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Matching model between Battery SoC and applications

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Executive Summary

Defining the relationship between the state of charge (SoC) of a vehicle's battery and different measures that translate the vehicle's charging profile is a challenge since there is not a direct relation between a vehicle that charges in a specific charging station. In this paper we propose a methodology, based on Pearson Correlation Coefficient (PCC) and machine learning, that allows to match charging curves of a vehicle and a charging station, within a fleet management environment. This enables energy prediction based on vehicle SoC through a regression model that takes the different energy-SoC associations obtained with the curve-matching process.

Integrating this approach within a sequential matching-validation-training methodology, it was possible to enhance a linear model absolute error on energy calculation across different electric vehicles (EV) thus predicting better vehicle-specific energy values which in turn leads to better price estimations on EV charges and movement reconciliation.

1 Introduction

In an ideal fleet management scenario, both EV and electric vehicle supply equipment (EVSE) are monitored. It should then be possible to perfectly identify the vehicle associated to a specific charge in an EVSE. However, current EV-EVSE communication standards do not include any direct vehicle identification data (as will be the case once ISO15118 becomes widespread), and other identification methods (eg. RFID cards) while useful do not offer an error-free scenario.

As the number of EV and EVSE grows exponentially [1] it becomes a challenge to associate them based solely on activity-aggregated metrics. What's more, establishing a connection between these two entities with activity-aggregated metrics does not take into account battery's health or the evolution of the available charging network. Typical vehicle battery's useful life is shortened throughout its use due to mechanisms already studied [2] and it affects its storage capacity which impairs the energy supplied over time. Different methods for charging infrastructure planning have already been reviewed [3] and the number of charging stations takes part as a decision variable and as a constraint. This means that horizontal scaling will be the path towards EV charging demand.

In turn, the process of assigning one EV charging to a specific EVSE gets even more complex. This association should then be based on charging profiles due to their impact on EV charging strategies [4]. Charging profiles can be obtained by collecting data from charging transactions, i.e., initial SoC and starting time, and they can vary according to different factors [5].

However there is not a telematic measure of a battery's energy level as opposed to SoC, which upholds the need to establish this association since the real energy values can only be obtained from the EVSE via data communication protocols such as the Open Charge Point Protocol (OCPP). With accurate energy values obtained from this association, it is possible to improve invoicing processes and predict energy supplied to an EV [6]. Another advantage comes from knowing if an EV has charged at a specific EVSE or not, allowing fleet managers to understand behavioural patterns on their network usage.

Nevertheless, observing a charge from the vehicle and infrastructure perspective is also quite different:

- For an EVSE, energy increase (meter values) is typically reported in 1 to 15 minute intervals and granular increments can be as low as 10 Wh. AC charging stations are unable to report SoC;
- For vehicle telematics units, only SoC variations are reported in 1% increments, which for recent vehicles would correspond to roughly 500 Wh. In addition, intermediate variations are sometimes only reported in case the main vehicle ECU (electronic control unit) is "alive", otherwise in some cases where start and end values are reports. Finally, location measurements (based on GPS) do not allow for enough precision to pinpoint a given EVSE but rather the overall location of the charging pool being used.

In order to solve this problem, a curve-matching approach has been developed to connect EV and EVSE charging curves, as measured by their own data measurement and collection devices, using PCC to measure similarity between them. Similarity between curves can be determined in multiple ways. Dongsheng and Haiyun (2015) [7] used the discrete Fréchet distance method to measure similarity between charge-discharge curves in order to analyze battery's state of health (SoH). However we are not measuring similarity between curves from the same source which means this method could produce low similarity values due to value offsets. Tao et al. (2017) [8] adapted the classical dynamic time warping (DTW) method by addressing the spatial transformations of the curves and applied it to study the degradation state of batteries through capacity curves from charging and discharging processes. DTW is specially useful in time-series data with a lot of variations along the time axis[9] which is not represented in our scenario since we are comparing charging curves that have the same time window. Value discrepancy can also impact the similarity estimation through this method. PCC on the other can provide an efficient similarity measure while not being sensitive to value offset, considering similar measured signal rates between reference and input sample [10], [11].

