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Supporting E-mobility Users and Utilities towards an Optimized Charging Service

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Abstract

In this work we describe the brokerage function between electric vehicle users searching for a charging spot and the charging stations providing the charging service. Matching supply and demand requires an interdisciplinary understanding of both the mobility of electric vehicle (EV) users and the load balancing mechanisms, at the charging station level as well as at low voltage grid level. As a result of a mobility study, we propose in this work a routing service for locating and reserving charging spots. Further, we extend the search for charging stations from a destination-neighborhood to public transportation node neighborhood in a multimodal route (using driving, walking, public transport) and evaluate the number and quality of solutions.
Further contributions address the load balancing functionality at the charging station and the low voltage grid level. In the proposed decentralized architecture charging stations control the charging of individual vehicles. We argue for the introduction of a bidirectional interface between the charging station and the DSO, and show how available power for charging stations can be dynamically calculated.

Keywords: e-mobility, EV routing service, multimodal route optimization, charging station, controlled charging, power flow calculation

1 Introduction

In 2011, the normal, gasoline car driver did not notice much of the long awaited and much discussed electro-mobility on the roads. Critics argue that, even if the electric vehicles (EV) were available and affordable, the most probable scenario, that of ”charging overnight at home”[8][9] fails to address some large user groups, such as residents of urban areas without own garage, vehicle fleets, vehicle with higher mileage, etc. In this work we address these type of use cases, in which EV-users are dependent of public charging stations.
A systematic study provides several approaches to tackle ”EV charging loads” in a spatial (geographic) and temporal dimension. The geographical aspect is related to the mobility model: a solution approach is to search for available energy in charging stations near the user's activity places, or to search for less congested charging stations. We show that the latter problem which is relevant in urban regions can be solved by suggesting multimodal routes (drive, walk, use public transportation).
The temporal aspects arise when the distribution network operator together with the charging station owner (a new actor in e-mobility) are trying to flatten the load peak and delay in this way investments in grid enhancement. The solutions investigated in this work are: controlled charging (that is an optimized scheduling of EV-charging tasks using time windows), and the LV-grid grid level computation of the available power at each charging station.
The addressed problems are not entirely new, but the interdependence between geographical allocation of charging tasks through optimized routing and the load distribution effect on local grids has to our knowledge not been addressed sofar.
The work is being performed within the national (austrian) project KOFLA [1], in the new mobility programme ”ways2go” and the results are currently tested in a lab environment.

The rest of the paper is organized as follows: in Section 2 we present relevant results from mobility studies in Austria. Section 3 describes the scenarios that lead to the design of a routing service, the interactions between EV-user and the service. Section 4 extends the scope of the routing service to multimodal trips mainly in cities. Section 5 proposes and argues in favor of decentralized charging architecture, which integrates the aforementioned routing service. Section 6 shortly presents the scheduling of charging tasks at the charging station and Section 7 describes the load balancing approach at the low voltage grid level. Finally, we summarize the contributions in Section 8.

2 The New Mobility

Mobility studies of Lower Austria [2] and Vorarlberg [3] show that no mobility pattern changes are expected with the introduction of e-mobility, if we can assure that charging stations are available at the activity stops and if charging is seamless and supported by ICT systems. The average length of one trip is about 16 km, and a person makes on average 2,9 trips per day by car. This leads to a day-trip length of around 46 km for passenger car drivers, which is much less than the driving range of modern electric vehicles, for all except for 2% who need to drive more than 100km per day (see Figure 1). The curves in Figure 2a) show the trip length until the next destination and the trip length since last charging. The model assumptions are: starting in the morning with full battery, full battery capacity is 20kWh, discharge rate 0,2 kWh/km, charging intensity 0,06 kWh/minute, charging is done always if the stop duration is larger than 30 minutes, so that the average trip length between charging stops is around 15 km.

