Training and Validation Methodology for Range Estimation Algorithms

Patrick Petersen[1], Adam Thor Thorgeirsson[2,3], Stefan Scheubner[2], Stefan Otten[1], Frank Gauterin[3] and Eric Sax[1]

[1]FZI Research Center for Information Technology, Haid-und-Neu-Straße 10-14, 76131 Karlsruhe, Germany

[2]Dr. Ing. h.c. F. Porsche AG, Porschestraße 911, 71287 Weissach, Germany

[3]Institute of Vehicle System Technology, Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany

Keywords: Automotive Systems Engineering, Verification and Validation, Testing, Range Estimation, Battery Electric Vehicles.

Abstract: Estimating the range of battery electric vehicles is one of the most challenging topics for the current trend in the automotive industry, the electrification of vehicles. Range anxiety still limits the adoption of battery electric vehicles. Since the range estimation is dependent on different influencing factors, complex algorithms to accurately estimate the vehicles consumption are required. To evaluate the accuracy of data-driven machine learning algorithms, an exhaustive training and validation procedure is mandatory. In this paper, we propose a novel methodology for the development and validation of range estimation algorithms based on machine learning validation approaches. The proposed methodology considers the evaluation of driver-specific and driver-unspecific performance. In addition, an error measure is introduced to assess the performance of range estimation algorithms. This approach is demonstrated and evaluated on a set of recorded real-world driving data. It is shown that our approach helps to analyze the performance of the range estimation algorithm and the influences of different parameter sets.

1 INTRODUCTION

Range prediction for battery electric vehicles (BEVs) has, in recent years, been intensively researched. As range is one of the key factors of customer satisfaction. The route-based range is principally dependent on the energy stored in the battery and the energy required to reach a destination following a given route. Predicting the energy required for a certain route is not trivial. The driving range is dependent on different factors, some of which can be easily modeled with physical relations. Other factors, such as the influences of driver and traffic behavior, are non-deterministic. Both of these heavily influence the driving speed, which is one of the most important influencing factors on the vehicle's consumption (Wu et al., 2015; Wager et al., 2016). By applying machine learning (ML) algorithms, these non-deterministic factors can be included in the range estimation.

A lot of the research about range estimation models focuses on including as many input parameters as possible, such as the influences of traffic (Grubwinkler et al., 2014), route (Yu et al., 2012), weather (Fetene et al., 2017), driving style (Bingham et al., 2012a), auxiliary consumers (Horrein et al., 2017) and vehicle characteristics (Tannahill et al., 2016). To validate and verify the model and evaluate its accuracy, the feature space should be covered sufficiently. With most ML algorithms, the size of the training data set correlates with the number of features, i.e. if the feature space is large, a large training data set is needed (Lewis, 1992). For non-ML models, the validation is still of great importance and having a realistic and representative test set is required. Additionally a suitable error measure needs to be chosen or formulated.

As a result, the validation becomes complex and time-consuming, especially when performed with real test drives. In this paper, a virtual framework for validation and performance evaluation is presented. The approach is based on real-world driving data to ensure coverage and realism. This allows a scalable approach without highly-sophisticated simulation models.

This paper is structured as follows: in Section 2, the state of the art in Automotive Systems Engineering (ASE) and validation approaches for ML algorithms are presented. In addition, open challenges

Petersen, P., Thorgeirsson, A., Scheubner, S., Otten, S., Gauterin, F. and Sax, E.
Training and Validation Methodology for Range Estimation Algorithms.
DOI: 10.5220/0007717004340443
In *Proceedings of the 5th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2019)*, pages 434-443
ISBN: 978-989-758-374-2

for the validation of range estimation algorithms are identified. In Section 3, our proposed validation concept for range estimation algorithms is described and its prototypical implementation will be discussed. In Section 4, the approach is demonstrated based on a small test campaign. Section 5 concludes this paper and discusses future work based on the results of this paper.

2 STATE OF THE ART

Due to the increasing complexity of Advanced Driver Assistant Systems (ADAS), the need for exhaustive test coverage increases (Mazzega et al., 2016). ISO29119-1 postulates that dynamic testing is essential for the validation of correct functional behavior (ISO, 2013). Boehm described a software program as a mapping from a space of inputs into a space of outputs (Boehm, 1976) meaning that covering the complete input space ensures the quality of a system. For complex and non-deterministic systems like range estimation algorithms, covering the complete parameter space is not feasible for automated test case generation. Therefore, another approach is to use real-world data for the evaluation of such systems e.g. in the domain of computer vision, recorded video data is a common method to solve this issue (Cordts et al., 2016).

In the automotive field, features are primarily tested in the real-world with the help of prototype vehicles. This ensures the highest possible realism for testing features in the verification and validation (V&V) process but fails to scale, since these few selected test drives are primarily tailored for manual in-depth debugging (Sax, 2008).

