Modeling of Mobility On-Demand Fleet Operations Based on Dynamic Electricity Pricing

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Abstract — **The 21st century is characterized not only by a growing need for mobility, but above all by an increasing variety of mobility forms. Individualization, connectivity, urbanization and post-fossil drive technologies will determine the mobility of tomorrow. Technical innovations and changing human needs are becoming the driving force behind novel forms of mobility and innovative business models. However, not only the mobility world is changing rapidly. Particularly renewable energy sources, like sun and wind are directly connected to planning uncertainty due to their dependence on weather. This leads to frequency fluctuations in the power grid. These fluctuations in turn are the reason for dynamic electricity prices to which especially large consumers can adapt in order to save money. This paper investigates to what extent an operating electric mobility on-demand fleet can adjust to changing electricity prices and whether this adaptation affects the service performance of the overall system. For this purpose, a model is built up, which considers traffic influences in the form of dynamic travel times as well as the passenger and battery management of the vehicles. The model suggests that a vehicle fleet with an adapted charging strategy to dynamic electricity prices can save money at all investigated fleet sizes. First results indicate that the service performance of the mobility on-demand fleet is not substantially affected. In addition, considerable cost savings can be realized by applying the dynamic charging strategy. The analysis of idle times of the vehicle fleet revealed further potential for optimization, which could potentially be used for the provision of ancillary services.**

Keywords — electric mobility, vehicle-to-grid, dynamic vehicle fleet simulation, dynamic electricity pricing, charging optimization

I. INTRODUCTION

The mobility sector is currently in a time of change with multiple underlying trends, such as digital transformation, shared mobility, autonomous driving and vehicle electrification. In addition, the pressure on established mobility providers is rising, as more and more new players enter the market with conceivably disruptive potential. Especially, the interconnection of formerly separated fields of industry brings many possibilities for new concepts in the transportation sector. In the course of the electrification of transport systems, the term Vehicle-to-Grid (V2G) is often called.

The share of renewable energies in Germany rose to 33.3% in 2018 [1] and thus represents the largest share of the total energy supply. However, as an increasing amount of renewable energy is fed into the grid, the complexity of grid management also increases. This is due to the fact that the production of renewable energy is hard to predict, as it heavily depends on environmental factors such as weather conditions. This is one of the main reasons why electricity exchange markets are experiencing price fluctuations, which leads to new products that enable customers to adapt their energy consumption to price fluctuations and thus save money [2].

II. VEHICLE-TO-GRID AND MOBILITY ON-DEMAND

A. *Vehicle-to-Grid*

The V2G technology can help to balance frequency fluctuations in the power grid. A thorough overview of V2G research can be found in [3], [4] and [5]. Schill et al. [6] conducted research about the potential of electric vehicles supporting the power grid in Germany. Their calculations show that by 2035 electric vehicles could significantly contribute to the cost-effective provision of power regulation. Apart from that, the simplest form of connecting electric vehicles to the electricity market is to adapt their charging behavior to dynamic electricity pricing. Erol-Kantarci et al. [7] show that a prediction-based charging scheme, which receives dynamic pricing information, leads to lower operating costs. This consideration could become particularly financially attractive if a fleet operator, for example a mobility on-demand provider, aligns the fleets‘ charging behavior with dynamic electricity prices without substantially affecting the service quality of the mobility fleet.

B. *Mobility On-Demand*

Mobility on-demand (MoD) has the potential to revolutionize mobility, as it is known today, by offering door-to-door service anytime. Providers, like Uber, Lyft or the German MOIA are on the rise and bring many simplifications for their customers. Concerning the vehicle, purchase, maintenance, refueling, paperwork become superfluous, and the search for parking space is eliminated. In contrast to the simple use, managing an MoD fleet is a rather complex affair. To deal with on-demand fleet management from a theoretical perspective, the so-called Dial-a-Ride-Problem (DARP) was defined. The core idea of the DARP is designing the optimal route and schedule for multiple user requested trips with predefined origins and destinations on a specific network [8]. Within the DARP, a distinction is made between static and dynamic approaches. The static case is characterized by the prior knowledge of all requests, whereas in the dynamic approach the requests are received in real time. In addition, there are many versions of DARP, with different input variables and objective functions. For a detailed examination of the various forms of the DARP, the interested reader is referred to the works of Cordeau and Laporte [8] and Molenbruch et al. [9]. Bongiovanni et al. [10] introduce the so called electric autonomous dial-a-ride problem (eADARP). In their

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research they include a battery management approach in addition to classic constraints of the DARP. However, to the best knowledge of the authors there has not yet been any research on the impacts of the operability of an on-demand transportation service fleet receiving dynamic electricity pricing information.

