Dynamic EV Battery Health Recommendations

Markus Eider
Deggendorf Institute of Technology
Deggendorf, Germany
markus.eider@th-deg.de

Andreas Berl
Deggendorf Institute of Technology
Deggendorf, Germany
andreas.berl@th-deg.de

ABSTRACT

Prolonging the lifetime of batteries in Electric Vehicles (EVs) becomes a more and more important issue for private users and fleet operators. In addition to the environmental point of view, a better battery health results in less cost, higher battery capacities and higher performance. To achieve this, the EV drivers or the fleet operators need to get proper information, which kind of actions will increase or decrease the batteries health. To this point, various tips and recommendations exist distributed over literature. Unfortunately, those kind of recommendations are hard to follow in the day-to-day routine. This paper suggests so called dynamic recommendations for battery health that are able to advise the user in specific situations with respect to battery use. Recommendations from literature are broken down into a list, which can be automatically computed. Recommendations will then be dynamically created in the current context of the EV and displayed to the user just in time.

CCS CONCEPTS

• **Human-centered computing** → **HCI theory, concepts and models**; **Activity centered design**; • **Applied computing** → **Physics**; • **Information systems** → *Data analytics*;

KEYWORDS

Electric vehicles, battery health, recommendations, user behaviour

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1 INTRODUCTION

Batteries make up roughly 50% of EVs cost [1, 16, 23, 27] and therefore represent a highly valuable part of the EV. Unfortunately, batteries are ageing during usage and time, leading to lower capacity and performance [2–5, 14, 16]. This process is also called **degradation**. The faster a battery degrades (e.g. due to the usage and charging behaviour of the user), the shorter the lifetime gets and the faster capacity and performance is lowered. EVs users, however expect high performance, high availability, and low costs from their EVs, respectively from their battery.

In order to prolong battery life and keep battery health on a high level, users should follow general rules, tips, and usage patterns that can be found in literature. These battery usage recommendations comprise the charging of the battery and the usage of the battery, respectively the EVs. In this paper these kind of recommendations are called **static recommendations**. Users can improve their battery health, e.g., by charging in special ways, driving battery-friendly, choosing suitable routes, and parking their car according to static recommendations. However, it is typically not easy to follow these static recommendations while performing day-to-day tasks with EVs. On one hand static recommendations are written down somewhere in literature, not available during a drive. On the other hand, it is not easy for the EVs user to interpret general recommendations in the current driving or charging context.

This paper suggests so called **dynamic recommendations** as a solution approach to this problem. Dynamic recommendations are processed from static recommendations, but given to the user just in time and based on the current charging/driving/routing/parking context. Data from the car is gathered and the behaviour of the user is analysed and concrete recommendations are created for the user at specific points of time. In this paper it will be shown that abstract static recommendations from literature can be put into a machine readable table and be processed automatically in order to generate dynamic recommendations. Additionally, two examples of dynamic recommendations will be shown.

The paper is structured as follows: Section 2 discusses background information and static recommendations. Section 3 introduces the concept of dynamic recommendations. Section 4 shows a machine readable representation of recommendations and an algorithm for automatically creating recommendations. Section 5 shows two examples of dynamic recommendations based on real world data. Finally, Section 6 concludes this paper.

2 BATTERY DEGRADATION AND RECOMMENDATIONS

In this Section, fundamentals of battery degradation are discussed while considering the battery as a black-box system. In addition, common ageing causes and static recommendations are described in order to derive dynamic recommendations for battery-friendly usage.

2.1 General Battery Degradation

Lithium-ion batteries are the one of the most expensive parts in EVs. They make up roughly 50% of the original vehicle price [27], though their price is dropping due to advancements in the past years (roughly 35% price drop between 2015 an 2017 [17]). Lithium ion batteries have several benefits, such as their high energy density,

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lifetime, efficiency as well as fast charging properties [8] and are suitable as energy storage systems in EVs [24].

