Agent-based Modeling and Simulation of Electric Taxi Fleets

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Abstract—**Electrification and on-demand services are one of the main driving forces within the current automotive sector. This paper presents an approach to modeling and simulation of on-demand applications on the example of an electric taxi fleet. With regard to the high daily mileage and just the same idle times, the characteristic mobility behavior of taxis offers ideal conditions for electrification. To support decision-making during strategic and operational planning, this paper suggests a stochastic model based on an agent-based simulation approach. The simulation engine consists of an event-driven architecture. Customer demand requests, a customizable fleet configuration and infrastructure settings form the main input interface. The simulation output describes use of the infrastructure and the spatial and temporal behavior of each agent.**
We verify our basic model design first with a combustion engine powered taxi fleet. An additional scenario with electric vehicles provides insights into feasible electrification strategies for the taxi system in Munich. The strength of the proposed model is its distributed, behavior-driven architecture. This is especially useful for on-demand fleets, as these mobility systems are characterized by a mixture of centralized and decentralized knowledge bases. The whole system behavior results from dynamic decision making. Our approach can be used to evaluate various mobility-as-a-service concepts.

Keywords—*On-demand mobility; mobility-as-a-service; agent-based simulation; fleet simulation; electromobility; electric fleet; taxi, Vehicle Routing Problems with Pickups and Deliveries*

I. INTRODUCTION

Increasing urbanization and stricter environmental regulation require a rethinking of existing transportation systems. Cities are forced to find new sustainable solutions to handle rising mobility demand [1]. Future mobility systems must have a minimal environmental footprint and ensure a high level of service quality for the customer. It is an ongoing challenge to use the existing infrastructure more efficiently, since space in urban areas is limited. Sharing concepts can make a positive contribution here [2].

Progress in technology will also change the way we organize our mobility [3]. The expansion of the internet of things helps optimize transportation tasks on an operational level. One of the ongoing challenges is realization of a seamless integration of different modes of transport [4].
Introduction of stricter environmental regulations will promote electric vehicles, as an electrified powertrain by definition has zero local emissions [5].

In this paper we take a closer look at an electrified taxi operation. A traditional taxi service is integrated into the public transportation network. It is a well-established example of a shared mobility system. Due to high daily and annual mileage, especially taxis offer a great opportunity for electrification. However, introduction of electric taxis is challenging. One reason is the well-known "chicken and egg problem" between vehicle propagation and growth of the infrastructure. There is a high dependency between the provided infrastructure and the chosen vehicle concept.

To evaluate different scenarios in a prompt, economical manner, simulation models are used. In doing so, technical, ecological and commercial issues can be addressed. Depending on the planning issue, it is of special importance to represent system dynamics at an appropriate level of detail. Creation of various model variations in a short time requires a modular architecture. Furthermore, it is important to reflect key cause-effect relationships on a suitable level of precision and to manage the computational effort at the same time.

Typical planning questions in an electric taxi system are related to infrastructure, vehicle concept and service design. Seen from an infrastructural point of view, it has to be sorted out, how many charging points are needed for a given fleet configuration and where these charging stations should be located. Seen from the vehicle concept point of view, it has to be evaluated which powertrain configuration fits best for a given usage pattern. In addition to these technical design issues, it is also important to investigate how the behavior of taxis and the quality of the mobility service changes. One obvious behavioral adaption is the introduction of charging activities. We assume that taxi drivers, the taxi company owners and the customers accept only minor changes to their daily workflow or the service quality provided.

II. RELATED WORK

Because the mobility demand of fleets is stochastic in nature [6], fleet simulation models typically use Monte-Carlo methods. Service orientated on-demand planning issues are often related to a dial-a-ride problem [7].
Kümmel [8] classifies taxi dispatching as a multi depot multiple vehicle capacitated dynamic vehicle routing problem with pickup and delivery time windows and deniable customer requests.

A. Strategic Planning

Bischoff [9] presents an approach simulating electric taxis with help of the agent-based, mesoscopic traffic simulation MATSim [10]. The simulation model includes an average speed-based energy consumption model and a dynamic vehicle dispatching unit. In MATSim, each transport entity is seen as an individual agent that is capable of interacting with surrounding agents and its environment. To describe the spatial-temporal mobility behavior, each taxi agent dynamically creates his own activity plan using a vehicle routing engine. The primary goal is to investigate implications for various demand scenarios and dispatch strategies.

Sellmair [11] looks closer into the optimization of the charging infrastructure design for electric taxi fleets. The basic idea is to maximize the economic benefit by minimizing the number of charging stations. His approach consists of an event-based simulation to represent the mobility behavior of a taxi fleet in Munich and an economic analysis.

