Analyzing and Modeling a City's Spatiotemporal Taxi Supply and Demand: A Case Study for Munich

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Abstract—**This paper presents a method for studying supply and demand in a taxi network in time and space by using the example of Munich. First, we introduce the necessary data collection that is linked to a fleet management system (FMS) operated by a local taxi agency and create a statistically sound database, which represents the mobility behavior on a trip level. Second, we derive key figures describing the city's taxi characteristics. Here both the temporal taxi supply and demand of 420 taxis over a period of 19 weeks is considered. As the taxi demand differs according to the city district, the investigated area has to be divided into various zones. We analyze their specific characteristics and describe key factors influencing taxi requests, such as weekdays, public holidays and number of point of interests within an area. Next, a model to predict a time-variant demand for individual districts is introduced. We classify the problem and choose an appropriate algorithm to forecast spatiotemporal taxi requests. As booking actions differ over time, a nonhomogeneous Poisson distribution is suitable for counting those events. In a final step, we validate the proposed model on a local and global scale. Our model helps to provide a better understanding of taxi fleet operations on a city scale. We use the suggested demand prediction as one input parameter for an agent-based fleet simulation that represents individual taxi movements.**

Index Terms—**fleet analysis, fleet simulation, poisson model, taxi demand, intelligent vehicles, transportation**

I. Motivation

A process of radical change is taking place within the mobility sector. As we want to have a worthwhile future, we need to address various environmental and social challenges now [1]. Ongoing urbanization leads to a constant growth in the mobility demand in cities. Nevertheless, the existing traffic infrastructure has only limited resources. The increasing traffic cannot be absorbed to the same extent that an expansion of the infrastructure is possible, due to scarcity of space. This results in unavoidable traffic congestion with a rising number of traffic bottlenecks, especially in metropolitan areas.

At the same time, the higher number of vehicles causes additional environmental burdens in cities. This includes higher emissions of CO_2, nitrogen oxide and fine dust. Another issue is increased noise pollution [2].

Long term mobility strategies try to solve these issues by combining several solutions. One key idea is to reduce or even avoid motorized individual traffic. This can be realized by expanding (car) sharing concepts, which better utilizes the limited traffic infrastructure. Another approach is to shift the current traffic to environmentally-friendly means of transportation. In this context, electromobility is seen as a promising technology to eliminate the use of fossil fuels [3]. A further possibility is to expand advanced traffic management systems, thereby optimizing congested traffic situations [4].

In this paper, we will focus on a conventional taxi system, as it is a well-established mode of transportation. Taxis provide personalized, convenient and on-demand door-to-door service for their customers. Existing taxi systems are built on an equilibrium between supply and demand. According to the local authorities, the supply of vehicles may or may not be restricted by a limited number of licenses for taxis. The demand is primary affected by spatiotemporal customer requests. As long as supply and demand is close to its state of equilibrium, all parties concerned (taxi companies, taxi drivers and customers) can benefit. Seen from a customer's perspective, the waiting time for a taxi should be as short as possible. Otherwise, if we consider the taxi driver's point of view, the workload should be high. Therefore, the spatial and temporal taxi demand and supply must be matched in an ideal way.

This paper addresses two main issues. First we introduce a method to describe taxi system characteristics and second suggest, based on our findings, a novel approach to model the spatiotemporal taxi demand on a city district scale.

In Section 2, related work on the topic of modeling taxi systems is presented. Section 3 describes the process for acquiring floating car data (FCD) from a selected taxi fleet in Munich, Germany. Based on this data, common operational patterns are analyzed in Section 4. In Section 5 a forecast model that represents the spatiotemporal taxi demand on a district level is introduced. Section6 summarizes our findings and draws a final conclusion.

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II. Related Work

On a global scale, the research field of taxi systems can be divided into analysis, modeling and prediction.

A. Analysis

Bischoff [5] analyzes the mobility behavior of taxis for a week in Berlin using FCD. His investigation considers both, supply and demand. The findings show that the demand is characterized by recurrent patterns. On a regular weekday, demand peaks occur in the morning and late afternoon. At the weekend, the number of taxi requests increases at night.

Lee [6] investigates taxi pickup patterns for the Jeju area based on telematics data. Location recommendations for empty taxis are derived using a cluster algorithm.

