DEC 2018 - NO. 4

BAVARIAN JOURNAL OF APPLIED SCIENCES®

# Usage Profiling in Electric Vehicles

Diana Schramm* Nicki Bodenschatz* Andreas Berl*

## ABSTRACT

**In the overall effort of reducing $CO_2$ emissions, the significance of alternative drive engines is growing. The transition from combustion engine vehicles to electric vehicles is high on the political agendas, with governments providing extensive funding to promote electric mobility. However, there are still challenges that hamper the dissemination of electric vehicles. One of those challenges is the limited range and the resulting range anxiety. Displayed vehicle range data contribute to this, as they are relatively inaccurate and might vary quite strongly during individual trips. This problem could be addressed by personalizing the range display according to the driving style of the current driver. Driver assistance services, like distance control, are becoming increasingly personalized nowadays, however, they are predominantly designed for internal combustion engine vehicles. In this paper, relevant input parameters for classifying the driving styles of electric vehicle users are identified. Furthermore, a system based on real-life driving data is developed to determine the driving style. Real-life driving data were collected in experiments and used to profile the driving style by means of fuzzy logic. Based on the results, an approach for a realistic classification of driving styles of electric vehicle users is discussed.**

*Die Wichtigkeit alternativer Fahrantriebe zur Reduktion von $CO_2$-Emissionen wird immer stärker. Der Umstieg von Verbrenner- auf Elektrofahrzeuge wird auch immer nachdrücklicher von der Politik gewünscht und gefördert. Jedoch gibt es immer noch Aspekte, die das Wachstum der Elektromobilität einbremsen. Einer dieser Aspekte ist die begrenzte Reichweite und die daraus resultierende Reichweitenangst. Auch die Reichweitenanzeigen in den Fahrzeugen tragen hierzu bei, da diese relativ ungenau sind und während einer Fahrt stark schwanken. Dies könnte durch die Personalisierung der Reichweitenanzeigen auf der Grundlage des Fahrstils des aktuellen Fahrers verbessert werden. Fahrerassistenzsysteme wie Abstandhalter werden heutzutage immer mehr personalisiert, jedoch sind diese meist für Verbrennerfahrzeuge ausgelegt. In dieser Arbeit werden die wichtigsten Parameter zur Bestimmung des Fahrstils bei Elektrofahrzeugen identifiziert und ein System entwickelt, welches auf Basis realer Fahrdaten den Fahrstil bestimmt. In Experimenten wurden reale Fahrdaten aufgezeichnet, welche zur Bestimmung des Fahrstils mit Hilfe von Fuzzy Logic genutzt wurden. Darauf aufbauend wird ein Ansatz diskutiert, der eine realistische Klassifikation des Fahrstils in Elektrofahrzeugen ermöglicht.*

## KEYWORDS

**Electromobility, range, driving style classification, fuzzy logic**

*Elektromobilität, Reichweite, Fahrstilklassifikation, Fuzzy Logic*

* Deggendorf Institute of Technology

## 1. Introduction

Electric vehicle (EV) technology, especially EV battery technology, is constantly improving. Thus, the potential of EVs to reduce $CO_2$ emissions [1] increases under the premise that the charged energy originates from regenerative sources. EVs can therefore reduce our ecological footprint and bring a real environmental benefit. Introducing more EVs may also mitigate health risks like fine dust pollution or slow down global warming [2]. There are, however, still issues concerning the attractiveness of EVs which need to be tackled in order to increase the number of EVs in our daily life. One issue is the lower range in comparison to combustion engine vehicles (CEV). Therefore, one of the biggest anxieties of EV drivers is not being able to reach their destination due to the low range and the imprecise remaining range calculation of the EV.

To address this issue, the calculation of the remaining range has to be improved in order to turn range prediction more precise. To this end, EV characteristics like battery type and age, as well as topological information like the elevation difference along the route are important. However, the driver himself is another relevant factor for determining a precise model. His/her driving style and behavior can have a huge impact on the driving range of an EV [3]. A sportive and very fast driver will have a significantly higher energy consumption than a very slow and foreseeing driver. Here, the differences in driving behaviors between EV and CEV users are relevant, as shown in [4]. The constant torque produced by EVs brings the benefit of maximum acceleration at any time. In a CEV, acceleration depends on the engine's rpm value (revolutions per minute). Another difference lies in braking behavior, as the EV regenerates energy when there is no acceleration and while braking. This process is called regenerative braking or recuperation. It affects the braking behavior of the driver quite strongly as the energy recovery mechanism already slows down the vehicle and less braking activity from the driver is necessary. Taking this into account, integrating the driving behavior could bring a real benefit in terms of improving the accuracy of range calculation for EVs. Besides, EV drivers' behavioral profile data may also be used for other driver assistance services, ultimately increasing user acceptance.

In a first step, a method for improving range prediction by usage profiling is discussed. EV drivers' usage profiles are directly derived from driving data originating from the EV's CAN bus. The Controller Area Network (CAN) bus is the EV's internal communication system. The proposed system is based on real driving data and is capable of identifying the driving style whilst driving, which may serve as an input for a range model that is constantly being updated during a trip. To this end, we analyze the existing related work of usage profiling methods in Section 2. We present our approach and discuss first results in the sections 3 to 5. Section 6 provides a conclusion.