By connecting EV and EVSE charging transactions it is possible to build EV-specific models based on real energy values, enhancing the accuracy of energy prediction based on initial and final SoC. Other studies have used different regression techniques to model energy consumption based on multiple factors, including environmental and driving activity-related factors [12]–[14]. Fukushima et al. (2018b) [14] stated that due to this factors and the uniqueness of EV model power units, each EV should have its prediction model. In this case the goal is to predict energy based on an EV charging transaction so driving-related factors cannot be accounted as well as environmental ones since they does not impact the energy provided by the EVSE.

Therefore this approach should enable a continuous process of curve-matching and training that helps in the first stage to identify and connect EV to EVSE charging curves and in the next stage to build EV-specific models that allow to better predict energy to be charged from SoC values (and hence obtain a seconday measurement for SoH)..

The goal of this study and the model developed is to be able to demonstrate that these methods could be use for one or all of the following:

- Automatically identify vehicles charging at a given EVSE (and vice-versa, i.e., in which EVSE a vehicle actually charged)
- Measure degradation of Battery performance (Battery State of Health) from EVSE charging curves
- Prove that accurate energy measurements can be estimated from SoC observation based on historical usage data

2 Methods

The implementation was based on R language (version 4.1.3) using *Rstudio*. Table 1 shows the specifications of all EVs (#164) considered initialliy for this study. Error margin is considered as 2% of the nominal battery capacity of each model and this allows to compare different EV models and variants, as explained later in this section. Firstly a linear model considering the nominal battery capacity of each EV is built, using equation (1) where Q_N refers to the nominal battery capacity of an EV, SoC_f and SoC_i refers to final and initial SoC of an EV charging transaction, respectively, and E refers to the total energy supplied to the battery for that charging transaction.

$$E = \frac{SoC_f - SoC_i}{100} * Q_N \quad (1)$$

The computing approach can be divided in 3 steps: matching, validation and training. Each one of them is described below in the following subsections. The matching process was applied to 4 months of 2022 (April, June, July and August) for all EVs and this is where the process connects EV and EVSE charging transactions, a mandatory step that without this connection it is not possible to enhance a linear model as described in (1). In this step an EV model initially built is used to transform SoC values in energy thus making charging curves comparable. The validation is applied to each month of data and aims to clear mismatches that can happen during the previous step, serving as a filter to produce accurate inputs for the following step. The last process involves the training of multiple regression models using information from valid transactions. It is applied to valid data from the first 3 months and only 4 new EV models were used to provide results for this article, comparing energy values for the final month.

Table 1: EV specifications

Fuel Type	Brand	Model	Battery capacity (kWh)	Error margin	# EV
Electric	Nissan	Evalia	40	0.8	3
		Leaf	39	0.78	24
			40	0.8	60
	Renault	Zoe	41	0.82	1
			44	0.88	7
		Kangoo	33	0.66	36
	Smart	Fortwo Coupe	17.6	0.352	15
Hybrid	Golf	GTE	8.7	0.174	18

2.1 Matching

The matching process follows these steps:

1. Calculate total energy of charging transaction using an EV model;
2. Limit search space of possible EVSE transactions by EV transaction' starting time;
3. For each EVSE transaction:
   3.1. Calculate geographic distance between EVSE and EV;
   3.2. Calculate total energy difference ;
   3.3. Calculate difference in starting time;
   3.4. Obtain EVSE charging curve;
   3.5. Preprocess EV and EVSE charging curves;

3.6. Merge charging curves;
3.7. Obtain EV energy curve using EV model;
3.8. Obtain differences of energies and perform cumulative sum;
3.9. Calculate PCC between both charging curves;
3.10. Add starting time and energy difference penalties to PCC.
4. Select EVSE transaction with highest final value (PCC + penalties).

The search space limitation is considering only EVSE transactions between minus 2 minutes and after 5 hours of the EV transaction' starting time. Geographic distance is calculated using *distVincentyEllipsoid* function from *geosphere* package with default parameters. There is a condition where if this distance is greater than 500m the cycle goes for the next EVSE transaction, thus providing another layer to filter the search space and improving the algorithm's efficiency.

