Classification of Electric Vehicle Fleets Considering the Complexity of Fleet Charging Schedules

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The increasing number of electric vehicles has a growing impact on the power grid. Therefore, charging processes need to be scheduled. In order to clarify and solve the challenges of scheduling the charging of a fleet, this paper analyses, categorizes and classifies different kinds of fleets of electric vehicles.

CCS Concepts • **Theory of computation** → **Scheduling algorithms** • **Theory of computation** → **Discrete optimization** • Theory of computation → Packing and covering problems • Theory of computation → Algorithm design techniques

KEYWORDS

Electric vehicles, vehicle fleet, fleet classification, charging scheduling, NP-completeness

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1 INTRODUCTION

The number of Electric Vehicles (EVs) is continuously growing, especially in the business sector. This steady growing demand of energy to charge the fleet could harm the power grid, especially if the fleet charging is not coordinated with regards to the available energy capacity of the grid. To prevent this, the charging processes have to be scheduled. To solve this Charging Scheduling Problem (CSP), adequate algorithms and heuristics have to be used.

In the CSP the goal is to find a cost optimized charging plan for the whole fleet, which is valid under certain restrictions, like the available grid capacity. It refers to the NP-complete problems which have tremendous computation time for large problem instances. However, there are existing algorithms and heuristics, which are capable of solving the CSP for EV fleets.

In the related work there are different approaches to solve the CSP. However, there are almost no hints, which algorithm or heuristic is

adequate for a specific fleet type. To answer this, it is necessary to understand the term fleet in the context of the CSP.

The goal of this paper is to establish a class system for fleets in the CSP to make them comparable and distinguishable from each other. These classes uncouple the understanding of the fleet business from the modelling of the CSP. They can be used as a basis to find the right heuristic or algorithm for a certain fleet.

To do this there is a discussion in the second Section about the solving methods in the related work. In the third Section, the initial situation of the CSP is explained and the constraints are defined. On this fundament, the single components are analyzed in the fourth Section. This analyzation allows a derivation of the suggested classes. In the fifth Section, there is a short conclusion of the opportunities of these classes.

2 RELATED WORK

This Section provides an overview of different heuristics and algorithms to solve the CSP. Xi and Siohansi [8] propose a decentralized price/quantity based approach. Mixed Integer Programming solution (MIP) is applied as described by Álvaro and Fraile-Ardanuy [1], Detzler and Karnouskos [2] or Sassi and Oulamar [6]. The latter also use a Min-Cost-Flow-Problem based heuristic [6]. Other approaches include for example a binary linear programming method [5] or stochastic approaches [4]. Also a partition into time slots allows discrete solving approaches [3-7]. All authors present different methods to solve the CSP, but they often use different constraints of the CSP and it is unclear which method applies to which fleet type. This paper tackles this problem.

3 CHARGING SCHEDULING PROBLEM

This Section explains the CSP and its constraints.

Figure 1 - Initial situation of the CSP

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Scenario	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Knowledge of tour start time	Y	Y	Y	Y	Y	Y	Y	Y	N	N	N	N	N	N	N	N
Knowledge of tour end time	Y	Y	Y	Y	N	N	N	N	Y	Y	Y	Y	N	N	N	N
Knowledge of energy consumption	Y	Y	N	N	Y	N	N	Y	Y	N	N	Y	Y	N	N	Y
fixed tours	Y	N	Y	N	Y	Y	N	N	Y	Y	N	N	Y	Y	N	N
Class	Known arrival and departure fleets				Known departure fleets				Known arrival fleets				Arbitrary presence fleets			