Liu [7] introduces a density peaks clustering algorithm to detect hot spots in taxi demand from uncertain fleet data. The main focus is on fast and efficient computation.

Hu [8] explores activity patterns of taxi drivers for the city of Shenzhen. This includes an analysis on a temporal and spatial scale, such as passenger in vehicle time, taxi driver searching patterns and pickup and drop-off locations.

B. Modeling and Prediction

Using data mining algorithms, simulation models can be created that represent characteristic taxi system dynamics. This allows for a forecast of both supply and demand.

Salanova [9] gives a general overview about state-of-the-art modeling techniques to characterize taxi systems.

Gonzales [10] identifies parameters affecting the taxi demand in New York. To design an appropriate model, he derives influencing factors from mobility, demographic, socioeconomic and employment data. The taxi demand across time and space is estimated using a hybrid cross-classification as well as a regression model.

Li [11] proposes passenger-finding strategies focused on taxi drivers. A large scale taxi GPS dataset is used as input for the L1-Norm support vector machine, thereby achieving a prediction accuracy of 85.3% for passenger-finding strategies.

Tang [12] applies a DBSCAN algorithm on taxi GPS data to analyze taxi pick-up and drop-off locations. He also introduces a spatial interaction model to study common passenger searching behavior.

Shi [13] optimizes the relationship between passengers and taxis by maximizing the social welfare. In doing so, he studies the allocation of taxi system resources with help of a double-ended queueing system.

He [14] proposes a spatial equilibrium model to balance taxi demand and supply that is improved by emerging e-hailing applications.

Maciejewski [15] presents a large-scale microscopic taxi simulation based on the agent based framework MATSim.

Wong [16] presents an algorithm to predict vacant taxi movements searching for customers. For this purpose, he introduces a two-stage model. In a first step, taxi drivers choose an appropriate zone. This is followed by a second stage, in which the circulation time is specified.

Anwar [17] focuses on unmet taxi demand, which arises when the taxi demand exceeds the supply. For this purpose, Anwar proposes a heuristic algorithm that only uses the observed taxi demand. No information on passenger queue length or arrival rates is needed.

Yang [18] presents an equilibrium model to describe both searching and meeting strategies between customers and taxi drivers. It is assumed that drivers aim to maximize profits, whereas customers try to minimize the full trip price. Based on this, he derives a meeting function that fulfills a stationary competitive equilibrium.

Yuan [19] introduces a recommendation system for taxis drivers and customers. The taxi demand and the taxi driver behavior is extracted from historic GPS profiles. With the aid of a probabilistic model, a taxi driver may maximize his profit if he spends his idle time at an appropriate parking space.

Moreira-Matias [20] proposes a methodology to predict the passenger demand arising at taxi stands. The forecast algorithm is a combination of a time-varying Poisson model and an ARIMA model. With this approach, 78% of the taxi demand for the city of Porto can be forecasted within a 30-minute timeframe.

To best of our knowledge, there is a lack of research on spatiotemporal pickup events on a city district level that considers more than only customer requests occurring at taxi stands. It is this issue that we will be addressing in this publication.

III. Data Acquisition

As the mobility behavior of taxis in Munich should be analyzed, we first need to monitor selected taxi fleets. Then in a second step, the collected mobility information can be stored in a database.

A. Fleet Management System

In the taxi business, it is the taxi agencies that dispatch order requests to available taxis. For this purpose, each vehicle registers and sends status updates to a central control unit. Since each taxi is equipped with telematics hardware, the latest occupancy status and the GPS position is known. If a taxi is occupied, the place of departure and destination can be identified. An available taxi may wait at a taxi stand or drive around to find customers as quickly as possible.

In some cities, such as Porto [20], legal requirements also force taxi drivers to head towards appropriate taxi stands. In Munich, the city in our case study, it is up to the driver to decide on the best-matching passenger-finding strategy.

B. Data Acquisition and Storage

Before the mobility behavior can be analyzed, we first have to collect the necessary datasets with help of a local taxi agency.

To trace new data, a service sends a cyclic XML request to a FMS (Fig. 1). The FMS sends back an XML response that is parsed and inserted into a relational PostgreSQL database.