The preprocessing of the charging curves attempts to correct artifacts that arise from telematics, such as invalid SoC values, and to perform subsets on both charging curves in order to limit the transaction time upon reaching maximum values. This is a crucial step since the timestamp-wise merge (through *xts* package) will be mainly affected by these artifacts and incorrect subsetting, which in turn will impact the PCC calculation due to an incorrect elimination of the time variable. EV's energy curve is obtained using its model, initially represented in equation (1), providing SoC' deltas as input. After the calculation we subtract from PCC result, 0.005% of energy difference and 0.01% of the total hours between the starting times of transactions. Percentages values for the differences were obtained empirically.

2.2 Validation

The validation process uses two different approaches, yielding different classification values, and it's applied to one month of EV charging transactions. The first one takes into account Radio Frequency Identification (RFID) cards used in EVSE transactions, which has liability issues due to owners switching cards or lack of updates in the assignment to vehicles.

In order to account for these challenges, there is a second and stringent validation approach that checks if the match respects the following set of conditions:

- An energy factor (energy obtained from the model divided by the EVSE transaction' energy) between 0.85 and 1.15;
- PCC >= 0.98;
- Geographic distance <= 100 meters;
- Unique EVSE transaction match, meaning there is only one match for that EVSE charging transaction.

The stringent validation only takes into account matching characteristics, being agnostic to user-related variables thus making it a reliable method. The uniqueness of EVSE transaction match should be considered within the universe of one-month worth of all matches for all EV that belong to the same operational context.

This validation approach will always be result-defining, meaning that if a charging transaction is validated through RFID card and it is not by this one, it is marked as in need for manual validation. This is established in order to have user-independent validated matches that can be accurate input for the next process.

2.3 Training

Validated matches from the previous process are selected for models' training process. From each validated match it is possible to extract SoC variations from the charging transaction and their respective energy. By performing multiple combinations, the full spectrum of initial and final SoC pairs of each charging transaction can be accounted as training data thus providing sample size even when an EV has few matches (between 5 and 10). EV with less than 5 valid transactions will not be accounted for this process.

Using the R packages *caret* and *caretEnsemble*, it is possible to train multiple regression models using the same cross-validation technique in one function call. Initialliy we perform data splitting in a 70/30 ratio of training/testing using *createDataPartition* function. Regarding the cross-validation technique we used repeated cross-validation with k=10 and repeats=10. A list of 10 regression models from *caret* package (*lm*, *svmLinear*, *enet*, *ridge*, *rlm*, *svmPoly*, *bridge*, *gamSpline*, *xgbLinear*, *knn*) was built pre-training so it is possible to change some parameters using "tuneGrid" argument of *caretModelSpec* function. The model *gamSpline* was trained using different degrees of freedom (from 1 to 4) while the others were run with default arguments.

A model for each EV is the result of this process and its able to predict energy values from final and start SoC, such as (1), without the need to use the vehicle's nominal battery capacity or fixed numerical variables. After the training process is complete a resampling method (n=10) is applied to get a collection of summary metrics on each model trained. The model with the lowest average Root Mean Squared Error (RMSE) is selected. Evaluation of the model is done by comparing energy predictions of valid matched EVSE charging transactions between current and new model. Model's efficiency is calculated using (2) where EM equals Error Margin from Table 1 for a specific EV, n refers to the number of valid charging transactions of an EV, $\hat{y_i}$ refers to the predicted energy of ith valid charging transaction while the y_i refers to the EVSE energy for the same transaction and η is the model efficiency, a value between 0 and 1. The nominator equals the count of values that the absolute difference between predicted and observed energy are lower than the error margin established for an EV.

