Real-Time Schedule Optimization in Shared Electric Vehicle Fleets

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Abstract: Use of electric vehicles in corporate carsharing has become a promising option. However, to make the use of electric vehicles economically feasible, a high degree of utilization is necessary. In the Shared E-Fleet project, solutions for shared car fleets are being researched, increasing utilization by sharing cars among different companies. In this work, we present a process and algorithms for real-time vehicle schedule optimization, aiming to minimize manual scheduling work, to optimize the schedule towards a goal function (e.g. minimizing emissions) and to compensate disruptions in real-time. We evaluate the approach using synthetic data and model trials, showing that schedule optimization increases utilization as well as quality-of-service.

1 INTRODUCTION

With raising costs of fossil fuels and technological progress, electric vehicles (EV) have become a suitable alternative for company car fleets. In a recent study (Plötz et al., 2013) a market potential of 1 million EVs until 2020 in Germany alone is identified, with especially high potentials in company car fleets (30 percent of new cars bought). However, prerequisite for an economical use of EVs is a high utilization of vehicles (Plötz et al., 2013) to offset the high fixed costs of EVs and charging infrastructures. The Shared E-Fleet project[1] aims at realizing these potentials by developing solutions for the shared operation of electric car fleets. Thus, even small and medium enterprises, which could not economically operate an EV alone, can reach critical mass when they unite.

The operation of corporate carsharing in EV fleets poses unique challenges. In comparison to conventional vehicles, charging times and limited range need to be taken into account when planning a schedule (Koetter et al., 2013). When operating at capacity, i.e. utilizing EVs almost fully, even minor disruptions of the schedule by late returns or lost battery capacity can have far-reaching consequences. To compensate for these disruptions and to create an ecologically and economically optimal schedule, continuous optimization is necessary.

In previous work we developed an algorithm for schedule optimization for planning purposes (e.g. composition of a car fleet) (Koetter et al., 2013). In this work we will build on these results to achieve a continuous optimization of shared EV fleet schedules, providing the following contributions: Partial optimization of the schedule in case of new bookings and real-time information, just-in-time selection of vehicles, compensation of errors and delays, economic and ecological schedule optimization.

This work is structured as follows: Section 2 gives an overview of relevant related work. Section 3 describes the Shared E-Fleet usage scenario and main process. Section 5.2 describes the optimization algorithms. The prototype and evaluation are summarized in Section 5. A conclusion and outlook is given in Section 6.

2 RELATED WORK

Relevant related work can be found in other EV optimization domains like routing and charging, as well as in different vehicle scheduling problems.

Various approaches for charging scheduling in EVs exist, some using real-time vehicle data as well (e.g. (del Razo et al., 2014)), but while these cover a partial problem in EV fleet operations, they do not cover booking of trips and scheduling of vehicles.

In (Bielli et al., 2011) an overview of fleet optimization problems is given. The problem described in this work partially matches the dial-a-ride-problem, but differs in that it offers customers dedicated cars.

A solution for the joint optimization of scheduling and charging is described in (Sassi and Oulamara,

[1] http://www.shared-e-fleet.de/

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2014). Similar to this work, tours with determined start and end dates need to be scheduled to a set of vehicles to maximize utilization and minimize charging costs. As tours cannot be moved in time, this problem differs from other routing problems in logistics. The work described proves the routing problem to be NP-complete and developed as well as benchmarked multiple optimization algorithms. While this provides a solution to charge and schedule optimization, it does not take into account the ongoing optimization necessary for EV fleet operations including the real-time aspect, the reaction to disruptions and the continuous change of bookings. Same as the authors of (Sassi and Oulamara, 2014), to the best of our knowledge we have not found other related work for the schedule optimization of shared EV fleets.

A summary of vehicle routing problems in logistics is given in (Pillac et al., 2013). Similarly to this work, approaches for continuous optimization and optimization in time slices are taken into consideration, providing methods for the efficient solution of NP-hard schedule optimization problems. However, the proposed solutions do not match the schedule optimization problem in shared fleets, as rather than trips with predetermined start, end and timing a set of locations needs to be served in no particular order. Additionally, the discussed algorithms do not take into account EVs.

In previous work we used a schedule optimization algorithm for the composition of fleets, checking ex-post which number and mix of vehicles is optimal (Koetter et al., 2013). In this work we reuse timeline data structures and concepts from this previous work for real-time schedule optimization.

3 USAGE SCENARIO

Shared E-Fleet provides an IT solution for the administration and operation of shared EV fleets. While all aspects of fleet management like user and vehicle management, access management and billing are covered, the schedule optimization focuses on booking and driving vehicles. In comparison to floating concepts like *Car2Go*[2], Shared E-Fleet is designed for a business use case and allows users to book a journey in a specific time-frame, starting and ending at a defined fleet station. This has the advantage that stricter time requirements for business trips can be kept and vehicle states can be planned, as future travel times as well as destinations (and in turn battery capacities) are known. A journey may encompass multiple trips, e.g. if third-party transportation is used or the vehicle is switched to increase range.

Figure 1 shows the process of booking and driving a journey. During booking, a user enters the details of the planned journey, including start and end station, begin and end time, as well as destinations or kilometers to drive. Then the system searches for alternatives to fulfill this booking. Using a route calculation service (Shekelyan et al., 2014), alternative routes and vehicles are taken into account to find a possible alternative to fulfill the request. If no alternatives are found (e.g. if no free vehicles for the booking time are left), booking is aborted. The user may select one of the alternatives, which is then reserved. The user may then abort or abandon the booking process. If the user confirms the booking, it is added to the schedule with the selected alternative. Note that at this point in time no specific vehicle is promised to the user yet. Rather, the reservation will be kept in the schedule, but may be moved between equivalent vehicles if necessary. The user may cancel the booking any time before it starts.

