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# Glossary

Fora do sítio, não !?    X

**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

O Presidente é o coordenador de MEIC.
O Gonçalo será sim o 1º dos argumentes (júri) X

Júri:

Presidente: Doutor Gonçalo Duarte

Vogais: Doutor David Pereira Coutinho
Doutor Artur Jorge Ferreira

**Janeiro, 2022**

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*Aos meus ...*

# Acknowledgments

(A completar)

# 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 and more specifically the driving range capability, is a decisive factor to be taken into account as it minimizes drive's anxiety while driving. 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 highly complex problems such as the EV driving range prediction, machine learning based solutions already provide accurate enough solutions for the problem. 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 and adapt from existing data, ~~adapting with changes and~~ while aiming to provide more real and accurate results.

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

# Resumo

(A completar)

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# Acronyms

**DTs** Decision Trees. 6

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

**KNN** K-Nearest Neighbor. 6

**LightGBM** Light Gradient Boosting Regression Tree. 6

**RF** Random Forest. 6
**RTs** Regression Trees. 6

**SOC** state of charge. 1, 3, 5, 7
**SOM** Self-Organizing Maps. 6

**XGBoost** Extreme Gradient Boosting Regression Tree. 6

# Glossary

**Big Data** Big data is a field that handles with large datasets that are too big and complex for traditional data processing . 1

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

**eRange** Electric range, the maximum driving range of an electric vehicle using only power from its on-board battery pack to traverse a given driving cycle . 1, 2, 3, 5, 6, 7

Falta definir este acronimo!!!

X

**Machine Learning** A branch of AI focused on learning from data. 1, 2, 3

**Neural Networks** A collection of connected synapse nodes, simulating a biological brain . 6

**Python** A hight level programming language. 5

**Time series** series of data points indexed by time. 2

# 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 namely the driving range capability is have increased competitiveness on vehicle's performance (Figenbaum *et al.*, 2015), a decisive factor for consumers (Egbue and Long, 2012).

electric range

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, and its ~~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, like will be shown in Chapter 2, making it a more accurate solution.

This project addresses ~~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 L learning phase and the E estimation phase.

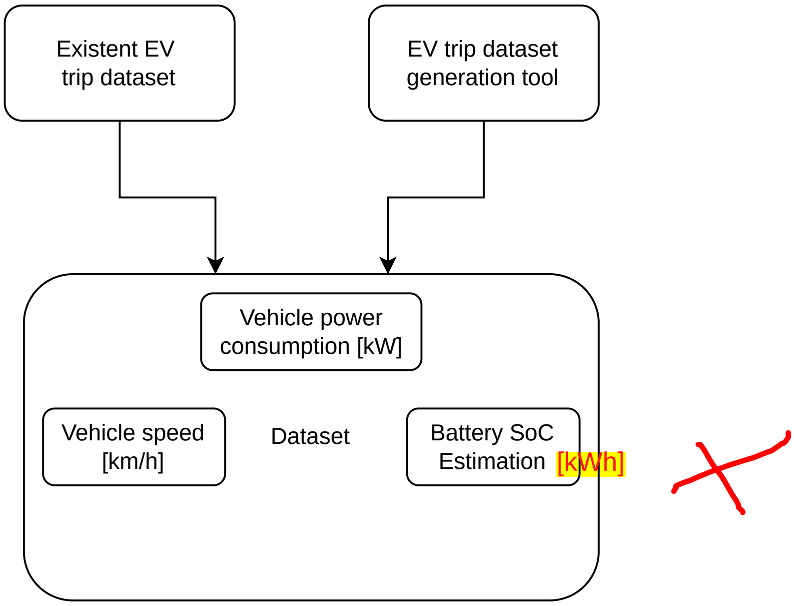


Figure 1.1: System overview - Dataset generation.

On the Dataset generation phase (Figure 1.1) a d Dataset will be created from historical traffic data~~set~~ from personally recorded vehicle trips, as well as external existing datasets such as *VED* (Oh *et al.*, 2019) or ~~as well~~ *Emobpy*, an external library that provides the generation of EV trip and consumption t 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 t Time series format.

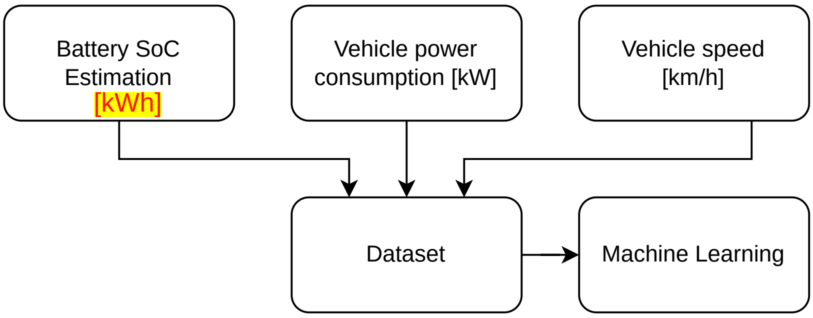


Figure 1.2: System overview - Learning phase.

