Whole Day Mobility Planning with Electric Vehicles

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Abstract: We propose a novel and challenging variant of trip planning problems – Whole Day Mobility Planning with Electric Vehicles (WDMEV). WDMEV combines several concerns, which has been so far only considered separately, in order to realistically model the problem of planning mobility with electric vehicles (EVs). A key difference between trip planning for combustion engine cars and trip planning for EVs is the comparatively lower battery capacity and comparatively long charging times of EVs – which makes it important to carefully consider charging when planning travel. The key idea behind WDMEV is that the user can better optimize his/her mobility with EVs, if it considers the activities he/she needs to perform and the travel required to get to the locations of these activities for the whole day - rather than planning for single trips only. In this paper, we formalize the WDMEV problem and propose a solution based on a label-setting heuristic search algorithm, including several speed-ups. We evaluate the proposed algorithm on a realistic set of benchmark problems, confirming that the whole day approach reduces the time required to complete one's day travel with EVs and that it also makes it cheaper, compared to the traditional single-trip approach.

1 INTRODUCTION

One of the most prominent drawbacks of the use of Electric Vehicles (EVs) is the range anxiety and long charging times. An average EV can travel about 150-200km on a fully charged battery, whereas charging the battery for the average range of 150 kilometers takes about 4-12 hours using a slow-charging technology (e.g., home outlet) and about 30 minutes using a fast-charging technology (e.g., CHAdeMO). EV users need to plan their trips so that they do not run out of battery mid-way; if charging is necessary, they need to plan it carefully so that charging does not delay their activities and they arrive for their duties on-time.

Although there is a wealth of literature on path planning with energy constraints and charging and related problems, the existing solutions focus on isolated planning of single trips and do not take into account the whole day context of mobility. In this work we propose to take a more holistic perspective, where we take into account not only the route planning and charging, but also the temporally and spatially constrained activities which need to be performed by the users. By taking the whole day activity and mobility model into consideration, our approach provides better solutions compared to single-trip planners that handle each requests independently.

Take for example the scenario in Figure 1. The user starts and ends in the home location A, may charge the EV at B and D and shop at B. The user's goal is to spend 8 hours at the workplace and to shop for 30 minutes. The initial (and maximal) capacity of the EV battery is 30 kWh and charging to full takes 60 minutes. In the naive plan shown in Figure 1a), the user first decides the order of activities, that is, first go to work and then do the shopping. Also the charging is postponed until necessary. By this approach, the user first goes to location C (the EV has enough charge to do that) and works for 8 hours. Next, the user wants to go home and make a stop for shopping. However the charge of the EV is not high enough to do so, and thus the user must first go to a nearby charging station at location C. Then the user can get to location B and do the shopping while also charging the EV. At the end, when the user gets home, the time overhead caused by charging is 45 minutes (we do not count the charging time while shopping).

By optimizing for the whole day formulation of the problem, the user can obtain the optimized plan shown in Figure 1b), where the shopping is scheduled before work. In that case, the user first arrives at B, does the shopping while recharging the battery to full and continues to work. On the way back, the EV does not have enough charge for the whole trip

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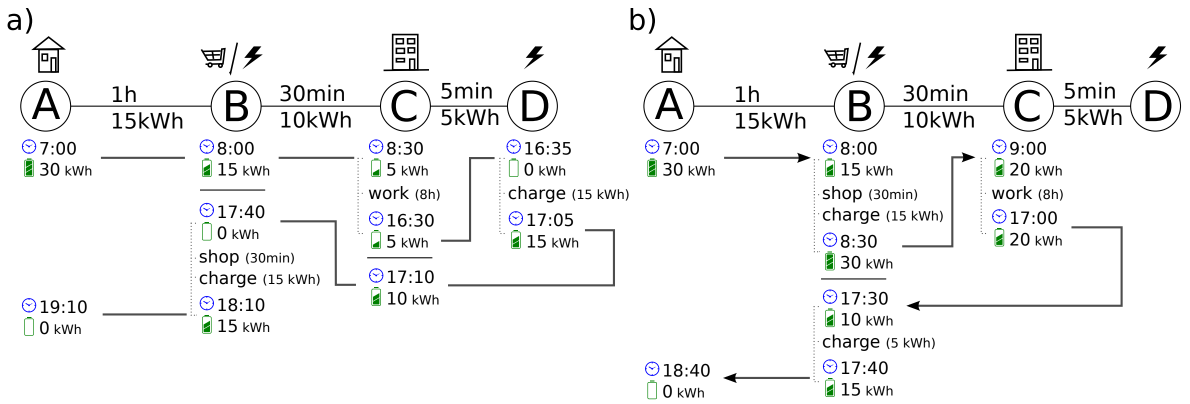

Figure 1: **Example scenario:** A - home location, C - work location, B, D - chargers, B - shop. Activities are 8h work, 30min shop. Maximal state of charge (SOC) - 30 kWh, charging to full takes 60 minutes. **a) Naive approach:** The user first decides the order of activities (work, shop). Charging postponed until necessary. **b) Whole day formulation:** Optimize the order of activities and charging (shop,work).

and thus a short (10 min) charging stop is scheduled. Overall, the user arrives 30 minutes earlier than in the naive case and spends only 10 minutes on charging overhead. Notice also that the total energy consumed from charging stations is 10 kWh less which might also save money.