## 2. Related work

A broad range of literature discusses the problem of range anxiety as a barrier to going electric. To tackle the problem of range anxiety, trust in range estimation needs to be increased [5], which may be achieved by enhancing range calculation accuracy. Different factors influence an EV's range, particularly route properties like the elevation profile, but also weather conditions, e.g. the outside temperature, as well as the individual driving style. The aspects of route properties and weather conditions were already addressed in an earlier publication [6]. We argue that taking the driving style into account and combining it with these indicators may substantially increase the accuracy of range estimations. Driving style profiling might contribute to a more accurate prediction of battery range and increase the trust in EVs and is therefore the focus of this paper.

One way to categorize existing studies on driving style classification is by the area in which the driving style is employed as a factor. Some researchers focus on driving safety. Their aim is thus to group drivers into different risk categories [7, 8]. Other research focuses on vehicle dynamics control [9] and the adoption of assistance services such as lane change or cruise assistance services [10]. Finally, the economic and ecological efficiency of driving behaviors is an additional area of focus [11], and the present paper belongs to that category.

In the above-mentioned research areas, user profiling is usually based on driving behavioral data generated from CEVs. Mostly data on gas pedal operation, brake pedal operation and the distance kept to the vehicle ahead are used to classify driving behaviors. These data can be grouped into three different categories [10]:

- Driving behavior signals
  e.g. gas pedal operation, brake pedal operation and steering angle
- Vehicle status signals
  e.g. velocity, acceleration and engine speed
- Vehicle position signals
  e.g. distance to the vehicle ahead, relative lane position and yaw angle

Different approaches are used to determine the driving style [12]. Some less common methods include correlation analysis [13], different clustering methods [7, 14] or data-dependent pointer models [12]. However, the majority of studies uses fuzzy logic as the common method for usage profiling in vehicles [8, 12, 15, 16].

Fuzzy logic depends on prior knowledge of the groups where the data can be divided into. However, fuzzy rules have no exact boundaries; they rather are descriptive rules by which arithmetic operations can be carried out. Fuzzy rules can describe behavior, for example the aggressiveness of a driver.

| If gap time is | If accelerator pedal rate is | If brake pedal rate is | Then driver index is |
|---|---|---|---|
| Low | Low | Low | **Less aggressive** |
| High | Low | Low | **Cautious** |
| Low | High | Low | **Aggressive** |
| Low | Low | High | **Aggressive** |
| Low | High | High | **Aggressive** |
| High | High | High | **Less aggressive** |
| High | Low | High | **Cautious** |
| High | High | Low | **Less aggressive** |

Table 1: Fuzzy rules of aggressiveness of a driver [17]

Table 1 presents a common example for fuzzy rules that allow to distinguish between aggressive or cautious driving behaviors. It is apparent that a user who is pressing the accelerator and brake pedals only gently while delaying the subsequent pedal pressing (gap) is most likely less aggressive than others. On the contrary, aggressive users tend to use both pedals with nearly no delay, while either or both pedals are pressed at a high rate. In this way, different user classes can be described and modelled according to these fuzzy rules.

Dörr et al. proposed an online system for driving behavior profiling in CEVs [18]. This profiling is done on the basis of data from the CAN bus of the vehicle and is calculated whilst driving. They propose three levels of driving styles: sporty, normal and comfortable. Parameters that are taken into account include speed, longitudinal acceleration, the time gap between two vehicles or the street type. Different driving parameters for different street types were also used for profiling. The driving behavior was determined by fuzzy logic and was tested through simulation only.

In this paper, we adhere to the basic concept of Dörr et al. The approach is adapted to EVs and their corresponding requirements. Furthermore, real-life driving data are used. The proposed system receives data directly from the EV in real time, processes and calculates the driving style and thus builds the basis for analyzing the driving behavior after or even during a trip.

## 3. Data Basis and Experiments

Driving behavioral profiling in this work is based on real-life driving data from EVs. Driving data therefore need to be transferred from EVs. The used data collection consists of multiple components, as it can be seen in Figure 1.

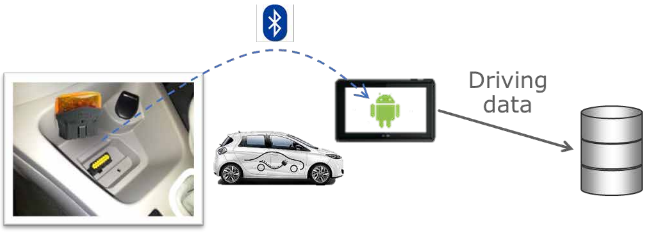


Figure 1: Data acquisition system

Data are acquired via additional hardware located in the EV and a software component, the so-called *InCarApp,* which also displays a range estimation based on altitudinal differences along the route and the current temperature. At first, an OBD (on-board diagnostics) module allows the acquisition of driving data from the EV's CAN bus. In a second stage, a tablet computer with the installed *InCarApp* receives the CAN data via Bluetooth. It filters, decodes and transmits them over a secured cellular internet connection to a server. This system allows collecting a range of different parameters from the EV that are relevant to the driving behavior.