At a defined time before the journey starts, all trips are fixed to a suitable vehicle (at the correct location, no other trips, sufficient charge), if one is available. An interval of one hour was chosen as a trade-off between optimization potential and user acceptance. Up to this point the schedule optimizer may switch vehicles if necessary. Note that existing bookings are prioritized over new bookings, so no intentional overbooking takes place. A vehicle will definitely be available if no delays or malfunctions in previous bookings have occurred. If no vehicle is available, the booking is impossible and the user is notified. Otherwise, the user is sent a notification indicating which vehicle to use including a virtual key to unlock it. If the user starts the journey, he checks in via an app. Then, he performs all trips in the journey in order. During trips delays and malfunctions may occur, which are communicated in real-time by the vehicle (Ostermann et al., 2014) and may necessitate changes in the schedule, as they may impact following trips with the same vehicle. Finally, after the last trip, the user checks out to finish the booking.

4 DYNAMIC OPTIMIZATION

In general, schedule optimization is a problem of selecting which trips are to be performed by which vehicles. This is a variant of the fixed interval scheduling problem (Kovalyov et al., 2007) with additional, usage scenario specific constraints. The schedule optimization aims to optimize a schedule in terms of a

[2]http://www.car2go.com

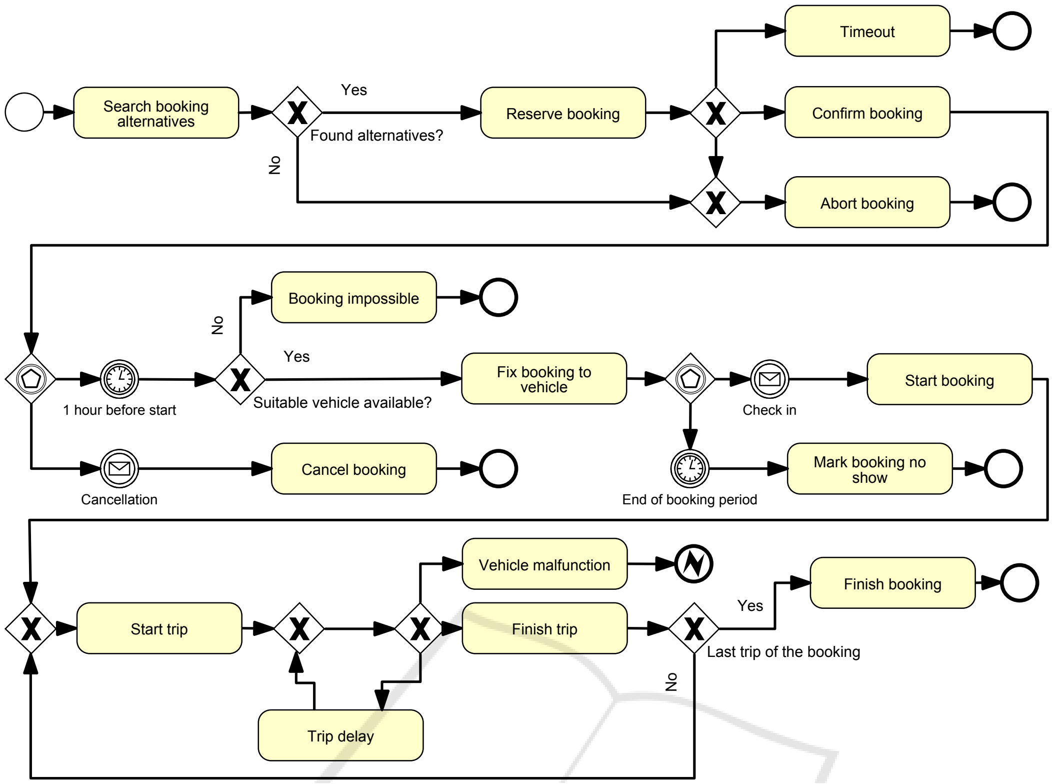


Figure 1: Main booking and driving process in Business Process Model and Notation (BPMN) 2.0.

goal function within existing constraints.

As a basis for optimization, we first describe the relevant data types. Note that for the sake of brevity, only attributes relevant for optimization are detailed in this work.

A trip $t \in T$ is a single step on a journey which is performed with a single mode of transportation. There are trips performed with fleet vehicles (T_f) and trips performed with external third party transportation (T_e). For schedule optimization, external trips $t_e \in T_e$ remain unchanged, as third party modes of transportation cannot be influenced. The impact of disruptions in third party transportation (e.g. late trains) are currently ignored in schedule optimization and subject for future work. A fleet trip is defined as follows:

$t \in T_f := (time_s, time_e, wp_s, wp_e, length)$

where $time_s$ and $time_e$ are the start and end time, $wp_s, wp_e \in WP$ the start and end waypoint and *length* the length of the trip in kilometers. A waypoint $wp \in WP$ is a defined location like an address or geolocation. A special kind of waypoint is a station $wp_{station} \in WP_{station} \subset WP$, which belongs to the fleet and offers parking as well as charging infrastructure.

A *booking* $b \in B$ represents a journey a user plans to undertake or has already made. It is defined as follows:

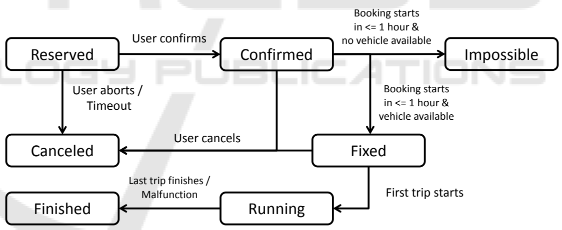


Figure 2: State diagram of bookings.