Obviously, this simple problem is easy to optimize, but the problem gets too complicated for a human when the number of locations and activities increases and the temporal constraints get more complicated.

Informally, the Whole Day Mobility Planning with Electric Vehicles (WDMEV) problem can be modeled as a search problem on a road network graph with specific vertices being charging stations and points of interest (POIs) where given activities can be performed in given time windows. Each edge in the graph (corresponding to road segments) has a particular time cost depending on the distance and maximal speed (we do not allow choosing the cruise speed) and energy cost depending mainly on the elevation profile (as the EV can recuperate energy when going downhill) and the speed.

Each of the activities the user wants to perform is associated with a particular location and is constrained by the earliest activity start time (the time when the activity can be started at the earliest), the latest activity end time, that is, the time when the activity must be finished at the latest, and the activity duration which is fixed. This gives us a time window in which the activity duration must fit. Each charging station is associated with a location, cost of charging per minute, and charging speed depending on the technology available at the charging station. The cost of charging can differ between the charging stations but is considered to be constant throughout the time (as is the case at most current charging stations). We are interested in minimizing the total time spent traveling and performing activities, the total money cost of the trip (where the money is spent on charging stations), or both at the same time.

The main challenges of solving the proposed problem are the following. The underlying Traveling Salesman Problem (TSP) makes the whole problem NP-hard (Krentel, 1988). However as was shown in the example, sequencing the activities up-front may significantly reduce the quality of the solution, or even make the problem unsolvable. This is mainly due to the temporal constraints which may be not satisfiable in some orderings. Another source of complexity is a limited capacity of batteries (and thus limited range of autonomy of the EV). The state of charge (SOC) of the battery must be taken into account during the optimization in order to ensure that a path worse according to the selected metric (e.g., time) but with a higher SOC is not discarded as this might lead to a solution whereas the better path might end in a dead-end (i.e., without enough SOC to reach the goal).

The contribution of this work is threefold:

- We formalize the novel Whole Day Mobility Planning with Electric Vehicles (WDMEV) problem.
- We propose a solution based on a label-setting heuristic search algorithm, together with a number of speed-ups.
- We experimentally analyze the algorithm and identify influences of the proposed heuristic and speed-ups.

2 RELATED WORK

A large number of models and algorithms related to particular sub-problems of the WDMEV problem have been formulated in the literature. The basic problem we can consider is the shortest-path problem on a graph and the corresponding Dijkstra's algorithm (Dijkstra, 1959). A multi-criteria version of the shortest path problem together with a modification of the Dijkstra's algorithm was introduced in (Hansen, 1980). In the multi-criteria version, the notion of the shortest path is superseded with the idea of the set of Pareto-optimal paths, that is, a set of paths which are not dominated on all criteria by any other path. A generalization of the Dijkstra's algorithm leads to the label-setting algorithm (Nemhauser, 1972) with arbitrary labels.

When considering EVs, the battery capacity and charging become crucial. In (Khuller et al., 2011) the authors present a number of gas station problems (including shortest path and TSP) where the vehicle has a limited tank capacity and can refuel at some of the graph nodes with either a variable or uniform price. The authors present a number of dynamic programming solutions and approximations. In (Artmeier et al., 2010; Sachenbacher et al., 2011) the authors study energy-optimal routing for electric vehicles by first casting it as a variant of the Constrained Shortest Path Problem (CSPP) (Beasley and Christofides, 1989) with an $O(n^3)$ algorithm, and second by solving it as a graph search problem with the A* (Hart et al., 1968) algorithm and a consistent heuristic yielding an $O(n^2)$ solution.

In practice, the EV routing problem is also solved by various commercial[1] and academic routing services (Fišer, 2017). The battery limit and charging is often considered not only for the single shortest path problem but also for TSP or VRP problems. In (Felipe et al., 2014) the authors consider the case of routing a fleet of vehicles as a Green Vehicle Routing Problem (GVRP), with multiple modes of recharging (as in our case) but without the temporal constraints. The Electric Vehicle Routing Problem (EVRP) with time windows solved in (Desaulniers et al., 2016; Schneider et al., 2014) is the closest fit to the WDMEV problem considered in our work. In contrast to the EVRP, our approach focuses on single vehicle routing with possible future extensions to time-dependent costs (both the time of driving and the cost of charging) and multi-criteria optimization (the label-setting algorithm can be easily modified for such a case). Moreover, our approach is based on an optimal algorithm and also most of proposed speed-ups preserve optimality. In (Arslan et al., 2015) the authors have shown that the minimal cost path problem for EVs (or for Hybrid Plug-in EVs in their case) is NP-hard by transforming it to the Shortest Weight-Constrained Path Problem (SWCPP) which was shown to be NP-hard in (Garey and Johnson, 2002).

Another important facet of our Whole Day Mobility Planning with Electric Vehicles (WDMEV) problem is time. Again, there are many temporal extensions of the individual sub-problems. The Shortest Path Problem with Time Windows (SPPTW) has been solved with a label-setting algorithm in (Desrochers and Soumis, 1988) and an optimal algorithm based on dynamic programming has been proposed by (Ioachim et al., 1998). A summary of time-constrained vehicle routing and scheduling problems (including TSP) and respective algorithms was published in (Desrosiers et al., 1995). An optimal algorithm was presented in (Dumas et al., 1995) and an approximation in (Bansal et al., 2004).