Gawlik et al. [12] investigate grid-related consequences of broad electrification in an urban area. To answer this question, it is assumed that the whole taxi system in Vienna is operated with electric vehicles. A fleet simulation with electric vehicles allows calculation of load profiles.

Garcias [13] uses mixed integer programming for designing an electric taxi fleet. He focuses on the charging infrastructure and vehicle dispatch optimization.

Chen [14] presents a multi agent-based approach for managing an electric taxi fleet. His model provides a solution to solve the dial-a-ride problem with the help of the simulation framework Anylogic [15]. Several simulation runs evaluate the relationship between passenger waiting time and design of a shared electric taxi fleet including its charging infrastructure.

Čertický [16] proposes an open-source, agent-based simulation testbed for demand-responsive transportation applications. The testbed is built on top of the AgentPolis Simulator [17]. A modular system architecture enables evaluation of centralized and decentralized, static and dynamic algorithm for passenger allocation and vehicle routing problems. Scenarios with a single ride and ride shared taxi operation confirm the basic functionality of the system.

Van Lon [18] introduces a generalized, agent-based simulator for a wide range of transportation and logistics problems such as the pickup delivery problem. Special focus is put on a modular, encapsulated and test-driven architecture.

B. Operational Planning

Operation of fleets is typically controlled by a fleet management system. The main tasks are order management and vehicle dispatching. The dispatch problem falls into the class of scheduling problems that is typically addressed within operational research domain [19].

Lee [20] proposes a discrete, event-based simulation to evaluate dispatch algorithms and relocation efforts of electric vehicles.

Lu [21] introduces an algorithm for dispatching battery electric vehicles. The proposed strategy considers the taxi demand, the remaining range of electric vehicles and the occupancy rate of the charging infrastructure.

Mirchandani [22] gives an overview of the logistical issues related to deploying electric vehicles with battery swapping.

Qu [23] proposes a discrete event-based Monte Carlo simulation to represent the operational behavior of electric taxis. His work investigates the charging influence on the electric grid.

Dutta [24] investigates the possibility of exchanging energy between electric taxis via inductive charging.

Tian [25] analyzes the usage pattern of 600 electric taxis in Shenzhen. Special focus is put on operational and charging behaviors. Tian [26] further introduces a real-time charging station recommendation system for electric taxis using data mining. Its prediction is based on historical recharging events and real-time trajectories.

Hou [27] suggests a shared electric taxi system that allows passenger transfer at specific hubs. Mixed-integer programming is applied to maximize the number of transported passengers per time period.

III. APPROACH

This paper addresses long-term and short-term planning questions for electric vehicle fleets. The approach presented can be used for decision making processes in order to electrify taxi fleets for a selected region.

Unlike existing approaches, we suggest an agent-based, demand-driven, decentralized fleet simulation model that is capable of representing dynamic, complex interactions between different participants on a mesoscopic level. Depending on the knowledge and skill level, each agent has its own behavior. All agents are acting independently of each other. Taxi agents, for example, get to accept or deny order requests. This way, the simulation becomes especially adaptable and flexible.

A. Role definition

The following paragraph addresses the basic concept. The chosen methodology is oriented toward the Multiagent Systems Engineering (MaSE) technique [28]. First we define actors and related tasks within the system. Fig. 1 shows a common scenario for the proposed electric taxi fleet simulation system.
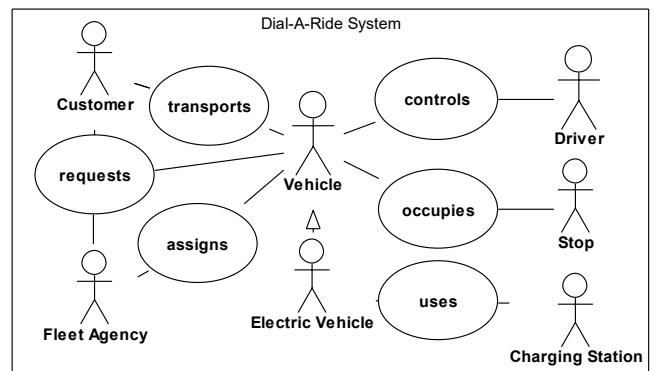
Fig. 1. UML use case diagram for the proposed electric taxi system

Main roles are given by customer, driver, vehicle, fleet management agency and further infrastructure facilities, such as stops or charging stations. In a typical pickup and delivery system, a customer requests a mobility service by contacting a fleet agency or by hiring a vehicle directly from the roadside. The order communication procedure includes information on the desired pickup time, the location and the number of

passengers. The fleet agencies' management system permanently collects and schedules all customer requests. Close to the scheduled service time, the fleet management system offers the pending order to a selected number of drivers and waits for a proposal. After a defined period of time, the agency evaluates received proposals and finally chooses the best matching offer. The winning vehicle is informed, picks up the customer and brings him to his desired destination. At that time the mobility service is terminated and the driver chooses his following activities. In the idle state the vehicle typically waits at stops (e.g. taxi stand or point of interest). Electric vehicles also may spend the waiting time at a charging station. Table I summarizes responsibilities for each role.