As to driving behavior analysis in the context of EVs, the relevant data differ from those of CEVs. The constant torque and the regenerative braking, known as recuperation, entail a very different pedal usage pattern compared to CEVs. Furthermore, there is an eco-mode or eco button in most EVs. Using this functionality does not only affect the intensity of acceleration, as it does in CEVs, but also brake pedal operation. On the one hand, acceleration will be decreased, however on the other hand, recuperation will be increased. This results in a higher impact of the eco-mode on pedal usage in EVs, as compared to CEVs. Therefore, the approach of analyzing EV usage has to be adjusted with respect to several new dimensions, like the influence of recuperation on the brake pedal. To demonstrate the feasibility of this new method of usage profiling described in this paper, it is currently designed for and tested on Renault ZOEs. Moreover, driving behavior profiling is only done for single trips, because the way an EV is driven by an individual person may differ from trip to trip, depending on various influencing factors like the current mood or traffic conditions.

Initial experiments served to identify the relevant data for usage profiling. For these experiments, a 9 km test route consisting of 50% city and 50% rural streets and minimal altitudinal differences was used. The test route was driven three times each for the chosen driving behavior-related classes "careful", "normal" and "sportive". For this experiment, drivers were instructed to stick to the prespecified driving behavior as long as traffic and safety allowed it. One driver employed all three investigated driving behaviors. The experiments were conducted in a row in order to minimize temperature differences and traffic-related influences.

After these initial experiments, the driving data were analyzed. The results of this analysis are described in the following section.

The intensity of accelerator pedal input differs significantly between the different driving behaviors. This is shown in Figure 2.

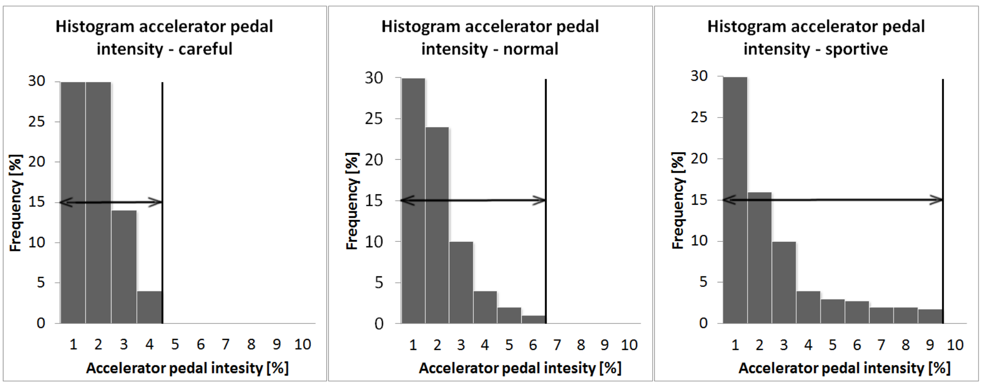


Figure 2: Histograms of acceleration pedal data for driving styles: careful - normal - sportive

This figure shows the different driving styles and their corresponding histograms: careful – normal – sportive (from left to right). The x-axis represents the intensities of accelerator pedal inputs shown as percentages, and the y-axis displays the frequency of the different intensities. To better identify the driving styles, frequencies of above 30 are not shown in this figure, however, they are later used for the analysis. This provides the possibility of gaining a better insight into higher intensities of accelerator pedal input as they demonstrate the key differences in driving styles. It is clearly shown that the range of intensities differs strongly in connection with the various driving styles as is marked with arrows. Careful drivers show a maximum intensity of accelerator pedal input of 40 %, normal drivers display intensities of up to 60 % and sportive drivers show intensities of up to 90 %. Consequently, the average values differ, too: for the careful driving style the average amounts to 9.6195 %, for the normal driving style it is 10.6723 % and for the sportive driving style it is 12.2748 %. These average values may also serve to identify the different driving styles.

The intensity of brake pedal operation is identified as the second indicator for usage profiling. Here too, it becomes obvious that there are differences in brake pedal intensity patterns, however, not in all driving styles. The frequencies of different intensities of brake pedal operation are shown in Figure 3.

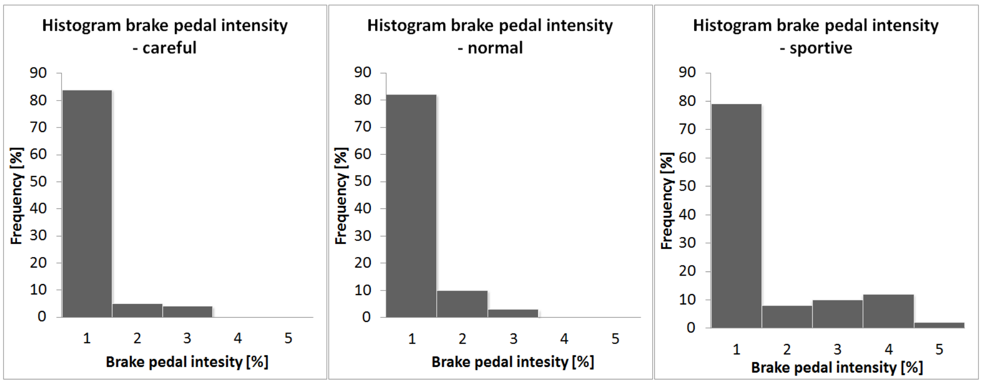


Figure 3: Histograms of brake pedal data for driving styles: careful - normal - sportive

