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Fleet Disposition Modeling to Maximize Utilization of Battery Electric Vehicles in Companies with On-Site Energy Generation

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Abstract

Various intelligent fleet disposition algorithms can be used to allocate mobility requests to a fleet of electric vehicles. However, none of these incorporate the issue of on-site energy generation at the company running the mixed fleets. This work presents an approach to distribute trips to a mixed fleet of conventional internal combustion engine vehicles and battery electric vehicles in coordination with a decentralized energy management, such that economic and ecologic target parameters are maximized. This includes a detailed charging schedule. A new algorithm based on a mixed integer linear program was developed that incorporates variable charging infrastructures, the mobility profile of a company and different vehicle classes, to produce an optimized usage schedule for the company. As main findings, the new developed model is capable of analyzing the financial and ecological potential of substituting individual ICEVs with BEVs and provides a customized recommendation for the optimal fleet composition, depending on the number of trips and the specification of the vehicles.

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Keywords: Battery electric vehicle, fleet disposition, trip allocation, charging management, corporate mobility, utilization, operating cost

1. Introduction

The goal of the federal government to achieve 1 million registered battery electric vehicles (BEVs) by 2020 (Nationale Plattform Elektromobilität, 2010) can only be reached by addressing all consumers in the vehicle market.

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Vehicle owners can be divided into private persons and corporate institutions. Company vehicles constitute close to 4.5 million cars, representing 10% of all registrations (Kraftfahrtbundesamt, 2015). Results of current research programs as the BMWI sponsored “Information and communication technology (ICT) for Electric Mobility II” demonstrate (Hacker et al., 2015): electrical powertrains can be applied to light trucks, buses and transport vehicles including service and delivery fleets. Commercial users in contrast to private owners exhibit features particularly suited for the application of electric vehicles: routing is more predictable, yearly mileage is higher and investment decision is based on TCO (Total Cost of Ownership) approach rather than purchase price (Hacker et. al., 2015). Furthermore, several analyses on the mobility behavior of commercial companies show that the region of operation is mostly limited to a radius of 50 – 100 km, often focused on the inner region of a city (Vogel, 2015). The integration of BEVs into commercial fleets allows reduction of local air pollution as well as noise exposure. In summary, commercial use of vehicles reveals a high potential for the application of BEVs.

TCO analyses have shown that BEVs require high mileages in order to overcompensate higher purchase prices with lower operating costs (Hacker et. al., 2015). At the same time, low range and lengthy charging periods restrict usability for long distance trips. The key to maximize utilization and avoid rejection of trips is to integrate BEVs into a shared fleet with multiple users. Trips can be freely assigned to any of the vehicles in the fleet, allowing BEVs to be preferred wherever feasible while simultaneously ensuring maximum coverage of all trips. A fleet disposition model to allocate each trip to a corresponding vehicle is required to ensure both feasibility as well as maximization of BEV benefits. The idea of this paper is to integrate on-site energy generation into the disposition model as well as including limited quantity and power of charging stations.

The model assigns trips depending on the actual minimization target: overall cost or overall emissions. In case of ecological optimization the simulation prefers recharging mainly with regenerative energy sources while at the same time maximizing the mileage of BEVs, aiming at a reduced carbon footprint. Optimizing overall costs can lead to preference of ICEVs, depending on the corresponding cost per kilometer. Likewise, recharging will be scheduled to periods of cheap energy availability, e.g., during nighttime. In general, the disposition model is capable of determining a detailed charging schedule for every BEV.

2. Related Work

Commercial fleet management tools are recommended for fleet sizes greater than 5 to 7 to ease administration of accounting, monitoring vehicle conditions and adhering to maintenance requirements (Grausam et. al, 2015). Some fleet management tools offer fleet disposition plug-ins in addition. However, only few solutions support range and charging restrictions of BEVs. The “comm.fleet” software assigns trips according to cost per kilometer, CO_2 emissions or overall utilization. In addition, it provides various options for users to specify their vehicle demand, e.g., features and number of seats (Community4you, 2015). “fleetster” specializes on corporate car sharing and offers a web and app based reservation interface which is independent of the fleet manager (Next Generation Mobility, 2015). Allocation of trips can either be chosen by the user or is determined automatically by cost comparison. However, both solutions focus on real time functionality, i.e. each user is appointed a vehicle immediately during the reservation process. Reservations scheduled earlier or later are not taken into account. Therefore, only local optima can be determined.

Research on global optimization of fleet disposition has been conducted with different aims. In general, static and dynamic scheduling has to be distinguished. Static approaches assume all trips are known at the beginning of the day and do not exhibit any changes. Dynamic methods focus on flexibility regarding unforeseen events such as break-downs or accidents and tolerate obligatory loss in optimality.

2.1. Static scheduling

Sassi and Oulamara (2014) examined the application of BEVs in fleets comprising up to 120 vehicles. The Electric Vehicle Scheduling and Charging Problem (EVSCP) proposed is defined as follows: for a given number of trips, BEVs, ICEVs and charging infrastructures a disposition schedule shall be deduced such that the kilometers driven by BEVs is maximized. This optimization problem can be classified as a variant of Fixed Interval Scheduling (FIS) with the additional constraint of limited energy of each BEV (Kovalyov et al., 2007).

Sassi and Oulamara prove that the EVSCP is NP-hard. Therefore, an approximation method is applied. Two different approaches are presented using mixed integer linear programming (MILP) and a sequential heuristic (SH). Assuming a 30 minute time limit, the SH algorithm is able to determine similarly good solutions as the full MILP algorithm. Maximum deviation ranges from 15% to 25%. Compared to MILP the SH approach performs considerably faster and exhibits higher probability to find a feasible solution.

The EVSCP aims only at maximizing the cumulative distance traveled by all BEVs. Neither actual operating costs nor inclusion of different vehicles are considered. Also Sassi and Oulamara do not incorporate driving or charging emissions. Finally, no restrictions on the number of charging stations are implemented.

