To charge or not to charge? Decentralized charging decisions for the smart grid

Stella Viktoria Schieffer

Supervisors:
Prof. Dr. Kay Axhausen
Rashid Waraich

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Institut für Verkehrsplanung und Transportsysteme
Institute for Transport Planning and Systems

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

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Picture credit cover page: Stella Subaru Electric Vehicle (“Autobild.de Serienstart Subaru Stella EV,” 2009)

Semester Project in the Department of Civil, Environmental and Geomatic Engineering

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Stella V. Schieffer
ETHZürich

Schaffhauserstr. 408
8050 Zürich
stellas@ethz.ch

Abstract

The rise of electric vehicles brings a number of challenges for our infrastructure and energy security. Waraich (Waraich et al., 2009) demonstrates that bad choices of charging times made by the owners of electric vehicles (EVs) or plug-in hybrid electric vehicles (PHEVs) can lead to severe problems for the electric grid due to peak loads. Coordinated charging decisions controlled by a centralized smart charging system as simulated by Clement-Nyns et al. (Clement-Nyns, Haesen, & Driesen, 2010), Kang (Kang & Recker, 2009) or Waraich (Waraich et al., 2009) could mitigate such bottlenecks but would incur significant infrastructural investments.

This research aims to develop decentralized smart charging strategies to reduce the dependence on communication systems and infrastructures and to facilitate individual on-board processing of the optimal charging times to reach a system optimum.

The report presents possible charging schemes for decentralized smart charging and vehicle to grid (V2G) systems and documents the implementation of one smart charging algorithm in MATSim. The chosen approach uses linear programming to first optimize the duration of charging events within the parking periods by minimizing the charging times in peak load hours. In a second step, probability density functions indicating the distribution of charging slots over the simulated day, guide the exact time choices.

The developed algorithm successfully shifts charging times to off-peak periods and the results clearly indicate the benefits of investments into high speed charging infrastructure. Finally, an outlook on future extensions and refinements of the charging algorithm is given.

Keywords

Decentralized charging, Smart grid, V2G, Electric Vehicles, PHEV, Agent based simulation, MATSim

Citation

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Glossary

$f(t)$	base load function [W]
P_{baseLoad}	lowest constant load in the reference system without PHEVs/EVs [W]
${}^{PHEV}P_{baseLoad}$	lowest constant load in the system with PHEVs/EVs considering load flattening effect [W]
n_{PHEV}	number of PHEVs
$\overline{P_{PHEV\_day}}$	average daily energy consumption per PHEV [Joule]
c_{baseLoad}	cost of producing electricity in off-peak times [CHF]
c_{peakLoad}	cost of producing electricity in peak times [CHF]
$c_{\mathrm{chargingflattening}}$	cost of charging electricity in off- peak times [CHF]
$c_{\mathrm{chargingpeak}}$	cost of charging electricity in peak times [CHF]
$p(t)$	probability density function to model chance of charging at off-peak prices
<	
ζ	scaling factor for $p(t)$
ΔF	difference between current and optimal frequency on electric network [s^{-1}]
$C(t)$	connectivity function giving the percentage of connected PHEVs at time t [%]
$E_{\mathrm{regulatory}}$	energy quantity (dis)charged to or from vehicle battery for V2G services [Joule]
SOC_{start}	state of charge at the beginning of a day [Joule]
x	solution vector of the linear programming optimization
E_{charged}	energy charged within one parking period [Joule]
$E_{\mathrm{discharged}}$	energy discharged within one parking period [Joule]
s_{charging}	charging speed of battery with given connection and battery type [Joule*s^{-1}]
$t_{\mathrm{chargingOff-peak}}$	duration of time in which electricity is charged within one off-peak time interval [s]
$t_{\mathrm{chargingPeak}}$	duration of time in which electricity is charged within one peak time interval [s]
$t_{\mathrm{parkingDuration}}$	duration of parking interval [s]

1. Introduction

The sustainable use of infrastructure and available resources related to energy and electricity has become of utmost concern for our society. Being driven by international discussions on global warming and energy security, a key research is aiming to prevent bottlenecks in the electric grid in the future and it focuses on smart grids and smart technologies.
Contributing almost 35% ("Schweizer Bundesamt für Statistik," 2010) to the total energy consumption, the transportation sector is a field where the application of smart technologies can have substantial benefits. A key technology in this market segment with the potential of reducing emissions, the harm to the environment and the dependency on oil imports are electric vehicles (EVs), respectively plug-in hybrid electric vehicles (PHEVs).
The EVs and PHEVs of the future will not only provide mobility to its owners, like our current combustion engine vehicles, but will become an integral part of the overall smart grid concept. This new generation of "smart cars" will also be able to interact with its owner and the electric grid to optimize its own charging patterns. This optimization mitigates further peak load increases and might even stabilize the electric load by shifting charging to off-peak times, also referred to as "load flattening".
Besides smart charging, the vehicle-to-grid concept (V2G) offers another innovative system extension increasing the reliability and performance of electric grids. This framework allows interaction both ways between the car and the electric grid. This scheme will enable not only general charging with load flattening effects but also frequency regulation down or up, meaning charging of car batteries if the grid frequency or supply are high respectively discharging of car batteries to the net if the net frequency is critically low. Urry (Urry, 2008) predicts that the emergence of such smart car technologies will be an "epochal shift" turning vehicles into "computers with wheels rather than cars with chips".

In spite of the obvious advantages related to EVs, major "socio-technical" challenges (Sovacool & Hirsh, 2008) remain to be overcome. Social and economic barriers might include social aversions to new technologies, system inertia, opposition from current stakeholders or market competitors and of course, the initial capital costs (Sovacool & Hirsh, 2008).
This research focuses on the technical difficulties caused by the additional, fluctuating loads of electric vehicles. Anticipated problems comprise the integration of the new demand within the existing daily electric load pattern under the constraint of minimizing the costs for electricity production, e.g. reducing peak loads, and system maintenance services including frequency regulation.

Previous studies at the Institute of Transport Planning and Systems (IVT) of ETH Zurich have simulated the effect of centralized charging schemes on the electric loads in the grid. The definition for centralized smart charging introduced by Waraich et al. (Waraich et al., 2009) states that the final decision to start or stop charging is made by a central entity, e.g. the utility service provider or some other managing unit.
Waraich et al. (Waraich et al., 2009) first demonstrates that simple charging schemes such as dumb charging or dual tariff charging are likely to cause significant peak load increases using the agent based simulation tool MATSim (Http://www.matsim.org, 2008). In a second step,

he implements a central smart charging algorithm able to find charging patterns which will not violate physical grid constraints under given agent demand constraints.

This research extends the previous work with a decentralized approach. In contrast to centralized charging the final decisions to charge or not to charge are made by the smart car alone. Advantages of such decentralized computing applications include (i) the avoidance of an information overload at the central processing unit, (ii) remaining within the resource constraints set by the communication distances and available connection bandwidth and (iii) eliminating communication needs altogether for locally relevant information (Duckham & Bennett, 2009).
In contrast to that, "centralized architectures with few central data stores lead to unscalable systems, with single points of failure" (Duckham & Bennett, 2009) and costly initial infrastructure investments.

In the following, a literature review will summarize research results of centralized and decentralized charging simulations. Section 3 will focus on the development of a decentralized smart charging approach, section 4 includes V2G considerations into the smart charging scheme. Finally the results from the implemented simulations are presented in section 5.

2. Literature Review

The social and infrastructural changes of a transition from traditional combustion engine vehicles to electric cars and their challenges for the existing electric grid are critical topics discussed among scholars. As introduced in the previous section, this thesis adopts the nomenclature introduced by Waraich et al. (Waraich et al., 2009) and categorizes the approaches broadly into centralized smart charging and decentralized smart charging systems. Although the work presented focuses on decentralized smart charging, a short overview of the existing research in both categories will be given for completeness.

2.1. Centralized Smart Charging

An abundance of research ranging from general benchmarking studies to detailed simulations has been conducted in the field of centralized smart charging.

A general benchmarking study published by Kang (Kang & Recker, 2009) evaluates the consequences for the Californian electric grid for four different scenarios using an activity based approach. Geo coded data from the Californian Household Travel Survey (CalTrans, 2001) serves as the basis for this study. Kang compares the load distribution for different circuit infrastructure for (i) uncontrolled charging after the last trip of the day, (ii) uncontrolled charging whenever the car stops at home, (iii) controlled charging after 10pm and (iv) charging at home and all public locations. The analysis shows that policies have to be developed considering the local infrastructure and load profiles to prevent undesired effects such as load increases due to available charging infrastructure in all public spaces.

Nyns (Clement-Nyns, Haesen, & Driesen, 2010) estimates the effect of different PHEV market penetrations on the Belgian electric grid. Using quadratic and dynamic programming, he minimizes the overall power loss on the network for an uncontrolled and a controlled charging scenario. In the uncontrolled scenario vehicles start re-charging right after arriving at their destination, in the controlled charging scenario, vehicles wait for a central signal to start charging. He concludes that the choice of method does not affect the results considerably and that coordinated charging can significantly reduce losses.

The central charging algorithm by Waraich et al. (Waraich et al., 2009) implements a smart charging algorithm within MATSim based on information on the agents' routes and personal schedules and feedback about grid violations from the PHEV Management and Power System Simulation (PMPSS). The system optimizes the charging schedule iteratively while trying to fulfill the agents' demand constraints and avoiding grid constraint violations.

2.2. Centralized Smart Charging with V2G

Han et al. (Sekyung Han, Soohee Han, & Sezaki, 2010) envision a centralized smart charging network with V2G in which a central aggregator sets up contracts with all vehicle owners to charge or discharge electricity. Using dynamic programming Han et al. find the optimal charging sequence, rate and lengths within a fictive 12h plug-in-time by maximizing the vehicle owner's revenue function under vehicle and system constraints.

Saber (Saber & Venayagamoorthy, 2010) uses an evolutionary particle swarm optimization (PSO) to minimize costs and emissions associated with the unit commitment of gridable vehicles (GVs) in a V2G system. He analyzes a system of 50,000 vehicles in which a central intelligent and autonomous unit chooses connected and registered vehicles for discharge. Saber sees great potential in extending this effective approach of balancing operational costs and emissions to real world applications.

Lund and Kempton (Lund & Kempton, 2008) model two national energy systems with and without combined heat and power (CHP) in EnergyPLAN (Lund, 2007) for four different vehicle fleets and varying wind penetration levels. The model uses real travel data from the US Department of Transportation Statistics to model the aggregated national transportation demand and applies night charging, intelligent charging at times of excess power production and intelligent charging combined with V2G to the system. Lund and Kempton demonstrate that countries benefit greatly from electric vehicles and V2G by reducing the $C0_2$ emissions and enabling the integration of higher levels of wind energy without excess electricity production.

2.3. *Decentralized Smart Charging*

In contrast to centralized smart charging, decentralized smart charging allows each smart car to choose its time for charging individually which would result in a far more dynamic and flexible system.
A major advantage of this approach is the minimal amount of overhead costs thanks to the absence of cost intensive communication infrastructure and a central managing unit. Instead, a smart charging algorithm is implemented in each car to optimize the global charging processes. The basic parameters used for the on board computation could be updated and synchronized daily via wireless internet connections at home or signals at main traffic hubs along routes.
Decentralized smart charging is a very young field of study; the methods and results of the few publications dealing with this approach are presented in the following:

3.3.1 Decentralized Smart Charging without V2G

Mets et al. (Mets, Verschueren, Haerick, Develder, & De Turck, 2010) evaluate the performance differences when balancing the local residential electric load with the charging needs of electric cars. They differentiate between (i) uncontrolled charging as the base case, (ii) load balancing decisions being made at household level by a *home energy control box* or *smart charger* and (iii) a load balancing decision made at a more global level in form of a peer-to-peer network or any other form of communication between home energy control boxes.
The charging algorithm allows the smart charger to choose its charging schedule and charging rates based on the predicted residential loads using quadratic programming. The simulation is implemented within the discrete event modeling software OMNet++ (Varga, n d) and uses average synthetic Belgian home profiles as load profile inputs. Arrival and departure time are based on a statistical availability model. The simulation was conducted for PHEV penetrations from 10-30%. The simulations demonstrated that the load balancing approaches reduced the maximum electric load by 8-38% in case (ii) and 8-42% in case (iii).

This last conclusion from the paper is interesting because it is an indication that decentralized computation and information processing can achieve results almost equivalent to centralized approaches.