$b \in B := (class, state, time_s, time_e, t_1 \ldots t_n)$

where *class* is the desired vehicle class, $state \in STATE_B$ is the state of the booking, $time_s$ and $time_e$ are the start and end time and $t_1 \ldots t_n \in T$ are a sequence of trips in the booking (i.e. the journey). Note that a journey has to start and end at a waypoint:

$wp_{s_{t_1}}, wp_{e_{t_n}} \in WP_{station}$

Figure 2 shows a diagram of the booking states $STATE_B$ and their relationships. A booking starts in the state *Reserved* as soon as an alternative is selected. This is to ensure the booking is still available when the user confirms, after which the booking state is changed to *Confirmed*. One hour before $time_s$ the booking is to be *Fixed*, i.e. for each trip $t_1, \ldots, t_n$ of the booking a vehicle is locked in. If not all trips can be fixed, the booking state is changed to *Impossible*. At any time before t_1 begins with check-in, the user may abort or cancel the booking, which is changed to the state *Canceled*. As t_1 begins, the booking state changes to running. At this point it cannot be canceled or changed by schedule optimization. After t_n has ended or a malfunction occurs, the booking is eventually *finished*.

A vehicle $v \in V$ is a fleet vehicle, which may either be an EV or a conventional vehicle. In this work, we focus on EVs, as conventional vehicles can be handled as an EV with infinite range and without the need of charging. We define a vehicle as follows:

$v \in V := (class, em, oc, range, rcp)$

where *class* is the vehicle class, *em* are the CO_2 emissions per *km* in *g*, *oc* is the operating cost per kilometer, *range* is the range in kilometers and *rcp* is the recharging percentage per minute. We approximated charging curves linearly with a pessimistic estimate, so real-life charge will be at or above the estimated level. This approach was found sufficient in (Sundstrom and Binding, 2010). Note that in our prototype a uniform charging infrastructure at the stations is assumed, though in practice different charging modes can be faster or slower. This could be amended by defining the available charging modes for each $w \in WP_{station}$.

A schedule E is a mapping of booking trips $t \in T_f$ to fleet vehicles $v \in V$ as follows:

$E := \{(t,v) | t \in T_f, v \in V \cup \{\varepsilon\}\}$

Note that a trip may be mapped to no vehicle (ε). These trips are *unscheduled*:

$T_{unscheduled} := \{t | \exists (t,\varepsilon) \in E\}$

For each vehicle, a vehicle schedule E_v is defined as follows: $E_v := \{(t,x) \in E | x = v\}$

The set of all trips scheduled to a vehicle are defined as follows: $T_v := \{t | \exists (t,v) \in E\}$

A goal function z calculates the utility of a schedule: $z : E \to \mathbb{R}$

During optimization, the utility of partial schedules must be calculated. To achieve linear scalability in regards to schedule size, a goal function needs to fulfill the following independence criterion:

$\forall E : z(E) = \sum_{(t,v) \in E} z(\{(t,v)\})$

This criterion stipulates that the utility of a schedule is the sum of the utility of each trip. This allows fast calculation of total utility when partial schedules are merged by adding the utility of the partial schedules.

Depending on the business goals of a car fleet operator, different goal functions may be used, which are detailed in (Koetter, 2015a). One example is the minimization of CO_2:

$z(E) = \sum_{(t,v) \in E} (-1 * length_t * em_v)$

Note that for this goal function the optimum is reached when no trips are performed, as no CO_2 will be produced. To avoid this unwanted result, the optimized schedule needs to fulfill a number of constraints:

The *satisfiability constraint (C1)* stipulates general consistency and plausibility conditions.

$\forall v \in V : \exists t_1, .., t_n \in T_v : (\forall t \in T_v : t \in t_1, ..., t_n \wedge length_t \leq range_v) \wedge (\forall i \in 1..n-1 : time_{e_{t_i}} + buffer \leq time_{s_{t_i+1}} \wedge wp_{e_{t_i}} = wp_{s_{t_i+1}})$

Each vehicle schedule has to be a sequence of trips, which do not overlap in time and have at least $mathitbuffer$ time between them. Each trip has to start where the last ended and no trips' length may exceed the range of a vehicle.

Additionally, each trip must be mapped to exactly one or no vehicle:

$\forall t \in T_f : |(t,x)| \leq 1$

Similarly, the *charge satisfiability constraint (C2)* stipulates sufficient charge must be available at all times. Given a consistent trip sequence $t_1, .., t_n$ for a vehicle v as defined in C1, C2 is defined as follows:

$\forall t_i \in T_v, i \in 2..n : length_{t_i} \leq range_v + \sum_{j=1..i-1} (rcp_v * (time_{s_{t_j+1}} - time_{e_{t_j}} + buffer)) - length_{t_j})$

Before each trip t_i sufficient state of charge (SoC) needs to be available in v, if previous trips are considered and standby times are used for charging.

The booking consistency constraint (C3) stipulates that trips must match the selected booking details, including route and vehicle class.

Two constraints cannot always be fulfilled: The *fixing constraint (C4)* stipulates that a trip has to be performed by a fixed vehicle if it was already communicated to the user.

The *completeness constraint (C5)* stipulates that all (or as many as possible) trips shall be mapped to vehicles ($T_{unscheduled} = \emptyset$).

If these constraints cannot be fulfilled, C5 takes precedence over C4.

To perform schedule optimization, a three-step algorithm is used. An *alternative search* tries to fit a new booking, a *partial optimization* optimizes only the schedule of a single vehicle, while a *full optimization* optimizes the whole schedule if necessary.