(Bach et al., 2017b) and (Langner et al., 2017) propose a data-driven development approach that suggests utilizing the steadily growing pool of recorded real-world driving data for the development of features and executing them in a Software-in-the-loop (SiL) environment. (Bach et al., 2015) introduces the Reactive-Replay approach, which enables the execution of a closed-loop feature on system level by utilizing recorded real-world driving data. Thus, feature maturity can be ensured in early development stages. Previous recorded data can now be reused for development and enables continuous tracking of software maturity without the need for running new test drives (Bach et al., 2017a). Reducing redundancy and simulation time can be achieved by carefully selecting test cases without loosing test coverage (Bach et al., 2017c).

For testing range estimation algorithms, real-world test drives are primarily used for validation (Rolim et al., 2012), (Tannahill et al., 2016). Statistically significant evaluation is achieved by collecting thousands of kilometers of real-world test drives. Various situations and scenarios need to be considered, such as different traffic situations or weather conditions, to achieve a sufficient test coverage. This approach lacks scalability due to the fact that for each new soft- ware version new data must be recorded. However, using simulations can be executed as often as needed (Yi and Bauer, 2017), (Enthaler and Gauterin, 2016). For creating realistic simulations, non-deterministic factors, such as environmental, traffic and driver behavior, need to be considered, requiring complex models (Helmer et al., 2015). Due to the fact that a lot of effort needs to be invested to create such models, a hybrid of simulation and real-world data is preferred. This hybrid allows the benefits of the realism of real-world data to be reused for the simulation based execution of future software versions.

Although selecting the best data for the validation of range estimation algorithms is still a challenge, the methodology for an accurate training and validation process is a major challenge as well.

It is necessary that data-driven range estimation algorithms adapt to driving characteristics of an individual or changing drivers to further improve the estimation of the energy consumption and range (Bingham et al., 2012b). Therefore, for the validation of such algorithms it is important to assess the driver-specific and driver-unspecific performance. A driver-specific performance indicates whether the algorithm adapts and optimizes its energy consumption estimations of one consistent driver. A driver-unspecific performance indicates whether the algorithm is capable of adapting to different drivers in an appropriate period of time. To validate ML algorithms, data samples must be split into a set of training data $\mathcal{D}$ and a set of test data $\mathcal{T}$. The classifiers are then trained on $\mathcal{D}$ and the accuracy measured by testing on $\mathcal{T}$. By testing on unseen data, an assessment of how the algorithm will perform in practice is achieved. In (Mitchell, 2012), several methods are suggested:

- Resubstitution
- Holdout
- Leave-one-out
- K-Fold Cross-Validation

Resubstitution uses the whole data set for both training and testing and will result in an optimistic biased accuracy estimation. Holdout uses half of the data for training and the other half for testing. The estimation will be pessimistic biased. Leave-one-out uses all but one data samples for training the classifier and the last data sample for the test. The estimate is unbiased but with large variance. K-fold cross validation is the middle road between holdout and leave-one-out as the number of splits is somewhere between 1 and N with N being the number of samples.

(Bolovinou et al., 2014) uses a 10-fold cross-validation to evaluate the performance of the initial range prediction (in km) using support vector regression (SVR), linear regression (LR) and a conventional, history-based range estimation. Mean absolute error (MAE) is used as an error measure.

(Fukushima et al., 2018) uses two validation methods, a leave-one-out cross-validation, where the test set consists of different BEV trips on the same route, and a two-fold cross-validation, where BEV trips on one route are used for training and trips on another route are used for testing, and vice versa. With these methods, the performance of ordinary least squares (OLS) and an own method in predicting energy consumption is measured, and the relative test error is used as an error measure. (Gebhardt et al., 2015) uses a leave-one-out cross-validation to test two range estimation approaches, where each test set represents a trip with a BEV. The relative error in the prediction of each trip's energy consumption is used as an error measure.

(Cauwer et al., 2017) splits selected data sets into 80% for training and 20% for testing of a model that combines a neural network (NN) and a multiple linear regression (MLR), which predict the energy consumption. The metrics root-mean-squared error (RMSE) and MAE are used to measure the performance of the initial prediction, and the prediction for each route segment. (Qi et al., 2018) splits a data set with real BEV data into 70% for training and 30% for testing of regression models for the estimation of the energy consumption, and the symmetric mean absolute percentage error (SMAPE) is used as an error measure. (Wang et al., 2017) tests only the goodness of fit of LR models estimating the energy consumption of BEVs. The goodness of fit is measured with R^2 and the Akaike information criterion (AIC). From the article, it can not be determined if the data was split in training and test sets or whether the goodness of fit is measured in-sample.

(Thibault et al., 2018) validates a physical model for the energy consumption with 35 real BEV trips and SMAPE is used as an error measure. (Wang et al., 2015) validates a physical model for the energy consumption with real BEV trips. However, no error measure for the performance is calculated, but it is shown that the measured energy consumption lies within the maximum and minimum values of the prediction. (Genikomsakis and Mitrentsis, 2017) validates a physical model for the energy consumption using simulated data. Driving cycles are used to specify the velocity profile. MAE, mean squared error (MSE) and mean absolute percentage error (MAPE) are used as error measures.