III. Network and Simulation Setup

In the following we introduce the dynamic electricity pricing-based dial-a-ride problem (DEPDARP). This offshoot of the DARP includes dynamic electricity pricing in the optimization of the vehicles‘ associated charging processes, therefore the trip planning is supplemented by a charging adaptation problem. In this paper the charging strategy of the vehicles is adapted considering dynamic electricity prices and aiming for a reduction of the system‘s overall charging costs. The model described in the following is intended to estimate the potentials of an operating MoD provider which arise from the adaptation to variable electricity prices. For this purpose, a node-edge network was set up.

A. Network

The network is based on an area in the city of Munich of approximately 10 km^2. Figure 1 shows the overall network consisting of 22 nodes, 12 double-lane and 22 single-lane links. The bold lines indicate two lanes for a link, the thin lines correspond to one-lane links.

The lengths of the individual edges and the associated free flow travel times were determined with Open Street Map. Furthermore, the daily traffic flows for the individual edges were extracted from the average daily traffic flow data for a usual working day of the local district administration department. The daily traffic flows were then distributed over 24 hours using a typical time series of traffic flows including the characteristic peaks (Figure 2).

We assume an average headway of 2 seconds per vehicle which corresponds to a capacity of 1800 vehicles per lane and hour. For links that are influenced by traffic lights, a cycle time of 90 seconds and an inter-green-time of 6 seconds is assumed. Based on these assumptions a share of about 40% green time in both directions results. This reduces

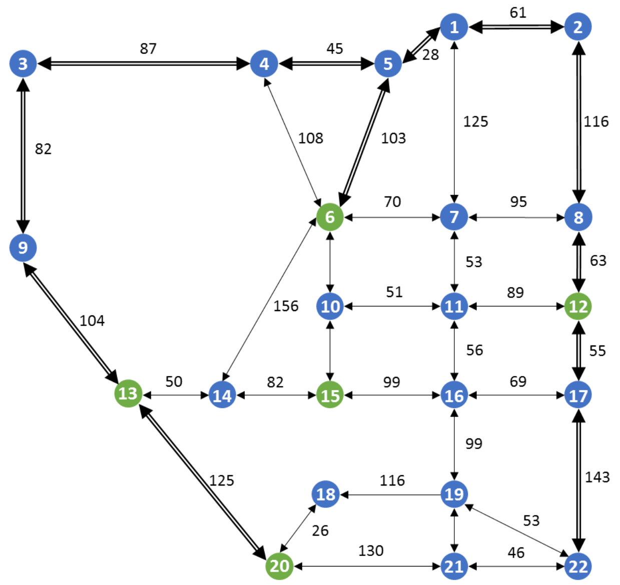

Fig. 1 Node-edge network with respective travel times in seconds

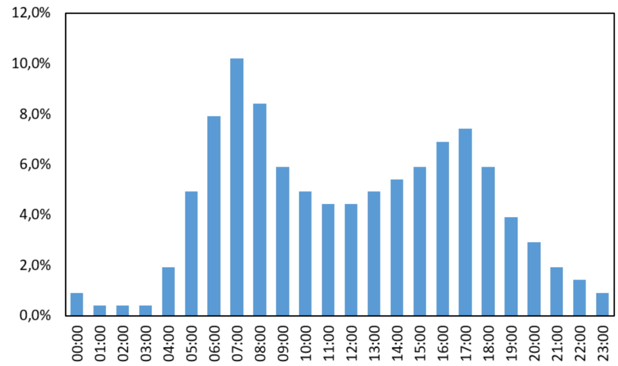

Fig. 2 Hourly traffic flow in percentage of the total daily traffic flow

the capacity of the links controlled by traffic lights by 60%. Based on empirical observations, free flow speeds of approximately 35 km/h on the links with a speed limit of 50 km/h including traffic lights, and around 55 km/h on the links with a speed limit of 60 km/h without traffic lights are assumed [11], [12] and [13]. The well-established US Bureau of Public Roads (BPR) function [14] was then used to determine the increase in travel times due to increased traffic flow. Input parameters are the hourly lane capacities and the respective traffic flows. In a further step, the charging stations for electric vehicles of the local energy provider that are located near nodes in the model were integrated into the network. As a result, nodes 6, 12 13, 15 and 20 are equipped with charging facilities.

