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Improving Battery Lifespan and Service Trip Reliability of Battery Electric Buses by Learning Energy Consumption

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Executive Summary

Electrification of public transport in cities puts lots of stress onto the vehicle's traction batteries and the power grid during charging. A self-learning operating strategy helps with this issue by limiting the charging power as much as feasible and avoiding extreme states of charge. Based on observations of the vehicle state and energy flows inside of the vehicle, the operating strategy plans an optimal SoC trajectory for the trip.

In addition to reducing stress to battery and power grid, the operating strategy ensures reliable service trips by checking if the current state of charge is sufficient for the estimated energy consumption in the near future. A situation where the current service trip is endangered can be recognized and mitigated early. The collected and learned data can optionally be shared between similar vehicles for faster learning by running the software on a cloud server.

Keywords: charging, battery life cycle, electric vehicle (EV), infrastructure, public transport

1 Introduction

To reduce air pollution and CO₂ emissions in cities, many transport associations migrate to electric vehicles for public transportation [1, 2, 3, 4]. Recent developments in battery research result in improved energy and power densities and facilitate a larger adoption of electric vehicles in traffic [5]. Migrating bus fleets to battery electric buses lets operators face new challenges. The range of such a bus is smaller than that of a conventional one. Thus, either the bus needs to recharge during regular service operation, or the operator needs more vehicles to perform the planned service [6]. Also, the battery is prone to degradation over time [7, 8]. Usually, batteries degrade faster when used with extremely high or low states of charge as well as very high charging and discharging currents. Avoiding such usage patterns could prolong a battery's life [8].

An energy storage management for trolley buses is described in [9]. Although the proposed system is able to reduce the peak load on the power grid, it involves adding a stationary battery storage system to the infrastructure and is therefore not able to reduce stress on the vehicle's traction batteries.

There are Eco-Driving energy management strategy and control strategies proposed in [10, 11, 12]. These papers focus on reducing the overall energy consumption while driving, potentially by improving the efficiency while driving. They do not, however, reduce stress on the battery or on the power grid during charging operations.

Another approach to reducing the energy consumption are presented in [13] by optimizing the route to be driven. However, this approach is not applicable to buses since bus routes are selected based on criteria other than ecological constraints.

There are also works on optimizing charging strategies to reduce peak load on the power grid. For example, in [14] the authors estimate the departure time of cars to distribute the charged energy along the charging time. That paper primarily focuses on correlating various data like car type, weekday or arrival time with the departure time to generate good estimations for future departure times. The paper however, as it is operating on the infrastructure, considers at most one charging operation and does not consider the vehicle after it has left the charging station.

Focusing on electric bus fleets, the authors of [15] propose an Eco-charging strategy. That paper reduces the peak load on the grid by making full use of the time available during charging, be it opportunity charging or overnight charging. Additionally, the SoC of the battery is considered for the whole day and optimized towards minimal charging power while still ensuring reliable trip service. The proposed Eco-charging strategy furthermore involves synchronizing multiple chargers during a pulsed charging operation to reduce peak load. The paper does not take the opportunity to further distribute the charged energy over the day to avoid very low or high states of charge. Also, the proposed strategy is not directly suitable for trolley buses as it requires infrastructure communication.

There is also a charging strategy for hybrid trolley buses proposed in [16]. The authors propose a strategy which reduces the available charging power of a catenary grid depending on the current grid load. The proposed strategy involves using grid utilization forecasts to further improve the grid load. Being only on the infrastructure side, the strategy is only able to reduce the peak grid load, but does not explicitly use the opportunity to reduce the vehicle's charging power to reduce stress on the battery.

The PhD thesis in [17] focuses on planning depots for overnight charged buses, also taking the grid load into account. Considering many aspects of the design of a bus depot, it designates a chapter to charging strategies. The author proposes an algorithm to schedule charging operations in a depot. Since that thesis only considers a bus depot, it is only partially applicable to opportunity chargers or hybrid trolley buses.