While providing the mentioned benefits, battery performance is impaired by battery degradation through chronological and utilisation causes. For example, Bouchhima et al. [2] explain that the battery health state describe the current EV performance [2]. This health state is influenced by permanent and inevitable degradation [4, 16]. This is why Li-ion batteries need to be observed and monitored [24] so that the degradation can be limited and safety as well as reliability can be guaranteed [28]. Users of EVs directly influence battery degradation through their utilisation behaviour [5, 25, 27]. Therefore, user behaviours which degrade the battery in an accelerated way need to be identified.

A common metric for the degradation level of a Li-ion battery is the SoH (State of Health) [10] i.a. but it is defined through multiple ways [7]. As and example, the State of Health (SoH) can be computed as the ratio between current and initial capacity [23] i.a. Besides this, manufacturers of EVs and Electronic Control Units (ECUs) keep their calculation approach secret [27]. Thus, it is unknown how the SoH provided by a Battery Management System (BMS) is calculated which makes a health analysis using EV driving data difficult. Hence, a more car-agnostic approach is needed for prolonging battery lifetime in electro mobility.

Batteries degrade in a non-linear way. This is because after the battery health drops below 80% SoH, the capacity fades rapidly [29]. Thus, the End-of-Life (EOL) of EV batteries is estimated to be 80% SoH [2] i.a. The small lifetime range with regards to the SoH classification therefore needs to be preserved. Hence, dynamic recommendations seem to be a suitable advice for users who want to improve the battery lifetime of their vehicle.

Battery degradation is a permanent as well as dynamical process [11, 21, 22]. It also is an outcome of aggregated battery operation and time, which means that degradation depends on the operation history [3, 5, 14]. The main effects of battery degradation, namely capacity and power fade, can be used to describe degradation but these again do not directly describe the SoH and can occur independently from each other [8] i.a. However, there are known influences for these main effects which in general cause battery degradation. The most important influences are the ambient temperature, battery current rate, Depth of Discharge (DoD) and the time intervals between full charge cycles [22].

Most studies on battery health and ageing are performed under strict conditions. This is criticised by You et al. [29] since batteries usually degrade under dynamic conditions in practise. Therefore, the practical operation needs to be considered also in order to understand the process of battery degradation. For this reason, EV performance data can be acquired from the EV Controller Area Network (CAN) bus [15, 23, 25], as done in this paper. Another approach, which is more accurate [24], uses a direct measurement of the battery parameters [24] i.a. Though it is difficult to perform [8] as it requires laboratory equipment [10, 24] and is therefore not applicable for typical EV users. With the driving data from the EV CAN bus, different driving behaviours can be determined as well [25]. These contain vehicle control actions such as the usage of acceleration or breaking pedals [25]. Hence, behaviour recommendations could be derived from driving data also.

2.2 Static Recommendations

Besides the general context of battery degradation, there exist static recommendations with give advice in order to reduce the effects of cyclic and calendaric ageing of Li-ion batteries. On one hand **cyclic ageing** takes place because charge throughput into and out of the battery during cycles of driving and charging [2, 22, 26] at typical EV use. On the other, **calendaric ageing** is observed over the course of time and the powered off state of the EV. It takes place if there is no current flow through the battery [12, 19, 21].

2.2.1 Recommendations to Reduce Cyclic Ageing. Cyclic ageing is primarily induced by current flow and the State of Charge (SoC) levels as well as changes. Therefore, static recommendations which reduce these influences are discussed in the following paragraphs.

Here, the degradation is accelerated by internal temperature rise due to high current or power flow [16] i.a. For example, this strongly occurs during fast charging [12, 18, 23] which is why generally, fast charging should be avoided. However, it could be identified in a prior paper [6], that fast charging at low temperatures (< 17 °C) is battery-friendly. In addition, delayed charging also can prolong battery lifetime [23] and therefore, users should wait between charging and driving and vice versa. Thus, high charge throughput during charging is not harmful in every case.