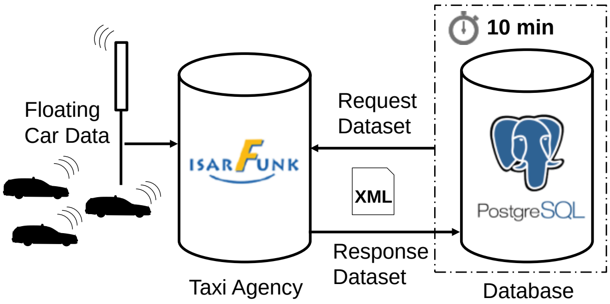

Figure 1. Data capturing architecture to a FMS system

Within the course of this study, data of a total of about 420 taxis over a period of 19 weeks (March to July 2015) was collected. This adds up to 2,122,592 trips and 81,978,033 trackpoints with a total distance of 9,969,366 km.

IV. Mobility Analysis of a Taxi Fleet Operation

In this section, the gathered taxi fleet data is analyzed from different perspectives. It is aimed to gain insight into typical taxi business operations for the city of Munich. In doing so, key figures are identified that provide a basis to validate taxi demand and mobility models in a later stage. We derive performance indicators to describe typical mobility characteristics as well as the temporal taxi supply and spatiotemporal taxi demand.

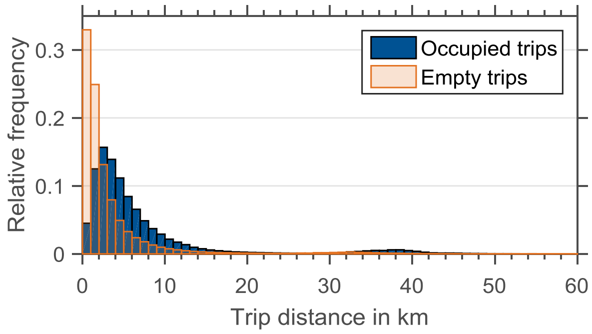

Figure 2. Trip distance differentiated by occupancy status

A. Overall Mobility Behavior

One of the most important figures used to describe the driving performance is trip distance (Fig. 2). In the given dataset, 73.7% of all trips are shorter than 5 km. The average trip length is 4.95 km with a standard deviation of 8.45 km. The visible rise between 30 km and 40 km can be explained by airport trips starting or returning to the city center. The distribution also shows that unoccupied trips (average trip distance 3.55 km, variance 1.61 km) are much shorter than trips with passengers (average trip distance 7.16 km, variance 4.29 km). This finding illustrates that taxi drivers in Munich commonly head towards taxi stands after dropping off a customer.

Fig. 3 depicts trip durations divided into shares with and without passengers. The average service duration is 14.77 minutes with a standard deviation of 12.56 min. Empty trips (including waiting and pause time) last 15.97 minutes on average with a standard deviation of 19.57 minutes.

Another relevant key figure for evaluating a taxi fleet system is the average utilization rate. Our analysis shows (Fig. 4) that a taxi is in unoccupied state for 59% of time on average.