Vytelingum et al. (Vytelingum, Voice, Ramchurn, Rogers, & Jennings, 2010) uses an agent-based approach in which agents adapt their micro storage management policies for their vehicle batteries in a gradual learning process to eventually converge to a global Nash equilibrium. In a day ahead planning process based on predicted market prices, the agents maximize their utility subject to their schedules, their defined price of storing energy, their charging efficiency and battery capacity. Learning parameters gradually adapt the daily storage profile and the used capacity range of the battery. Vytelingum argues that such an iterative learning process is a more realistic representation of actual human behavior which mirrors learning processes and is not influenced by daily random fluctuations in the electric load.
Within his framework, Vytelingum can reach a complete flattening of the load profile with a PHEV market penetration of 38% of 4kWh storage devices and reaches Nash equilibrium

within 30-50 iterations, equivalent to 30-50 learning days. The results achieve electricity savings of up to 13% for the agents.

3.3.2 Decentralized Smart Charging with V2G

Andersson et al. (S.-L. Andersson et al., 2010) evaluate PHEVs as regulating power for ancillary services in Sweden and Denmark. Their framework implements a decentralized charging system for V2G services in Matlab.
Four battery stages are defined: (i) regulation up (discharging to the net), (ii) regulation down (charging from the net), (iii) waiting and (iv) charging. If the V2G demand is activated on the grid and if de-charging the car battery does not compromise the personal driving schedule, V2G charging is initiated.
The paper concludes that PHEVs are extremely sensible for regulation down as this implies cheap charging for the cars, but also the general capacity payments are very lucrative. Yet, Andersson poses the question how quickly the ancillary service market will be saturated and points out the insecurities related to regulation up.

Ota et al. (Ota, Taniguchi, Nakajima, Liyanage, & Yokoyama, 2009) discusses a more electrotechnical approach to the question. He proposes V2G control by autonomous distributed smart storage for the ubiquitous power grid in Japan which links the charging decision to (i) the network frequency and (ii) the state of charge of the smart storage within the vehicle. The framework is based on the fact that the frequency drops upon plugging in new loads to the network thus recognizing the need for V2G services. On the other hand, the own state of charge can act as a suppressor of V2G at low charging levels or allow V2G when sufficiently charged.
Ota's group supports its research with experimental measurements on the Japanese electricity grid but has not developed a working software or hardware yet.

3. Charging schemes for decentralized smart charging

3.1 Qualitative Requirements for a charging scheme: parameters and constraints

The charging scheme has to fulfill the boundary conditions and requirements set by

(i) the agent as the user,
(ii) the smart car and
(iii) the electricity grid.

The **agent** aims at maximizing his own utility, e.g. expecting reliable services for his travel and minimizing costs. His boundary conditions which he ideally communicates to the smart car are his desired driving schedule and routes. The schedule directly relates to the required states of charge (SOCs) for each route and will be passed to the smart car as the **set system constraints**.

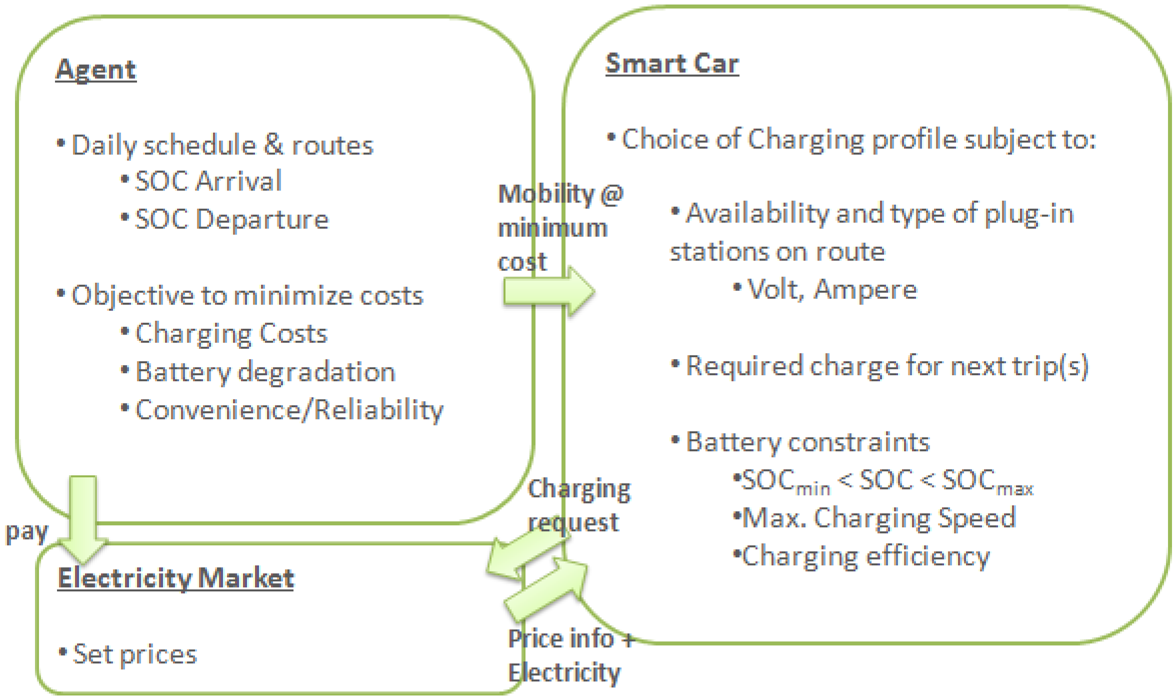
The **smart car finds the optimal charging solution** within these constraints which will not violate its own or any other infrastructural technical constraints, such as the availability of plug-in stations along the route, its battery constraints or the limitations of the power connection. Very detailed applications in the future could also consider the route dependent possibility to recharge the battery on down-hill trips through regenerative braking to increase accuracy of required charge forecasts (Wilhelm, 2010). In this model, the smart car can function as a black-box for the agent who will not have to worry about the details of the charging algorithm.

The **electric network sets the electricity prices** and manages the charging requests of the smart car and the various other network loads. Its challenge is to manage the overall energy supplies and demands while keeping the net frequency stable. The payment for its comes from the agent.

In the end, the perfect smart car serves the interests of both, the electricity market and the agent: it optimizes the charging processes globally such that the agent's utilities are maximized and violations on the electricity market and thus also operating and maintenance costs are minimized.
This interesting three party arrangement highlights the potential impact of electric cars on society and reveals that all actors should have financial incentives to push the development of electric car technologies.

The parameters described in this section are summarized in Figure 1.

Figure 1 Decision parameters, constraints and interaction of agents



3.2 Possible charging schemes

In the following three decentralized charging schemes are presented and discussed. All schemes focus on reaching a global market optimum for a given penetration level of PHEVs but differ in the necessary requirements for infrastructure or the degree of flexibility. Yet, they all share certain common assumptions about the daily demand, price and load patterns which will be presented in the following section.

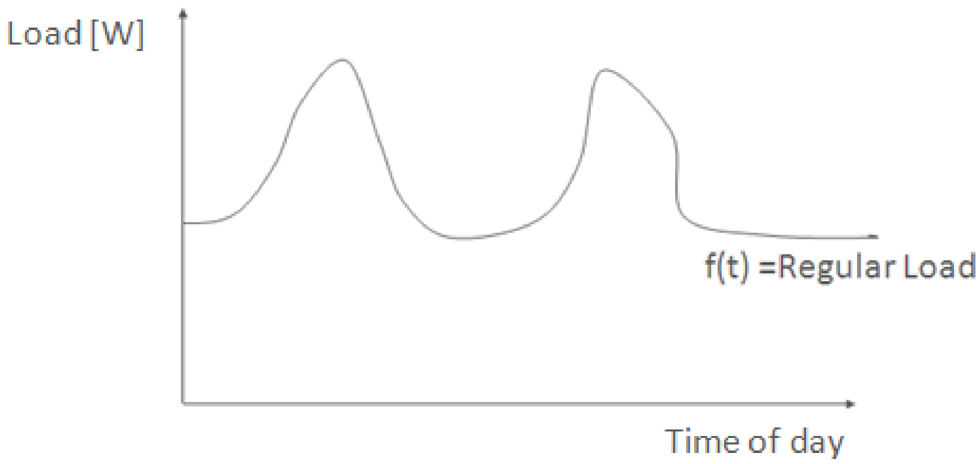
3.3.3 Assumptions

Assumption 1: Base load

It is assumed that the base load changes only gradually over time and that a statistically regular load curve can be approximated from existing data for every day in a certain region and time of the year.

This base load curve for the regular load including industrial and residential loads in a network can be modeled as a function of time *f(t)* (Figure 2).

Figure 2 Simplistic depiction of a modeled base load curve *f(t)* over one day



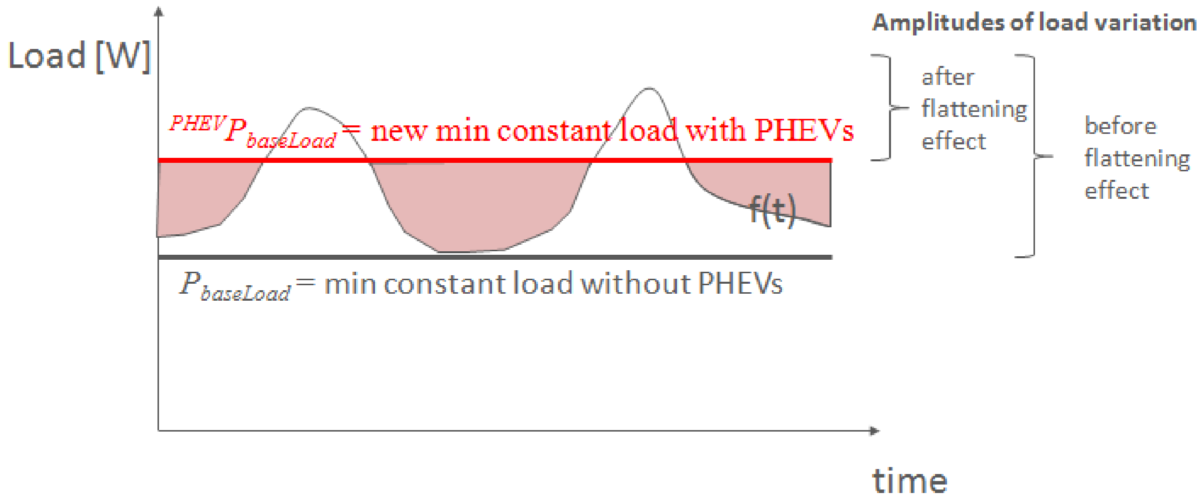
Assumption 2: Desired load flattening effect of PHEVs
Second, in an optimal system the PHEVs will have the maximal possible load flattening effect to reduce their own electricity costs and infrastructure costs for grid regulation. This will shift the initial constant required base load $P_{baseLoad}$ up to a new ${}^{PHEV}P_{baseLoad}$ related to the PHEV market penetration as visualized in Figure 3.

The new ${}^{PHEV}P_{baseLoad}$ will be such that the integral between the new ${}^{PHEV}P_{baseLoad}$ and the regular load curve f(t) will be equal to the total load consumption of the PHEVs:

$$\begin{aligned} &\int_0^t ({}^{PHEV}P_{baseLoad} - f(t))dt = n_{PHEV} * \overline{P_{PHEV\_day}} \\ &\forall\, {}^{PHEV}P_{baseLoad} \geq f(t) \end{aligned} \tag{1}$$

where n_{PHEV} is the number of PHEVs in the market and $\overline{P_{PHEV\_day}}$ is the average daily consumption of energy in Joules per PHEV.

Figure 3 Visualization of the load flattening effect



Assumption 3: Cost difference and derivation of system optimum prices

In a simplistic but general model, it will be assumed that the cost for the electricity provider for the constant baseLoad, $c_{baseLoad}$, will be different and lower than for times where peak power is required, $c_{peakLoad}$.

$$\Delta Cost = C_{PHEV} - C_{baseLoad} \tag{2}$$

$$C_{PHEV} = \int_0^t c_{baseLoad} * {}^{PHEV}P_{baseLoad} dt + c_{peakLoad} * \int_{\forall f(t) \geq {}^{PHEV}P_{baseLoad}\, t_1}^{t_2} f(t) dt \tag{3}$$

$$C_{baseLoad} = \int_0^t c_{baseLoad} * P_{baseLoad} dt + c_{peakLoad} * \left(\int_o^t f(t) dt - P_{baseLoad} \right) \tag{4}$$

Furthermore, it is assumed that the resulting cost difference at system optimum for the electricity producer, *ΔCost* (2), will directly be transferred to the PHEV car owners as off-peak charging costs, $c_{chargingflattening}$. These are subject to a chosen profit margin for the electricity provider, *r* (5).

$$c_{chargingflattening} = \frac{\Delta \mathrm{Cost}(1+\mathrm{r})}{\text{total charging time}} \tag{5}$$

Charging in peak times is penalized with higher prices, $c_{chargingpeak}$, related to the electricity production costs for the energy supplier (6):

$$c_{\text{charging,peak}} = c_{peakLoad}(1+r) \tag{6}$$

The proposed charging scheme, thus follows a general dual-tariff system, which is derived from system optimum. Whenever an agent charges within one of the times where he contributes to the flattening effect, he will only pay $c_{\text{charging,flattening}}$. If the agent chooses to charge in the peak time, he will be charged the full peak price $c_{\text{charging,peak}}$.