Besides this, the SoC (State of Charge) level and difference is an important key influence for battery degradation [12, 23]. During charging, it is recommended not to exceed an SoC of 80% [13] as this is harmful for the battery. Also, the DoD (Depth of Discharge) is often used as measure, which is the difference between 100% and SoC at a certain point in time [20]. In general, it should be avoided to frequently discharge the battery to a high DoD ([2] i.a.) in order to prolong battery lifetime. Furthermore, the SoC difference during charging or discharging should be kept low, as this also accelerates battery degradation [2, 16, 18].

At EV driving, the utilisation by users has a high influence on battery health. Here, the discharge rate depends on route topology, vehicle load, speed, acceleration and the driving style [1, 22]. Again, this discharge rate influences the level of cyclic ageing. This is summarised in an experiment presented by You et al. [29], where different route types are analysed for their battery health impact [29]. There, capacity fade was highest, if highway drives are performed. A more slightly fade was observed with urban routes and the least capacity fade was determined for city routes. Thus, users should plan their trips on city streets or urban roads.

2.2.2 Recommendations to Reduce Calendaric Ageing. The process of calendaric ageing is independent from cyclic ageing [11, 19], as there is no charge transferred from or to the battery [21]. Since EVs are parked for 80% to 95% of their overall lifetime, this degradation type is highly important ([19] i.a.) and recommendations to reduce its effects on battery health must be considered. The following paragraphs summarize the key influences for calendaric ageing, namely the battery temperature as well as SoC levels.

In calendaric ageing, the most influential degradation cause is the ambient temperature [12] i.a. Here, the EV battery should be kept in a range of 15 to 50 °C, as summarized by Rezvanizaniani et al. [22]. In this context, the rate of degradation is doubling with every temperature increase of 10 °C [22]. Hasan et al. [9] specify this range even narrower. They describe that batteries should be operated between 25 and 30 °C [9]. Extreme temperatures outside of these ranges are considered harmful for battery health [15] i.a.

Similar as in cyclic ageing, the SoC level needs to be considered as ageing influence [2] i.a. On one hand, a high SoC during parking should be avoided since this decreases battery lifetime ([23] i.a.). On the other hand, keeping an EV parked at a low SoC (of 30% to 40%) minimizes capacity fade [11]. Thus, an EV should be parked with its battery being charged to a SoC of 50% or less [12, 23].

3 DYNAMIC RECOMMENDATIONS

This Section provides a definition and the properties for dynamic recommendations. This way, required inputs for generating recommendations can be identified. Besides this, it is discussed which information dynamic recommendations are providing and how users can benefit from them.

Definition [***Dynamic recommendation***]: A **dynamic recommendation** in the context of EV battery health is a **specific** recommendation for **driving**, **parking** or **charging** of the EV. The dynamic recommendation will be pesented to the user **right on time** when it can be applied. The presented **recommendations** are based on static recommendations from current state of the art. Recommendations are made **dynamic** by monitoring an analysing the EV over time in order to select a specific recommendation based on the current state of the EV.

Dynamic recommendations are based on EV data in the past, current situation and in the future. In contrast to this, static recommendations also consider EV use but are independent from EV data. However, it is known from literature that battery health is a consequence of cumulative battery usage [3, 5, 14] and therefore, dynamic recommendations need to be provided considering the specific environmental and EV internal dynamics in the past and current situation as well as prognostics on parameter change. With this characteristic, dynamic recommendations can tell for how long in the future they should be followed. For example, if a low ambient temperature is predicted within the next month on average, certain recommendations can be given to the user which are valid for this time frame.

The dynamic recommendations are derived from static recommendations in the literature. They inherit dynamic properties in contrast to static recommendation, as they consider specific parameter values, the user decisions and behaviour as well as chronological aspects. This is because of the following reason. Static recommendations are always valid as they are not depending on certain inputs (e.g. a city drive should be preferred instead of taking urban routes [29]). However, a respective recommendation should only be generated if it is applicable to parameter ranges or user behaviour (at charging/driving/parking) at the current moment. In this paper, the behaviour is not taken as input right now but it can also be used if available. This way, users are just in time provided with only the relevant information for battery friendly EV utilisation.

