33rd Electric Vehicle Symposium (EVS33)
Portland, Oregon, June 14-17, 2020

Delivery routes and charging profiles for electric vehicles in logistics fleets

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Summary

Delivery traffic becomes more and more focus in projects, that deal with the transformation of drive-train technologies. Within the Germany-wide research project *ZUKUNFT.DE*[1], the simulation tool and user interface ”Load Profile Generator (LPG) for electric vehicles in logistics fleets” was created. The tool was developed to determine the current needs of conventional logistics fleets, which operate on the so-called ”last-mile”. The individual electrification potential of battery electric delivery vehicles and the respective load profiles represent the main results.

Keywords: BEV, charging, fleet, freight transport, simulation

1 Introduction and state of the art

1.1 Introduction

Within the last two decades, the sending volumes in German road transport of goods have increased significantly. According to [1] and [2] the number of parcels is predicted to keep rising - especially in the Business-to-Customer (B2C)-sector. Companies in the CEP (Courier, Express, and Parcel) market are already facing frequent challenges due to growing expectations of private customers (overnight and same-day delivery) and seasonal fluctuations in sending volumes [3]. This is accompanied by the ongoing efforts to ensure environmentally sustainable development of the transport sector. Additionally, special efforts are made to reduce local emissions in urban agglomerations. In 2011, the European Union already set the objective that urban logistics will drive CO_2-neutral by 2030 and to create the respectively needed

[1]This work is sponsored by the research project ”*ZUKUNFT.DE*” within the funding guideline ”Elektromobilität” funded by the German Federal Ministry of Transport and Digital Infrastructure (BMVI)

infrastructure for alternatively driven vehicles [4]. Thus, numerous projects and works have been initiated that deal with the electrification of commercial or logistic vehicle fleets (s.[5],[6],[7],[8]). The project *ZUKUNFT.DE* does not only focus on the fleets' electrification but also advances vehicle concepts as well as the innovative energy supply of CEP companies' depots (location where the vehicles are loaded with parcels). To simulate user-defined load profiles and provide an initial assessment of the local charging infrastructure at the CEP's location, the user-interaction model LGP for logistics fleets is being created. The present work is a further development of the Load Profile Generator for Electric Vehicle Home Charging (s.[9]).

1.2 Background on parcel delivery

It is commonly known that by ongoing globalisation and digitalisation, more purchasing processes are done online and delivered by one of the traffic modes. More and smaller parcels are to be delivered [2]. In transportation planning, traffic performance within logistics fleets describes the number of delivered parcels combined with their respective transport distance. From 2000 to 2017, the traffic performance in Germany increased by 30 % in freight transport compared to 15 % in passenger traffic [10]. Besides, the modal split within freight transport has been proven to be constant in the last years [11]. In the road transport of goods, it is to be distinguished between long-distance transports and the last-mile. Usually, the transportation chain from sender to recipient runs in three (or more) stages. The first and last stage (last-mile) is conventionally being processed with light-duty vehicles of up to 3.5 t total weight. They usually run in round trips on a daily basis sending out and collecting parcels on their respective route. In between, there are heavy trucks running long distances and bundling large freight. In Germany, CEP companies deliver parcels of up to 31.5 kg on the last-mile [3].

On the last-mile of delivery traffic, there are numerous and constant optimisation approaches in order to operate as efficiently as possible in terms of delivery routes. Furthermore, there are current innovative logistics concepts to improve processes, such as collaboration between companies, urban micro depots or crowd delivery, which are discussed and tested [12],[13]. This way it is intended to minimize fix costs or to cut the number of necessary routes to deliver the incurring sending volumes.

Besides, current political intentions of the European Commission and the German Government require the promotion of alternative fuels for delivery vehicles [4],[14]. Recent projects (e.g.[7],[15]) focus on the battery-electric drivetrain in the vehicle concepts as it is seen as the most promising technology in logistics [13]. Furthermore, electrifying the logistics fleets is discussed as the most likely innovation besides the so-called "micro depot" [16].

Regarding the daily trip distances of logistics fleets, it is seen that - depending on the location of the CEP depot - up to 90 % of all routes are shorter than 80 km which is within the range of current battery-electric light-duty vehicles (120-180 km) [13]. However, real energy consumptions mostly tend to differ from the nominal value given by the manufacturer which is why the simulation of the electric range should be modelled in sufficient detail (see [17]). There is also a general difference in rural last-mile routes which can have a length of up to 300 km per day [1]. Accordingly, electric vehicles in CEP fleets are expected especially in more urban areas. There they can also contribute to noise reduction and thus may extend the delivery hours, which allows to avoid delivery during times with heavy traffic [4]. In [13] it is stated that electric vehicles have the potential to completely replace conventional combustion vehicles in CEP fleets in the case that they have a load volume of more than 12 m^3 and a load weight of at least 1.000 kg.