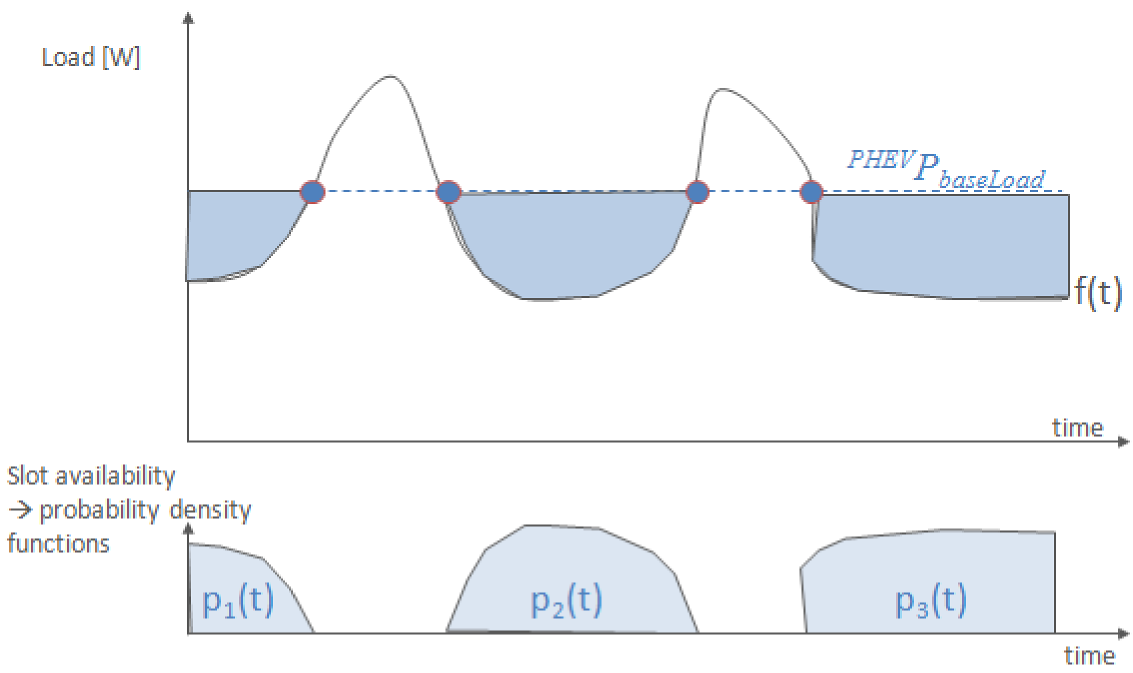
In this system the price policy is clearly structured and transparent such that all agents know *a priori* what their maximum utility for a given day and schedule can be.

3.3.4 Charging without pre-booking

The implementation without pre-booking makes use of the system information on the desired ${}^{PHEV}P_{baseLoad}$ related to system optimum and *f(t)*. With these two pieces of information, the general shape of the load valleys is known. From the depth of the valleys representing the load available for car charging, it can be deducted how many cars can charge at the same time in order to “fill up” the valley, meaning how many charging slots are available at any time of the day.

The number of charging slots can also be expressed as a probability density function (*p(t)*) governing the distribution of charging slots available at optimum system price $c_{\text{charging,flattening}}$ (see Figure 4).

Figure 4 Relation of charging slots in valley to probability density functions



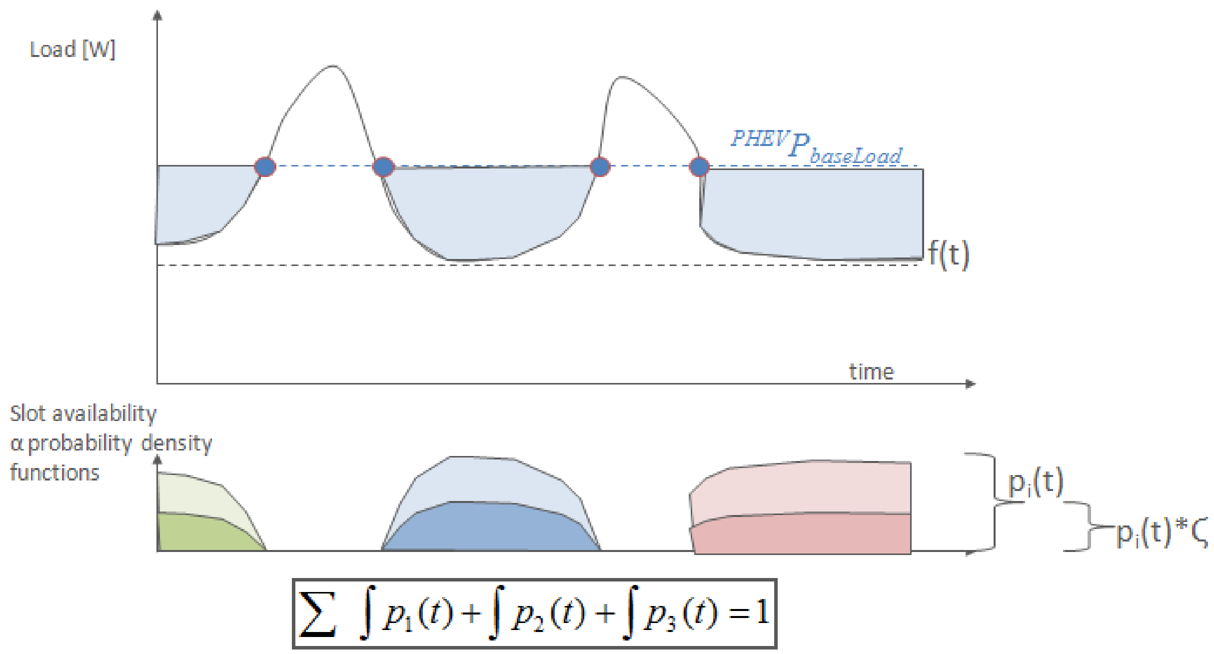
The n probability density functions $p_i(t)$ for the n valleys need to be chosen, such that the shape of the valley is captured and such that (7) holds true (see also Figure 5)

$$\sum_{i=1}^{n} \int_{t_{i1}}^{t_{i2}} p_i(t)dt = 1 \tag{7}$$

For this property to be true, the density functions might have to be multiplied by an appropriate scaling factor ζ (8).

$$\zeta * \sum_{i=1}^{n} \int_{t_{i1}}^{t_{i2}} p_i(t)dt = 1 \tag{8}$$

Figure 5 Scaling parameter ζ to fulfill the properties of probability density function



Knowing the probability density functions, it is possible to transform random numbers of a homogenous distribution, z, to equivalent time positions within the slot distribution (9)-(11).

$$z = \int_{o}^{t_x} p\ (t)dt \tag{9}$$

$$z = \left[\int p\ (t)dt\right]_0^{t_x} = \left[\int p\ (t)dt\right]_{t_x} - \left[\int p\ (t)dt\right]_0 \tag{10}$$

$$t_x = f(z, p(t)) \tag{11}$$

The strengths of this approach are:

- the minimal initial requirements on communication and infrastructure thanks to self-organization
- the delay of a more infrastructure-heavy model to the future improving the current net present value of the policy
- the focus on reaching system optimum
- the user friendliness allowing for changes of plans and any-time charging without slot pre-booking
- the opportunity to adjust the system to new or real time market conditions

A threat might be the potential for system abuse. Individual car owners might want to reconfigure or hack their car computer to minimize their charging costs.

3.3.5 Charging with pre-booking

In the case of pre-booking, the model described in the previous section without pre-booking remains mainly as it is. The function of the probability density functions is replaced with a slot managing system which would be a central administrative entity within the electricity network. This entity would receive charging plans and slot requests from smart cars, and confirm slot bookings at optimum prices for PHEVs in advance or suggest better charging times to agents, if all slots in a time period have already been booked.

This model is very accurate and easy to adjust to new market conditions, but is obviously a lot more communication and technology intensive. Also, it might be regarded to be less user friendly, because slots need to be pre-booked, which makes it less flexible and more restrictive.

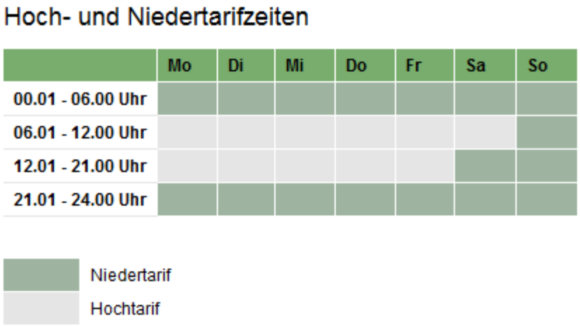
3.3.6 Charging with pre-booking and trading

The last model extends the model with pre-booking even further. Instead of leaving all decisions up to a central entity, a general market participation with all PHEVs acting as micro-traders could distribute and re-distribute the slots once assigned more dynamically.

This version frees the pre-booking model from its "time restrictions" making it dynamic and interactive. The challenge with this system will be the even higher requirements for infrastructure and communication. In such a system it is necessary for all agents to be informed about real-time prices in order to make decision on whether to swap their charging slots with other agents. This would require an entirely new form of energy market in which everyone has the capacity to trade micro-loads/slots with each other and to transfer micro-payments.

This is a disruptive break from the current contract setup for individuals in which clear price brackets are guaranteed for generalized peak and off-peak hours (Figure 6). The new capacities of a micro-trading system also bear considerable risks related to network security and leave many implementation questions, e.g. regulations to prevent system abuse and hacking open. To be more realistic: the emergence of such a micro-load electricity exchange will still require a lot of time as well as social, political and economic willingness to be implemented. Yet, it might arguably become necessary eventually to integrate the increasing dynamics of all inputs and output loads including V2G services from electric cars and intermittent energy from renewable sources with the electric grid.

Figure 6 Typical pricing schedule for private households (from electricity provider EBM)



Source: http://www.ebm.ch/strom/geschaeftskunden/tarifzeiten.html ("EBM Strompreise Privatkunden," 2010)

3.4 *Discussion*

3.4.1 Infrastructure Requirements

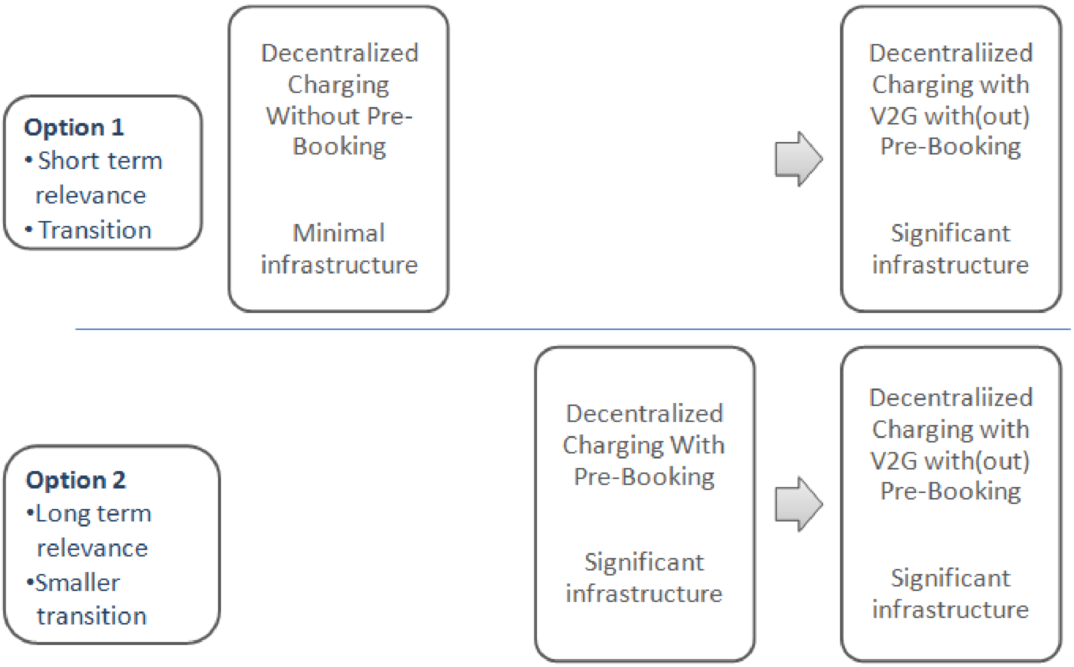
Comparing the three charging models, it can be seen that option 1 with no pre-booking is the least infrastructure intensive of all and that the micro trading system is practically infeasible at the moment to realize due to its infrastructure costs and practical implications. Thus, excluding the micro trading option, two infrastructure development options are depicted in Figure 7.