Next, dynamic recommendations should provide a certain priority. Depending on the EV operation and parameter development, multiple recommendations could be provided at once. However, users need advice which recommendation has the most beneficial impact on battery health. Therefore, each recommendation needs to comprise a priority that could be represented by a weight factor. Especially in the case if there are contradicting recommendations, this weight can help to solve these contradictions. For example, at an ambient temperature of 10 °C over one month, there can be the recommendation to use fast charging [6]. However, if the temperature rises above 17 °C for one day, slow charging should be preferred [6]. In such case, a contradiction is present and can be solved using weights. This could be realised by coupling the weights to a dedicated weighting function which for example could use the ambient temperature as input. In the example, suggesting slow charging could have a higher priority than fast charging during the month.

Lastly, dynamic recommendations should be consistent over the course of time. This means that provided recommendations should not oscillate within durations of multiple days. Otherwise, dynamic recommendations could be provided in an alternating pattern, showing strong differences or even contradict. A solution to this can be the storage of previously generated recommendations and using these in a feedback loop of the algorithm.

Static recommendations from literature are assumed to prolong battery lifetime in general. Since dynamic recommendations are based on battery-friendly parameter ranges of static recommendations, it is concluded that dynamic recommendations as well prolong the lifetime. However, if a dynamic recommendation is derived from own data analysis of EV operation data, long-term experiments are required in order to verify their correctness. Also, it depends on the willingness and options of the users to follow the recommendations, in order to increase the lifetime of EV batteries. If a user refuses to follow the proposed suggestions or if certain circumstances such as immediate appointments occur, the dynamic recommendations are not performed and battery lifetime is not improved.

4 COMPUTATION OF DYNAMIC RECOMMENDATIONS

Based on the related work in Section 2 and the properties of dynamic recommendations in Section 3, preconditions for dynamic recommendations as well as an exemplary processing algorithm are introduced. These are required to generate dynamic recommendations from EV operation and user behaviour data. With this in mind, Section 4.1 provides a table of decisions and recommendations for the algorithm proposed in Section 4.2.

4.1 Representation of Recommendations

In the following, preconditions for dynamic recommendations are described. These preconditions are summarised in Table 1 (left side), which are based on static recommendations from literature (see Section 2) as well as assumptions proposed in this paper.

For the dynamic recommendations, restrictions on the data basis, chronological scope and priorities are set in this paper. As battery health depends on cumulative and long-term battery operation [3, 5, 14], the current situation as well as long-term operation data should be considered. Also a prognosis of the future (e.g. ambient temperature development) should be incorporated when generating dynamic recommendations. For now, only the current data is analysed. As explained in Section 3, dynamic recommendations are

Table 1: Preconditions and dynamic recommendations

Charge/ discharge rate [C]	SoC [%]	Ambient temperature [°C]	Route type	N°	Recommen-dation group	Parameter	Unit	Range/ options	Literature references
$cRate < 1$	-	$ambTemp < 17$	-	1	Charging	Power	[C]	[1, P_{max}]	[6, 22]
$cRate \geq 1$	-	$ambTemp \geq 17$	-	2	Charging	Power	[C]	[0, 1[	[6, 12, 18, 22, 23]
-	$soc \geq 80$	-	-	3	Charging	Power	[C]	[0]	[11, 23]
-	-	-	-	4	Charging	Charging delay	boolean	{true}	[23]
$cRate \geq 1^*$	-	$ambTemp \geq 17^*$	-	5	Driving	Power	[C]	[0, 1[	[6, 15, 16, 22]
-	$soc < 33^*$	-	-	6	Driving	SoC	[%]	[33, 80[	[2]
-	-	-	*routeType == urban*	7	Routing	Route type	enum	{city}	[29]
-	-	-	*routeType == highway*	8	Routing	Route type	enum	{city, urban}	[29]
-	$soc \geq 50$	-	-	9	Parking	SoC	[%]	[33 50[	[12, 23]
-	-	$ambTemp < 15$	-	10	Parking	Location	enum	{garage}	[22]
-	-	$ambTemp \geq 50$	-	10	Parking	Location	enum	{garage}	[22]

generated from user behaviour information amongst other data. However, there currently is no such information available in order to process this. The user decisions would be required to provide only the relevant advice to users. Therefore, this information is left out as precondition in this paper. In order to consider the decisions without relying on a user input, machine learning or AI may be used. These techniques could learn from the typical EV operation by the user and provide future prognoses. Regarding priorities, these are also not considered right now. However, these could be introduced as weights based on certain parameters such as the ambient temperature.