4.1 Partial Optimization

Partial optimization rearranges only the trips of a single vehicle schedule and can be performed quickly, thus enabling immediate user feedback (e.g. during the booking process). Partial optimization is used if a booking is performed or cancelled, if real-time information about vehicle delays or malfunctions arrives or if a vehicle is not returned on time. Partial optimization for a vehicle v is performed as follows:

1. Order T_v by $time_s$ to get a sequence $t_1,..,t_n$
2. For $i \in 1..n$
   (a) Try adding (t_i,v) to E_v considering vehicle state taking into account current delays, malfunctions and estimated charge at return
   (b) If constraints C1-C3 are fulfilled, add (t_i,v) to $E_{v_{new}}$
   (c) Else add (t_i,ε) to $T_{unscheduled}$
3. Replace old vehicle schedule E_v with $E_{v_{new}}$

Note that trips of running and fixed bookings are added first due to chronological ordering. Also note that partial optimization may violate constraint C5.

A vehicle state is updated whenever real-time data arrives and has the following attributes: The *availability* of the vehicle indicates if a trip is currently performed. The *estimated remaining charge* gives an estimated SoC for the time the vehicle finishes its current trip. It is used instead of *range* when evaluating C2. The *estimated return time* gives an estimated time of the vehicles arrival at wp_e of its current trip. It is used instead of $time_e$ for all constraints and further calculations. If the vehicle is late or has less SoC than anticipated, it is possible the following trips cannot be scheduled to the vehicle without violating constraints.

4.2 Full Optimization

Full optimization is performed periodically in the background by a scheduler. The optimization algorithm as well as the goal function is encapsulated using interfaces. Though other algorithms are possible, for the prototype we implemented a greedy algorithm:

1. Create an empty Schedule $E_{opt} := \emptyset$
2. Sort all bookings b and vehicles v by vehicle *class*
3. For each *class*
   (a) Sort all bookings b by $state_b$
   (b) Add trips of completed and running bookings to previously assigned vehicle, as they cannot be reassigned anymore
   (c) Fixed, confirmed and reserved bookings may be optimized in this order
   (d) Separate trips t of optimizable bookings in time chunks TC (e.g. 1 day) by $time_e$
   (e) For each time chunk TC
      i. Calculate optimal subschedule E_{sub} for all v with *class* and $t \in TC$ using a backtracking algorithm
      ii. Add optimized subschedule to optimized schedule. $E_{opt} := E_{opt} \cup E_{sub}$
4. Compare old and optimized schedule to select E_{new}
   (a) If E_{opt} does not fulfill C1-C3: $E_{new} := E_{old}$
   (b) Else if E_{opt} does not fulfill C5 and E_{old} does: $E_{new} := E_{old}$
   (c) Else if E_{opt} does fulfill C5 and E_{old} does not: $E_{new} := E_{opt}$
   (d) Else if both E_{opt} and E_{opt} fulfill C5:
      i. If $z(E_{opt}) > z(E_{old})$: $E_{new} := E_{opt}$
      ii. If $z(E_{old}) \leq z(E_{opt})$: $E_{new} := E_{old}$
   (e) Else if both E_{opt} and E_{opt} do not fulfill C5:
      i. If $|T_{unscheduled_{opt}}| > |T_{unscheduled_{old}}|$: $E_{new} := E_{opt}$
      ii. If $|T_{unscheduled_{opt}}| \leq |T_{unscheduled_{old}}|$: $E_{new} := E_{old}$
5. Return E_{new}

This optimization algorithm uses a recursive step to calculate optimal subschedules E_{opt}, which is detailed in the following:

1. Subschedule optimization is called with a sequence of trips $t_1,..,t_n \in TC$, an existing schedule E_{opt}, a set of Vehicles V_{class} and an initial utility u, which is equal to $z(E_{opt})$
2. Determine initial vehicle state for all $v \in V$ from current state and trips in E_{opt}
3. Initialize choice list $cl := \emptyset$
4. $\forall v \in V_{class}$
   (a) Test if t_1 can be added to v without violating constraints
   (b) If yes:
      i. $E_{opt} := E_{opt} \cup \{(t_1,v)\}$
      ii. Calculate utility and add it to total utility: $u' := u + z(\{(t_1,v)\})$
      iii. Recursively call subschedule optimization with $t_2,...,t_n$, E_{opt}, V_{class} and u'
      iv. Add returned utility and mapping to choice list : $cl := cl \cup (u_{new},(t_1,v))$
      v. $E_{opt} := E_{opt} \setminus \{(t_1,v)\}$
5. Select best mapping $m_{opt} := (t,v)$ where $(u,(t,v)) \in cl$ and $u = max(\{u|\exists(u,x) \in cl\})$
6. Add best mapping to optimized schedule: $E_{opt} := E_{opt} \cup \{m_{opt}\}$
7. Calculate new utility: $u_{new} := u + z(\{m_{opt}\})$
8. Return u_{new} and E_{opt}

Full optimization uses backtracking to recursively calculate optimized timeline chunks. While the runtime of backtracking is exponential, due to the constant size of timeline chunks, an overall linear runtime is achieved (for further details see (Koetter et al., 2013)). An approximate optimum is created by combining these local optima. Completed and running trips cannot change vehicle anymore, fixed trips have priority in the greedy algorithm. Only if they don't fit in the schedule of the fixed vehicle, are they moved. After fixed trips have been distributed, confirmed trips and reserved trips are distributed. This allows maximal optimization potential with minimal disruptions to end users.

4.3 Alternative Search

During alternative search, alternatives for the requested booking and all provided routes are searched as follows:

1. Get a set of routes $R := \{(t_1, .., t_n)\}$ for alternative request from external route search
2. Intialize set of alternatives: $A := \emptyset$
3. For each $r \in R$
   (a) Use subschedule calculation with all vehicles in the requested vehicle class, the trips in r and a copy of E to create E_{new}
   (b) If $\forall t \in r : (t, \varepsilon) \notin E_{new}$
      i. Add route as alternative: $A := A \cup r$
4. Return a

An alternative is found if the trips of a booking can fit the current schedule while fulfilling all constraints. As an immediate answer to the alternative search request is required to continue the booking process, the search time needs to be minimized. Moving existing trips to fit the alternative requires longer search times, as no old bookings may be removed to fit the new alternative. Thus, existing trips are not moved during alternative search.