2.2. Dynamic scheduling

As part of the project "Shared e-fleet" the Fraunhofer IAO investigated scheduling of BEVs and ICEVs during practical operation (Kötter, 2015). The users request a vehicle via browser or smartphone app. An algorithm compares existing reservation requests and determines which vehicle is best to be assigned. Compared to static scheduling the dynamic approach takes care of a number of uncertainties (Kötter, 2015):

- User behavior: user covers a longer distance than originally specified or does not use the vehicle at all
- Energy availability: grid provides a lower power level than expected
- Failures: accidents or break-downs which impede operation

Real-time information is integrated in the algorithm in order to take these uncertainties into account. The actual vehicle is assigned only two hours prior to each trip's departure time to maintain flexibility in the allocation. Possible optimization objectives encompass overall costs, CO_2-emission and distance traveled by BEVs.

In comparison to *2.1* the algorithm distinguishes between vehicles with different use values. Mathematically, this problem is known as a Generalized Assignment Problem (GAP) which qualifies as NP-hard (Martello and Toth, 1990). Kötter developed a consecutive algorithm, in which all trips are divided into sets of a certain size. Each trip set then is allocated to the fleet under consideration of ongoing trips or charging periods. The allocation is repeated until all trip sets have been computed. Thus, Kötter determines and concatenates multiple local optima.

Kötter's approach allows individual scenario optimization such as the minimum total fleet size or the maximum share of BEVs. The advantage of this method is the integration of live information with a real time response. However, the resulting solution only represents an approximation, which might leave potential unused. Furthermore, charging is not scheduled according to varying energy costs.

2.3. Priority-based scheduling

A focus on dynamic scheduling of trips is also presented by Döppers in a graph-based method to assign trips to fleets consisting exclusively of BEVs (Döppers, 2012). This approach is different to *2.1* and *2.2* because every trip offers the flexibility to start in a given time interval instead of at a fixed time point. In addition, Döppers allows recharging BEVs en route. Also, trips are distinguished by priority and not by different vehicle class. The aim of the optimization is to primarily minimize the number of rejected high-priority trips. Secondly, the overall number of successfully assigned trips shall be maximized. Finally, all vehicles should be booked as balanced as possible.

This variant can be classified as a quadratic assignment problem (QAP) due to two objective targets. The QAP is also known as an NP-hard problem (Burkard et al, 2012). Döppers applies a graph-based ant algorithm to approximate a solution in short time.

The ant algorithm can easily accommodate unexpected events. However, Döppers chooses to simplify the problem by using only identical BEVs. The optimization objectives neither allow financial nor ecological benefits to be assessed or maximized. Thus on-site energy generation cannot be taken advantage of.

3. Method & Approach

On-site energy generation creates a high potential for BEV use due to availability of cheap energy, partial independence of grid power and occasionally even excess of energy. In order to fully utilize these advantages, recharging schedules need to be considered as integral part of the allocation process rather than subsequently determining charging periods. Parameters of energy availability can be optimally matched only by including the energy data into the decision process.

Sub-section *3.1* presents the overall functionality of the model including all input parameters as well as output data. Furthermore, possibilities are shown for embedding the model into an energy management system regulating the facility's energy demands.

The mathematical problem classification is introduced in sub-section *3.2*. Despite time-dependent input parameters, the objective has been successfully formulated as a linear problem with integer variables. Problem description and computation are executed in MATLAB, using the integrated solver *intlinprog*.

3.1. Framework

The functionality of the model is outlined in figure 1. First, the vehicle fleet is defined. Relevant parameters include vehicle class, consumption, range, maximum charging power and running costs. Technical details can be derived from manufacturer specifications or separate vehicle concept simulations independent of the disposition model. Running costs include wear and tear, maintenance and fuel cost and can be determined either based on historic data or publicly available databases, e.g., provided by the German automobile club ADAC (ADAC e.V., 2106). Fixed costs such as insurance and tax do not depend on the distance travelled by the vehicle and therefore are not relevant for the disposition model itself.

Then, a vector containing all trips is passed on to the disposition model. This includes start and end time, required vehicle class and expected travelling distance. The destination itself is not considered in the simulation, as no charging possibilities outside the company premises are assumed as a worst-case scenario. Furthermore, energy consumption is assumed to be independent of the exact routing. However, factors influencing energy demand such as driver behavior, average speed and general topology can be considered manually by adapting the consumption value.

Subsequently, the disposition model is given the quantity and maximum power of every charging unit on the premises. The simulation, therefore, is capable of limiting the number of simultaneously charging vehicles as well as modeling the expected charging time for each combination of vehicle and charging station. Hereby analyses on investments into expensive charging infrastructure can be conducted to verify profitability.

