A Novel Approach on Battery Health Monitoring

Markus Eider, Nicki Bodenschatz, Andreas Berl
Deggendorf Institute of Technology
[markus.eider, nicki.bodenschatz, andreas.berl]@th-deg.de

Philipp Danner
Bayernwerk AG
philipp.danner@bayernwerk.de

Hermann de Meer
University of Passau
demeer@uni-passau.de

***Abstract*—In this paper, a novel approach for improving battery lifetime is proposed. To reach this goal, electric vehicle internal data is analysed, the battery health influence of driving and charging parameters is estimated and recommendations for battery health optimal charging are generated. The presented system collects data from the electric vehicle using the controller area network bus and stores it on a central server. The data is then transformed and analysed to determine the health influence of certain charging characteristics. Using this knowledge, recommendations can be generated and provided to the electric vehicle owner. This process of generating recommendations can be performed continuously. The proposed approach provides several benefits in electro mobility. First, the acquisition of electric vehicle data is performed in a non-intrusive way. Solely an on-board diagnostics interface is required to read out the vehicle internal data. Thereby any electric vehicle can be equipped with the system presented in this paper. Second, the recommendations guide the vehicle user in specific behaviour without affecting availability and range for the next trips.**

I. Introduction

Currently, there is a worldwide interest on environmentally friendly transportation and energy sources. Especially with the ongoing improvement of battery-powered Electric Vehicle (EV) technology, present requirements of the conventional transportation need to be met or overpassed. This challenging task leads to more sophisticated investigations and developments as for example the driving range is heavily influenced by the EV battery performance. Therefore, battery capacity has been increased in the past years but also the research on battery health has advanced in order to preserve battery performance and remaining useful lifetime (as summarized in [1]).

In EVs, Lithium-Ion batteries are used due to their comparable high energy density and low price. However, batteries degrade inevitably due to different causes. A metric to describe the battery health is the State of Health (SoH) of the battery. This SoH and its influence factors are widely discussed in literature while its definition is not identical with all authors. In an abstract sense, the battery SoH can be defined by the comparison of the state of the battery at the beginning of operational life and the current state [2]. This difference is usually given relatively to the initial state in percentage, e.g. 98% of the initial health state. The SoH determination in general is influenced by either battery internal changes due to chemical reactions or external effects indicated by battery performance changes. This relationship is discussed in detail in the related work section of this paper. Accurately measuring the internal chemistry ageing is quite complex [3] and hardly usable in EVs, therefore the focus of this work lies on the external effects. The detailed SoH calculation method of different EV manufacturer is not publicly known, thus no more details about the interpretation of the SoH values, derived from EV battery health management as used in this paper, can be given. Additionally, the SoH is a parameter to determine battery health at a specific point of time although certain battery usage behaviours influence battery health over longer periods of time. Although related work describes only a battery SoH degradation, in this paper, the SoH value could also improve as it is a measured value by the manufacturer and the measurement conditions were not constant (usage of the car in real world and not in a laboratory).

In this paper, we propose a system to generate EV usage recommendations for prolonging EV battery lifetime, looking at the battery as black-box system. Therefore, an analysis of an EV's historical performance data is used to formulate EVs battery usage (driving and charging) recommendations. Especially the request for fast charging the EVs at any environment condition was an important focus on the design of the first recommendation.

The paper is structured as follows: A summary of the main influences for battery degradation with the focus on EVs is provided in Section II in order to extract possible countermeasures against battery ageing. Then, a recommendation on fast charging is presented in Section III which can be followed by Electric Vehicle Owners (EVOs) without impairing their daily use significantly. The data acquisition, extraction, pre-processing, health influence estimation and generation of recommendations are presented in Sections IV-A to IV-C, respectively. Additionally, the system is applied on historical data of a fast charging experiment in Section V in order to analyse its performance. The results of this analysis are explained in Section VI and discussed in Section VII.

II. Related Work

The SoH of batteries is basically determined by battery capacity fade [4] and battery power fade [5] in literature. Capacity fade can be described as loss of usable energy storage capability, whereas power fade means the loss of instantaneous power, that the battery can deliver. Power fade is also highly related to the internal battery impedance rise [5]. According to [6], power fade mainly occurs on charge power, whereas the discharge power only has very slight loss over time. Another factor, which needs to be considered concerning the battery SoH is the field of application. For some battery-powered application the determination of the SoH will probably focus more on capacity fade (induces shorter operation duration) than power fade.