In left part of Table 1, the columns 1 up to 4 describe the necessary preconditions for generating dynamic recommendations. Here, numerical values are on one hand derived from literature and on the other hand based on own assumptions (labelled with asterisks). These values are used as references to be compared with current inputs, which are the charge/discharge rate *cRate*, the SoC *soc*, the ambient temperature *ambTemp* and the route type *routeType*. The latter can be interpreted as an enumeration type.

Furthermore, the recommendations themselves are then listed in the right part of Table 1 with a respective number in the first column, their output information in columns 2 up to 5, while the involved references from literature are shown in column 8. It should be mentioned that both the preconditions and recommendations are connected between each lines. The outputs of the recommendations provide information about user behaviour (Recommendation group), the parameter and its unit to be changed and the exact value range it should be held in.

For example, the first charging recommendation is based on a previous paper [6] where it could be identified that using fast charging (> 20 kW) at low ambient temperature (< 17 °C) is beneficial for battery health [6]. In the case of the chosen EV, the charging power corresponds to roughly 1 C (1 C resembles to fully charge an EV within one hour). Therefore, the recommendation for choosing fast charging is provided, if the charging rate is above 1 C and the ambient temperature of 17 °C is undercut. On the contrary, it was shown in the paper that using fast charging at higher ambient temperature leads to accelerated battery degradation. This result is used for the second charging recommendation.

In the following, the assumptions used for Table 1 are described. First, it is known that drawing high power from the battery at high ambient temperature leads to battery degradation (as explained by Dudézert et al. [5] amongst others). However, no specific temperature is specified in related work with regards to formulating recommendations. Therefore, the same temperature limit is assumed for recommendation N^{o}5. Besides the temperature, two assumptions are made regarding the SoC. It is known, that frequently high DoD is harmful to battery health ([1] i.a.) and therefore, a limit of one third of the maximum SoC (33%) was set for recommendation N^{o}6. In addition, a recommendation to park the EV in a garage is provided, since temperatures of 15 to 50 °C should be avoided [22]. For instance, the garage should provide a temperature of roughly 20 °C to reduce ageing effects.

Furthermore, there can be recommendations which are based solely on user intent. This is the case with the fourth recommendation which suggests to waiting between driving and charging and vice versa. It is only depending on the input that the user wants to perform a charging process which is currently not available.

4.2 Processing of Dynamic Recommendations

The contents of Table 1 can be automatically computed by considering each table entry as a boolean variable (or predicate). Let A_x (with $x = 1 \dots n$) be a predicate or boolean variable. Then, a dynamic recommendation R_y (with $y = 1 \dots m$) can be derived by:

$$A_1 \wedge A_2 \wedge \dots A_n \Rightarrow R_y \tag{1}$$

This computation step is used for all recommendations in Table 1 (right side) and shown as short form in Algorithm 1.

There, a procedure GETRECOMMENDATIONS is defined with the input parameters as used in Table 1 (left). In the procedure, a dynamic list *recs*, compatible to a *Recommendation* representation, is initialised first which will be filled with recommendations in the procedure. This is done by checking the input parameters for the defined conditions as shown in lines 4, 8, 14 etc. If a condition is satisfied, a respective recommendation will be created and added to the dynamic list *recs*. In line 38, a recommendation on delaying charging processes is created without any condition, as this currently is independent from any inputs. Finally, the list of created recommendations is provided in line 40.