$$\eta = \frac{\sum_{i=1}^{n}(|\hat{y_i} - y_i| < EM)}{n} \qquad (2)$$

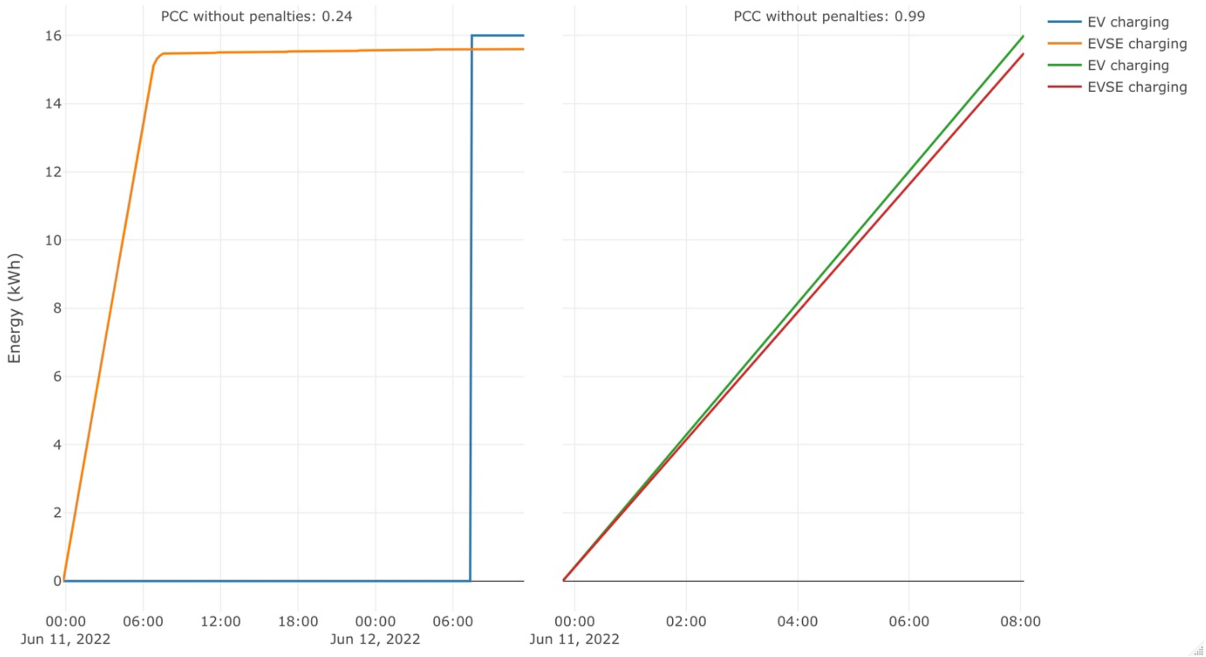
3 Results

3.1 Matching

From a total of 9043 charging transactions to be matched, only 2256 of them were not able to connect with an EVSE charging transaction. From the number of EV chargings that got a match (6787), there are 5444 unique EVSE charging transactions which means there is a maximum of 60.2% correct matching. It is possible to state that for this EV fleet, 60.2% (possible maximum) of the chargings were done at a charging station that was being monitorized. In turn, every five EV charging transactions there is at least two that take place outside of the EVSE network. Regarding the different number between EV chargings that got a match and the unique EVSE charging transactions, it is a consequence of the matching process itself. This can happen because there is no constraints that limit the search space to not already assigned EVSE transactions and there is no threshold for the final score of a match. It allows for all the possibilites to be accounted, even a match with low score can be a correct connection. Enabling the potential identification of problems that can arise from instruments used to collect data.

Figure 1 shows an example of how the preprocessing step impacts PCC values when calculating the similarity between curves. Despite the timestamp-wise merge of both curves it is possible to see that in the not preprocessed EV and EVSE charging curves there is a mismatch between the peaks and evolution of energy. In this case, the EV did not communicate values while being charged, indicating only the initial SoC during the actual charging and final SoC at the end. By allowing a correct subset of EV charging curve based on initial and peak of supplied energy from EVSE it is possible to increase PCC value by 0.75, meeting a requirement for the stringent validation approach.

Figure 1: EV and EVSE charging curves without (left) and with (right) preprocessing



3.2 Validation

From a total of 6787 matches, 2866 (42.2%) were validated using both approaches while 3921 (57.8%) were marked as in need for manual validation. The number of correct validated matches is closer to the maximum value for correct matching that we could possibly achieve. None of the validated matches were solely validated by RFID cards which means the validation process was correctly implemented. Also the matching process has proven efficient to deal with the issues presented by RFID cards. However, this type of validation should be accounted for because it helps the fleet manager to identify incorrect card usage or incorrect information on its database. It should also not be the unique layer of validation due to the reasons above mentioned.

