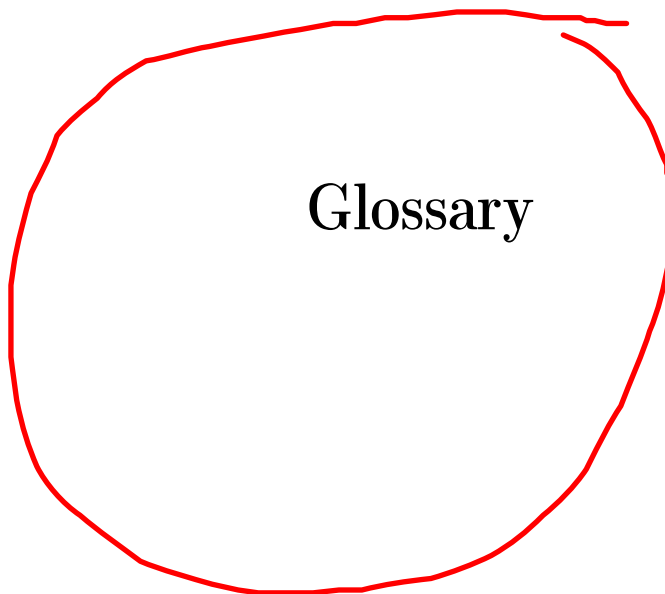


12



Glossary

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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

Júri:

Presidente: **Doutor Gonçalo Duarte**

Vogais: 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

**Janeiro, 2022**





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X ?  
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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 ~~is~~  ~~a decisive factor to be taken into account as it minimizes drive's anxiety while driving.~~ ~~and more specifically the driving range capability,~~ 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 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

<b>DTs</b>	Decision Trees. 6
<b>EV</b>	Electric Vehicle. 1, 2, 3, 5
<b>EVs</b>	Electric Vehicles. 1, 5
<b>KNN</b>	K-Nearest Neighbor. 6
<b>LightGBM</b>	Light Gradient Boosting Regression Tree. 6
<b>RF</b>	Random Forest. 6
<b>RTs</b>	Regression Trees. 6
<b>SOC</b>	state of charge. 1, 3, 5, 7
<b>SOM</b>	Self-Organizing Maps. 6
<b>XGBoost</b>	Extreme Gradient Boosting Regression Tree. 6



# Glossary

<b>Big Data</b>	Big data is a field that handles with large datasets that are too big and complex for traditional data processing . 1
<b>Dataset</b>	A structure containing data for a model. 2, 3, 5
<b>eRange</b>	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 <i>Falta definir este acronimo!!!</i>
<b>Machine Learning</b>	A branch of <b>AI</b> focused on learning from data. 1, 2, 3
<b>Neural Networks</b>	A collection of connected synapse nodes, simulating a biological brain . 6
<b>Python</b>	A high level programming language. 5
<b>Time series</b>	series of data points indexed by time. 2





# 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), namely the driving range capability is a decisive factor for consumers (Egbue and Long, 2012).

The Electric Vehicle (EV)'s autonomy also known as <sup>electric range</sup> 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, <sup>and its</sup> 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, <sup>like will be shown in Chapter 2,</sup> 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 <sup>addresses</sup> ~~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~~ <sup>E</sup>arning phase and the ~~E~~ <sup>E</sup>stimation phase.

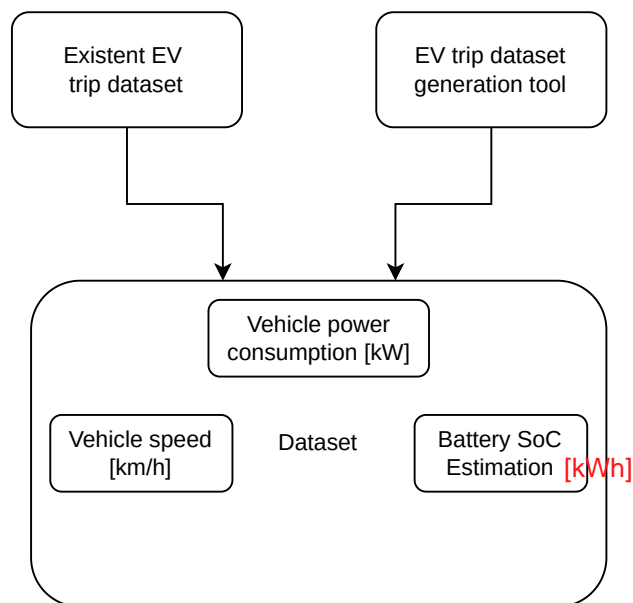


Figure 1.1: System overview - Dataset generation.