B. Simulation

The simulation setup to test the model consists of 10 runs each with an on-demand fleet size of 5, 10, 15, 20, 25 and 30 vehicles. There are two scenarios for each run:

a) Static electricity prices are applied

b) Dynamic electricity prices are applied

The transport demand of the mobility on-demand service

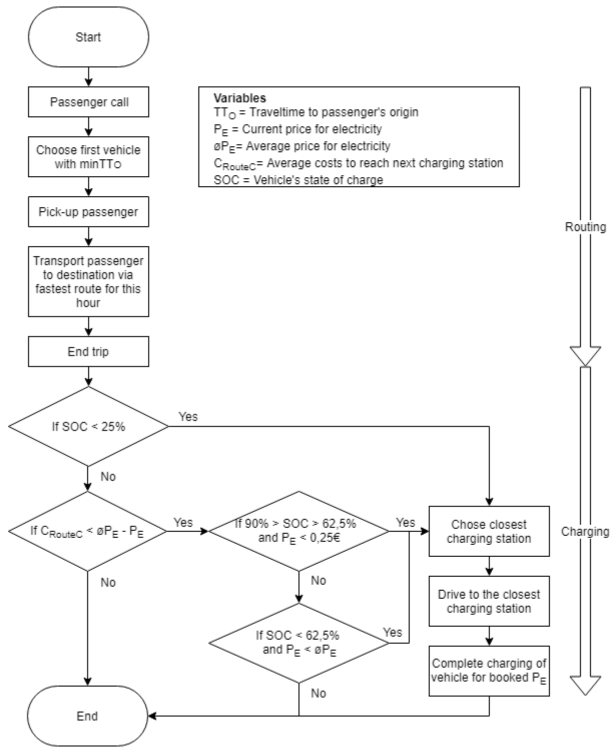

Fig. 3 Flowchart for the fleet decision algorithm and charging optimization on dynamic electricity prices

is set to 0.1 percent of the total network flows for each hour and is generated randomly within the respective hour. In addition, the trips' origins and destinations are also determined randomly, following the condition that the minimum travel time at free flow speed is set to five minutes. Additionally, a trip is only operated under the condition that a vehicle can reach the passenger within a maximum of 15 minutes. Otherwise the trip will not be operated and marked as unfulfilled. The shortest paths are determined for each hour of the day with the corresponding travel times using the Dijkstra [15] algorithm and are later used in the dynamic route assignment of the simulation. In the simulation, we assume that the traffic share of the on-demand fleet is small enough to not influence the route choice of other road users and thus the network equilibrium is maintained. The simulation of electricity prices is carried out in quarter-hour intervals and is based on a typical daily chart of the intraday trade of the European Power Exchange (EPEX) spot market [2]. In order to guarantee dynamics in the assumed electricity prices, each 15-minute interval the electricity price is varied with a range of ± 0.05 Euros per kilowatt-hour for each of the ten simulation runs compared to the typical daily chart (Figure 4).

In this paper we set up a dynamic DARP, in which the vehicles additionally adapt their charging strategy to dynamic electricity prices with the side-constraint that every customer is served by a separate vehicle. At the beginning, each vehicle is assigned to one node of the network. The fleet is distributed from node 1 to node 22. If the number of vehicles is greater than the number of nodes the assignment is continued on node 1. The state-of-charge (SOC) of the vehicles' batteries is assumed to be 100% before the simulation starts. The vehicle specifications can be found in Table I and are given in real-world and simulation units, which can be converted by using an average vehicle speed of 40 km/h. The framework conditions of the simulation are pictured as a flowchart in Figure 3.

The fleet reacts on incoming passenger calls. The vehicle that is able to arrive fastest at the passenger is called to the origin node of the trip. If two vehicles are equidistant from the passenger, the vehicle with the lower ID-number is preferred.

The passenger is then transported to the trip destination. The respective travel times are derived from the BPR-function, taking into account the average hourly traffic flows and the roads' capacities. After the passenger has been dropped off at the destination, the vehicle checks whether it should drive to the closest charging facility in order to recharge the battery. Both the current SOC of the vehicle and the current electricity price play a role in the decision. In addition, a vehicle will never drive to the charging station if the costs of getting to the charging station are higher than the price savings. The detailed decision making process can be

TABLE I. RELEVANT VEHICLE SPECIFICATIONS FOR SIMULATION

Variable	Unit 1	Unit 2
Vehicle Energy Consumption	12 kWh/100 km	0,08 kW/min
Battery Energy	20 kWh	20 kWh
Battery Range	167 km	250 min

a. Unit 1 used for real world and Unit 2 for simulation application.