In this paper, the authors present an operating strategy software concept to run on a device in electric buses to reduce the peak load on the grid and stress on the battery. At first, the authors describe the process of data collection during operation. Then, they present the processing, evaluation, and storage of the collected data. Finally, they describe how the collected data is used to generate an optimized state of charge trajectory, reducing stress and aging of the traction battery.

The work on the operating strategy started in 2014 during the SaxHybrid^{PLUS} project in Saxony. In the scope of the project, a 18m plug-in hybrid electric city bus was modified and tested in real-world public transportation scenarios in Dresden and Leipzig, Germany [18]. The vehicle which was used during that project is shown in Figure 1. The operating strategy is a piece of software running on a device which is installed in the vehicle and connected to the CAN bus. It collects various runtime data at runtime and dispatches recommendations to the rest of the vehicle. The same ideas and concepts have been applied to other propulsion technologies later.

After the SaxHybrid^{PLUS} project, the operating strategy was improved during a trolley bus project in Arnhem [19, 20] and is now part of the Smart Fleet Management software from Kiepe Electric [21]. The operating strategy is currently being applied to pure battery buses.

Because city buses have a regular schedule with planned routes and timetables, the energy consumption of such a bus can be predicted with high confidence. Such data can be collected during regular service. While it would not be feasible to collect energy consumption data for passenger cars on each road, city buses allow for such methods due to their limited area of operation and repeating service trips.

Making the operating strategy self-learning eliminates the use of an additional interface for the timetable which would need the operator to serve those interfaces. Having the operating strategy learn the routes and energy demands during regular service gives the operator a plug-and-play experience while still prolonging the battery lifespans of the bus fleet.

The only interfaces which need to be served for the operating strategy in addition to drive train monitoring data are the current service line and destination.

2 Reducing Stress on the Battery and Grid

The operation strategy reduces stress on the traction battery by avoiding large charging currents and very high or low states of charge. The general idea is to consider the timetable of the bus as fixed and try to



Figure 1: The city bus which was modified and evaluated during the SaxHybrid^{PLUS} project in 2014 during a recharge operation

distribute the required charging power as wide as possible along the time with externally available energy.

By reducing the charging power as much as possible, load on the grid is more evenly distributed, leading to lower peak power demands.

2.1 Data Collection, Processing and Storage

During regular service operation, the operating strategy tracks the vehicle's GNSS location and its velocity, as well as the current line and destination and externally available and consumed energies.

The exact method of the data acquisition is out of scope of this paper. In real applications, the data may be transferred to a device running the operating strategy via a CAN bus. Localization data may be enhanced by performing a sensor fusion on various input data.

2.1.1 Discrete Location Steps

A discrete location step is the smallest unit of vehicle movement. Once a small distance, measured using the vehicle's velocity, has been traveled, the operating strategy considers this movement as a step. The operating strategy associates the starting GNSS position as well as the consumed traction energy and externally available energy during that discrete location step. Discrete location steps are not stored permanently.

The externally available energy is determined by the integration of the currently available charging power over the duration of the current step.

Due to the nature of a catenary grid, trolley buses have multiple location steps with externally available energy. Opportunity charged battery buses however usually see very short presence of externally available energy, leading to a single location step with externally available energy.

2.1.2 Track Sections

A track section is the smallest unit of vehicle movement stored persistently in a local database. Multiple discrete location steps can be aggregated into one track section. Such a track section covers a driven distance of configurable length, with a typical value being ca. 50 m. During a service trip, the operating strategy tries to recognize a track section from the local database based on the current vehicle's state. If it is unable to do so, it creates a new track section based on recent discrete location steps. Once created, a track section's id and its start and end positions are immutable. To avoid the creation of low-quality track sections next to the road, a minimum quality of the GNSS signal is necessary to create the section. One exemplary metric of the GNSS signal quality is the number of satellites visible to the vehicle.

A track section may refer to one or more follow-up track sections. A track section B is a follow-up track section of track section A, if the vehicle enters B immediately after leaving A.