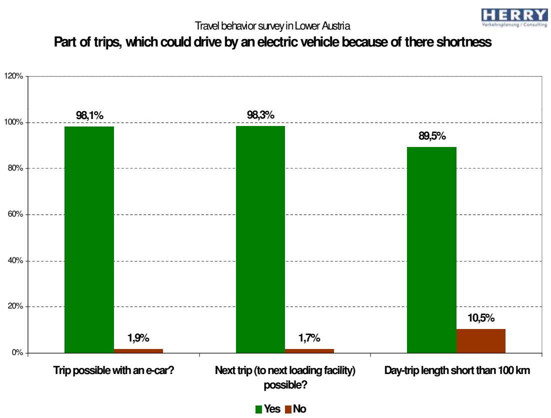

Figure 1: Feasibility of trips with EVs

In Lower Austria the duration of stay at a destination is approximatively three hours, if we build a weighted average over the user activities (see Figure 2b). This enables a 50% recharge (full normal charging is achieved in around 300 minutes). But the average duration of stays at destinations are different during the day. A full charge is possible if a person arrives in the morning (mostly workplace) or in the evenings (mostly residence) at destination, because the person will be at destination for 350 minutes in average. Between 10:00 am and 05:00 pm the average duration of a stay is around 200 minutes.

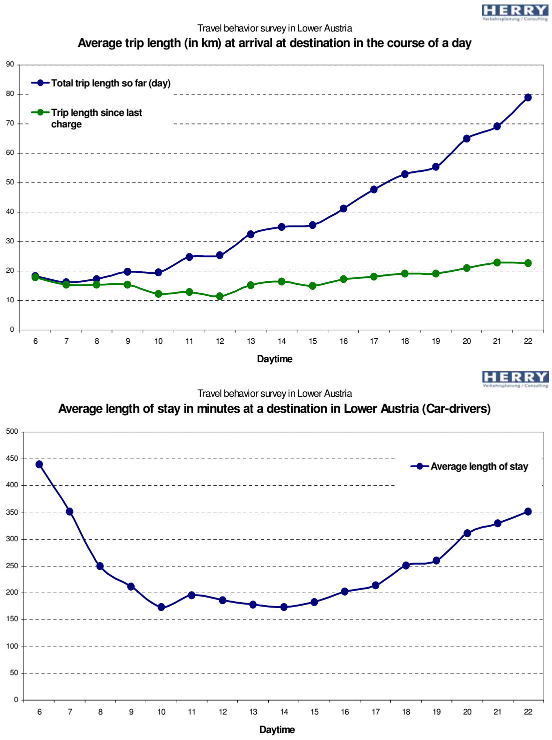

Figure 2: a) Average cumulative trip length (in km) during the day, b) Average stay duration (in minutes)

3 A Routing Service for EV-users

3.1 Routing Scenarios

There is no need to fully charge the battery at once. In order to learn from the user behavior we analyzed the charging pattern of company and private users, that participated in the pioneering e-mobility project VLOTTE in Vorarlberg, Austria [15]. Interestingly, in 44% of the charging stops only 10% of the battery was charged. In only 4% of the stops, the users charged 50% of their battery at once. Thus, the early perception that e-car users, similarly to gasoline car users, will charge when the battery becomes empty, has changed. We have found that charging is to be subordinated to the real activity of the user at the next stop in the daily trip. We propose to support the user before and during the trip by the use of a simple telematics application to search and reserve a charging spot situated in the vicinity of the destination, reducing in this way the so called user range anxiety. A simpler service proposed by the standardization group in ETSI is called charging spot notification [14] and is based on

broadcasting charging spots in the current vicinity of the vehicle.
A careful use case analysis shows that EV-users require better access and control on the information about charging spot availability:

- to query anytime the availability and characteristics (see below) of the charging stations in the vicinity of the destination
- to initiate a booking (reservation) on a selected charging station
- in case no available charging spots are found to get notified when a charging spot becomes available
- to search around the current location in emergency case (traffic jam, unexpected energy consumption because of heating, cooling etc.). The search could be triggered automatically by context information.