2 Scientific approach and simulation model

This work was carried out as part of the funded research project *ZUKUNFT.DE* that aimed at the electrification of the last-mile in Germany's road transport of goods - with a special focus on urban agglomerations. Within that project interviews with responsible employees of four big participating CEP companies were conducted. These interviews should serve as a source of knowledge for the definition of delivery routes and help to deduce the charging behaviour of electric vehicles for various logistics fleets. In addition, the operating vehicles were equipped with GPS loggers, which tracked the delivery operations for two weeks in October 2019. This GPS data was used as a database for the replication of delivery routes on a yearly scale. To collect the input data for the delivery routes a user interface is created using the Matlab App Designer. The interface allows the user to enter very specific relevant operational characteristics of the fleet and the logistics depot. These characteristics are used in the model both for the range simulation of the electric vehicles and the delivery route modelling. The latter is done by creating a given number of delivery routes for each operating day and assigning the appropriate characteristics, such as route length, topography, and load weight according to the user's input. Hence, range simulation of the electric vehicles is implemented route specific regarding each route's respective driving requirements. Therefore a process is developed which assigns the vehicles of both BEV models to routes in a way that maximizes the usage of the electric vehicles. As a result, all delivery vehicles are assigned to a route for each operating day which results in vehicle-specific, yearly mobility and location profiles. Based on the location profiles and a load curve that describes the battery charging process, individual load profiles are generated. For a final consideration, these are aggregated to a total fleet load profile. Fig.1 demonstrates the concept of the scientific approach of this work.

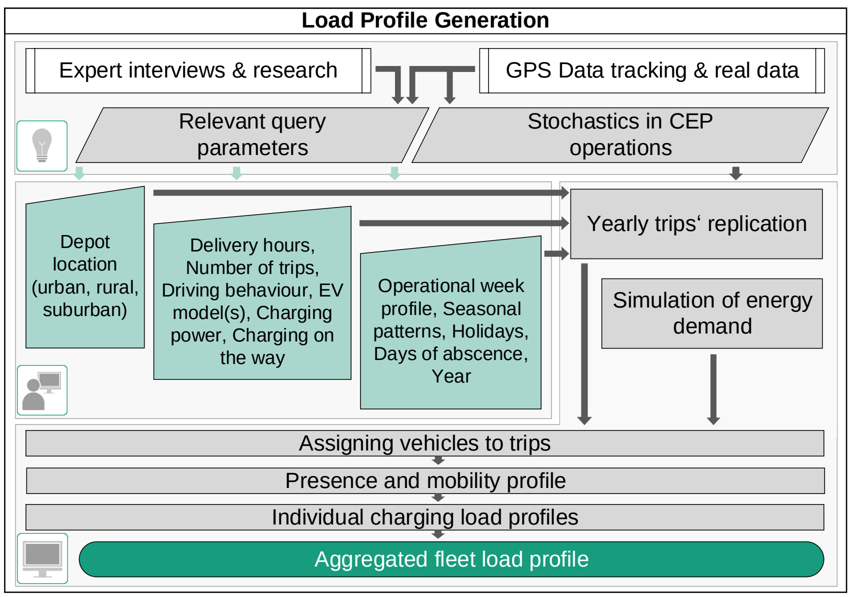

Figure 1: Methodology of the Load Profile Generator (LPG) for the use case of last-mile vehicles in CEP fleets

2.1 Data basis

2.1.1 GPS data

The vehicles' mobility behaviour is derived both from collected GPS data and expert interviews that were conducted with responsible employees of 8 logistics depots spread throughout Germany. The results of the expert interviews contribute to the configuration of the query parameters of the user interface. The GPS data, that has been used for this work, was tracked in October 2019 among 27 light-duty vehicles in daily use over a period of two weeks. Information regarding stopping times, speed and coordinates were collected and processed to daily delivery routes. For plausibility checks, routes with a length of fewer than ten kilometres are not taken into account. In order to determine the statistical distribution of the delivery stop duration, stops with a duration of fewer than 90 seconds are not considered, since it can be assumed that they are due to the traffic situation and do not constitute delivery stops. Besides route length, further parameters such as vehicle speed, delivery stop duration, and the stochastics, in general, are used as validation basis for the LPG.
In general, information on driving behaviour is derived from GPS data. Examples may be the standard deviation of departure times or daily route duration. Fig.2 displays the distribution of route length of all the tracked routes. The respective kernel density estimation is remodelled in the LPG.