The operating strategy associates additional data to each track section which is updated each time the vehicle visits the track section. For each line and destination, the operating strategy associates the follow-up track sections, travel durations, the consumed traction energy and the externally available energy. When updating the associated data of a track section, a weighted average from the previously stored values and the new measurements builds the new stored values.

As mentioned earlier, the length of a track section is configurable. Longer track sections require less storage space but may consolidate multiple charging opportunities. Shorter track sections are more precise with regards to charging opportunities and more responsive in the case of redirections but increase memory and storage requirements and computational load on the device.

When using the operating strategy in battery buses with opportunity charging, the track section length has a high influence on the aggregation of multiple charging opportunities in track sections. Each track section with an opportunity charger becomes a track section with available energy. The stored amount of externally available energy converges to $f \cdot E_{max}$, with E_{max} being the actual amount of externally available energy on this track section and f being the fraction of the times the bus stopped to charge on this section.

2.1.3 Routes

A route is a larger trajectory of the vehicle which is also stored persistently in the local database. A route describes a service trip with a certain line and destination, happening at a certain date and time. It refers to an ordered list of track sections which were driven during that service trip. A route also stores the consumed and available energies with each track section, in addition to the averaged energies which are associated anyway with each track section. It is worth mentioning that a route may contain the same section multiple times, for example when the bus drives a loop during the route.

A route may cover sections, which are not associated with a track section. For example, a tunnel may be such a route section, where no GNSS signal of sufficient quality is available to create a track section. With these route sections, consumed or available energies can be associated to sections without having GNSS data available.

Once stored, a route is immutable and is never updated. Instead, new routes are created, and old routes are deleted after some time. The stored routes in the local database can be considered as a log of recent service trips.

A route may refer to one follow-up route. Follow-up routes work like follow-up track sections, except that every route may only refer to at most one follow-up route due to its immutable nature.

2.2 Predicting the Vehicle's Trajectory

Based on the vehicle's current state and information stored in the local database, the operating strategy tries to predict the vehicle's trajectory for a given distance. The exact distance is variable and should at least cover the maximum driving range with the traction battery. The purpose of predicting the vehicle's trajectory is to estimate the energy demand as well as the externally available energy for that trajectory.

The operating strategy initially tries to determine the track section on which the vehicle is currently driving and then, based on the current track section, predict the rest of the trajectory.

2.2.1 Route-Based Prediction

Having a route-based prediction is the preferred case, leading to a prediction with higher confidence. The operating strategy checks if the current track section was served within a route on the same line and destination at the same time and weekday in the last few weeks, the number of weeks to look back being configurable. The operating strategy needs to consider some distance behind the vehicle to eliminate ambiguous track sections on the same route. If such a route could be unambiguously determined, the sections listed in that route and potential follow-up routes describe the predicted vehicle's trajectory. Once no follow-up routes are available to predict the vehicles trajectory for the remaining distance, the track-based prediction is used to predict the remaining distance.

For each section on the predicted trajectory, the operating strategy estimates the energy demand, the externally available energy and the duration on that section based on the stored values associated with the route and the track sections. Because those values are stored per route and per track section, the

operating strategy pessimistically assumes the larger value for the energy demand and the smaller value for the externally available energy.

2.2.2 Track-Based Prediction

If a route at the same time and weekday in the past cannot be determined, the restrictions for matching past routes are lowered. The operating strategy tries to find the latest route matching the current track section, line, and destination without requiring the same time and weekday.

Once such a route could be determined, the track sections from that route describe the predicted vehicles trajectory. As with the route-based prediction, follow-up routes are also considered.

When no route can be determined to build a trajectory prediction, the operating strategy uses stored track sections from the local database. Since a track section may contain multiple follow-up sections, the track section with the smallest time offset to the previous track section is selected from the pool of plausible follow-up track sections to predict the vehicle's next trajectory.

When estimating the energy consumption and availability, the operating strategy only considers the energies associated with the track sections. Due to the higher uncertainty of that prediction, safety margins for state of charge recommendations need to be increased later.