In our case, the combination of time windows on the locations to visit and resources consumed on the edges (but also replenished at some locations) needs to be considered. A very recent work (Veneti et al., 2016) have considered a closely related problem in the sea transportation domain. The authors propose a special case of Time-Dependent Shortest Path Problem (TDSPP) where the path must visit a specified sequence of nodes and also a TSP variant, both including bi-criteria optimization. The particular criteria are fuel consumption and safety. In addition to temporal constraints in the ports to visit, the properties (e.g., cost) of the graph change in time depending mainly on the weather situation. Closely related is also the Trip Query Problem (TQP) (Li et al., 2005) which consists of the problem of planning a trip over points of interest such that each belongs to a specific category and at least one point of interest from each category has to be visited, also studied as generalized TSP (Rice and Tsotras, 2013). A temporal extension of a similar problem (Multi-Type Nearest Neighbor) was studied in (Ma et al., 2009). In our current problem, we do not consider multiple locations for each activity. Instead , we focus on the temporal and SOC constraints which, to our best knowledge, have not been studied in combination yet.

3 PROBLEM DEFINITION

In this section we propose a formal definition of the WDMEV problem. Let $G = (V,E)$ be a directed graph representing the underlying road network, where V is a set of vertices and E is a set of edges and each

[1] http://www.evjourney.com; https://abetterrouteplanner.com; https://www.egomap.eu

edge $(u,v) \in E$ is associated with two cost attributes, a non-negative time cost $tc(u,v)$ and an energy cost $ec(u,v)$, which can be negative due to recuperation.

Let $C \subseteq V$ be a set of charging stations where each charging station $c \in C$ has a set of available charging rates $P_c \subseteq P$ and charging costs per time unit of charging $cc_c(\rho)$ for each charging rate $\rho \in P_c$. P is a set of all possible charging rates. The time required for charging is the function

$$ct : P \times [0, \beta_{\max}) \times (0, \beta_{\max}] \rightarrow \mathbb{N}^+$$

mapping a charging rate, an initial SOC and a final SOC on the charging time. $\beta_{\max} \in \mathbb{R}^+$is the maximal state of charge. Besides the maximal $\beta_{\max}$ we define the minimal state of charge $\beta_{\min}$ below which the battery should not drop at any point in the plan. This parameter represents the need of drivers to keep some energy reserve. Otherwise the inaccuracy of the consumption estimates may lead to a fully depleted battery during the plan execution even though in the plan the SOC was not expected to drop below 0.

Let $A \subseteq V$ be a set of activities to be planned. Each activity $a \in A$ is associated with the following time constraints: $\mathrm{EST}(a)$ is the earliest start time, $\mathrm{LET}(a)$ is the latest end time, and $\mathrm{AD}(a)$ is the activity duration which also implies the latest possible start time $\mathrm{LST}(a) = \mathrm{LET}(a) - \mathrm{AD}(a)$.

The initial state of the problem is specified by the starting location $s \in V$ and an initial battery state of charge β_{init}.

The goal is to find a sequence of tuples $\pi = (\langle v_i, \tau_i, \beta_i, \gamma_i \rangle | i \in \{1, ..., k\})$ defining an order of the visited nodes $v_i \in V$ with the time $\tau_i \in \mathbb{N}_0$, state of charge $\beta_i \in [\beta_{\min}, \beta_{\max}]$ and money cost of the $\gamma_i \in \mathbb{R}_0^+$ such that the SOC never drops bellow allowed level and all activities are performed $\forall a \in A \exists i \in \{1, ..., k\} : v_i = a \wedge \mathrm{EST}(a) \leq \tau_i \leq \mathrm{LST}(a) \wedge v_{i+1} = a \wedge \tau_{i+1} - \tau_i \geq \mathrm{AD}(a)$. Also the sequence has to start and end at the initial location ($v_1 = v_k = s$). The time and money costs are non-decreasing ($\forall i, j \in \{1, ...k\} : i > j \implies \tau_i \geq \tau_j \wedge \gamma_i \geq \gamma_j$) but the SOC alters in both direction. It can decrease by moving and increase due to the recuperation or charging. If the vehicle is charged it must stay at the charging station while the SOC increases - $v_i \in C \wedge v_{i+1} = v_i \wedge \beta_{i+1} > \beta_i$. The properties of the charging (cost, amount of energy recharged, etc.) can be derived from the two consecutive states.

We consider the optimization metric of the WD-MEV problem to be a weighted sum of the time and money costs, formally

$$f(\pi) = w_\tau \tau_k + w_\gamma \gamma_k$$

where $w_\tau, w_\gamma \in [0,1]$ are the criteria weights. Naturally, the problem can be cast as a multi-criteria optimization and the proposed solution would be easy to modify. Nevertheless we leave this extension for future work for simplicity of exposure.

4 SOLUTION APPROACH

Our solution is based on the idea of the label-setting algorithm. The difference between the classic Dijkstra's algorithm and the label-setting algorithm is that instead of maintaining a single label for each opened vertex, the label-setting algorithm maintains a Pareto set L_v of all non-dominated labels

$$l_v = (A_{vis}, \tau, \beta, \gamma)$$

where $A_{vis} \subseteq A$ is the set of activities already visited, τ is the time required to get to state v, β is the current SOC, and γ is the money cost of the path leading to v respective to the label l_v. In order to determine the Pareto set L_v, we use the following definition of the dominance relation $\prec$.