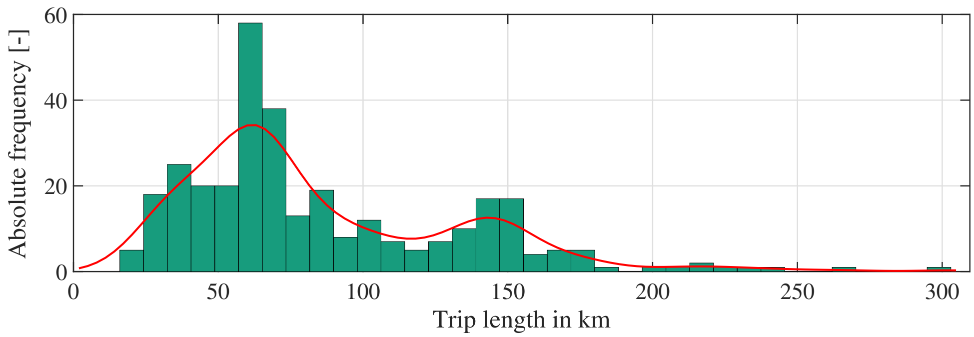

Figure 2: Distribution of daily delivery routes tracked with GPS loggers (n=318)

2.1.2 Vehicle models

Four electric vehicle models are considered for the simulations in the LPG. Three of the light commercial vehicles have a permissible weight of up to 3.5 t and one of them up to 7.5 t (s.Table 1). However, the user can create his very own vehicle model and save it under any name.

Table 1: Considered light commercial vehicle models

BEV	Nom. battery capacity (kWh)	Nom. energy demand (kWh/100km)	Max. charge power (kW)	Load volume (m^3)	Max. load weight (kg)
A	35.8	21.5	7.4 (40)	10.7	975
B	55	32.5(-37.1)	7.2	10.5	900
C	41	20.5(-24.9)	7.2	6	1016
D	62	50	7.4	23	3060

2.2 User interface of the Load Profile Generator (LPG)

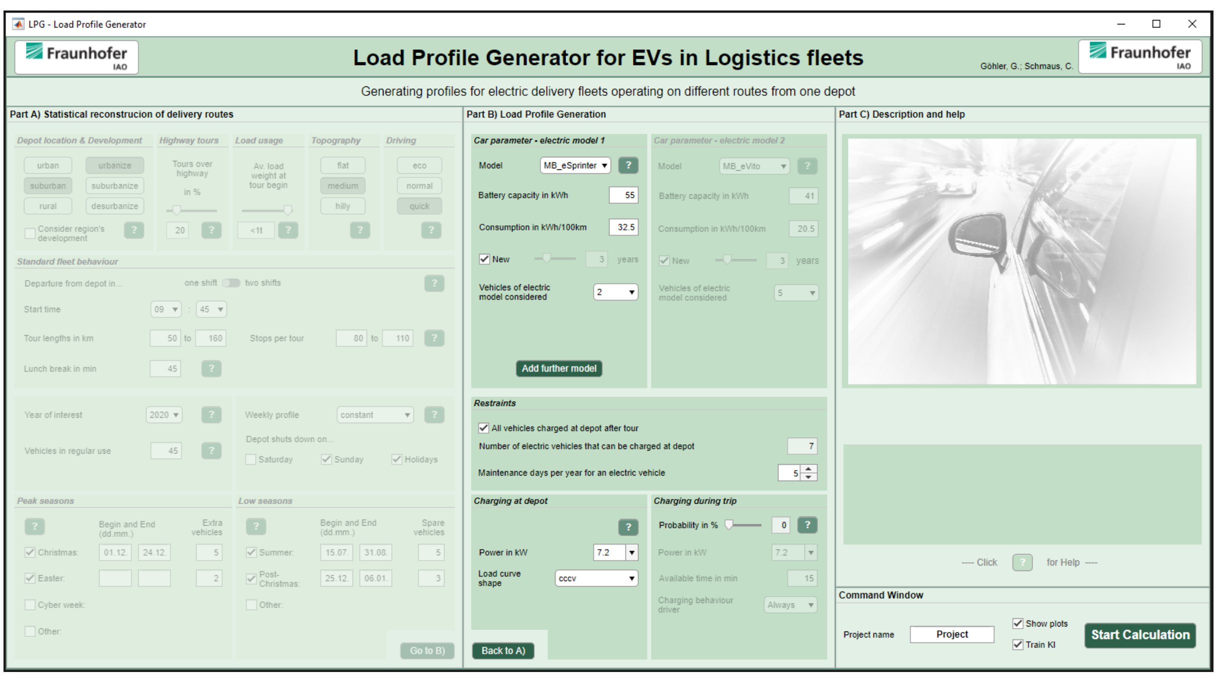

Figure 3: User interface of the Load Profile Generator for logistics fleets

The user interface of the LPG is split into three parts of which two (A&B) are meant for user input whereas the third part (C) serves as user interaction and help window. Part A allows the user to reproduce the operation of the fleet during the year. Based on a categorisation of the depot location, the LPG asks for the standard behaviour of the logistics fleet including the duration of the route, the number of stops per route, the starting times and the overall driving behaviour of the assigned drivers. Besides, it allows to model the daily and seasonal deviations from this standard behaviour regarding the sending volumes.