The first option suggests to start the decentralized smart grid with a system with minimal infrastructure and capital costs. This allows a short time-to-market. The system can later be upgraded as needed, e.g. to a V2G infrastructure. The first mover advantage will also generate valuable knowledge from the pilot phase which will be crucial to plan the next steps.

The second option would be to start planning long term and to introduce a decentralized grid with significant infrastructure investments in a few years time. Such a system will undergo less change when finally being upgraded to a V2G system.

Yet, a third option, not explicitly listed in Figure 7, would be a combination of the two: starting with a decentralized grid without pre-booking, and slowly adding on infrastructure to allow for slot pre-booking and eventually V2G.

Figure 7 Infrastructure development options



3.4.2 Flexibility for the V2G network and the user

Flexibility and system reserves are important for the user to allow for spontaneity in his daily planning. The no pre-booking option of a completely self-regulating system seems thus to be the most user friendly system version.

3.5 Conclusion

From the above discussion, option 1, the decentralized smart charging without pre-booking is chosen as the most sensible and immediate development path for the PHEV/EV industry and the electricity providers. It allows the market to experiment with a new service model in a pilot phase and to gain important hands-on knowledge in order to plan for the significant infrastructure investments related with the expansion and refinement of the industry in the future. It is the least invasive development path that allows the economy as well as society and its users to adapt to coming changes in the mobility and energy sector.

4 V2G Framework

The previous section introduced the decentralized charging scheme to cover the deterministic electricity load on the network and the expected travel demand. The V2G framework extends this scheme and suggests a set-up in which the connected vehicles supply the frequency regulation for the stochastic load variations. The following section on the V2G framework only presents a potential way to implement V2G in MATSim. The actual implementation has not started yet.

This thesis focuses on V2G for the application of frequency regulation only. The importance of this highly dynamic market is bound to increase with the macro-trends pointing towards a future with a larger penetration of intermittent energy sources and variable electric loads. Secondly, the author believes that frequency regulation is a more suitable service segment to initially introduce V2G with respect to market size and strategic market positioning.
Since the entire frequency regulation market can be satisfied with a relatively low penetration of electric vehicles, approximately 5.5% in Germany (S.-L. Andersson et al., 2010), the market has a size that is attractive and manageable even at initially low EV adoption rates.
In terms of market positioning, the expensive battery technology with its limited life time due to battery degradation seems more suitable to provide small regulatory energy opposed to peak energy at the moment. Established competitors such as gas or water turbines can provide large quantities of electricity at short notice and low prices. PHEVs and EVs might thus have a more distinct head start in providing very small quantities of electricity. This situation might certainly change, if the provision of larger amounts of energy from car batteries becomes economically viable through advances in battery technology, e.g. the reduction of battery degradation costs, or an increase in charging speeds and capacity.

4.1 V2G Services

Adopting the terminology of Andersson et al. (S.-L. Andersson et al., 2010), the vehicle can provide two types of services to the grid: (1) regulation up, meaning discharging to the grid, or (2) regulation down, meaning charging the vehicle battery by drawing electricity from the grid. In return for providing such services to the market, the vehicle owners could profit from capacity and service payments, making it less expensive for the users to own a PHEV or EV (Kempton & Tomic, 2005). Previous studies on the European market (S.-L. Andersson et al., 2010) estimate the potential monthly revenue from ancillary services of vehicle owners at 6-160 Euros in Denmark (Larsen, E. Chandrashekhara & Ostergard, 2008) or 20 Euros in Portugal (Camus, Esteves, & Farias, 2009).
Also, the additional buffer against frequency variations is beneficial for the reliability and stability of the network and could allow the integration of more intermittent energy sources, e.g. wind or solar (Larsen, E. Chandrashekhara & Ostergard, 2008).

4.2 V2G Strategy

The goal of the presented ancillary service scheme is to distribute the services "fairly" between all connected vehicle owners. Regulation down is always attractive for the vehicle owners as it implies cheap charging (S.-L. Andersson et al., 2010). In contrast to that, regulation up is more critical as it may interfere with the effective charging needs of the user.
The chosen strategy thus attempts to distribute both services evenly among all connected vehicles to reach a non-discriminatory system at user and system optimum. The following assumptions are made:

1. The difference between the desired and the current frequency *ΔF* on the electric grid is known to all connected vehicles, i.e. it is constantly monitored by all connected vehicles.
2. The number of vehicles that is connected to the grid at any time is approximately known and can be modeled by a function of time *C(t)*.

Whenever the frequency exceeds a critical *ΔF,* each vehicle in the decentralized grid would thus know indirectly, how much regulatory power $E_{regulatory}$ it has to contribute to stabilize the electric grid:

$$E_{regulatory}(t) = \frac{\Delta F}{C(t)} \tag{12}$$

The strengths of this approach include:

- The simplicity of the computation which can easily be integrated into the board computer
- The compatibility of the setup with the previously proposed decentralized charging scheme operations
- The intrinsic self-regulating character of the approach.

Weaknesses include:

- The effectiveness of this de-centralized decision depends on the accuracy of the connectivity function *C(t).*
- It is assumed that all connected cars will be able to provide V2G. In reality C(t) should be refined to reflect the number of cars which are parking, connected to the grid and have the possibility to provide V2G energy. The ability to provide V2G energy might be dependent on the current state of charge of the car's battery and the agent's contract/personal preference.

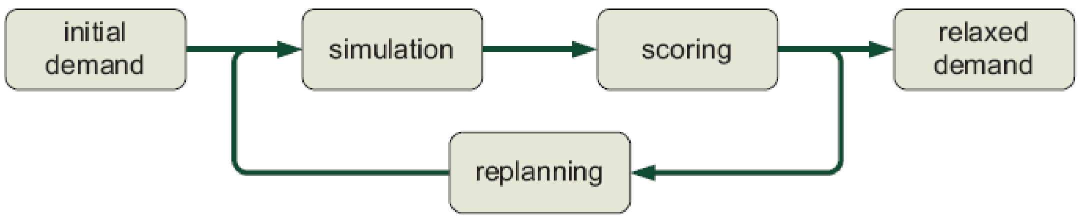
5 Implementation of charging scheme without pre-booking in MATSim

This chapter will show how the discussed decentralized charging scheme is implemented in MATSim to integrate it into the previous work by Waraich et al. (Waraich et al., 2009).

5.1 The simulation framework MATSim

The travel demand simulation framework MATSim (Http://www.matsim.org, 2008) is an agent based tool to simulate large scale traffic scenarios. All agents have respective daily plans such as commuting or leisure shopping trips which can be executed and scored by assigning utilities. Traffic generated by agents and modeled in the execution might lead to congestion and thus have a negative effect on the utility. Activities such as working or leisure activities increase the agent's utility. In order to maximize their own utilities, agents can replan their days by controlling degrees of freedom, such as their route or mode choice and exact travel times. This iterative replanning process is based on Holland's (Holland, 1992) co-evolutionary algorithm and eventually reaches relaxed user equilibrium. The process is visualized in Figure 8.

Figure 8 Co-evolutionary simulation process in MATSim (Waraich et al., 2009)



Relating this process to the charging schemes discussed in this report, it is obvious that charging considerations can affect an agent's utility considerably. Bad charging decisions can lead to insufficient battery levels when needed, or increase the costs associated with charging in peak periods. Incorporating such costs into the utility can thus influence the agent behavior in the model.

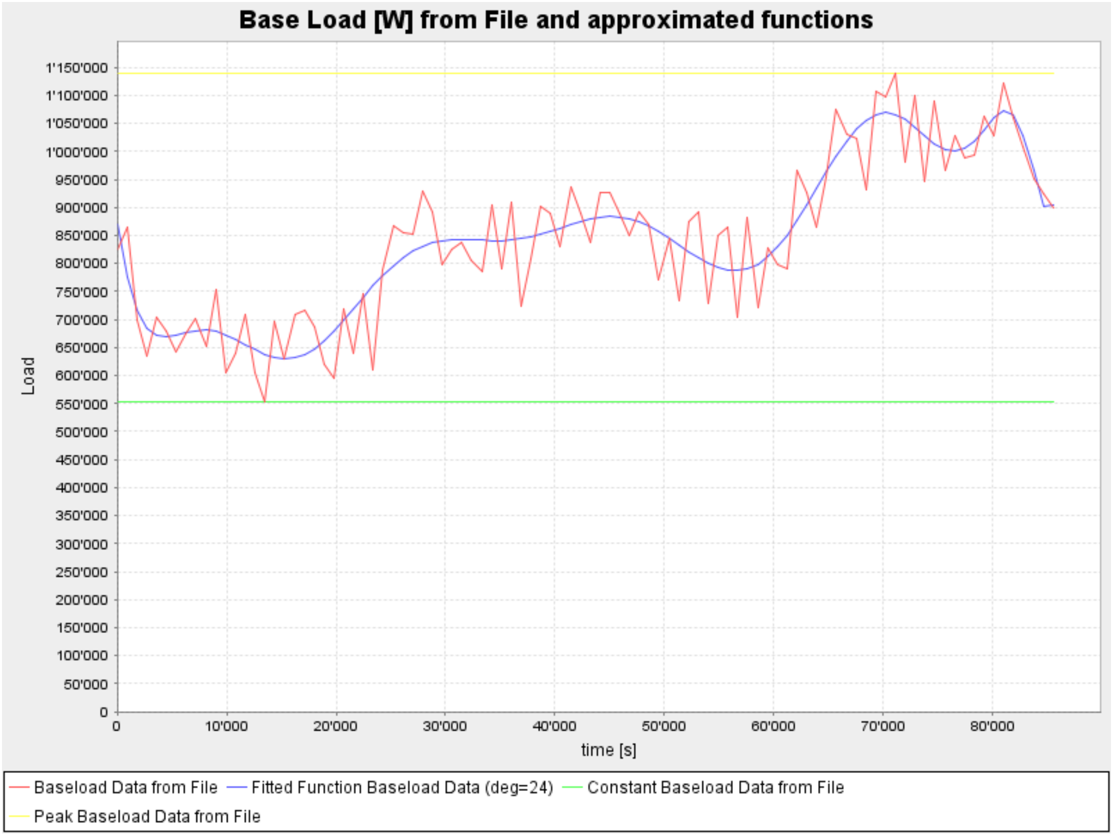
Feeding back utilities derived from the charging procedure to the simulation has not been implemented yet and will be part of the next steps to integrate the charging procedure into MATSim.

The following section gives an implementation outline of the most important functions which were added to MATSim.

5.2 Base load curve

To model the base load curve, 15 minute-bin load data given as a percentage of the peak load representative for a residential area in Switzerland is read and fitted to a polynomial function. The function can be scaled by choosing the desired peak load value and the degree of the polynomial function can be adjusted. For the purposes of the analysis a default degree of 24 is chosen.

Figure 9 Example of fitted base load functions



5.3 Defining system peak and off-peak times

As described in detail in section 3, the load flattening effect of the PHEVs will result in a new constant base load level ${}^{PHEV}P_{baseLoad}$. This shifted base load is found using an iterative bisecting algorithm. As long as the PHEV penetration is smaller than the flattening penetration, which would result in a completely flat load curve over the day, the solution will be between the minimum constant load $P_{baseLoad}$ and the maximum peak load of f(t) (Figure 10). By iteratively bisecting the known solution space, the solution space can be halved in each step to reach quick convergence. If the integral between the current trial in the step and the base load curve (visualized with the shaded regions in Figure 10) is within the defined convergence criterion, currently set at 5% of the expected total PHEV consumption per day, the current trial is accepted as the solution.