TABLE I RESPONSIBILITES IDENTIFICATION

Actor	Responsibility
Agency	Receives order requests
Agency	Schedules order requests
Agency	Dispatches order requests
Agency	Controls fleet status
Vehicle	Sends updated status information to agency
Vehicle	Provides physical passenger transport
Driver	Responds to mobility service requests
Driver	Performs driving task
Driver	Ensures legal compliance with working hours
Customer	Places mobility service order
Charging Station	Provides a charging opportunity
Stop	Provides parking space

B. Agent and Ressource Definition

In the next step, we separate the system into active and passive components. An active component is described by a complex behavior, while passive elements show only primitive features. We model active elements as agents and passive elements as objects placed in a given environment. Each agent has its own life cycle and its own decision-making module. Interfaces provide interaction with other entities.
In our electric taxi model we define two types of agents. We aggregate the vehicle and driver role and refer to this combination as taxi agent. This choice is made since a taxi shows complex behavior by providing the practical mobility service to its customer.
The second agent type is the fleet agency. The reason for this choice is its large number of communication interfaces as well as complex scheduling and dispatch algorithms.

All infrastructural roles are modelled as passive elements. A stop is part of the environment and provides a limited capacity of parking spaces. Charging stations are treated equally. The only difference is the additional interface to take energy from the grid. Since we assume a passive customer in our model, we abstract the latter role as a passive mobility service request.

C. Agent – Environment Interaction

In our model, each agent lives in a given environment with its own state, knowledge and behavior. We assume that every taxi agent has a memory to store basic location information about existing facilities such as taxi stands. With this knowledge, a taxi is able to select an appropriate location after completing an order event. The concrete implementation of the chosen filter algorithm is encapsulated to the outside world.

The second example for an agent-to-infrastructure interaction is a charging request. We assume that every taxi driver has knowledge about the charging station positioning only, and not about its current occupancy state. After deciding to charge, the electric taxi autonomously selects all supported charging points inside a self-defined radius relative to its current location. If the search is successful, the taxi heads for the actual charging point and checks the actual availability of the spot at its arrival. If the chosen charging location is still free, the charging process can be initiated.

Otherwise, the taxi needs to look for another free charging station or has to wait, if all other charging stations are out of the remaining range. As we assume a charging point to be a passive element, we neglect reservation possibilities.

D. Agent – Agent Interaction

The communication between agents is solved by a messaging service. This feature is especially of interest for executing an order request. The sequence diagram in Fig. 2 illustrates an order request consisting of a communication act between a customer, a fleet agency and a taxi.
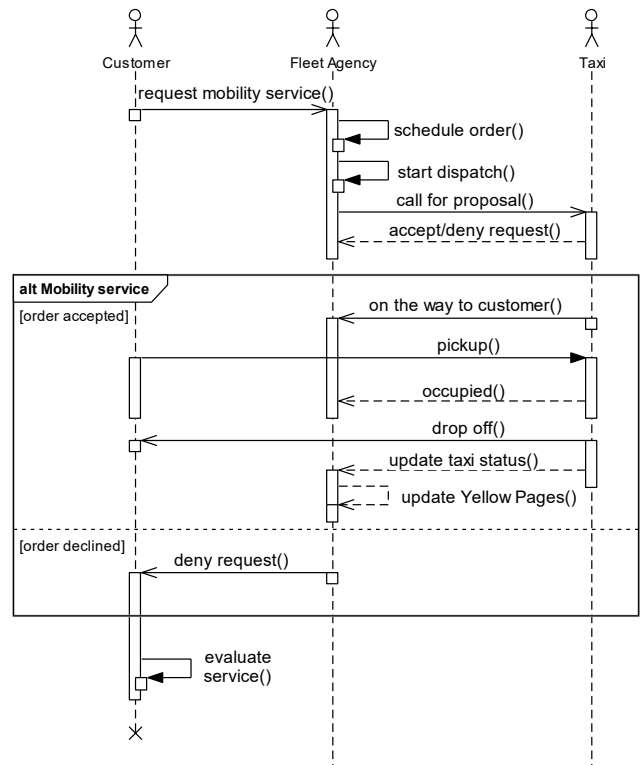

Fig. 2. Order interaction protocol

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First, a customer requests a taxi. The fleet agency receives the order and schedules its execution. Just before reaching the scheduled time, the fleet agency starts a dispatch behavior. This step is for finding a suitable taxi for the transportation task. The search continues until a taxi accepts the offered job request. In certain situations, several taxis have to be asked, since a driver may refuse the proposal. If no active taxi is able to fulfill the order, this customer request is finally denied. In all other cases the first accepting taxi creates a pickup event and drives toward the pickup location. The customer is then picked up and will be driven to his desired destination, where he is finally dropped off.