As in the histograms of the accelerator pedal data, the order from left to right is careful, normal and sportive. The x-axis shows brake pedal intensity as percentages, and the y-axis displays the frequency of the different intensities. It is obvious that the differences between the various driving styles are not as striking as the differences in connection with the accelerator pedal. This constitutes one important difference between EVs and CEVs. As EVs recover energy when the accelerator pedal is not hit, the brake pedal is much less used and there is also less need for strong braking action. Thus, differences that seem small at first sight are also of relevance to driving behavior. It was shown that in comparison to the careful driving behavior, there is a higher frequency of the 10–20 % brake pedal intensity in normal driving behavior. For the sportive style, the frequency of between 10–20 % is less often documented, however, a high frequency of the 20–30 % brake intensity is registered. Furthermore, there are brake pedal intensities of above 30 %, unlike in normal or careful driving styles. These differences also become apparent when looking at the average values of brake pedal intensities. The average of brake pedal intensity for the careful driving style amounts to 2.3349 %, for the normal driving style it is 2.6178 % and for the sportive driving style it is 4.5536 %.

The eco-mode button is another influencing factor. When the driver activates the eco-mode button it will decrease the intensity of the accelerator pedal and increase energy recovery. Accelerator pedal and brake pedal patterns will therefore be different when the eco-mode button is switched on. A normal driver is more likely to activate the eco-mode button than a sportive driver. However, when the eco-mode button is activated, the accelerator pedal needs to be pushed stronger in order to achieve a certain degree of acceleration and thus this specific accelerator pedal pattern could be classified as sportive, too. Hence the ratio of eco-button usage during a trip is a crucial parameter for usage profiling in electric vehicles.

We therefore identify the following parameters as relevant data:

- Intensity of accelerator pedal operation
- Intensity of brake pedal operation
- Use of eco-mode button

## 4. Design of Usage Profiling

In the following section, the general processes of fuzzification and defuzzification are explained. Furthermore, the specific design of usage profiling for EVs is described.

The fuzzy logic is an extension of the classical propositional or Boolean logic. While propositional logic is only capable of differentiating between true and false (an element is part of a set or not), fuzzy logic also allows statements to be partly true or false. Differentiating subsets provides more room for interpretation. Membership functions, the so-called fuzzy sets, are established to represent the degree of affiliation of an element to a group. The degree of membership of an element in a given set is then represented as a number from 0 to 1. 0, if the element is not part of the set (false) and 1, if it is completely part of the set (true). Every number in between shows how strongly an element belongs to a set. The accelerator pedal intensity can be considered as an example, for it can vary between “weak”, “middle” or “strong”, as can be seen in Figure 4. For our first approach, the fuzzy set was modelled with triangle and trapezoid functions.

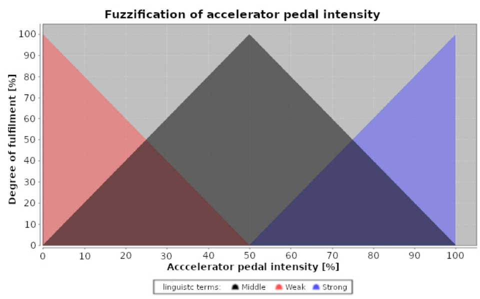


Figure 4:
Fuzzification example of the accelerator pedal intensity

The x-axis represents the accelerator pedal intensity as a percentage and the y-axis indicates the degree of fulfilment with respect to the 3 different linguistic terms. Weak is thus 0%, middle is 50% and strong would be 100%. These are called linguistic terms and the boundaries between these categories are fluid. Hence a distribution will be defined for each term that describes the degree of fulfilment. Here it can be seen that one input value can correlate to more than one linguistic term. An accelerator pedal intensity of 45 % would fulfil the term “weak” by 10 %, however, the term “middle” would be fulfilled by 90 %. This is called fuzzification. Different membership functions can be used for fuzzification. In Figure 4, the very common triangular membership function is used. The trapezoid function, which is also frequently employed, will be mentioned in a later section of this paper.

Rules can be employed to connect the fuzzifications of the different input parameters. One rule consisting of the input parameters “average of accelerator pedal intensity” and “average of brake pedal intensity” and the corresponding linguistic terms “low”, “medium” and “high” can be described as follows:

IF acceleratorpedalAverage IS high AND brakepedalAverage IS high THEN drivingStyle IS sportive

In fuzzy logic, as many rules as needed can be described with linguistic terms. Each rule may consist of several linguistic terms that are connected with “and”, “or” and “not”. One or more linguistic output terms are derived from each rule to define the driving styles “careful”, “normal” and “sportive”. This is called inference process. Hence the rules are linked by logic as geometric functions. Many different rules need to be applied for a functioning system and it needs to be ensured that an output value can be generated for every possible combination.