5 PROTOTYPE AND EVALUATION

We implemented the algorithms for booking, alternative search, partial and full optimization in a Java prototype, which we evaluated with synthetic tests as well as in three long-term model trials with end users.

The schedule optimization prototype is part of the larger Shared E-Fleet architecture (Ostermann et al., 2014) and provides its services to a combined user and administration frontend, while using third-party route search (Shekelyan et al., 2014).

Figure 3 shows the architecture of the prototype. A booking component provides booking functionality to the frontend, while in turn using the alternative search algorithm to find alternatives for booking requests. The optimizer contains algorithms for partial and full optimization. If a real-time notification about delays, malfunctions, returns, etc. is received, the *state* of the respective EV is updated and a partial optimization is performed. The scheduler periodically fixes trips, removes timed-out reserved bookings and triggers full optimization. All components use the schedule as a shared data-structure, which is read- or write-locked when in use. The schedule is stored in a database, from which it is reread if the prototype is restarted. To improve run-time, completed and cancelled trips are periodically moved to an archive, so only current and future trips need to be handled during optimization. Technical details of the prototype can be found in a technical report (Koetter, 2015a).

We tested the prototype using randomly-generated synthetic test-data and self-validation of consistency and constraints. First trials showed a high utilization of vehicles to be possible, provided journeys take half a day or less.

Figure 4 shows an example schedule before and after optimization. The car fleet consists of two conventional vehicles, *combustion1* and *combustion2*, and two EVs, *ev1* and *ev2*. Before optimization, four trips are distributed equally among vehicles. Note that conventional vehicles do not have charging times. During optimization, the goal of CO_2 minimization is considered. As EVs produce less CO_2, they are prioritized and two trips are scheduled to each. Note that both vehicles cannot be fully charged after the first trip, which leads to prolonged charging times after the second trip compared to the schedule previous to optimization.

5.1 Model Trials

We further evaluated the prototype during three model trials with a fleet of eight BMW i3 vehicles. Vehicles were made available to technology parks for a year to be used by real-life small and medium enterprises. During model trials, we continuously improved the algorithm under real conditions. While vehicles provided a range of over 100 kilometers, users tended to book journeys with less than 50 kilometers and less than 3 hour duration, as shown in Figure 5. Thus, a potential for optimization was given. We found 64 percent of trips to be performed without any re-optimization. Of the remaining 36 percent trips differ-

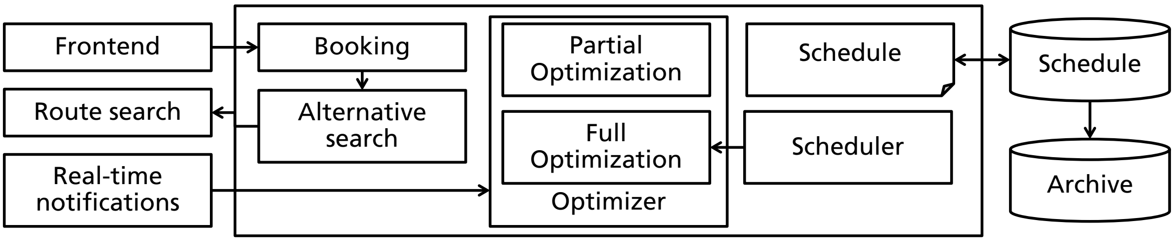


Figure 3: Overview of prototype architecture and control flow.

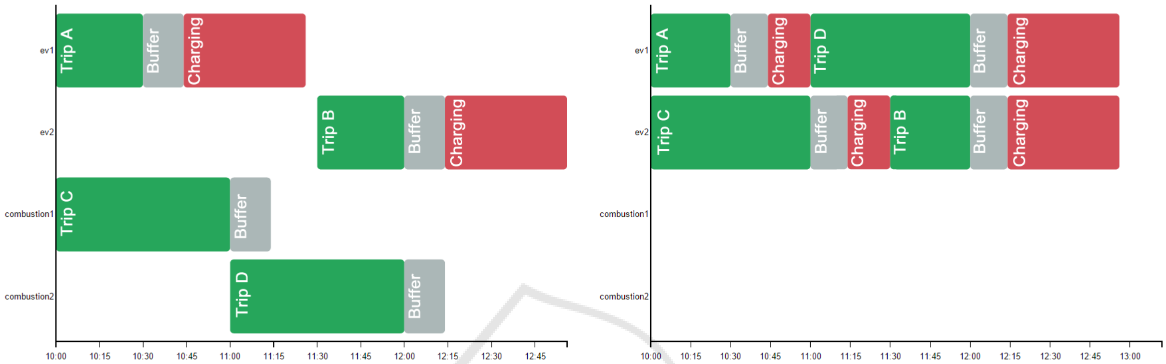


Figure 4: Example schedule before (left) and after optimization (right). Trips in green, buffer times in grey, charging times in red.