Knowing ${}^{PHEV}P_{baseLoad}$ and thus the intersection times with *f(t)*, the peak and off-peak times can easily be defined. The intersection times are determined by solving for the roots of the objective function *f(t)-currentTry*. An example output of this procedure is shown in Figure 11.

Figure 10 Two consecutive steps of the bisecting algorithm to find ${}^{PHEV}P_{baseLoad}$

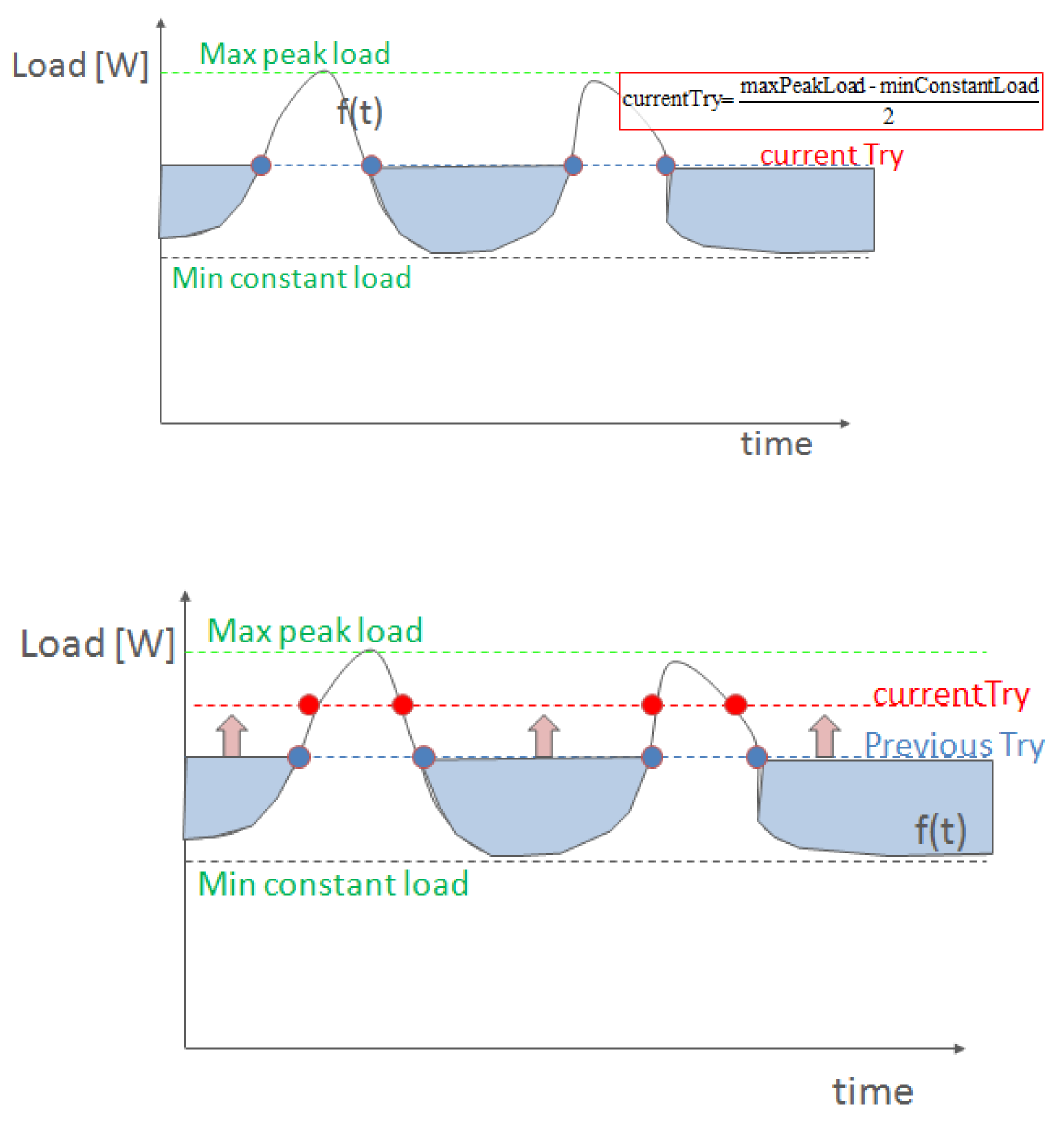
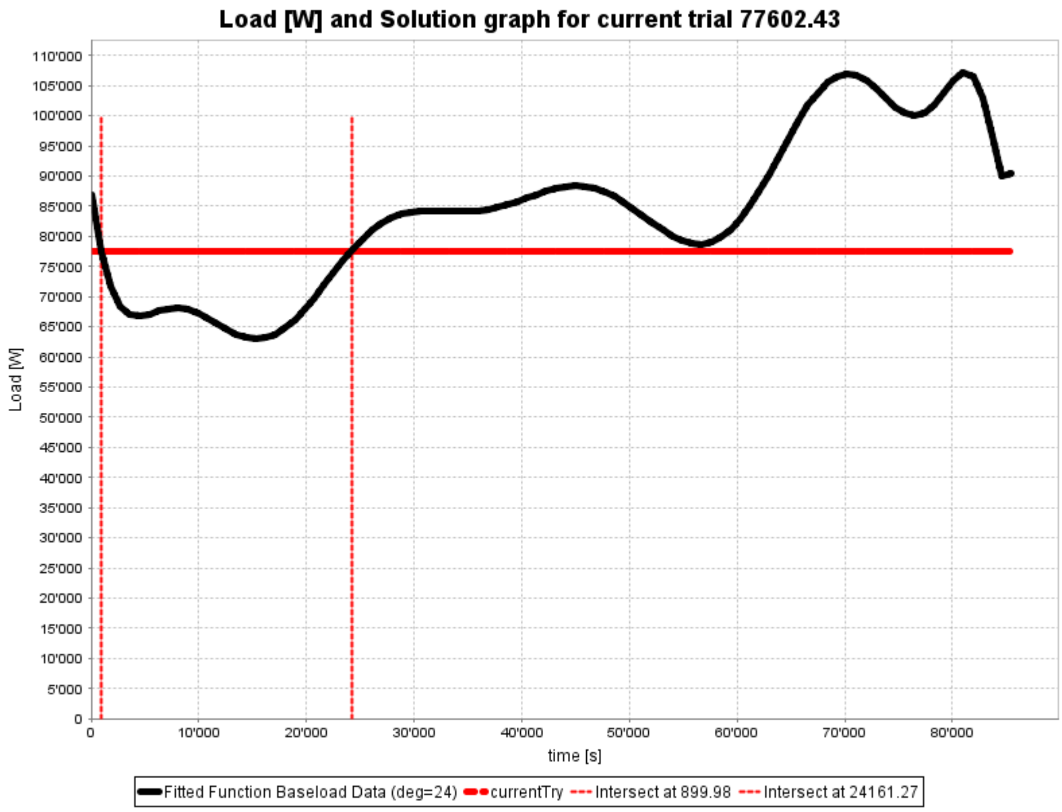
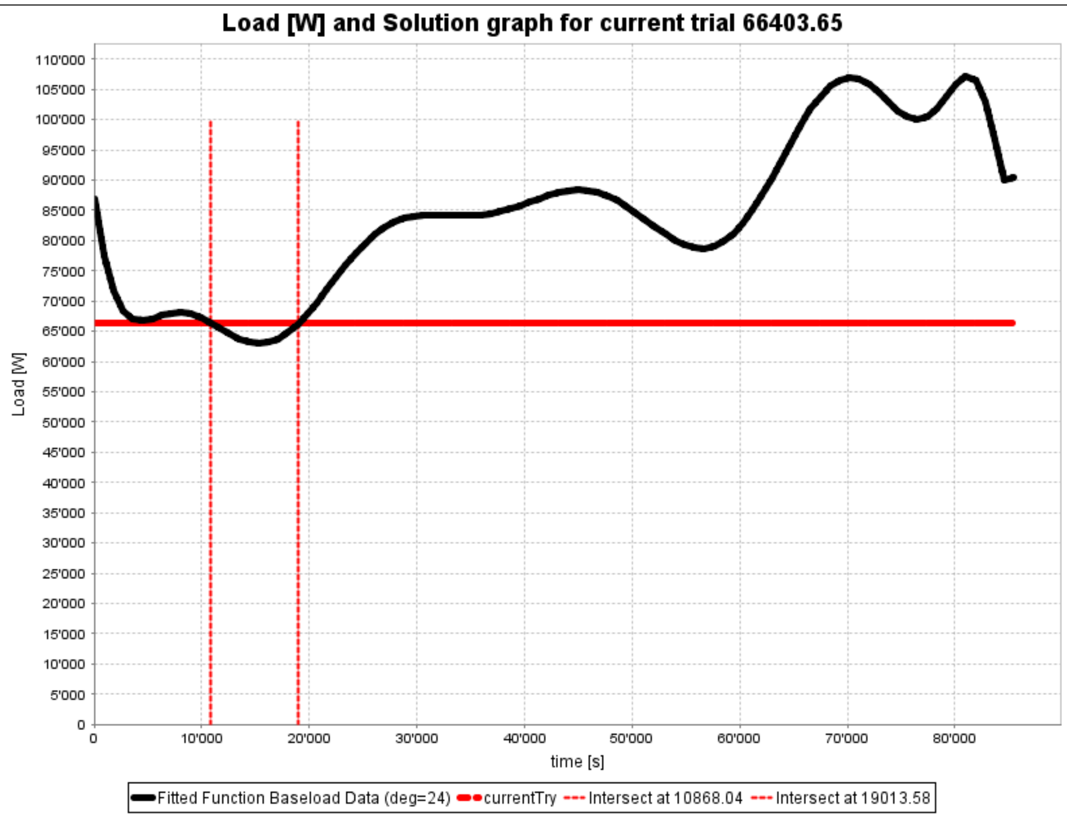


Figure 11 Example output: first two iterations of bisection procedure

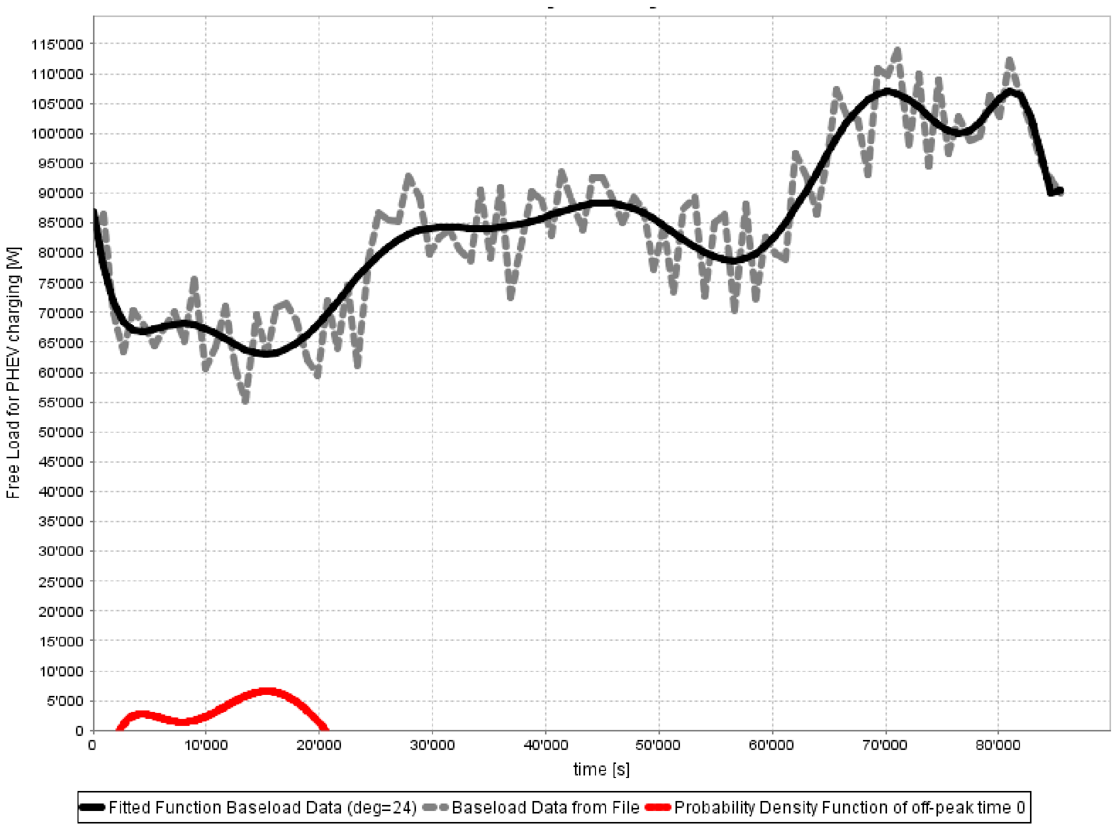




5.4 Probability weight functions

From the off-peak times in section 5.3. the probability density functions can be determined. Values for the unscaled probability function ${}^{PHEV}P_{baseLoad}$-$f(t)$ (red in Figure 12) are read at one minute intervals and are then fitted to a polynomial function of a specified degree (currently set at a degree of 5).