In part B the characteristics of electric vehicles are entered. Four different vehicles are available, whereas the LPG enables to create a user-defined model and determine all the relevant vehicle parameters individually. Also in Part B, the user selects the charging power as well as one of the charging curves or again creates a user-defined one. Additionally, the LPG is capable to consider charging processes that take place outside the depot on the vehicles' routes (e.g. at public charging stations). In this case, the user can determine the probability to charge during the route and the relevant parameters such as duration and electric power. Fig.3 displays the user interface of the Load Profile Generator.

2.3 Overall delivery route modelling

In the simulation, the model first recreates the set of daily delivery routes. This set - whose number of routes is user-defined - serves as the basis for modelling the operational course of the whole simulation year. Simulating the yearly delivery operation is done by assigning eight properties to each route of the year depending on the user's input. Table 2 contains all of the route properties and their respective value options. Properties "Highway", "Infrastructure", and "Topography" are constant for each route in the yearly course instead of changing from day to day.

Table 2: Properties of modelled CEP routes

	Property	Model values	Unit
1	Route length	[min, max]; min,max $\epsilon\mathbb{N}$	km
2	Route start	[min, max]; min,max ϵ[00:00,11:45]	hh:mm
3	Highway	{yes; no}	-
4	Infrastructure	{urban; suburban; rural}	-
5	Topography	{flat; medium; hilly}	-
6	Load weight	{<100; <250; <500; <1000}	kg
7	No. of stops	[min, max]; min,max $\epsilon\mathbb{N}$	-
8	Charged energy	[0, max]; max $\epsilon\mathbb{R}^+$	kWh

The properties 1 (Route length), 2 (Route start), and 6 to 8 (Load weight, No. of stops, and Charged energy) are subject to certain stochastic deviations and are not consistent neither for each route nor on every operating day. However, property 8 (charged energy while driving) only assumes values greater than zero with a certain probability. Routes, where no charging processes are considered, have the constant value zero in property 8.

Given the start time of each daily delivery route and its duration, the arriving time can be calculated accordingly to the respective property values. This way the route duration is calculated in a very precise way and follows equation 1. The time of each delivery vehicle returning to the depot is calculated by adding start time and route duration. It is assumed that the electric vehicles are plugged in for charging immediately after returning so that the arriving time equals the start point of the charging process.

$$T_{tot,r,d} = \sum_{n=1}^{s-1}(T_{stop,n} + \frac{S_{in,r,d}}{s-1} \cdot \frac{1}{\bar{V}_{in,r}}) + T_{stop,s} + \frac{S_{out,r,d}}{\bar{V}_{out,r}} + T_{city,r,d} + T_{hw,r,d} + T_{lunch} \quad (1)$$

$T_{tot,r,d}$: Total duration of route r on day d in h
$T_{stop,n}$: Duration of stop n on route r in h
$T_{stop,s}$: Duration of last stop s on route r in h
$S_{in,r,d}$: Route length within service area of route r on day d in km
$\bar{V}_{in,r}$: Av. speed on route r within the service area in km/h
$S_{out,r,d}$: Distance from depot to service area of route r and back on day d in km
$\bar{V}_{out,r}$: Av. speed on route r outside the service area in km/h
$T_{city,r,d}$: Stochastic extra time for city route r on day d in h
$T_{hw,r,d}$: Stochastic extra time for highway route r on day d in h
T_{lunch}: Duration of lunch break in h
s: No. of delivery stops of route r on day d

According to the results of the interviews carried out within the research project, the route durations may vary due to daily and seasonal fluctuations not only on a stochastic but also on a systematic base. This is mainly reflected in the number of delivery stops per route and the load weight. Thus, the LPG allows the selection or creation of a weekly intensity profile, which represents the deviation of the sending volume of the average for each weekday. Also, the seasonal impact affects the sending volumes and thus the number of stops and load weight. As an example, the pre-Christmas season is regarded as a period of significantly higher sending volumes according to the interview partners. This can, depending on the user input in the LPG (”Extra vehicles”), be reflected in the number of driving vehicles as well (see Fig.3).

2.4 Electric range simulation

In order to systematically assign delivery routes to the available electric vehicles, the electric range has to be modelled in a precise and route-specific way. Therefore, this section deals with the simulation of electric range taking into consideration some of the route properties as well as driver and vehicle characteristics. Based on the nominal values for energy demand $E_{v,n}$ and battery capacity $C_{Nom,v}$ the theoretical range can be calculated. Yet, this usually proves not to be achievable in practice. Numerous parameters have an impact on the energy demand of electric vehicles. Table 3 displays all the parameters that are considered for the route specific energy demand.