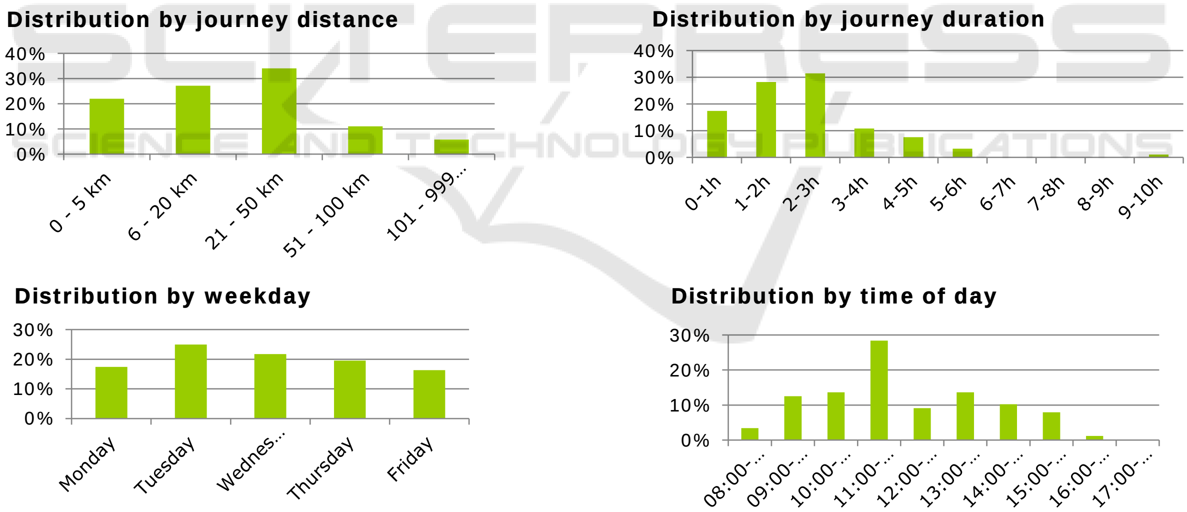


Figure 5: Statistical evaluation of model trial in Stuttgart.

ent causes necessitated a re-optimization. We found users to be optimistic regarding their planned return times, as cars would often be returned late, necessitating re-optimization. During partial optimization, the following trip would be removed from the vehicle schedule and then added to a different vehicle's schedule during full optimization. Often, the following trip was already fixed, making an additional notification to the user necessary, as the vehicle change needed to be communicated. We found the earlier and the more precise delays can be detected and communicated by the vehicle, the better the planning and in turn the end-user experience. Another scenario for re-optimization was the cancellation of bookings by users, which occurred for about 13 percent of bookings. In addition, hardware problems at the beginning of the model trials necessitated the temporary removal of single cars from the fleet. Schedule optimization proved to allow business continuity and quality of service in spite of these disruptions.

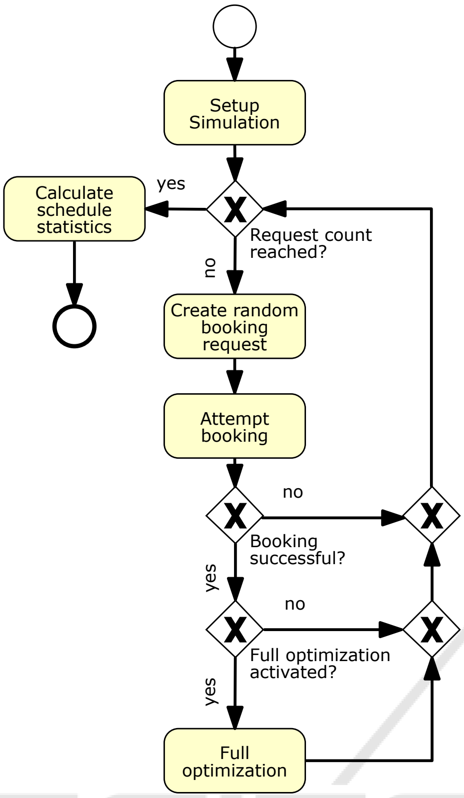


Figure 6: Schedule optimization benchmark process in BPMN 2.0.

further model trials are currently still running, this time using heterogeneous fleets, to further investigate the impact of schedule optimization on CO_2 and cost.

5.2 Synthetic Evaluation

While model trials provide insights into schedule optimization in practice, they are not sufficient for quantitative evaluation. As all parts of the system are evaluated simultaneously, many influences and variables cannot be controlled. For example, hardware problems unrelated to schedule optimization provide insights into rescheduling in face of disruptions, but distort many metrics like goal fulfillment. Thus, we performed an additional evaluation with synthetic test data.

For this evaluation, a benchmark tool was built to interface with the schedule optimization. The benchmark process is shown in Figure 6. During setup an empty schedule is created according to the benchmark settings. These settings include:

- Business hours: Which hours of the day are business hours? (e.g. 7:00-17:00)
- Number of requests: How many booking requests are to be attempted?
- Seed: A seed for pseudorandom booking generation.
- Time interval: The time interval of the trial within which requests are to be generated. (e.g. October 1st 2016 0:00 to November 1st 2016 0:00)
- Use full optimization: Whether or not full optimization is to be used.
- Goal function: The goal function to be used. (minimizing emissions or cost)
- Vehicle fleet: The fleet to be used.
- Customer profile: Determines how booking requests are generated.

During the benchmarks booking requests are created according to a customer profile. The profile used creates booking requests within the business hours, using the following length and duration:

```
lengthKM = Math.max(10.0,
    ((25.0 * rand.nextGaussian()) + 25))
durationMinutes = rand.nextInt(211) + 30
```

To investigate the effect of schedule optimization regarding goal functions, heterogeneous fleets, consisting of both conventional vehicles and EVs are used. The vehicles are shown in Table 1. As conventional vehicles, data of three representative vehicles is used (Deffner and Goetz, 2012). For EVs, data of three common vehicles is used (Bloch, 2014). Prices and emissions are calculated using average fuel prices and wind energy (Deffner and Goetz, 2012). CO_2 emissions for EVs are calculated from emissions occuring during energy production. Note that charging rates are for regular charging, which is available at any station. The possibility of DC charging was not considered as it was not available during the model trials. However, faster charging times can increase fleet utilization. In the evaluation, three fleets are used as listed in Table 2. Regardless which fleet is evaluated, the benchmark uses one central station at which all trips begin and end.

