the need different types of accuracy on eRange estimation depending on the SOC state (Zhang *et al.*, 2012), this approach minimizes the performance impact of minimum cost route searching from high accuracy eRange prediction.

Other studies have focused on delivering higher eRange estimation accuracy, making use of more complex models. The use of an adaptive history based model approach (Coutinho, 2021) that relies on past information about vehicle's instant consumption energy, to determine an adaptive average energy consumption.

2.2 Machine Learning and EV Range prediction

The use of machine learning for a multitude of cases (Amershi *et al.*, 2019) in fields such as big data (Condie *et al.*, 2013; Zhou *et al.*, 2017) and data mining (Bose and Mahapatra, 2001) has proven its robustness on solving complex problems.

As a result, some approaches for the eRange problem have already applied machine learning for solving it, most commonly using Regression Trees (RTs) and (...especificar).

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One example of RTs usage in a hybrid model of Self-Organizing Maps (SOM) integrating RTs has been studied as a solution for keeping meaningful knowledge extraction on bushy trees.

Decision Tree (DT), Random Forest (RF), and K-Nearest Neighbor (KNN), have already been used in ensemble stacked generalization (ESG) approach (Ullah *et al.*, 2021) proving its effectiveness.

Another similar approach uses gradient boosting to provide better predictive performance from ensemble methods when using multiple learning algorithms such as of XGBoost and LightGBM (Zhao *et al.*, 2020).

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Future Work & Planning

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