The generated ~~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, like depicted in ~~(~~Figure 1.2~~)~~.

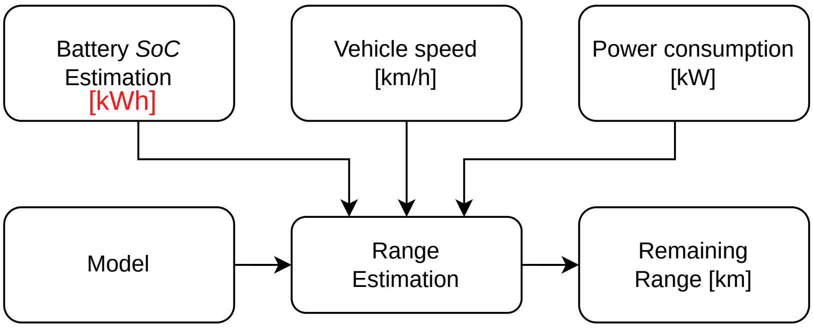


Figure 1.3: System overview - Estimation phase.

After training and learning 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~~ document is structured as follows: Chapter 2 refers the ~~the referencing of~~ existing solutions of the eRange estimation problem and their reliance on available Datasets in Section 2.1, ~~Section 2.2~~ while mentions Machine Learning and its usability in existing eRange estimation solutions. On ~~Section~~ Chapter 3 will be discussed the future work and planning for the next stage in the development of this work.

# 2

# State of Art

## 2.1 EV Range prediction

concerning related problems to the area

Presently or Nowadays

~~In today's day and age,~~ EVs have spired multiple studies, such as statistical measurement of charging (Brighente *et al.*, 2021), regenerative braking (Yoong *et al.*, 2010), charging topologies (Yilmaz and Krein, 2013) and eRange prediction (Varga *et al.*, 2019).

The eRange prediction is an important EV feature to present to consumers as it reduces driver's anxiety while driving, this ~~problem~~ has been previously studied before, prompting multiple ways to tackle the problem.

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

To this end, existing Dataset ~~solutions~~ such as the *VED* Dataset (Oh *et al.*, 2019) that 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*.

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.

eRange estimation !?

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

, the proposed approach by

*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 was proposed by (Coutinho, 2021), ~~that~~ which 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 Neural Networks, linear regression (De Cauwer *et al.*, 2017), Regression Trees (RTs) and Self-Organizing Maps (SOM) (Lee and Wu, 2015).

Decision Trees (DTs), 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 in yielding more acceptable values for proposed evaluation metrics.

Approaches using RTs with gradient boosting provide better predictive performance from ensemble methods when using multiple learning algorithms such as of Extreme Gradient Boosting Regression Tree (XGBoost) and Light Gradient Boosting Regression Tree (LightGBM) (Zhao *et al.*, 2020).

Studies in hybrid models of RTs and SOM have improved upon previous solutions by keeping meaningful knowledge extraction on bushy trees (Zheng *et al.*, 2016).

# 3

# Future Work & Planning

## 3.1 Intro

The initial stage of this project was completed with another 4 curricular units, focusing on finding usable datasets for a replication of eRange estimation through "basic" ~~SOC based estimation,~~ and adaptive history based model approaches proposed by (Coutinho, 2021). Additional research on ~~of~~ existing related works, has also been executed for better understanding of the problem regarding eRange estimation and its difficulties.

## 3.2 Planning

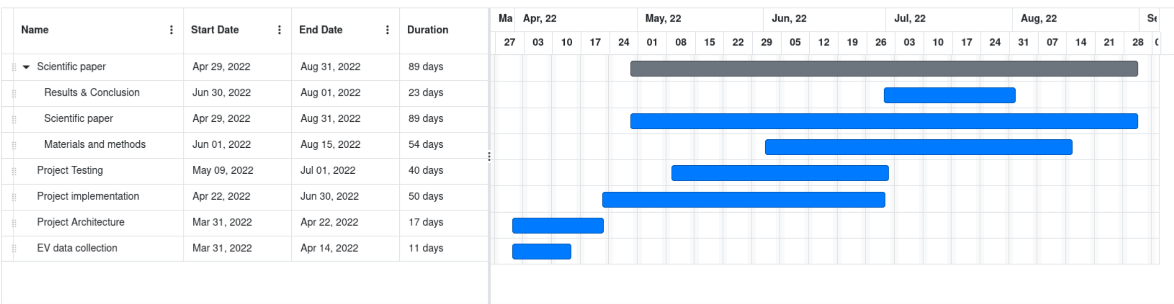


Figure 3.1: Project planning.

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