The combined user dialog corresponds to the state diagram in Fig.3. In order to avoid abuse,

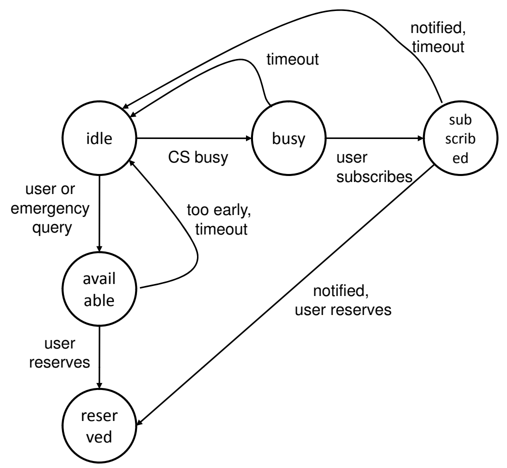

Figure 3: State diagram associated with the EV-user dialog

the reservation (of a charging point and a time slot) cannot be done earlier than a certain duration before the arrival.

3.2 EV-User Dialog

In order to realize the interaction pattern above, we propose an application protocol between car and the routing service running over a wireless data channel. The communication networks current available are the cellular networks GSM/UMTS/LTE, but in the future, ITS services dedicated short range communication running on top of DSRC or G5 (IEEE 802.11p) technology could host this routing service too.
In order to offer optimal routing support, the user is asked to provide the next stop location. As an increasing number of vehicles have a navigation system, entering the next stop location and estimating the arrival time can be done locally, although research is needed to improve this estimation by using map, weather and traffic information.
As shown in the table below, we provide in the charging request message a number of user preferences to better match the request with the charging stations found by the service: some parameters refer to loyalty programs supported, price and green energy importance, comfort versus urgency.

Table 1: Parameters of the query message

Parameter	value
timestamp	
destination (next stop)	coordinates
expected arrival time	
expected departure time	
expected State of charge (SoC)	
may use public transport	yes/no
charging rates supported	slow/normal/quick
price importance	high, low
waiting importance	high, low
walking distance importance	high, low
renewable importance	high, low
payment means	card name, null

The response of the routing service can be:

- List of (Station-name, station-ID, station location, price, supported service) or
- Message: ”No station in walking distance from destination” or
- Message: ”All [n] stations in walking distance from destination are busy”

The reservation request message is similar to the query request, with the difference that it addresses a specific charging station and that the user leaves some contact address information. In the reservation response, the charging station is committed to the requested stay duration and a certain amount of energy (see Section 6). Security and privacy aspects related to authentication of users are at this stage for further discussion.

4 Multimodal Routing

Finding a charging station with adequate properties in vicinity of the desired destination (as described in Section 3) may not always be possible. Several issues must be taken into consideration such as: 1) too long walking distance between charging station and destination, 2) inadequate availability of charging stations in acceptable vicinity of the destination, 3) high costs for a particular EV-user to use certain charging stations, and 4) grid load conditions. One approach to address these aspects entail a public transport multimodal routing solution aiming to provide adequate charging capabilities as well as acceptable end-to-end mobility for the EV-user. In this work a multimodal routing approach is introduced and preliminary results assessing properties and quality of multimodal routes are presented.

4.1 Multimodal Routing Scheme

Multimodal routing includes several means of transportation. In this section we focus on multimodality encompassing EV-mobility, walking and public transport solely. The considered use case scenario extends the use case of section 3.1 by enabling the EV-user to use charging stations in vicinity of public transport stops that can provide transport connectivity to the final destination. Following this scenario, a heuristic has been specified to identify relevant charging stations. The aim of the heuristic is *not* solely to identify the optimal shortest time route but provide a relevant selection of charging stations enabling a selection on other criteria than time, see Table 1. The heuristic is based on the presumptions that: 1) An EV-user can maximally accept to walk T_{walk} seconds between two points on a route (charging station to public stop station and public stop station to destination) leading to a maximum total walking time of $2T_{walk}$. 2) The user will maximally accept to spend T_{pt} seconds in public transport transit (from entering a first public transport station to leaving the final public transport station). 3) The desired EV driving range is limited to EV_{range} e.g. to satisfy low battery EV range constraints.