Due to the connections of preconditions and recommendations in Table 1, there can be multiple recommendations per condition (see lines 9 to 12). This is however since there is no information

Algorithm 1

```
1: procedure getRecommendations(cRate, ambTemp, soc, routeType)
2:     recs := dynlist(Recommendation)
3:
4:     if cRate < 1 ∧ ambTemp < 17 then
5:         r := Recommendation(Charging, Power, C, 1, Pmax)
6:         recs.add(r)
7:     end if
8:     if cRate ≥ 1 ∧ ambTemp ≥ 17 then
9:         r := Recommendation(Charging, Power, C, 0, 1)
10:        recs.add(r)
11:        r := Recommendation(Driving, Power, C, 0, 1)
12:        recs.add(r)
13:    end if
14:    if soc ≥ 80 then
15:        r := Recommendation(Charging, Power, C, 0)
16:        recs.add(r)
17:    end if
18:    if soc ≥ 50 then
19:        r := Recommendation(Parking, SoC, %, 33, 50)
20:        recs.add(r)
21:    end if
22:    if soc < 33 then
23:        r := Recommendation(Driving, SoC, %, 33, 80)
24:        recs.add(r)
25:    end if
26:    if routeType == isUrban then
27:        r := Recommendation(Routing, Route Type, enum, city, city)
28:        recs.add(r)
29:    end if
30:    if routeType == isHighway then
31:        r := Recommendation(Routing, Route Type, enum, city, urban)
32:        recs.add(r)
33:    end if
34:    if ambTemp < 15 ∨ ambTemp ≥ 50 then
35:        r := Recommendation(Parking, Location, enum, garage)
36:        recs.add(r)
37:    end if
38:    r := Recommendation(Charging delay, boolean, true)
39:    recs.add(r)
40:    return recs
41: end procedure
```

about the user's intent in EV utilisation. Another boolean input would be necessary, which represents if the user wants to initiate a charging process or do a trip in order to split the statement body of the condition in line 8.

5 EXAMPLES

In this Section, the priorly discussed processing algorithm is tested on real EV driving data. This is available in the form of historical data acquired from different EVs. In this case, driving data collected from a Nissan Leaf model 2012 is used. Here, the EV is equipped with a data collection system which reads out the CAN bus via a dedicated On-board Diagnostics (OBD) port adaptor. The acquired data is then sent to a database.

The following two Sections show the application of the processing algorithm on data from different trips driven with the EV. The goals of the applications are: (1) to test if the algorithm is working correctly and (2) to demonstrate that not only a single recommendation is generated but multiple recommendations are provided at specific circumstances.

5.1 Single Recommendation

This Section describes the test of the decision algorithm for recommendation $N^0 6$ as this recommendations takes only one input, i.e. the SoC. A dynamic recommendation is only produced, if the SoC falls below the threshold of 33%. This allows to see if a recommendation is correctly generated if the condition is satisfied.

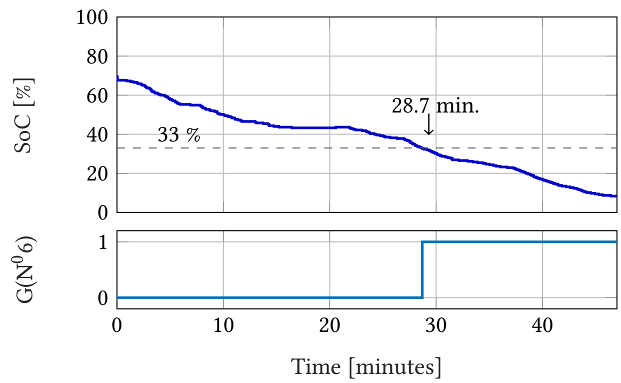

Figure 1: Generation of a single recommendation

For this test, driving data of a single trip from October 2017 is taken. Figure 1 (upper graph) shows the development of the SoC during the trip duration of roughly 47 minutes. Here, the SoC is within a range of $[8.4, 70.2]$% and shows a nearly steady decline over the trip time frame. Shortly after 20 minutes however, there is a slight increase in SoC which is caused by recuperation of the EV. This means that a height potential loss was converted to electrical energy and stored in the battery while driving downhill.

