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Microscopic Demand Modeling of Urban and Regional Commercial Transport

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Abstract

Commercial transport is an intrinsic part of the evaluation of traffic volumes. However, it is often limited to freight transport, and while this is a significant element, it disregards the share of trips contributed by plumbers, electricians, care services, and the like. These businesses add a significant part to the commercial traffic volume, especially in urban areas. The reasons, commercial passenger transport lacks behind are wide-ranging, one of the leading causes being difficulties in gathering sufficient data.

In this paper, we present a microscopic approach to model commercial travel demand, including but not limited to freight traffic, based on data from a national survey and open data. We differentiate between vehicles of businesses that have a fixed daily schedule, with only small variations of their trip purposes and vehicles of businesses that can predict their daily schedules only to a certain degree. The latter have varying trip purposes and decide on a short-term base if and what sort of trip is to be pursued. Vehicles with fixed daily schedules include plumbers, electricians, care services, and delivery trucks. Due to our database, we produced a model for these vehicles exemplary for delivery by determining the number of trips for a day and assigning destinations to those trips afterward. We also take the number of private trips into account, laying the foundation of being able to incorporate the commercial transport model into a passenger transport model.

We show that our model can overcome the lack of regional data. Based on generic data, the application of our approach shows promising results for the urban and regional commercial travel demand of a model region. By basing our model on generic data, we introduced an opportunity to model commercial travel demand not only in one model region but also for other urban areas in Germany and possibly in various areas in Europe, assuming that structural data is similar.

Keywords: commercial transport; travel demand model; microscopic

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1. Introduction

Analyzing the total traffic volume of a region, commercial transport plays a significant role. However, while modeling passenger's travel demand has received much attention in the last decades, modeling commercial travel demand lacks behind. Furthermore, when commercial travel demand is modeled, it is often represented solely by freight transport [1]. This only accounts for part of the total commercial traffic volume, since in addition to cargo carriers also business trips and especially trips by plumbers, electricians, care services, and the like contribute to this traffic volume. In private travel demand models, these trips are often underrepresented due to missing empirical data. Additionally, they are often not modeled explicitly. That means that usually non-commercial trips are weighted or calibrated higher to compensate this lack of data.

Several studies show that the quota of commercial transport on the total traffic volume in urban areas is between 10 and 15%, with light vehicles making up 60% of those commercial trips [2, 3]. Considering that light vehicles rarely conduct deliveries of goods, the share of non-freight traffic is especially significant in urban areas. The underrepresentation of commercial travel demand models is mainly due to difficulties during the process of gathering information. Evidentially, people traveling a lot for business do not report all trips they take, and a correction factor of 2.0 needs to be applied to recorded commercial trips, meaning that every commercial trip reported by a person accounts for two commercial trips in reality [4]. Moreover, it is unfeasible to identify vehicles conducting commercial trips in traffic counts – specifically light vehicles – from measurements using conventional survey techniques like radar or induction. Even extensive video analysis can prove not to be beneficial, as a vehicle's appearance rarely displays information of the trip purpose. These challenges of gathering sufficient data constitute for the lack of appropriate demand models. However, using models to illustrate commercial vehicle movements makes it possible to account for all travel demand within a model and makes these models more sensitive to policy changes.

The scope of this paper is to demonstrate an approach to model all aspects of commercial transport including but not limited to freight transport based on generic data. The model suggested in this paper is based on an agent-based microscopic modeling approach. This method allows for high sensitivity towards policy changes in the model region. Furthermore, it allows for a possible combination with other microscopic models, i.e., microscopic private transport models and even land use models.

2. Literature Review

In literature, there are several studies presenting microscopic approaches to modeling commercial travel demand. However, only a few studies take commercial passenger travel demand into account while mostly freight transport is modeled since this is already a very complex system and requires the consideration of many factors such flow of goods, transport providers, and the production process. Schröder, Zilske et al. [5] have produced a multi-agent based freight model, in which they regard the shipper, the transport service provider, and the carrier by modeling each part as agents within the model. With their concept, they have laid a solid foundation for incorporating further transport users in a multi-agent simulation environment, which used to only take passenger transport into account.

Even though modeling freight transport is an intrinsic part of commercial travel demand modeling, it is essential to also take other commercial movements into account, especially in cities and metropolitan areas. The fact that commercial transport is often equated with freight transport shows that a definition is necessary before going into more detail on the matter. The authors define that the term commercial transport is not only applicable to freight transport but rather to all trips that have a business purpose.