Figure 12 Unscaled probability density functions



5.5 Charging sequence

To determine the charging sequence, a linear optimization problem is formulated which minimizes the time in which the vehicle charges at peak charging rates. The constraints to be satisfied are to have sufficient charge to complete all of the agent's activities and to satisfy the battery constraints, i.e. the possible charging speed and staying within a range of 10-90% of battery charge to prevent quick battery degradation. The optimization is done for a one day interval from 0:00 to 24:00 o'clock under the assumption that the starting state of charge is equal to the state of charge at the end of the day, i.e. the same day routine can readily be repeated on the next day.

Setting up the optimization problem

To set up the optimization problem, the day is divided into time periods differentiated by the purposes, driving, parking in peak times and parking in off-peak times. The variables to solve for include the optimal starting SOC, SOC_{start}, and the charging durations for both types of parking periods, $t_{\mathrm{chargingPeak}}$ and $t_{\mathrm{chargingOff-peak}}$. The length of the solution vector, *x*, is naturally dependent on the agent's personal schedule; (13) is an example of how *x* might be structured. The entries of *x* relating to the driving periods are set to 1 by default; their role will be explained in the section on constraints.

$$x = \begin{pmatrix} SOC_{\mathrm{start}} \\ t_{\mathrm{chargingPeak}} \\ \mathrm{driving} \\ t_{\mathrm{chargingOff-peak}} \\ \ldots \\ t_{\mathrm{chargingPeak}} \end{pmatrix} \tag{13}$$

The objective function

To minimize the sum of charging times within the times of peak loads, an objective function is formulated, which has an entry of 1 in all vector entries related to peak charging times. Continuing the example from (13), the objective function to minimize will be:

$$\min \sum \mathrm{charging\ Time}_{\mathrm{peak}} = \begin{pmatrix} 0 & 1 & 0 & 0 & \ldots & 1 \end{pmatrix} \begin{pmatrix} \mathrm{SOC}_{\mathrm{start}} \\ \mathrm{t}_{\mathrm{chargingPeak}} \\ \mathrm{driving} \\ \mathrm{t}_{\mathrm{chargingOff-peak}} \\ \ldots \\ \mathrm{t}_{\mathrm{chargingPeak}} \end{pmatrix} \tag{14}$$

Equality constraint

The equality constraint ensures that the SOC at the beginning and end of the day is the same by setting the sum of all charged energy equal to the used energy for driving. The energy charged, $E_{charged}$, within a time interval depend on the possible charging speed, $s_{charging}$, and the charging duration (14):

$$E_{\text{charged}} = s_{\text{charging}} * t_{\text{charging}} \tag{14}$$

Similarly, the energy discharged during a trip, $E_{discharged}$, will depend on the known required energy consumption for the route, E_{trip}.

$$E_{\text{discharged}} = E_{\text{trip}} * 1 \tag{15}$$

Since the exact energy consumption E_{trip} is known in Joules for every agent and trip, the respective entry in the solution vector for the driving times can take the value 1. Keeping this dummy variable in the solution vector is important to validate the physical feasibility of the trip and charging sequence; this will be presented in the following section on inequalities.

Writing (14) and (15) in terms of the solution vector x, gives

$$\sum E_{\text{charged}} + \sum E_{\text{discharged}} = 0 \tag{16}$$

$$= \begin{pmatrix} 0 & s_{\text{charging}} & 1 & s_{\text{charging}} & \dots & s_{\text{charging}} \end{pmatrix} \begin{pmatrix} \text{SOC}_{\text{start}} \\ \text{t}_{\text{chargingPeak}} \\ \text{driving} \\ \text{t}_{\text{chargingOff-peak}} \\ \dots \\ \text{t}_{\text{chargingPeak}} \end{pmatrix} \tag{17}$$

$$= \begin{pmatrix} 0 & s_{\text{charging}} & 1 & s_{\text{charging}} & \dots & s_{\text{charging}} \end{pmatrix} * x \tag{18}$$

Inequality constraints

To ensure that the SOC of the battery never falls below a minimal or above a maximal percentage of the battery capacity (e.g. 10-90%) during the entire sequence of activities of the daily schedule, the inequalities (19) and (20) are to express the SOC in each time period.

(19) presents the upper bound on the SOC.

$$SOC(t) = \begin{pmatrix} SOC_{start} \\ SOC(t_i) \\ SOC(t_j) \\ SOC(t_k) \\ \dots \\ SOC(t_l) \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & 0 & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & \mathrm{s}_{\mathrm{charging}} & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & \mathrm{s}_{\mathrm{charging}} & \dots & \mathrm{s}_{\mathrm{charging}} \end{pmatrix} \begin{pmatrix} \mathrm{SOC}_{\mathrm{start}} \\ \mathrm{t}_{\mathrm{chargingPeak}} \\ 1 \\ \mathrm{t}_{\mathrm{chargingOff-peak}} \\ \dots \\ \mathrm{t}_{\mathrm{chargingPeak}} \end{pmatrix}$$

$$= \begin{pmatrix} 1 & 0 & 0 & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & 0 & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & \mathrm{s}_{\mathrm{charging}} & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & \mathrm{s}_{\mathrm{charging}} & \dots & \mathrm{s}_{\mathrm{charging}} \end{pmatrix} * \ x$$

$$\leq \begin{pmatrix} batteryCapacity * 90\% \\ batteryCapacity * 90\% \\ batteryCapacity * 90\% \\ batteryCapacity * 90\% \\ batteryCapacity * 90\% \end{pmatrix} \tag{19}$$

(20) presents the lower bound on the SOC.

$$\begin{pmatrix} batteryCapacity * 10\% \\ batteryCapacity * 10\% \\ batteryCapacity * 10\% \\ batteryCapacity * 10\% \\ batteryCapacity * 10\% \end{pmatrix} \leq \begin{pmatrix} 1 & 0 & 0 & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & 0 & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & \mathrm{s}_{\mathrm{charging}} & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & \mathrm{s}_{\mathrm{charging}} & \dots & \mathrm{s}_{\mathrm{charging}} \end{pmatrix} \begin{pmatrix} \mathrm{SOC}_{\mathrm{start}} \\ \mathrm{t}_{\mathrm{chargingPeak}} \\ 1 \\ \mathrm{t}_{\mathrm{chargingOff-peak}} \\ \dots \\ \mathrm{t}_{\mathrm{chargingPeak}} \end{pmatrix}$$

$$= \begin{pmatrix} 1 & 0 & 0 & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & 0 & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & 0 & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & \mathrm{s}_{\mathrm{charging}} & \dots & 0 \\ 1 & \mathrm{s}_{\mathrm{charging}} & \mathrm{E}_{\mathrm{trip}} & \mathrm{s}_{\mathrm{charging}} & \dots & \mathrm{s}_{\mathrm{charging}} \end{pmatrix} * \ x = \begin{pmatrix} SOC_{start} \\ SOC(t_i) \\ SOC(t_j) \\ SOC(t_k) \\ \dots \\ SOC(t_l) \end{pmatrix} \tag{20}$$

Note, that the entry of the solution vector associated with the driving periods needs to be set to 1 within this setup of the problem to formulate the expression for the SOC for every time period, as it is done in (19) and (20).

Upper and lower bounds

Finally upper and lower bounds on the solution are introduced to guarantee a realistic solution vector. As mentioned, the entries related to driving are defined by setting the upper and lower bound to 1, the charging times are bounded by a minimal charging time of zero seconds and a maximum charging time equal to the duration of the parking duration in the respective period, $t_{parkingDuration}$.

$$\begin{pmatrix} \mathrm{batteryCapacity} * 10\% \\ 0 \\ 1 \\ 0 \\ \cdots \\ 0 \end{pmatrix} \le x = \begin{pmatrix} \mathrm{SOC}_{\mathrm{start}} \\ t_{\mathrm{chargingPeak}} \\ \mathrm{driving} \\ t_{\mathrm{chargingOff-peak}} \\ \cdots \\ t_{\mathrm{chargingPeak}} \end{pmatrix} \le \begin{pmatrix} \mathrm{batteryCapacity} * 90\% \\ t_{\mathrm{parkingDuration}} \\ 1 \\ t_{\mathrm{parkingDuration}} \\ \cdots \\ t_{\mathrm{parkingDuration}} \end{pmatrix} \tag{21}$$

6 Results

The implemented charging methods were tested with 100 agents and 100% PHEV ownership on a fictitious network.
Up to now, a global and uniform electric base load profile is assumed at all locations.

Table 1 Literature values for battery capacity, depth of discharge and charging speed

Author	***Battery Capacity***	***Min-max charge***	***Charging speed***
Andersson, 2010 (S.-L. Andersson et al., 2010)	10kWh	10-90%	3.5kW (230V, 16A) 15kW
Kempton & Tomic, 2005 (Kempton & Tomic, 2005)			10-15kW
Nissan Leaf (Schrieber, 2010)	24kWh		Quick charger: 50kW

6.1 Test runs

The simulation showed that the developed charging algorithm effectively shifts charging times to off peak charging times. Different runs were conducted to test the functionality of the algorithm and to evaluate the influence of parameters such as the base load scale and the charging speed on the charging algorithm.

Three scenarios were tested (see Table 2). The battery capacity was kept constant at 24kWh. Scenarios 1 and 2 both have charging speeds equivalent to regular electricity connections of 3.5kW, they only differ in their base load scale. The base load scale is the maximum base load demand on the electric grid during the day, in the chosen scenarios 10^5 W respectively 10^4 W. These chosen values are random assumptions for the fictitious network with only 100 agents.

Scenario 3 assumes quick charging stations of 15kW at all locations. Thus, the comparison with scenario 2 makes it possible to evaluate the impact of investments in upgraded charging infrastructure.

Table 2 Literature values for battery capacity, depth of discharge and charging speed

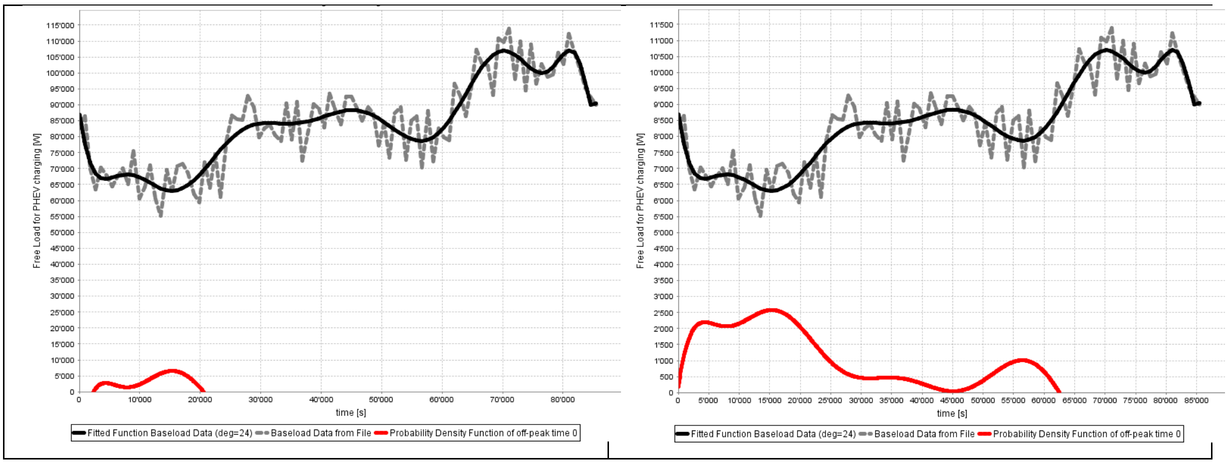
	Base Load Scale	***Charging speed***	***Battery capacity***
Scenario 1	10^5 W	3.5kW	24kWh
Scenario 2	10^4 W	3.5kW	24kWh
Scenario 3	10^4 W	15kW	24kWh

6.2 Influence of the base load scale

As seen in Figure 13, the ratio between the total energy consumption of the PHEVs and the base load consumption has a great influence on the distribution of optimal charging slots over the day and thus the shape of the probability density functions.
The distribution of charging slots and the restrictions on the charging times of the agents are thus highly dependent on the location's load profile (i.e. residential or industrial area) and the market volume of electric vehicles.