After setup, the benchmark tool creates synthetic bookings from the customer profile using a fixed random seed, making the benchmark process repeatable. Each booking is attempted to be booked by searching for alternatives and booking the best alternative. Note that exactly one route will be generated, as only a flat distance is specified. If no alternatives are found, the booking cannot be completed, indicating a lack of vacancies in the schedule. If full optimization is to be used, it is performed after each successful booking. If the specified number of requests has been attempted, the benchmark concludes with calculating the statistics of the resulting schedule.

Table 1: Benchmark vehicle data.

Model	Type	Cost in € / km	g CO_2 / km	Battery Capacity in kWh	Consumption in kWh / 100 km	Recharged kWh / hour
CombustionLarge	Conventional	0.152	272.000	—	—	—
CombustionMedium	Conventional	0.113	200.000	—	—	—
CombustionSmall	Conventional	0.089	159.000	—	—	—
Tesla Model S	Electric	0.092	8.064	85.00	33.60	3.03
BMW i3	Electric	0.057	4.944	22.00	20.60	2.75
Renault Twizy	Electric	0.032	2.808	7.00	11.70	2.33

Table 3: Benchmark for large fleet and medium number of requests.

Optimization strategy	Random	Random	Emission	Emission	Cost	Cost
Use full optimization	false	true	false	true	false	true
Fulfilled bookings	491	493	489	488	489	488
Unfulfilled bookings	9	7	11	12	11	12
Total kilometers	12329,00	12395,00	12301,00	12271,00	12301,00	12318,00
Total CO_2 in kg	1462,79	1557,56	975,18	719,17	1024,38	844,63
Total cost in €	1066,60	1099,79	919,38	844,00	918,13	842,54
Total usage hours	309,00	309,00	309,00	309,00	309,00	309,00
Fleet utilization	34,572	34,891	34,487	34,509	34,487	34,524
CO_2 per km in g	118,65	125,66	79,28	58,61	83,28	68,57
Cost per km in €	0,0865	0,0887	0,0747	0,0688	0,0746	0,0684
Full opt. gain	Util. gain %	0,92	CO_2 saved %	35,27	Cost saved %	9,12
Partial opt. gain	—	—	49,66	114,41	15,91	29,72

Table 2: Benchmark vehicle fleets.

Model	Small Fleet	Medium Fleet	Large Fleet
CombustionLarge	0	1	1
CombustionMedium	2	1	2
CombustionSmall	0	1	2
Tesla Model S	0	1	1
BMW i3	2	1	2
Renault Twizy	0	1	2

Multiple benchmarks have been performed with all possible combinations of the following settings:

- Number of requests:
  - Low: 1 request per vehicle per day
  - Medium: 2 requests per vehicle per day
  - High: 4 requests per vehicle per day
  - Very high: 8 requests per vehicle per day
- Use full optimization: Yes or No
- Goal function: Random, Minimize Cost or Minimize Emissions
- Vehicle fleet: Small, Medium or Large

Table 3 shows the full results for a large fleet and medium utilization. Detailed results can be found in a technical report (Koetter, 2015b). Full test input and result data can be found online[3]. An overview of benchmark results is given in Figure 7. Optimization potentials for emissions and costs rise with lower utilization, as more bookings can be moved to optimal vehicles, e.g. with low utilization most trips can be moved to EVs to minimize emissions. With higher

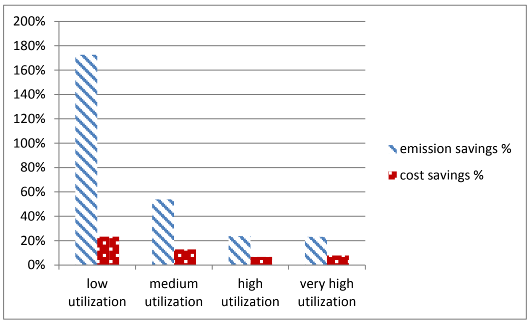
[3] www.shared-e-fleet.de/images/sefevaluation_raw_data.zip

utilization, lower potentials can be realized, as even suboptimal vehicles need to be used. Optimization potentials with low utilization are very high but would not be practical, as in such cases vehicles should be removed from the fleet to save additional fixed costs. High utilization allows emission savings of 25-30 percent, and cost savings of 7-11 percent. Very high utilization allows emission savings of 11-23 percent and cost savings of 6-10 percent.

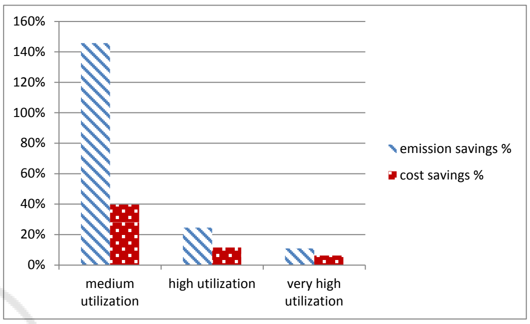
When only using partial optimization, savings are lower throughout the benchmarks. With high and very high utilization, using partial optimization actually produces worse results than no optimization at all. This is because the greedy approach of partial optimization achieves early gains and fills optimal vehicles, leaving only small gaps for later bookings. Without full optimization, these cannot be filled and a disproportionate amount of trips are booked on suboptimal vehicles, thus producing suboptimal schedules. This indicates partial optimization alone is not sufficient for schedule optimization, validating the three-step approach described in this work.

the utilization of a fleet indicates the percentage of time vehicles are in use during business hours. The diagram in the bottom right of Figure 7 shows the relation between utilization and successful booking attempts. The more a schedule is filled, the less vacancies remain for future bookings. Thus, with rising utilization, booking is less and less successful. In practice, a success rate of only fifty percent means every second user is denied a booking request, leading to low user acceptance. Considering a success rate of 80 percent as acceptable, a utilization of about 55 percent is achievable.