Hunt and Stefan [6] have produced a microscopic commercial vehicle movement model for Calgary, Canada that focuses mainly on tour-based journeys meaning that every journey starts and ends at the same location with an iterated number of stops between the first and last trip. The proposed model consists of three individual sub-models, each representing a different type of movement pattern. These patterns are (1) internal-external movements, (2) fleet allocators, and (3) tour-based movements, with the primary focus put on the tour-based microsimulation. The data basis for the model was a survey conducted at about 3,100 business establishments within the Calgary area in which the participants were asked to provide detailed information on their trips, comparable to trip diaries. Based on the gathered data, the model first generates the number of tours for which then the primary purposes of the tours and vehicles are determined. Subsequently, the model generates start times for the tours. After these steps the iteration process starts, beginning with the purpose of the next stop. For this stop, the next location and duration are determined. This loop repeatedly iterates until the next stop purpose is “return-to-establishment”. With this trip, a tour is finished.

The disaggregate commercial model (DCM) by Gliebe et al. is another model to determine commercial movements within a metropolitan area [3]. This approach is very similar to the one described before. However, no duration of activity is determined. The model determines the utility of “staying” or “leaving” every 5 minutes. The sum of these 5-minutes-intervals is the duration of the relevant activity. The data basis of this model is also a survey conducted in the area, in which 562 establishments were surveyed.

There have also been approaches to macroscopically model commercial trips [7] as a whole. Machledt-Michael describes a trip-chaining model applicable to commercial vehicle movements. For this purpose, she began by determining homogenous groups of vehicle types through clustering methods. Through this method, she identified three Clusters: (1) passenger cars, vans, delivery trucks, motorcycles, and other motorized vehicles, (2) trucks including 7,5t and over, and semi-trailer trucks, and (3) construction vehicles. For each vehicle clusters, activity catalogs are saved. These catalogs are then used to choose an activity plan for a vehicle stochastically. During the next step, a business location is determined for each vehicle, after which the location for the specified activity is chosen. The trips are then temporally and also spatially distributed. In the last step, Machledt-Michael suggests performing impact analysis. This model approach is also based on a survey explicitly conducted to model commercial vehicle movements.

The presented models show many similarities, especially when comparing the models of Hunt and Stefan with the disaggregated commercial model by Gliebe et al. [3]. The models depicted above show that a sufficient data basis is necessary to model commercial transport accurately. However, in most cases, such data does usually not exist and has to be collected for this particular purpose. We try to close this gap by developing a microscopic travel demand model for urban and regional commercial traffic based on data from a nationwide survey and open source data (e.g., OpenStreetMap).

3. Model approach

The model approach we chose was based on the pattern of Hunt and Stefan [2, 6], respectively Gliebe et al. [3]. However, as mentioned above, the existing models all rely on data collected explicitly for the model. For our approach, we used a nationwide survey, which allowed us to design a spatially independent model. Furthermore, for the application of our data, we used OpenStreetMap data to determine the number of businesses, their economic sector, and estimation of employees. Based on this data, we were able to determine the vehicle fleet.

Data

The data base for the proposed modeling approach was the national survey “Kraftfahrzeugverkehr in Deutschland” (KiD), an excessive survey of over 70.000 vehicles [8]. The survey included both private and commercial trip purposes, although the priority was put on commercial movements. This survey included information on over 300 characteristics of the vehicles, their conducted trips, trip chains, and their geographical data. The survey participants, car owners, were polled randomly from the National Vehicle Register Germany, which results in a sample of vehicles that are spatially distributed all over Germany. The benefit of this sample is that models based on this data are applicable in different areas and are not limited to one specific region.

Although the survey included extensive information on many characteristics, the information on specific occupations of the vehicle owners is not as revealing as preferred and only a small number of specific professions is identifiable.

Model structure

The structure of our commercial travel demand model is illustrated in Fig. 1. The modeling process starts off the same for each vehicle. Based on land use and structural data, business establishments including the respective numbers of employees, industries, and vehicle fleets, are generated. The following steps are carried out depending on the specific way business establishments schedule the trips of their fleet. We distinguish between vehicles with a fixed daily schedule and vehicles with a flexible daily schedule. If the vehicles usually have the same purpose and pattern for all of their trips, we define those as vehicles with a fixed daily schedule. All other vehicles are defined as vehicles with a flexible daily schedule. This decision is influenced by many factors which need to be taken into account when modeling the vehicle's or driver's behavior.