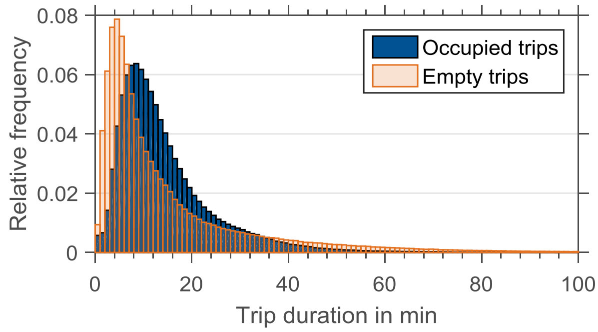

Figure 3. Trip duration differentiated by occupancy status

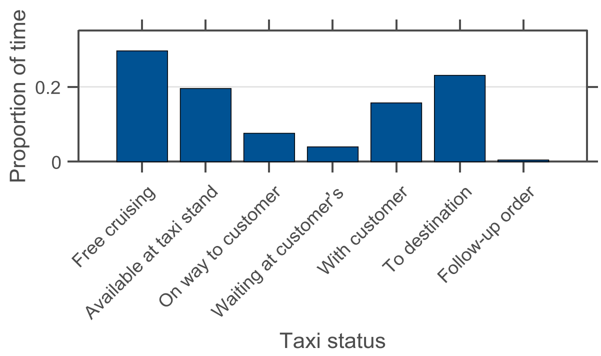

Figure 4. Relative temporal distribution of occupancy status

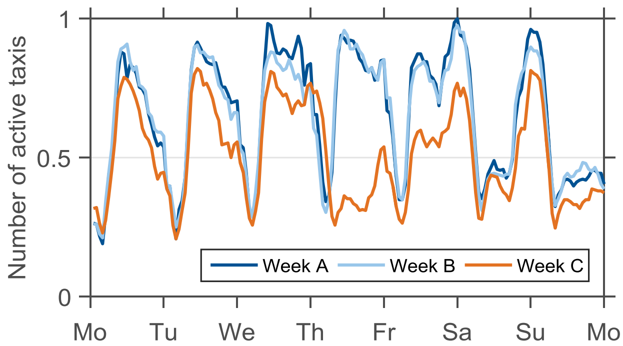

Figure 5. Normalized taxi supply for selected weeks

B. Taxi Supply

As the taxi system is a supply and demand system, it is important for taxi drivers and customers to keep both in balance.

If the taxi supply is low, customers may wait an unacceptable long time for taxi service. If the taxi supply is high, the utilization rate and earnings involved are low.

Fig. 5 shows the normalized taxi supply for three different weeks. It can be seen that the taxi supply follows a similar pattern, except for public holidays. From Monday to Thursday, the number of active taxis rises in the morning and reaches its peak at noon. On

Friday and Saturday, the taxi supply increases in the evening hours. This is traceable, since the demand peak is not created by business traffic, but instead by leisure traffic. If there is a public holiday (Thursday at Week C), the supply is different, often similar to a regular Sunday.

C. Spatiotemporal Taxi Demand

As a model for the local taxi demand should be construct, we have to investigate temporal and spatial patterns. In this section, the demand is examined from three different perspectives.

First, we analyze the number of weekly customer requests for the given taxi fleet. Second, we focus on local demand hot spots, and third, we investigate factors influencing the taxi demand.

1) Global temporal demand

Similar to the taxi supply, the global taxi demand shows repetitive patterns on a weekly timescale as long as there is not a public holiday during the week (Fig. 6).

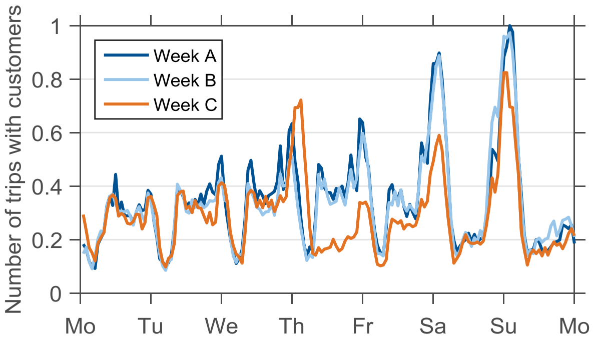

Figure 6. Normalized global taxi demand for selected weeks

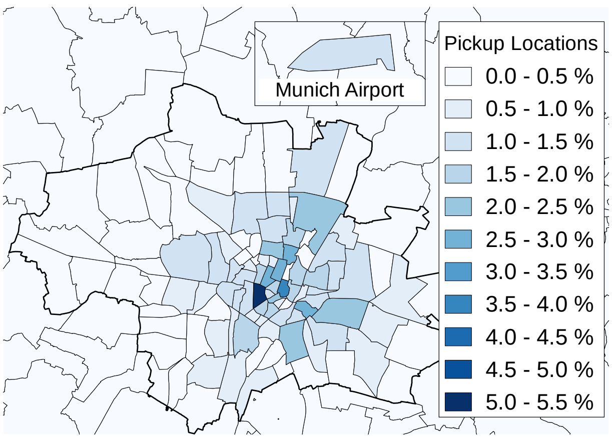

Figure 7. Spatial distribution of the trip departures for one day

During a regular week, the taxi demand is almost equal from Monday to Thursday. The lowest number of requests is made in the early morning hours. Daily demand peaks in the morning and in the afternoon are about half the size of the weekly demand maximum. As the taxi supply is about 80% to 90% on a common weekday, there is a strong competition between taxi drivers within this period. On weekends and public holidays, the demand during the daytime is at a low level. These characterized patterns can be explained by two different customer groups. On a weekday's morning, business persons mainly use taxis to get to their appointments and in the evening, ordinary people head out for home. The latter behavior becomes particularly evident on Friday and Saturday nights as well on nights before a public holiday. At those times, people end their leisure activities across the city and generate a taxi demand that reaches its peak late at night.