Definition 1. Let l_v, l'_v be two labels of the same node v. We say that l_v is dominated by l'_v (denoted as $l_v \prec l'_v$) iff the following conditions are satisfied:

$$\begin{array}{rcl} A_{vis} & \subseteq & A'_{vis} \\ f(\tau,\gamma) & \geq & f(\tau',\gamma') \\ \beta & \geq & \beta' \end{array} \quad (1)$$

where $f(\tau, \gamma)$ is the criteria function minimized by the algorithm.

The pseudo-code of the proposed solution is shown in Algorithm **??**. In each iteration of the algorithm, a label l_v of a vertex $v \in V$ is polled from the priority queue Q. The labeled state is expanded and the new labels are added to the queue (Line 12). There are four possible ways to expand the states, each representing one action the user can do: (i) driving, (ii) performing an activity, (iii) charging, and (iv) charging during an activity. We distinguish between actions and activities in the context of the search as activities are just one type of actions of the user which also include driving and charging. The four possible expansions are the following:

(i) Driving Let v be the polled node and $l_v = (A_{vis}, \tau, \beta, \gamma)$ the label currently being expanded. For each outgoing edge $(v,u) \in E$, a new label

$$l_u = (A_{vis}, \tau + tc(v,u), \min(b - ec(v,u), \beta_{\max}), \gamma)$$

is added to the queue. The labels with the SOC bellow $\beta_{\min}$ are discarded.

(ii) Performing an activity An activity can be performed iff the current location v is an activity location ($v \in A$) and the activity has not been performed

Algorithm 1: Pseudo-code of the proposed WDMEV solution.

1 **Algorithm** `plan()`
2 Q: heap of labels $l_v = (A_{vis}, \tau, \beta, \gamma)$ ordered by criteria function f and then by β
3 $l_s = (\emptyset, 0, \beta_{\mathsf{init}}, 0)$ % initial label
4 $Q \leftarrow \{l_s\}$
5 $L_s \leftarrow \{l_s\}$
6 $\forall v \in V \setminus \{s\} : L_v \leftarrow \emptyset$ % initialize the Pareto-set for each node
7 **while** $Q \neq \emptyset$ **do**
8   $l_v \leftarrow$ `extractMin(`Q`)`
9   **if** `isGoal(`l_v`)` **then**
10   **return** l_v
11   **else**
12     $Q' \leftarrow$ `expand(`l_v`)`
13     $Q' \leftarrow$ `prune(`Q'`)`
14   **forall the** $l_u \in Q'$ **do**
15   **if** $\nexists l_u^* \in L_u : l_u \prec l_u^*$ **then**
16         $Q \leftarrow Q \setminus \{l'_u \in L_u | l'_u \prec l_u\}$
17         $Q \leftarrow Q \cup \{l_u\}$
18         $L_u \leftarrow L_u \setminus \{l'_u \in L_u | l'_u \prec l_u\}$
19         $L_u \leftarrow L_u \cup \{l_u\}$
20   **end**
21   **end**
22   **end**
23 **end**

so far ($v \notin A_{vis}$). The starting time τ_s (implying also the end time $\tau_e = \tau_s + \mathrm{AD}(v)$) is set to the earliest available moment ($\tau_s = \max(\tau, \mathrm{EST}(v))$) satisfying the activity time constraints. With time-independent costs, a later start can never result into a better solution. If the location conditions are met and the end time also satisfies the time constraints ($\tau_e \leq \mathrm{EST}(v)$), a new label $l_v = (A_{vis} \cup \{v\}, \tau_e, \beta, \gamma)$ is added to the queue.

(iii) Charging To reduce the search space, we limit the variants of the charging action. The charging action can be applied if the battery is bellow a threshold β_t (e.g., 80% of $\beta_{\max}$) and the level to which the battery is recharged is discretized (e.g., with 20% step) to a set of SOC levels B. If the current location is a charging station ($v \in C$), a new label

$$l_v = (A_{vis}, \tau + \tau_c, \beta_i, cc_v(\rho) \cdot \tau_c)$$

is added to the queue for each charging rate $\rho \in P_v$ and resulting SOC level $\beta_i \in B : \beta_i > \beta$ where

$$\tau_c = ct(\rho, \beta, \beta_i)$$

is the time required for the charging.

(iv) Charging during an activity Because the driver does not have to be present while the charging is in the process, he/she can also do an activity if it is at the same location as the charger. Similarly to the case of charging only, a new label is added to the queue for each charging rate. The difference is that the time parameter of the labels is calculated in a different way. The user stays at the location v until the charging has ended and until the activity has finished, therefore the time is set to

$$\tau_{c+a} = \max(\tau_e, \tau + \tau_c)$$

where τ_e is the end time of the activity as calculated above.

5 SPEED-UPS

In order to improve the performance of Algorithm 1, we propose a number of speed-ups. The proposed speed-ups fall in three categories. The first category is pruning, which is used to prune some of the expanded labels (Algorithm 1 Line 13) based on the impossibility of reaching the goal from them. The second category is a heuristic guiding the search based on the A* algorithm principle (Hart et al., 1968). The last category is dominance relaxation where the notion of dominance is relaxed so that more labels are considered dominated and thus pruned.