Battery degradation can be categorized in different ways. One classification, used by some authors [2] [7], is to differentiate between calendrical and cyclic ageing. Calendrical ageing concerns the battery ageing effects due to storage without usage. Here especially the storage condition, like temperature and the storage State of Charge (SoC), is the main ageing factor [7] [8]. Cyclic ageing is induced by all effects, which occur due to the active usage of the battery in multiple discharge-charge cycles in addition to calendrical ageing. This primarily includes charging rates, temperature influences and the Depth of Discharge (DoD) [8]. Here, we focus on the cyclic ageing influence factors, as an EV is usually used quite often.

In the context of e-mobility, the most critical stress factors on batteries according to [9] and [10] are:

- (Ambient) temperature
- Current flow including discharging as well as charging (fast charging)
- Depth of Discharge (DoD)
- Time intervals between full charge cycles

As we are especially interested in the effect of fast charging at any environmental condition, we only focus on the temperature and current flow stress factors here.

Temperature can influence the battery in positive and in negative ways. High temperature, for example, promotes the kinetics of inserting and removing lithium ions to/from the electrodes, thus reduces the internal impedance of the battery. Small internal battery impedance favours higher charging and discharging rates up to a certain level. However abnormal temperatures are known to promote battery life degradation [11] (see Fig. 1). This is due to chemical reactions, which react slightly different at certain temperature ranges. As result, chemical side products could lead to irreversible morphology changes within the battery and thus accelerate battery ageing [12] [13]. The specific temperature effects on battery ageing depend on the used materials within the battery [14]. Concerning EV batteries, mechanisms like active cooling and heating systems try to regulate the batteries temperature in order to minimise ageing effects. This, however, can only be done in a limited range. Nevertheless, extreme environmental temperature will have an impact on battery life.

With higher discharging and charging rates, increased battery ageing can be observed. This means, the higher the charging/discharging current is, the more battery degradation in form of capacity fade as well as impedance rise increase occurs [15] [16] [17]. The effect of the charging rate (measured as C-rate[1]) and at different temperatures on the battery cycle life performance is shown in Fig. 1. In addition, high discharging/charging rates lead to elevated internal temperature and its corresponding side effects. Especially with EVs, a high

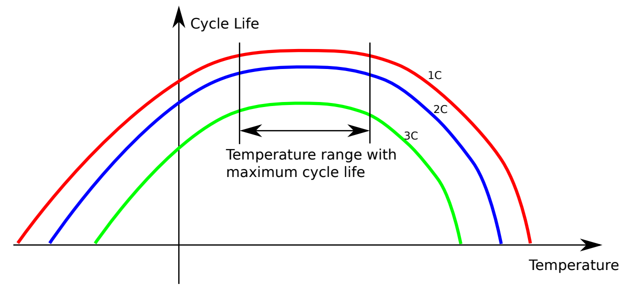

Fig. 1. Illustration of Lithium-Ion battery cycle life vs. temperature and charging rate (see [10])

charging rate (commonly known as fast charging) is desired to reduce the refuel time.

Battery degradation due to very high voltage (overcharging) is neglected in this paper, as the Battery Management System (BMS) usually prevents this kind of stressful battery operation. In addition, most of the papers in literature focus on extraction of different battery ageing factors and possibilities to reduce them. However, a lot of these experiments have in common that they were carried out in laboratory environment with a lot of different fixed parameters and open-circuit as well as half-cell battery measurements. The analysis in this paper is based on real driving performance data of EVs using, among others, the battery SoH value gathered directly from the EV. The goal is to provide a system that is applicable to almost all EVs, even retrospectively.

III. Recommendations

In this paper, a battery health monitoring system is established, which is used to prolong the EV battery lifetime. The system monitors the SoH value, which is provided by the EV BMS. We observed from driving data, obtained from the EV Controller Area Network (CAN) bus in the past, that this SoH value does not only degrade but can also increase slightly over time. This observation is probably due to the changing measurement conditions in real world use of the EV. Nevertheless, the influences leading to an SoH decrease and increase are analysed by the health monitoring system as well as recommendations are provided by the system so that users can actively contribute to SoH development. This paper focuses on the influences of charged energy and ambient temperature during fast charging.

The battery health monitoring system generates recommendations at specific points in time if possible. It does so by taking EV performance data, analysing the data and finally deciding if certain user actions can help to reduce the regular battery degradation. This condition leads to the proposal of a respective recommendation to the EV user.