In order to understand and model taxi movements in a spatiotemporal perspective, it is essential to consider concrete pickup and drop-off locations. As an example, Fig. 7 depicts the relative pickup actions for one day. It clearly shows that customer pickup events are mainly concentrated in the city center and associated districts as well as the airport.

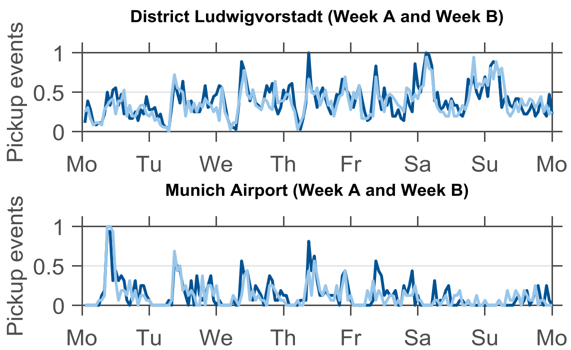

Figure 8. Normalized temporal taxi demand for selected districts

2) Local demand

One of our findings is that the number and time of taxi bookings depends on the chosen area. Fig. 8 shows the taxi demand at the airport and at a city center district. At the airport, there is a high taxi demand during the day, but between 11:30 pm and 6:00 am, requests decrease to nearly zero. This pattern is a result of the ban on night flights in Munich. In contrast, if we consider the city center district Ludwigvorstadt, a considerably different demand pattern is given.

Our analysis in Fig. 9 shows that it is not the population density that affects the taxi demand. Instead it is the number of points of interest, or more in general, the utilization mixture between work, living and leisure that mainly influences the taxi demand.

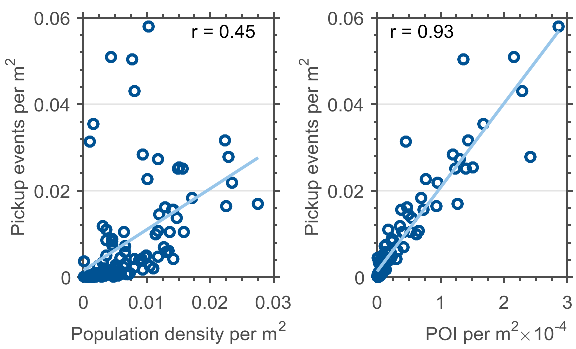

Figure 9. Linear regression model between departures and population density, respectively POI density

Another finding, we can conclude from our dataset, is that special events have a significant impact on the taxi demand. As an example during the annual Oktoberfest, the global taxi demand is exceedingly high and on the same level as normal peak demand on Friday or Saturday night.

V. Modeling the Spatiotemporal Taxi Demand

It is our aim to simulate movement patterns of all 3400 taxis in Munich. However the mobility data shown in chapter IV is based on a fleet of about 420 taxis. That's why we need to generate a synthetic but representative spatiotemporal demand model. In doing so, we assume that taxis have similar usage patterns as the analyzed ones.

A. Problem Classification

On an abstract level, the taxi demand can be considered as a sum of independent, physically separated, discrete events. Our key task is to predict the number of booking requests that arise in a certain time and space. Bungartz [21] and Fahrmeier [22] propose a Poisson distribution for this kind of event-based counting issue.

B. Nonhomogeneous Poisson Distribution

Before we apply a homogeneous Poisson distribution, we have to check if all requirements are met by our dataset. According to [22], the following assumptions must be valid:

- Two events cannot happen at the same time. This criterion is fulfilled if we choose a high temporal resolution.
- The probability that the event is happening within a short time period Δt is close to $\lambda\Delta t$. λ is the event rate. If we choose Δt small, the probability of occurrence is low. This requirement is met by our dataset.
- The number of events in two disjoint time periods is independent of each other. This is valid, as a booking request is a spontaneous event of an individual consumer and does not rely on other moments in time.
- The probability that an event is happening within a period of time is only dependent on its duration and not on the specific timeline. This requirement is not fulfilled by our dataset, as the taxi demand varies over the course of day.