2.3 Predicting the State of Energy

2.3.1 Estimating the Minimum and Maximum State of Energy

Once a vehicle trajectory consisting of multiple route or track sections has been established, the operating strategy generates a trajectory for the state of energy (SoE) of the traction battery.

The operating strategy only considers energies for the prediction and converts the state of charge (SoC) of the traction battery into an SoE, representing the amount of energy stored in the battery. Because the open-circuit voltage of the traction battery usually is not constant over the SoC, the stored energy is not constant over the SoC, either [22].

The operating SoE range of the battery is limited by a lower bound SoE_{low} and an upper bound SoE_{high} . Both values may be derived from equivalent SoC values. Limiting the operational range of the SoE can be useful for further prolonging the battery lifespan or for reserving some of the capacity for degradation effects [23]. Due to the higher uncertainty of the track-based prediction compared to the route-based prediction, SoE_{min} should be further lifted by an additional safety margin.

The operating strategy assumes that the energy demand by heating, ventilation, air conditioning (HVAC) and other auxiliary systems is independent from the route of the vehicle. E_{aux} is as the sum of all route-independent energy consumption, including HVAC systems.

Based on the route or track prediction, each track section i has an expected traction energy consumption $E_{trac,i}$ (which is negative in the case of recuperation) and externally available energy $E_{ext,i}$, based on average values from the past.

For each track section i laying ahead, the operating strategy estimates a minimum state of energy $SoE_{min,i}$ and a maximum state of energy $SoE_{max,i}$. $SoE_{min,i}$ is required for a reliable operation on track section i and all its predicted follow-up track sections. $SoE_{max,i}$ ensures that recuperated energy can be stored in the battery. Starting at the last track section, the operating strategy iterates backwards over the predicted track sections. For the end of the last track section n , $SoE_{min,n}$ is set so SoE_{low} and $SoE_{max,n}$ is set to SoE_{high} .

For each track section i with its predicted follow-up track section $i+1$ the required SoE range on entering is estimated as follows:

$$SoE_{min,i} = \max(SoE_{low}, SoE_{min,i+1} + E_{trac,i} + E_{aux} - E_{ext,i}) \quad (1)$$

$$SoE_{max,i} = \min(SoE_{high}, SoE_{max,i+1} + E_{trac,i} + E_{aux}) \quad (2)$$

The resulting minimum and maximum SoE for each track section can be visualized in a diagram resembling a dripstone cave. Figure 2 shows an exemplary course of the externally available power and the consumed traction power for a small route. When creating and storing track sections in the local

database, the powers are integrated over the time on each track section to obtain values for $E_{trac,i}$ and $E_{ext,i}$. Figure 3 shows the minimum and maximum SoE for the route demands from Figure 2 using the integrated energies from the local database. The external power supply has been artificially disabled in this example for some time to show the effects of an external power supply to the minimum SoE.