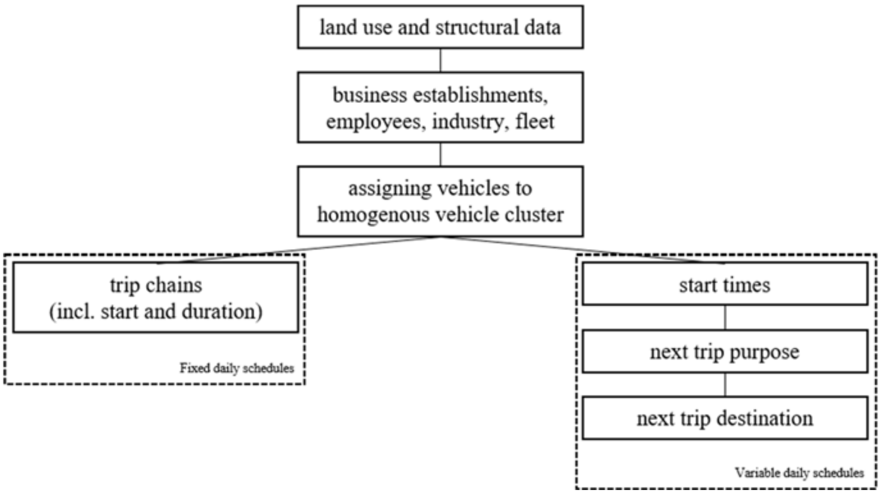

Fig. 1: Structure of the commercial transport model

Homogenous vehicle clusters

As mentioned above, with the given data structure and the included characteristics it is not possible to assign single vehicles to specific occupations. However, it is also not plausible to assume that one model will apply to every type of vehicle. For instance, trucks assumably show a very different kind of behavior than passenger cars, even if both are making commercial trips. Therefore, it is necessary to identify groups of vehicles that show similar movement patterns. As the data basis is very heterogeneous, applying clustering without prior preparation of the data proved not to be beneficial. Due to the heterogeneity of the data we first aggregated the vehicles based on their industry sectors. We differentiated nine vehicle types and 21 industry sector, resulting in 189 groups, which were then clustered. For this classification, we used a clustering approach, for which we initially chose linearly independent characteristics that best describe a vehicle's behavior: Number of trips, daily mileage, duration of trips, and start time of the first trip.

For these characteristics, a distance matrix was produced, which was used to apply the single-linkage approach to identify outliers. After removing those, we were able to apply the ward-clustering method to the adjusted distance matrix. The result of the clustering methods is a dendrogram, which is a graphical representation of the findings. This dendrogram was cut off at the 10th level, resulting in three general clusters, which fit for most of the vehicles and only few adjustments had to be made. The clusters we identified are:

- Light vehicles: Passenger vehicles, trucks (up to and including 3,5t) and others
- Medium vehicles: Trucks (over 3,5t) and Busses
- Heavy vehicles: Semi-trailer trucks.

Vehicles with fixed daily schedules

After the clustering, we modeled the travel patterns of the vehicles depending on the variability of their trips. There are certain occupations that allow for minimal variation in their daily schedules. These include, among others, delivery trucks, care services, pharmacy suppliers, and garbage trucks. The number of trips and the primary activity is given at the beginning of the day for all the listed occupations.

As mentioned before, it is only for very few occupations possible to identify them in the survey data, such as delivery trucks. Due to this limitation, we chose to carry out the part of the model for vehicles with fixed daily schedules exemplary for delivery trucks. For these vehicles, we generated their trips by subsetting the data to only include the trips of the determined vehicles. From these catalogs of trips, we stochastically polled trip chains and assigned them to the vehicles of the model area, including starting times and duration of activities.

For these vehicles, it is not necessary to determine a purpose for the individual trips. The purpose of delivery trucks is primarily the delivering of goods, except for the last trip which is the return-to-establishment trip.

After generating the trip chains of the vehicles, we assigned destinations to each trip. For this, we partitioned the model area and identified the location of the respective businesses. Next, we determined the number of vehicles of the businesses by analyzing aerial images, for which we then set the destination of the first trip by distributing the fleet of a business evenly among the area. The next destination of the next trip can then either be in the same travel demand zone or one of its adjacent zones. This way we ensure that the structure of the trips is close to the findings of the underlying survey. The survey data showed that delivery trucks have a specific pattern of movement: they first drive from their business establishment to the area in which they will deliver their goods. Within this area the make several trips of very short distance and duration. At the end of their shift, the drivers drive back to the business establishment, resulting in a longer trip.