The recommendations can be divided in two classes. On the one hand, there are recommendations regarding the driving behaviour of an EV user. These can cover different driving aspects, such as the route properties or also the driving style. On the other hand, recommendations about the charging

[1] A charging rate of 1C is defined by one time the rated capacity of the battery per hour, e.g. for a 2.4 Ah battery, 1C is 2.4 A and 2C is 4.8 A charging/discharging current.

behaviour of an EV user can be considered. These can contain suggestions for a certain SoC difference to be charged or also about a slow or fast charging mode, which should be used. The aspects which can be covered by the recommendations, of course, depend highly on the available data, which can be gathered and analysed. A recommendation is provided in textual form to the EV user, to be displayed by a driver assistant system in the EV. This could be a tablet mounted in the vehicle or the user's mobile devices.

For the analysis of available data, a mathematical decision making process, which identifies negative influences on the battery SoH value, is established (see Sections IV-B and IV-C). These influences are parameter ranges which cause the SoH to decrease, derived from EV data. Also, the decision making process is based on the suggestions of related work. Its algorithms automatically generate recommendations for the battery owner to reduce the impact of the SoH negative influences.

IV. Architecture

In order to derive recommendations for prolonged battery life, based on long-term and current physical circumstances, a detailed description of the data acquisition and processing procedures is given in this Section. As a requirement, data needs to be collected from the EV. In the case of this research, driving data from the CAN bus of the EV is available. The process for obtaining this kind of data is explained in Section IV-A. Transformation and analysis of the acquired data is then described in Sections IV-B and IV-C respectively. These data processing steps are implemented in a prototype, in order to test the system in the context of an experiment using real driving data.

A. Data Acquisition

The driving data of the EV is collected using an On-board Diagnostics (OBD) module which provides data from the CAN bus in a numerical format. However, this module needs to be configured at each vehicle startup in order to convert data packages of certain parameters. This configuration is derived from a previous re-engineering process of the EV's CAN bus. Configuration of the OBD module is done using an Android tablet mounted in the EV, which connects to the module via Bluetooth and programs it for the configuration including all known parameters. During driving, the converted data is sent from the OBD module to the tablet, using the same Bluetooth connection, as shown in Fig. 2. Finally, the tablet is sending the data to a central server via an encrypted mobile internet connection.

The data, which is collected in this process, contains CAN values such as the SoC, SoH, ambient temperature and vehicle speed in different resolution. The obtained SoH is computed by the BMS in the vehicle. Additionally, Global Positioning System (GPS) coordinates can be obtained using the tablet's built in receiver. In general, the CAN bus derived data is collected in an interval of one second during a trip. However, as the OBD module is listening passively on the CAN bus,

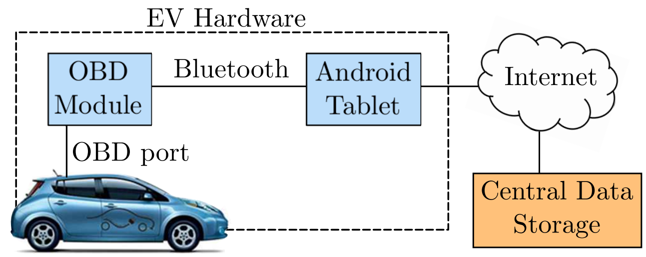

Fig. 2. Data connection from the EV CAN bus to the central database

data is received only once the electronic control units are transmitting new values if these are updated. Active requests are not performed as these could lead to potential risk for the driver, due to unwanted changes in the vehicle dynamics. Thus, some parameter values as the SoC are updated only after multiple seconds or minutes, depending on the rate of change.

B. Data Preprocessing

In this section, the pre-processing steps of the accumulated driving data are described. Fig. 3 provides a rough structure of the data processing flow.