In a last step, the generated output values will be converted into a numerical value. This is called defuzzification. Defuzzification also uses distributions that can be the same membership functions as for the fuzzification. In the following section, we describe the design of our approach for a fuzzy logic for EVs. We have identified the relevant data for EV usage profiling in the chapter above. In a first validation of our usage profiling approach, the following parameters were chosen as input aggregation for calculating the driving style:

- Average of accelerator pedal intensity [%]
- Average of brake pedal intensity [%]
- Ratio of eco-mode button activation [%]

The input value range is adjusted according to the experimental average values so that during fuzzification, different linguistic terms are created for the different driving styles. This may also be seen in connection with the fuzzification of the average brake pedal intensity.

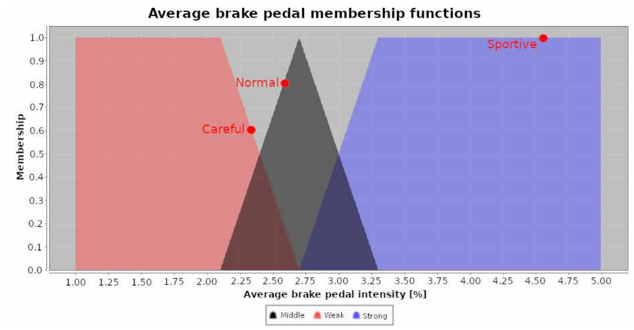


Figure 5: Fuzzification of the average brake pedal intensity

In Figure 5, the distribution of the fuzzification of the average brake pedal intensity and the identified driving style are shown. The x-axis represents the average brake pedal intensity as a percentage and the y-axis displays the degree of fulfilment with respect to the 3 different linguistic terms. The value range of brake pedal intensity is limited from 1 % to 5 % as the averages from the experiments are in this range. A trapezoid membership function was chosen for the terms “weak” and “strong” and a triangular membership function was chosen for the term “middle”, because these functions provided the best results for our limited test data. However, further experiments are planned in the future, so that the membership functions can be adjusted accordingly, for instance with machine learning techniques. For our experiment, however, the average brake pedal intensities for the different driving styles are depicted with red markings in Figure 5. It can be seen that the range of the different brake pedal averages is very close as the total range is only from 1 to 5. Furthermore, there is only a small difference between the careful and the normal brake pedal intensity. This is due to the fact that the braking behavior of EVs is very different from CEVs. Therefore, brake pedal intensity alone is not sufficient for classifying the driving style.

The accelerator pedal is a clearer indicator for the driving style, as is shown in the respective membership functions in the figure below.

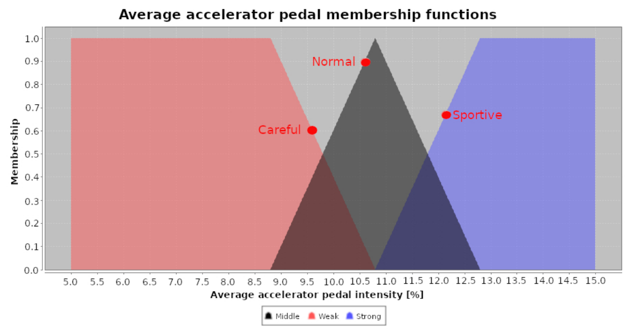


Figure 6: Fuzzification of the average accelerator pedal intensity

Figure 6 shows the distribution of the fuzzification of the average accelerator pedal intensity and the identified driving style. The x-axis depicts the average accelerator pedal intensity as a percentage and the y-axis displays the membership to the 3 different linguistic terms. For the linguistic terms “weak” and “strong”, a trapezoid membership function was used and for the linguistic term “middle”, a triangular membership function was used to best fit the driving styles. It can be seen that the average acceleration is a good indicator for the driving style and it can be very well distinguished. Moreover, with a range from 5 to 15, the value range is broader than the one for the brake pedal intensity. The driving styles lie further apart from each other and are thus better distinguishable.

The eco-mode button ratio was identified as a last input. Comparable to Figure 4, it was fuzzified with triangular membership functions for all three driving styles.

A set of rules was created for calculating the output values from the fuzzified input values, as depicted in Table 2.

| Rule block | | | | | |
|---|---|---|---|---|---|
| Rule | accelerationAverage | brakeAverage | ecoAverage | drivingStyle | weight |
| 01. | weak | weak | weak | careful | 1.0 |
| 02. | weak | weak | middle | careful | 1.0 |
| 03. | weak | weak | strong | careful | 1.0 |
| 04. | weak | middle | weak | careful | 1.0 |
| 05. | weak | middle | middle | careful | 0.8 |
| 06. | weak | middle | strong | careful | 1.0 |
| 07. | weak | strong | weak | normal | 0.4 |
| 08. | weak | strong | middle | careful | 0.5 |
| 09. | weak | strong | strong | careful | 0.6 |
| 10. | middle | weak | weak | normal | 0.7 |
| 11. | middle | weak | middle | careful | 0.2 |
| 12. | middle | weak | strong | careful | 0.4 |
| 13. | middle | middle | weak | normal | 1.0 |
| 14. | middle | middle | middle | normal | 0.6 |
| 15. | middle | middle | strong | careful | 0.2 |
| 16. | middle | strong | weak | normal | 0.8 |
| 17. | middle | strong | middle | normal | 0.6 |
| 18. | middle | strong | strong | careful | 0.1 |
| 19. | strong | weak | weak | sportive | 0.6 |
| 20. | strong | weak | middle | sportive | 0.4 |
| 21. | strong | weak | strong | normal | 0.3 |
| 22. | strong | middle | weak | sportive | 1.0 |
| 23. | strong | middle | middle | sportive | 1.0 |
| 24. | strong | middle | strong | sportive | 0.8 |
| 25. | strong | strong | weak | sportive | 1.0 |
| 26. | strong | strong | middle | sportive | 1.0 |
| 27. | strong | strong | strong | sportive | 1.0 |