Table 1: Summary statistics for EV valid transactions counts

	Minimum	1st Quantile	Median	Mean	3rd Quantile	Maximum
# Charges	1	9	18.5	21.71	31.5	64

Within the 2866 valid charging transactions, only 132 EV have at least one valid match leaving 32 EV without inputs for the training process. This can be due to various factors: i) vehicles are not charging at EVSE monitored by the platform; ii) vehicles metadata is incorrect; iii) vehicle telematics units (or EVSEs) are sending wrong data (less likely). There are two possible approaches to generate new models for these EV. The first one is to manually validate the transactions that were marked as such in order to have data while the second focus on widening the collection period for the EV charging transactions thus providing new charges that can be matched.

Table 1 represents the summary statistics for the counts of valid transactions by EV. 50% of EV have between 9 to 32 valid charging transactions while there is 25% with less than 10 valid charging transactions. 19 out of the 132 EV have less than 5 valid transactions which is not enough to train a regression model. The same principle of the EV that did not have a single valid transaction can be applied in this case in order to have sufficient data. This leaves 113 EV for the training process, which is 68.9% of the total initial pool of EV.

3.3 Training

Table 2 shows the summary statistics of RMSE for the resamples of all models after training from *caretList* runs. The last column refers to the number of EV that got that model as selected to replace linear model. All models present very similar RMSE distributions which can be explained by the low number of input features. In this case we only had start and final SoC which do not bring a lot of entropy to the model or a lot of coefficients that need to be calculated.

Introducing non-linear modelling seems to achieve better results with *gamSpline* presenting the lowest statistics overall (4/6). The number of EV selected is representative of this, nonetheless one has to take into account that *gamSpline* model had tuning parameters that allowed for flexibility during training process. This means that these models could fit data in a wider range of possibilities while other models had their parameters as default. Despite this, linear models behaved really well, presenting the second lowest average of RMSE statistics. By exploring tuning parameters for all models, it could be possible to understand the regularization of this type of models in order to enhance their RMSE values.

20 EV had their model selected as *rlm* which supports this trend. Although *xgbLinear* model presents the highest summary statistics, one EV had the lowest average RMSE during the resampling process. This EV had the highest number of training data considering the combinations of initial and final SoC which could be a factor considering that there is a difference of 10000 samples between this EV and the EV with the second highest number of training samples.

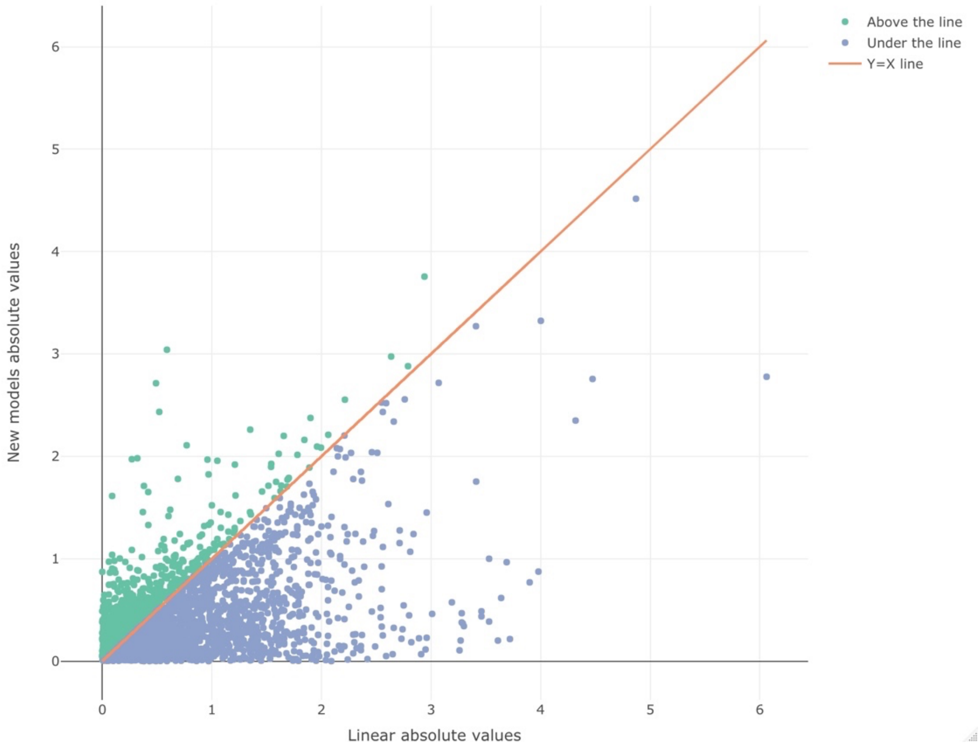
Table 2: RMSE summary statistics for the resamples of all models and number of EV with each model