For dispatching purposes, the fleet agency requires the latest taxi status. This is why each taxi sends status updates asynchronously to its connected taxi agency.
Reasons for rejection of an order request are related to the taxi state. For example, if an electric car's battery soon runs down, the driver will head for a suitable charging location. In cases where a driver wants to take a break or finish his working day, orders may also be refused.

The whole system dynamically balances the order demand and service supply. Its performance results as the aggregation of single agent behaviors. With this demand-driven, auction-based approach, it is possible to evaluate a wide range of on-demand and shared mobility concepts.

E. Agent Internal Design

The next step is to specify the behavior of taxi agent and the fleet agency agent in detail.

Taxi Agent

The taxi agent's behavior is realized by a finite state machine (Fig. 3).

Fig. 3. Finite state machine for the taxi agent

Basically, the taxi can be logged out or logged into the fleet management system. After performing the login action, the driver first heads for the most suitable stop nearby. As soon as the vehicle reaches the stop, the driver waits for a customer request or, if necessary, drives to a charging station. If a new order request is received and accepted, the taxi drives off to the pickup location. After bringing the customer to the desired

destination (status occupied), the taxi has to decide how to proceed. Available destinations are a charging station, a stop or home. If the taxi needs to recharge, it has to drive to a charging point. It may happen, that another vehicle is already occupying the selected charging point. In this case, the taxi moves to another charging point or waits at the first selected station. The latter choice depends on the vehicle's actual state of charge. This is necessary to prevent vehicles' batteries from completely running down. After charging, the taxi can proceed to another facility or head directly to a customer. If the taxi driver has to stop working because he has exceeded the maximum permissible working hours, he can drive home.

Fleet Agency Agent

The fleet agency is mainly responsible for order management. To realize this function, different dispatch algorithms can be implemented. We assume in our model that all customer requests are spontaneous without a prebooking option. For this reason, scheduling and dispatching is a single step.

The dispatch operation itself is a classical optimization problem. To reduce complexity, we apply a simple heuristic approach. The selection of suitable vehicles is done with help of a distance criteria such as "Nearest Idle Taxi" or "Next Idle Taxi at Nearest Taxi Stand". We further reduce the solution space by preselecting vehicles close to the pickup location. Since the decision to accept or deny a job request lies completely in the hands of a taxi, we only send the call for proposal message to these taxis. Each taxi concurrently evaluates the given service order and proposes its costs. In the last step, the taxi agency ranks all proposals, selects the best matching taxi and sends acceptance and decline messages.

F. Supply Control

Since the supply of taxis varies over time, we introduce a closed control loop to adjust the number of active vehicles according to the fleet size. A bang-bang controller fits well for this purpose. It manages both login and logoff actions according to its control deviation. Since each taxi agent owns an independent decision-making module, the final choice to perform a login and logout action remains with the taxi. Login requests are evaluated on the basis of a minimal inactive time. Logoff actions show an intrinsic or extrinsic nature. Each time a new shift begins, the taxi samples a desired active time. As soon as this time is exceeded, it starts a ride home. An external logoff request from the vehicle controller is rated by the taxi on behalf of its minimal active time.

G. Vehicle Routing

The taxi agency agent and the taxi agent adopt its behavior elastically on a changing environment. This flexibility requires a dynamic route choice capability. The shortest path planning problem is a combinatorial optimization issue. Common solvers are based on Dijkstra [29], A* [30] or contraction hierarchy algorithm [31].

To lower the computational effort for navigation, we reduce the number of routing operations. This is possible for customer trips since we assume that those origin-destination relationships form a fixed, unchangeable simulation input. For this reason, time and energy related trip characteristics can be

calculated in a preprocessing step. All other routes (to customers, to stops, to charging points) need to be calculated during runtime since those rely on the latest system state. The routing engine requires a road network, optimization criterion and an origin-destination combination as input.

IV. MODEL INTERFACES & SIMULATION CORE

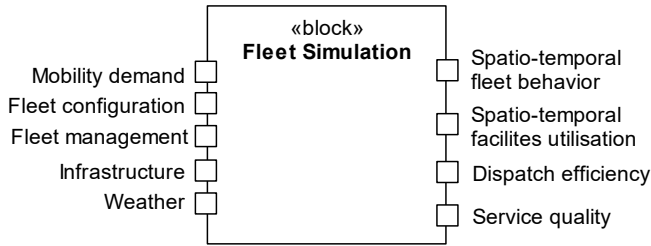In this chapter, we characterize the input and output interfaces (Fig. 4) and describe the simulation core.