Table 2: Fuzzy logic rule block

The table provides an overview on the different rules. In the left column, all 27 rules are listed. The columns "accelerationAverage"," brakeAverage" and "ecoAverage" represent the three parameters. The three linguistic terms "weak", "normal" and "strong" were assigned to each parameter. Each row is a permutation of the three linguistic terms pertaining to the parameters. The right column "drivingStyle" is the result of the rule. It had been assigned the three linguistic terms "careful", "normal" and "sportive". Hence this table can be transformed into the Fuzzy Control Language (FCL). The Fuzzy Control Language is a programming language especially designed for the evaluation of fuzzy statements. It is a domain-specific programming language. Therefore, it is only capable of interpreting statements to the fuzzy logic. One rule (Rule 22) transformed into FCL is shown below as an example:

*"**IF** accelerationAverage* **IS** *strong **AND** brakeAverage **IS** middle **AND** ecoAverage **IS** weak **THEN** drivingStyle **IS** sportive **WITH** 1.0"*

The rules cover all possible combinations to ensure a working system. The design of these rules depends on prior knowledge to judge a certain behavior. The keyword "WITH" at the end of every rule represents a factor for the strength of a rule. Rule 22 with a factor of 1.0 is therefore stronger than rule 21 with a factor of 0.3. These factors are used to adjust the system and are chosen according to the experiments so that the system calculates the driving styles correctly. Despite the limited amount of test data, however, the first draft of these rules seems promising. With more test data available, the results may be refined in the future.

## 5. Results

After the calculation via the fuzzy system the output value is retrieved. This value represents the driver's driving behavior during an individual trip. However, the developed system does not only classify a driver into one driving style category, but provides a percentage value incorporating two driving styles for the profile of an individual trip. This means that a driver can be 75 % sportive and 25 % normal, which allows a better insight into the driving profile of a driver.

Thus, the system calculates a numerical number that correlates with the driving styles as output. This is done with a scale of between -10 and 10 that is used for defuzzification by the system. The distributions of the defuzzification of the driving style are shown in Figure 7.

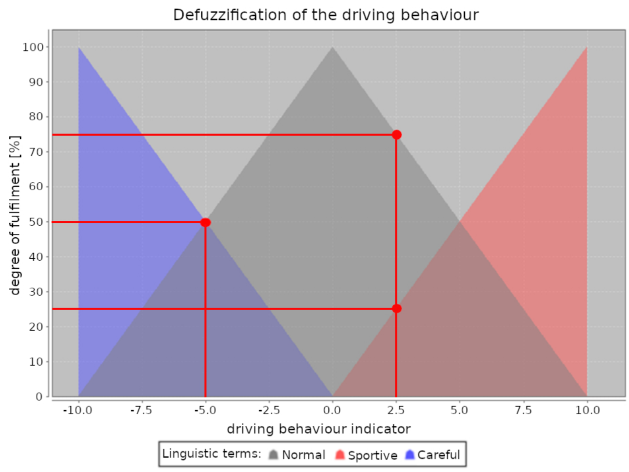


Figure 7: Defuzzification of the driving style on the defined scale between -10 and +10

The x-axis shows the described scale of between -10 and 10 for the driving style outputs and the y-axis displays the degree of fulfilment of the linguistic terms. The linguistic terms are divided into "careful", "normal" and "sportive" and refer to the driving styles. The value of -10 characterizes a 100 % careful driver, the value of 0 characterizes a 100 % normal driver and the value of 10 characterizes a 100 % sportive driver. As the transitions between these values are fluid, a classification and a percentage mix of two driving styles is possible. Marked in red on the left-hand side is the value of -5 which would refer to a "careful" as well as a "normal" driving style at 50 % each. The value of 2.5, which refers to a 25 % sportive and a 75 % normal driving style, is also marked in red.

As this classification is based on the gathered test data, it may lack accuracy for different trips or drivers. However, this may be improved by larger-scale experiments. Nevertheless, our experiment demonstrates that it is possible to generate real-time and real-life usage profiling for EVs with the system we have established.

## 6. Conclusion

In this paper, the suitability of fuzzy logic for driving style classification with real-life driving data was demonstrated. Moreover, the differences between EVs and CEVs with respect to driving style classification were evaluated. Furthermore, a lack of driving style classification methods for EVs was shown as the majority of related work refers to CEVs.