To address the last issue, Scott [23] and Ihler [24] introduces a nonhomogeneous Poisson distribution, in which the degree of heterogeneity depends on $\lambda(t)$. Moreira-Matias [20] adopted this approach to predict the demand at taxi stands.

1) Concept

Our approach differs from [20] to that effect that we establish a demand prediction not only for single taxi stands, but for complete city districts. In doing so, we allocate demand requests to specific geographic locations over time. The idea is that the passenger demand is related to activities, which people perform within a certain area (see POI analysis). This allows us to represent the taxi demand on the spatial level more accurately. The division into zones is valid, since Poisson distributions mathematically satisfy the addition rule.

2) Design

Let X be the random variable to count the number of events happening within a certain time period within an area. If we assume a nonhomogeneous Poisson distribution, the probability function is:

$$f(x) = P(X = x) = \begin{cases} \frac{\lambda(t)^x}{x!} e^{-\lambda(t)}, x \in \mathbb{N}_0 \\ 0,\ else \end{cases} \tag{1}$$

For our use case, $\lambda(t)$ represents the time-variant demand rate within a district. As requests differ across the weekday as well as the time of day, the event rate has to be resolved on a closer level of detail. Scott [23] suggests a function:

$$\lambda(t) = \lambda_0 \delta_{d(t)} \eta_{d(t),h(t)} \tag{2}$$

Here, d(t) describes the day of the week and h(t) describes the temporal resolution within a day. Parameters δ and η must comply with restriction in eq. (3).

$$\sum_{i=1}^{w} \delta_i = w \ \wedge \ \sum_{i=1}^{D} \eta_{j,i} = D \ \forall j \tag{3}$$

In total, the event rate $\lambda(t)$ is composed of three different parameters, as illustrated in Fig. 10 and Fig. 11:

- λ_0 is the average rate of taxi demand events over a full week for the given area (w = 7).
- δ_i represents the day effect or the relative change for day i. For example, the taxi demand on Sunday is different from the one on Monday.
- $\eta_{j,i}$ considers the time of day effect or the relative change in time period i for a given day j. This takes into account demand peaks within a day. If we want to resolve the demand in one-hour time slides, D has to be set to 24.

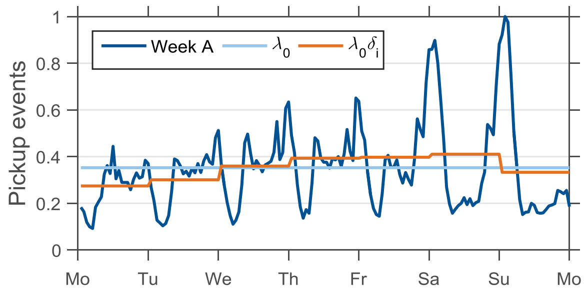

Figure 10. Variation of parameters λ_0 and δ_i over the course of a week

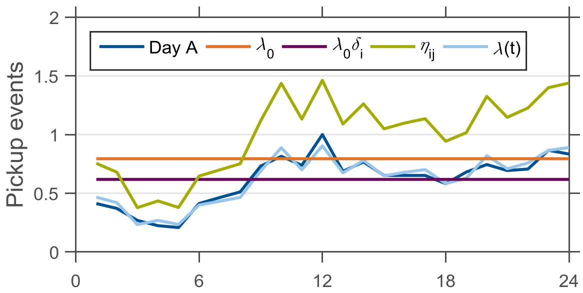

Figure 11. Hourly event rate λ(t) composed of λ_0, δ_i and $\eta_{(j,i)}$

The set of unknown parameters can be estimated with the aid of a prior probability distribution and a likelihood function. The latter function is derived from the previously assumed Poisson distribution. Using our collected mobility data, we create a posterior probability distribution and sample the unknown parameters. Details about the parameter identification procedure using the Markov Chain Monte Carlo method are described in [20].