A realization of this heuristic consists of two main steps: I) An off-line *initialization* step where all charging stations within T_{walk} seconds of a public transport stop are identified and II) and on-line *charging station request* step. The latter consists of the following process:

A. Identify the closest public transport stop P_{ds} (destination stop) within T_{pt} walking distance. If none are found, return no solutions.

B. Identify public transport stops $P^i_{css}, i = 0...N$ (charging station stop) where N corresponds to the amount of stops that can be reached within T_{pt} seconds from P_{ds}. The travel time to each station can be calculated from a shortest-path-tree [18]. Note, that the travel time is considered in the opposite direction than of the EV-user route. However, assuming that the public transport route is symmetric, this approach is more computationally feasible than calculating a shortest path tree from each P^i_{css} to the P_{ds}. Based on P^i_{css} look-up all charging stations $CS^j_{all}, j = 0...M$ where M are the amount of charging stations within walking distance of the stops in P^i_{css}.

D. Of the charging stations CS^j_{all} filter out irrelevant charging stations based on desired EV range. In this case charging stations are considered in a radius defined by the distance from the EV to the destination stop + 2000 meter to avoid excessively long routes.

D. For each remaining charging station calculate two routes: 1) driving from the current location of the EV to the charging station and 2) walking and using public transport from the charging station to the destination. Note, that each public transport route calculation is time dependent based on when the EV-owner can reach P^i_{css}.

E. The routes calculated for each charging station in D. are sorted by total travel time and returned to the EV-user for a final selection.

Several relevant extensions could apply to this heuristic. E.g. in step E., more criteria may be used to sort and rank the results such as CS availability and user preferences. Further, in step D., frequency of the public transport connection should be taken into consideration in case the calculated connection cannot be reached due to unforseen events.

4.2 Evaluation Scenario

The proposed multimodal routing scheme has been evaluated to clarify the potential gains and costs. In this work, primary focus is on scenarios where public transport is widely available and expected to provide support for EV-mobility in park-and-ride like scenarios. Based on availability of relevant data, an evaluation scenario case have been built around Vienna, the capital of Austria. The city public transport network offers public transport by bus, tramway and subway. The latter covers most parts of the city area and forms the public transport backbone with 90 stations carrying around 1.5 million people a day corresponding to 64% of all public transport [17]. The following results are delimited to consider multimodality between EV-mobility and subway. To assess the impact of multimodal routing, a region has been chosen of approximately $16\,km$ by $16\,km$ covering Vienna, its immediate surroundings and the full subway net. The region is depicted in Figure 4. In this scenario independent start and destination locations are generated to form a trip simulating driving needs. The start locations are randomly generated (uniform) all over the region to simulate trips starting in the city as well as the surroundings. Destination locations are randomly chosen from a database of points-of-interest (from data.wien.gv.at containing schools, restaurants, hotels, sport centers, etc.) to ensure commonly relevant destinations.

To define charging station locations a starting point is taken in parking locations of the considered region from OpenStreetMaps [16], which have not been marked as private or restricted. This leads to a total of 568 parking locations. Introducing the probability p_{CS} that a parking location offers a charging station it is possible to study the impact of future penetration levels of charging stations.

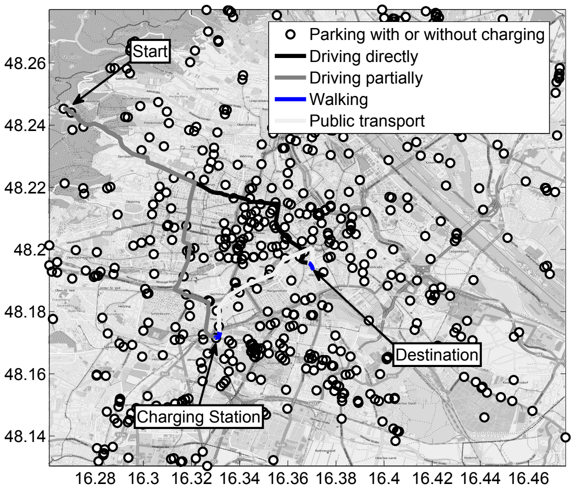

Figure 4: Map of Vienna including public parking areas (potentially offering charging) and an example of a direct route and multimodal route via a charging station.

