Electric Vehicle Travel Optimization—Customer Satisfaction Despite Resource Constraints

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Abstract—Consumers and producers of mobility products have been co-creating a mobile world—all within the limits of political regulation and infrastructure realities. With the advent of electric vehicles, the existing mobile world requires adaptation: Producers need to create new ecosystems and mobility concepts ([1], [2]), infrastructure requires adaptation ([1]) and lastly consumers might revisit their expectations.

Particularly challenging is the market introduction phase of electric vehicles. Neither have the potentials of the infrastructure and the electric vehicles been fully exploited, nor have consumers become accustomed to electric vehicles and shaped their expectations accordingly. Making electric vehicles a success story requires the satisfaction of customer expectations in the face of both electric vehicle and infrastructure realities.

This paper suggests an optimization approach which maximizes customer satisfaction for existing electric vehicle and infrastructure realities. For various degrees-of-freedom (DoF) of the mobility system, the improvement potential is analysed with respect to consumption, charging time, cost and travel time. Moreover, the optimization complexity is analysed, which scales with the number of DoF. The approach enables market entry of electric vehicles and provides the means for future e-navigation and e-travel-planning.

I. INTRODUCTION

ELECTRIC vehicle (EV) market penetration rate will greatly depend on customer satisfaction, which effects the customer’s willingness both to buy and to promote the specific product ([3]). Customer satisfaction is the result of a comparative process, throughout which the customer compares his expectations to his actual perception of the product. Customers’ expectations have been shaped over decades by internal combustion engine (ICE) vehicles and both cheap and available resources. The goal is to meet these expectations despite EV constraints and infrastructure realities.

Several surveys have been conducted as to what customers expect from future mobility ([4]) and electric mobility in particular ([5], [6], [7]). In summary, customers seem to be mainly concerned about range, charging time and total cost of ownership (TCO) of electric vehicles, with TCO becoming a predominant decision criterion in the stages posterior to the market introduction phase. Currently, EV’s range, charging time and TCO are inferior to ICE vehicles. This is particularly true if the range, charging time and cost are considered independently. However, in electric mobility they are strongly connected, leaving great potential for improvements through intelligent coordination.

The more constrained the user-perceivable EV properties are, the less likely is a high degree of customer satisfaction with all its economical implications. This paper demonstrates how intelligent coordination of electric vehicles overcomes both energetic and temporal constraints and potentially reduces the running cost of EVs and hence considerably improves customer satisfaction. Admittedly, EVs may not yet be suitable for all customers. Well-coordinated EVs are however satisfying a large number of customers.¹

The paper is organized as follows: Section II introduces the problem, starting with a sample user journey. Section III describes the general problem of coordinating EVs within time, energy and space. Treating the entire mobility system at once would span a very large optimization space. To mitigate this, the mobility system is split into four decoupled sub-optimization spaces in section III-A. Section III-B discusses possible optimization approaches for each of the subspaces. One of the sub-optimization spaces is the main subject of this paper, namely the journey level. Section IV gives a formal mathematical description of the mobility system at the journey level, which provides the means for the complexity analysis in section IV-G. Optimization results are shown in section V. The optimization potential at the journey-level is computed for the individual case as well as the general case.

II. PROBLEM DESCRIPTION

A. A Specific User Journey

Mrs. Miller plans a trip from Gifhorn (GF) to Wolfsburg (WOB). In Wolfsburg she intends to meet with a colleague for a business lunch. Later Mrs. Miller drives to her office in Braunschweig (BS).

Mrs. Miller has several alternative options to travel the sequence of trips GF-WOB-BS. Assuming that she wants to arrive on time for the business lunch in Wolfsburg, several options exist, which differ in departure and travel time as well as energy consumption and travel cost. Fig. 1 visualizes a set of travel choices.