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

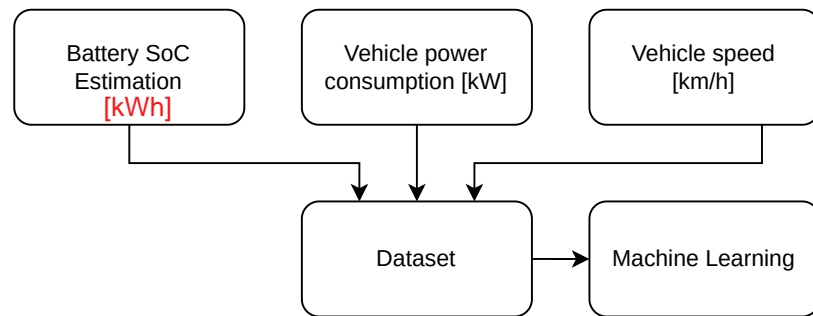


Figure 1.2: System overview - Learning phase.

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).

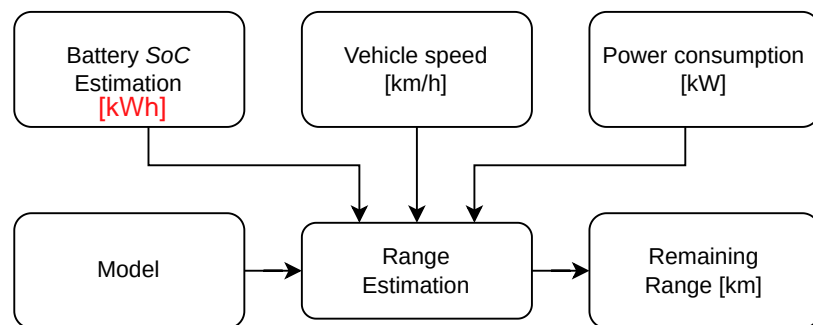


Figure 1.3: System overview - Estimation phase.

After training 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 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, while Section 2.2 mentions Machine Learning and its usability in existing eRange estimation solutions. Chapter 3 will be discussed the future work and planning for the next stage in the development. of this work.



## State of Art

### 2.1 EV Range prediction

~~In today's day and age~~ <sup>Presently or Nowadays</sup> EVs have spired multiple studies, <sup>concerning related problems to the area</sup> 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). X

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

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

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 distinct 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.

Existing work has demonstrated the use for <sup>eRange estimation</sup> ~~this~~ <sup>!?</sup> feature on EVs, showing the need for different types of accuracy on eRange estimation depending on the SOC state (Zhang X ?).

, 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 <sup>was</sup> ~~proposed by~~ (Coutinho, 2021), <sup>which</sup> ~~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 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 ~~al-~~ ~~ready~~ 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).



# 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~~ <sup>proposed by (Coutinho, 2021).</sup> and adaptive history based model approaches. 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

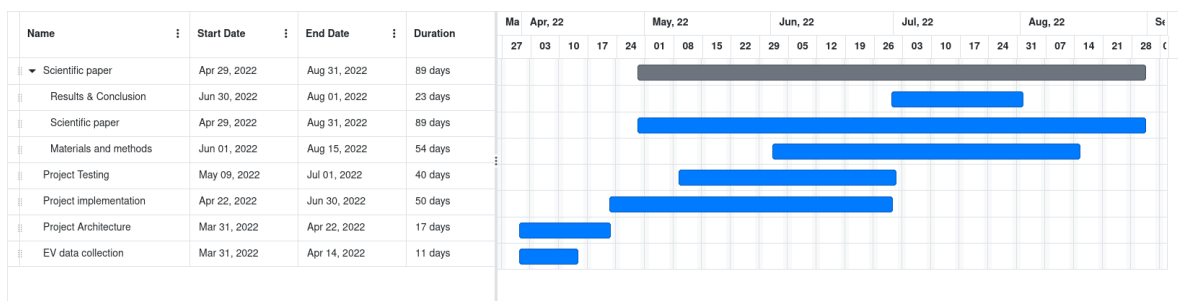



Figure 3.1: Project planning.







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