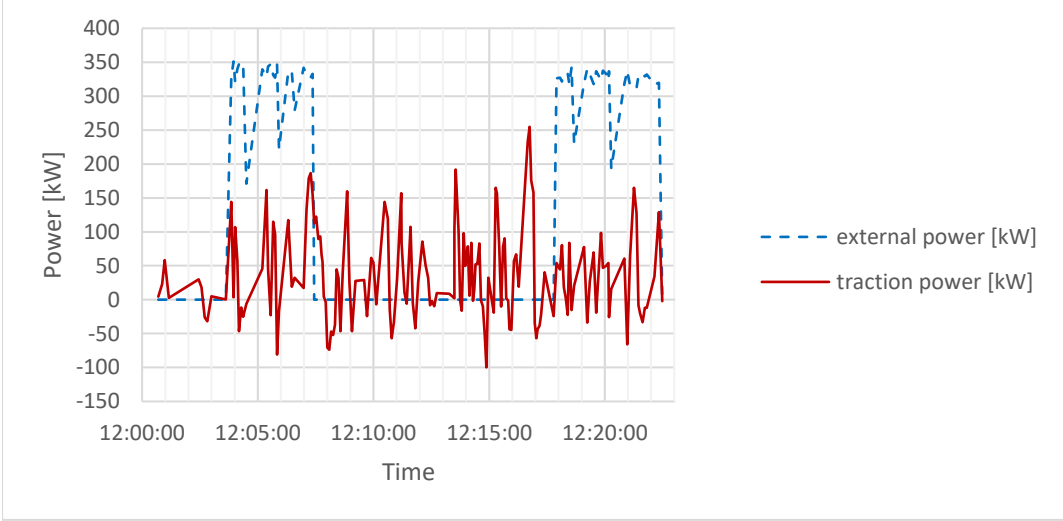


Figure 2: Externally available power and consumed traction power in Kilowatts during a route. Negative traction power values imply recuperation.

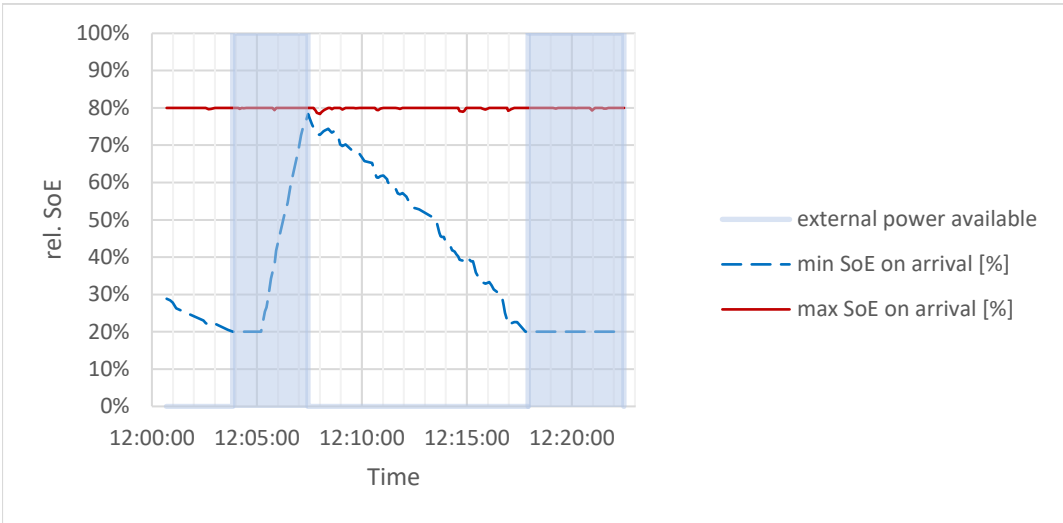


Figure 3: Prediction of minimum and maximum relative SoE in percent based on the recorded externally available and consumed power consumption shown in Figure 2.

2.3.2 Generating the Guidance State of Energy

Once the minimum and maximum energy for each track section have been established, a guidance SoE trajectory is generated for the sections. To accomplish this, a ‘rubber band’ algorithm is applied to the minimum and maximum SoE curves. The rubber band algorithm generates a curve with the gentlest slopes possible while respecting the constraints given by the minimum and maximum SoE for each track section. The initial SoE is set to the vehicle’s current SoE and the final SoE can be set to any valid value. A defensive choice of the final SoE may be the maximum value of the battery’s operating range.

Figure 4 shows a generated guidance SoE curve for the minimum and maximum SoE values from Figure 3. Note that the course of the actual SoE will follow the actual energy consumption. At the latest when external power becomes available, the guidance SoE will be updated to start from the actual SoE and the vehicle may follow the guidance.

The operating strategy performs a linear interpolation of the guidance SoE values and assigns the interpolated values to each section transition.