Model	Minimum	1^{st} Quantile	Median	Mean	3^{rd} Quantile	Maximum	# EV
lm	0.1047	0.2806	0.3856	1.0554	0.5267	60.2312	1
svmLinear	0.1112	0.3028	0.4087	1.1147	0.5719	60.2317	0
enet	0.1047	0.2788	0.3815	0.9611	0.5135	60.3297	4
ridge	0.1047	0.2788	0.3815	0.9663	0.5135	60.2456	0
rlm	0.1047	0.2798	0.3846	0.9154	0.5194	60.2311	20
svmPoly	0.1164	0.2883	0.4204	1.2714	0.6912	60.245	0
bridge	0.1051	0.2790	0.3883	1.1230	0.5257	60.2315	0
gamSpline	0.1002	0.2402	0.3431	0.9743	0.4791	60.2312	87
xgbLinear	0.1287	0.3965	1.0058	2.2314	2.3687	127.7420	1
knn	0.1378	0.4157	0.9651	2.2294	2.3058	60.2520	0

Figure 2 compares the linear and new models' predicted energy values for all validated charging transactions. The equation Y = X line indicates that the energy predicted equals the same as a linear model (current model). Points under the line indicates that absolute new model predictions are lower than linear ones. This means that the prediction is closer to the real energy values from EVSE than linear ones.

There are a total of 1868 "Under the line" and 956 "Above the line" points. The energy predicted by all new models improved the linear predicted energy in 66.14% transactions. Despite these results there are still values that are a bit concerning, regarding the new models predictions. For example, it is possible to identify cases where linear absolute value is below 1 kWh and the new model predicted an absolute value above 2 kWh. This can indicate that some outliers are present for some EV or that even the new model its not performing as it should, meaning a replacement is not advisable (or the metadata is simply incorrect or inaccurate).