Fig. 4. Input and output interface definition

A. Simulation Input

Our simulation input interface handles time series and static data. It is designed to set up different scenarios in a short time. The following section describes each data stream in detail.

Mobility Demand

Our behavioral model is demand-driven. In this context, it has to be taken into account that demand data in a pickup and delivery system is statistically distributed and varies over the time of the day, the day of the week and the location. Origin-destination relationships for taxis meet a Poisson distribution [32]. In [33], we have designed a nonhomogeneous Poisson regression model for Munich. This enables us to scale the demand according to the fleet size.

Fleet Configuration

The fleet configuration defines the number of simulated taxi agents. A taxi itself consists of a vehicle concept and its own behavior. A vehicle concept again comprises a powertrain concept and thermal management unit. The behavior class is subdivided into auxiliary, charging, operation, order and routing strategies.

Fleet Management

The fleet management input sets the operation mode of the fleet agency. Since the performance of a taxi system depends on the balance between supply and demand, one has to choose both time series streams carefully. Taxi drivers anticipate the demand and adapt their behaviors to the situational needs. A performance indicator to describe these circumstances is the course of active taxis over time. It aggregates information about the shift deployment and its adaption to the changing demand.

Infrastructure

Since agents live in a common environment with shared infrastructure elements, locations and features of each facility are fixed input parameters. We classify facilities into charging

point (CP) and stop, e.g. taxi stand (TS) or point of interest (POI). Stops are placed independently from charging station locations, so that each one has its own parking queue. Charging stations are separated in several charging points with inherent plug-ins. To represent the physical road network, we use map data from OpenStreetMap [34].

Weather

The weather input stream includes a time series of temperature values with a 1 h resolution. This data enables us to calculate the auxiliary energy demand of electric vehicles.

B. Simulation Core

The simulation core is built on a discrete event approach. A conservative time synchronization algorithm [35] ensures causality between different event executions. Each agent has its own event list that is synchronized with a central simulator event list. A multi-threaded architecture improves the simulation performance.

We use the multi-agent middleware JADE [36]. The platform is written in Java and provides features such as agent life-cycle management and a message service. Its implementation is compliant with FIPA (Foundation for Intelligent, Physical Agents) specifications [37]. In JADE, each agent has its own thread of execution. This design ensures proper encapsulation, since an agent cannot provide call-back functions or its own object reference to other agents. Agents use their communication interfaces to exchange data.

C. Simulation Output

Each simulation run creates an output database that logs time series data. This includes information on the temporal-spatial behavior of a single taxi agent. It is the event handling that limits the maximum temporal resolution. The same applies for the fleet agency agent. In this context, it is of particular interest to calculate key performance indicators like the dispatch efficiency. Since the complete environment is observable, it is also possible to track the infrastructure utilization. To evaluate the service quality, the waiting time and further order related data can be logged.

V. RESULTS

We take the taxi system of Munich as an example to evaluate two different scenarios.

First, we analyze a scenario with an internal combustion engine (ICE) powered taxi fleet. The second scenario is a taxi operation with battery electric vehicles (BEV).

The demand data [33] reflects the taxi order events for one week within the entire metropolitan area of Munich and was provided by a local taxi agency, which manages around 400 vehicles. To avoid scaling error, we choose the same fleet size for our simulation. This represents 11 % of all taxis in Munich. We sample the desired active time of the taxi between 8 hours and 10 hours per shift and choose the minimum inactive time as 0 hours. The latter choice represents an ideal two-shift operation. The minimum active time is 6 hours. We place all taxi stand facilities according to the current situation in Munich. To set up the initial positions of all taxis, we assume that one half of them are equally distributed to the home

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locations of four major taxi companies in Munich. The other half is assigned to private taxi operators. We distribute their homes to addresses in the 18 major city districts of Munich, weighted by the number of inhabitants.

The fleet agency uses a dispatch heuristic that selects the taxi waiting at the nearest taxi stand.