Figure 13 Influence of the base load scale on probability density functions

Base load scale: 10^5 | Base load scale: 10^4

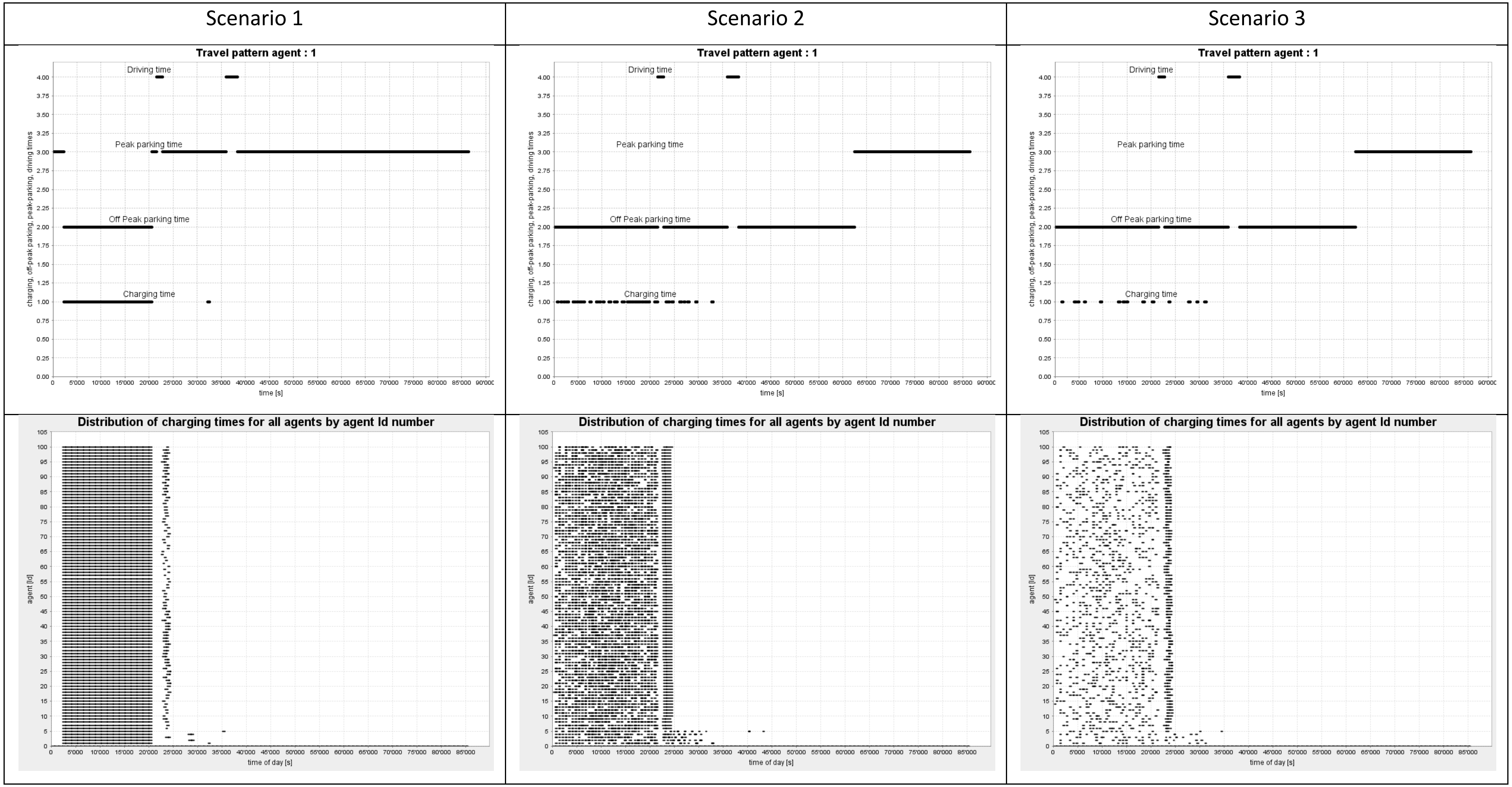


6.3 Influence of the charging speed

The charging speed has a great influence on the required charging time of the agents.
Figure 14 shows a comparison of the daily schedules of agent 1 (row 1) and an overview of the assigned charging slots of all agents (row 2).
It can be seen, that the charging times of the agents are significantly shorter in scenario 3 with a charging speed of 15kW. In scenarios 1 and 2, the agent has to charge almost throughout the entire optimal charging periods to be able to fulfill the energy demands of his driving schedule.

Note: for better visibility, the graphs of Figure 14 are displayed as enlarged versions in Appendix A-F.

Figure 14 Influence of the charging speed



7 Discussion & outlook on future work

The approach of using probability density functions to guide the charging choices for decentralized charging applications is very promising and will be extended in the future. A number of possible areas of improvement are presented in the following.

Objective functions
One important aspect will be to develop more differentiated cost functions. The current setup does not allow for switching of the propulsion system which results in the failure of the linear optimization. The simulation is thus not capable of analyzing systems using the currently existing battery technology and PHEV systems.
To solve this problem the objective function can be extended from only minimizing the charging time in peak hours to also minimizing the driving times with insufficient charge, i.e. the times where the agent would have to swap his battery or switch to the combustion engine.

Secondly, the current objective function does not take into account the probability density functions. It would be beneficial to add additional weights to the objective function to account for the likelihood of being able to charge at low rates within the respective parking periods. For example, charging in a time slot with very low values of the probability density function should be penalized, whereas charging times with very high values of the probability density function should automatically be more attractive within the objective function.

Probability density functions
Generally, probability density functions should also be implemented for the peak times. Analogous to the considerations on adding weights to the objective function for the off-peak times, similar weights could be added to the peak times to discourage charging in times of high loads on the electric grid.

SOC
The current analysis is focused on one day analyses assuming that the SOC is the same at the beginning and at the end of the day. This is sensible within the MATSim framework and for working days with recurring similar schedules. Yet, depending on the research question, it might be valuable to loosen the constraint on the SOC in the future.

Feedback to the agent's utility

So far, only the charging procedure has been implemented, but still needs to be properly integrated within the existing MATSim framework. For this purpose, negative and positive feedbacks need to be defined as functions of the agent's effective electricity costs for charging and the time spent driving without sufficient electric charge.

Location information

In reality, the infrastructural constraints and the loads on the electric grid might vary from location to location. Thus, by considering location based information such as different probability density functions or charging infrastructures (already integrated into the simulation framework MATSim) can add more detail to the simulation.

V2G

Finally, the ideas on the integration of V2G in the established system as introduced in chapter 4 will be implemented.

8 Acknowledgements

First of all, I would like to thank Prof. Dr. Axhausen for giving me the opportunity to participate in this exciting project.

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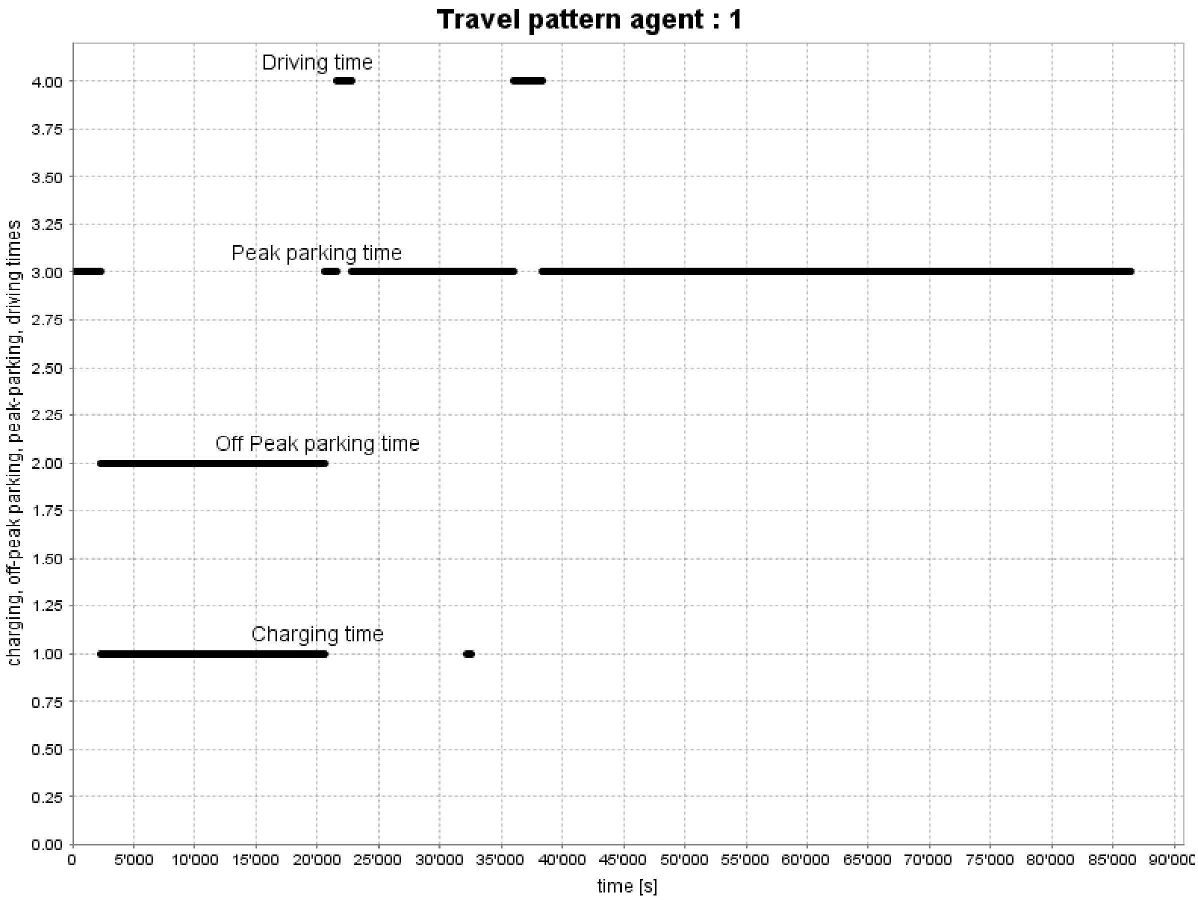
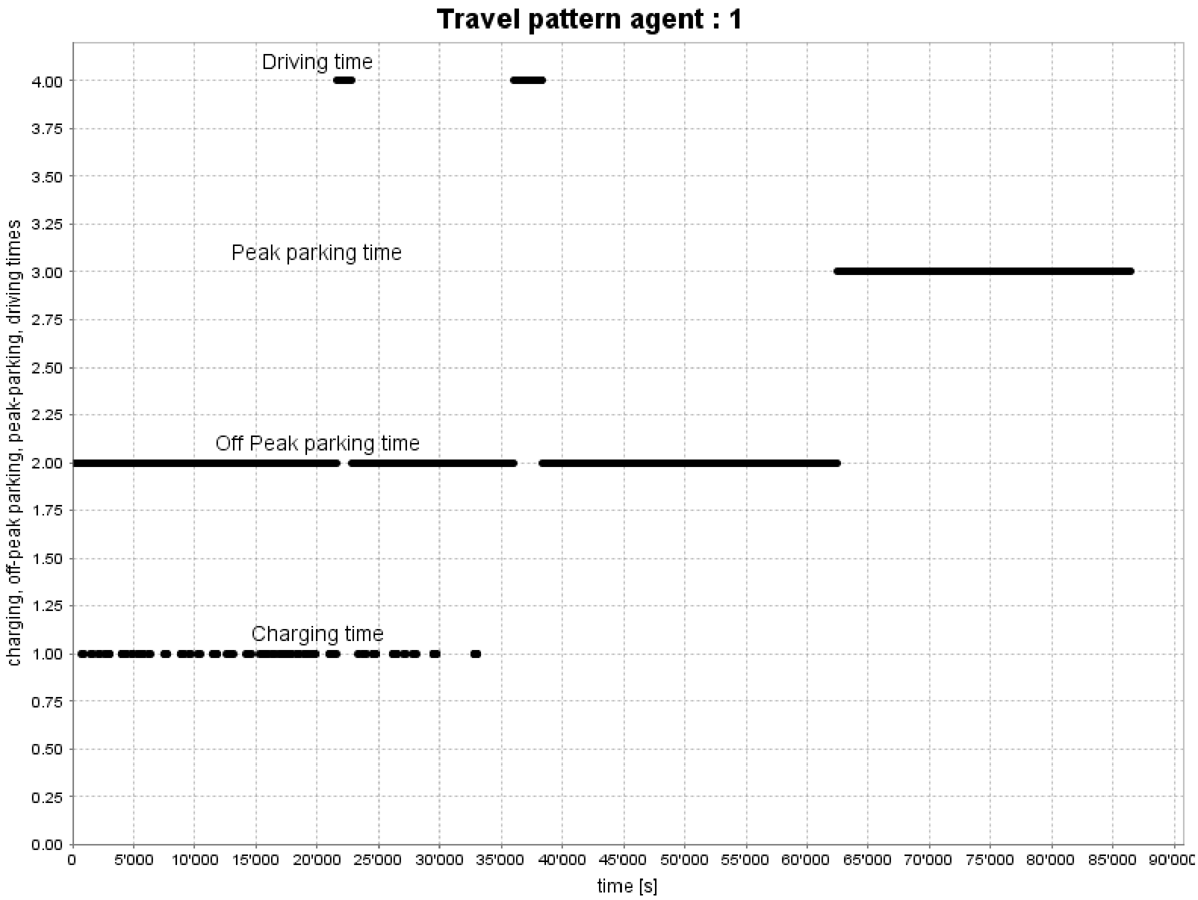
10 Appendix

