# 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

Júri:

Presidente: Doutor Gonçalo Duarte

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**Janeiro, 2022**

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*Aos meus ...*

# 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

# Contents

# List of Figures

# List of Tables

# Acronyms

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

**RTs** Regression Trees. 5

**SOC** state of charge. 1, 2, 5
**SOM** Self-Organizing Maps. 5

# Glossary

**dataset** A structure containing data for a model. 2, 5, 6

**eRange** electric range. 1, 2, 5

**machine learning** a branch of AI focused on learning from data. 2

**python** programming language. 6

**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.

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

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

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 which has prompted previous studies in the past to provide a solution (Coutinho, 2021; Varga *et al.*, 2019).

relate with "Prediction of electric vehicle range: A comprehensive review of current issues and challenges"

Prior work (Coutinho, 2021) on eRange estimation demonstrated that using a history-based algorithm on am adaptive model provides a more reliable eRange prediction than a basic SOC - manufacturer data relation, this is mainly due to taking into account the vehicle's driving history.

Machine learning is often a viable tool for complex problems, this is due to its nature of learning from previous data to gradually achieve better results. As its broad use on a large variety of problems is vast and could be applied to most problems (Mitchell, 2006), the eRange estimation problem could be one of which, through the use of machine learning, achieve better results Varga *et al.*, 2019, requiring an initial phase to learn from the model and then estimate through real-time SOC variations. This project approaches the eRange estimation problem with the use of machine learning based model to increase its accuracy.

The proposed solution is divided into three phases: a dataset generation phase, a learning phase and an estimation phase. On the dataset generation phase, 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 was an external library that generates 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. This dataset will 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. After training the model with the dataset, the estimation phase performs the eRange prediction on live SOC monitoring of a driving EV. The following figures represent an overview of the system:

remove VED dataset if not valid

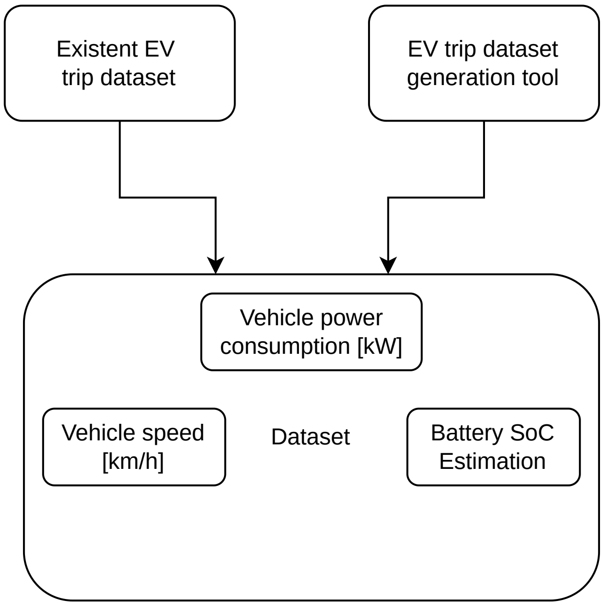


Figure 1.1: System overview - Dataset generation.

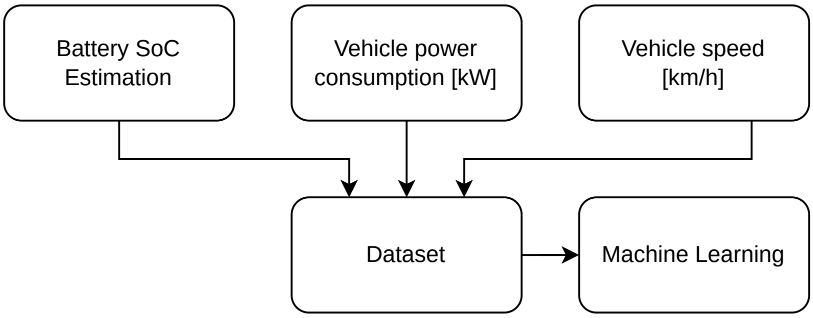


Figure 1.2: System overview - Learning phase.

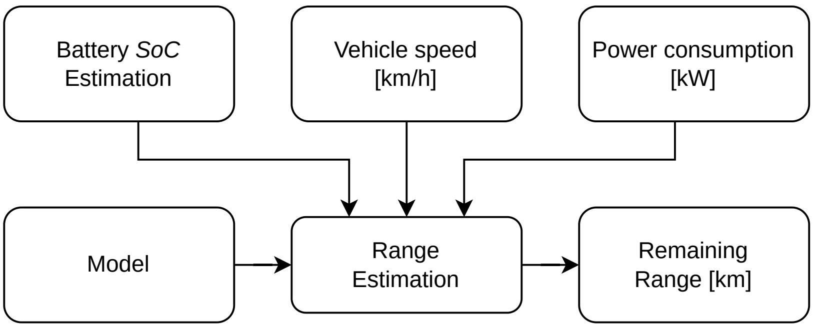


Figure 1.3: System overview - Estimation phase.

# 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).

What is EV range prediction - the problem

In today's day and age, the EV range prediction problem has been previously studied before, prompting multiple ways to tackle the problem (Varga *et al.*, 2019).

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 (... ). descrever

Another approach has used machine learning in a hybrid model of Self-Organizing Maps (SOM) integrating Regression Trees (RTs) (Zheng *et al.*, 2016) (... ). descrever

The dataset used to obtain the results from past studies have an important role in determining the effectiveness of the chosen solution.

To this end, existing dataset solutions already exist such as the VED dataset (Oh *et al.*, 2019) (althouth containing only three electric vehicles  model 2013 *Nissan leaf*).

Another adopted 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 (... ).

descrever

## 2.2 Machine Learning and EV Range prediction

Machine learning usage on complex problems

Machine learning usage EV world

Machine learning algorithms for

classicEVX history based comparisson

referir as técnicas mas especificar noutros capítulos

resumo das técnicas usadas no fim do state of the art

# 3

# Planning

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