Table 3: Values of energy demand’s influence parameters and their respective factors for demand calculation

Property	Characteristics	Demand factor	Values of f	Reference
Route territory structure	{urban; suburban; rural}	$f_{city,r}$	{0.97; 1.082; 1.164}	[17]
Highway	{highway, no highway}	$f_{hw,r}$	{1.148; 1}	[17]
Topography	{flat; medium; hilly}	$f_{topo,r}$	{1; 1.03; 1.06}	[18]
Load	$\{<100kg; <250kg; <500kg; <1t\}$	$f_{load,r}$	{1; 1.03; 1.06; 1.12}	Simulation
Av. Temperature T	$-0.3°C < T < 18.1°C$	f_{temp}	$1.374 > f_{temp} > 1$	[17],[19]
Driving behaviour	{eco; normal; quick}	f_{drive}	{0.91; 1; 1.15}	[17]

Equation 2 shows that each parameter is given - depending on its respective value - an isolated demand factor that realistically represents the energy demand. The demand factors are partly selected and adapted precisely from other studies and partly simulated with the Simulink toolbox Qss. This is a toolbox for the backward quasi-static modelling and simulation of ”Hybrid and Electrical Power-trains” (HEP). It is assumed that the influence parameters affect the energy demand of all electric vehicle models equally.

$$E_{v,r} = E_{v,n} \cdot f_{hw,r} \cdot f_{city,r} \cdot f_{topo,r} \cdot f_{load,r} \cdot f_{temp} \cdot f_{drive} \tag{2}$$

$E_{v,r}$:	Electric energy demand (route specific energy demand) of vehicle v on route r in kWh/100km
$E_{v,n}$:	Electric energy demand of vehicle v due to NEDC in kWh/100km
$f_{city,r}$:	Demand factor for city driving on route r
$f_{hw,r}$:	Demand factor for highway driving on route r
$f_{topo,r}$:	Demand factor for topography on route r
$f_{load,r}$:	Demand factor for load weight on route r
f_{temp}:	Demand factor for temperature
f_{drive}:	Demand factor for driving behaviour

Proceeding from the route specific energy demand to the respective electric range, the State-of-Health (SOH) and the usable part of the nominal battery capacity η_{Use} is taken into consideration as well. Here, η_{Use} is assumed to be a constant value of 0.95 whereas the SOH varies with the age of the vehicle according to [7]. It is mentioned that all electric vehicles within one model are considered to be equal in all relevant parameters such as age (SOH) and energy demand.
Thus, the electric range for the considered electric vehicle models are determined route specifically with equation 3.

$$S_{R,v,r} = C_{Nom,v} \cdot \eta_{Use} \cdot SOH_v \cdot \frac{1}{E_{v,r}} \tag{3}$$

$S_{R,v,r}$:	Calculated range of vehicle v regarding driving demands on route r in km
η_{Use}:	Usable part of nominal battery capacity
$C_{Nom,v}$:	Nominal battery capacity of vehicle v in kWh
SOH_v:	State of Health of battery in vehicle v
$E_{v,r}$:	Electric energy demand of vehicle v on route r in kWh/100km

Knowing the route specific range demand and the range of the electric vehicle models, it is further systematically implemented a decision logic that assigns the electric vehicles to routes in a way that maximizes the usage of the electric vehicles (see Fig.4). Hence, the list of routes is sorted according to priority and route length. This is done in a way that aims to ensure that the longest possible routes are driven electrically. Decision variables are the availability and range of both electric vehicle models as well as the relation of both models' theoretical range. These variables are processed to binary states, so each decision variable can be specified by two different states. The systematic approach of the assignment of routes then determines the electric vehicle model with the lower theoretical range in a first step and is compared with the range demand for the respective route. Therefore, a safety margin range of ten kilometres is taken into account. In the case that the range of the smaller vehicle model is sufficient, its availability is verified. If there are vehicles available, one of them will perform the respective route and the number of available vehicles is decreased by one. If there was no vehicle available, the same consideration would be done for the vehicle model with the longer theoretical reach. Only in the case that there is also no vehicle of such model available, the route is driven by a conventional vehicle (ICEV). An alternative reason for a route being driven by an ICEV is a range demand that exceeds the theoretical range of both electric models. This general process is conducted for each route on every operating day within the simulation year. Fig.4 displays this decision logic on the vehicle assignment.
As a result, each vehicle receives an allocation of delivery routes for the entire year and thus a binary location profile in the logistics depot. According to the interview results mentioned in section 2.1.1, vehicles conventionally and mostly drive on the same route each day. This is taken into account and is used for validating the decision logic as well as the model parameters. The location profiles are then linked to the selected charging curve and charging power in order to generate the individual vehicle load profiles for the simulation year. It is important to know the initial SOC at the beginning of the charging process, which is done by subtracting the consumed energy from the battery capacity. If the vehicle has been enabled to recharge during the route, the charged energy is added accordingly.