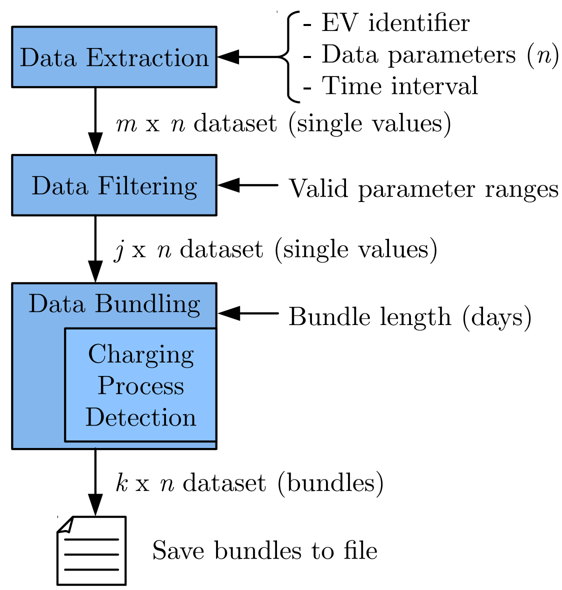

Fig. 3. Computation steps in the data preprocessing component

In order to convert the raw data stored in the database into statistical measures which are used by the health influence analysis as well as the proposal of recommendations, the following processing steps are required to be taken. At first, data needs to be extracted from the database. Then, invalid values are filtered to prevent further analysis to be influenced by these. Lastly, the driving data is bundled into periods of hours or days, depending on the application of the resulting data. Usually, the SoH changes slowly over time due to long lasting influence factors, therefore the period could be scaled as multiple days, for example.

For the extraction of data from the central database, the following frame conditions have to be considered. First, data can be queried for a certain EV by using an identifier, as the EVs are registered in the database with a unique identification number. Secondly, driving parameters need to be chosen in order to be taken into account for extraction. A third condition is the interval for fetching the data, i.e. the time window to be extracted from the historical data. In order to analyse long-term driving data of an EV, the time interval should be chosen in a range between multiple months or years. The parameters to be extracted depend on the specific health influences which should be analysed (e.g. SoC parameter in the case of the DoD influence).

These EV identifier, data parameters and time interval are currently included as parameters for a data extraction script. It queries the database for the chosen parameters and returns a collection of driving data representing the EV performance for the specific time window. This collection contains rows of data, each starting with a timestamp and followed by the floating point parameter (e.g. ambient temperature) values.

Under certain circumstances, parameters take on values of invalid ranges, which leads to the necessity of a data filtering process. This effect is observed at startup of a Nissan Leaf model 2012, where for example the SoC is significantly higher than the specified nominal battery capacity. In this case, values of $40.9\,$kWh were read although the battery is specified to $24\,$kWh. It is assumed that the Electronic Control Unit (ECU) sending these values did not perform a successful measurement prior to sending this value. Therefore, these values cannot be used for further data processing and have to be filtered out. Table I provides an overview for valid parameter ranges and resolution for EVs of type Nissan Leaf, model 2012. The limits for the ambient temperature ϑ_{amb} were chosen to include temperature ranges usually observed in Europe.

TABLE I
PARAMETER LIMITS FOR FILTERING

Parameter	**Unit**	**Lower limit**	**Upper limit**	Resolution
SoH	%	0	100	1
SoC	Wh	0	$24,000$	1
ϑ_{amb}	°C	-25	50	0.5

It is assumed that certain actions such as a fast charging processes do not have an immediate effect on battery health. The SoH could rather be changed by a collection of actions. As an example, this could be due to fast charging during multiple consecutive hot days in the summer. Thus, the data bundling component iterates over the filtered data and gathers data rows in bundles of a certain amount of days (bundle length). This is illustrated in Fig. 4, where $\mathrm{d_i}$ represents a single data row. The quantity of days can be specified as parameter for the component. Then, a single bundle is created, which contains lists for each parameter. For example, in the case of x data rows with the entries (1) timestamp, (2) SoH, (3) SoC, (4) ϑ_{amb}, a bundle of four lists with the respective number of x entries is created.

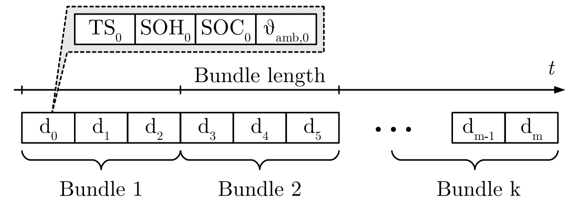

Fig. 4. Bundling process of the data pre-processing

Recommendations on battery-friendly EV charging should be derived from the driving data and this requires information on previously performed charging processes. Therefore, the process of detecting charging operations is explained in this paragraph. Since the driving data, available in this paper, is only acquired during tours, a charging process cannot be directly determined. However, the SoC can be analysed to indirectly derive charging processes based on the following principle: If the SoC rises more than 5% of the maximum battery SoC (SoC_{max}) between two data points, a charging process was performed. The difference of 5% SoC_{max} was chosen as it is assumed to be higher than recharging by EV recuperation and small enough for even slight charging at a charging station. For the Nissan Leaf, this SoC differnce is 1.2 kWh. In Alg. 1, the proposed condition is used in order to derive the difference of SoC values ΔSoC and average ambient temperature $\bar{\vartheta}_{amb}$ from before and after charging. If no charging process is detected between two timestamps, SoC and ϑ_{amb} values are removed from the lists.