Only a few validation approaches describe a driver-specific validation of range estimation algorithms. (Ondrúška and Posner, 2014) uses a data set with 50 different drivers. A separate model is trained for each driver, in order to predict the energy consumption of a trip. The models are validated with different sizes of training sets, but always tested on the whole data set for each driver, i.e. a variable combination of in- and out-of-sample testing. The relative error is used to measure the performance of the models.

(Tseng and Chau, 2017) uses randomly selected 80% of collected BEV data to train a regression model, and the rest is used to test the performance of the predicted energy consumption. Since the selection is done randomly, the validation is not driver-specific. RMSE and the accumulative error over a whole trip are used as error measures.

Up to now, there is no general methodology for data selection and validation of range estimation algorithms for driver-specific and driver-unspecific evaluation. Only one or the other is used for the evaluation of such algorithms. Even though it is important to evaluate the performance of a range estimation algorithm in the two different use-cases. There is also a need for a standardized and non-biased error measure for the evaluation. In addition, the process of splitting data samples into a set of training data and a set of validation data is done randomly, which could lead to a possible bad distribution of training and validation data e.g. training on drives with low velocities and validation on drives with high velocities. Thus, a data selection method is needed to ensure balanced training and validation data sets.

In the following, we present a methodology for the validation process. Covering the data selection and the standardized training and validation concept of data-driven learning range estimation algorithms. Additionally, a universal error measure is introduced to assess the performance of such algorithms.

3 CONCEPT FOR TESTING RANGE ESTIMATION ALGORITHMS

In the context of evaluating the performance of range estimation algorithms, considerable attention needs to

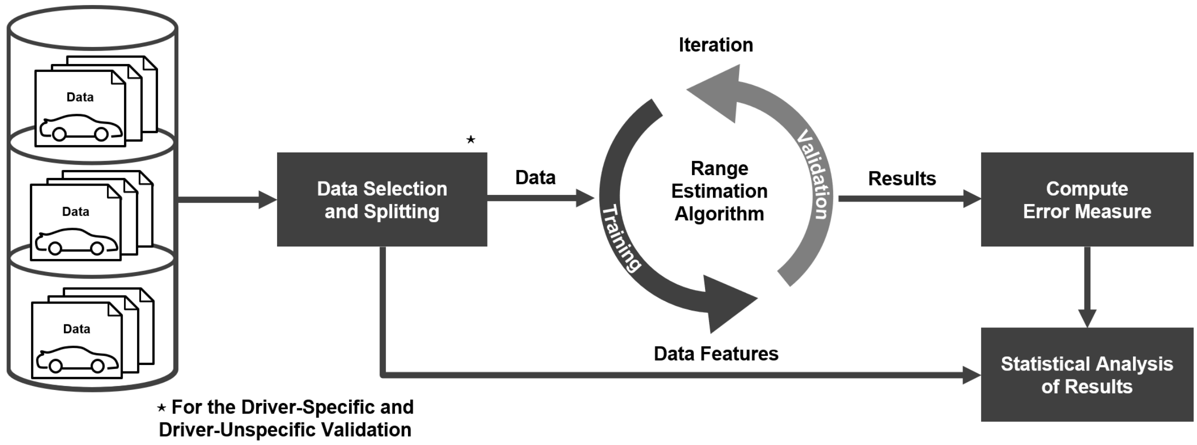


Figure 1: Overview of the training and validation methodology for range estimation algorithms.

be paid to the training and validation phase. Thus, our goal was to create a methodology which enables the assessment of driver-specific and driver-unspecific performance. Figure 1 shows an overview of our proposed methodology covering the data selection, splitting the data into training and validation sets for the driver-specific and driver-unspecific validation and the statistical analysis of the results based on our introduced error measure. In the following, the individual methodology steps shown in the Figure will be described.

To ensure the highest possible realism for training and validation, we suggest the usage of recorded real-world data from different drivers. Since driving style has a significant impact on a vehicles energy consumption, its inclusion in the validation will improve the evaluation of the range estimation. On that account, the accuracy of the range estimation with consistent driving style can be measured, as well as its robustness during changes in driving behavior, such as driver changes. For the driver-specific evaluation, we suggest a k-fold cross-validation where the data set includes only a single driver. For the general, driver-unspecific evaluation, we suggest a leave-one-out cross-validation with a data set including more than one driver. Both approaches test the out-of-sample performance, which is always the case in real applications. Figure 2 shows the concept for the driver-specific and driver-unspecific evaluation.