Table 1 - Fleet condition combinations and classes

The EV-Fleet Owner (EFO) has different types of EVs, which are necessary to fulfill the tours of the business plan. These tours start and end at locations of the EFO. There, the EVs have to be charged at Charging Stations (CSs). The CSs are supplied with energy by one feeder line (on joint grid capacity) per location (see Figure 1). The goal is to schedule the charging processes in a cost optimal way, so that the business plan can still be fulfilled. For these charging processes, there are constraints. **(1) Charging availability:** EVs can only charge when they are not on a tour. **(2) CS-EV-Compatibility:** The CS adapter and the EV adapter must fit together. **(3), Location matching:** An EV can only use a CS at the same place. **(4) Charging powers of CS/EV:** The minimal and maximal charging power of a CS/EV adapter have to be respected. **(5) Grid capacity compliance:** The drain of charged energy must not exceed the grid capacity. **(6) Single charging of EV at CS adapter:** Only one EV can charge at a single CS adapter at the same time. **(7) No multiple charging processes by one EV:** One EV can only charge at one CS at the same time **(8) Battery capacity compliance:** The State of Charge (SoC) of an EV cannot be below 0% or above 100%. **(9) Tour readiness:** Every tour must be carried out by one EV. The SoC must be higher than the energy consumption of the tour.

4 CLASSIFICATION APPROACH

The constraints of the CSP are the same for every kind of fleet, but there is a difference in the specific characteristic of the CSP for every fleet. In order to reduce this large variety, fleet classes are established to cluster and confine the CSP complexity. This requires a closer look on the input information of the CSP.

4.1 Input information analysis

Input information	Constraint	Result
EV Charging adapter	2,9	Technical input
EV Charging power	4,5,9	Technical input
EV Battery capacity	8,9	Technical input
CS Charging adapters	2,9	Technical input
CS Charging Power	4,9	Technical input
CS location	3,9	Technical input
EV location	3,9	Technical input
Grid capacity	5,9	Technical input
Grid energy price	-	Optimization criteria
EV to tour assignment	1,3,9	Estimation necessary
Tour start	1,9	Estimation necessary
Tour end	1,9	Estimation necessary
deltaSoC	9	Estimation necessary

Table 2 - Overview input information

In the first column of Table 2, is the type of input information for the EVs, the CSs, the grid and the tours. In the second column are the constraints, which are affected by the information in the first column. In the third, there is an interpretation of the information. Every technical information is necessary to create a valid charging schedule. For example, it is necessary to know the EV charging adapter, to charge at a compatible CS. The grid energy price is necessary to optimize the charging costs. The last four rows, are the most interesting ones, because some EFOs cannot provide this information, due to their business model. For example, a taxi fleet cannot plan the tours in advance. They have to react to the demands of customers. In consequence, it is not clear, when these EVs are available for charging, which makes a scheduling impossible. To make an optimization possible, it is necessary to establish algorithms which calculate these parameters in advance. These algorithms make the CSP much more complex.

4.2 Fleet classification approach

If the last four rows of input parameters are missing, algorithms are necessary to estimate them. This increases the complexity. Based on this, we suggest to classify the fleets by this input information. Therefore, the fleets are classified in the following four classes:

1. known arrival and departure fleets, 2. known departure fleets, 3. known arrival fleets and 4. arbitrary presence fleets.

Based on the combination of these conditions and the resulting 16 different fleet scenarios we identified four classes of fleets (see Table 1). In this table, all combinations of the four conditions are illustrated. Every condition can be formulated as a question that can be answered with yes (Y) or no (N).

5 CONCLUSION

Overall this paper provides a general information of the input parameters and the constraints of the CSP. It also suggests different classes for the fleets. By dividing the fleets in these classes, it is possible, to solely focus on the modelling and the solving of the CSP. It is not necessary to understand the business goals or the fleet type. It does not matter if it is a taxi fleet, a bus fleet or a train fleet. If the classes and the technical inputs can be derived from it, a CSP can be established. This uncoupling of the CSP modelling from the business interpretation of a fleet, makes the charging cost optimization more straightforward and much easier. It makes it also possible to arrange the fleet in specific classes. This allows it to derive and compare the mathematical model, and therefore also the complexity of the different EV fleets.

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