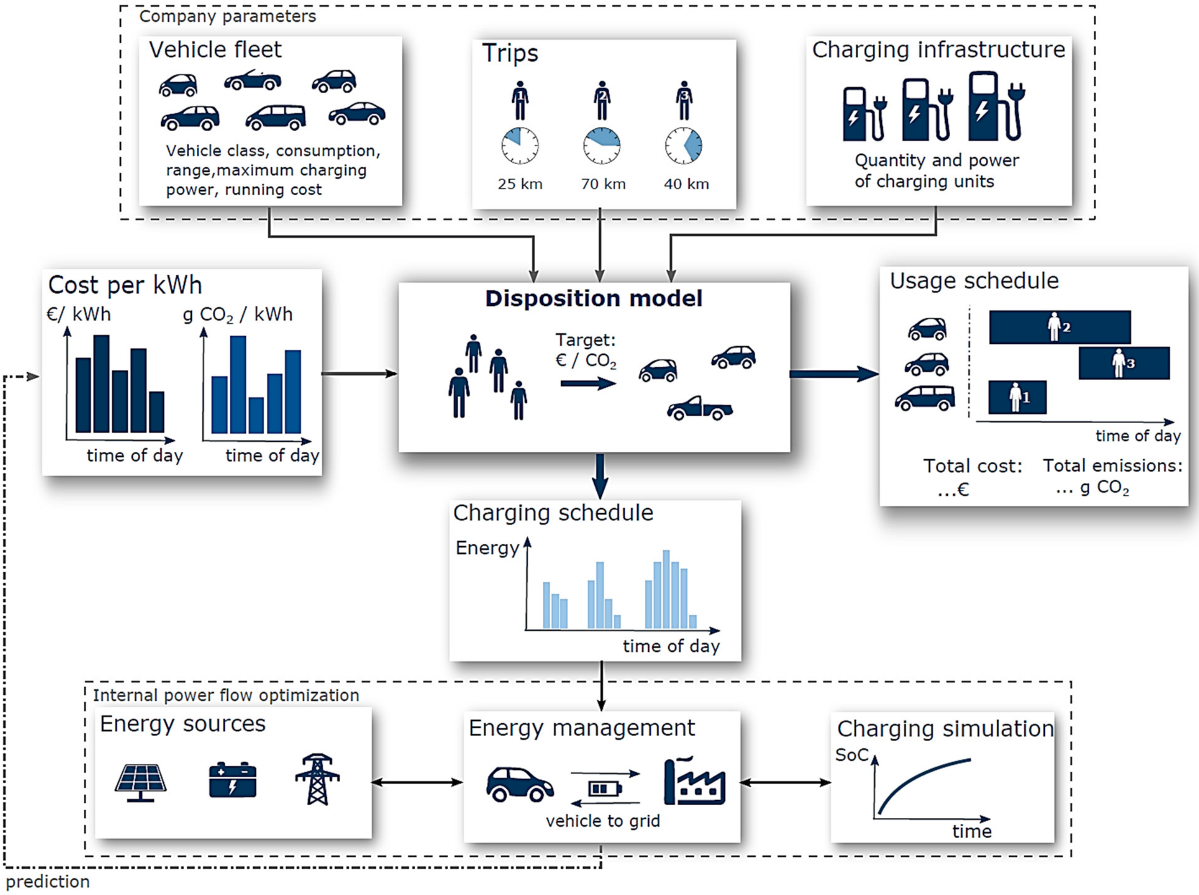

Fig. 1. Interfaces and interdependencies of fleet management simulation.

In addition to fleet and infrastructure properties, time dependent energy data is considered. Cost and CO_2-emissions associated with every kWh over time of day can be plotted to facilitate optimization of target parameters. This particular timeline is a result of the available energy source, the company internal energy consumption and the parameters of grid power.

Upon setting the optimization target to overall cost or overall emissions, the algorithm transforms the input parameters to a linear problem with integer variables and uses branch-and-bound techniques to solve the problem as efficiently as possible, see sub-section *3.2*. Each vehicle class is treated as a separate problem and solved consecutively.

The model provides a usage schedule as a direct output, i.e. which vehicle is allocated to which user at what time. It also includes the achieved target values on cost and emissions. Furthermore, the model indicates which cars were left unused, since it tries to cover all mobility needs with the lowest cost vehicles. If this behavior can be observed in multiple scenarios, fixed costs can be saved by selling idle cars or by appointing these vehicles to different tasks.

In addition to the usage schedule the model provides a vector containing the amount of energy that needs to be charged over time of day. This information can be passed on to an energy management module, which balances local energy demand – e.g., for the production line – charging power and energy generation. Each installed energy source can be modeled based on parameters such as weather conditions regarding solar arrays or power demand regarding stationary batteries. The energy management module is not part of the work presented in this paper.

The communication of the expected charging load offers two main advantages: it enables the energy management to plan in advance coordinating energy flows such that charging demand can be fulfilled at minimum cost – both ecologically and economically. Vehicle-to-grid benefits can also be realized on a local scale. The energy management can decide to integrate the BEV's connected battery into the local power circuit as extended capacity to the stationary batteries, e.g., to buffer temporary shortages on renewable energy due to poor weather conditions. The existing charging schedule may be altered as well, if vehicle-to-grid integration outweighs additional charging costs – as long as the required state of charge is guaranteed prior to every trip. Thus, further savings can be achieved without affecting the usage schedule itself.

Including a separately developed simulation that is able to map charging curves for maximum charging speed or battery lifetime optimization can ensure additional variability. The actual charging process can be regulated based on these results. The modeling of real charging curves also increases the flexibility to shift charging periods, as the disposition algorithm assumes much slower linear charging behavior as a worst-case scenario and therefore schedules more time than actually needed.

3.2. Algorithm

The optimization problem of allocating all trips to the fleet is only solvable, if a feasible solution exists at all. Failure may result either from too many overlapping tours or insufficient recharging periods. While recharging slots depend on the actual usage schedule and therefore cannot be determined in advance, a minimum number of vehicles to cover all trips can be calculated and compared with the actual size of the fleet.

To ascertain the minimum number of vehicles required, each trip is allocated to an imaginary vehicle, starting with trip 1 to vehicle 1. The algorithm then tries to allocate the next trip to the first vehicle as well. If the vehicle is occupied during the specified time frame, another imaginary vehicle is added. For all subsequent trips, every imaginary vehicle is reviewed in ascending order and selected if possible. If no vehicle is available, a new one is added. However, this does not consider any range restrictions. Once all trips have been assigned, the resulting size of the imaginary fleet equals the minimum number of vehicles required.

If the fleet specified by the user contains less vehicles than necessary, trip 1 is removed and the allocation of all remaining trips to an imaginary fleet is repeated. Subsequently, trip 2 is removed from the original set of trips and the minimum number of vehicles is determined. If no removal of a single trip reduces the minimum number of vehicles to equal or less the original fleet size, removing additional trips one by one is iterated until the condition is fulfilled. The goal is to delete only as few trips as possible. If multiple combinations are found, minimum cumulated distance is preferred.

3.2.1. Problem classification

At first thought, the task of allocating trips to vehicles under combination specific costs represents a variant of the generalized assignment problem (Martello and Toth, 1990). Each vehicle serves as an agent and has a limited budget, i.e. its maximum range, to complete a number of given tasks – in this case trips. However, each trip has to be completed in a certain time frame and therefore can only be assigned to vehicles available during the specified time period. Furthermore, neither variable budgets – resulting from recharging electric vehicles on site – nor determination of a charging schedule are taken care of in the conventional assignment procedure. Both effects have a great impact on the resulting total cost and emission level.

The approach chosen in this paper introduces a time scale with a fixed number of time steps. The overall time span is determined to 24 hours, since it can be assumed that all vehicles are fully recharged and all parameters have been restored overnight. Thus, multiple days can be split up in consecutive simulations of 24 hours length. Every cycle starts and ends at 6:00 AM in order to enable charging at nighttime, rather than requiring all batteries to be fully charged already by midnight. The 24 hours then are divided into time steps of 15 minutes length each, amounting to 96 steps in total.