Alg. 1 Charging process conversion

```
procedure CONVERTCHARGINGS(bundles, SoC_max)
    for bundle in bundles do
        for row = 0; row ≤ length(bundle) - 1; row ++ do
            if SoC_row ≥ SoC_row+1 - 0.05 * SoC_max then
                                        ▷ No charging process detected
                remove(SoC_row)
                remove(ϑ_row)
            else
                                        ▷ Determine ΔSoC
                SoC_row = SoC_row+1 - SoC_row
                                        ▷ Determine ϑ̄_amb
                ϑ_row = 0.05 * (ϑ_row + ϑ_row+1)
            end if
        end for
    end for
end procedure
```

To simplify the data in the bundles, averages are generated over the parameter lists for SoH, ΔSoC and $\bar{\vartheta}_{amb}$ as shown in Fig. 5. Due to charging process detection, there are 0 .. k timestamp and SoH values and 0 .. n ΔSoC and $\bar{\vartheta}_{amb}$ values. For the timestamps, the first one in the bundle is chosen for a simplified bundle representation.

Then, differences of the averaged SoH values $\overline{\mathrm{SoH}}$ between the bundles are created. This allows to derive the SoH change between bundles.

$$\begin{bmatrix} [\mathrm{TS}_0, \mathrm{TS}_1, \ldots \mathrm{TS}_k], \\ [\mathrm{SoH}_0, \mathrm{SoH}_1, \ldots \mathrm{SoH}_k], \\ [\Delta\mathrm{SoC}_0, \Delta\mathrm{SoC}_1, \ldots \Delta\mathrm{SoC}_n], \\ [\overline{\vartheta}_{\mathrm{amb},0}, \overline{\vartheta}_{\mathrm{amb},1}, \ldots \overline{\vartheta}_{\mathrm{amb},n}] \end{bmatrix} \xrightarrow{Averaging} \begin{bmatrix} \mathrm{TS}, \\ \overline{\mathrm{SoH}}, \\ \overline{\Delta\mathrm{SoC}}, \\ \overline{\overline{\vartheta}}_{\mathrm{amb}} \end{bmatrix}$$

Fig. 5. Averaging process for each bundle with datasets 0 .. k and 0 .. l

C. Health Influence Estimation and Recommendations

In this Section, the functionality of the health influence estimation as well as the recommendation generation is described. Both of these steps depend on the data extraction and pre-processing modules. The health influence estimation is executed once for an EV, providing an estimation about the influence of the average charged energy or average charging temperature on the SoH. This estimation can be reused for the recommendation generation, to be considered in a classification step. The bundling period used for the data pre-processing module is within the range of multiple days for the battery health influence estimation, whereas the recommendations are based on bundles within few hours in order to provide suggestions based on data of the current day or trip.

The battery health influence estimation performs a classification of input parameter ranges which are causing the SoH to change. These ranges are later used to derive recommendations from current driving data. Therefore, the data extraction and pre-processing module are executed repeatedly, while the bundle length is iteratively changed. For example, this could be an iteration from 7 to 30 days. This is done in order to determine the highest correlation between bundle parameters and SoH change. The overall time window for data extraction should be considerably larger than the bundle period so that a sufficient amount of bundles is generated. After this, the bundles are sorted depending on the following SoH change, which could be either a SoH decrease or increase. On the one hand, bundles which keep the SoH to stay at the same value are omitted. On the other, parameter ranges which lead to an SoH decrease are used for the generation of recommendations.

Recommendations for battery friendly EV usage are generated automatically and periodically using current driving data. The data is again transformed by the data extraction and pre-processing modules in order to derive statistical measures of a small time interval. In this step, the data extraction is called with a time frame of a few hours in order to get a representation of the last trips and charging processes. This allows to determine current EV internal and external circumstances. The bundle length for data pre-processing is chosen with the same value as the time window for data extraction. This way, a single bundle with statistics of the last hours is generated.

For generating recommendations, the pre-processed driving data is compared to the parameter ranges which cause the SoH to decrease. Thus, the generated statistical measures of driving enable a comparison with SoH reducing ranges. If the current driving data values correspond to an SoH decrease, the recommendation is formulated.