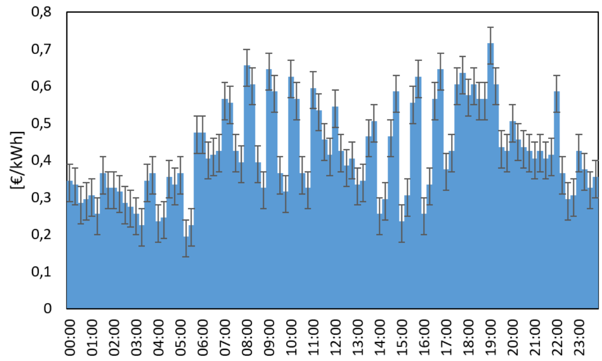

Fig. 4 Typical price trend at the EPEX intrady market

found in Figure 3. For each passenger call, the vehicle is selected that can reach the origin fastest. Vehicles that are still on a trip or charging at the moment of the call will also be included into the selection. In order to ensure comparability after each simulation run, the batteries of the vehicles are fully recharged. In the static scenario at the average price and in the dynamic scenario at the currently valid dynamic price is applied. To calculate the total charging cost of each scenario, the complete recharge of all batteries after the simulation and the charging costs during the simulation are summed up.

IV. RESULTS

To test the overall setup, 120 simulation runs are carried out, each covering a period of 24 hours. As mentioned earlier, a static and a dynamic charging scenario is investigated. Every scenario consists of 10 runs, each with a fleet size of 5, 10, 15, 20, 25 and 30 vehicles. According to the authors, the number of simulation runs seems to be reasonable to show a first tendency of the model.

The results of the test simulation will be structured into three main parts each taking into account a static and a dynamic electricity price scenario: the service quality of the MoD fleet, the total electricity costs of the MoD fleet and the MoD fleet employment over 24 hours.

A. Service Quality

Figure 5 shows the results of the service quality in terms of cancelled trips and passenger waiting times for the static and dynamic price scenarios. On the abscissa the fleet size and on the ordinate the waiting time (left) and the number of cancelled trips (right) are displayed. It can be seen that the number of cancelled trips drops with the increase in fleet size. However, the static and dynamic scenario do not

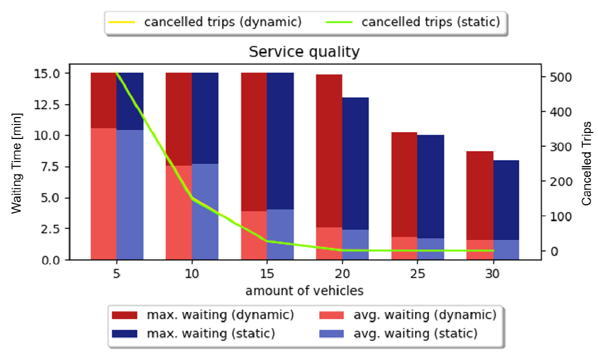

Fig. 5 Service quality in terms of cancelled trips and waiting times

substantially differ in terms of cancelled trips. The maximum waiting times similarly decrease with the rising fleet size. For the first three steps (5 and 10 vehicles), the maximum waiting times are close to the maximum of 15 minutes. For the following steps they start to decline with the grow in fleet size. The difference between the static and dynamic scenarios does not show a large difference in the individual simulation steps for the maximum waiting times. The average waiting times are fairly equal for the static and dynamic scenario and fall with an increasing fleet size.

The results indicate that the dynamic charging strategy does not cause any substantial deterioration of the service quality compared to the static charging scenario.

B. *Electricity Costs*

The total electricity costs for the simulated period of 24 hours are determined by summing up the charging costs for the static and the dynamic scenario respectively. Note that all vehicles must fully charge their batteries after the end of their last trip. In the static scenario this is done at the average price, in the dynamic scenario the dynamic price valid in the current time interval is used. Figure 6 shows the cost ratio between the static and dynamic charging strategy. The abscissa indicates the fleet size and the ordinate the charging costs. For the first three fleet sizes, the total costs for both the static and the dynamic scenario increase. That is due to the increasing amount of served trips with a higher amount of vehicles. From a fleet size of 15 vehicles upwards, the costs for the entire fleet remain fairly constant. This phenomenon can be explained by the fact that from this fleet size on, all trips are served and the costs only vary due to the detours induced by charging the batteries. The number of detours again falls slightly with the increase in fleet size, which is accompanied by a slight reduction in overall costs, both in the static and the dynamic scenarios.