A differentiation is made between route alternatives (e.g. D¹, D²) and charging strategies (e.g. C¹). For the trip from Gifhorn to Wolfsburg Mrs. Miller chooses a route which compromises the fastest and the most energy-efficient route (D²). This gets her to Wolfsburg early, as can be seen in fig. 1. The duration of the business lunch suffices to fully recharge the EV if choosing a fast charging strategy (C¹). Both medium (C²) and slow charging (C³) result in sub-100% battery state-of-charge (SoC) at the time of departure. Charging time is negatively correlated with charging cost. Mrs. Miller chooses not to charge (C¹). This limits her decision space for the consecutive trip from Wolfsburg to Braunschweig. Route alternative D² becomes energetically infeasible, while route alternative D³ is temporally infeasible. Mrs. Miller is left with the

¹Based on travel profiles as described in [1], [8] and [9]
time-optimal route and the respective route choice, departure and travel time.

Mrs. Miller has made a travel decision. She was well-aware of the earliest possible departure time from Gifhorn, the latest possible arrival time at Wolfsburg, how much time she intended to spend in Wolfsburg, which future trips she had planned and how much money she was willing to spend for time savings. Presumably Mrs. Miller was not aware of the vehicle and infrastructure properties. She did not know whether an early departure from any one location may save overall travel time due to favourable traffic conditions, whether staying at a certain location longer in order to prolong the charging interval would avoid a timely and possibly costly detour to find an available charging station later on or if choosing a slow but energy-efficient route could eliminate a charging stop altogether.

Even though a user might be well aware of some properties, it is more than challenging to make an optimal travel choice. This is due to distributed knowledge, the size of the problem and the mutual dependency of mobility system properties and user decisions.

Table I shows a trip example, indicating the improvement potential of mobility planning. The table quantifies the implications of alternative travel choices with respect to time, energy consumption and the energy-equivalent cost. Values are presented for a route of around 80 km and two discrete travel alternatives, namely “energy-optimal route” and “time-optimal route”. Energy-equivalent cost is differentiated for three different charging strategies, namely “fast charging”, “medium charging” and “slow charging”.

TABLE I

<table>
<thead>
<tr>
<th>travel time</th>
<th>energy-optimal route</th>
<th>time-optimal route</th>
</tr>
</thead>
<tbody>
<tr>
<td>travel time</td>
<td>117 min</td>
<td>57 min</td>
</tr>
<tr>
<td>energy consumption</td>
<td>9.7 kWh</td>
<td>17.1 kWh</td>
</tr>
<tr>
<td>energy- equivalent</td>
<td>fast charging</td>
<td>8.92</td>
</tr>
<tr>
<td>energy- equivalent</td>
<td>medium charging</td>
<td>4.46</td>
</tr>
<tr>
<td>energy- equivalent</td>
<td>slow charging</td>
<td>1.55</td>
</tr>
</tbody>
</table>

B. General Description

More in general a user has a set of activities. Each activity can be described as an appointment, which is specified by a starting time, duration and location. The user makes decisions on how to realize a sequence of trips connecting consecutive appointments. In particular this includes decisions on when to depart, which route to choose, where to park and whether—and if so how—to charge the vehicle at the appointment location.

All possible combinations of travel choices form the choice set. The size of the choice set depends on the DoF of the mobility system as well as the resolution of the mobility parameters. A travel choice is optimal if the journey properties minimize the user’s cost criteria.

Finding a single optimal trip involves two primary quantities, namely travel time and energy consumption. Finding a good trade-off between the two is sufficient to determine a unique criterion over which to optimize.

When finding the optimal sequence of coupled trips, the main objective is to guarantee that over the entire sequence of trips the user reaches each appointment in time and that the SoC of the vehicle never falls below a predefined threshold. Travel time and energy consumption are still important, yet other quantities such as waiting time (time the user waits for the charging process to end), charging cost, the number of charging events, etc. gain importance due to their potential to inconvenience the user.

III. Problem Formulation

The user journey of section II-A has illustrated the energetic, spatial and temporal interconnectedness of electric mobility. In favour of easier comprehension, a journey with a low level of complexity was chosen. In reality, the choice set depends on a range of vehicle properties, on user-vehicle interaction as well as vehicle-infrastructure interaction.