Instead of allocating trips to individual vehicles of the fleet, the algorithm allocates every time step t of each vehicle m to a specific state, represented by the state vector $\boldsymbol{x}_{m,t}$. Each possible state for the vehicle m and time step t is divided into multiple binary variables, indicating whether the vehicle is driving, parking or charging, see *3.2.2*. The cost for each time step of each vehicle is independent of previous or succeeding time steps across the fleet. Therefore, the cost for a specific time step t can be determined by multiplying every possible state $\boldsymbol{x_{m,t}}$ at t with a corresponding constant factor, see *3.2.4*.

This approach enables a linear design of the problem based on binary state variables and variables containing the amount of energy charged at each time step. Thus, the problem can be formulated as a MILP (Natali, 2008) with a cost vector c, a variable vector x, an inequality constraint matrix A and vector b, an equality constraint matrix A_{eq} and vector b_{eq}, a vector of integer variables x_{int} and lower and upper bounds lb and ub for every variable:

$$\min c^T x \quad \text{subject to} \begin{cases} x_{\text{int}} \in \mathbb{Z} \\ A \cdot x \leq b \\ A_{eq} \cdot x \leq b_{eq} \\ lb \leq x \leq ub \end{cases} \tag{1}$$

3.2.2. Variables

The problem definition refers to time steps t as part of all 96 time steps T_{steps}, vehicles m as part of the vehicle set M containing v entries, trips f as part of the trip set F containing n entries and locations l as part of the location set L containing k charging stations and one parking lot p:

$$\begin{aligned} & m \in M = \{1, \dots, v\}, \\ & t \in T_{steps} = \{1, \dots, 96\}, \\ & f \in F = \{1, \dots, n\}, \\ & l \in L = \{1, \dots, k, p\}; \end{aligned}$$

As mentioned in *Problem classification*, the state vector $\boldsymbol{x_{m,t}}$ for each vehicle m and time step t is divided into multiple binary variables. The first set of sub-variables refers to the execution of trips. At time point t a vehicle m can perform one of the n trips:

$$x_{m,t,f} = \begin{cases} 1 & \text{if trip } f \text{ is executed;} \\ 0 & \text{otherwise.} \end{cases} \qquad \forall f \in F = \{1, \dots, n\} \tag{2}$$

If no trip is active, the vehicle is parked on site. As charging infrastructure can be limited, it is important to distinguish the exact position on site, i.e. whether the vehicle is connected to one of the k charging stations or located in the separate parking lot p:

$$x_{m,t,l} = \begin{cases} 1 & \text{if based on site at location } l; \\ 0 & \text{otherwise.} \end{cases} \qquad \forall l \in L = \{1, \dots, k, p\} \tag{3}$$

The individual modeling of every time step causes one disadvantage: While searching for feasible solutions, the algorithm might suggest a vehicle to switch charging stations repeatedly during its stay on site, so every charging station can be assigned to the vehicle it currently fits best to. However, in reality it is highly impracticable to frequently repark vehicles given the high effort in time. Prohibiting relocation entirely also does not reflect realistic conditions, as it might make sense to invest the time to move a vehicle once in a while, as long as this event occurs only rarely. A punishment for every required relocation on site needs to be enforced via the cost function in order to allow reparking in principle but restrict it to the minimum.

To ease computation, it is crucial to maintain the linearity of the problem, including the cost function. However, relocations between charging stations and the parking lot cannot be identified for every time step by only one linear function. A single function is only capable of detecting one difference in state between two time points. In other words, the cost function itself cannot identify every single change between charging stations and the parking lot. Therefore, separate coefficients indicating a relocation have to be introduced for every time step, which then easily can be taking into account by the cost function:

$$x_{m,t,rl} = \begin{cases} 1 & \text{if relocated on site to location } l; \\ 0 & \text{otherwise.} \end{cases} \qquad \forall\, l \in L = \{1, \dots, k, p\} \tag{4}$$

Note that the relocation variables $\boldsymbol{x_{m,t,rl}}$ cannot reach values freely, but depend directly on the location variables $\boldsymbol{x_{m,t,l}}$. The specific logic applied is explained as part of the constraints.

Selecting a charging station and determining the duration of the connection only represents part of the charging schedule. The second part required contains the scalar amount of energy $x_{m,t,E}$ in kWh the vehicle shall charge during the time step t:

$$x_{m,t,E} \in \mathbb{R}_0^{\,+} \tag{5}$$

Altogether, the state vector $\boldsymbol{x_{m,t}}$ for each time step t of each vehicle m consists of all trip, location, relocation and energy variables:

$$\vec{x}_{m,t} = \begin{bmatrix} \vec{x}_{m,t,f} & \vec{x}_{m,t,l} & \vec{x}_{m,t,rl} & x_{m,t,E} \end{bmatrix}^T \tag{6}$$

Adding all state vectors $\boldsymbol{x_{m,t}}$ yields the overall variable vector $\boldsymbol{x}$:

$$\vec{x} = \begin{bmatrix} \vec{x}_{m=1,t=1} & \dots & \vec{x}_{m=1,t=96} & \vec{x}_{m=2,t=1} & \dots & \vec{x}_{m=v,t=96} \end{bmatrix}^T \tag{7}$$

All entries of $\boldsymbol{x}$ except the charging energy variables $x_{m,t,E}$ are integer variables with logical value. The lower bound for the charging energy equals 0 and the upper bound is represented by the maximum charging power divided by 4, since every time step equals one quarter of an hour. The application of MILP requires the charging process to be modeled linearly, which has been confirmed an acceptable approximation (Kasten and Zimmer, 2011). However, when specifying the maximum charging power of each vehicle in the algorithm, it is important to enter the average power applied during a complete recharge, not the maximum power the battery can take.