V. Experimental Test

For an experimental test of the proposed system, historical data of an EV is analysed and processed. The EV, used in this test, is a Nissan Leaf model 2012. It is equipped with the data acquisition system in order to build up a data basis for later analysis. The Leaf is consequently charged in a fast way using the CHAdeMO standard, where the used charging stations provide a power of 20 to 50 kW. Additionally, the EV is frequently used by two commuters to drive to work and switched between them every week. This should homogenize the influence of EV usage so that specific trips will not have significant influence on the SoH development.

Additional EVs have not been included in this experimental test as the age, mileage and SoH of the available EVs differ from the EV in this test. It is also known that battery health degradation is non-linear [18] and hence, the EVs cannot be compared in the test. Thus, driving data from only one EV is analysed.

Although this fast charging experiment is planned for a whole year starting on 18/05/2017, a first analysis of the results obtained during the last seven months is provided. Here, the analysis is performed until the date of 13/12/2017, containing 30 weeks of driving data.

VI. Results

In the progress of the first half year, the SoH is changing as shown in Fig. 6. For this graphs, the SoH and ambient temperature ϑ_{amb} are averaged for periods of 14 days from the raw data of $584,246$ data rows. This allows to see the rough change while omitting short time development. In the upper graph, it can be seen that the SoH is at $88.5\,\%$ on average at the start of the experiment followed by an increase of half a percent. As the EV was equipped with the data acquisition system at the start of the experimental phase, no data is available for the time prior to this SoH rise. Thus, no evaluation on the specific value can be provided.

After the experiment start, the SoH trend shows a correlation with the ambient temperature. Comparing both parameters, it can be seen that the SoH drops once the average temperature rises to almost $25\,^{\circ}\mathrm{C}$ on average. This trend is observed for the SoH as long as the temperature is above $20\,^{\circ}\mathrm{C}$. Here, the Pearson correlation coefficient for the ambient temperature is $r_{\vartheta,1} = -0.17$. From the fourteenth week on, the SoH rises again as the temperature falls below $20\,^{\circ}\mathrm{C}$ after approximately 13.5 weeks ($r_{\vartheta,2} = -0.85$).

Thus it is assumed, that an ambient temperature above $20\,^{\circ}\mathrm{C}$ is decreasing the SoH whereas temperatures below are increasing it. It should also be noted that the battery internal temperature is estimated to be higher than the ambient temperature during charging. Additionally, one should be aware of extremely low temperatures, such as below the freezing point. These temperatures are currently not included in this test so