The multimodal routing scheme has been implemented for evaluation using existing open source tools for respectively shortest time public transport and road network routing. These operate from geographical data and context information (speed limits, road type) from OpenStreetMap.org [16]. Further, public transport schedule information for 2011 has been provided by Wiener Linien.

4.3 Evaluation of Multimodal Routing

In the evaluation, three schemes are compared: *Reference:* driving directly to destination without charging nor parking, *Destination vicinity charging*: driving to charging station reachable within T_{walk} seconds from destination, and *Multimodal* which is destination vicinity charging with the multimodality enabled. A simulation is conducted of several independent trips (start-destination sets) evaluating for each scheme the total travel time and for the charging station lookup schemes also the amount of charging stations identified. The parameters used for the study are listed in Table 2. To avoid assessing remote locations e.g. as in a forest or in water, trips which have a starting or destination point too far from a map way node have been discarded. A maximum distance of $350\,m$ has been found to provide an acceptable discrimination of start/destination points.

The result statistics are depicted in Figure 5 for increasing charging station penetration levels: $10\%\,(p_{CS} = 0.1)$, $50\%\,(p_{CS} = 0.5)$ and $100\%\,(p_{CS} = 1)$. Sub-figure a) depicts the availability of at least a single charging station for a trip. In the lowest penetration case the chance of finding a charging station driving to the vicinity of the destination is lower than 10%. In this setting the multimodal scheme shows a significant improvement to around 40% underlining its

Table 2: Main parameters used in the simulation of routing schemes.

Parameter	*Value*
Trips evaluated	484
Walking speed	5 km/h
Trip start time	09:00:00 (weekday)
T_{pt}	$900\,s$
T_{walk}	$300\,s$

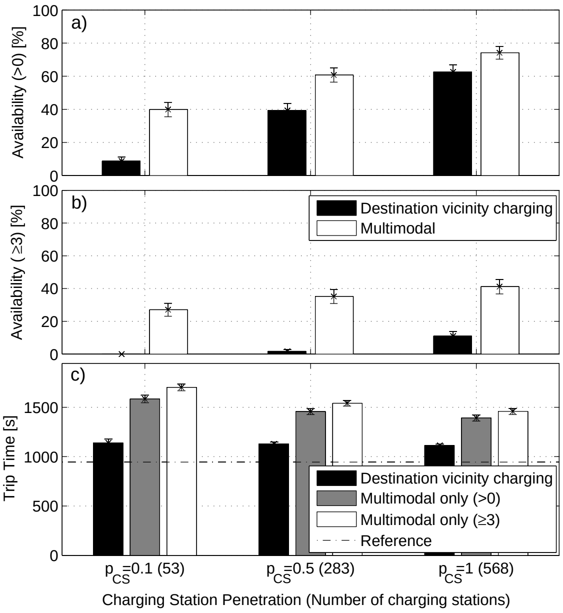

Figure 5: Charging station availability and trip time increases for different levels of charging station penetration on public parking places.

advantage in low penetration scenarios. For increasing penetration the differences are reduced but still with multimodality offering a clear advantage.

Identifying several charging station options to choose from is necessary to address the initially introduced issues of availability, grid load etc. To address this aspect sub-figure b) depicts the cases where at least 3 charging stations can be reached. In this case the multimodal scheme is superior. The significant advantage is clearly that access to the public transport network provides access to a large set of charging stations reachable within $T_{pt} + T_{walk}$. In fact, 30% of trips for the 100% penetration level offer access to more than 20 charging stations (not depicted).

The multimodal scheme, however, comes at a cost of increased travel times. This is seen from sub-figure c). It depicts average total travel times of the destination vicinity charging scheme compared to the trips made using public transport. The latter is depicted for both the single fastest multimodal trip as well as for cases where the 3 fastest multimodal trips are considered. The dash-dotted line shows the average reference driving time directly to destination with-

out charging nor parking. Note, that the average reference driving time itself is delimited by the region size and thus, does not represent trips started outside the region. In the 10% penetration case it is observed that an average trip time increase traveling via public transport of around 450 seconds must be expected compared to vicinity charging. For 100% penetration this cost decreases to around $330\,s$. It can, however, also be observed that requesting a trip via one of the 3 fastest charging station routes provides only a small increase in the average expected travel time. This is expectedly due to the fact that different charging station options enables the EV-user to reach the same public transport connection.
The results show a clear advantage of the multimodal scheme provided that EV-users can accept the increased delays. In future work it will be studied how more structured approaches of charging station location selection in conjunction to public transport may mitigate parts of the increased delay cost.