With the number of trips n, vehicles v and charging stations k the total size of $\boldsymbol{x}$ amounts to:

$$size\left(\vec{x}\right) = \underbrace{96}_{\substack{\text{time}\\\text{steps}}} \cdot \underbrace{v}_{\text{vehicles}} \cdot \left(\underbrace{n}_{\text{trips}} + \underbrace{2 \cdot (k+1)}_{\substack{\text{location and}\\\text{relocation}}} + \underbrace{1}_{\text{energy}} \right) \tag{8}$$

3.2.3. Constraints

The time step approach requires several constraints to ensure the allocation of trips is feasible in reality. The first constraint requires trips to be carried out only during their scheduled period t_f:

$$\sum_{m}\sum_{t \notin t_f} x_{m,t,f} = 0 \qquad \forall f \in F = \{1, \ldots, n\} \tag{9}$$

Each trip can only be carried out by exactly one vehicle m in order to avoid trips being torn apart. Thus, every vehicle can either perform all time steps of a specific trip f or none at all. If f is assigned to m, the sum of all allocation variables $x_{m,t,f}$ shall equal the duration of the trip T_f. Elsewise if f is not assigned to m, the allocation variable at the last time step t_{end} must be 0 and shall exclude T_f:

$$\sum_{t} x_{m,t,f} - T_f \cdot x_{m,t_{end},f} = 0 \qquad \forall m \in M = \{1, \ldots, v\}, \quad \forall f \in F = \{1, \ldots, n\} \tag{10}$$

Every single trip f needs to be assigned to a vehicle. Therefore, $x_{m,t,f}$ across all vehicles and time steps must equal the trip's duration T_f:

$$\sum_{m}\sum_{t} x_{m,t,f} = T_f \qquad \forall f \in F = \{1, \ldots, n\} \tag{11}$$

Each vehicle can either be dispatched or parked on site. If the vehicle is driving, it can only perform one of the trips. If it is parked on site, it can either occupy one of the charging stations or be located in the parking lot:

$$\sum_{f} x_{m,t,f} + \sum_{l} x_{m,t,l} = 1 \qquad \forall m \in M = \{1, \ldots, v\}, \quad \forall t \in T_{steps} = \{1, \ldots, 96\} \tag{12}$$

Charging is only possible if the vehicle is connected to a charging station, denoted by the location state variable $x_{m,t,l}$. Furthermore, the energy charged $x_{m,t,E}$ cannot exceed the maximum energy per time step limited by the maximum power of the charging station $P_{max,l}$. To disable charging at the parking lot, $P_{max,p}$ is set to zero:

$$x_{m,t,E} - \sum_{l} \frac{P_{\max,l}}{4} \cdot x_{m,t,l} \le 0 \qquad \forall m \in M = \{1, \ldots, v\}, \quad \forall t \in T_{steps} = \{1, \ldots, 96\} \tag{13}$$

The remaining range is not allowed to fall below a specified minimum reserve R_{min} at any time point. To compare the total distance traveled by the arbitrary time point t^*, all trip allocation variables $x_{m,t,f}$ up to t^* are multiplied with their distance per time step, derived as the total distance D_f divided by the duration of the trip T_f. The counterpart to kilometers traveled is the amount of range charged between trips, which can be calculated by dividing the overall energy charged by the vehicle specific energy consumption B_m in kWh/100km. The difference of kilometers traveled and range charged may not exceed the usable range R_m - R_{min}:

$$\sum_{t \in \{1,\ldots,t^*\}} \left(\underbrace{\sum_{f} \left(\frac{D_f}{T_f} \cdot x_{m,t,f} \right)}_{\text{distance traveled}} - \underbrace{\frac{100}{B_m} x_{m,t,E}}_{\text{charged range}} \right) \le R_m - R_{\min} \qquad \forall m \in M = \{1, \ldots, v\}, \quad \forall t^* \in T_{steps} = \{1, \ldots, 96\} \tag{14}$$

Analog to constraint (14), at no time point may the current range exceed the maximum battery range R_{max}. Assuming that every vehicle is fully charged in the morning, this constraint can be formulated by demanding that more or equal energy has to be consumed than recharged by any time point t^*:

$$\sum_{t\in\{1,\dots,t^*\}} \left(\underbrace{\frac{100}{B_m} x_{m,t,E}}_{\text{charged range}} - \underbrace{\sum_f \left(\frac{D_f}{T_f} \cdot x_{m,t,f} \right)}_{\text{distance traveled}} \right) \leq 0 \qquad \forall m \in M = \{1, \dots, v\}, \quad \forall t^* \in T_{steps} = \{1, \dots, 96\} \tag{15}$$

At the end of the day, all vehicles have to be fully recharged, i.e. the energy charged has to equal the amount of energy used over all trips:

$$\sum_t \left(\underbrace{\frac{100}{B_m} x_{m,t,E}}_{\text{charged range}} - \underbrace{\sum_f \left(\frac{D_f}{T_f} \cdot x_{m,t,f} \right)}_{\text{distance traveled}} \right) = 0 \qquad \forall m \in M = \{1, \dots, v\} \tag{16}$$

Every charging station can only accommodate one vehicle at a time. Note that this only affects the k charging stations. The parking lot can hold multiple vehicles simultaneously:

$$\sum_m x_{m,t,l} = 1 \qquad \forall l \in L = \{1, \dots, k\}, \quad \forall t \in T_{steps} = \{1, \dots, 96\} \tag{17}$$

If a vehicle is relocated on site between charging stations or the parking lot, the relocation variable $x_{m,t,rl}$ needs to be set. To detect changes, the state of each location at time step t is compared with its previous state at t_{prev}. However, relocation does not apply if a vehicle returns from a trip, as the time effort to park the vehicle is assumed to be equal for all locations:

$$-2 \cdot x_{m,t,rl} + \underbrace{\left(-x_{m,t_{prev},l} + x_{m,t,l} \right)}_{\substack{\text{detecting state change} \\ \text{of location } l}} + \underbrace{\sum_l x_{m,t_{prev},l}}_{\substack{\text{check if vehicle} \\ \text{was already on site}}} \leq 1 \tag{18}$$

$$\forall m \in M = \{1, \dots, v\}, \quad \forall l \in L = \{1, \dots, k, p\}, \quad \forall t \in T_{steps} = \{1, \dots, 96\}$$

$$2 \cdot x_{m,t,rl} + \underbrace{\left(x_{m,t_{prev},l} - x_{m,t,l} \right)}_{\substack{\text{detecting state change} \\ \text{of location } l}} - \underbrace{\sum_l x_{m,t_{prev},l}}_{\substack{\text{check if vehicle} \\ \text{was already on site}}} \leq 0 \tag{19}$$

$$\forall m \in M = \{1, \dots, v\}, \quad \forall l \in L = \{1, \dots, k, p\}, \quad \forall t \in T_{steps} = \{1, \dots, 96\}$$

Constraint (18) is responsible for setting the state change variable $x_{m,t,rl}$ if l was occupied by m and m was on site before. Constraint (19) ensures that if no change was detected for m or m was not on site the previous time step, $x_{m,t,rl}$ is not set.