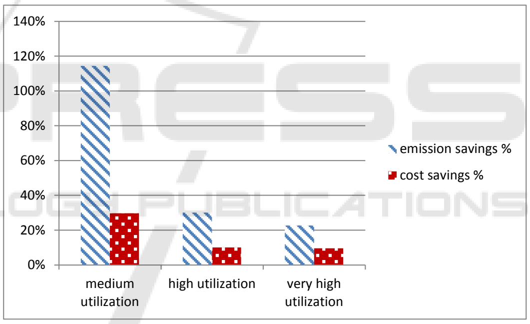
Fleet utilization is almost constant between different optimization strategies, differing by less than one percent. This however is not true for a very high number of requests, where utilization is 2-10 percent lower if full utilization is used. This is because full optimization moves trips with more kilometer to electric vehicles if possible, necessitating recharging times during the day, especially if multiple bookings on the same day are scheduled to the same vehicle. These charging times lower utilization, as they block the vehicle for additional trips. In comparison, scheduling bookings randomly distributes long trips more evenly, achieving higher utilization at the cost of the optimization goal. Further research in this phenomenon could improve the algorithm depending on the priorities of a car fleet operator.



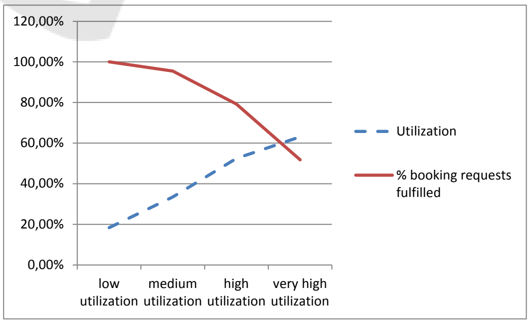
(1) Optimization potential in small fleet



(2) Optimization potential in medium fleet



(3) Optimization potential in large fleet



(4) Utilization and service level

Figure 7: Overview of benchmark results.

6 CONCLUSION AND OUTLOOK

In this work, we describe processes and algorithms for dynamic real-time schedule optimization, allowing a high utilization of electrical car fleets, a compensation of disruptions and malfunctions and an economic and ecological optimization of operations. We implemented these techniques in a prototype and evaluated them in long-term model trials with real users as part of a fleet management system as well as in a benchmark, showing considerable savings can be achieved.

In future work, we would like to further enhance optimization algorithms and evaluate them with heterogeneous vehicle fleets in additional model trials.

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REFERENCES

Bielli, M., Bielli, A., and Rossi, R. (2011). Trends in models and algorithms for fleet management. *Procedia-Social and Behavioral Sciences*, 20:4–18.

Bloch, A. (2014). E-autos im h"artetest (in german). *Auto, Motor und Sport*, 16. http://www.auto-motor-und-sport.de/vergleichstest/elektroautos-6-modelle-im-haertetest-8498096.html.

Deffner, Jutta, B.-H. B. H. T. and Goetz, K. (2012). Elektrofahrzeuge in betrieblichen Fahrzeugflotten - Akzeptanz, Attraktivitt und Nutzungsverhalten (in German). *ISOE-Studientexte*, 17. http://www.isoe.de/uploads/media/st-17-isoe-2012.pdf.

del Razo, V., Goebel, C., and Jacobsen, H.-A. (2014). Benchmarking a car-originated-signal approach for real-time electric vehicle charging control. In *Innovative Smart Grid Technologies Conference (ISGT), 2014 IEEE PES*, pages 1–5. IEEE.

Koetter, F. (2015a). Dynamische Einsatzoptimierung von gemeinsam genutzten Elektrofahrzeugflotten (in German). http://www.shared-e-fleet.de/images/Dynamische_Einsatzoptimierung_von_gemeinsam_genutzten_Elektrofahrzeugflotten.pdf.

Koetter, F. (2015b). Evaluation of Dynamic Schedule Optimization. http://www.shared-e-fleet.de/images/evaluation_schedule_optimization.pdf.

Koetter, F., Klausmann, F., and Renner, T. (2013). Potenzialermittlung für integration von elektrofahrzeugen in fuhrparkflotten. *Informatik-Spektrum*, 36(1):35–45.

Kovalyov, M. Y., Ng, C., and Cheng, T. E. (2007). Fixed interval scheduling: Models, applications, computational complexity and algorithms. *European Journal of Operational Research*, 178(2):331–342.

Ostermann, J., Renner, T., Koetter, F., and Hudert, S. (2014). Leveraging electric cross-company car fleets through cloud service chains: The shared e-fleet architecture. In *Global Conference (SRII), 2014 Annual SRII*, pages 290–297. IEEE.

Pillac, V., Gendreau, M., Guéret, C., and Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European Journal of Operational Research*, 225(1):1–11.

Plötz, P., Gnann, T., Kühn, A., and Wietschel, M. (2013). Markthochlaufszenarien für elektrofahrzeuge. *Karlsruhe: Fraunhofer-Institut für System-und Innovationsforschung ISI*.

Sassi, O. and Oulamara, A. (2014). Joint scheduling and optimal charging of electric vehicles problem. In *Computational Science and Its Applications–ICCSA 2014*, pages 76–91. Springer.

Shekelyan, M., Jossé, G., Schubert, M., and Kriegel, H.-P. (2014). Linear path skyline computation in bicriteria networks. In *Database Systems for Advanced Applications*, pages 173–187. Springer.

Sundstrom, O. and Binding, C. (2010). Optimization Methods to Plan the Charging of Electric Vehicle Fleets.