A. Combustion Engine Scenario

Since balance of supply and demand is essential for the system performance, the first analysis considers the fleet size control. Fig. 5 compares the temporal course of active taxis over a week. With an average deviation of 0.12 %, the basic controller functionality is proven. The same applies to the shift distribution in Fig. 6. The average shift duration is 9.11 hours with a standard deviation of 0.72 hour.
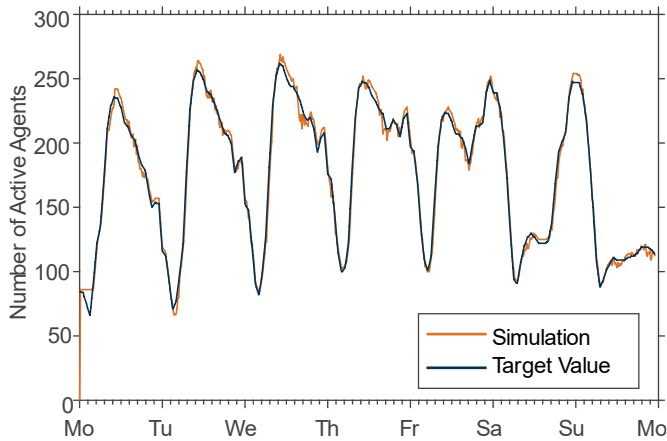
Fig. 5. Course of active taxi agents over a week
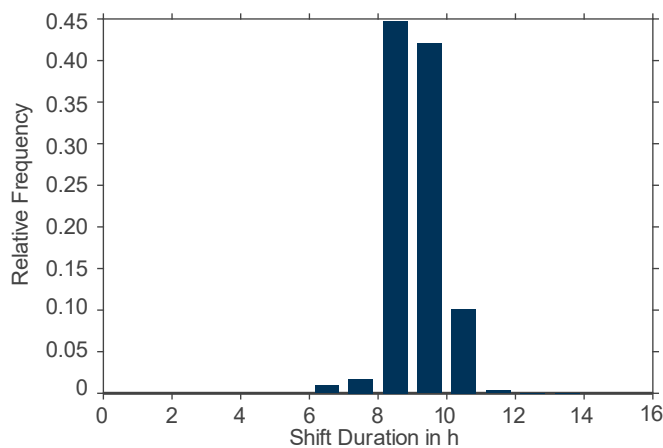
Fig. 6. Distribution of the shift duration over a week

A second analysis describes the distribution of track distances with regard to the taxi status "On the Way to Customer" (Fig. 7), "Occupied" (Fig. 8) and "On the Way to Stop" (Fig. 9). Track distances travelled to customer show a mean value of 2.7 km (σ = 3.6 km) in the simulation compared to a mean value of 1.5 km (σ = 1.7 km) of the original dataset. Distances with customer have both a mean value of 7.2 km (σ = 9.4 km), since this is fixed input. The simulated mean value of distance without customer is 5.2 km (σ = 6.7 km) compared to the reference with 3.6 km (6.8 km). These results lead to the following conclusion. Our presented model represents the

qualitative mobility characteristics. Primary differences relate to short trip distances. An explanation for this behavior is that all customer orders are handled centrally by a single fleet agency. This way, direct booking requests from the roadside are neglected. Because of the chosen taxi stand based dispatch algorithm, two extra trips to a customer and back to a stop may be introduced. Fig. 10 represents the variation of taxi status shares over one week. The course illustrates the influence of variable customer demand.
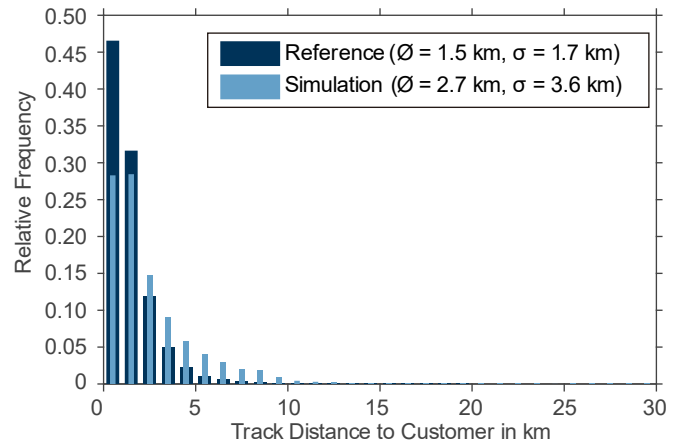
Fig. 7. Distribution of track distances with state "On the Way to Customer"
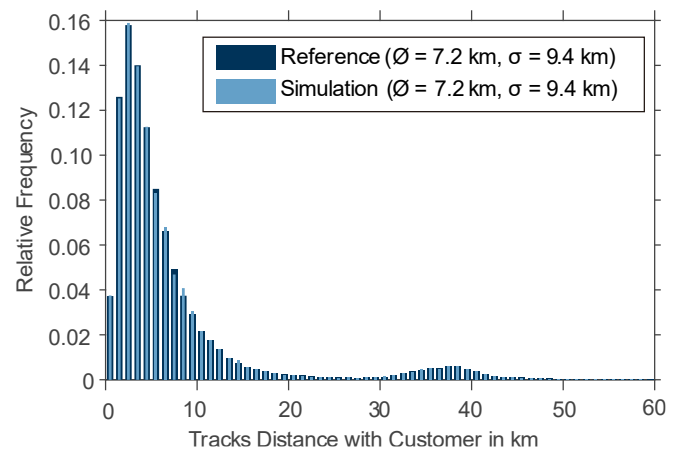
Fig. 8. Distribution of track distances for state "Occupied"
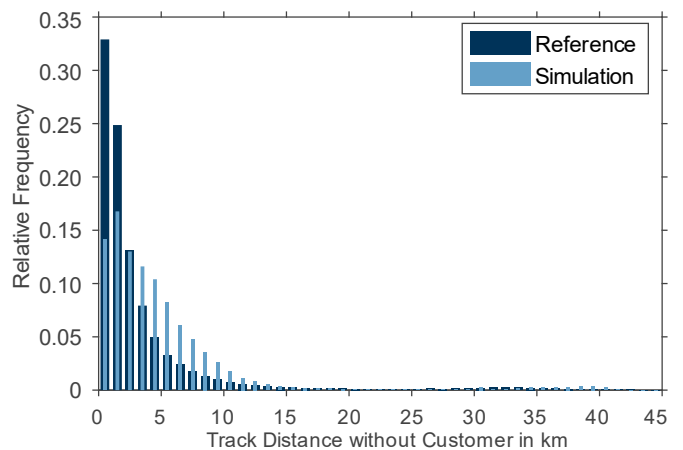
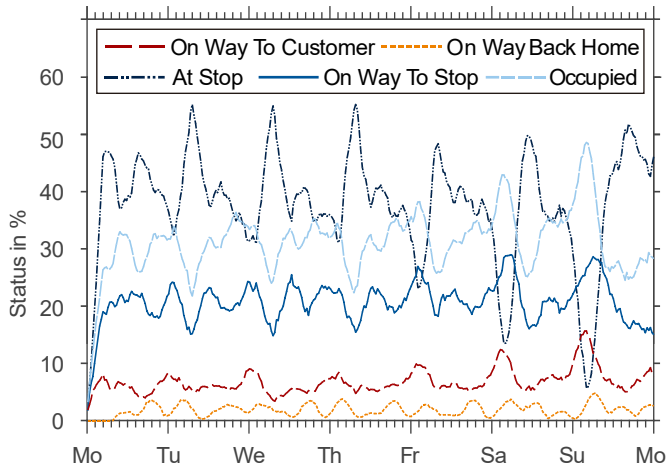Fig. 9. Distribution of track distances with state "On the Way to Stop"