3.2.4. Cost vector

Analog to $\boldsymbol{x}$ the cost vector $\boldsymbol{c}$ consists of sub vectors $\boldsymbol{c_{m,t}}$ containing the cost per vehicle m and time step t:

$$\vec{c}_{m,t} = \begin{bmatrix} \vec{c}_m \cdot \dfrac{\vec{S}_f}{\vec{T}_f} & \vec{c}_k & \vec{c}_{rl} & c_{E,t} \end{bmatrix}^T \tag{20}$$

$$\vec{c} = \begin{bmatrix} \vec{c}_{m=1,t=1} & \cdots & \vec{c}_{m=1,t=96} & \vec{c}_{m=2,t=1} & \cdots & \vec{c}_{m=v,t=96} \end{bmatrix}^T \tag{21}$$

The first entry refers to the cost incurred if f is assigned to m. The parameter c_m represents the cost of every vehicle per distance driven: in case of economic optimization c_m equals the running cost per kilometer. In case of ecological optimization c_m refers to the emissions caused by driving, which only applies to ICEVs and correlates with the fuel consumption. c_m then is multiplied with the total distance S_f divided by the duration T_f to derive the cost per time step associated with every f.

The cost parameter c_k punishes the occupancy of any of the charging stations. The goal is to avoid blocking of charging stations by vehicles that do not require charging during their parking period. Hereby ICEVs will always be located in the parking lot during their stay on site. The value of c_k is chosen sufficiently small not to impact the total result, as in reality there is no actual cost induced by parking at a charging station.

As mentioned previously, any relocation on site needs to be punished to reduce fleet handling efforts. The value of c_{rl} can be specified by the user and is independent of the vehicle as well as the origin and destination of the relocation.

Every kWh of energy is associated with a certain price and emission level, depending on the time the energy is requested. These parameters $c_{E,t}$ are a result of the prediction of the energy management model, see figure 1.

4. Results

The overall computation time varies greatly with the number of trips and the ratio of BEVs to charging stations. The maximum problem size that can be solved completely within 2 hours comprises approximately 30 trips and 8 vehicles, depending on the ratio of BEVs to ICEVs as well as how many charging stations are available. Larger problems can be computed as well, however the best resulting solution cannot be certified as the global optimum.

The user interface generates two main graphs: the usage schedule gives an overview of the allocation of trips to vehicles over time of day, allowing straight forward verification by the user. The charging schedule contains the amount of energy charged during every time step as well as the energy price or emission level over time, depending on the selected optimization objective. In addition, the graph offers a filter to inspect the charging schedule of every vehicle separately.

Figures 2 and 3 outline the graphs for a simulation of 30 trips and a vehicle fleet consisting of 2 ICEVs and 3 BEVs (Appendix B: trip set A, vehicle set A). The energy price curve is a fictive example of a test company generating energy on-site (Appendix A).

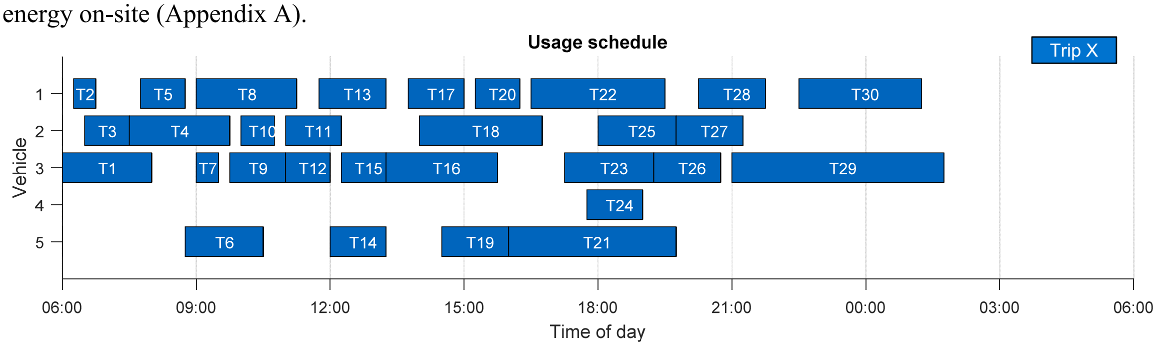

Fig. 2. Usage schedule for a simulation of 30 trips with 2 ICEVs, 3 BEVs and 3 charging stations (Appendix B: trip set A, vehicle set A).

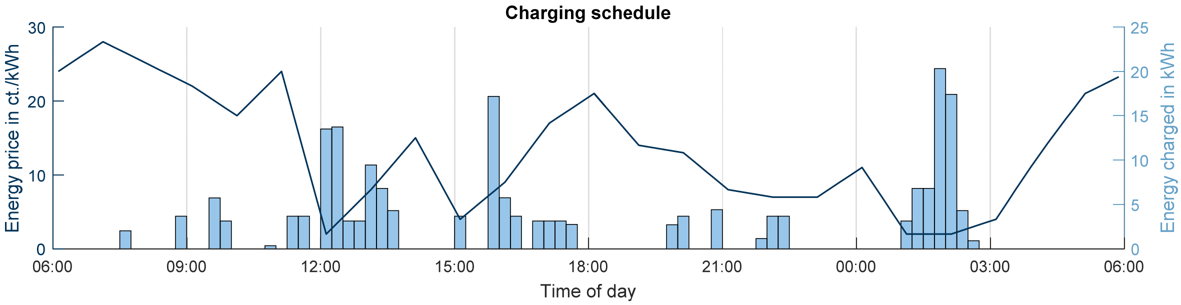

Fig. 3. Charging schedule for a simulation of 30 trips with 2 ICEVs, 3 BEVs and 3 charging stations (Appendix B: trip set A, vehicle set A).

4.1.1. Maximizing BEV potential

One of the main advantages of the model presented in this paper is the possibility to assess variations of the vehicle fleet, taking into account company specific energy data. The functionality can be used to investigate the effects of substituting conventional ICEVs with BEVs. 20 trips, 5 ICEVs and the energy price curve of figure 3 serve as test data to determine the financial potential of a one by one replacement of each ICEV with an equivalent BEV, assuming an own charging station for every BEV (Appendix B: trip set B, vehicle set B, C, D, E, F). Vehicle specifications and costs are based on ADAC data (ADAC e.V., 2016), which includes current fuel prices and brand typical workshop costs.