5.1 Temporal Consistency Forward-Checking

Labels from which any of the remaining activities cannot be reached in time can be pruned. To preserve optimality, we use an optimistic lower bound of the minimal time required to get to an activity based on a maximal travel speed ϖ_{max}. This lower bound $\tau^*(v,a) = \tau_t^*(v,a) + \tau_c^*(v,a)$ consists not only of estimate τ_t^* of the travel time but also of estimate τ_c^* of the minimal time required for charging, if the current state of charge is not enough. The condition which all labels $l_v = (A_{vis}, \tau, \beta, \gamma)$ must satisfy is formulated as:

$$\forall a \in A \setminus A_{vis} : \mathrm{LST}(a) \geq \tau + \tau_t^* + \tau_c^*$$

where $\tau_t^* = dist(v,a)/\varpi_{\mathsf{max}}$ is the optimistic estimate of the travel time from v to a and $\tau_c^* = \max(0, ec^*(v,a) - \beta)/\max(P)$ is the optimistic estimate of charging time with $ec^*(v,a)$ as minimal energy required to get from v to a.

5.2 State of Charge Consistency Forward-Checking

This consistency checking prunes away all labels from which it is impossible to get to any charging station $c \in C$ or back to the start s without getting the state of charge below $\beta_{\min}$. For all labels $l_v = (A_{vis}, \tau, \beta, \gamma)$ the following condition must hold

$$\beta \geq \min_{c \in C \cup \{s\}} ec^*(v,c) - \beta_{\min}$$

5.3 Remaining Travel Time and Activity Duration Heuristic

The heuristic modifies the ordering of the priority queue (heap in Algorithm 1, Line 2). We order the heap by a modified criteria function:

$$f^*(\tau,\gamma) = w_\tau(\tau + h_\tau) + w_\gamma \gamma$$

where h_τ is the heuristic we propose. For a label $l_v = (A_{vis}, \tau, \beta, \gamma)$ the heuristic value h_τ combines the sum of durations of all unvisited activities $\bar{A_{vis}} = A \setminus A_{vis}$ and an estimate of the minimal travel time required to achieve the goal. To keep this heuristic admissible (to preserve optimality) the travel time can never be overestimated. Since the path must visit all of the activities, we can take the most expensive unvisited activity in terms of the travel time as the estimate. We consider the most expensive activity to be the one to which the path from the current location v, combined with the path from the activity to the destination s, is the longest among all of the unvisited activities. The remaining path must go through the activity to the destination in every case and since the estimate is the shortest one, its duration can never exceed the duration of the path going through all unvisited activities. Formally, the heuristic h_τ:

$$h_\tau = \max_{a \in \bar{A_{vis}}} (\tau(v,a) + \tau(a,s)) + \sum_{a \in \bar{A_{vis}}} \mathrm{AD}(a)$$

where $\tau(x,y)$ is the duration of the shortest path from x to y.

5.4 Dominance Relaxation

The ε-dominance relaxation (Batista et al., 2011) modifies the conditions of dominance from Equation 1 with relaxation ratios $\varepsilon_f, \varepsilon_\beta \in [0,1]$ to

$$\begin{array}{rcl} A_{vis} & \subseteq & A'_{vis} \\ f(\tau,\gamma) & \geq & \varepsilon_f \cdot f(\tau',\gamma') \\ \beta & \geq & \varepsilon_\beta \cdot \beta' \end{array} \qquad (2)$$

This relaxation does not preserve optimality but it is expected to greatly reduce the search space with only a small impact on the solution quality.

6 EVALUATION

This section provides an experimental evaluation of the proposed algorithm and its comparison with a baseline solution. First, we describe the baseline solution and the set of used benchmarks. Next, we evaluate our proposed whole day algorithm (Section 4) against the baseline solution, evaluate the quality of the speedups proposed in Section 5 and evaluate the effect of dominance relaxation on the quality of the solution and the execution time of the algorithm.

Baseline Solution

To evaluate the effect of the global approach to solving the WDMEV problem, we evaluate it against a baseline solution. The baseline solution is based on the same label-setting algorithm (Section 4) with the following modifications.

The most important modification is that, similarly to a human user, the activities are approached in a sequential manner, without considering all possible orderings. We use a simple heuristic to sequentially order the activities before planning. The activities are ordered by the latest possible arrival time $\mathrm{LST}(a)$ so that the most urgent activities are performed first.

Another modification is the use of reactive charging behavior. A typical user does not plan the charging until the battery has dropped below some threshold β_t which for the baseline algorithm is set to $\beta_t = 0.5 \cdot \beta_{\max}$. The charging is planned for each leg of the day plan separately.