Each mobility subsystem has some influence on temporal, energetic or spatial properties of both the mobility system and the individual travel plan. The extend to which a subsystem influences the properties of the individual travel plan greatly varies for different subsystems.

A hierarchical mobility framework has been developed, which assigns each subsystem to one of four mobility levels. Along the mobility levels the DoF grow and so does the potential to influence energetic, spatial and temporal properties of the travel plan. However, at the same time the complexity of the underlying optimization problem increases.

For a comprehensive analysis of the problem’s complexity please refer to section IV-G. Section V quantifies the improvement potential for the trip and journey level with respect to temporal, energetic and spatial properties of the travel plan.

A. Mobility Framework

In the following a conceptual mobility framework is presented, which uses the concept of mobility levels in order to hierarchically structure the mobility system into subsystems. Fig. 2 provides an overview of the mobility levels and their subsequent tasks. A more detailed treatment of the different mobility levels can be found in [10].

The two major tasks of the component level are inter- and intra-component coordination. Taking the example of an air conditioning system, the notion of intra-component coordination is illustrated. The example of an in-vehicle energy management system serves to demonstrate inter-component coordination.

Intra-component optimization: For some input parameters like target cabin-temperature and humidity and some output parameter like cabin-heat-flow, a control unit minimizes the required energy consumption and reaction time of the air-conditioning system.

Inter-component optimization: The air-conditioning system is an
Fig. 2. The electric mobility system is represented by four mobility levels. Major tasks of individual mobility levels are described. Out of the four levels, the component level is the least integrated level while the mobility level is the highest aggregation level.

integral part of the intra-vehicle energy net which is controlled by the energy management system. Alongside the air-conditioning system, the drive train, the infotainment system and other auxiliary consumers compete for power, which is limited by the vehicle’s battery. If the total power request exceeds the maximum power supply of the battery, individual component requests are controlled by the energy management system. The resulting portions of energy serve as inputs to the intra-component level.

On the trip level the major tasks are time and energy optimal routing as well as resource aware routing. A single origin-destination-relationship is optimized under the assumption of an optimally controlled component level. For a particular start SoC, specific component properties, traffic states, route topography, etc. time and energy optimal routes are to be found. The trip level incorporates multi-modal routing. A single route then consists of a walkway, a drive and again a walkway. It considers car parks and charging stations, their location, availability and impact on energy, time and distance. Moreover, residual range prediction is performed on the trip level. If residual range is insufficient to reach the destination, a charging station is scheduled within the residual range of the vehicle. A charging station can be seen as an intermediate destination in between appointments.

The journey level considers a sequence of trips together with a period of stay at each destination. The journey level mainly handles coupling effects of trips within multi-destination sequences. It deals with high-level combinatorial problems. Solutions include charging strategies, route sequences and parking strategies.

The mobility level is concerned with supply and demand management of users and transportation mediums. Users are no longer strongly connected to private vehicles; they may participate in mobility services such as car and ride sharing. Car sharing services enable the user to flexibly change the car at intermediate destinations. Ride sharing and dynamic carpooling services coordinate shared trips. Several multi-modal extensions such as public transport may be additionally included in the problem formulation.

Each higher level of the framework adds at least one additional DoF to the problem formulation. Each additional DoF increases the improvement potential of the travel plan. Yet, each additional DoF also increases complexity of the optimization problem.

(i) Optimization methods become easily integrable.
(ii) The decomposition into sub-optimization schemes reduces the size of the search space.

Note that with the decomposition step the optimal solution might (and in practice often does) deteriorate. The following optimization methods can be applied to the individual mobility levels.

On the component level conventional control strategies can often be applied ([11], [12]). For example, consider the intra-component operational strategy used for an air conditioning system ([13]) or the inter-component control strategy of an energy management unit as described in [14].

On the trip level optimization routines are mainly path finding strategies on graphs. A conclusive overview of algorithms is provided by [15]. According to some cost function the optimal paths need to be found from one starting location to many destination locations, such as parking spots and charging stations, and vice versa. The specific problem formulation determines the graph properties and cost functions of the search algorithm.