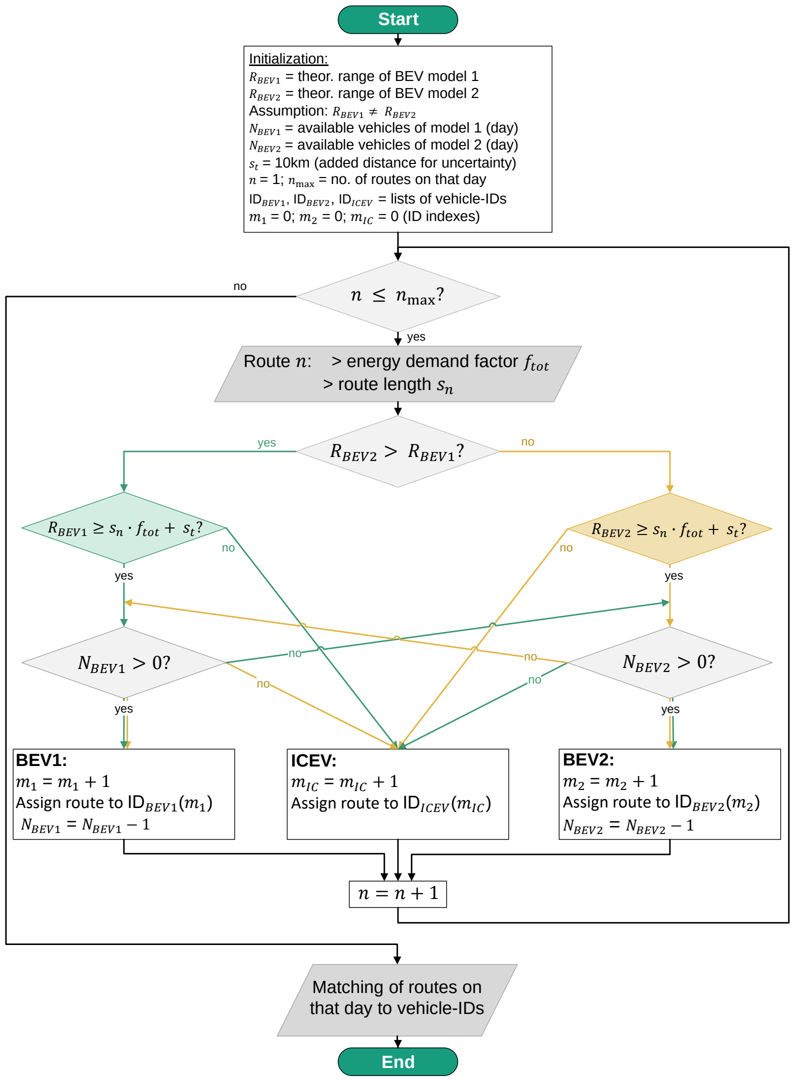

Figure 4: Systematic decision logic in order to maximize the usage of the electric vehicles

3 Simulation results

3.1 Case study

For exemplary results, a specific logistics depot in Germany is chosen, which is cooperating in the research project. In the following, the characteristics of the depot are described, which are based on the interview results with the depot's running employee. Being located near one of Germany's ten largest cities, the depot is using between 40 and 45 vehicles in the everyday operation with a backup of about five to ten vehicles. Usual route lengths are said to range from 50 to 160 km. Some of the routes lead to another city closeby with more than 100k residents. Those routes run along a heavily trafficked motorway which is said to frequently cause delays in the delivery service. Scheduled departure times in the morning are between 09:30 am and 10:00 am with arrival times between 4:00 pm and 6:00 pm unless there are any significant delays or highly intense operating days with high sending volumes. The operational weekly course is created user-defined with its peak on Tuesday and Wednesday whereas Mondays and Saturdays have low sending volumes. Pre-Christmas season is stated as a significantly more intense period, whereas the summer holidays tend to show much lower sending volumes.

Within the project, seven electric delivery vehicles are already being used and tested, five of them are from type C and two of type B (see Table1). In the following, the simulation results, according to this case study, are presented as one exemplary use case of the LPG.

3.2 Electrification potential

An interesting analysis before generating load profiles for electric vehicle fleets is supposed to be the examination of the electrification potential. For each specific use case, the Load Profile Generator can visualize simulation results of how many yearly routes can be driven by the considered electric vehicle models as well as which delivery routes are beyond the electrification potential. Fig.5 shows simulation results for the presented case study. The sum of all routes is the yearly basis of all delivery routes simulated (turquoise bar). It includes the routes driven by electric vehicles as well as ICEV-routes. Secondly, it is displayed what routes can be driven by the specific electric vehicle model regarding the route-specific energy demand and neglecting the number of actually available vehicles of this model (green bar). Thus, the user gets direct insight into the usable route lengths for the chosen vehicles. The red bar shows, how many routes are already driven by electric vehicles in the simulation case. Both the red and green bars are displayed for each vehicle model respectively.