Fig. 10. Course of taxi status shares over a week

B. Electric Vehicle Scenario

A second scenario assesses the possible impact of an electric taxi fleet. Table II gives an overview of the chosen electric vehicle concept and charging station configuration.

TABLE II. ELECTRIC FLEET SCENARIO PARAMETER

Parameter	Value	Unit
Battery Capacity	51.5	kW
Mean Total Energy Consumption	20.6	kWh/100 km
Max. Charging Power – Type 2 Connector	3.7	kW
Max. Charging Power – CCS Connector	40	kW
Min. Range Limit at End of Trip	15	km
Recharge Range Trigger at End of a Trip	30	km
Min. State of Charge at Charge End	70	%
Max. State of Charge at Charge End	85	%
Max. Search Radius for Fastest Connector	4	km
Number of AC Charging Points (Type 2)	452	-
Number of DC Charging Points (CCS)	100	-

The powertrain concept features a range of 250 km, as we assume a battery capacity of 51.5 kWh and a mean total energy consumption of 20.6 kWh/100km for real taxi usage. This includes both powertrain and all auxiliary consumers. Since taxis hardly rely on a public charging infrastructure during its operating mode, each vehicle has a fast charging capability (CCS interface). All remaining parameters are the same as in the first scenario.

Based on these parameter settings, a customer has to wait for a taxi service 4.1 min. compared to 3.6 min. with an ICE fleet. This increase is a consequence of a more complex dispatch effort. An electric taxi may deny customer requests due to an insufficient remaining range. The number of served customers is at the same level in both scenarios. An electric taxi serves 11.8 (σ = 4.9) orders and an ICE taxi 11.7 (σ = 3.8 km). As a result, orders are dispatched less equally. In total, 311 of 40,995 service requests cannot be fulfilled by the chosen

electric fleet. The distance driven per shift drops about 6.3 %. Fig. 11 compares the distance per shift for both scenarios. Table III summarizes main results.