To address this issue, a system was developed that is able to classify the driving behaviors of EV drivers using fuzzy logic. This system is based on real-life driving data from EV users and is specifically designed for EVs. Important EV-specific input parameters were evaluated and the differences as compared to CEVs were described. The basic driving behavior indicators accelerator pedal, brake pedal and eco-mode button usage were used as inputs for the classification. This shows that EV users' driving styles are correctly classified by means of the developed system and by using basic driving data only.

Another important aspect of this work is the real-life experiment, which was conducted in an EV with an integrated data collection system. Thus, the developed system is based on real-life driving data. Further experiments using the developed system therefore can easily be conducted. By gathering more test data, the accuracy of the system is expected to be markedly improved. The fuzzy sets may be refined, e.g. by machine learning techniques. In addition, the accuracy of the FCL results can be improved.

Our classification system provides a percentage value for the degree of fulfilment of all driving styles. Thus, by classifying the driving style during an individual trip e.g. as 40 % careful, 60 % normal and 0 % sportive, a better assessment of driving behavior can be provided. In consequence, not only a dominant driving behavior would be evaluated, but also tendencies toward other driving behaviors. This allows for better adjustment of different assistance services, such as range prediction or adaptive cruise control.

In future work, additional parameters like speed in relation to the speed limit or street type will be evaluated. Further experiments that will be combined with a psychological questionnaire are planned in order to improve the developed system.

## Acknowledgements

The authors would like to express their special thanks to Benjamin Temme for the great work in connection with his Bachelor of Engineering thesis *“Entwicklung eines Prototypen zum automatisierten Usage Profiling bei Elektrofahrzeugen“* (Development of a prototype for automated usage profiling in electric vehicles).

This research was funded by the European Union Horizon 2020 research and innovation programme under grant agreement No. 713864.

## Conflict of interest statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

## References

[1] Rodrigues Teixeira, Ana Carolina; Sodré, José Ricardo (2018): Impacts of replacement of engine powered vehicles by electric vehicles on energy consumption. In: *Transportation Research Part D: Transport and Environment* 59 (March), S. 375–384.

[2] Wang, Jianhui; Liu, Jianguo; Shi, Haiqing; Geng, Yinghui (2015): Hidden Benefits of Electric Vehicles for Addressing Climate Change. In: *Scientific Reports* 5 (Article number 9231).

[3] Bingham, Chris; Walsh, Chris; Carrol, Steve (2012): Impact of driving characteristics on electric vehicle energy consumption and range. In: *IET Intelligent Transport Systems* 6 (1), S. 29–35.

[4] Helmbrecht, Magnus; Olaverri-Monreal, Cristina; Bengler, Klaus; Vilimek, Roman; Keinath, Andreas (2014): How Electric Vehicles Affect Driving Behavioral Patterns. In: *IEEE Intelligent Transportation Systems Magazine* 6 (3), S. 22–32.

[5] Franke, Thomas; Rauh, Nadine; Günther, Madlen; Trantow, Maria; Krems, Josef F. (2016): Which factors can protect against range stress in everyday usage of battery electric vehicles? Towards enhancing sustainability of electric mobility systems. In: *Human Factors* 58 (1), S. 13–26.

[6] Kluge, Christian; Schuster, Stefan; Sellner, Diana (2017): Statistics instead of Stopover. Range Predictionc for Electric Vehicles. In: A. Fink, A. Fügenschuh und M. J. Geiger (Hg.): Operations Research Proceedings 2016. Selected Papers of The Annual International Conference of the German Operations Research Society (GOR) [August 30-September 02 2016; Helmut-Schmidt-Universität Hamburg]. 1st ed. 2017 (25. Mai 2017): Springer.

[7] Evans, Leonard (1996): The dominant role of driver behavior in traffic safety. In: *American Journal of Public Health* 86 (6), S. 784–786.

[8] Lu, Jianbo; Filev, Dimitar; Prakah-Asante, Kwaku; Tseng, Fling; Kolmanovsky, Ilya V. (2009): From vehicle stability control to intelligent personal minder: Real-time vehicle handling limit warning and driver style characterization. In: 2009 IEEE Symposium on Computational Intelligence in Vehicles and Vehicular Systems (CIVVS 2009) proceedings. March 30-April 2, 2009, Sheraton Music City Hotel, Nashville, TN, USA. [Piscataway, N.J.]: IEEE.

[9] Plöchl, Manfred; Edelmann, Johannes (2007): Driver models in automobile dynamics application. In: *Vehicle System Dynamics - International Journal of Vehicle Mechanics and Mobility* 45 (7-8), S. 699–741.

[10] Nishiwaki, Yoshikiro; Miyajima, Chiyomi; Kitaoka, Norihide; Itou, Katsunobu; Takeda, Kazuya (2007): Generation of Pedal Operation Patterns of Individual Drivers in Car-Following for Personalized Cruise Control. In: 2007 IEEE Intelligent Vehicles Symposium proceedings (Vol. 86), S. 23–36.

[11] Mensing, Felicitas; Bideaux, Eric; Trigui, Rochdi; Ribet, Julien; Jeanneret, Bruno (2014): Eco-driving: An economic or ecological driving style? In: *Transportation Research Part C: Emerging Technologies* 38 (January), S. 110–121.