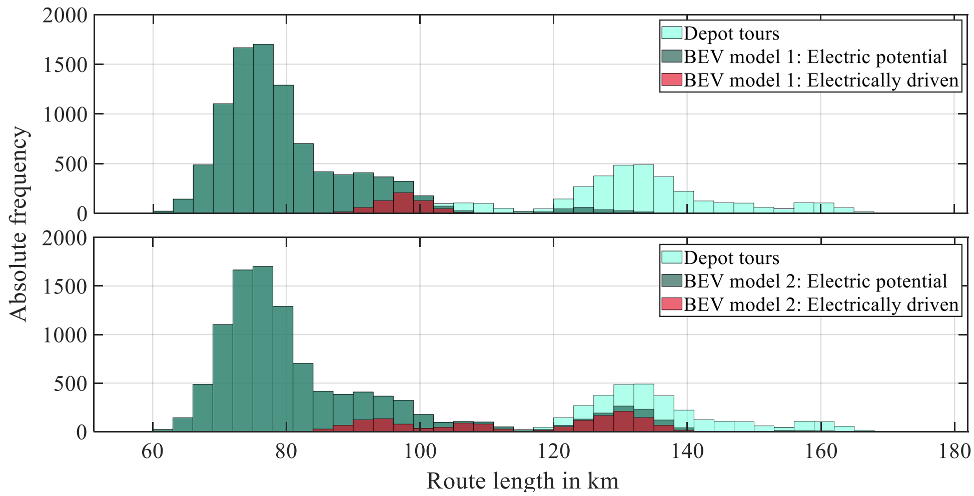

Figure 5: LPG results on the electrification potential in the case study

In this particular simulated case, it is clearly visible that a high number of yearly driven routes are inside the electrification potential. Here, there are two vehicles used in model 1 (upper plot) and five vehicles in model 2 (bottom plot). The logistics fleet can be expanded by a large number of further electric vehicles. Especially, many short routes with a length between 60 and 80 km can be driven electrically with further BEVs. For specific projects, these results can be used to analyse the maximum plausible number of electric vehicles. After this is done, the load profiles for this number of vehicles can be examined.
Fig.6 also displays the route length but additionally includes the respectively simulated energy demand normalized by the manufacturer's nominal demand. Each point is a simulated route and its colour provides information on the assigned vehicle's drivetrain technology. For each route that is driven with an ICEV, the consumption ratio is the theoretical energy demand that would be necessary when being driven electrically. This insight can be helpful when an increase of the electrification potential is desired. Route-specific scatter points need to be shifted to a location underneath the limit of the electrification e.g. by measures such as driving behaviour. Besides, real sample data of the case study depot is shown in Fig.6 illustrating that in fact, vehicles are still driving shorter distances than actually possible due to range scepticism.

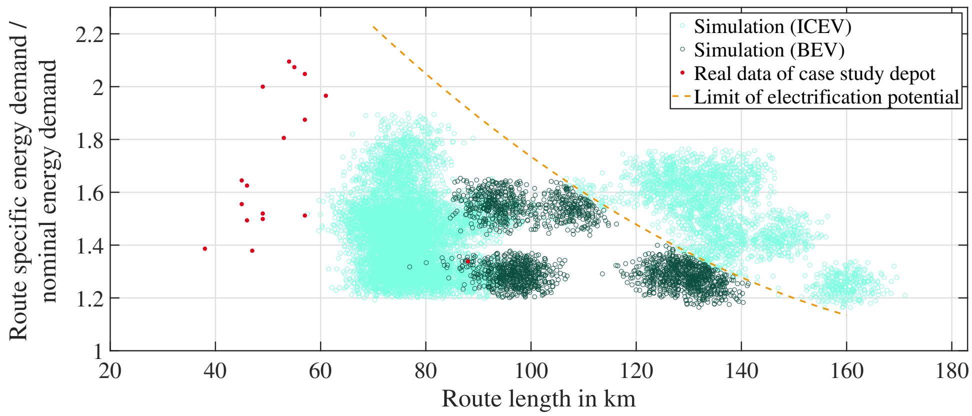

Figure 6: Simulation results and real data on route length and consumption - as well as the electrification potential of the simulated vehicle models

3.3 Load profiles

The load profiles are generated for the whole simulation year in time steps of five minutes. Fig.7 displays fleet load profiles of the LPG which are averaged over a number of weeks. Since single weeks do not give representative results, this is done for each respective season's duration in summer (low season) and early winter (peak season). Basically, load profiles for electric mobility in CEP services specify quite constantly in their overall shape since the delivery services are based on the conventional and constant logistics concept. For energy system planning it's relevant to know what is the absolute value of expected peak loads and for how long these peak loads usually occur. Also, it is key to see when peak loads are to be expected. Generally, peak loads are seen in the early evening and they mostly reach values slightly lower than the theoretical maximum power. Moreover, there is no significant change to be noticed between low and peak season regarding the peak loads (s. Fig.7). The fact that peak loads remain almost unchanged in this analysis is due to the fact that higher sending volumes are based on a greater distribution of arrival times.