3.1 Driver-specific Validation

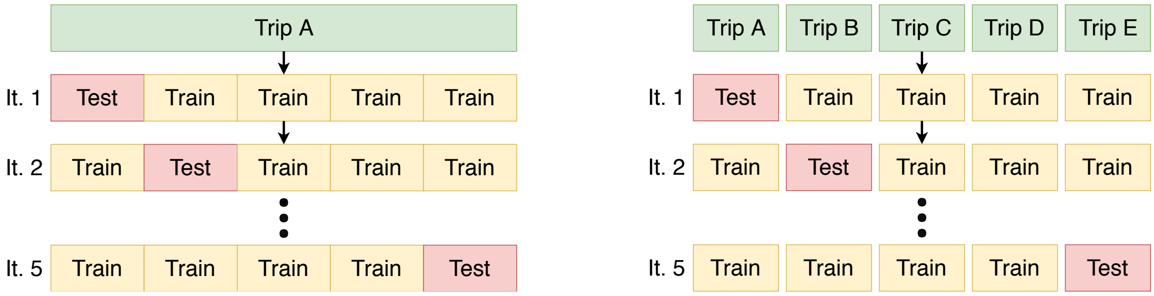
To evaluate driver-specific performance of a range estimation algorithm, it must be ensured that data from the same driver is used. Due to the protection of privacy, the driver for certain trips is usually not known. Also, the driving behavior of a driver could vary between trips, which could lead to the false assumption that this data comes from a different driver. Therefore, we split each recorded real-world drive into segments for the k-fold cross-validation to ensure that the same driver is used for training and validation. Figure 2a shows the procedure exemplary for one trip. In this scenario, the data is split into $k = 5$ segments and for each iteration, one segment will be used for the validation and the rest for training. This enables the assessment of the driver-specific performance of the used range estimation algorithm on different segments.

3.2 Driver-unspecific Validation

To evaluate the performance of a range estimation algorithm for the more general case of inconsistent driving behavior, the validation technique needs to be different from the driver-specific evaluation. To represent a changing driver or another driving behavior, the training and validation is done on different trips. To this end, one complete trip is left out for the validation, and other trips from the data basis are used for training. In Figure 2b, an example of the procedure for five trips is shown. In each iteration, one trip will be selected for the validation and the rest for training, leading to five results. The order of trips used for training is randomized.

3.3 Error Measure

For the evaluation of the performance of the range estimation algorithm, a suitable error measure needs to be chosen or formulated. Since the actual measured energy consumption could be close to zero for some segments, because of the ability of BEVs to recuperate energy, the percentage error is not an appropriate



(a) K-fold cross-validation for driver-specific training and validation.

(b) Leave-one-out cross-validation for driver-unspecific training and validation.

Figure 2: Exemplary visualization for the k-fold cross-validation and leave-one-out cross-validation for splitting the data into a training and validation set.

error measure, as the error is divided by the actual value. The RMSE is not as convenient to interpret as the MAE, and could over-penalize large errors. Thus, we introduce our non-biased error measure: The absolute error of the prediction of energy consumption ε is shown in Equation 1.

$$\varepsilon = \frac{|E_{\mathcal{A}} - E|}{s} \tag{1}$$

This is calculated by the absolute difference between the initial energy consumption prediction $E_{\mathcal{A}}$ of a range estimation algorithm $\mathcal{A}$ and the actual measured energy consumption E normalized by the length of the validation segment s. The initial prediction for the energy consumption was chosen due to its importance for the charge planning at the beginning of each trip. In addition, the initial prediction is the most challenging, as it has the longest prediction horizon and therefore the highest amount of uncertainties. For n training and validation iterations, the weighted sum $\bar{\varepsilon}$ of the absolute error of the prediction of energy consumption is then calculated. This is shown in Equation 2.

$$\bar{\varepsilon} = \frac{\sum_{i=1}^{n} \varepsilon_i * s_i}{\sum_{j=1}^{n} s_j} \tag{2}$$

The weighted mean absolute error (wMAE) is calculated for the driver-specific ($\bar{\varepsilon}_\alpha$) and driver-unspecific ($\bar{\varepsilon}_\beta$) validation iterations, which describe the performance of $\mathcal{A}$ in each situation. Through weighting with the length of the validation segment, the error measure takes longer trips more into account, which is reasonable due to the higher difficulty for an accurate initial prediction. Since the driving behavior influences the learned parameters used for the estimation, only those validation segments should be evaluated which require those parameters for the estimation. This prevents validation of the initial parameters, which were not trained during the training phase. As with all recursive algorithms learning with lots of data, newer data points have more significance than older ones. Thus, to deal with this characteristic behavior, it may be reasonable to validate with all possible permutations of the training data.

In summary our methodology addresses the challenges identified in state of the art evaluation of range estimation algorithms: a non-biased validation for the driver-specific and driver-unspecific performance of range estimation algorithms with a given error measure, which evaluates the most challenging prediction for such algorithms, the initial prediction. Different trip lengths are also taken into account for a significant evaluation. In addition, our methodology covers the process of selecting suitable (out-of-sample) algorithms data for the validation phase for the driver-specific and driver-unspecific performance evaluation.

4 EVALUATION

To demonstrate the practicability of our validation methodology, we implemented a framework for the evaluation of a range estimation algorithm. Our data basis consists of 21 recorded real-world test drives from different drivers. The accumulated length of the data basis is approximately 2088.03 km. Each recorded data contains logged signals from the Controller Area Network (CAN). Table 1 gives an information overview of the used data.