TABLE III. RESULTS OF THE BASIC ELECTRIFED SCENARIO

Parameter	ICE	BEV	Unit
Mean Time to Customer	3.6	4.1	min
Mean Number of Passengers	11.8	11.7	-
Denied Rides	3	311	-
Mean Distance per Shift	226	211	km
Mean Charging Time per Shift	-	127.1	min

An electric vehicle agent uses about 22 % of its time for charging. This comes to an average charging time per shift of 127.1 min. The time for charging is mainly taken from previous waiting actions at taxi stands. CCS and Type 2 connector are almost equally in usage. The mean charging time at a CCS charging point is 65 min compared to 189.2 min for Type 2. Fig. 12 shows the number of charging taxis over the course of one week. The mean number is 38.2 with a minimum of 1 and a maximum of 115 charging vehicles at the same time. The average number of charging actions per vehicle is 0.86. 80 % of all vehicles charging only once within a shift.
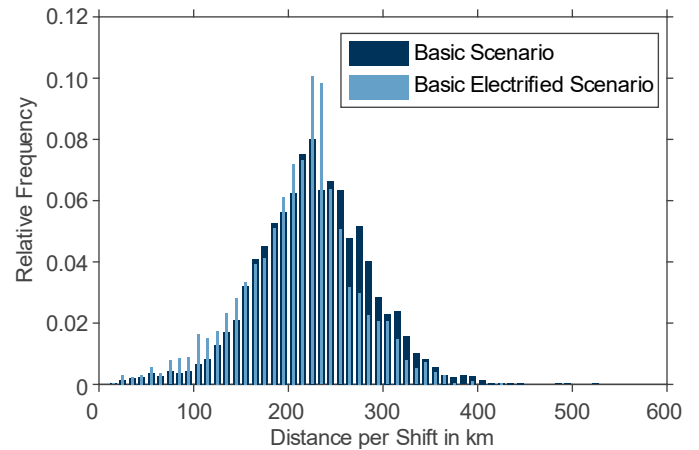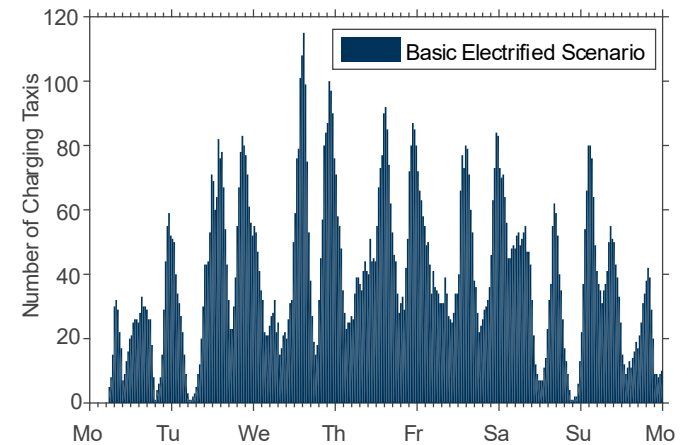

Fig. 11. Comparison of the distance per shift

Fig. 12. Course of charging vehicle over a week

VI. Conclusion

This paper presents a behavior model to describe the system dynamics of a taxi fleet. The simulation system supports decision-making in strategic, tactical and operational planning for on-demand mobility systems. Since such systems are complex, randomized and decentralized in nature, we have realized a stochastic-driven, agent-based approach.

The main benefit of the proposed architecture is its high flexibility due to a strong encapsulation between agents. Each agent has its own life-cycle and lives independently of others in a given environment. The entire fleet behavior is a result of a competition for limited resources. Taxis compete for new customer orders or infrastructure spaces in their environment.

As they have only restricted knowledge of the latest system state, interactions between agents or its environment get essential. Both the communication and the internal structure of each agent is realized as a finite state machine. The simulation core forms a discrete event approach.

Internal and external events trigger individual behaviors. The needed input is a stochastically distributed customer order stream, an infrastructure and fleet configuration, a fleet management strategy, a road network and a weather stream. Each simulation run generates data about use of the infrastructure, the temporal-spatial behavior of each agent and the mobility service quality.

Scenarios with a combustion engine and an electric taxi fleet provide evidence of the basic functionality. Results show that an electric taxi operation in Munich is possible with a powertrain designed for at least a 250 km range in real taxi usage.

The next steps are to include a roadside pickup model and evaluate further vehicle and dispatch strategies. It is a plan to evaluate different mobility concepts, such as shared, autonomous vehicle fleet.

Contributions

Benedikt Jäger (jaeger@ftm.mw.tum.de) was involved in all development stages, such as the requirement definition, system analysis, design, implementation and testing. He primarily developed the research question and the concept of the presented simulation model.

Michael Wittmann wrote his master thesis about an agent-based simulation for electric fleets at the Institute of Automotive Technology. He implemented the event based simulation core.

Fares Agua and Julian Renz included the JADE framework and performed simulation runs.

Markus Lienkamp made an essential contribution to the conception of the research project. He revised the paper critically for important intellectual content. Mr. Lienkamp gave final approval of the version to be published and agrees to all aspects of the work. As a guarantor, he accepts responsibility for the overall integrity of the paper.

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