Vehicles with variable daily schedules

For vehicles that do not have a fixed schedule at the start of the day, we needed to model the number of trips as well as the purpose of each trip. The way we represented travel behavior for those vehicles was first to determine if the respective driver makes another commercial trip, a private trip or the trip back to the business establishment. If the decision is to make another commercial trip, the purpose of this trip is then further specified. The model decides after every activity, if and what kind of trip is carried out further.

The trip purposes we used for the model were adopted from the data source and aggregated for private transport:

1. Picking up, delivering, transporting goods, products, machines, equipment
2. Trip to provide professional service (installation, reparation, consulting, visit, supervision)
3. Picking up, bringing, carriage of passengers
4. Other professional errands
5. Return to establishment
6. Private trip

By taking the total number of trips and the number of private trips into account and having private trips as a purpose option, our approach makes it possible to merge the presented commercial transport model with a passenger transport model. The latter takes commercial trips into account by aggregating them into one purpose. Combining the two models results in a model with a degree of detail that cannot be reached by regarding commercial trips through a single purpose. However, since passenger models are also based on data that in regard commercial trips as well, we need to remove specific trips from the passenger model to not over-represent commercial trips in the combined model.

Since these purposes form a discrete set of choice alternatives, we used a discrete choice model to determine the decisions made throughout the day. It is necessary to use a nested logit approach to comply with the independence of irrelevant alternatives.

We identified the influencing variables as the number of trips and the origin of the last stop. Based on these variables, we applied the following utility functions to the data set:

$$U_{c1} = ASC_{c1} + \sum_{i=1}^{n} \beta_{O_{n,1}} \cdot O_n \quad (1)$$

$$U_{c2} = ASC_{c2} + \sum_{i=1}^{n} \beta_{O_{n,2}} \cdot O_n \quad (2)$$

$$U_{c3} = ASC_{c3} + \sum_{i=1}^{n} \beta_{O_{n,3}} \cdot O_n \quad (3)$$

$$U_{c4} = ASC_{c4} + \sum_{i=1}^{n} \beta_{O_{n,4}} \cdot O_n \quad (4)$$

$$U_b = \beta_{cb} \cdot a_c + \beta_{a_{pb}} \cdot a_p \quad (5)$$

$$U_p = ASC_p + \beta_{a_{cp}} \cdot a_c + \beta_{a_{pp}} \cdot a_p \quad (6)$$

with:
ASC: alternative specific constant
O: Origin
n: Index identifying type of Origin
β: parameter to be estimated
a_p: number of private trips
a_c: number of commercial trips

The indices c1, c2, c3, and c4 are identical to the trip purposes mentioned above, while the index b is used for the trip purpose "return to establishment," and the index p indicates a private trip purpose. The types of origin were adapted from the data source:

1. Transition point (Station, harbor, etc.)
2. Construction site
3. Agricultural or forestry area
4. Personal establishment
5. External establishments industry/construction
6. External establishments commerce/service
7. External establishments other
8. Customer household
9. Other business origin

After estimating the parameters of the nested logit model for the mentioned utility functions, we applied them to the given data set. For this part, we distinguished between the clusters we determined before, meaning that we calculated and applied the parameters for heavy, medium, and light vehicles. The calculations of all models resulted in high ρ^2-values, verifying the quality of the models' adaptation.

Due to the lack of information about destination choice in the survey we used as a data basis, modeling the decision process has proven to be ineffective. This is because there is no information on alternative destinations and furthermore, to comply with the privacy policy of the respondents, all geographical information of origins and destination has been altered. Because of this, we decided to model the destination choice of each vehicle depending on the purpose of the trip and the economic sector of the vehicle. To do so, we created subsets of our data depending on the purpose of the trip and the economic sector. From these subsets, we were able to poll the land use at the destination stochastically. We categorized the land use into residential areas, industrial and commercial areas, areas of mixed usage, areas of special functional usage, and park- and farmland.

This allowed us to match the distribution of destinations in accordance with the underlying data. In this step, we also distinguished between the three homogenous vehicle clusters, as the choice of destination differs between the types of vehicles. Comparing the choice of destination of the three clusters, heavy and medium vehicles are more similar to each other than to light vehicles. While the latter are more prone to operate in residential areas, trucks are attracted by industry and commercial areas. This is reasonable since firstly, industry and commercial areas are build to accommodate for larger and heavier vehicles and secondly, customers making use of services offered by companies using heavier vehicles, are often businesses with their establishment located in industry or commercial areas. On the other hand, services offered by companies using lighter vehicles include care services, services offered by craftsmen or sales representatives. These are services often used by customers located in residential and mixed areas.