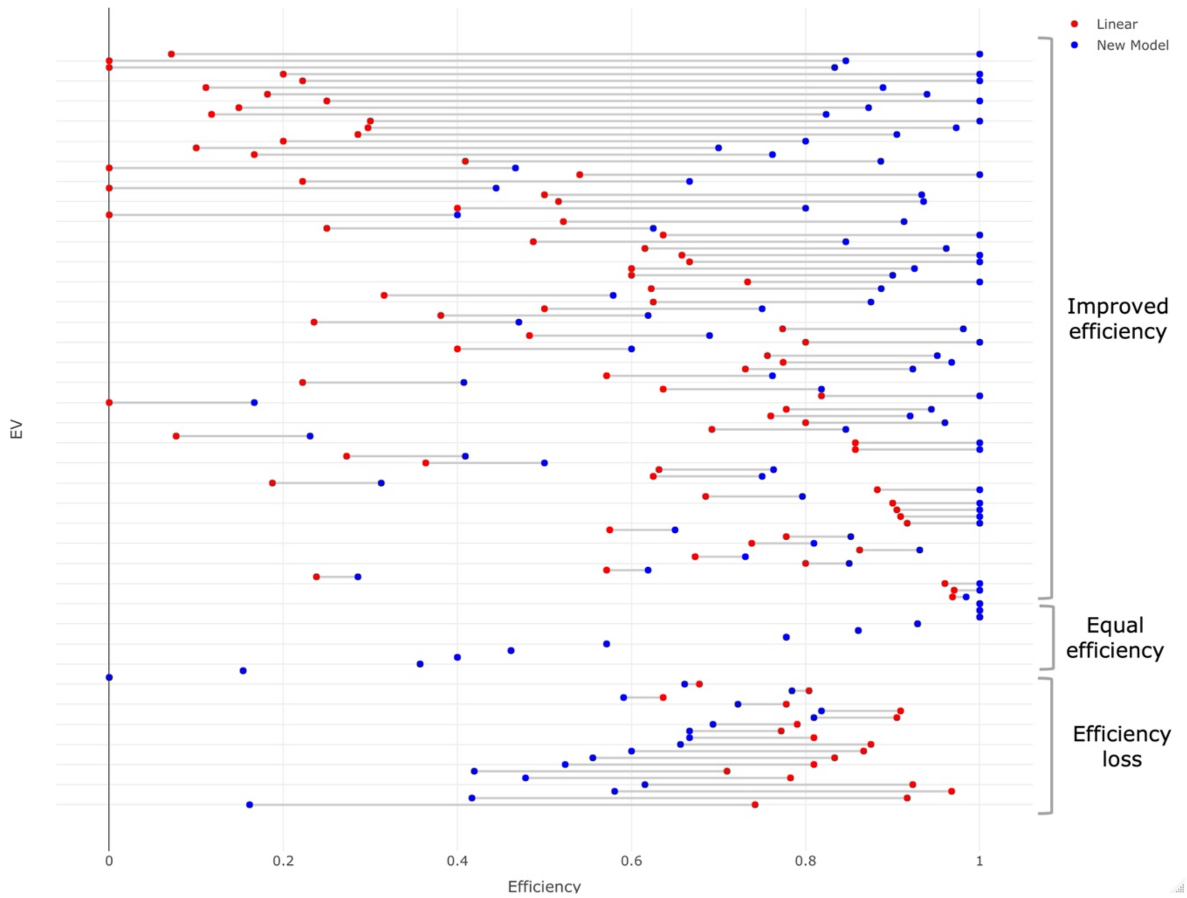
Figure 2: Difference between absolute linear and new models' predicted energy values



In order to classify the new model's performance versus the initially built one, their efficiencies were calculated and compared between all 113 EV. Figure 3 shows the dumbbell plot between their efficiencies. There are 19 new EV models that have a lower efficiency compared to initially built ones. These models can be interpreted as outliers to the process. Efficiency is greatly influenced by error margin and total EV chargings matched which means low error margins produce small windows for differences between predicted and real values and if the model's efficiency is calculated with a low n value its efficiency is greatly decreased as well. If the new model does not capture the correct coefficients due to lack of input data it will be difficult to predict energy values below small error margins.