Journey level optimization can be reduced to a combinatorial optimization problem. Constraint programming is one possible approach to generate optimal or near-optimal solutions efficiently, dynamic programming is another. It might be possible to extend the trip level approach to the journey level. However, it is not yet clear whether trip level routines can deal with the parameter dependencies and temporal effects of the journey level.

On the mobility level open-ended, distributed systems are treated, which negotiate many drivers and transportation mediums. Negotiation can be either of collaborative or competitive nature, thus optimization needs to take into account game-theoretic aspects. Solutions can be found through a range of methods such as constraint optimization, genetic algorithms or Monte Carlo based methods.

In order to reduce the complexity and dimension of the optimization problem, it has been decoupled into a hierarchical formulation. Component, trip, journey and mobility level each represent separate optimization problems. The optimization results of lower levels serve as inputs to the higher levels forming an integral hierarchy. The result space of a lower level, which is made available to a higher level, must not necessarily contain the best solution only; it may contain a set of alternatives. This is done to compensate the fact that the optimal solution on the lower levels might not be optimal in the context of the higher levels.

IV. Problem Formalization

A. Temporal Structure

A user wants to travel along a sequence of $n$ destinations. At destination $i$, $i = 1, \ldots, n$, the user has an appointment $A_i$ which is defined by a starting time $t^A_{S_i}$, an end time $t^A_{E_i}$ and a location $L_i$.

The evolution of the vehicle SoC over time can be represented by a continuous function, say $SoC(t)$. Typically the SoC decreases during driving and increases during charging. Due to the particular nature of EVs, the SoC may also increase during driving (recovery) and decrease during charging (Vehicle2Grid).

Fig. 3 depicts the temporal sequence of the mobility events that are related to a single appointment $A_i$. The user leaves with an EV from the car park of destination $i-1$ at time $t^D_{E_{i-1}}$ in order to drive to destination $i$. The user travels along route alternative $R^{D_i}$ which consumes energy and hence reduces the SoC. On arrival at the car park of destination $i$ the user walks to location $L_i$; the user arrives at $t^D_{E_i}$; the appointment starts at $t^A_{S_i}$.
After the appointment is finished, the user returns to the car park. The walk back to the car park needs to take place at the latest so that destination $i + 1$ is reached in time. The vehicle may recharge while being parked. Possible recharging strategies are fast, medium, slow and no charging as well as smart charging (Vehicle2Grid).

Fig. 3. Temporal structure of the mobility events of appointment $i$, namely the driving, walking, charging and parking events. For simplicity the index $i$, which represents the $i$th event, has been omitted.

All time variables are in the following format:

$$i t^Y_{e, i}, \quad i = 1, \ldots, n$$

The index $i$ at the lower left indicates the appointment; valid values for $Y$ are $D$ (drive), $W$ (walk), $A$ (appointment), $P$ (park) and $C$ (charge); valid values for $Z$ are $S$ (start) and $E$ (end).

If several events of the same type are associated to a single appointment, they are expressed as $Y_j$ where $Y$ is as above and $j \in \mathbb{N}$. In particular this notation can be used for smart charging (includingVehicle2Grid), where several charging events are scheduled during the parking interval $[t_{S}^{C_{1,i}}, t_{E}^{C_{1,i}}]$:

$$[t_{S}^{C_{1,i}}, t_{E}^{C_{1,i}}], [t_{S}^{C_{2,i}}, t_{E}^{C_{2,i}}], \ldots, [t_{S}^{C_{m,i}}, t_{E}^{C_{m,i}}]$$

B. Spatial and Energetic Structure

The road network is represented by a directed graph $G := (V, E)$, with $V$ being the set of vertices and $E$ the set of edges. Edge length is denoted by $s_k$, $k = 1, \ldots, |E|$. The road network is not treated in greater detail within this paper as it is mainly relevant on the trip level.