The data basis was also enriched by external sources for historic traffic information, which was used for the range estimation algorithm described in (Sautermeister et al., 2017). For the k-fold cross-validation of the driver-specific performance a drive was splitted into $k = 3$ segments. In Figure 3, a box plot shows the calculated absolute error for the driver-specific, driver-unspecific evaluation and its variance.

The figure shows that for the driver-specific evalua-

Table 1: Overview of the used data for the training and validation evaluation

Number of trips	21
Total length	2088.03 km
Shortest trip	13.87 km
Longest trip	219.93 km
Average length	99.42 km
Average trip length on highway	60.82 km
Average positive slope	0.64°
Average negative slope	1.06°
Average absolute curvature	1.62 rad
Average velocity	67.65 km/h

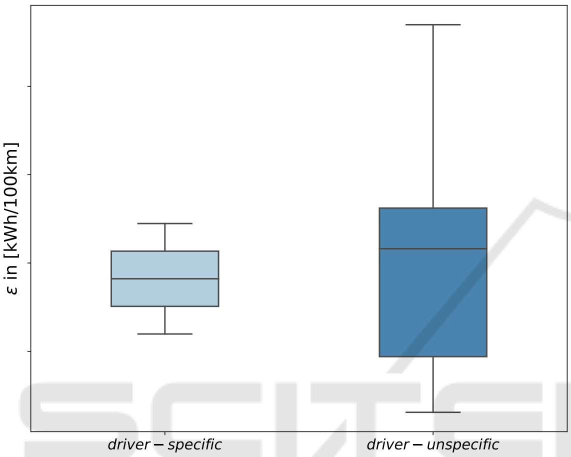


Figure 3: Box plot showing the absolute error for driver-specific (ε_α) and driver-unspecific (ε_β) estimation of energy consumption.

tion, the absolute error for each iteration of the k-fold cross-validation has a greater variance than the error for the driver-unspecific leave-one-out evaluation. Less training data for the driver-specific evaluation may be the cause of this result due to splitting one trip into a training and validation segment. The mean training length for the driver-specific evaluation was 66.29 km compared to 2042.21 km for the driver-unspecific evaluation.

To further utilize the methodology, we examined 7 different parameter sets such as different learning rates for the range estimation algorithm. For each parameter set, we obtained an error measure pair, $\bar{\varepsilon}_\alpha$ and $\bar{\varepsilon}_\beta$. In Figure 4, each pair was plotted in a scatter plot to visualize the performance of each parameter set. The blue line represents the Pareto frontier, which highlights feasible choices for parameter sets of the used range estimation algorithm. Therefore, the best parameter set can be chosen based on different criteria e.g. the best parameter set for the driver-specific or driver-unspecific performance. Its up to the developer to choose the parameter set, which has the desired performance.

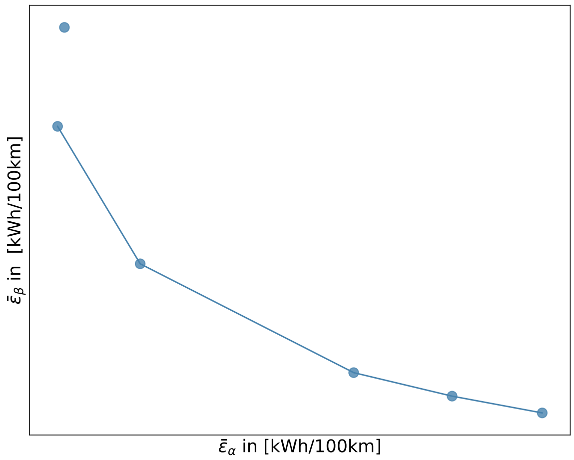


Figure 4: Scatter plot showing the weighted mean absolute errors $\bar{\varepsilon}_\alpha$ and $\bar{\varepsilon}_\beta$ for the given parameter set evaluation. Showing the Pareto frontier for the parameter sets with the lowest error measure.

To further investigate the performance of specific parameter sets during the driver-specific and driver-unspecific evaluation, certain features were factorial analyzed. For the factorial analysis independent driving patterns where chosen, which describe a certain dimension of the driving pattern in regards to the energy consumption during the trip. (Ericsson, 2001) worked out 16 driving pattern factors with significant effect on emissions and fuel-use for internal combustion engine vehicles. (Braun and Rid, 2018) further investigated the driving patterns which influence the energy use of BEVs. Furthermore (Hu et al., 2017) explored the influence of driving behavior, personal driving style, traffic conditions and infrastructure design on the energy consumption of BEV. Therefore we analyzed 15 features which cover personal driving style, route and traffic characteristics of the training and validation data during each iteration. Table 2 shows the chosen features. Then we analyzed the correlation between the error measure and absolute difference between the training and validation data of the features ($\Delta F = |F_T - F_V|$) in each iteration. This was done for the driver-specific and drive-unspecific validation. In Table 3 the Pearson correlation is calculated to show the relationship between each feature and the error measure.