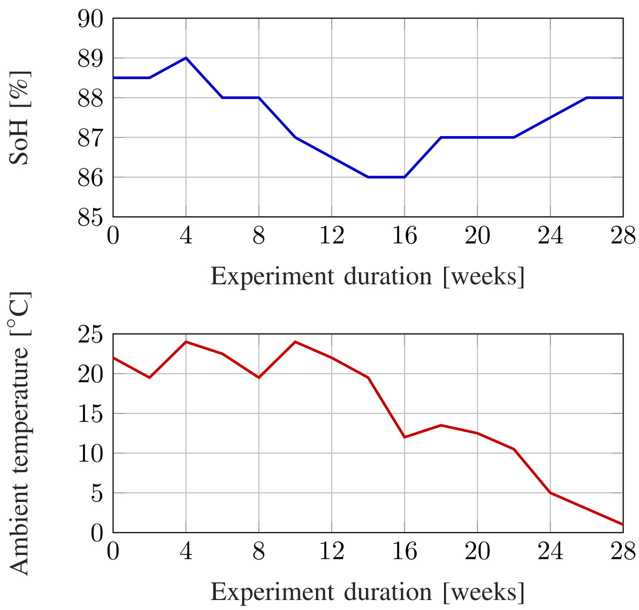

Fig. 6. Development of SoH and ambient temperature during the experiment

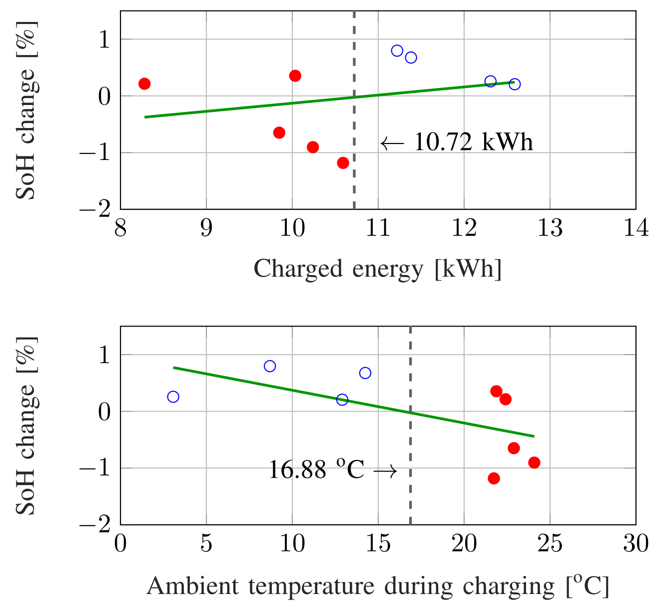

Fig. 7. Charging process parameters and their average influence on the SoH (Solid line illustrates the linear fit and the dashed one is the average of charged energy or ambient temperature)

far (as shown in Fig. 6). From the related work though, it is known that these ranges are critical for battery health [1].

The data pre-processing component is used on the driving data of the fast charged Nissan Leaf. It is called repetitively with bundle lengths of a range of 1 to 30 days. Here, it is observed that the highest correlation between charged energy and ambient temperature with the SoH is present with a bundle length of 22 days. The Pearson correlation coefficients for all of the bundles are $r_{\Delta SoC} = 0.27$ and $r_{\vartheta} = -0.61$. This rough correlation is shown in Fig. 7, where the resulting nine bundles are illustrated. Therefore, the results presented in the following paragraphs are based on bundles of the period length of 22 days.

In Fig. 7 it can be seen that the correlations between charging energy and SoH as well as temperature while charging and the SoH change could be linear. This is because the linear fit with the order of one (solid line) shows a slight pattern in the scattered data points. Also, the experiment halves are shown with distinctive markers and colours in order to illustrate a clustering of the temperature ranges ([16.88, ∞] °C in red and [$-\infty$, 16.88[°C in blue). Here, filled circles (in red colours) depict the first experiment half until the end of August, when the ambient temperature is high (above the average temperature of 16.88 °C). Blue circles represent the second experiment half during low ambient temperature observation. In short, during the first three months, the ambient temperature was above 16.88 °C and the charged energy was less than 10.72 kWh, shown by the dotted lines respectively, in Fig. 7.

Interpreting the scatter plot in Fig. 7, a general beneficial health change can be derived. If the ambient temperature is low (less than 16.88 °C) and the energy to be charged is high (more than 10.72 kWh), fast charging processes should be preferred. This differs from literature, since fast charging is considered harmful for battery health [9], [10]. It is assumed, that the influence of low ambient temperature may contribute to the finding proposed in this paper. In addition, no evaluation can be given on the effects of high charged energy on hot periods as well as on low charged energy during cold days. This is because the available data doesn't include these cases. It was also observed by the colleagues driving the EV that the range during winter days was highly influenced by increased usage of cabin heating. Thus, energy demand during colder days was higher. Therefore, only one recommendation regarding charging behaviour of users can be derived for now:

Fast charging should be used at cold temperatures (0 to 16.88 °C) *if a high SoC difference* (> 10.72 kWh) *is going to be charged.*

Although an SoH increase is observed in some cases within the ranges defined in the recommendations, they are used nevertheless. Similar to the recommendation, Hannan et al. [1] recommend a battery temperature range of 15 to 50 °C for charging (as illustrated in Fig. 1). However, the recommendation used in this test is based on the available driving data and hence, the ambient temperature.

In the following, the generation of recommendations is tested using the experimental data. For this, the bundling period in the data pre-processing step is set to one hour. This value is chosen for a first analysis. Other values need to be evaluated considering validity and practicality in further work. Starting from there, the input parameter values for SoC and ambient temperature are averaged and the results for the SoC are subtracted from a static value of 24.0 kWh. This is required

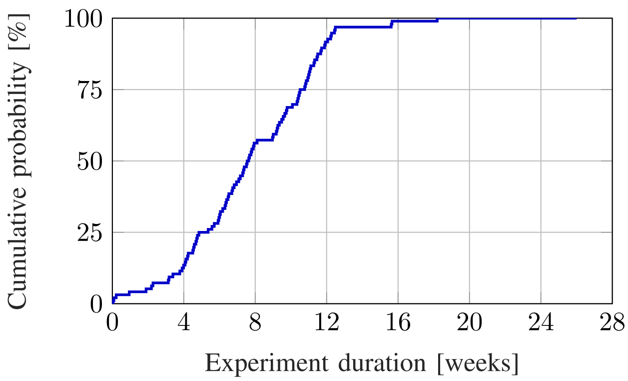

Fig. 8. Recommendations generated for the trial period

to calculate the average distance to the maximum capacity of the Nissan Leaf and to estimate the possible charge if a battery SoC of $100\,\%$ is desired after charging. Then, the recommendations are generated by iterating through all of the one hour bundles of driving data during the trial period.