4. Results

We were able to apply our model to the region of Karlsruhe, Baden-Württemberg, Germany. We extracted the number of businesses in our model region from OpenStreetMaps. Using the provided attributes of OpenStreetMaps we determined the economic sector of the respective businesses. Within the model region, we identified 2.954 businesses. Based on the size of the respective business, we determined the number of employees. Based on the number of employees and the economic sector of a business, we used the nationwide survey KiD, described above, to

stochastically determine the vehicle fleet of each business. The number of vehicles was then adapted to fit the distribution of commercially registered vehicles in Karlsruhe. Using this approach, we were able to distribute the 28.077 commercially registered vehicles in Karlsruhe among the businesses. Furthermore, we determined the quota of active vehicles on a business day, again based on the KiD survey. 62.5% of vehicles of cluster 1 are active on a business day. Regarding vehicles of cluster 2, the quota is 66.0% and 62.5% of vehicles of cluster 3 are active on a business day.
In the following step, we applied our model to the vehicles, depending on whether or not these were delivery trucks. It should be noted, that as of now, our model only calculates internal traffic and originating traffic and disregards through traffic and destination traffic. Through this step, we obtained a list of trips for the commercial vehicles of the region. This allowed us to calculate the traffic volume within the region's network and therefore to compare our results to actual traffic counts. The values of the counting stations used for comparison are made available by the road traffic management center Baden-Württemberg [9]. The comparison of these results is shown in table 1. For this comparison, we are only taking heavy traffic into account, as these vehicles can be easily differentiated from light vehicles at the counting stations and moreover, are almost always commercial vehicles. The comparison of the counting values at the stations 1, 2, and 4 and the model values shows, that our model usually results in higher traffic counts, although they are generally on the same scale. These are counting stations at roads that are less affected by through traffic, meaning that the results can be directly compared. However, the fact that the model values are higher by 20 to 30% can be explained by the fact that we did not consider any private traffic in the assignment. As a consequence, the major routes were more attractive due to the lower travel times. At counting station 3, the values are much higher than the model values. This can be explained by the fact, that this road is heavily affected by through traffic in reality, especially of heavy vehicles.

Table 1: Comparison of counting values and model values

Counting station	Counting value [vehicles/24 h]	Model value [vehicles/24h]
1 (L560)	487	583
2 (L605)	223	302
3 (B36)	1.541	318
4 (B10)	949	1.230

5. Conclusion

In this paper, we introduced a microscopic approach to model commercial transport demand. Using cluster analysis, it was possible for us to prove a connection between the type of vehicle used and their behavior, regardless of the industry sector to which the vehicle is assigned. The data, on which the model was based, also allowed for the determination of model parameters that are independent of specific regional areas. If the model was only based on survey data from a spatially limited region, those parameters could only be applied to this specific region meaning that the model could not be applied in other regions.

Our approach allows us to eventually merge this microscopic commercial transport model with a microscopic passenger model, as we take previous private trips into account and model private purposes. This means that once we combine the two approaches, we will have a much more detailed model of a region as commercial trips have specific purposes and are no longer aggregated to a general trip purpose.

Combining this microscopic commercial transport model with a land-use model allows for modeling several scenarios, but also to build a model that dynamically adapts to changing situations in the respective areas. If e.g., a city is developing a new residential area, this area will attract much commercial traffic during construction, such as construction workers and deliveries of building materials. Once the residents have moved in and the area is populated, the commercial travel demand will lessen by a great margin.

The application of our model shows results within the range of actual values. This means that our model can be applied independent of a specific region, making it applicable in multiple regions of Germany and Europe, since we can assume that the structural data in these areas are similar to those we used in the presented model. Our results also show that the commercial travel demand model can be established solely based on generic data. However, there are still adjustments to be made. A calibration of the model is inevitable to sufficiently prove the quality of the model, and even though our model is based on generic data, in this step we certainly need local data, such as trip diaries or business establishment surveys. This is especially important when trying to identify light commercial vehicles, as they cannot be detected by generic measurements and surveys. Yet, the approach we propose as a whole is still less costly than models completely based on regional specific data, as the data needed for calibration can be less extensive than data necessary for both modeling and calibration.

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