Benchmark Set

As a testing location we use a rectangular area of the real-world road network in Germany bounded by Munich, Regensburg and Passau with the transport network extracted from OSM[2] and limited to main roads between cities, leading to a graph with 75k nodes and 160k edges. We select 18 locations acting as possible POIs for activities and 8 of the 18 locations acting also as charging stations. Each benchmark problem is generated based on one of the following temporal template by randomly assigning locations for the activities:

[2]https://download.geofabrik.de/europe/germany/bayern.html

	Template: Worker		
#Act.	**Activity name**	**Time window**	**Dur.**
1	**Work**	**[8:00,18:00]**	**8h**
2	**Shopping**	**[7:00,21:00]**	**30min**
3	**Entertaining 1**	**[16:00,23:57]**	**1h**
4	**Entertaining 2**	**[16:00,23:58]**	**1h**
5	**Entertaining 3**	**[16:00,23:59]**	**1h**

	Template: TSP		
#Act.	**Activity name**	**Time window**	**Dur.**
1	**Work 1**	**[8:00,18:00]**	**1h**
2	**Work 2**	**[9:00,19:00]**	**1h**
3	**Work 3**	**[10:00,20:00]**	**1h**
4	**Work 4**	**[11:00,21:00]**	**1h**
5	**Work 5**	**[12:00,22:00]**	**1h**

The most important aspect of each template is the number of activities, which range from 1 to 5. The variation between the number of activities was achieved by taking only the first n activities from the template. For each template and each number of activities we have generated 50 random instances (500 in total).

Consumption function for edge (u,v) was approximated in (Eisner et al., 2011; Fišer, 2017)

$$ec(u,v) = \begin{cases} \kappa dist(u,v) + \lambda \Delta_e(u,v) & \text{if } \Delta_e(u,v) > 0 \\ \kappa dist(u,v) + \delta \Delta_e(u,v) & \text{otherwise} \end{cases}$$

with $\Delta_e(u,v) = elev(v) - elev(u)$ and coefficients set to $\kappa = 0.2, \lambda = 2$ and $\delta = 1.5$. Each charging station $c \in C$ provides the same set of charging rates $P_c = \{11kW, 30kW, 50kW\}$ with equal pricing. The charging time was simplified with linear approximation $ct(\rho, \beta_s, \beta_e) = \frac{\beta_e - \beta_s}{\rho}$.

The parameters of the algorithm were set as follows. The battery capacity $\beta_{\max}$ was set to 26kWh and the charging threshold β_t for the proposed algorithm was set to $0.8 \cdot \beta_{\max}$. The charging SOC levels B were set to 20%, 40%, 60%, 80% and 100% of $\beta_{\max}$. The optimization metric was set purely to time, that is, $w_\tau = 1, w_\gamma = 0$.

6.1 Whole Day vs. Single-Trip Approach

In this experiment we compare the baseline single-trip approach against our proposed whole day approach based on a number of quality metrics. The first metric is the *duration* of the whole day plan (i.e., makespan) including the travel times, times spent on activities and time spent on charging, if the charging is not performed in parallel with an activity (in that case we take the maximum of the durations of the activity and

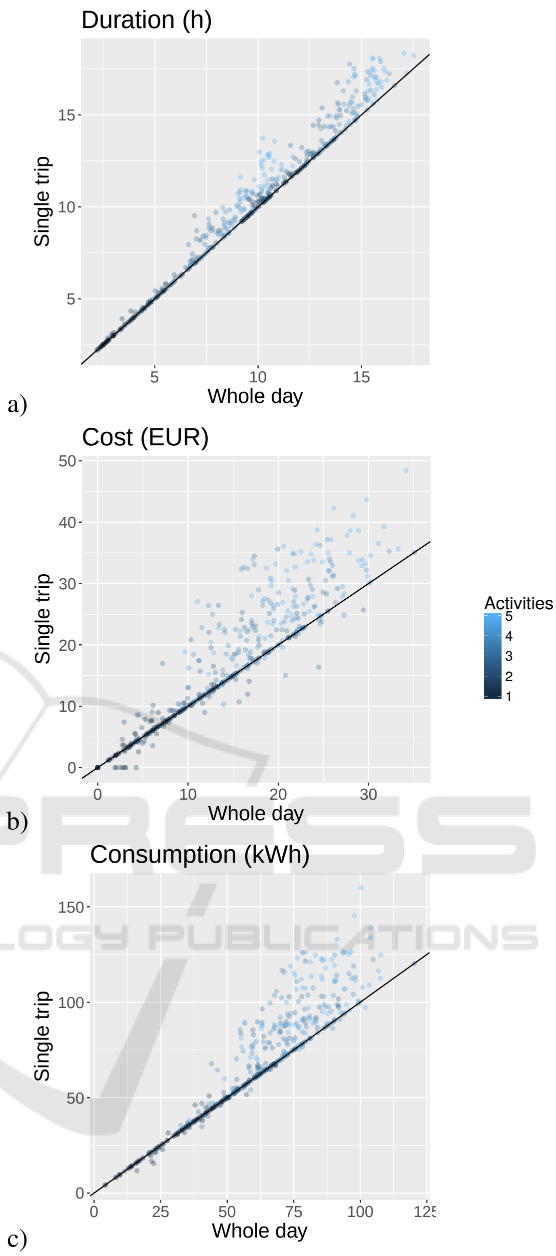

Figure 2: Ratios of the single-trip baseline and the proposed whole day global approach.

charging). The second metric is the *consumption* of the electric energy (measured in kWh) for driving throughout the whole day. The energy which was charged but not used for driving is not included. The last metric is the *cost* of the whole day plan. We assume that the cost comes only from charging that is proportional to the time spent by charging, which is based on the current mode of operation of most commercial charging stations. As in both our algorithms, the EV can be charged to only a set of available SOC levels, this may result in charging some excess energy which is not spent throughout the day. This excess energy is also payed for and thus is included in the cost metric. Note that the algorithm proposed in Section 4 performs a single-criteria optimization where the optimized metric is time only (that is, the duration of the day plan).