The cost per kilometer specified for every vehicle includes fuel, oil and maintenance. Based on the set of trips the model then provides the operating cost for the entire fleet, which includes energy costs for BEVs. The different vehicle fleets can only be compared if fixed costs and loss of value are taken into account as well. Assuming German tax law, company vehicles are depreciated linearly over 6 years. After this time period the accounting value drops to 1 € (IHK Rhein-Neckar, 2016). The minimum loss of value per year therefore results to 1/6 of the purchase price. However, the vehicle’s lifetime is limited by its mileage. The model assumes 90% loss of value after 200.000 km for BEVs and 250.000 km for ICEVs respectively. Assuming the set of trips is representative for the mobility profile of the test company, the kilometers driven by each vehicle can be extrapolated to a full year consisting of 40 work weeks of 5 days each. Thus, the loss of value per year either correlates with the vehicle’s age or overall mileage, whichever value dominates. The yearly total sum of operating cost, loss of value and fixed cost can be compared for each fleet compositions, outlined in figure 4.

The operating cost drops significantly due to cheaper availability of electricity compared to fuel. At the same time, the higher purchase price of equivalent BEVs increases the loss of value per year. The fixed costs – mainly consisting of tax and insurance – are mostly independent of the vehicle type and only weakly influence the overall result.

In the fourth fleet composition of the example shown, all 20 test trips can be covered solely by the 3 BEVs. Nevertheless, high utilization reduces flexibility on the charging times and leads to high average energy prices, as shown in figure 4. Introducing further BEVs in the next fleet compositions can not only lower cost, but also increase reliability of the fleet in case of unforeseen events such as delayed returns, breakdowns or accidents.

Altogether, substituting ICEVs in the given test company can reduce the total fleet cost by 22%. Furthermore, overall emissions (not depicted) drop from 35 tons per year for a conventional fleet to 16 tons per year for a purely electrical fleet. In combination with a local energy management system as presented in section *3.1*, even further savings can be generated by leveraging vehicle-to-grid methods.

However, the achievable savings both in terms of cost and emission depend greatly on the BEV chosen for each replacement as well as the considered assumptions regarding value depreciation and repetitiveness of the trips. Substitution of BEVs only is beneficial if the reduction in operating cost overcompensates the increase in loss of value. Likewise, any proposition is only valid for the trips specified and needs to be critically interpreted in case of high variances of the mobility profile of the company. In addition, the results display that a charging strategy is not dominant of only a few BEVs are used. Also, the simulation results are mainly depended of the assumptions which were made.

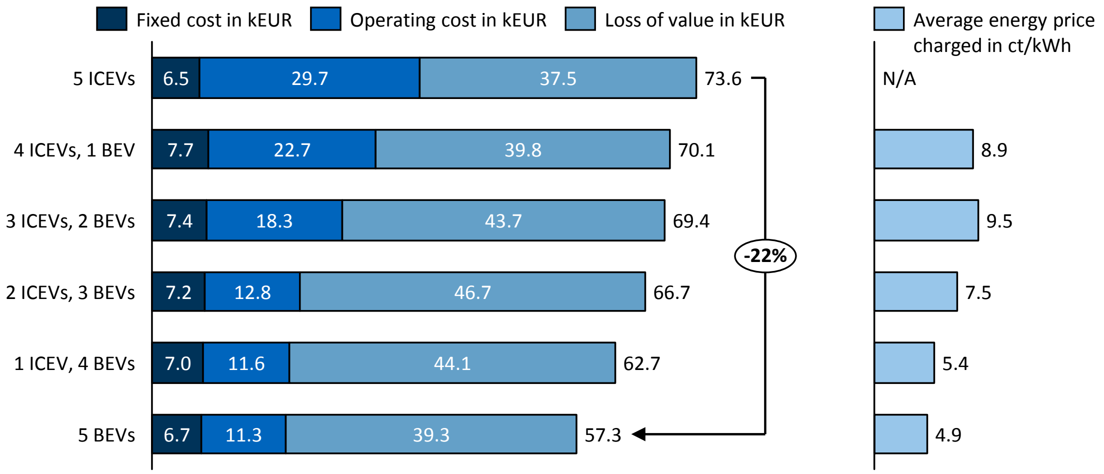

Fig. 4. Yearly fixed cost, operating cost and loss of value in kEUR next to average energy price of charging periods for different fleet compositions. Optimization objective was set to operating cost (Appendix B: trip set B, vehicle set B, C, D, E, F).

4.1.2. Impact of charging infrastructure

Another potential scenario analysis refers to lengthy recharging processes as one of the main obstacles to high utilization of BEVs at the present time. This issue can be addressed by the integration of high power DC charging stations, which in case of the Tesla Supercharger are capable of charging vehicle batteries at up to 120 kW instead of maximum 3.7 kW at ordinary wall boxes – applied to the Tesla Model S, 270 km of range are recharged within only 30 minutes (Tesla Motors, 2016). However, high investment cost and few suitable vehicle batteries limit the usage of such infrastructure.

The disposition model is capable of assuming a limited charging infrastructure and therefore determining potential benefits of high power charging stations. Figure 5 outlines the comparison of one low and one high power charging station applied to the previous test company with 20 trips as well as 3 ICEVs and 2 BEVs capable of high power charging (Appendix B: trip set B, vehicle set G, trip set B).

If existing vehicles allow fast charging, two effects ensue from shortened charging periods: on the one hand, more trips can be handled by BEVs due to reduced down-time. On the other hand, charging can be concentrated to periods of cheap energy availability, reducing the average charging price. The benefits obtained represent a key factor to determine the profitability of different charging stations. As further interpretations, the savings in the yearly operating costs can be used for higher financial investments and the compensation of the battery aging.

