Electric Vehicle X Driving Range Prediction – EV X DRP

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Abstract

The 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 driving range capacity is a decisive factor to be taken into account as it minimizes drive's anxiety while driving. An EV's driving range depends on multiple factors that must be factored in to accurately infer results. ~~As m~~ Machine learning has become a widely used approach for highly complex problems, and provides better accuracy for existing EV driving range prediction implementations. This project explores the implementations of a machine learning based model, with training from publicly available datasets, aiming to provide accurate results through evaluation metrics.

1 Introduction

On today's day and age, the global concern on climate change has been a major focus on recent international agreement, incentivizing many car manufacturers to introduce EVs as the eco-friendly solution for sustainable transport for the future. EVs have grown popularity in recent years and as a result, car manufacturers have increased competitiveness on vehicle's performance [8], namely the driving range capacity, as it is a decisive factor for consumers ~~[7]~~.

The EV's autonomy, ~~also known~~ designated here 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 [11]. The eRange can be estimated through many driving data parameters, such as vehicle design, driver's behavior, whether weather, road inclination and SOC (state of charge) estimation and its accuracy allows consumers to rely on its vehicle for longer travel time and efficient charging plans. However, eRange estimation is a complex problem with multiple influencing factors [13], fueling previous studies in the past to provide a solution for this challenge.

The rise in popularity of machine learning in a variety of fields has proven itself as decisive tool for finding solutions in complex problems. Due to the complex nature of eRange prediction, existing works has relied on machine learning to increase its prediction accuracy.

This project focuses on comparing machine learning approaches on the eRange estimation problem with training data from readily and publicly available datasets, allowing for reproducibility and future research easier through an open-source Python application.

2 State of the Art

Nowadays, EVs have motivated multiple studies concerning related problems in this field, such as statistical measurement of charging [4], regenerative braking [15], ~~charging topologies [14]~~ and eRange prediction [13].

When proving a solution to eRange prediction, EV driving data is required when relying on supervised machine learning. To this end, existing datasets are available for use in supplying the needed training features for an eRange prediction model. These features ~~are~~ can be split into two categories: time-series, where the data varies according to time and constant, where the same value is preserved for the duration of the trip. Time-series features are generally the SOC; energy consumption; speed; acceleration and elevation. While constant ~~such~~ features are vehicle information ~~as~~ such battery capacity, average energy consumption (AEC), full battery energy (FBE), full driving distance (FDD), weight; trip information such as commute type city or highway; total energy consumption and total distance.

There are Publicly available EV trip datasets like *VED* dataset [10] and *Charge Car* project of the CREATE Lab at Carnegie Mellon University [1]. The cloud based EV dataset supplied by the National Big Data Alliance of New Energy Vehicles (NDANEV) [3] already contain enough time-series training data, however the latter does not disclose EV model or battery information due to a privacy agreement, making it harder ~~for eRange prediction models to predict more accurately without this missing information~~.

~~Existing~~ Previous work ~~has demonstrated the use of machine learning~~ in eRange estimation on EVs, showing the need for different types of accuracy on eRange estimation depending on the SOC state, and other features.

The application of machine learning in this problem has been implemented in various other published works through ensemble stacked generalization (ESG) [12], gradient boosted regression trees with XGBoost and LightGBM [16], Self-organizing maps (SOMs) [9, 17] and neural networks [6]. Although more complex than previous solutions, it will be shown that the use of machine learning for the eRange estimation problem had reduced the prediction error, and thus further justifying its usage on this problem.

3 Methodology

The goal of this work is assessing eRange machine learning prediction solutions through the same training set of publicly available data.

The algorithm integrates EV trip datasets viable for training, thus requiring EV trips time-series with the following features: SOC, power consumption, distance and speed, as well as vehicle information: AEC, FBE and FDD. For this reason, both *VED* and *ChargeCar* datasets [1] were chosen for the construction of this project's dataset. When configuring the algorithm's training, multiple datasets can selected, as well as a minimum trip type and minimum driving time, as these factors have been tested and found to gratelly influence machine learning's training fitness.