5 System Architecture Considerations

In E-mobility, the adopted business model has a certain impact on the system architecture. Early EV charging systems considered that energy is the only product a charging station sells. The liberalization of the energy market in Europe allows of course to buy EV charging energy from the home utility, independently of the grid and the charging station provider (energy roaming). The expected advantage for the user is the existence of one single bill, and for the home energy provider - to maintain the loyalty of the customer. This business model has however several drawbacks: a) energy charging is only a part of a service offered by a service provider [4], in this case the charging station owner. A variety of other services will emerge, such as: multimodal mobility (combined use of public transportation and EV), parking services (because parking space in the cities probably accounts for the main share in the charging bill), loyalty programs combining shopping with park & charge and many more. With such models, the advantage of the single home energy bill disappears. b) The business model of independent charging station owners fosters the competition such that, charging at the next street corner may be less expensive than charging energy from the "home" energy provider.
Many e-mobility projects have opted for a system that centrally controls each EV charging operation and transaction. The effect is that the power meter at every charging point belongs to the grid operator and is controlled by a central server that

- capitalizes all energy accounting and payment processes
- centralizes communication with the user/vehicle
- complicates the realization of a business model of open, interworking and independent charging stations

In contrast, we advocate a decentralized architecture that (see Figure 6) provides control, payment and resource management functions at the charging station level. Acting as a service provider, the charging station provides a reservation service to the approaching user, a load forecasting service to the low voltage grid operator (DSO) (needed for load balancing). Through sending regular availability and price updates, every charging station contributes to a wider area brokerage of demand and supply, performed by the routing service. In the future, more sophisticated energy storage and energy production services will enhance the portfolio of the charging station as service provider.

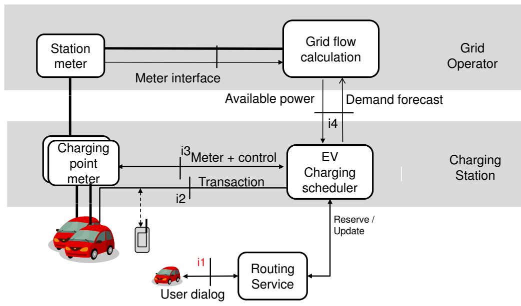

Figure 6: Charging system overview

So far, we have discussed how E-car users can benefit from a recommendation, routing and reservation service. In the second part of this work we want to address the benefits for the grid operator, namely, to learn about the expected load at each charging station, to balance it between charging stations.

6 Controlled Charging at the Charging Station

With the increase of EV penetration, controlled charging, i.e. the coordination of charging time slots will become indispensable both in residential areas such as apartment blocks with electrified parking lots, and at public charging facilities. A controlled charging strategy schedules the charging jobs in such a way that it reduces load peaks caused by swarming behavior of users that plug-in their cars approximately in the same time. Compared to other works in which the authors proposed to schedule the charging operations [10][12], our mathematical model uses the time windows corresponding to the users' sojourn (parking) time. Further required are the amount of energy required by the car and the charging rates (in kW) supported by both the vehicle and the charging station. For details on the optimization procedure, see [13].

The optimization program solves basically an (online) admission problem: incoming reservations for charging tasks to be started in the near future are accepted only if a feasible schedule can be found, otherwise the routing service has to find another charging station nearby. In practice, in order to decide whether to accept a charging request, it is enough to check if the charging resources (remaining power and free charging places) are sufficient for the desired charging period. The remaining power is the difference between the available power and the cumulated scheduled power.