For all the fleet sizes examined, the results indicate that the dynamic charging strategy can substantially reduce the overall costs of the MoD service.

C. *Fleet Employment*

The employment of the vehicle fleet consists of the times at which the fleet transports passengers drives to the charging stations (driving times), the times at which the fleet is at the charging stations (charging times) and the times at which the fleet has no tasks (idle times). Both scenarios run with identical input conditions. In the dynamic scenario, the vehicles merely adapt their charging strategy to the dynamic electricity prices.

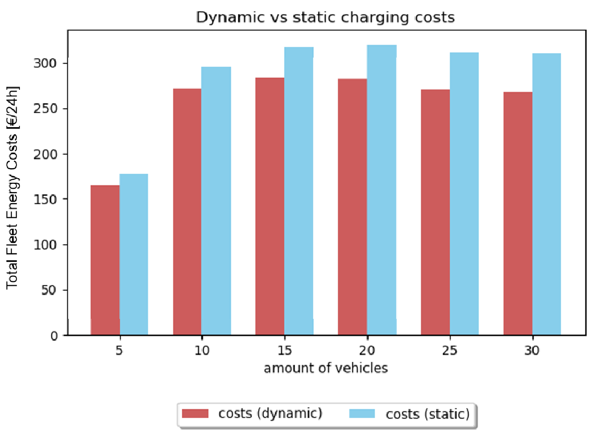

Fig. 6 Electricity costs for static and dynamic scenario

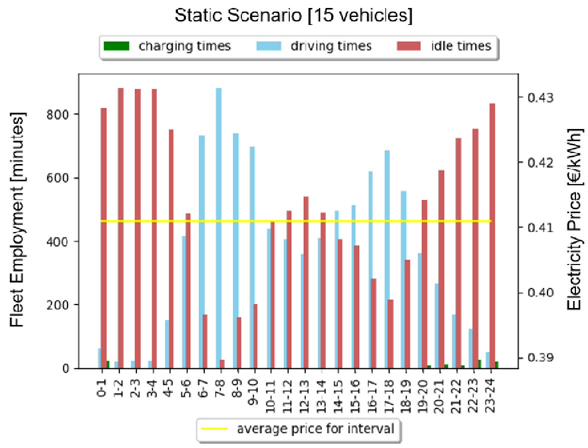

Fig. 7 Fleet employment in the static scenario

Figure 7 shows the fleet employment for the static electricity price scenario. The abscissa shows the hourly intervals of a full day and the ordinate indicates the employment in minutes (left) and the electricity price for charging in Euros per kilowatt-hour (right). The average electricity price in this specific case with a fleet size of 15 vehicles is around 0.41 Euros per kilowatt-hour. It can be seen that the driving times correspond to the assumed transportation demand (Figure 2). The idle times in turn correspond strongly to the low points of the driving times. The charging times are distributed relatively evenly over the entire day, whereby in the early morning hours the criterion of an SOC of less than 25% can only rarely be met. In total, the three types of employment result in 900 minutes for each hourly period considered. These are made up of the number of the considered vehicles and the minutes per hour.

For the dynamic electricity price scenario, the chart changes especially in terms of charging times (Figure 8). Compared to the static scenario, the vehicles tend to charge more often, which is because they do not only charge if their battery's SOC is below 25%, but also adapt their charging strategy to the price signal (Figure 3). It is striking that the vehicles do not charge directly in the favorable morning hours, as their SOCs tend to be too high at these times. However, charging times increase in the course of the day. In the dynamic price scenario, the average charged price is