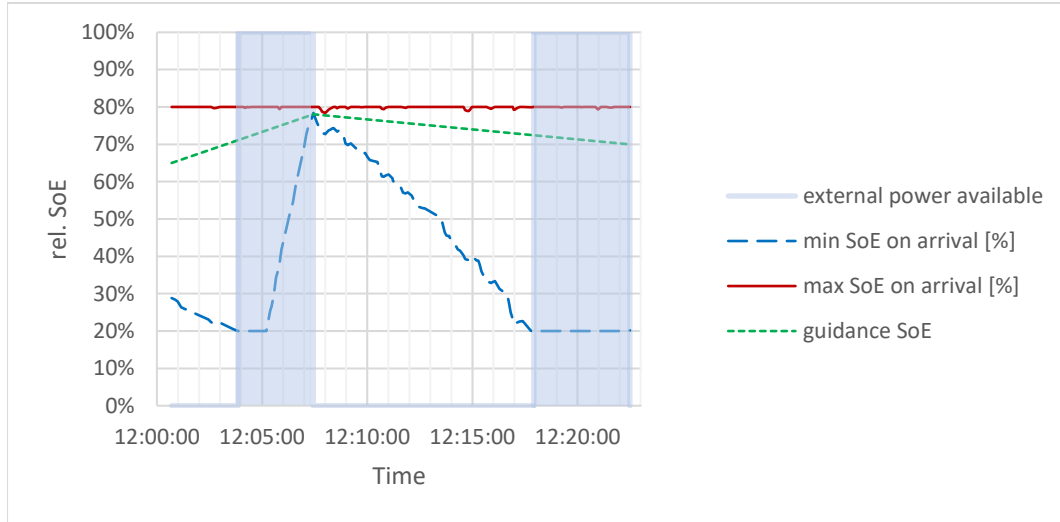


Figure 4: Generation of a guidance SoE using the rubber band algorithm based on the minimum and maximum SoE shown in Figure 3. The final SoE has been set to 70% for demonstration purposes.

While recharging, the vehicle shall follow the guidance SoE. The operating strategy recommends a charging power which is proportional to the difference between the actual and the guidance SoE. In the case of the actually available charging power is lower than the required charging power to follow the guidance SoE, the actual SoE falls behind the guidance SoE. In that case, the operating strategy recalculates the SoE prediction and may recommend emergency measures as described in section 3 of this document to the vehicle.

While being on a track section, the operating strategy determines the current guidance SoE value by performing a time-based interpolation of the guidance SoE at the start and the end of the current section. If the vehicle lingers longer than predicted on the current track section, the operating strategy also interpolates the guidance SoE of the following sections according to the current delay and uses that interpolated guidance SoE.

This mechanic ensures proper handling of mutually exclusive charging opportunities on consecutive track sections. Say, for example, there are two chargers available on two consecutive sections 1 and 2, the vehicle arrives at the first track section at $t = t_0$ with an energy level of SoE_0 . The operating strategy predicts the amount of energy E_{total} to be charged during both track sections and distributes it along both charges $E_1 + E_2 = E_{total}$. It also predicts the time spent Δt_{total} distributed along these two sections $\Delta t_1 + \Delta t_2 = \Delta t_{total}$. The energy and time can be distributed arbitrarily between the two sections, depending on the predicted route and the distribution of the time spent at each charging opportunity in the past. If the vehicle recharges on the first charger, it stays longer on the first section than predicted: $t > t_0 + \Delta t_1$. The guidance SoE in that case will be generated from the second section: $SoE(t) = SoE_0 + E_1 + E_2 \cdot (t - t_0 - \Delta t_1)$. If the vehicle would recharge on the second charger instead of the first one, the vehicle arrives at the track section earlier than predicted. In that case, the operating strategy pessimistically assumes the charging duration to be t_2 and will recommend to charge the total amount of energy E_{total} in that time.

When the guidance SoE lies below the optimal SoE of the battery, the operating strategy shifts the guidance SoE slightly towards the optimal SoE of the battery. On sections without a charging opportunity, the vehicle is not able to follow the guidance SoE as the traction energy is not controlled by the operating strategy. However, due to the calculated SoE bounds for each section, a vehicle breakdown is always avoided. Although the guidance SoE trajectory is not necessarily optimal with respect to extreme SoE values, it provides a good heuristic for reducing stress on the battery.