Car parks are defined as edge attributes $e P^k_e$, with $k \in \mathbb{N}$ being the capacity of the car park, $e$ the edge to which the car park is attached and $f$ a time dependent availability function (binary or distribution function). The same formalism applies to charging stations, which are represented by $e C_{f', k'}$ with $k' \in \mathbb{N}$. Parking is a necessary requirement for charging, hence $k' \leq k$ holds. A possible data acquisition and information distribution scheme for parking space availability is presented in [16].

Several other attributes are associated to each edge $e$, such as the expected mean velocity on the edge, the edge on which the initial speed is expected to be in the piecewise constant function $e V^Y_e(t)$ where $Y \in \{D, W\}$ (driving, walking) and $t$ is the time of the day. Velocity data is derived from traffic information. The temporal resolution of traffic information is 5-60 min depending on the road class.

The energy associated to an edge $e$ is described by the function $e E^Y_e(t, \epsilon_{prev}, \epsilon_{acc})$. Just as $e V^Y_e(t)$, it is piecewise constant in $t$. The energy depends not only on time, but also on the neighbouring edges. Velocity is considered non-negative while $e E^Y_e \in \mathbb{R}$.

C. Constraints

From a consumer perspective, it is important to respect appointment times and guarantee that the SoC of the vehicle never falls below a certain level. We thus require

$$t_{E}^{W_{1,i}} \leq t_{S}^{A} \quad \text{and} \quad t_{E}^{A} \leq t_{S}^{W_{2,i}}$$

for all appointments and

$$\text{SoC}(t) \geq \text{SoC}_{min}$$

at all times $t$.

Parking spaces and charging stations must be feasible to be used. They are considered feasible if their availability function exceeds the availability threshold value and if the minimal route length from the appointment location $L_i$ to the parking space $P$ does not exceed the maximum walking distance $s_{max}$, i.e.

$$\sum_{k \in R(L_i, P)} s_k \leq s_{max}$$

where $R(L_i, P)$ is the shortest walking route from $L_i$ to $P$. Driving related constraints including traffic are handled by the routing component.

D. Schedules

A schedule defines the mobility events of a user for a particular journey. For each appointment $i$ it consists of

- the starting time of the drive from appointment $i - 1$ to appointment $i$, $t_{S}^{D}_{i}$
- the driving route from the parking spot of appointment $i - 1$ to the parking spot of appointment $i$, $R_{i}^{D}$
- the walking route from the parking spot to the appointment $i$, $R_{i}^{W_{1}}$, and the walking route from the appointment back to the parking spot, $R_{i}^{W_{2}}$, which are typically the same
- the parking spot during the appointment, $P_{i}$
- the charging intervals during the appointment, $[t_{S}^{C_{i,i}}, t_{E}^{C_{i,i}}]$, and the associated charging type for each interval, $C_{f}^{i}$. 

For simplicity we allow at most one charging interval for each appointment and we assume that we have a method for determining its start and end time based on the other parameters.

We say that a schedule is feasible if under expected conditions (such as traffic) no constraints are violated. In particular that means that the user is able to reach all appointments in time and the SoC of the vehicle never falls below a predefined minimum level.

E. Cost Function

An aggregated cost function is considered for the optimization. It is of the form

$$\alpha_{1} f_{1}(K_{1}) + \cdots + \alpha_{M} f_{M}(K_{M}) = \sum_{j=1}^{M} \alpha_{j} f_{j}(K_{j})$$

where $K_{j}$ are the single cost criteria, $f_{j}$ are continuous, monotonically increasing functions and $\alpha_{j} \in \mathbb{R}$, $j = 1, \ldots, M$. In many cases it is sufficient to set all $f_{j}$ equal to the identity function, i.e. $f_{j} := id \forall j$. Without loss of generality we assume that the goal is to minimize the cost function.