[12] Suzdaleva, Evgenia; Nagy, Ivan (2018): An online estimation of driving style using data-dependent pointer model. In: *Transportation Research Part C: Emerging Technologies* 86 (January), S. 23–36.

[13] Eboli, Laura; Mazzulla, Gabriella; Pungillo, Giuseppe (2017): The influence of physical and emotional factors on driving style of car drivers: A survey design. In: *Travel Behaviour and Society* 7 (April), S. 43–51.

[14] Guo, F.; Fang, Youjia (2013): Individual driver risk assessment using naturalistic driving data. In: *Accident Analysis and Prevention* 61 (December), S. 3–9.

[15] Lin, Na; Zoung, Changfu; Tomizuka, Masayoshi; Song, Pan; Zhang, Zexing; Li, Gang (2014): An Overview on Study of Identification of Driver Behavior Characteristics for Automotive Control. In: *Mathematical Problems in Engineering* 2014 (Article ID 569109).

[16] Kikuchi, Shinya; Chakroborty, Partha (1992): Car-following model based on fuzzy inference system. In: *Transportation Research Record* (Record 1365), S. 82–91.

[17] Constantinescu, Zoran; Marinoiu, Cristian; Vladoiu, Monica (2010): Driving Style Analysis Using Data Mining Techniques. In: *International Journal of Computers, Communications & Control (IJCCC)* 5 (5), S. 654–663.

[18] Dörr, Dominik; Grabengiesser, David; Gauterin, Frank (2014): Online driving style recognition using fuzzy logic. In: 17th International IEEE Conference on Intelligent Transportation Systems (ITSC) proceedings, S. 1021–1026.

## Diana Schramm, B.Sc.

Diana Schramm holds a Bachelor of Science in Mathematics from the University of Applied Sciences Regensburg. She has been working in various electromobility-related projects at Deggendorf Institute of Technology since 2014. She analyzes driving data from electric vehicles and, based on her findings, develops models to optimize remaining range calculations for different vehicles types. She currently develops a personalized range prediction method based on driving behavior within the EU Horizon 2020 project ELECTRIFIC.

*Diana Schramm studierte Mathematik an der Technischen Hochschule Regensburg. Seit 2014 beschäftigt sie sich in verschiedenen Projekten im Bereich der Elektromobilität an der THD mit der Analyse gewonnener Fahrzeugdaten aus Elektrofahrzeugen und entwickelt aufbauend auf ihren Erkenntnissen Modelle zur Optimierung der Reichweitenanzeige für verschiedene Fahrzeugtypen. Derzeit arbeitet sie im EU Horizon 2020 Projekt ELECTRIFIC an der Personalisierung der Reichweitenanzeige anhand des Fahrverhaltens.*

Contact / *Kontakt*
**diana.schramm@th-deg.de**

## Nicki Bodenschatz, M.Sc.

Nicki Bodenschatz M.Sc. studied Business Informatics at Deggendorf Institute of Technology (DIT). He has been employed as a researcher at DIT since 2017, and is, for the most part, engaged in the Horizon 2020 project ELECTRIFIC. His core area in the project is the automated scheduling of charging processes for operators of electric vehicle fleets.

*Nicki Bodenschatz M.Sc. studierte Wirtschaftsinformatik an der Technischen Hochschule Deggendorf (THD). Seit 2017 ist er wissenschaftlicher Mitarbeiter an der THD und arbeitet hauptsächlich im Horizon 2020 Projekt ELECTRIFIC. Schwerpunktmäßig beschäftigt er sich mit der automatisierten Ladeplanung für Betreiber elektrischer Fahrzeugflotten.*

Contact / *Kontakt*
✉ **nicki.bodenschatz@th-deg.de**

## Prof. Dr. rer. nat. Andreas Berl

Andreas Berl majored in Computer Science and minored in Psychology at the University of Passau in 2005. After his stay as a visiting scientist at the Computing Department of Lancaster University (UK), which was funded by a DAAD scholarship, he earned his Ph.D at the University of Passau in 2011. He continued teaching and researching at the University of Passau for several years, mostly in EU-funded research projects. In 2015, Andreas Berl was appointed Professor of Computer Science to DIT's Faculty of Electrical Engineering, Media Technology and Computer Science. His research activities focus on networked systems, virtualization, smart grid and electromobility.

*Andreas Berl schloss 2005 sein Studium der Informatik mit dem Nebenfach Psychologie an der Universität Passau ab. Nach einem Aufenthalt als Gastwissenschaftler am Computing Department der Lancaster University (UK), der durch ein DAAD-Stipendium finanziert wurde, promovierte er 2011 an der Universität Passau zum Dr. rer. nat. Anschließend war er mehrere Jahre lang an der Universität Passau im Bereich Lehre und Forschung tätig, überwiegend im Rahmen von europäischen Drittmittelprojekten. Seit Februar 2015 hat Andreas Berl die Professur für Grundlagen der Informatik an der Fakultät für Elektrotechnik, Medientechnik und Informatik der THD inne. Seine Schwerpunkte in der Forschung sind Vernetzte Systeme, Virtualisierung, Smart Grid und Elektromobilität.*

Contact / *Kontakt*
✉ **andreas.berl@th-deg.de**