Due to the limited number of data most of the Pearson correlation coefficients are not significant at the significance level of 0.05. However, the features describing the driving style correlate differently which substantiates our approach to separately evaluate the driver-specific and driver-unspecific performance of the range estimation algorithm. In general, changes in the route and traffic characteristics

Table 2: The chosen features for the driving style, route and traffic characteristics that were calculated for each training and validation data set during each iteration.

	Feature	Denotation
driving style	Relative positive acceleration	RPA
	Relative negative deceleration	RNA
	Percentage of time when speed $< 2\ km/h$	PC_STOPP
	Percentage of time when va is $3-6\ m^2/s^3$	PC_va3_6
	Percentage of time when acceleration exceeds $2.5\ m/s^2$	PC_a25
route	Relative positive slope	RPS
	Relative negative slope	RNS
	Relative absolute curvature	RAC
	Percentage of highway	PC_H
	Average speed limit	AVG_SPL
	Standard derivation speed limit	AVG_SPL
traffic	Average ratio of v_{online}/v_{lim} [1]	AVG_vOL
	Standard derivation ratio of v_{online}/v_{lim}	STD_vOL
	Percentage of travel distance where $v_{online}/v_{lim} < 0.5$ during the trip	PC_vOL_50
	Percentage of travel distance where $v_{online}/v_{lim} > 0.9$ during the trip	PC_vOL_90

[1] v_{online} describes the measured average velocity of each segment of a route. v_{lim} describes the speed limit of each segment of a route.

Table 3: Pearson correlation coefficient and p-value between features and the error measure for the driver-specific and driver-unspecific validation.

	Feature	Pearson correlation coefficient (r)		Pearson correlation p-values	
		driver-specific	driver-unspecific	driver-specific	driver-unspecific
driving style	RPA	0.05	0.02	0.73	0.93
	RNA	0.06	−0.03	0.64	0.91
	PC_STOPP	−0.12	0.28	0.34	0.21
	PC_va3_6	−0.05	−0.34	0.71	0.10
	PC_a25	0.13	0.29	0.32	0.21
route	RPS	0.18	0.34	0.16	0.13
	RNS	0.02	−0.10	0.88	0.66
	RAC	0.25	0.28	0.05	0.21
	PC_H	−0.04	0.35	0.76	0.12
	AVG_SPL	−0.27	0.31	0.03	0.17
	STD_SPL	−0.15	0.49	0.23	0.02
traffic	AVG_vOL	−0.24	0.47	0.06	0.03
	STD_vOL	−0.26	0.41	0.04	0.06
	PC_vOL_50	0.05	0.02	0.72	0.93
	PC_vOL_90	−0.08	0.13	0.53	0.58

between training and validation tend to be stronger correlated with the estimation error. Significant results for AVG_SPL and STD_SPL have a weak oppositely correlation for the driver-specific and driver-unspecific evaluation. The same phenomena can be observed for the significant correlation for AVG_vOL and STD_vOL. Traffic has a significant influence on the velocity prediction of such algorithms, hence also on the estimated energy consumption. This is reasonable for learning algorithms which tend to perform worse in unknown situations and are therefore sensitive for differences in training and validation data.

5 CONCLUSION AND FUTURE WORK

We introduced this contribution with an analysis of the current challenge of range prediction for battery electric vehicles. Depending on different factors, range estimation requires novel algorithms to cope with the complexity. Improving the accuracy of these algorithms is essential to address range anxiety, which, in turn, is necessary to increase acceptance of battery electric vehicles. Thus, being able to measure the accuracy of range estimation algorithms is of great importance. We analyzed the current approaches for the training and validation of ML and non-ML range estimation algorithms. We identified the demand for a standardized methodology for the training and validation process to evaluate the driver-specific and driver-unspecific performance.

We then introduced our data-driven training and validation methodology of range estimation algorithms, which allows the evaluation of driver-specific and driver-unspecific performance. Furthermore, an error measure for such algorithms was introduced, which is, in contrast to some publications, non-biased and can handle segments with zero consumption. Also the focus of the error measure was put on the most crucial estimation for such algorithms: the initial prediction. Through weighting with trip length, shorter and easier estimations carry less weight than longer and tougher estimation challenges, which allows a more significant evaluation. We presented our methodology by analyzing a small set of recorded real-world data. Reusing already recorded data allows easier and faster evaluation of range estimation algorithms under development. Additionally, we analyzed the correlation between the error measure and the feature differences in the training and validation data sets. These features covered the driving style, route and traffic characteristics. The results can be utilized to improve the developed range estimation algorithm in regards to factors which influence the energy consumption of BEVs. Different results for the driver-specific and driver-unspecific correlation such as for the traffic features have shown that our methodology to evaluate both the driver-specific and the driver-unspecific performance of a range estimation algorithm is reasonable.