The following cost criteria have been considered:

- consumed energy
- charging cost
- travel time
- waiting time
- walking distance
- SoC at the end of the last appointment
- number of charging events

On the routing level the cost criteria are limited to consumed energy and travel time.
F. Method

Optimal travel schedules are determined by a central service which collects and aggregates all necessary information. The basic method to identify the optimal travel schedules consists of the following three steps:

1) generate schedules from all possible parameter combinations described in section IV-D
2) check constraints to determine all feasible schedules
3) use exhaustive search to determine all optimal schedules

In practice, steps one and two go hand in hand to exclude as many non-feasible schedules as possible before generating the decision space. This can greatly reduce the number of schedules to consider. For example, if the driving time of a certain route exceeds the available time between two appointments, then all schedules containing that route can be excluded right away. This does however not help much with some constraints, such as keeping the SoC above a certain level.

G. Complexity Analysis

For a fixed ordered set of appointments we define $S$ as the set of all feasible schedules. Complexity analysis is mainly concerned with the cardinality of $S$.

1) Trip Level: Consider a trip level schedule as shown in fig. 2. It features exactly one starting location $L_1$ and exactly one destination location $L_2$. We consider $r$ distinct routes. For example, for $r = 3$ we might consider the fastest, the most fuel efficient and the shortest route connecting $L_1$ and $L_2$.

Furthermore we define discrete-time intervals of length $T_f$ for which traffic is assumed constant and discrete-time intervals of length $T_p$ for which parking lot and charging station availability is constant. Typically the temporal resolution of traffic changes is lower than the temporal resolution of changes in parking lot availability, hence $T_f \leq T_p$.

Let $\tau$ be a lower bound on the time required to get from $L_1$ to $L_2$ and define $T := \min\{T_f, T_p\}$. Then if $q$ is the number of distinct time variants, it can be limited by

$$q \leq \left\lfloor \frac{2T^2 - T_f - \tau}{T} \right\rfloor + 1$$

Let $p$ be the number of parking spots in the vicinity of $L_2$. We consider $c$ distinct charging strategies. For example, for $c = 4$ we might consider fast, medium, slow and no charging. The number of parking and charging related combinations to consider is then at most $p \cdot c$. Thus the cardinality of $S$ on the trip level turns out to be

$$|S| \leq q \cdot r \cdot p \cdot c.$$ 

Note that the bound can be sharp, i.e. there are cases where $|S| = q \cdot r \cdot p \cdot c$.

2) Journey Level: Now, consider a journey, which describes a sequence of multiple trips. The preconditions that have been introduced on the trip level still hold for the journey level, thus

$$q_i \leq \left\lfloor \frac{c_i T_f^2 - T_f^2 - T_i}{T_f} \right\rfloor + 1 \quad \forall i$$

As a result, for a journey of $n$ sequential trips it holds that

$$|S| \leq \prod_{i=1}^{n} (q_i \cdot r_i \cdot p_i \cdot c_i)$$

and the bound is again sharp.

In practice the number of routes, the number of parking spots and the number of charging types can be considered as design parameters of the problem, so we can assume $r_i = \bar{r}$, $p_i = \bar{p}$ and $c_i = \bar{c} \forall i$. If this is not the case, we simply put $\bar{r} := \max_i r_i$, $\bar{p} := \max_i p_i$ and $\bar{c} := \max_i c_i$. Thus we get

$$|S| \leq \left( \prod_{i=1}^{n} q_i \right) \cdot (\bar{r} \cdot \bar{p} \cdot \bar{c})^n$$

In many cases it might be reasonable to use a different time resolution for each appointment (e.g. 10 minute steps for the first appointment, 15 minute steps for the second appointment, etc.) such that $q_i = \bar{q} \forall i$, otherwise we set $\bar{q} := \max_i q_i$. Therefore we get

$$|S| \leq (\bar{q} \cdot \bar{r} \cdot \bar{p} \cdot \bar{c})^n$$

Note the bound can be sharp and that $n$ is in the exponent, so $|S|$ grows exponentially fast as $n$ grows. Therefore the running time of an algorithm doing exhaustive search over all possible schedules also grows exponentially in the number of appointments.