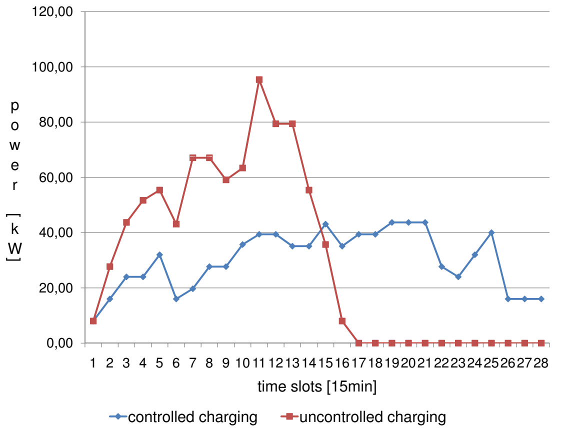

Figure 7: Power consumption for controlled versus uncontrolled charging

Figure 7 illustrates the superiority of controlled over uncontrolled charging applied to a charging station with 24 charging points, 30 randomly generated charging tasks that are distributed over a period of 8 hours. In the controlled (scheduled) case we have limited the available power to 44kW, for the uncontrolled case, the charging begins when the car is plugged in and causes significant load peaks up to 96kW.

7 Grid Flow Calculation

As mentioned above, the charging station can create the schedule only if has an estimate of the available power during the planning time horizon. For a static approach, it would be sufficient to consider the contractual power at the outlet, but such an approach would require heavy investments for enhancing the low voltage grid. Previous work recognized the tight link between the LV grid and the charging operation of an EV, for example [11][6].
In this section we propose to calculate the available power for all charging stations situated in a low voltage grid, using power grid flow calculation. For this purpose, we require the metering information of all station meters as well as the demand forecast of the EV charging scheduler described in the previous section. The program calculates the available power at each charging station and the estimated losses in the LV grid, which are important for optimizing the energy delivery schedules to the EVs. The available power is the maximum power in kW of a charging station without any grid component overloads and without any node undervoltage.

7.1 Grid Flow Calculation Methods

A condition for the flow calculation is the availability of power values of all demands (households, companies and so on) and of decentralized sources (PV, small wind turbines, etc.). In case metering infrastructure is not available, typical day load profiles can be used. In order to simplify and speed up the calculation methods, a DC load flow analysis method including electric current iteration is adopted under following assumptions:

- The demand and power factor of all consumers and sources in the low voltage grid from the past and the present are well known.
- All loads are symmetric and therefore the positive-sequence polyphase system can be used in the calculation.
- In the first iteration the voltages of all nodes are similar and equal to the rated voltage.
- Only radial systems without intermeshing are supported.

The proposed Easy Grid Analysis Method (EGAM) has five steps with one decision, see Figure 8. Step 1 initializes components and node voltage values as well as load profiles of consumers to the correct node. Step 2 and 3 are the DC load flow calculation with electric current iteration. The results are stable, if these computations run in two iterations. An additional calculation changes the values maximally 0.0004%. Step 4 reduces the absolute failure of EGAM with correction values and Step 5 calculates the grid losses of the total low voltage grid. The accuracies of the calculated values are compared with the results of an extended Newton Raphson calculation in NEPLAN (a popular software tool from BCP Busarello + Cott + Partner AG, Zurich, Switzerland).
For the evaluation, we used a low voltage grid in the city of Bregenz (Austria). The largest node voltage errors of EGAM are between -0.22% and 0.14% of the nominal voltage [5]. Therefore the DC load flow calculation with electric current iteration is accurate enough for our calculations. The EGAM must be fast, because of the repeated usage. One load flow calculation inclusive grid loss computation takes 0.6ms. This is equivalent to a load flow analysis of one year with a resolution of 10 minutes taking about 31 seconds.