Figure 2 shows a comparison of the proposed solution (the x-axis) and the baseline solution as would be found by a human user (the y-axis) for each of the considered metrics. Let us first focus on the duration metric Figure 2(a) for which our proposed algorithm optimizes. Clearly, the optimized global solution is always better than the single trip baseline solution, sometimes with the difference in hours.

Somewhat unexpected are the results shown in Figure 2(b) and (c) which show that although the algorithm explicitly optimizes only for the time metric, it outperforms the baseline solution in the two other metrics for most instances as well. This relates to the situation in the introductory example, where by optimizing the problem as a whole, future energy needs can be anticipated and detours necessary for charging can be eliminated.

In order to make a fair comparison, we evaluate the ratio of the proposed solution to the baseline solution for each metric. Figure 3 shows a boxplot[3] for each of the metrics. All three boxplots show that the more activities are needed to perform during the day, the bigger speed-up can be obtained from whole day optimization. For five activities, which is still a very reasonable number for an average user, the time spent on a day activity plan may be more than 20% and on average nearly 10% shorter using whole day optimization. For an average 10h workday (including e.g., shopping), this accounts for 2 and 1 hour respectively which is a very significant amount of time to be saved.

As already discussed, similar patterns can be observed for the metrics for which the algorithm does not explicitly optimize. Figure 3(b) shows that for five activities a day, the proposed approach saves nearly 20% energy (and subsequently charging costs) on average.

6.2 Effect of the Speed-Ups

In this section, we evaluate the effect of the pruning speed-ups and the heuristic (Section 5) on the performance of Algorithm 1 in terms of opened states, which directly translates to the execution time. We decided to use the opened states as the main performance measure because it is independent of the experimentation environment and immune to measurement errors (no need to calculate the scenarios multiple times).

Figure 4 shows the comparison of ratios of the opened states of the proposed solution without any speed-ups and using the particular combination of speed-ups. The combinations of speed-ups excluding the heuristic perform significantly worse than the heuristic itself and any combination including it. The

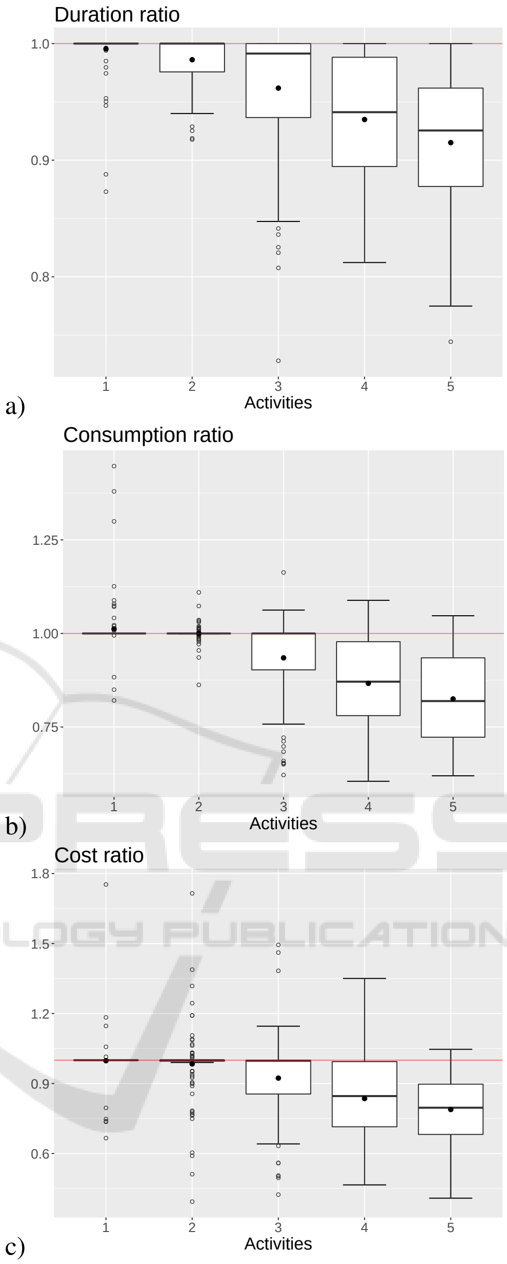

Figure 3: Ratios of the single trip baseline and the proposed whole day global approach in dependence on the number of activities.

[3]The boxplots show median (strong line), mean (black dot), the box showing Q1 (the 25th percentile) and Q3 (the 75th percentile) and the whiskers shows the lowest and highest point within 1.5 IQR of the lower and higher quartile respectively. The outliers are shown as circles.