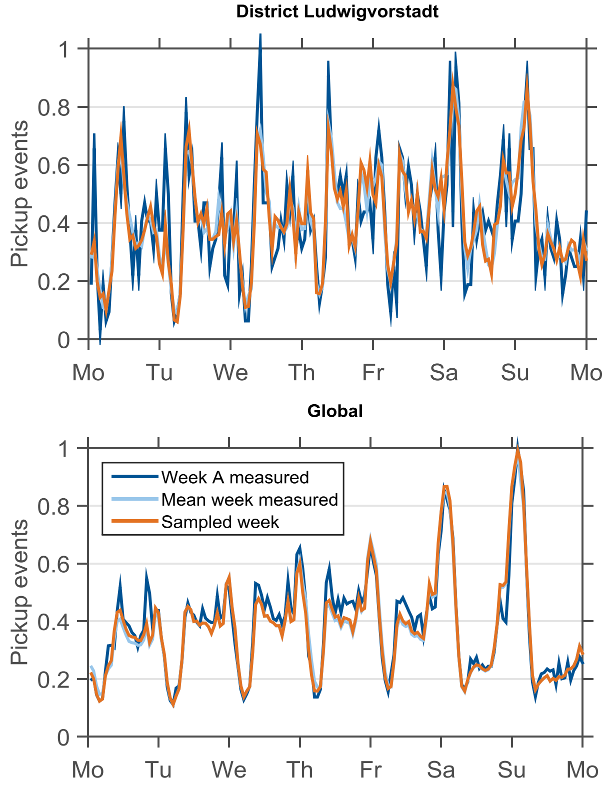

Figure 12. Comparison between tracked and predicted taxi demand

TABLE I. VALIDATION OF THE PROPOSED POISSON MODEL

Day of the week	Average Number of trips		
	Measured data	Predicted data	Error in %
Mo	4900	4907	0.2
Tu	5402	5445	0.8
We	5832	5830	0
Th	6132	6151	0.3
Fr	6404	6403	0
Sa	6645	6633	0.2
Su	5590	5591	0
Σ	40905	40960	0.1
Distance in 1000 km	292.8	295.5	1.0
Duration in 1000 h	10.0	10.1	1.2

C. Validation

In a final step, we validate our synthetic demand list against collected data on a city district and a global scale (Fig. 12). Table I compares mean values for the number of trips and the sum of both, the trip distance and duration for 10 iterations. In total, the daily and weekly demand events as well as mobility figures are represented with accuracy of about 0.1 % respectively 1.0 %.

VI. CONCLUSION

In this paper, a method to analyze taxi systems and a forecast model to predict the taxi demand is introduced. With regard to the first part, we present the underlying data collection by means of a fleet management system and analyze both, the temporal and spatial supply and demand patterns.

In the second part, a model to predict the taxi demand on a city district scale is suggested. We classify the problem and conclude that a nonhomogeneous Poisson distribution fulfills all requirements for forecasting pickup events. Our approach expands existing concepts to the effect that we predict the taxi demand on a city district scale. This is of special advantage for representing taxi requests on a detailed geographic origin-destination level.

In a final step, the presented model is validated by means of historic taxi bookings. The evaluation shows a high correlation between measured and predicted data.

For our particular use case, the taxi demand model will be used as input parameter for a demand-driven fleet simulation. Since both temporal and spatial patterns are represented by our model, we will put our future focus on optimizing future mobility-on-demand systems.

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He developed the research question and the presented method respectively concept. He defined the basic conditions and set the goals. Mr. J. had main influence on the requirements definition, the system analysis and design. He proofed the concept and confirmed all findings.

Michael Wittmann received his Master's degree from Technical University of Munich in mechanical engineering in 2015. He works at the Institute for Automotive Technology since November 2015 as an associated researcher in the field of Smart Mobility. Currently his research is focused on methods for large scale floating data analyses.

He wrote his Master thesis about a demand-driven agent simulation to investigate electrification potentials of vehicle fleets at the Institute of Automotive Technology. Mr. W. implemented the proposed data acquisition platform as well as the shown algorithm.

Markus Lienkamp is head of the Institute for Automotive Technology since 2009. After his study and PhD at the University of Darmstadt he joined VW, where he hold different positions from vehicle dynamics to department manager of electronics and vehicle research in the end.

He made an essential contribution to the conception of the research project. He revised the pater critically for important intellectual content. Mr. L. 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.