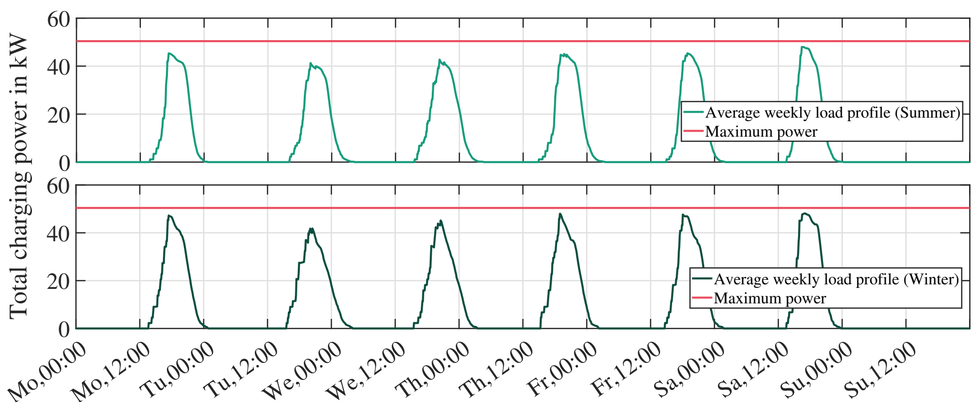

Figure 7: Mean weekly fleet load profiles in low summer season and peak christmas season

In this application case, it is shown that the days Tuesday and Wednesday on average lead to lower peak loads compared to the other days. These days are modelled as most intense regarding the sending volumes and delivery stops. Also, the duration of the respective peak loads is seen to be shorter in peak season than in low season. These effects result from a higher distribution of vehicle arrival times on long working days. Besides this, there are several operational actions that can be done in order to make the load profiles of uncontrolled charging less demanding for the power grid. Some of them, which can be validated with the LPG, are discussed in the following section.

4 Conclusion

The LPG can be used for the electrification of last-mile delivery traffic. Various vehicle models are already available for the electrification of the vehicle fleet. Further models can be configured and saved for individual planning of the logistics fleet. For each individual case, the electrification potential and the resulting load profiles are examined in the tool. The simulation shows that most of the routes of a logistics fleet can already be carried out with electric vehicles today. In the simulated case study it is seen that high peak loads - usually close to the theoretical maximum power - should be expected. Therefore an individual planning of the infrastructure at the logistic location is essential. Changing the charging curves does not significantly change the peak loads compared to a simultaneous charging of all vehicles with maximum power. The winter peak season and the weekdays with high sending volumes lead to slightly lower peak loads. Investments in the electricity grid at logistics depots are to be minimized while electric mobility is to be expanded. According to various simulations with the LPG, we can conclude the following 3 suggestions:

- **Vehicles leave the depot in two shifts:** Where it is common to have one scheduled point of time to make the delivery vehicle leave the depot, it can be helpful to split the departures into two equal shifts. Thus, electric vehicles' arrivals are spread over a longer period of time and thus the charging peaks occur with a lower probability. Also, less space is needed for loading delivery vehicles at the same time.
- **Lunch break is used for recharging:** A minimum of 45 minutes is mandatory for a drivers' lunch break in Germany. If there is the possibility that this time can be used for recharging the electric vehicles, less energy needs to be charged in the evening when all vehicles return to the depot. Possible charging points may be companies with charging infrastructure or public charging stations.
- **Load Management:** Light-duty vehicles that are now available can be charged with a maximum power of 7.2 kW. Yet, in order to keep the peak loads at a low level, the charging power can be limited to 3.7 kW. Simulations in the LPG will show that there is enough time for reduced charging power to fill up the vehicles' batteries until the next day of delivery. Alternatively, power throttling or an intelligent load management system can serve as a measure for peak shaving.

We consider that in the representative exemplary depot, a high percentage of the yearly depot routes can be driven with the selected electric vehicle models B and C. Yet, there are routes that exceed the range of currently available vehicle concepts.
On the one hand, this leaves the potential for further research and development of new light-duty vehicle concepts with larger batteries.
On the other hand, modifications of the route planning and innovative logistics concepts enable an even higher percentage of last-mile routes being driven electrically. Numerous approaches are found that minimize and optimize the route distances in CEP services. Moreover, logistics concepts such as the micro-depot are currently being discussed and shall not be ignored in this context.
Finally, this can also be supplemented by measures that lower the actual energy demand of the existing vehicles, for instance a more economical driving behaviour.

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