The cumulative probability of generating the charging recommendation is shown in Fig. 8. It can be seen, that the recommendations are generated primarily in the first experiment half, when the ambient temperature is roughly above $20\,°\mathrm{C}$. At around 12 weeks, the system stops to provide the recommendation, which correlates with the temperature decrease shown between weeks 10 and 15 in Fig. 6. However, a slight increase in the number of provided recommendations is observed in weeks 15 and 18 respectively. This relates to an intermediate temperature rise shown between weeks 16 and 20 in Fig. 6.

VII. Discussion

The health monitoring and recommendation system was used on historical data accumulated during an experiment, where a Nissan Leaf was consequently fast charged. It is observed that the highest correlation between charged energy and ambient temperature correlates strongest with the SoH if bundled as averages in 22 day periods.

For generating the recommendation defined in Section III, an energy gap of less than $10.72\,\mathrm{kWh}$ to the maximum battery capacity as well as an ambient temperature outside the range between 0 and $16.88\,°\mathrm{C}$ is selected as precondition. While testing the recommendation generation on the experimental data, it is observed that this recommendation is provided primarily during the first half of the experiment, which was performed during summer season.

This shows, that the chosen value ranges are followed for providing the recommendation and therefore, the system performs correctly. Further, the selected hard value ranges for generating a recommendation could be exchanged by a weighted recommendation. For example, a recommendation could be weighted in a range of 0 to 1, where a value of 0 means no recommendation and a value of 1.0 means a very important recommendation as the chance for improvement is higher.

VIII. Conclusion

In this paper, a system to estimate the BMS derived SoH influence of charging parameters such as the charged energy and ambient temperature as well as a generation of charging recommendations is proposed. The resulting recommendation is used to guide an EVO's vehicle usage in order to prolong the EV battery lifetime.

The data computation and analysis proposed in this paper requires a data acquisition system to store EV driving performance data from the EV CAN bus on a central database. From there, data extraction and pre-processing components transform and bundle the data for consecutive health assessment components. The pre-processing component contains filtering of raw data to omit invalid data, bundling of data within an arbitrarily set time period and influence analysis. From the analysis in the last step, SoH influencing parameter ranges are determined and later used for recommendation generation.

Then, an experimental test shows the application of the proposed system based on historical data from a consequent fast charging experiment using a Nissan Leaf EV. Overall, the system satisfies the requirements of determining the health impact of the driving parameters as well as the generation of recommendations at the correct timing. The computation is based on the assumption, that the SoH parameter values can improve by a slight percentage during short periods of time. It is shown that charging high energy amounts at low ambient temperatures correlates with an SoH improvement with Pearson correlation coefficients of $r_{\Delta SoC} = 0.27$ and $r_{\vartheta} = -0.61$. However, it needs to be tested in more cases, if the derived recommendation improves the SoH under its precondition for generation. Moreover, long-term experiments are required in order to determine a battery lifetime prolongation. From the available data, this cannot be determined right now.

Furthermore, other modelling approaches need to be analysed in the future. For example, the static value ranges for generating the usage recommendations could be based on fuzzy logic, e.g. providing the suggestions if a crisp condition applies during a trip. Also, techniques like machine learning such as Artificial Neural Network (ANN) would be an option to automatically learn from correlations within the obtained data. This way, the precision of the proposed methodology could be improved strongly. However, machine learning requires a high volume of data, which is currently not available from the presented experiment. Therefore, a simple statistical evaluation is used to determine recommendations.

Besides other techniques, the existing system needs to be tested in other cases. For example, it is required to know, if the proposed configuration is compatible to other EV types and if it is functioning during winter or spring time. This is because the system was only tested on one EV and its driving data between a period of May and December 2017. Also, it needs to be tested if the results of the system are reproducible with consequently slow charged EVs or ones charged in arbitrary ways.

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