For the algorithms training eRange target, output fata from an implementation of the "History-based" eRange prediction approach from the Classic EV X project [5] was used for training the algorithms. ~~The~~ This approach relies on vehicle's trip energy history for its estimation and uses multiple vehicle battery parameters such as AEC, FBD and FBE provided with the manufacturer as well as SOC and energy consumption. Due to the fact that this implementation does not take into account features as speed, road inclination, distance traveled and driving patterns, machine learning algorithms can train from this approach and improve on future trips with these additional parameters.

Two machine learning algorithms have been implemented in the model: linear regression and ESG from [12] are implemented for assessment. The ESG algorithm as described in its paper follows the Wolpert stacking technique, combining two models, the first one, base-model (Level-0) three regressors: Decision Tree (DT), Radom Forest (RF) and K-Nearest Neighbors (KNN); while the other meta-model (Level-1) is Ada-boost, combining base model predictions to a single output.

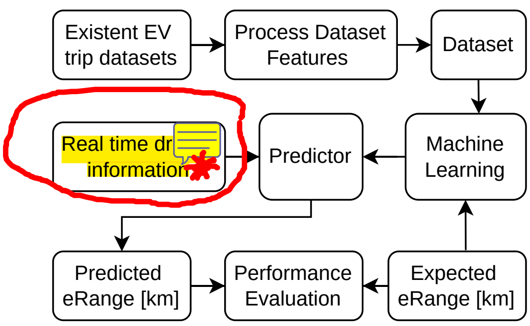

Figure 1: Project overview

TENHO DÚVIDAS!

ML approach	MAE	MSE	MAPE	RMSE	r^2
ESG	10.31	117.98	20.70	10.86	-5.79
LR	**2.44**	**6.73**	**4.87**	**2.6**	**0.83**

Table 1: ESG and Linear Regression

Once the machine learning algorithms are trained, various evaluation metrics are then used to assess each algorithm performance: Mean Absolute Error (MAE), Mean squared error (MSE), Mean Absolute Percentage Error (MAPE), Root MSE (RMSE) and r^2. These ~~are~~ metrics are then used to infer algorithm accuracy and thus ensuring the best fitting algorithm for selected test trip.

Falta referência a Table 1 e Figure

4 Results and Conclusion

On a conventional 47 minutes trip from the VED dataset 2 for Nissan Leaf model (2013), with the "History-based" delta step of 50w, a minimum instance energy of 2.5kW and N=10, the prediction differences in selected eRange prediction models can be seen on the following graph with predictions all implemented algorithms: "basic" and "history based" non machine learning approaches [5] (in blue and red, respectively); the ensemble stacked generation decision tree based approach [12] (in green) and the linear regression approach (in purple).

The "history-based" approach [6] shows an increase in eRange when regenerative breaking is charging the battery and "plateau" sections when the minimum instance energy is not enough to trigger a recalculation for the eRange. Although these sections have been smoothed out by linear regression machine learning algorithm. The ESG algorithm suffered the most compared with liner regression with this training set, showing sub-optimal results on all metrics, one possible cause for this performance reduction could be missing original dataset training features such as elevation.

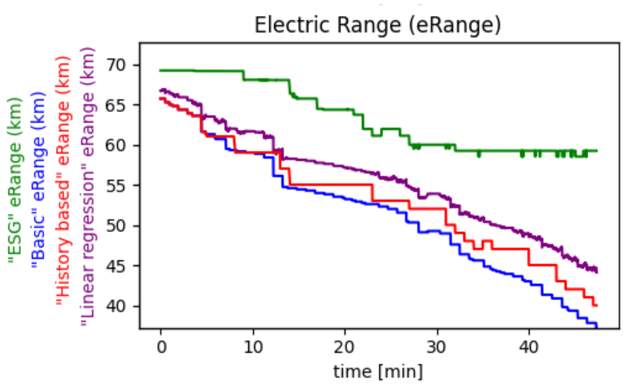

Figure 2: Machine learning eRange predictions and expected results

The project's goal for eRange prediction algorithms assessment and real time execution for EV trips has been achieved and demonstrates that different dataset features influence the prediction's accuracy of given machine learning algorithms. The source code can be obtained from the Github page [2] and supports the addition of further datasets and machine learning algorithm implementations in the future.

Acerca da implementação dos algorimtos no carro e em real time for future work!

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