Until roughly 29 minutes from the trip start, the SoC is above 33%. In this case, the precondition for generating recommendation $N^o 6$ is not satisfied. This is visualised in the bottom graph in Figure 1, where the generator function $G(N^o 6)$ describes if the algorithm is providing recommendation $N^o 6$. Hence, $G(N^o 6)$ is 0 until 29 minutes. After this time frame, the recommendation is provided and $G(N^o 6)$ is 1.

This test shows, that the proposed algorithm can be applied to real driving data and generates recommendations correctly with regards to the preconditions in Table 1. However, as there are other recommendations proposed in this paper, further tests are needed. This is discussed in the following Section.

5.2 Multiple Recommendations

This Section contains two tests, which visualise that multiple recommendations can be generated simultaneously and that different combinations are possible. Therefore, two trips in Figures 2 and 3 are chosen, where the ambient SoC and ambient temperature ϑ_{amb} are within different ranges and exceed the thresholds of the proposed preconditions. These trips were driven also in October 2017, just as in the test of Section 5.1.

In the first test of this Section, the ambient temperature ϑ_{amb} moves within $[13.3, 15.0]$ °C, being at 15°C between 4.2 and 10.7 minutes after trip start. The SoC is within a range of $[61.8, 86.2]$% and drops below 80% after 8.4 minutes, as shown in Figure 2.

As shown in the two bottom graphs in Figure 2, recommendations are generated in specific cases as defined in Table 1. $G(N^o 3)$ is 1, i.e. recommendation $N^o 3$ is generated, as long as the SoC is