7.2 Results of the LV Grid Calculation

The results obtained from the computation are the available charging power and the estimated

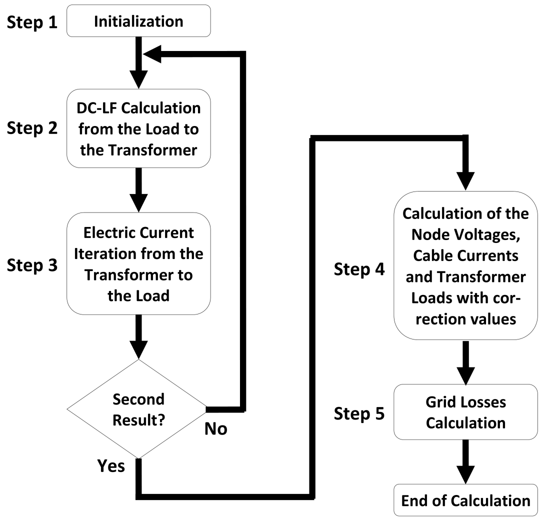

Figure 8: Flow chart of the Easy Grid Analysis Method (EGAM)

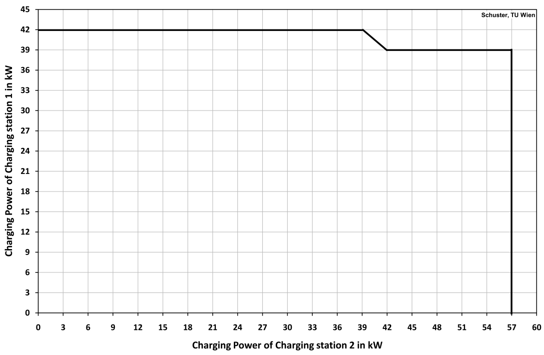

Figure 9: Polygonal line of available powers of two charging stations at one time step

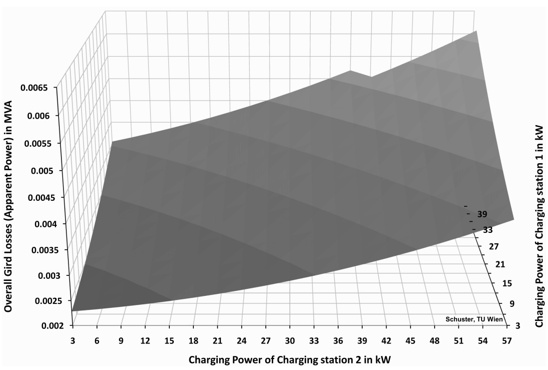

Figure 10: Total grid losses (MVA) over the charging power (kW) of two charging stations in one low voltage grid

grid losses in the low voltage grid. If the grid supplies more than one charging station, the available power values are interdependent. This leads to our desired result, namely, the charging stations have to coordinate their decisions via the LG grid computed feasible region. To illustrate this idea, we consider the analyzed LV grid that has two charging stations. Figure 9 shows the polygonal line of the available power at a certain time: charging station No.1 can charge with max. 42 kW, if the other station is not charging EVs. Conversely, charging station No.2 can provide 57 kW when station No.1 is idle. However, when both stations are charging, feasible power load combinations have to be situated in the feasible region inside the polygon. The available power is required not only for the current time slot, but has to be estimated for the planning horizon, e.g. 12 hours. Currently, we investigate update strategies aiming to reduce the computational load.
Every point in Figure 9 features certain grid losses in the low voltage grid. The EGAM calculates the losses in every point stepwise. With this information the EV Charging scheduler in the Charging Station (see Figure 6) can optimize the charging schedule. Figure 10 illustrates the total grid losses in MVA over the allowed power levels of the two charging stations. The losses increase quadratically with the charging power. Therefore the optimal point is reached, if the EVs charge with minimum feasible power.

8 Conclusions and Future Work

In this work we presented a number of ways to help EV-users in finding public charging spots and to optimize the EV-created load in the grid.
Based on user mobility needs that have been extrapolated to e-mobility, we have sketched the design of a routing and reservation service. We have shown that, by including public transportation alternatives from the charging point to the destination, the availability of charging spots drastically increases, particularly at low charging station densities.
Furthermore, we have proposed a distributed architecture that allows to perform energy balancing at three levels: at the charging station using controlled charging, at the LV grid using grid flow calculation and at the Routing area using the brokerage function.
Further steps will be to integrate these three mechanisms in order to evaluate the combined performance of these mechanisms, measured in charging resource utilization and service delivery performance.

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