V. RESULTS

This chapter specifies the optimization potential of EV-user-infrastructure coordination. The notion of best (resp. worst) schedules refers to schedules minimizing (resp. maximizing) a cost function of the form described in section IV-E over the set of feasible schedules. The parameters in the cost function depend on consumer preferences and specify for example how much a customer values time savings with respect to additional costs. Feasible schedules do not violate any of the constraints stated above; they represent a possible travel choice of the user with the aid of a state-of-the-art navigation system. Results are shown for a scenario-based analysis. Firstly, an individual scenario’s best and worst journey are compared. Secondly, mean improvement values are shown, which have been derived from multiple scenarios.

Fig. 4 shows the comparison of the best and the worst feasible journey for an individual scenario as in section II-A. For a sequence of trips (going from Wolfsburg to Gifhorn and back to Wolfsburg, then from Wolfsburg to Braunschweig and back to Wolfsburg) the graph presents the evolution of the vehicle’s SoC over time. For this particular sequence of events and its specific environment there are approximately 80 million feasible schedules to be considered, which is in accordance with the considerations of section IV-G. The best/worst feasible journey is based on a cost function that weights energy consumption, travel time, charging cost and the number of charging events.

![Fig. 4. Comparison of the best and the worst feasible journey with respect to a specific cost function. Graph shows the evolution of energy over time for the sample scenario; driving and charging are linearised.](image-url)
Going from the specific to the general case, fig. 5 shows the mean improvement potential for a set of scenarios. The maximum relative improvement potential describes how much the value of a travel parameter can be maximally reduced. For the cost function term $j$, it is obtained by setting $\alpha_i = 0$ for $i \neq j$ and $\alpha_j \neq 0$ \(^2\) and then comparing the best with the worst feasible schedule. On the trip-level the travel improvements are a consequence of routing strategies. On the journey-level the improvements are mainly resulting from temporal shifts of driving, parking and charging events. As can be seen in fig. 5, the improvement potential of both “consumed energy” and “duration” is dominated by trip-level optimization whereas “charging cost” and “end energy” are mainly influenced on the journey level.

Fig. 5. Mean improvement potential of travel parameters.

However, journey-level improvement potential is strongly related to trip-level routing strategies. The journey-level improvement potential is compared for two routing strategies, “fastest routes only” and “energy-optimal routes only”. Fig. 5 shows the difference between the two. In general, fast routing strategies reduce travel time. Hence, the number of possible temporal shifts of travel events increases, which increases the size of the search space and generates additional improvement potential.

Fig. 6. Difference in journey-level improvement potential as a consequence of trip-level routing strategy. Results are shown for the comparison of a fast and an energy-optimal routing strategy.

VI. SUMMARY

At an economical level, this paper aims at improving customer satisfaction, which results from conformity of customer expectations and electric mobility realities. Users expect less restricted range, charging time and cost. It is claimed that the latter restrictions can be significantly reduced through intelligent optimization schemes, of which journey level optimization is the subject of this paper.

In order to reduce the search space, an optimization framework has been proposed, which segments the mobility system into subspaces. Separate optimization approaches have been proposed for each subspace. For journey-level optimization, the complexity analysis shows exponential growth of the search space with the number of appointments throughout the journey. To evaluate the improvement potential, exhaustive search has been implemented and optimization results have been shown.

Results strengthen the assumption that electric vehicle travel can be significantly improved through optimization. Analysis shows particularly great improvement potential for journey level parameters like charging cost. However, even trip level parameters such as the consumed energy can be further improved on the journey level.

VII. CONCLUSION AND RECOMMENDATIONS

While this paper has shown that journey optimization creates added value, exhaustive search has been used to determine optimal solutions. As with this approach computing time grows exponentially with the number of appointments, finding more efficient methods for determining optimal or near-optimal solutions is important.

One limitation of the current approach is that it does not allow for intermediate charging stops at the trip level. This is crucial in real world applications in order to manage longer trips and should therefore be incorporated into the model.

Finally, a tighter integration of individual mobility levels is desirable. Further work is necessary to determine its influence on complexity and its improvement potential.

REFERENCES