During service operation, the guidance SoE trajectory is recalculated regularly based on the actual SoE of the vehicle and the power demand of HVAC and auxiliary systems. Without the recalculation, the difference between the actual and the guidance SoE would be larger than necessary, leading to a very high power demand when accessing a charging opportunity.

3 Taking Emergency Measures

Knowing the energy demand for the near future allows the operating strategy to detect situations in which the currently stored energy and the next charging opportunities may be not sufficient to perform a service trip reliably, potentially leading to a vehicle breakdown.

HVAC and auxiliary systems make up nearly the half of the overall energy consumption over a year, with up to 70% in summer or winter [24]. Internal monitoring data on real-world city buses also show a share of 50% of HVAC and auxiliary systems in the total energy consumption. That makes reducing the HVAC and auxiliary power a potentially effective way to reduce the overall power consumption in an emergency situation.

After generating the minimum SoE the track sections laying ahead, the minimal SoE of the next track section may be higher than the current SoE of the traction battery. In that case, a vehicle breakdown may happen during the prediction window. The difference between the current SoE and the calculated minimum SoE is the energy deficit which would be needed to avoid a vehicle breakdown. Since the probable time point of the vehicle breakdown can also be estimated, the duration until then and the energy difference form an average power deficit. If the vehicle’s power consumption could be reduced by that power deficit, a vehicle breakdown might be avoided.

That average power deficit translates into a recommended power reduction of heating and/or air conditioning (HVAC), a traction power reduction, or a power reduction of other auxiliary systems. If the vehicle follows that recommendation, the vehicle breakdown may be averted. By considering the longest time interval possible, the average power deficit and therefore the emergency measures come out as small as possible, compromising passenger comfort as little as possible.

As with the calculation of the guidance SoE, the recommended power reduction is recalculated regularly based on the current actual SoE and power demand of HVAC and auxiliary systems. Thus, the operating strategy may intensify the emergency measures if needed.

Figure 5 shows an exemplary course of the minimum and the actual SoE as predicted by the operating strategy. The actual SoE is estimated based on the actual current SoE of the vehicle. Since the actual SoE lies below the minimum SoE, a vehicle breakdown may occur. The exact time point where the actual SoE undercuts the minimum SoE allowed by the battery is also marked in the diagram. The figure also shows the course of the actual SoE if the calculated power reduction is successfully applied. The figure also shows the course of the actual SoE if the calculated power reduction is successfully applied.

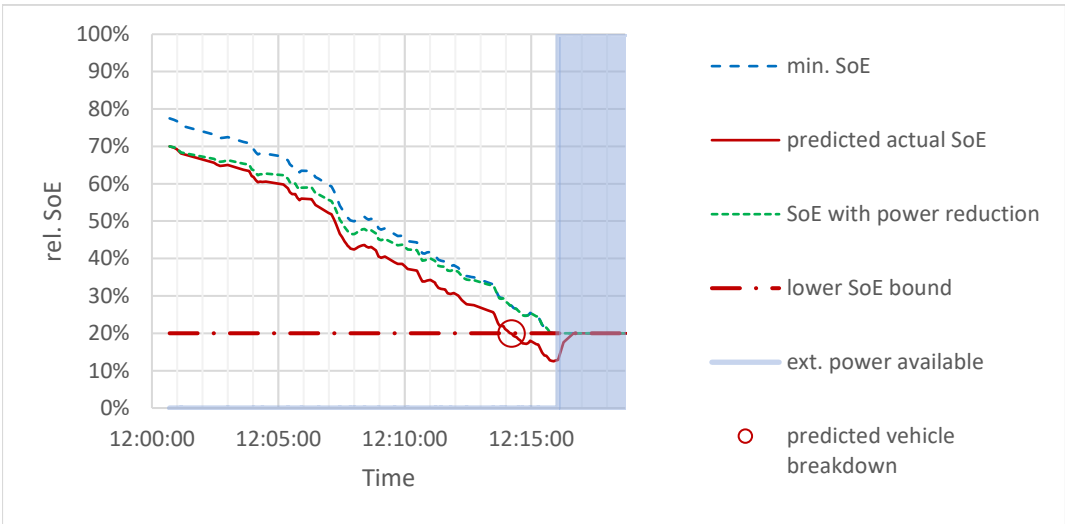


Figure 5: Minimum relative SoE, predicted actual relative SoE, predicted relative SoE with emergency power reduction applied and external power availability over time in case of a potential vehicle breakdown.