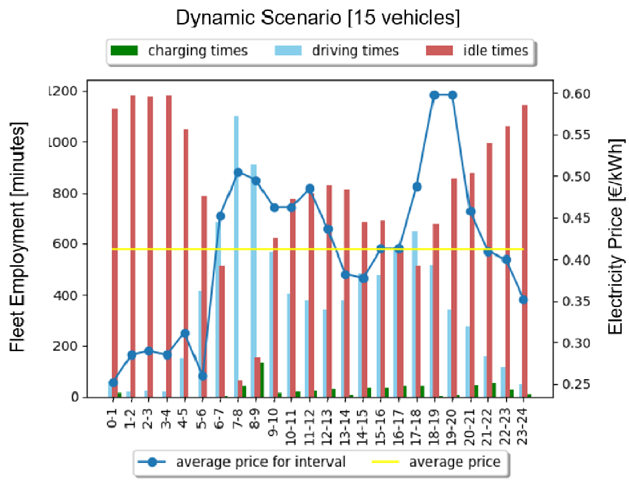

Fig. 8 Fleet employment in the dynamic scenario

around 0.37 Euros per kilowatt-hour. As far as drive and idle times are concerned, the employment of the vehicle fleet hardly differs in the two different price scenarios.

The results for all examined fleet sizes show that the employment of the vehicle fleet hardly differs in the two scenarios. However, the vehicles charge their batteries in the dynamic scenario at a substantially lower average price than in the static scenario.

V. Discussion

In this section the derivable potentials of the test results are presented, but also the limitations of the chosen approach are shown and impulses for further investigations are given. This section is structured as follows: the potentials to be derived from the results and the possible future extensions of the investigations.

A. Potentials

This paper shows that only a negligible reduction of the service quality of the MoD fleet can be observed by the adapted charging strategy in the dynamic scenario. However, the charging costs are considerably reduced for all the investigated fleet sizes. Switching to an electricity contract with dynamic price adjustment would therefore be very attractive for many MoD providers. But not only MoD providers could profit from the findings of this paper. The charging strategy of private electric vehicles could also be adapted to electricity price fluctuations. Though, it might still take some time until dynamic electricity pricing will be available to every electric vehicle driver.

Concerning the employment of the vehicle fleet, it is shown that although the vehicle fleet is heavily inquired at peak times, the exact opposite can be observed during off-peak times. The idle times of the vehicles are in the early morning and late evening hours (Figures 7 and 8). Due to the low electricity prices, these times could ideally be used for battery charging or providing other ancillary services. Assuming that the vehicles remain operational at all times (e.g. through full automation), the early evening hours could be used to deliver food, groceries or parcels for instance, as potential customers are usually at home during these hours of the day. The idle times in the late evening and early morning hours could potentially be used for warehouse logistics. However, it must be ensured that the vehicles' batteries are ideally fully charged before the morning peak of passenger transport in order to not sacrifice potential profit. From an economic point of view, the use of the vehicles for ancillary services is only rewarding if the transport and maintenance costs as well as the loss in value of the vehicles and its batteries are lower than the expected revenues.

B. Limitations and Future Research

Even though, the derived results are already quite promising there still is still is some room for further improvement and future extensions of the introduced DEPDARP. In order to determine the statistical significance of the results, one of the next steps is to determine the required sample size and to redesign the simulation based on these findings. Currently each passenger is served by a separate vehicle, which could be expanded to a ride-pooling system in the future. On top of that, a reallocation strategy could also be considered. Moreover, the specifications of individual vehicles could be changed and a heterogeneous fleet could be established.

The occupancy of the charging stations is currently neglected. Thus, in the model presented, it is possible for several vehicles to charge simultaneously at one charging station. This shortcoming should be corrected in future work. In addition, a vehicle is currently fully charged at the same price even if the charging time slips into the next price interval. In order to be able to make a well-founded decision, it would be necessary to make a prediction of the price development in the next price intervals. It should also be considered in the future that the charging process of a vehicle is stopped when a passenger call is received and no other vehicle is in the vicinity.

In terms of the services provided by the vehicle fleet, it is planned for the future to design a cost-benefit algorithm which will be compared with the expected yields in order to achieve the most economic behavior of the overall system. Building on this, it would be appropriate to determine the optimum fleet size for the best possible cost-benefit ratio taking into account transport revenues from passenger transport and ancillary services and charging cost. Furthermore, it would also be very interesting to include maintenance costs and, for example, battery degradation costs.

VI. Conclusion

The simulation setup presented in this paper suggests that charging electric MoD vehicle fleets on the basis of dynamic electricity prices reveals high economic potential for the providers without substantially influencing the service quality. In the course of the further expansion of renewable energies and the associated planning uncertainties, the issue of the dynamic pricing of electricity will become even more important in the future. Nowadays, vehicles are not utilized for most of the time of the day. It is time to change that fact and reduce vehicles' idle times by optimizing their usage.

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