Future work will focus on to further investigate influences on estimation errors for range estimation algorithms. In addition, the impact of different lengths of the training and validation segments will be evaluated. The steadily increasing database of recorded real-world data requires exhaustive evaluation. Therefore, concepts for coping with the evaluation of a larger data basis need to be addressed. The recent trend of fog computing, especially in the automotive industry, might offer a scalable and more centralized computing architecture for computing complex algorithms or their evaluations in the cloud (Xiao and Zhu, 2017). Further analysis of the data regarding test coverage is reasonable, due to planning future test drives to collect novel data. Thus, features to describe and categorize these data sets need to be developed. Data-driven approaches can be used to select drives for a minimal test set for the validation of range estimation algorithms. Execution time for computing evaluations can be reduced by using these minimal test sets instead of running evaluations on the whole data basis. They can also be used in automated parameter optimization, to further increase the accuracy of range estimation algorithms.

REFERENCES

(2013). ISO/IEC/IEEE International Standard - Software and systems engineering –Software testing –Part 1:Concepts and definitions. *ISO/IEC/IEEE 29119-1:2013(E)*, 2013:1–64.

Bach, J., Bauer, K.-l., Holzäpfel, M., Hillenbrand, M., and Sax, E. (2015). Control based driving assistant functions' test using recorded in field data. *Proc. 7. Tagung Fahrerassistenzsysteme*.

Bach, J., Holzäpfel, M., Otten, S., Sax, E., Holzäpfel, M., Sax, E., Otten, S., and Sax, E. (2017a). Reactive-Replay Approach for Verification and Validation of Closed-Loop Control Systems in Early Development. *SAE Technical Paper 2017-01-1671*, (May).

Bach, J., Langner, J., Otten, S., Holzapfel, M., and Sax, E. (2017b). Data-driven development, a complementing approach for automotive systems engineering. *2017 IEEE International Symposium on Systems Engineering, ISSE 2017 - Proceedings*.

Bach, J., Langner, J., Otten, S., Sax, E., and Holzapfel, M. (2017c). Test scenario selection for system-level verification and validation of geolocation-dependent automotive control systems. *2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, (June):203–210.

Bingham, C., Walsh, C., and Carroll, S. (2012a). Impact of driving characteristics on electric vehicle energy consumption and range. *IET Intelligent Transport Systems*, 6(1):29–35.

Bingham, C., Walsh, C., and Carroll, S. (2012b). Impact of driving characteristics on electric vehicle energy consumption and range. *IET Intelligent Transport Systems*, 6(1):29.

Boehm, B. W. (1976). Software Engineering. *IEEE Transactions on Computers*, 25(12):1226–1241.

Bolovinou, A., Bakas, I., Amditis, A., Mastrandrea, F., and Vinciotti, W. (2014). Online prediction of an electric vehicle remaining range based on regression analysis. In *2014 IEEE International Electric Vehicle Conference (IEVC)*. IEEE.

Braun, A. and Rid, W. (2018). Assessing driving pattern factors for the specific energy use of electric vehicles: A factor analysis approach from case study data of the

Mitsubishi i–MiEV minicar. *Transportation Research Part D: Transport and Environment*, 58(2018):225–238.

Cauwer, C. D., Verbeke, W., Coosemans, T., Faid, S., and Mierlo, J. V. (2017). A data-driven method for energy consumption prediction and energy-efficient routing of electric vehicles in real-world conditions. *Energies*, 10(5):608.

Cordts, M., Omran, M., Ramos, S., Rehfeld, T., Enzweiler, M., Benenson, R., Franke, U., Roth, S., and Schiele, B. (2016). The Cityscapes Dataset for Semantic Urban Scene Understanding. *Proc. of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

Enthaler, A. and Gauterin, F. (2016). Method for reducing uncertainties of predictive range estimation algorithms in electric vehicles. *2015 IEEE 82nd Vehicular Technology Conference, VTC Fall 2015 - Proceedings*.

Ericsson, E. (2001). Independent driving pattern factors and their influence on fuel-use and exhaust emission factors. *Transportation Research Part D: Transport and Environment*, 6(5):325–345.

Fetene, G. M., Kaplan, S., Mabit, S. L., Jensen, A. F., and Prato, C. G. (2017). Harnessing big data for estimating the energy consumption and driving range of electric vehicles. *Transportation Research Part D: Transport and Environment*, 54:1–11.

Fukushima, A., Yano, T., Imahara, S., Aisu, H., Shimokawa, Y., and Shibata, Y. (2018). Prediction of energy consumption for new electric vehicle models by machine learning. *IET Intelligent Transport Systems*, 12(9):1174–1180.

Gebhardt, K., Schau, V., and Rossak, W. R. (2015). Applying stochastic methods for range prediction in e-mobility. In *2015 15th International Conference on Innovations for Community Services (I4CS)*. IEEE.

Genikomsakis, K. N. and Mitrentsis, G. (2017). A computationally efficient simulation model for estimating energy consumption of electric vehicles in the context of route planning applications. *Transportation Research Part D: Transport and Environment*, 50:98–118.

Grubwinkler, S., Hirschvogel, M., and Lienkamp, M. (2014). Driver- and situation-specific impact factors for the energy prediction of EVs based on crowd-sourced speed profiles. *IEEE Intelligent Vehicles Symposium, Proceedings*, (Iv):1069–1076.