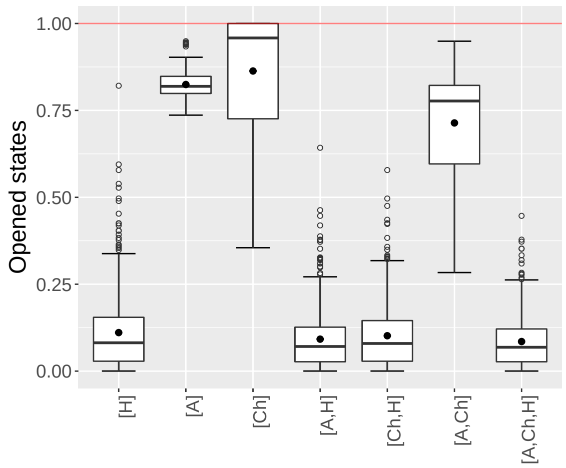

Figure 4: Opened states in dependence on the used speed-ups relative to no speed-ups: H – heuristic (Section 5.3), A – activity temporal consistency (Section 5.1), Ch – charging consistency (Section 5.2).

best result is obtained by combining all speed-ups, which is not surprising. The combination of all speed-ups reduces the solution time by 90% on average, which shows that the proposed speed-ups are a significant improvement.

6.3 Effect of the Dominance Relaxation

The last set of experiments evaluates the performance in terms of opened states and the quality of the solution (the plan duration metric) when applying the dominance relaxation speed-up. In this experiment all speed-ups from the previous section (pruning and heuristic) were used in combination with multiple settings of dominance relaxation described in Section 5.4.

Figure 5 shows the ratios of the algorithm using the given dominance relaxation value and using no dominance relaxation. The left column shows the SOC relaxation ε_β which relaxes the dominance only on the SOC, whereas the right column shows the criteria relaxation ε_f which relaxes the dominance on the optimization function $f(\tau,\gamma)$, which in our case equals to the time τ. The results show that even though the number of opened states are reduced to 50% with SOC relaxation coefficient decreased from $\varepsilon_\beta = 1$ to $\varepsilon_\beta = 0.99$, the quality of the solution is practically intact.

As expected, there is a significant decrease in the number of states also with criteria relaxation coefficient set to $\varepsilon_f = 0.99$, but the impact on the plan duration is much greater than with SOC relaxation ε_β. The results suggest that the best trade-off between execution time and quality of the solution might be provided by the combination of $\varepsilon_\beta = 0.99$ and $\varepsilon_f = 0.99$. Indeed, such a combination reduces the execution time to 25% while not increasing the plan duration above 2.5% for 90% of the instances. An interesting result is that lower criteria relaxation coefficient ε_f leads to a higher number of opened states. This is probably caused by pruning away to many labels resulting in exploration of number of detours which would not be otherwise explored thanks to the heuristic.

7 CONCLUSION

In this work, we have proposed a novel Whole Day Mobility Planning with Electric Vehicles (WDMEV) problem together with a label-setting algorithm to solve it. We have shown that optimizing the WDMEV problem significantly improves the results when compared to a naive approach employed by humans in terms of plan duration, energy efficiency and overall cost. Moreover, we have provided a number of speed-ups and evaluated their effect on performance of the algorithm.

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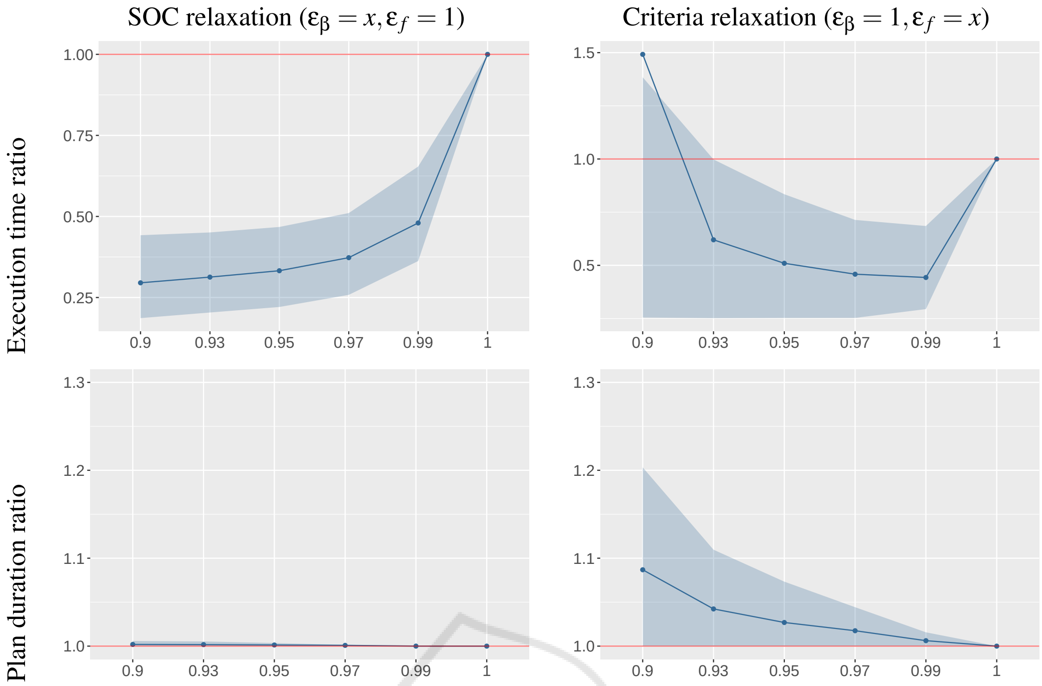

Figure 5: Effect of dominance relaxation on plan duration and execution time. The filled area represents data between the 1st and the 9th quantile.

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