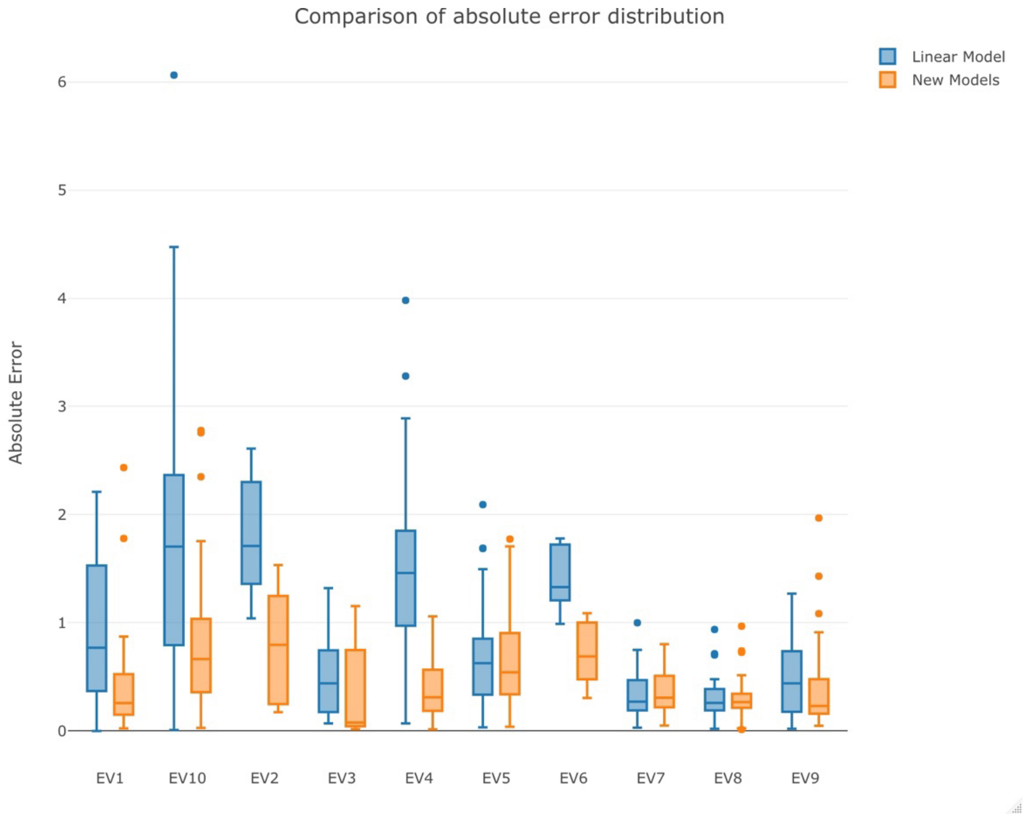
There are 12 new EV models that had the same efficiency as current models while there are 82 new models with higher efficiency. An even efficiency is indicative that the current model, which is dependent on the battery capacity, is able to accurately predict the energy charged by an EVSE. However, batteries' storage capacity is affected by their use which means in the long run this initially built models will no longer be accurate to predict energy values. This is represented by the new models that improved current model predictions regarding the same EVSE reference values, showing that for the majority of EV (82/113) an approach considering only battery capacity is not good enough. This may translate to some relationship to the battery health status because a linear equation based solely on its capacity can no longer represent the energy that is supplied to it.

Figure 3: Dumbbell plot of 113 efficiency differences between linear and new models



To gain more insights on models comparison 10 boxplots were built representing 10 EV randomly sampled. Figure 4 shows their distribution of absolute error (energy predicted – EVSE energy), comparing linear and new models. The data represents 4 months of valid charging transactions (309 transactions: EV1 – 46; EV2 – 9; EV3 – 9; EV4 – 33; EV5 – 62; EV6 – 15; EV7 – 14; EV8 – 54; EV9 – 27; EV10 – 40). The majority of new trained models show a skewness of absolute error distribution, however there are models with similar and slightly worst performance than a linear one. In example, we have EV7 with slightly higher median absolute error, maintaining a linear model for curve matching should be considered with some reserves that the approach should be reviewed later. EV9 has better results however it produces some outliers. This has to be taken into account if this model is going to replace a linear one as it can predict energy that will affect PCC values due to penalties. On the other hand we have the case of EV6 that the use of trained model allowed to have an improvement of more then 75% of the absolute error under 1 kWh compared to 0% from the linear model. This analysis should be done to every model in order to consider or disregard the need to replace linear ones.

Figure 4: Boxplot of absolute error across 10 different EV



4 Conclusion

This paper shows a new approach to build EV-specific models that predict energy values charged based on vehicle SoC, which possible within an environment where EVSE transactions are also monitored. The study has revealed that an assessment has to be done for each built EV-specific model as it can produce models that do not improve over the simplified one based on the nominal battery capacity of an EV. This can also be due to poor identification and manual definition of a vehicle's metadata. Nevertheless, the majority of cases have shown that their efficiency improved when applying this approach, indicating that it is possible to calculate energy values closer to reference (from EVSE) for charging transactions. With these models it is possible to predict energy values without knowing in which EVSE an EV charged or understand which EV is not charging in a managed EVSE network. This provides movement reconciliation for EV fleet managers and more accurate energy-related operations applied to charging transactions. In the next steps the authors will focus on establishing a relationship between these models and the battery's State of Health (SoH), study the possibilities for fine-tuning of regression models and reimbursement operations for EV transactions outside monitorized networks (eg. home charging).

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Presenter Biography

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