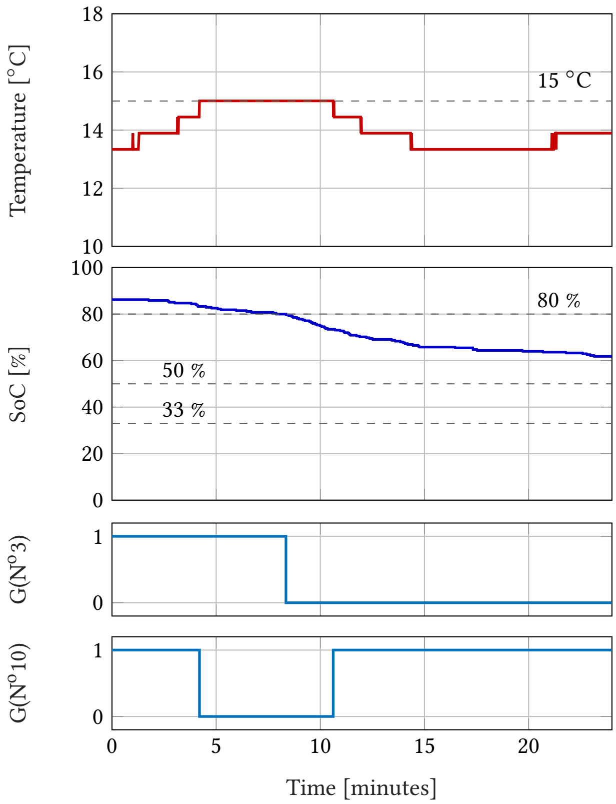

Figure 2: High SoC test with multiple recommendations

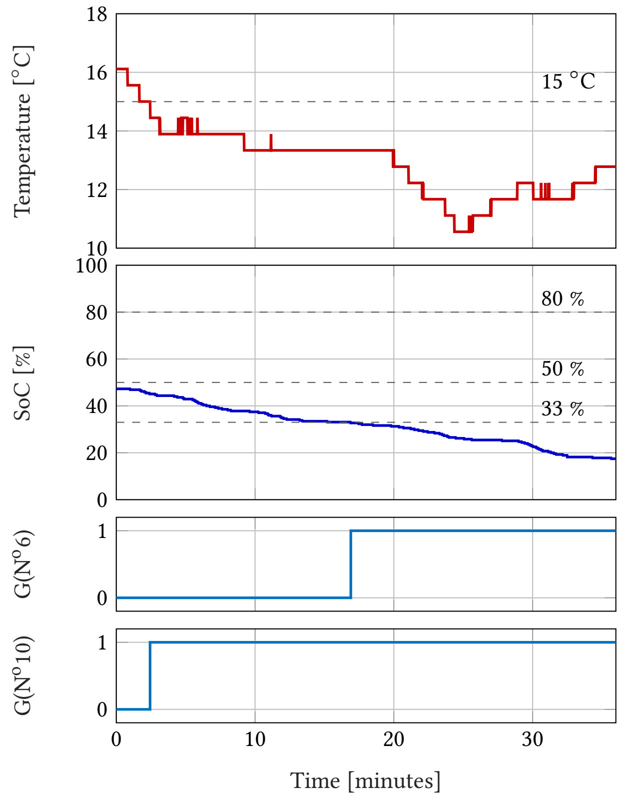

Figure 3: Low SoC test with multiple recommendations

above 80% and therefore satisfies the condition of recommendation N^{o}6 from the trip start until 8.4 minutes. Also, G(N^{o}10) is also 1 or 0 according to the recommendation precondition ($\vartheta_{amb} \leq 15$ °C).

More interestingly, G(N^{o}6) never reaches 1 (not shown in Figure 2), as the SoC is always above 33%. In addition, recommendations N^{o}4 and N^{o}9 are always 1, as N^{o}4 does not require any inputs and for N^{o}9, the SoC has to be at least 50%. Other recommendations (1, 2, 5, 7, 8) could not be tested here, as the inputs *cRate* and *routeType* are not directly available from the EV CAN bus right now.

In the second test in this Section, the ambient temperature is within $\vartheta_{amb} = [10.6, 16.1]$ °C and the SoC is within the range of $[17.5, 47.3]$% (see Figure 3). ϑ_{amb} drops underneath 15 °C after 2.4 minutes and SoC $\leq$ 33% is satisfied after 2.4 minutes.

As this test describes a different scenario as in the prior test, other combinations of recommendations are provided. Besides the graphs of G(N^{o}6) and G(N^{o}10) in Figure 3, G(N^{o}4) is always 1 again, due to the independence of inputs. G(N^{o}3) and G(N^{o}9) are always 0. This is due to the fact that the SoC is never above 50%.

The results visualised in the Figures 2 and 3 as well as the test description show that different combinations and numbers of recommendations can be provided at specific points in time. This fulfils the property of dynamic recommendations that these should be provided at exactly those times when they apply to driving data. Therefore, the proposed algorithm is suitable as a first solution to implement Table 1 and to process real driving data.

6 CONCLUSION

This paper has presented the concept of dynamic recommendations for EV battery health that can be presented to the user just in time in order to improve driving, charging and parking behaviour. The main contributions of this paper are the following:

(1) Dynamic recommendations have been proposed. In contrast to typical battery health tips and recommendations that can be found distributed in literature, dynamic recommendation are presented to the EV user exactly when they can be performed. Dynamic recommendations are able to improve driving, charging and even parking with respect to battery health.
(2) The state of the art of EV battery health recommendations has been broken down into a machine readable table that enables the dynamic generation of recommendations for EV users. Relevant parameters and recommendations have been analysed and groups of recommendations have been created.
(3) A first simple algorithm has been shown in the paper that allows for the automatic interpretation of the recommendation table and can be used to create dynamic recommendations.

Depending of the current situation of the EV, recommendations can be created just in time to modify the behaviour of the EV user.

(4) Finally, the paper shows two realistic examples of dynamic recommendations. Based on real world data gathered from EVs, input parameters are taken for the control system and dynamic recommendations are created exactly at the point of time, when they are useful to the EV user.

In future work, the dynamic recommendation system for battery health needs to be further improved. On one hand the list of recommendations needs to be extended. On the other hand, the recommendation system needs to be fully developed in order to be able to display recommendations on the EV user's smart phone.

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