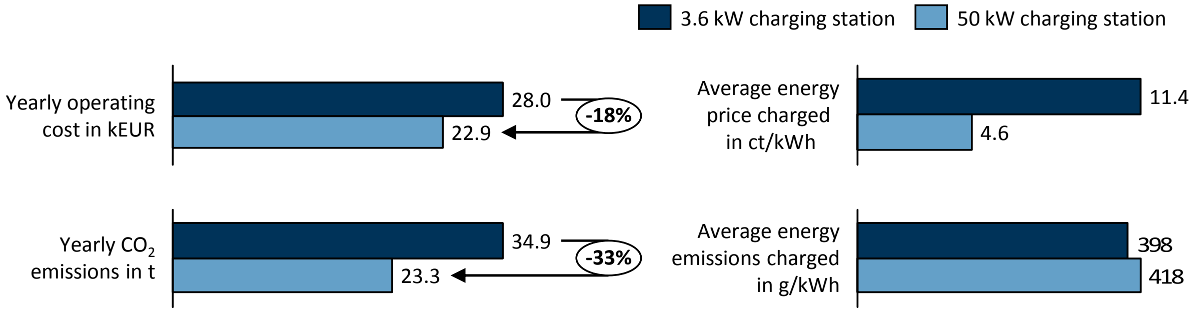

Fig. 5. Comparison of yearly operating cost, CO_2 emissions, energy price and energy emissions of charging periods for a low and high power charging station. Optimization objective was set to operating cost (Appendix B: trip set B, vehicle set G).

5. Conclusion

Previous research on disposition of fleets containing BEVs concentrated only on feasibility and optimization of running costs. However, companies capable of on-site energy production, e.g., with solar arrays, can realize considerable additional saving potentials by coordinating charging periods. This paper presents a disposition model that includes energy parameters and limited charging infrastructure in the process of vehicle allocation. A time-step based approach allows the transformation to a mixed integer linear program, using a MATLAB integrated solver. The model offers two optimization targets: overall cost and overall emissions. Thus, utilization of BEVs is tailored to the specific parameters of the assessed company.

The model is capable of analyzing the financial and ecological potential of substituting individual ICEVs with BEVs. It provides a customized recommendation for the optimal fleet composition, depending on the number of trips and the specification of the vehicles. Moreover, the impact of investments into high power charging infrastructure can be simulated to optimize BEV utilization. Finally, conveying the charging schedule to a site specific energy management system contributes to additional savings through vehicle-to-grid methods.

For Further research the authors suggest the combination and integration of a energy management system, which can by either integrated iteratively or additionally. In addition the results can made more realistic if the simulation can react to disturbances for different vehicles. In this paper, an average consumption for the vehicles is selected. An improvement for the results can be made by using a route specific energy consumption which is developed in further researches by the authors.

Acknowledgements

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Appendix A. Energy price and emission curve

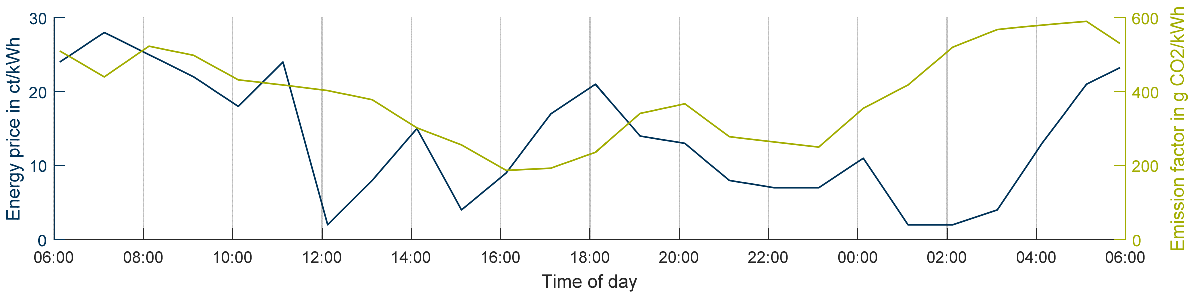

Fig. 6. Fictive energy price and emission factor over time of day for a test company generating energy on-site.

Appendix B. Trip sets, vehicle sets and charging station sets

Table 1. Trip sets.

Number	Start time	End time	Distance	Set A	Set B
1	06:00	08:00	59	x	x
2	06:15	06:45	34	x	
3	06:30	07:30	24	x	x
4	07:15	08:00	21		x
5	07:30	09:45	48	x	
6	07:45	08:45	35	x	x
7	08:45	10:30	54	x	x
8	09:00	09:30	51	x	
9	09:00	11:15	81	x	x
10	09:45	11:00	62	x	
11	10:00	10:45	28	x	
12	10:45	13:15	143		x
13	11:00	12:15	53	x	x
14	11:00	12:00	31	x	
15	11:45	13:15	71	x	x
16	12:00	13:15	45	x	
17	12:30	13:00	43	x	x
18	13:15	15:45	106	x	x
19	13:45	15:00	52	x	
20	14:00	16:45	101	x	
21	14:30	16:00	62	x	x
22	15:00	17:15	108		x
23	15:15	15:45	24	x	
24	16:00	19:45	57	x	
25	16:30	19:30	112	x	x
26	17:15	19:15	71	x	
27	17:45	19:00	42	x	
28	18:00	19:45	56	x	x
29	19:00	21:00	87		x
30	19:15	20:45	47	x	
31	19:45	21:15	63	x	
32	20:15	21:45	48	x	x
33	21:00	01:45	76	x	
34	21:30	23:15	53		x
35	22:30	01:15	64	x	x
36	23:30	02:45	114		x

Table 2. Fleet sets (ADAC e.V., 2016; The Mobility House, 2016).

Number	Make and model	Vehicle type	Consumption in L/kWh /100km	Range in km	Max.charg-ing power in kW	Set A	Set B	Set C	Set D	Set E	Set F	Set G
1	Renault Zoe Z.E. Intens	BEV	13.3	165	14.7	x		x	x	x	x	
2	BMW i3	BEV	12.7	191	3.5							
3	Mercedes B 250 e	BEV	12.9	146	12.5	x			x	x	x	
4	Kia Soul EV	BEV	16.6	169	9.3							
5	Nissan Leaf Acenta	BEV	14.7	184	54.0	x				x	x	x
6	Nissan e-NV200	BEV	15.0	200	7.5						x	
7	Tesla Model S 70	BEV	15.8	443	56.0							x
8	VW Polo 1.2 TSI BMT	ICEV	4.8	938	-		x					
9	VW Golf Sportsvan 2.0 TDI	ICEV	4.7	1064	-		x	x				
10	KIA Soul 1.6 CRDi Spirit	ICEV	5.2	1038	-		x	x	x			x
11	Opel Zafira Tourer 1.4 Turbo	ICEV	6.5	892	-	x	x	x	x	x		x
12	VW T6 Transporter 2.0 TDI	ICEV	7.0	1000	-	x	x	x	x	x	x	x