Helmer, T., Wang, L., Kompass, K., and Kates, R. (2015). Safety Performance Assessment of Assisted and Automated Driving by Virtual Experiments: Stochastic Microscopic Traffic Simulation as Knowledge Synthesis. In *Intelligent Transportation Systems (ITSC), 2015 IEEE 18th International Conference on*, volume 2015-Octob, pages 2019–2023. IEEE.

Horrein, L., Bouscayrol, A., Lhomme, W., and Dépature, C. (2017). Impact of heating system on the range of an electric vehicle. *IEEE Transactions on Vehicular Technology*, 66(6):4668–4677.

Hu, K., Wu, J., and Schwanen, T. (2017). Differences in energy consumption in electric vehicles: An exploratory real-world study in Beijing. *Journal of Advanced Transportation*, 2017:1–17.

Langner, J., Bach, J., Otten, S., Sax, E., Esselborn, C., Holz, M., and Eckert, M. (2017). Framework for using real driving data in automotive feature development and validation.

Lewis, D. D. (1992). *Representation and Learning in Information Retrieval*. PhD thesis, Amherst, MA, USA. UMI Order No. GAX92-19460.

Mazzega, J., Köster, F., Lemmer, K., and Form, T. (2016). Testing of Highly Automated Driving Functions. *ATZ worldwide*, 118(10):44–48.

Mitchell, H. B. (2012). *Data Fusion: Concepts and Ideas*. Springer Berlin Heidelberg, Berlin, Heidelberg, 2nd ed. 2012 edition.

Ondrúška, P. and Posner, I. (2014). The route not taken: Driver-centric estimation of electric vehicle range. In *Proceedings of the Twenty-Fourth International Conferenc on International Conference on Automated Planning and Scheduling*, ICAPS'14, pages 413–420. AAAI Press.

Qi, X., Wu, G., Boriboonsomsin, K., and Barth, M. J. (2018). Data-driven decomposition analysis and estimation of link-level electric vehicle energy consumption under real-world traffic conditions. *Transportation Research Part D: Transport and Environment*, 64:36–52.

Rolim, C. C., Gonçalves, G. N., Farias, T. L., and Rodrigues, Ó. (2012). Impacts of Electric Vehicle Adoption on Driver Behavior and Environmental Performance. *Procedia - Social and Behavioral Sciences*, 54:706–715.

Sautermeister, S., Ott, F., Vaillant, M., and Gauterin, F. (2017). Reducing Range Estimation Uncertainty with a Hybrid Powertrain Model and Online Parameter Estimation. *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, pages 910–915.

Sax, E. (2008). *Automatisiertes Testen Eingebetteter Systeme in der Automobilindustrie*. Hanser, Carl, München.

Tannahill, V. R., Muttaqi, K. M., and Sutanto, D. (2016). Driver alerting system using range estimation of electric vehicles in real time under dynamically varying environmental conditions. *IET Electrical Systems in Transportation*, 6(2):107–116.

Thibault, L., Nunzio, G. D., and Sciarretta, A. (2018). A unified approach for electric vehicles range maximization via eco-routing, eco-driving, and energy consumption prediction. *IEEE Transactions on Intelligent Vehicles*, pages 1–1.

Tseng, C.-M. and Chau, C.-K. (2017). Personalized prediction of vehicle energy consumption based on participatory sensing. *IEEE Transactions on Intelligent Transportation Systems*, 18(11):3103–3113.

Wager, G., Whale, J., and Braunl, T. (2016). Driving electric vehicles at highway speeds: The effect of higher driving speeds on energy consumption and driving range for electric vehicles in australia. *Renewable and Sustainable Energy Reviews*, 63:158–165.

Wang, J., Besselink, I., and Nijmeijer, H. (2015). Electric vehicle energy consumption modelling and prediction based on road information. *World Electric Vehicle Journal*, 7(3):447–458.

Wang, J., Liu, K., Yamamoto, T., and Morikawa, T. (2017). Improving estimation accuracy for electric vehicle energy consumption considering the effects of ambient temperature. *Energy Procedia*, 105:2904–2909.

Wu, X., Freese, D., Cabrera, A., and Kitch, W. A. (2015). Electric vehicles' energy consumption measurement and estimation. *Transportation Research Part D: Transport and Environment*, 34:52–67.

Xiao, Y. and Zhu, C. (2017). Vehicular fog computing: Vision and challenges. *2017 IEEE International Conference on Pervasive Computing and Communications Workshops, PerCom Workshops 2017*, pages 6–9.

Yi, Z. and Bauer, P. H. (2017). Adaptive Multiresolution Energy Consumption Prediction for Electric Vehicles. *IEEE Transactions on Vehicular Technology*, 66(11):10515–10525.

Yu, H., Tseng, F., and McGee, R. (2012). Driving pattern identification for ev range estimation. In *2012 IEEE International Electric Vehicle Conference*, pages 1–7.