Emergency measures without prediction, potentially activated on a critically low SoE or SoC, would detect a potential vehicle breakdown later, therefore requiring more extreme measures to avert the breakdown. While a late detection might force the driver to switch HVAC and auxiliary systems completely off, the predictive approach would only require an adjustment of the cabin temperature by a few Kelvins.

In rare cases where no feasible power reduction may be sufficient to avoid a vehicle breakdown, the driver and the operator may be informed as early as possible to consider further actions.

4 Fleet-Wide Learning

The operating strategy can operate on vehicles without an active internet connection autonomously. However, multiple vehicles of the same fleet can share some of their data so that similar vehicles can learn from each other.

There is a modified version of the operating strategy which can run on a back-end cloud server. Vehicles upload their measurements of the current vehicle state to the server. The server software performs its data processing for the data of all vehicles. As a result, the fleet learning server generates its own database of track sections and routes. The vehicles then download the resulting track sections and routes from the server. This accelerates the learning process because it eliminates the necessity for every vehicle to drive a route to predict the energy demand on that route. Another advantage is the automatic merging of data from multiple vehicles, increasing the overall precision of the prediction.

If, for some reason, the internet connection breaks, the operating strategy on the vehicle falls back to operating autonomously in offline mode.

5 Conclusion and Outcomes

As of writing, the operating strategy is still to be tested in real-life scenarios. For that reason, no experimental statements regarding its ability to prolong the battery lifespan can be made. However, there are ongoing projects in which the operating strategy is being deployed to electric bus fleets.

Many aspects of the operating strategy have been developed and tested using real-world monitoring data from real bus fleets. In particular, the prediction of the vehicle's trajectory as well as the prediction of the state of energy have gone some iterations and improvements using that real-world monitoring data.

6 Further Applications and Extensions

The concept of collecting and using route- or track-related data during service trips leads to new ideas for further improving efficiency and reliability or reducing more costs.

For example, by monitoring the availability of catenary systems, passing a catenary section insulator can be predicted with high confidence. The vehicle may reduce its power consumption and switch to battery operation for a short time to avoid the flash when passing the insulator. Especially hybrid trolley buses have higher power demands on the catenary grid due to the necessity to recharge the traction battery, leading to higher currents and a longer electric arc when passing a section insulator while recharging. While a traditional trolley bus may roll through such a section insulator by not accelerating, a hybrid trolley bus will still consume power from the catenary while rolling. Thus, detecting section insulators early may reduce wear on some parts of the pantograph of the trolley bus.

Currently, fleet-wide learning only works between vehicles of the same type. It might be worth evaluating if there is a data set which can be shared along vehicles of the same fleet with different types. For example, different buses of different sizes might have different energy consumptions on a track section, but routes and the order of track sections might be shared.

The operating strategy only considers a single vehicle when generating a SoE trajectory. Having a bus schedule in combination with the predicted energy demand of each vehicle available on a server application may allow generating optimal SoE trajectories for a whole fleet. An operating strategy could reduce the peak load on the energy grid by scheduling charging operations. Thinking this further, the operating strategy could schedule charging operations depending on estimated energy prices, leading to lower costs during operation.

Based on monitoring the energy demand of track sections, an algorithm may generate evaluations or recommendations on ecological driving to operators and bus drivers. Also, monitoring track-section-specific energy demands of vehicles may open many opportunities for predictive maintenance.

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Presenter Biography



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