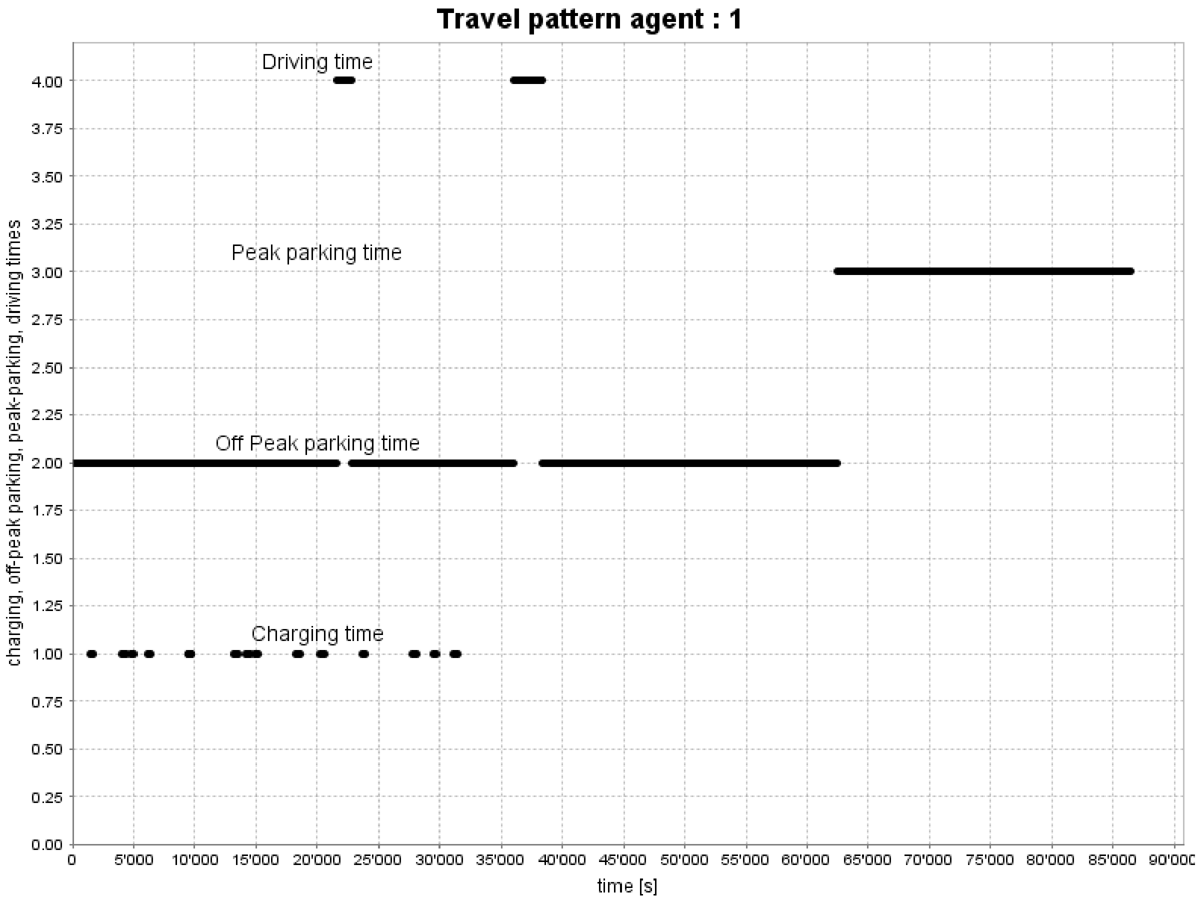
Appendix A: Scenario 1 - Travel pattern for agent



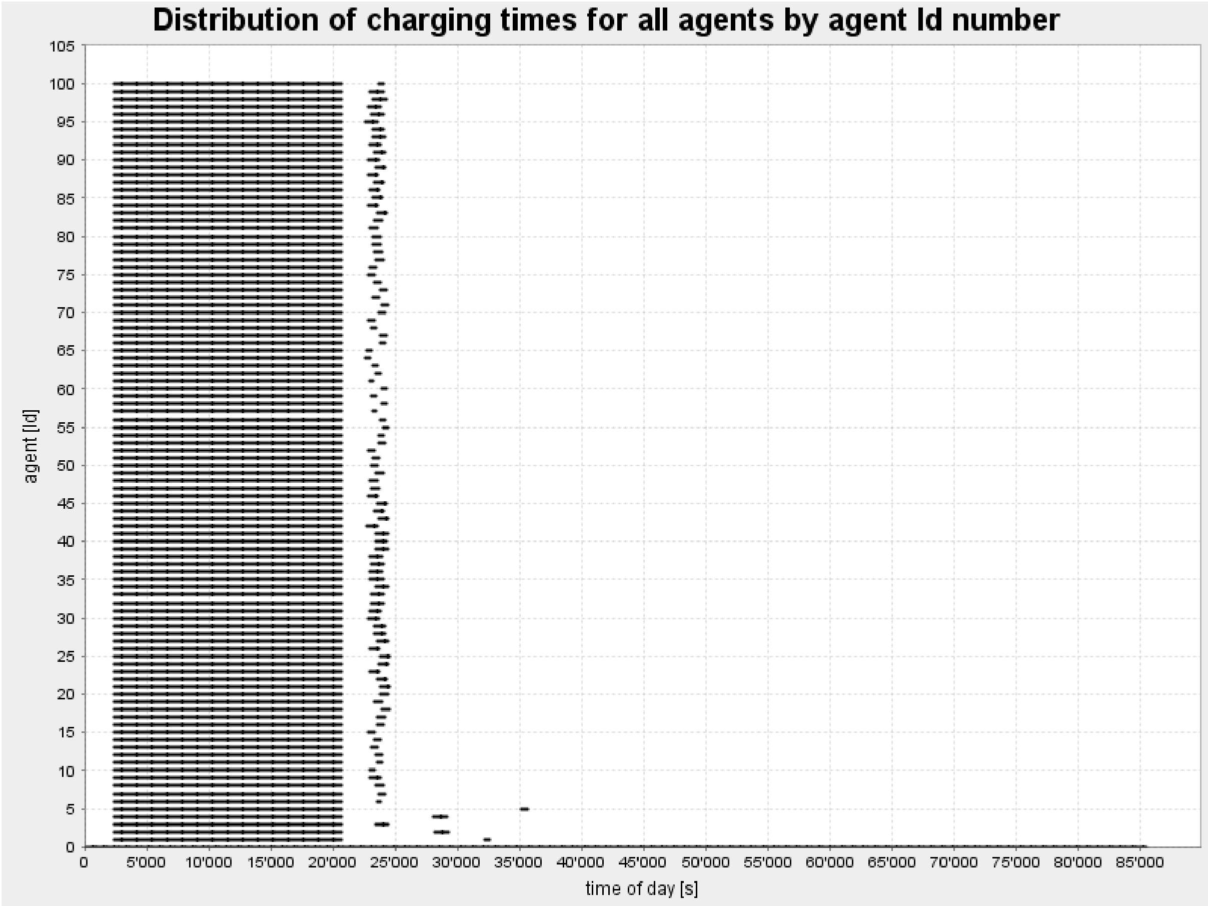
Appendix B: Scenario 2 - Travel pattern for agent



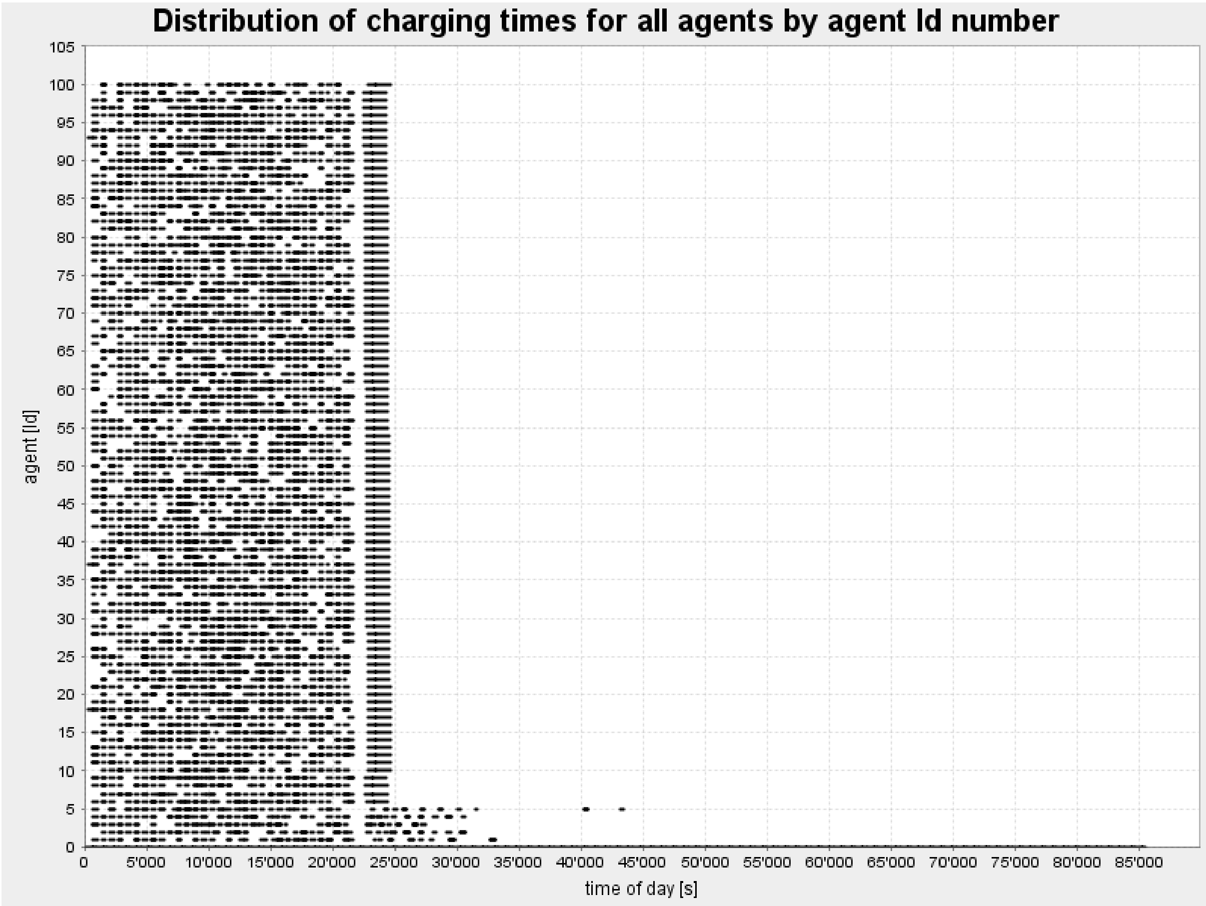
Appendix C: Scenario 3 - Travel pattern for agent



Appendix D: Scenario 1 –Charging times all agents



Appendix E: **Scenario 2 –Charging times all agents**



Appendix F: Scenario 3 –Charging times all agents